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The Financial Industry 4.0

Edited by
Thanh Ngo, Dominique Guégan, Dinh Tri Vo,
Aviral Kumar Tiwari and Tu Le

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Thanh Ngo
Dominique Guégan
Dinh Tri Vo
Aviral Kumar Tiwari
Tu Le

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Editors
Thanh Ngo
Massey University
New Zealand

Dominique Guégan
IPAG Business School
France

Dinh Tri Vo
IPAG Business School
France

Aviral Kumar Tiwari
Indian Institute of Management
India

Tu Le
Vietnam National University
Vietnam

Editorial Office
MDPI
St. Alban-Anlage 66
4052 Basel, Switzerland

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About the Editors

Thanh Ngo

Thanh Ngo is a Senior Lecturer at School of Aviation, Massey University, New Zealand. His works involve efficiency and productivity analysis in banking and finance, sustainability, agriculture and manufacturing sectors, aviation, and transportation economics. Dr. Ngo's research papers have been published in Transportation Research Part A, Annals of Operations Research, Transport Policy, Business Strategy and the Environment, and International Journal of Managerial Finance, among others. He is currently a member of the Editorial Board of International Journal of Financial Studies (MDPI) and an Associate Editor for Asian Economic and Financial Review (AESS).

Dominique Guégan

Dominique Guégan is Emeritus Professor at the University Paris 1 Panthéon-Sorbonne. Her domains of expertise are Risk measures in finance, Financial Regulation, Deterministic dynamical systems, Nonlinear time series, Nonparametric statistics, Contagion and Systemic risks, Extreme value theory, and Fintech technology. She belongs to the LaBex "Financial Regulation", through the Finance team of the University Paris 1—CES and she is affiliated to the Financial Engineering Department inside NYU (New York, USA) and to the IPAG Business School (Paris and Nice, France). She has supervised 37 PhD and published 10 books, 110 academic papers and 30 book chapters. She also participates to several international projects supported by Governments or supra-national bodies, and she is regularly invited in the most well-known universities in Europe, USA, Australia, and Asia.

Dinh Tri Vo

Dinh Tri Vo is an Associate Professor at IPAG Business School, Paris. He received his MSc. in Management from the CNAM and his Ph.D. degree in Management Science (Finance & Insurance) from Paris Saclay University, France. He teaches finance and banking courses such as Financial Analysis, Financial Markets, and Global Banking and Financial Regulation, in both the "Grande Ecole" and dual degree programs (IPAG-Greenwich MSc. International Banking and Finance). His main research interests are insurance markets, impact investing, and sustainable finance. Besides teaching and research, he has consulting activities and publishes commentaries in some magazines and newspapers.

Aviral Kumar Tiwari

Aviral Kumar Tiwari is an Assistant Professor of Economics at the Indian Institute of Management Bodh Gaya (IIMBG) in the Department of Economics and Business Environment. Prof. Tiwari is a C-EENRG fellow at the Department of Land Economy (University of Cambridge) and a Research Fellows at University of Economics Ho Chi Minh City, Vietnam. Prior to joining IIMBG, he worked as Associate Professor at Rajagiri Business School (RBS), India and Montpellier Business School (MBS), Montpellier, France from where he received his post-doc as well. After graduating with a degree in Economics from Lucknow University, Lucknow, India, he received his M.Phil. (in Labour Economics) and Ph.D. (in Energy and Environment) from ICFAI University Tripura. He is basically an applied economist with broad empirical interests with a focus on but not limited to emerging economies in particular Asia. His research interests focus on various issues concerning energy, environment, tourism, macroeconomy and growth & development etc. He has published widely in peer-reviewed international journals and contributed more than 100 ABDC-A &A* research papers so far. He is the only Economist included from India in the career ranking of World's top 2% scientists list of 2021 published by Stanford University Study. He is ranked at first position in India as a researcher by IDEAS. He is one of the Highly Cited Researcher 2020 by Clarivate™ of Web of Science™. He is one of the recipients of M J Manohar Rao Award (for young econometrician) for 2014 from The Indian Econometric Society, 2015. He is Life member, Indian Economic Association (India) and member at several other international associations such as International Association for Energy Economics (IAEE), USA, Association for Comparative Economic Studies, USA, Western Economic Association International, USA etc. He holds different editorial positions at more than 10 journals of international repute (ABDC, Scopus and ABS indexed journals).

Tu Le

Tu Le is a researcher at the Institute for Development & Research in Banking Technology, University of Economics and Law, Vietnam. His works focus on efficiency and productivity measurement in the field of banking and finance, and the industry sector, and the impact of e-commerce on economic growth, and Fintech. His recent papers have been published in Annals of Operations Research, International Journal of Managerial Finance, Managerial Finance, Post-Communist Economies, Central Bank Review, and Review of Economic Analysis. He is also a member of the reviewer board in several journals including Journal of Risk and Financial Management, Journal of Economics, Finance and Administrative Science, Journal of Asian Business and Economic Studies, and so on.

Preface to "The Financial Industry 4.0"

Technology has been introducing and enabling new paradigms in different industries. In the financial sector, the rapid growth of technology-based financial firms (e.g., Fintech and InsurTech) has put incumbent financial institutions (e.g., banking, insurance, and credit institutions) under pressure to transform their business strategies and operations to cope with these changes. The main emphasis of this book is on The Financial Industry 4.0 to provide insightful understanding about the benefits as well as the challenges that financial institutions are facing.

We extend our thanks to the authors of the book's chapters for their dedicated efforts in delving into the presented topics. We appreciate the time and effort they invested in exploring the presented topics, and we trust that their work will enhance our comprehension of the financial sector under the emerge of the Industry 4.0.

Thanh Ngo, Dominique Guégan, Dinh Tri Vo, Aviral Kumar Tiwari, and Tu Le
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Article

The Role of Betting on Digital Credit Repayment, Coping Mechanisms and Welfare Outcomes: Evidence from Kenya

Richard Chamboko [1,2,*] and Sevias Guvuriro [3]

1 International Finance Corporation, World Bank Group, Washington, DC 20433, USA
2 Institute for Intelligent Systems, University of Johannesburg, Johannesburg 2092, South Africa
3 Department of Economics and Finance, University of the Free State, Bloemfontein 9301, South Africa; guvuriros@ufs.ac.za
* Correspondence: richardchamboko@gmail.com

Abstract: Digital financial services and more importantly, mobile money, have become an important financial innovation to advance financial inclusion in developing and emerging economies. While digital financial services have improved the lives of many Kenyans, to the growing betting segment of the Kenyan population, these innovations have also brought great convenience to betting. The innovations have allowed easy access to digital credit which can be used for betting. Despite betting or gambling being a widely studied area, particularly in developed countries, little is known about its interaction with financial innovations such as digital financial services in developing and emerging economies. Using data from a 2017 digital credit survey in Kenya, this study investigates if bettors are more likely than non-bettors to be financially distressed or engage in welfare-undermining coping strategies and potentially experience inferior welfare outcomes. The study uses a representative sample of 1040 digital borrowers, of which 304 were digital bettors. Using multivariate logistic regressions, the study found that, after controlling for socio-economic and demographic factors, bettors are significantly more likely than non-bettors to be financially distressed, engage in welfare undermining coping strategies, and have inferior welfare outcomes.

Keywords: digital financial services; digital credit; betting; financial distress; coping strategies; welfare outcomes

JEL Classification: D60; E42; E51; G23; G29; O12; O33

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1. Introduction

Digital financial services, and more importantly mobile money, have become an important financial innovation to advance financial inclusion in developing and emerging economies. The advent of digital financial services has provided those who are marginalized, traditionally financially excluded, and occupying the lower rungs of a socio-economic status ladder, with an opportunity to partake in the formal financial system. Increased financial inclusion has become possible due to deliberate policy interventions, the growing availability of mobile phones (including smartphones), and internet connectivity in developing and emerging economies (Chamboko et al. 2018). Individuals can remotely access financial services through their phones and hence enjoy improved convenience, improved accessibility, and reduced costs of using financial services (Chamboko et al. 2020).

A growing body of literature also reports a positive and significant impact of digital financial services on household welfare outcomes. Digital financial services facilitate a stable path of consumption amidst financial and income shocks (Suri and Jack 2016) and increase per capita consumption levels, thereby reducing poverty levels in the long run (Munyegera and Matsumoto 2016; Suri and Jack 2016). Wieser et al. (2019) show that digital financial services increase the likelihood of poor rural households to send and receive peer-to-peer cash transfers, reduce the cost of remittances, reduce food insecurity, and increase non-farm self-employment. Msulwa et al. (2020) also show that access to formal financial services such as savings, credit, and insurance has a positive and significant impact on consumers' asset holding.

In the Kenyan financial market, the availability of financial services through mobile money services is widely celebrated as it has led to the growth of financial inclusion from 26.7% (2006) to 82.9% (2019) (Central Bank of Kenya et al. 2019). With increased access to digital credit in Kenya, consumers can conveniently access loans on their digital platforms, particularly mobile phones, and can use the same channels to make payments and store value. About thirty-four percent of the mobile-phone-owning Kenyan adult population (77% of the adult population) had once taken a loan through a mobile phone (Gubbins and Totolo 2018). Importantly, the number of digital loans has surpassed that of traditional loans at a ratio of about 10:1 by 2018 (MicroSave Consulting 2019).

While digital financial services have improved the lives of Kenyans, the rise in digital credit provisioning has nonetheless facilitated access to cash that can be used for betting. Gambling in Kenya takes on various forms, including sports betting (e.g., SportPesa, Betin, and Betway), casinos, pool games, bingo, phone-in-talk shows, scratch cards, and lotteries. The most common are sports betting, where bettors wager money on an outcome of an uncertain sports event with the hope of winning more money (Prasad and Jiriwal 2019; Williams et al. 2017). King et al. (2014); Gainsbury et al. (2013) and Gainsbury et al. (2012) pointed out that increased access to mobile devices (smartphones and tablets) has made some gambling activities an "anytime, anywhere" activity. A GeoPoll survey shows a startling prevalence of betting in Kenya, estimating that about 57% of the adult population (above 16 years) have participated in betting in the past, with a high prevalence among smartphone owners (Roxana 2019). Kisambe (2017) reports that Kenya (76%) leads in Sub-Saharan Africa in terms of youth gamblers, and among these youth gamblers, 96% use their mobile phones. The Kenyan FinAccess Household Survey of 2019 reports a conservative 1.9% prevalence of self-reported betting activities among mobile money users in Kenya. It is however important to highlight that the FinAccess survey could be understating the betting level in Kenya since it is an adult survey, which does not report underage bettors. In addition, the 2019 FinAccess Household Survey shows that among those who indulge in betting, 22.6% bet daily, 51.7% bet weekly, 6.9% bet monthly, and 17.1% bet intermittently, especially when there are big prizes to be won. Furthermore, close to 20% of the Kenyan adult population holds the opinion that betting is a good source of income (Central Bank of Kenya et al. 2019), and Schmidt (2020) reports that many Kenyans see gambling as a legitimate activity to earn a living in an economy unresponsive to their employment demands.

The Kenyan government recognizes the potential danger that is posed by gambling in an inadequately regulated environment. The growing prevalence of betting and more so the frequency of betting among bettors can potentially have harmful effects. The government of Kenya has recently raised taxes for betting, lottery, and gaming and for companies running prize competitions from around 10% to 20%, but this has faced resistance, resulting in some of the major companies in this business closing their operations in Kenya. Continued pressure on the government resulted in outright cancellation of the tax as gazetted and signed in the 2020 Finance Bill (iGaming Business 2020).

Despite gambling in general being a widely studied area, particularly in developed countries, little is known about betting, an activity gamblers engage in, and its interaction with financial innovations such as digital financial services, especially in developing and emerging economies. This study thus contributes to the literature by exploring the role of betting on digital credit repayment, coping mechanisms, and welfare outcomes in Kenya (a digitized African society). We first investigate if bettors are more likely to be financially distressed as illustrated by late repayments, having multiple loans due, failing to make all payments, and receiving reminders to repay loans. Secondly, we evaluate the possibility of bettors engaging in welfare-undermining coping strategies such as the selling of assets and borrowing to repay loans. Finally, we investigate the potential impact of betting on food and medical uptake by bettors. As far as our search is concerned, this is the first peer-reviewed paper to study the relationships between digital financial services, betting, and welfare outcomes in the form of foregoing food and medical uptake in a developing country setting.

The rest of the paper is structured as follows. Section 2 provides brief literature on gambling and new financial technology. Section 3 discusses the data and measurements and methods employed in this paper, whilst Section 4 presents results and discusses the findings of the study. Section 5 concludes.

2. Gambling and New Financial Technology

Two important theories are key in explaining gambling, i.e., the theory of planned behavior (Ajzen 2011; McEachan et al. 2011) and the habitual behavior theory (Van Rooij et al. 2017). The intention to engage in a behavior (gambling) depends on beliefs about and attitudes towards the behavior, perceived social and subjective norms surrounding the behavior, and the extent to which people perceive to have behavioral control over their own behavior (Van Rooij et al. 2017). With new financial technology that is accessible with any mobile phone, behavioral intentions and actual behavior in gambling are brought close to each other. Moreover, Van Rooij et al. (2017) argue that with online gambling, the thresholds for digitally accessing content are very low and costs of initiation quite low, so the role of habitual behavior hypothetically becomes larger.

As the literature suggests, gambling has undesirable and unavoidable effects. It is addictive and becomes compulsive. Compulsiveness is explained by both the strength model (Baumeister et al. 2007) and the process model (Inzlicht et al. 2014), leading to impulsive choices being pursued. In Kenya, the absence of regulations that, for instance, allow gamblers to impose time limits, spending limits, and placing themselves in exclusion limits paves the way for this compulsiveness. Gambling is also associated with a greater degree of delay discounting i.e., growing impatience, especially as the gambling habit becomes strong (Orford 2011). Self-control and exercise of willpower are overridden. In fact, the capacity to favor abstract and distal goals when they are threatened by competing concrete and proximal goals (Baumeister et al. 2007; Fujita 2011) diminishes in compulsive gambling. Gambling effects are substantial in digital gambling because the breadth involvement and depth involvement (LaPlante et al. 2014) are quite high due to the accessibility of the addictive object. In other words, the gambler has access to gambling opportunities on the device readily available, allowing for between-session and within-session chasing of gambling (Nigro et al. 2019; Sacco et al. 2011).

Brevers et al. (2018) discuss satisfaction derived by gamblers from online gambling, now with new financial technology as ready-to-consume rewards redefining humans' self-control abilities. However, rewards from gambling are very unlikely, such that Jerome Cardano (1525) wrote "... The greatest advantage of gambling comes from not playing at all. There are so many difficulties and so many possibilities of loss that there is nothing better than not to play at all" (cited in Orford 2011, p. 50). Clinical case studies across the world, surveys of Gamblers Anonymous members, and in-depth interview studies suggest "indebtedness, stealing, deceiving and lying, arguments, violence and the breakdown of relationships, as well as personal depression and suicidal feelings" (Orford 2011) as some of the effects of gambling. Håkansson and Widinghoff (2020) find that over-indebtedness is associated with combined online casino gambling and sports betting, expected over-indebtedness is associated with online gambling, and problem gambling is associated with a history of having borrowed money for gambling. Problem gambling also leads to psychological distress via a direct pathway, i.e., problem gambling is included as a predictor in the model, and via an indirect pathway, i.e., debts accumulated as a result of problem gambling drive psychological distress (Oksanen et al. 2018). Thus, the spread of digital gambling in Kenya, a developing economy with a youthful and mostly unemployed population and a non-banking adult population in need of financial inclusion, is an issue that requires policy intervention. Hence this paper's aim to explore the potential role of betting on financial distress, coping strategies, and the welfare of bettors.

3. Data and Methods

This study employs data from a Kenyan nationally representative digital credit survey conducted in 2017. The sample constitutes 3130 participants among Kenyan mobile phone users. The data are the property of the Central Bank of Kenya, Kenya National Bureau of Statistics, and Financial Sector Deepening Kenya, and the authors obtained permission to use the data for this study. Since the survey was conducted telephonically, the sample was drawn from mobile phone users in Kenya and was weighted to be representative of mobile phone owners in the country. Given that one can only use digital credit when one has access to a mobile phone, the subsample that reported to have used digital credit can be considered as representative of digital credit borrowers in the country. Out of the total sample (3130), about a third (1040) reported that they are digital credit users, and about 29% (304) of these digital credit users were identified as bettors. The key questions in the instrument that enabled us to assess the likelihood of being financially distressed included whether the participant was ever late in repaying a loan they took from the mobile phone, whether they received an SMS from the lender as a reminder for repayment on an overdue balance, and whether they were ever in a situation when payments were due on multiple loans at the same time and could not make all payments. For the welfare-undermining coping strategies, information on whether participants had to sell assets to pay loans or borrow to repay loans was gathered. Welfare outcomes included going without food or without medicine or medication that was needed.

Descriptive statistics are used in understanding the sample studied and the occurrence of betting and loan repayment behavior. The Chi-square test for association is used to ascertain if there is a relationship between the outcome variables and explanatory variables without controlling for other factors (Chamboko et al. 2017). Univariate logistic regression is used to determine if there is a relationship between the outcome variables and the individual explanatory variables. Further, multivariate logistic regression is used to check for an association between betting and the outcomes variables (proxy measures of financial distress, undesirable coping strategies, and welfare outcomes), controlling for education, age, gender, locality, and income. For the multivariate analysis component, the following specifications are implemented using the binary logistic regressions:

$$\begin{aligned} LatePayment_i \;&=\; \beta_0+\beta_1 Bettor_i+\beta_2 Agegroup_i+\;\beta_3 Gender_i+\beta_4 Education_i \\ &\quad +\beta_5 Locality_i+\beta_6 Incomegroup_i+\;\varepsilon_i \end{aligned}$$

$$\begin{aligned} ReceivedSMS_i \;&=\; \beta_0+\beta_1 Bettor_i+\beta_2 Agegroup_i+\;\beta_3 Gender_i+\beta_4 Education_i \\ &\quad +\beta_5 Locality_i+\beta_6 Incomegroup_i+\;\varepsilon_i \end{aligned}$$

$$\begin{aligned} MultipleLoans_i \;&=\; \beta_0+\beta_1 Bettor_i+\beta_2 Agegroup_i+\;\beta_3 Gender_i+\beta_4 Education_i \\ &\quad +\beta_5 Locality_i+\beta_6 Incomegroup_i+\;\varepsilon_i \end{aligned}$$

$$\begin{aligned} SoldAssets_i \;&=\; \beta_0+\beta_1 Bettor_i+\beta_2 Agegroup_i+\;\beta_3 Gender_i+\beta_4 Education_i \\ &\quad +\beta_5 Locality_i+\beta_6 Incomegroup_i+\;\varepsilon_i \end{aligned}$$

$$\begin{aligned} BorrowToPay_i \;&=\; \beta_0+\beta_1 Bettor_i+\beta_2 Agegroup_i+\;\beta_3 Gender_i+\beta_4 Education_i \\ &\quad +\beta_5 Locality_i+\beta_6 Incomegroup_i+\;\varepsilon_i \end{aligned}$$

$$\begin{aligned} WithoutFood_i \;&=\; \beta_0+\beta_1 Bettor_i+\beta_2 Agegroup_i+\;\beta_3 Gender_i+\beta_4 Education_i \\ &\quad +\beta_5 Locality_i+\beta_6 Incomegroup_i+\;\varepsilon_i \end{aligned}$$

$$\begin{aligned} WithoutMeds_i \;&=\; \beta_0+\beta_1 Bettor_i+\beta_2 Agegroup_i+\;\beta_3 Gender_i+\beta_4 Education_i \\ &\quad +\beta_5 Locality_i+\beta_6 Incomegroup_i+\;\varepsilon_i \end{aligned}$$

where the main explanatory variable *bettor* is a binary (Yes/No) derived from a survey question "Have you tried any of the digital betting services?". A more detailed description of the other covariates in the models is provided in Table 1.

Table 1. Bivariate relationship between betting and socio-demographic variables.

Variable	Sample	Bettor (Yes)	Bettor (No)	Chi-Square	*p*-Value
Gender	n = 1040				
Male	55%	39.43	60.57	46.0114	0.000
Female	45%	20.25	79.75		
Locality	n = 1040				
Urban	49%	29.62	70.38	0.9895	0.320
Rural	51%	26.70	73.30		
Education	n = 1040				
None-primary	28%	27.56	72.44	47.4835	0.000
Secondary	46%	18.57	81.43		
Tertiary	26%	44.53	55.47		
Age group	n = 1040				
16–25	15%	35.81	64.19	41.0758	0.000
26–35	42%	21.86	78.14		
36–45	27%	39.86	60.14		
46–55	10%	13.01	86.99		
56+	6%	23.33	76.67		
Income group	n = 1040				
0–10,000	59%	26.63	73.37	6.6618	0.083
10,001–20,000	22%	32.06	67.94		
20,001–40,000	13%	35.43	64.57		
40,001+	6%	37.14	62.86		

The outcomes variables are derived from the survey questions and are defined as follows:

LatePayment: Have you ever been late in repaying a loan that you took from your phone?
ReceivedSMS: Received SMS from the lender to encourage repayment on your overdue balance?
MultipleLoans: Have you ever been in a situation when payments were due on multiple loans at the same time and you could not make all payments?
SoldAssest: Sold assets or belongings to pay loan?
BorrowToPay: Borrowed to pay loan?
WithoutFood: In the last 12 months, how often have (you) or your family gone without enough food to eat?
WithoutMeds: In the last 12 months, how often have (you) or your family gone without medicine or medical treatment that was needed?

The welfare variables *WithoutFood* and *WithoutMeds* required respondents to indicate the frequency at which they experienced the situations. Four options were provided, and from these, a binary variable indicating whether or not the person experienced the situation was constructed. All responses given as "often; sometimes or rarely" equal 1, and "never" equal 0.

4. Results and Discussion

As shown in Table 1, fifty-five percent of the participants were males, and 51% lived in rural areas. About 28% had primary or no formal education, 46% had secondary education, and 26% had tertiary education. Middle-aged people (26–45 years) dominated the sample (69%), while the remaining 31% was shared almost equally between those under 26 years and those above 45 years of age. In terms of income, more than half (59%) of the sample earned 10,000 shillings or less (1 US \$ $\approx$ 108 Kenyan shillings), 22% earned 10,001–20,000 shillings, 13% earned 20,001–40,000 shillings, and 7% earns 40,000 shillings or more. Table 1 also shows significant variation of betting by participants' gender, education, age, and income group (Chi-square tests). About 39% of males and 20% of females were bettors. Almost half of those with tertiary education, about a fifth of those with secondary school, and almost a third of those with primary or no formal education were bettors, a pattern that suggests that betting is common among educated adults. Except for those in the age range of 46–55 years, for all other age categories, more than a fifth of the participants were bettors, and more than a quarter of each income group reported betting. Schmidt (2019, 2020) emphasized that gambling in Kenya is viewed as a legitimate and transparent way of earning a living and is motivated by limited employment and income-earning opportunities, but it is also viewed as a future-income-earning opportunity, especially among the affluent. These are all possible explanations why betting is high among the educated, as well as young and middle-aged adults, and cuts across all income groups.

The bivariate relationships between betting and financial distress, as well as undesirable coping strategies and selected welfare outcomes, are presented in Table 2. The prevalence of having multiple payments due at the same time and not being able to make all payments was 20%, that of receiving an SMS as a reminder for delayed due payment is 53%, and that of being late in repaying digital loans was 48%. In terms of undesirable coping mechanisms, the prevalence of borrowing to pay an existing loan was 16%, while that of selling assets/belongings to be able to repay the loan was 5%. With respect to welfare outcomes, the prevalence of having gone without food at some stage is 29%, while that of going without required medicine is 22%. Chi-square tests were employed to check on the associations of these covariates and outcomes. Bettors (57%) were significantly more likely to receive an SMS for their digital credit repayment from a lender to encourage repayment on overdue balance than non-bettors (51%) ($p = 0.065$). Bettors (54%) were also more likely than non-bettors (45%) to be late in repaying a loan taken through their phones, and this relationship is statistically significant ($p = 0.007$). The results also reveal that bettors (25%) were significantly more likely than non-bettors (17%) to have payments that were due on multiple loans at the same time and to be unable to make all payments ($p = 0.004$).

Regarding betting and coping mechanisms, the results show that bettors (8%) were more likely to sell assets or belongings to pay loans compared to non-bettors (4%), and this relationship is statistically significant ($p = 0.015$). However, bettors (18%) and non-bettors (15%) did not show any differences in terms of borrowing to repay loans ($p = 0.211$). The bivariate analysis between betting and selected welfare outcomes did not show any significance, although the percentages for going without food (30.9% vs. 29.6%) and without needed medicine or medication (23% vs. 21%) were higher for bettors compared to non-bettors.

Table 3 presents the univariate and multivariate association between betting and *digital credit repayment* outcomes. The results of interest are those from the multivariate regressions. After controlling for income, age, gender, location (rural/urban), and level of education, the results show that bettors were almost twice more likely than non-bettors to have payments due on multiple loans at the same time and could not make all payments, and this relationship was significant (odds ratio (OR) = 1.84, $p = 0.002$). Similarly, bettors were almost one and half times more likely than non-betters to receive an SMS from a lender encouraging repayment on the overdue balance, and this association is statistically significant (OR = 1.4, $p = 0.043$). Bettors were also one and a third significantly more likely than non-bettors to be late in repaying a digital loan (OR = 1.33, $p = 0.072$).

As is reported in Table 4, after controlling for income, age, gender, locality (rural/urban), and level of education, being a bettor is significantly associated with selling assets or belongings in order to pay loans. In fact, bettors are more than twice as likely as non-bettors to do so (OR = 2.39, $p = 0.012$).

When "being a bettor" is the explanatory variable for a binary logistic regression model and "going without food" is an outcome, and income, age, gender, locality (rural/urban), and level of education (Table 5) are controlled for, bettors are one and half times more likely than non-bettors to have gone without food at some point in the past 12 months, and this association is significant (OR = 1.56, $p = 0.017$). However, going without medication has no significant association with being a bettor.

Table 2. Bivariate relationship between betting and digital credit repayment/coping strategies/welfare outcomes.

		Ever Been Late in Repaying a Loan Taken from Phone (%)		Received SMS to Encourage Repayment on Overdue Balance (%)		Payments Due on Multiple Loans at the Same Time and Could Not Make All Payments (%)		Borrowed to Pay Loan (%)		Sold Assets or Belongings to Pay Loan (%)		Gone without Enough Food to Eat (%)		Gone without Medicine or Medical Treatment that Was Needed (%)		All
Factor		Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	All
Bettor (%)	Yes	54.28	45.72	57.24	42.76	25.00	75.00	17.76	82.24	7.57	92.43	30.92	69.08	23.03	76.97	29%
	No	45.11	54.89	50.95	49.05	17.26	82.74	14.67	85.33	3.94	96.06	29.62	70.38	20.52	79.48	71%
	Total	48%		53%		20%		16%		5%		29%		22%		
	Chi-Square	7.2467		3.4107		8.2140		1.5613		5.9536		0.1735		0.8100		
	p-value	0.007		0.065		0.004		0.211		0.015		0.677		0.368		
Sample (n)		1040		1040		1040		1040		1040		1040		1040		1040

Table 3. Association between betting and digital credit repayment.

Factors	Ever Been in a Situation When Payments Were Due on Multiple Loans at the Same Time and You Could Not Make All Payments (Yes/No)				Received SMS from the Lender to Encourage Repayment on Overdue Balance (Yes/No)				Ever Been Late in Repaying a Loan That You Took from Your Phone (Yes/No)			
	Univariate		Multivariate		Univariate		Multivariate		Univariate		Multivariate	
	Coefficient	SE	Coefficient	OR (SE)	Coefficient	SE	Coefficient	OR (SE)	Coefficient	SE	Coefficient	OR (SE)
Bettor	0.469 ***	0.164	0.610 ***	1.840 (0.356)	0.253 *	0.137	0.337 **	1.401 (0.233)	0.368 ***	0.137	0.296 *	1.344 (0.221)
Education (base outcome: primary or no formal education)												
Secondary	0.144	0.210	−0.030	0.970 (0.246)	−0.126	0.169	−0.090	0.913 (0.193)	−0.090	0.168	−0.034	0.966 (0.203)
Tertiary	0.004	0.197	−0.078	0.924 (0.209)	−0.225	0.155	−0.189	0.827 (0.155)	−0.120	0.154	−0.054	0.947 (0.177)
Urban	−0.028	0.164	0.013	1.013 (0.179)	0.034	0.131	0.016	1.016 (0.147)	−0.042	0.131	−0.079	0.923 (0.133)
Female	−0.072	0.156	−0.073	0.929 (0.169)	0.017	0.125	0.130	1.138 (0.169)	−0.159	0.124	−0.153	0.857 (0.127)
Age (base outcome: 55+ years)												
16–24	0.705	0.519	0.545	1.725 (0.938)	0.340	0.313	0.328	1.389 (0.487)	0.548 *	0.327	0.383	1.467 (0.535)
25–34	0.982 *	0.483	0.813	2.255 (1.120)	0.718 **	0.283	0.739 **	2.094 (0.657)	1.034 ***	0.297	0.879	2.409 (0.787)
35–44	1.206 *	0.488	1.215 ***	3.372 (1.684)	0.597 **	0.291	0.597 *	1.818 (0.582)	0.609 **	0.306	0.533	1.704 (0.569)
45–54	1.081 *	0.517	1.234 ***	3.435 (1.824)	0.688 **	0.321	0.637 *	1.89 (0.671)	0.733 **	0.334	0.591	1.805 (0.663)
Inc in 000 (base outcome: 40+ shillings)												
≤10	−0.197	0.309	0.001	1.001 (0.367)	−0.154	0.253	−0.112	0.893 (0.268)	−0.191	0.252	−0.015	0.984 (0.292)
10 < Inc ≤ 20	0.168	0.333	0.147	1.158 (0.427)	−0.047	0.278	−0.209	0.811 (0.254)	−0.451	0.277	−0.340	0.711 (0.221)
20 < Inc ≤ 40	−0.319	0.377	−0.288	0.749 (0.302)	−0.119	0.299	−0.278	0.756 (0.251)	−0.441	0.299	−0.313	0.730 (0.241)
constant	-		−2.347 ***	0.095 (0.056)	-		−0.289	0.748 (0.310)	-		−0.578	0.560 (0.236)
Pseudo R2	-		0.0249		-		0.0135		-		0.0197	
Sample (n)	1040		1040		1040				1040			

Notes: Inc = income group; level of significance: $p < 0.01$ ***, $p < 0.05$ **, $p < 0.10$ *.

Table 4. Association between betting and coping mechanism.

Factors	Sold Assets or Belongings to Pay Loan				Borrowed to Repay a Loan			
	Univariate		Multivariate		Univariate		Multivariate	
	Coefficient	SE	Coefficient	OR (SE)	Coefficient	SE	Coefficient	OR (SE)
Bettor	0.691 **	0.288	0.869 **	2.386 (0.825)	0.228	0.183	0.063	1.066 (0.231)
Education (base outcome: primary or no formal education)								
Secondary	0.303	0.396	0.777	2.175 (1.077)	−0.498 **	0.222	−0.517	0.595 (0.159)
Tertiary	0.222	0.373	0.356	1.428 (0.640)	−0.544 ***	0.202	−0.661	0.516 (0.123)
Urban	0.868 ***	0.309	1.181	3.260 (1.088)	0.168	0.181	0.149	1.161 (0.223)
Female	−0.543 *	0.289	−0.420	0.656 (0.218)	−0.063	0.172	−0.047	0.954 (0.190)
Age (base outcome: 55+ years)								
16−24	0.505	0.806	0.697	2.009 (1.676)	0.229	0.440	0.087	1.091 (0.533)
25−34	0.447	0.752	0.483	1.622 (1.264)	0.333	0.401	0.236	1.266 (0.553)
35−44	−0.033	0.795	−0.126	0.880 (0.733)	−0.006	0.418	0.012	1.013 (0.457)
45–54	1.047	0.786	1.512	4.538 (3.713)	0.042	0.461	−0.025	0.975 (0.491)
Inc in 000 (base outcome: 40+ shillings)								
≤10	0.686	0.738	0.685	1.984 (1.573)	0.486	0.413	0.844	2.327 (1.091)
10 < Inc ≤ 20	0.636	0.781	0.292	1.340 (1.099)	0.594	0.439	0.593	1.810 (0.877)
20 < Inc ≤ 40	0.101	0.879	−0.238	0.787 (0.716)	0.688	0.460	0.634	1.885 (0.943)
constant	-		−4.994 ***	0.006 (0.007)	-		−2.054 ***	0.128 (0.078)
Pseudo R2	-		0.0765		-		0.0132	
Sample (n)	1040		1040		1040			

Notes: Inc = income group; level of significance: $p < 0.01$ ***, $p < 0.05$ **, $p < 0.10$ *.

Table 5. Association between betting and welfare outcomes.

Factors	Gone without Enough Food to Eat				Gone without Medicine or Medical Treatment that Was Needed			
	Univariate		Multivariate		Univariate		Multivariate	
	Coefficient	SE	Coefficient	OR (SE)	Coefficient	SE	Coefficient	OR (SE)
Bettor	0.061	0.148	0.443 **	1.558 (0.290)	0.148	0.164	0.307	1.359 (0.276)
Education (base outcome: primary or no formal education)								
Secondary	0.918 ***	0.197	0.322	1.380 (0.339)	0.722	0.212	0.030	1.031 (0.269)
Tertiary	0.697 ***	0.186	0.233	1.263 (0.286)	0.344	0.205	0.030	0.767 (0.188)
Urban	0.208	0.141	0.450 ***	1.569 (0.257)	−0.018	0.157	0.204	1.227 (0.220)
Female	0.335	0.137	0.218	1.244 (0.210)	0.291	0.154	0.052	1.053 (0.195)
Age (base outcome: 55+ years)								
16−24	−0.487	0.319	−0.625	0.534 (0.205)	−0.325	0.342	−0.568	0.566 (0.228)
25−34	−0.555 *	0.285	−0.459	0.631 (0.213)	−0.692 *	0.309	−0.634	0.530 (0.189)
35−44	−0.304	0.293	−0.225	0.798 (0.276)	−0.469	0.318	−0.561	0.570 (0.209)
45–54	−0.557 *	0.332	−0.343	0.709 (0.276)	−0.156	0.348	−0.233	0.792 (0.321)
Inc in 000 (base outcome: 40+ shillings)								
≤10	2.387	0.521	2.551 ***	12.82 (3.847)	2.173 **	0.597	2.555 ***	12.880 (3.510)
10 < Inc ≤ 20	1.423	0.543	1.556 **	4.743 (2.963)	1.280 ***	0.623	1.586 **	4.887 (2.682)
20 < Inc ≤ 40	0.715	0.588	0.894	2.445 (1.622)	0.646	0.676	1.004	2.730 (2.172)
constant	-		−3.162	0.042 (0.029)	-		−2.978	0.050 (0.040)
Pseudo R2	-		0.0849		-		0.0689	
Sample (n)		1040				1040		

Notes: Inc = income group; level of significance: $p < 0.01$ ***, $p < 0.05$ **, $p < 0.10$ *.

The risks associated with gambling in general are well-known, and Effertz et al. (2018) posit that the discussion about the gambling risks is as old as gambling itself. Research on online gambling is relatively recent, however, and Papineau et al. (2018) put the time frame of research focusing on online gambling and public health concerns as having started about twenty years ago, with the advancement in technology facilitating online gambling. In the current study, digital financial services, facilitated by accessibility of advanced technology-savvy gadgets such as smartphones and tablets, allow for ease of access to gaming and online applications for gambling. Effertz et al. (2018) argue that gaming and online applications for gambling are faster, more attractive, and less costly, yet they are more addictive when compared to traditional gambling opportunities. Zhang et al. (2018) find that mobile phones, especially smartphones, are the most commonly used platforms for online gambling among Asian individuals. Black et al. (2017) and Papineau et al. (2018) report gambling problems to have more adverse effects among online gamblers compared to offline gamblers. The current study reports such negative effects of digital betting on credit repayment, coping mechanisms, and welfare outcomes in a digitized developing economy.

The self-reported financial distress measures show that bettors have a higher likelihood of becoming financially distressed when compared to non-bettors. Mihaylova et al. (2013) and Håkansson and Widinghoff (2020) also report that online gambling is associated with problem gambling, overspending, and over-indebtedness. Online gambling as a behavioral addiction (Mallorquí-Bagué et al. 2017) is in our study found to be associated with negative outcomes. Participants in our study embraced financial innovations that are accessible via mobile phones and tablets, thus making finances accessible through digital means and at the same time have the opportunity to gamble. This puts them in a position to easily engage in online or digital gambling.

The current study also indicates that betting is associated with undesirable coping mechanisms as shown by the tendency to use assets or other belongings to repay loans among bettors. These undesirable coping mechanisms are exemplary of what Black et al. (2017) and Papineau et al. (2018) consider as extra burden impacts of online gambling on the lives of gamblers. Together, the association between betting and being financially distressed and engaging in undesirable coping mechanisms, as well as the risk of going without food among bettors, suggest an impaired quality of life among bettors. A study by Papineau et al. (2018) shows that online gambling impacts gamblers' work, relationships, mental and physical health, finances, and quality of life. Although financial innovations such as digital financial services improve peoples' lives, for the betting segment of the population, the negative effects of betting pose a considerable threat given that it enables problem gambling, Black et al. (2013) and other earlier researchers argue to be a public health problem that is costly to the society.

5. Conclusions

Digital financial services and, more importantly, mobile money, have become an important financial innovation to advance financial inclusion in developing and emerging economies. A growing body of literature also reports a positive and significant impact of digital financial services on household welfare outcomes. Nevertheless, to the growing betting segment of the Kenyan population, digital financial services have brought great convenience to betting by allowing easy access to digital credit that can be used for betting. Using survey data from Kenya, this study shows that digital betting is associated with undesirable outcomes on credit repayment, coping mechanisms, and the welfare of bettors. When controlling for socio-economic and demographic factors, bettors were shown to be more likely than non-bettors to be financially distressed, engage in welfare undermining coping strategies, and have inferior welfare outcomes. These findings suggest the need for educating the public about the possible effects of betting and gambling in general.

This study has some limitations. First, it only shows associations between betting and identified outcomes, and it does not infer causal relationships. As such, studies that can isolate the effects of betting on these outcomes using careful identification strategies are needed. The second limitation in the data is that there is no specific survey question that captures the amount of the wagers. For example, a 100 shillings wager every day, though higher in frequency, is less significant than a 2000 shillings wager three times a week. In addition, no information was gathered with respect to an increase in the amount of a wager over time. These data limitations can be addressed by developing a specific questionnaire that gathers detailed information with regard to gambling and welfare outcomes in Kenya.

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Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion

David Mhlanga

School of Accounting, University of Johannesburg, Johannesburg 2006, South Africa; dmhlanga67@gmail.com

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Abstract: This study sought to investigate the impact of AI on digital financial inclusion. Digital financial inclusion is becoming central in the debate on how to ensure that people who are at the lower levels of the pyramid become financially active. Fintech companies are using AI and its various applications to ensure that the goal of digital financial inclusion is realized that is to ensure that low-income earners, the poor, women, youths, small businesses participate in the mainstream financial market. This study used conceptual and documentary analysis of peer-reviewed journals, reports and other authoritative documents on AI and digital financial inclusion to assess the impact of AI on digital financial inclusion. The present study discovered that AI has a strong influence on digital financial inclusion in areas related to risk detection, measurement and management, addressing the problem of information asymmetry, availing customer support and helpdesk through chatbots and fraud detection and cybersecurity. Therefore, it is recommended that financial institutions and non-financial institutions and governments across the world adopt and scale up the use of AI tools and applications as they present benefits in the quest to ensure that the vulnerable groups of people who are not financially active do participate in the formal financial market with minimum challenges and maximum benefits.

Keywords: artificial intelligence; digital financial inclusion; finance; industry 4.0

JEL Classification: G2; G4; O; O16

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1. Introduction

Digital financial inclusion is increasingly becoming central in the debate on how to ensure that people who are at the lower levels of the pyramid become financially active (Peric 2015). Banks and non-bank institutions are coming together to widen financial access using digital financial approaches to include those who are financially excluded and the underserved populations (Peric 2015). Banks and non-banking institutions are building on digital ways that were in use for years through the direct application of artificial intelligence (AI) to improve access even to the people who were previously served by the formal financial institutions (Alameda 2020; Peric 2015). The fourth industrial revolution is bringing changes in the traditional banking sector built in the industrial revolution premised on paper and physical distribution of cash (Alameda 2020).

The term fintech or financial technologies is used to describe different innovative business models that have great potential to transform the financial services industry (Mamoshina et al. 2018). The fintech business model offers various financial products or services in an automated fashion through the wide use of the internet (Paul 2019). Technologies that are driving industry 4.0 such as AI, machine learning, cognitive computing and distributed ledger technologies can be used to supplement fintech new entrants and traditional incumbents (Lopes and Pereira 2019a). Some other AI technologies that can be applied in the fintech sector to promote financial inclusion including *audio processing, knowledge representation, speech to text, deep learning, expert systems, natural language processing, machine learning*

(ML), robotics, and symbolic logic (Paul 2019). It is believed that the popularity of AI technologies boomed in 2011 when companies like Google, Microsoft, IBM and Facebook embarked on a massive investment in AI and machine learning to be applied in the commercial space.

The traditional banking market is equipped with millions of customers with a history that spans over hundreds of years, and some of these customers may be worth billions (Alameda 2020; Peric 2015). The challenge which is currently there is that these customers are not digital (Alameda 2020; Loufield et al. 2018). On the other hand, fintech start-ups have a rich digital vision but to win the trust of customers is a huge obstacle to them (The World Bank 2020). The occurence of the disturbances caused by COVID-19 brought another perspective of fintech to customers as it was the only option available to engage in banking as well as buying. Banks resorted to digital banking while shopping in many countries was done online using various banking applications to perform transactions. In addition, the existence of various tech corporations like Google, Apple, Facebook Amazon in America and Baidu, Alibaba and Tencent in Asia who take pride in having millions of customers with financial returns in the billions and decades of history and a pure digital vision will act as examples a for banks to embrace digital technology and to understand the importance of AI in finance (Alameda 2020).

The World Bank stated that digital financial services which include the use of mobile phones have been launched in more than 80 countries (The World Bank 2020; Chu 2018). As a result, millions of formerly excluded and underserved poor individuals are migrating from cash-based transactions to formal financial services where a variety of services like payments, transfers, credit, insurance, securities and savings are offered to them (The World Bank 2020). Mobile phones and other digital tools including AI are widely used and the rate at which financial inclusion is rising is commendable (Salampasis and Mention 2018; Bill & Melinda Gates Foundation 2019). With digital financial inclusion, financial services are provided to customers at an affordable cost in ways that are sustainable to customers (Gomber et al. 2017). Digital financial services provide unlimited benefits to the previously excluded customers but it comes with a lot of risks which result from the introduction of non-financial firms in the provision of new technologies used in the process (The World Bank 2020; Rathi 2016).

Another risk in digital finance lies in the existence of new contractual relationships between financial institutions and third parties which involve the use of agent networks, other risks result from different regulatory treatment of deposit-like products as compared to real deposits, there are other risks which result from unknown and unpredictable costs to inexperienced and vulnerable consumers, together with risks that result from the use of new kinds of data which come with new privacy and data security issues (The World Bank 2020; Rathi 2016). However, experts are indicating that the use of AI (particularly algorithms) can help to fight some of the risks (Chu 2018; Killeen and Chan 2018). Motivated by the fact that in the industry 4.0, AI is increasingly becoming common while on the other hand digital financial inclusion is becoming central in the debate on how to ensure that people who are at the lower levels of the pyramid become financially active, for instance, groups of women, youths, small businesses among many disadvantaged groups. This study, therefore, intends to investigate the impact of AI on digital financial inclusion, that is to understand the channels in which AI can help to improve financial inclusion.

1.1. History and Definition of Digital Financial Inclusion

Financial inclusion refers to the number of adults having access to banking or financial services. The Global Findex Survey reported that in the 15+ age group, 79.9% of the population had accounts with financial institutions in the year 2017 (Demirguc-Kunt et al. 2017). This meant a strong growth compared to 53.1% reported in the previous edition of the survey in 2014, and 35.2% in 2011. Nearly half of the world's adult population (or 3.5 billion people) are unbanked and underbanked (with limited or non-transactional access to finance). Of these 1.7 billion adults in the world without an account, China, India, Pakistan and Indonesia account for the largest unbanked persons.

The first step towards financial inclusion is having an account (Sarma 2015). Increasingly, digital payments are being used for financial transactions (Muneeza et al. 2018). Digital financial inclusion is explained by the World bank as the deployment of cost-saving digital means to reach the financially excluded and the generally underserved population groups with formal financial services that are tailor-made to satisfy their needs (Alameda 2020). Wang and He (Wang and He 2020) also described digital financial inclusion as broad access to and use of formal financial services by the excluded or underserved individual. Digital financial inclusion began to attract the attention of many people as a result of the success of M-PESA, one of the payment innovations introduced in Kenya (Beck et al. 2018). With M-PESA, mobile money is used for digital payments (Dubus and Van Hove 2017; Van Hove and Dubus 2019). According to Wang and He (Wang and He 2020), digital financial inclusion in China represents more than a payment instrument as it includes three basic business formats which include digital payments, digital investment and digital financing.

Digital financial inclusion put more emphasis on the importance of information communication technology (ICT) in expanding the scale as well as the use of financial services by the previously disadvantaged individuals (Lauer and Lyman 2015; Wang and He 2020). The journey started with microcredit, microfinance and financial inclusion, then the journey is now striving for digital financial inclusion (Lauer and Lyman 2015). The word microcredit was first used to refer to institutions like the Grameen Bank of Bangladesh which was created to provide small loans to the poor (Chatterjee and Sarangi 2006; Wang and He 2020). In the early 1990s, the word microcredit was dominating before it was replaced by the word microfinance which was described as the supply of a variety of financial services which include savings, insurance, loans (Karlan and Morduch 2010; Wang and He 2020).

The field-based operation which was used by banks like Grameen where microcredit, microfinance and financial inclusion was developed, weakened the efficiency of these banks in serving the poor (Visser and Prahalad 2013). The existence of ICT and AI made it possible for financial inclusion to change to digital financial inclusion which is the fourth stage which will change the lives of those individuals at the bottom of the pyramid (Visser and Prahalad 2013). Wang and He (Wang and He 2020) indicated that to do business with people at the bottom of the pyramid requires unique business models and radical innovations such as AI. Wang and He (Wang and He 2020) noted that digital financial inclusion is different from traditional financial inclusion because digital financial services reduce transaction costs in rural areas due to lower marginal costs. When relying on ICT digital financial services require no physical outlets. However, coming up with new technologies face higher start-up costs to have them established, but their marginal costs normally move towards zero when business volume increases (Liao et al. 2020).

The use of AI and various ICT tools helps to overcome the major problem of traditional financial inclusion which is information asymmetry (Gomber et al. 2017). Online services and products offer a lot of information to customers which could not be accessible without the use of digital services. The availability of this information helps to reduce information asymmetry between the financial institutions and individuals (Gomber et al. 2017).

The important components of digital financial inclusion include but are not limited to digital transaction platforms, which allow customers to make payments and to store electronic value (Peric 2015; GPFI 2017). The other important aspect provided by digital finance is devices which are used by customers which can either be digital devices like mobile phones that can transmit information or instruments like payment cards that can be used to connect with digital devices like point of sale terminals (Alameda 2020; Bill & Melinda Gates Foundation 2019). Moreover, digital financial inclusion is characterized by retail agents with digital devices connected to communication infrastructure that will transmit and receive transaction details. This activity allows customers to convert cash into electronically stored value also referred to as cash in or to convert back the stored values back into cash which can also be referred to as cash-out (Peric 2015). With digital financial inclusion, additional financial services like credit, insurance and even savings can be offered by banks and non-banks to the financially excluded and those underserved individuals through digital tools like AI.

As articulated by Peric (2015) the benefits of digital financial inclusion include access to formal financial services by the financially excluded individuals, and the fact that digital financial services and products are offered at a lower cost to the customer and the provider. This allows customers to transact in irregular tiny amounts to assist them to manage their uneven incomes (Koh et al. 2018). Additionally, with digital financial inclusion, it is possible to have additional financial services tailor-made for customers' needs and financial circumstances which are made possible by the value storage services embedded in it and the data generated within it (Bourreau and Valletti 2015). Digital financial services also help to reduce risks of loss, theft, and other financial crimes posed by cash-based transactions, as well as the reduced costs associated with transacting in cash and using informal providers (Muneeza et al. 2018). Again, it can also promote economic empowerment by enabling asset accumulation for women, in particular, increasing their economic participation (David-West 2015; Peric 2015).

1.2. Industry 4.0

Industry 4.0, also known as the fourth industrial revolution, can be described as the advent of cyber-physical systems involving entirely new capabilities for people and machines (Schwab 2015). While these capabilities are reliant on the technologies and infrastructure of the third industrial revolution, the 4IR represents entirely new ways in which technology becomes embedded within societies and even our human bodies (Schwab 2015). 4IR is defined as the fusion of technologies that is blurring the lines between the physical, digital, and biological worlds (Schwab 2015; Moloi 2020). The term 4IR was first coined by Klaus Schwab, founder and executive chairman of the World Economic Forum. *"The 4IR is sometimes described as an incoming thunderstorm, a sweeping pattern of change visible in the distance, arriving at a pace that affords little time to prepare. While some people are ready to face the challenge, equipped with the tools to brave the change and take advantage of its effects, others do not even know a storm is brewing"* (Deloitte 2018a).

The 4IR is affecting almost every facet of our daily life, impacting how individuals relate to technology and changing how and where work is done (Schwab 2019). Another way to have an understanding of industry 4.0 is to appreciate the technology used in this revolution. Some of the technologies include artificial intelligence and robotics, ubiquitous linked sensors, virtual and augmented realities, additive manufacturing, blockchain and distributed ledger technology, advanced materials and nanomaterials, energy capture, storage and transmission, new computing technologies, biotechnologies, geoengineering, neurotechnology, space technologies. These are some of them that are driving the fourth industrial revolution in the 21st century (Schwab 2019; Moloi 2020).

1.3. Brief Definition and History of Artificial Intelligence

As propounded by Hassani et al. (2020), artificial intelligence has multiple definitions. As a result, no one definition can define artificial intelligence (Hassani et al. 2020). Legg and Hutter (2007) came up with 70 definitions of artificial intelligence covering multiple views. Colom et al. (2010) defined artificial intelligence as a general mental ability for reasoning, problem-solving, and learning while Snyderman and Rothman (1987) defined artificial intelligence as a general mental ability for reasoning, problem-solving, and learning. Gottfredson (1997) also defined artificial intelligence where more emphasis was given to learning swiftly and the ability to learn from experiences. Hassani et al. (2020) also defined AI as an intelligent system created to use data and to analyze the data as well as involving the performance of certain tasks without the need for programming. AI has a strong capacity to create a foundation for decision making and support through insights and results, collected from vast and complex data sets which are compressed into the manageable scale (Hassani et al. 2020).

There were generations of scientists, mathematicians and philosophers who had the concept of AI in their minds by the 1950s (An Editorial with 52 Researchers 1994). Gottfredson (1997) insinuated that the history of AI began in the periods of human classical civilization with myths and rumours of artificial beings endowed with intelligence or consciousness by master craftsmen. The attempt by the classical philosophers to describe the process of human thinking as the mechanical manipulation of symbols gave more meaning to the concept of AI (Colom et al. 2010). As articulated by Colom et al. (2010), the effort in describing human thinking as mechanical manipulation culminated in the invention of programmable digital computers in the 1940s. These programmable computers were machines premised on the abstract essence of mathematical reasoning (Hassani et al. 2020). The ideas around the developed device influenced several scientists to start discussing, with seriousness, the possibility of coming up with an electronic brain (Gottfredson 1997).

According to Hassani et al. (2020), artificial intelligence was mentioned for the first time in 1956 at a computing conference. In 1956 in a workshop at Dartmouth College during the summer of 1956, the research on AI began. The people who attended the workshop became the leaders of AI for decades (Hassani et al. 2020). Considerable investment in AI boomed in the first decades of the 21st century due to availability of large data sets, powerful computer hardware and due to the availability of new methods. This motivated the application of machine learning to many problems in academia and industry (Frank 2019; Hassani et al. 2020). In this century AI has evolved from being an academic field to become a key factor in the social and economic mainstream technologies including banking, medical diagnosis, autonomous vehicles as well as voice-activated assistance (Frank 2019).

1.4. Literature Review

The literature on digital financial inclusion is available, especially literature on how mobile phones are increasingly influencing financial inclusion. Ozili (2018) insinuated that digital financial inclusion is a critical component of the efforts applied in trying to include the groups of people who are not part of the formal financial system. Ozili (2018) went on to argue that digital finance is beneficial to financial users, providers governments and the general economy. However, Ozili (2018) believes that there are many issues which still need to be resolved in digital finance, about regulation among others.

Additionally, Dawei et al. (2018) also argued that it is a paradox in a globalized world to have a third of the population who are not part of the formal financial system, yet literature points out that financial services can assist to improve the welfare of the households and to promote small businesses. Dawei et al. (2018) believes that the inherent limitations of the conventional financial system hinder the prospects of the excluded population. However, Dawei et al. (2018) believes that digital financial inclusion through digital currency and mobile technology can help penetration of financial systems in the unserved parts of the world or country. It is believed that the high cost for small-ticket financial transactions makes these services virtually impossible and unavailable (Dawei et al. 2018).

Dawei et al. (2018) went further to state that digital currency and mobile technology allow small transactions at an affordable cost which is a benefit to small businesses and vulnerable groups. Digital currency and mobile transactions can also help to reduce time and to make transactions in bulk and with accuracy (Dawei et al. 2018). Many developing nations such as Brazil, India, Nigeria and other African nations like Kenya and Zimbabwe embraced mobile technology to overcome the problem of financial exclusion.

Sapovadia (2018) also argued that digital financial inclusion is different from traditional banking in that it serves the clients without requiring historical records. Sapovadia (2018) went further to state that digital financial inclusion uses data technology and AI to unravel credit assets of clients and mitigate information asymmetry. It is believed that the availability of AI and big data allow the use of alternative information like shopping history, online behavior pattern, transaction record and many other potential information sources of information not common to the convectional banking for credit scoring. Credit Ease Financial Cloud is one of the examples of big data which provides open and always accessible functions of anti-fraud, risk management, real-time loan granting and targeted marketing to external and internal people.

In addition, Levin et al. (2018) also argued that the crisis of the 1960s created the need for the growth and development of electronic trading and the development of financial services technology. The author believes that technology like AI is important in the financial sector as people are preparing for the new era. Hotchkiss and Lee Kuo Chuen (2018) support Levin et al. (2018), Hotchkiss and Lee Kuo Chuen (2018) argued that the development of innovations like fintech and blockchain technology has taken the attention off the people around the world and the attention of the banking world. Hotchkiss and Lee Kuo Chuen (2018) stated that digital financial inclusion is doing great things in Myanmar, one of the fastest-growing economies in Southeast Asia where approximately 52 million people who live in the country are gaining access through digital financial inclusion.

Killeen and Chan (2018) also stated that bitcoin blockchain is creating new ways of transacting with security without the need for an intermediary. Killeen and Chan (2018) went on to insinuate that the use of ledger to verify and record identity and asset ownership for individuals to have access to the transactional account is free from the limitation associated with centralized controls when blockchain is used. Killeen and Chan (2018) believe that blockchain is satisfying the old needs previously served by convectional banks more efficiently which risks rendering the existence of the old central institutions like development banks and large scale investment firms obsolete. Killeen and Chan (2018) further argued that global financial institutions must try to respond swiftly to the changes in culture and dynamic values accompanied by blockchain innovation.

David-West (2015) also believes that digital financial inclusion can help many households who were previously excluded to have access to formal financial services. David-West (2015) believes that documentation requirements, costs and literacy issues are some of the factors forcing households and individuals to adopt informal financial services. The existence of mobile money and digital currency has revolutionized the traditional perspective of financial access and inclusion. Moreover, digital financial currency and mobile money have led to the introduction of new financial service providers such as mobile money operators sometimes referred to as agents in many African countries such as Kenya and Zimbabwe. The existence of mobile money also resulted in policy changes that led to the existence of other operators which led to the unbanked community being offered financial services (David-West 2015).

Rathi (2016) also stated that digitization has enabled a large population of individuals who were not financially active to be able to enjoy financial services due to the fact that digital tools make the financial services affordable to many. Rathi (2016) also reiterated that developing nations such as India are relying on digital technology to provide financial services to the unbanked population. In a way, digital technology is allowing the previously unbanked population to be included in the mainstream formal financial market. Chu (2018) also argued that digital technology is expanding financial inclusion where it is made possible for the unbanked to be able to access banking services like savings, insurance, and other financial services crucial to the unbanked population and those living in poverty. Chu (2018) argued that financial inclusion is important to bridge the gap between the physical, digital and the psychological use of money. Chu (2018) also believes that bringing together the digital financial tools such as blockchain with the psychological tools like financial education can allow the unbanked to have access to financial services which can help to break the poverty cycle.

Salampasis and Mention (2018) in the paper, *fintech: harnessing innovation for financial inclusion*, argued that financial inclusion has been taken as the soft side of financial services with limited attention given to it from the regulators, and policymakers despite its importance in the empowerment of the marginalized population. Salampasis and Mention (2018) argued that many disadvantaged people in society are left out of the formal financial market, thus creating inequality and general dependence syndrome by those who are unable to access financial services and making the fight against poverty difficult. However, Salampasis and Mention (2018) also suggested that the emergence of fin-tech, a new breed of financial innovation, is increasingly closing the gap between unbanked, underbanked and developed societies. Salampasis and Mention (2018) believe that digital technology is opening previously closed doors in the digital economy for many individuals leading to more equitable growth and society.

Muneeza et al. (2018), in the paper, *the application of blockchain technology in crowdfunding: towards financial inclusion* via *technology*, posit that the advent of innovative digital technologies such as blockchain and crowdfunding is showing new sustainable ways to support the economically poor and the vulnerable people. Muneeza et al. (2018), after an investigation of the development of crowdfunding in Malaysia, found out that crowdfunding is a necessary way to promote financial inclusion while blockchain can assist in mitigating the risks faced by platform operators.

In summary, the empirical literature review discovered that literature on digital financial inclusion is available, especially literature on how mobile phone technologies are influencing financial inclusion. In this review, it was noted that digitization has enabled a large population of individuals who were not financially active to be able to enjoy financial services because digital tools make the financial services affordable to many. The review also discovered that digital technology is expanding financial inclusion where it is made possible for the unbanked to be able to access banking services like savings, insurance, and other financial services crucial to the unbanked population and those living in poverty. The other important aspect noted was that financial inclusion is important to bridge the gap between the physical, digital and the psychological use of money. Authors like Arifin (Muneeza et al. 2018) indicate that the emergence of innovative digital technologies such as blockchain and crowdfunding is showing new sustainable ways to support the poor.

1.5. Research Methodology

This study article is premised on desktop research to investigate the impact of AI on digital financial inclusion. The study used unobtrusive research techniques to analyze objectively the impact of AI on digital financial inclusion. The techniques include conceptual and documentary analysis of peer-reviewed journals, reports and other authoritative documents on AI and digital financial inclusion.

Table 1 gives an estimated number of journal articles, reports and other authoritative documents which include news articles and web page articles that helped to shape the direction of the study. Some of the journal reports and news articles listed were not necessarily referenced in the paper as they contributed to ideas which led to the development of the paper. The criteria used in the selection of the articles, reports and other important documents were simply the relevance of the articles in the provision of information useful for the main objective of the study which was to investigate the impact of AI on digital financial inclusion. Conceptual analysis and document analysis were used in the study because documents come in a variety of forms, making documents a very accessible and reliable source of data. Obtaining and analysing documents is often far more cost-efficient and time-efficient compared to conducting field research or experiments.

Table 1. Journal articles, reports and news articles that shaped the trajectory of the study.

Journal Articles	Reports	Other Documents Web Pages Articles and News Articles
66	33	40

Source: Author's Analysis.

2. Results

2.1. The Influence of AI in Driving Digital Financial Inclusion

Fintech companies are increasingly applying AI applications for many purposes which include but are not limited to the following: to manage and detect risk, risk measurement, fraud detection, consumer protection (Paul 2019). Other prominent areas of use include credit scoring, chatbots, capital optimization, market impact analysis, trade signalling, and 'reg tech' applications (Paul 2019).

2.1.1. Risk Detection, Management and Measurement

One major reason for many vulnerable groups—like women, youths and small businesses-like smallholder farmers—being excluded from the formal financial market in the traditional banking sector was driven by issues around risk (Beck et al. 2009). Many of these vulnerable groups were viewed as high risk due to the limited capability to detect and measure the risk among them (Park and Mercado 2015, 2018). Some of the factors that exacerbated this was lack of data (Park and Mercado

2018). However, AI is transforming financial inclusion through the widespread use of algorithms to automate risk detection management and measurement (Peric 2015; Muneeza et al. 2018). The use of AI is making it possible for the previously excluded groups to be able to access financial services using various digital tools such as cell phones or instruments like payment cards that can be used to connect with digital devices like point of sale terminals (Alameda 2020; Bill & Melinda Gates Foundation 2019).

In Kenya, M-Pesa, where M represents mobile while Pesa is another word for money in Swahili, is one of the mobile phone-based money transfer service operated by Safaricom which was able to offer payments services, and micro-financing service lunched in 2007 (Osah and Kyobe 2017; Burns 2018). The service has since spread to many countries which include Tanzania, Mozambique, DRC, Lesotho, Ghana, Egypt, Afghanistan, South Africa, India, Romania and Albania among many other countries (Jacob 2016; Burns 2018). The ability of a mobile device using AI intelligence could make it possible for people to make deposits, to withdraw money, to transfer money, pay for goods and services, to have access to credit and savings (Van Hove and Dubus 2019). This helps the low-income earners to be able to access these services which they could not access in the traditional banking system (Wang and He 2020). Additionally, through the use of AI intelligence, registration of accounts was achieved digitally; approximately 17 million accounts were registered in Kenya in its initial stages in 2012 while 7 million accounts were registered in Tanzania in 2016 (Van Hove and Dubus 2019; Wang and He 2020).

AI also plays an important role in preventing currency risk (Paul 2019). Through digital finance, individuals and small businesses (SMEs) have the option to add funds in the fiat currency which allows a shift in the volatility risk to the financial intermediary (FI) (Paul 2019). Many FIs are using bitcoin as a vehicle currency with the United States dollar as the dominant vehicle currency used in 88 per cent of trades (Global Partnership For Financial Inclusion 2016; Paul 2019). The use of bitcoin as a vehicle currency and block chain's platforms means that the recipient and the sender are not exposed to the volatility of virtual currency (Paul 2019). The ability to prevent risk is allowing small income earners to participate in the financial market as a result of the strength of AI technology (Alameda 2020). In short, financial markets are adopting more and more to AI to come with more exciting nimble models which are being utilized by financial experts to pinpoint trends, identify risks, conserve manpower and to ensure better information and for future planning (GPFI 2017).

2.1.2. AI and Information Asymmetry

The credit rationing theory credited to Stiglitz (Berardi 2011). This theory asserts that when information asymmetry (also referred to as imperfect information) is present in a competitive loan market, credit rationing will be the major feature of that credit market. Among a group of borrowers with fully observable and identical characteristics, some will receive loans while others will not get anything (Stiglitz 1989; Yuan et al. 2011). In the process, some disappointed borrowers will be more than willing to pay an interest rate which is more than the market interest rate. However, financial institutions will not be willing to respond to excess demand for loanable funds through raising the interest rate for borrowers (Stiglitz 1989). The major reason given was that in many circumstances when the interest rate is high, safer borrowers do not borrow as they are disuaded from borrowing (Yuan et al. 2011).

In addition, when the interest rate is high, borrowers will invest in high-risk projects which will limit the probability of paying back the loan (Berardi 2011). This condition will limit the participation of other potential players in the credit market. Accordingly, this explanation will help to explain why some economic agents will be excluded in the financial market and the increase in financial exclusion in the formal financial markets. According to the credit rationing theory, one of the major factors which cause the market to malfunction in developing nations is information asymmetry (Bell et al. 1997). It is believed that information asymmetry through adverse selection and moral hazards is the primary source of market inefficiencies (Bell et al. 1997). As a result of these inefficiencies in the market, high-risk borrowers like small scale farmers will be excluded from the group of potential borrowers

(Yuan et al. 2011). This will mark the reason many economic agents are financially excluded in the formal financial markets.

However, digital tools like AI can overcome the problem of information asymmetry (Kaya and Pronobis 2016). Digital financial inclusion through AI can have access to various online shopping platforms and various online social networks which produces a large amount of information on individuals which will help to do away with the problem of information asymmetry between financial institutions and individuals (Wang and He 2020; Yang and Zhang 2020). Digital tools improve access to credit to vulnerable groups especially those without collateral security based on big data analysis and cloud computing (Wang and He 2020). Many digital technologies which use AI technology utilize other credit score mechanisms to create collateral free-loan products (Matsebula and Yu 2017). One example of the bank which offered collateral-free loans was the Grameen Bank that won a Nobel Prize in 2006 together with Prof. Muhammad Yunus. The bank distributed collateral-free loans of united states dollars (USD) 24 billion to borrowers (Karlan and Morduch 2010; Wang and He 2020). In a way, AI solutions are assisting financial institutions and credit lenders to make smarter underwriting decisions through the use of many factors that assess accurately traditionally underserved borrowers in the credit decision-making process (Paul 2019).

2.1.3. AI and Customer Support and Helpdesk through Chatbots

Through the use of AI, banks are now adopting customer support and help desks which are impacting more on increasing efficiency and reducing the cost of customer support. Banks are offering an electronic virtual assistant (EVA). Moreover, with AI, financial institutions can provide personalized banking where chatbots and AI assistants, use AI to come up with personalized financial advice and natural language processing to provide instant, self-help customer service (Alameda 2020; Paul 2019).

Besides, AI is used as a relationship manager, banks are introducing chatbots for this purpose. This allows vulnerable households in rural areas to access financial advice and help which they cannot enjoy when dealing with human beings (Paul 2019). The HDFC bank of India has already introduced a chatbot for relationship manager purposes (Paul 2019). It is alleged that many bank staff have an urban orientation which makes it difficult for them to have the patience to deal and talk to the rural customers (Journal of Digital Banking 2019). Through the power of AI, banks can come up with natural regional language processing-based AI-trained robots for training and talking to the rural customers in regional language (Paul 2019). These robots explain various banking products offered by the bank, the robots can also explain the amount of debt rural customers have and even offer suggestions on the need to save (Siddiqui and Siddiqui 2017). AI-trained robots can become financial advisors to rural households (Deloitte 2018b; Paul 2019). As a result, AI is helping a lot to allow previously vulnerable groups to be able to access formal financial services (Wang and He 2020).

Additionally, some customers can access banking services through their mobile phones, where they can transact even while at home in the remote parts of their countries as long as they are connected to mobile networks. Furthermore, the use of AI can help a lot in account opening as individuals can open accounts or deposit through the use of phones (Paul 2019; Wang and He 2020). The use of blockchain has also allowed usability of accounts to be more effective; it takes approximately 10 minutes to transfer money which is faster than the conventional means mainly used in developing nations (Paul 2019). When using blockchain technology in digital finance payments, there is no need for payments to go through the national payments system and as a result, there is no need for physical branches. This makes payments more feasible as the cost of the transfer is the percentage of the value of the transferred (Paul 2019). On some instances, AI can facilitate quantitative trading. AI-powered computers can have a deep analysis of large and complex data sets very fast and more efficiently than human beings. This will result in automated trading which saves valuable time (Wang and He 2020).

2.1.4. Fraud Detection and Cybersecurity

Ramping up cybersecurity and fraud detection efforts is becoming a necessity for any financial institution or bank because of huge quantities of digital transactions which are carried out via online accounts every day, sometimes through mobile phone and applications (Lopes and Pereira 2019b; Paul 2019). AI is playing a big role in the improvement of security of online finance. The ability of AI to offer this kind of security to online finance makes it possible for the people at the bottom of the pyramid concerning financial inclusion to be able to participate in the formal financial sector (Reim et al. 2020). Further, fintech companies are using AI applications to advance consumer protection and user experience, manage risk, detect fraud in many countries (Paul 2019). Various national stock exchanges in many countries are contemplating the use machine learning to identify market patterns to improve monitoring and prevent manipulation of its high-frequency trading (HFT) markets (Journal of Digital Banking 2019; Deloitte 2018b). In reality, AI-enabled cybersecurity systems are increasingly being used to guard against and prevent possible security breaches. In addition, AI is influencing wealth management through robot advisors that provide automated financial planning services like tax planning advice, insurance advice, health, investment advice and many other crucial services (Journal of Digital Banking 2019). The HDFC bank of India is using AI for its Mobile Banking App, and On Chat, which makes use of Natural Language Processing where users can interact, confirm and pay for services within chat (Paul 2019).

2.2. Challenges of AI

Though AI is promising and doing a lot in fuelling digital financial inclusion, however, there are challenges associated with reaping the benefits from intelligent algorithms (Deloitte 2018b). Some of the challenges relate to data quality, responsibility requirements to roll out AI technology (Sundblad 2018). The prediction power of AI depends chiefly on the availability of quality data, However, limited availability of the right quality and quantity of data may act as an obstacle of the power of AI (Harkut and Kasat 2019). The prediction power of an algorithm depends highly on the quality of data fed as an input. Sometimes even in quality data, biases can be hidden (Sundblad 2018). In the financial sector, some reference data are often affected by quality issues (Sundblad 2018). The concept of AI is premised on having a data-quality program in place (Sundblad 2018). Moreover, the use of intelligent machines represents a challenge concerning liability (Harkut and Kasat 2019). The questions which remain unanswered are who/what shall be responsible in case something goes wrong? Financial institutions are sometimes reluctant to give machines full autonomy since the behavior of machines is not fully foreseeable (Deloitte 2018b; Sundblad 2018). In many cases, they tend to keep the human supervisor in place to validate the critical machine activities and decisions like blocking payments or releasing payments (Sundblad 2018). This, in a way, partially defeats the purpose of using machines in the first place (Sundblad 2018). In some instances, compliance and operational security standards are relatively strict and insufficient understanding of AI's inherent risks, the culture of the firm and regulation can all act as barriers to widespread adoption of AI in financial services firms (Harkut and Kasat 2019).

2.3. Conclusion and Policy Recommendations

The research was premised on investigating the impact of AI on digital financial inclusion. Digital financial inclusion is becoming central in the debate on how to ensure that people who are at the lower levels of the pyramid become financially active. On the other hand, fintech companies are taking advantage of the availability of AI to apply its applications to ensure that the goal of digital financial inclusion is realized that is to include groups of low-income earners, the poor, women, youths, small businesses in the mainstream financial market. The study discovered that AI has a strong influence on digital financial inclusion in areas related to risk detection, measurement and management, addressing the problem of information asymmetry, availing customer support and helpdesk through chatbots and fraud detection and cybersecurity. On the aspect of risk, AI is transforming financial inclusion through the widespread use of algorithms to automate risk detection management and measurement. This enables vulnerable groups of women, youths and small businesses such as smallholder farmers, who were excluded from the formal financial market in the traditional banking sector driven by issues around risk, to access banking services. Considering issues related to information asymmetry, digital financial inclusion through AI can have access to various online shopping platforms and social networks which produces a large amount of information on individuals; this will help to do away with the problem of information asymmetry between financial institutions and individuals, thus increasing the financial inclusion. These are some of the areas where AI is influencing digital financial inclusion among many other issues discussed. It is also important to note that though many people have a lot of misgivings about AI in the industry 4.0, it is, however, important to notice that AI is providing subatantial assistance in the digital financial inclusion sphere. Therefore, this study recommends that financial institutions and non-financial institutions adopt and scale up the use of AI as it presents benefits in the quest to ensure that people who were previously unable to participate in the formal financial market can do so with ease.

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Blockchain-Enabled Corporate Governance and Regulation

Dulani Jayasuriya Daluwathumullagamage * and Alexandra Sims

Department of Accounting and Finance, Department of Commercial Law, University of Auckland, Auckland 1021, New Zealand; a.sims@auckland.ac.nz
* Correspondence: d.jayasuriya@auckland.ac.nz

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Abstract: There is considerable hype about blockchain in almost every industry, including finance, with significant investments globally. We conduct a systematic review of 851 records and construct a final article sample of 183 for the sample period 2012 to 2020 to identify relevant factors for blockchain adoption in corporate governance. We conduct textual and empirical analysis to develop a decentralized autonomous governance framework and link traditional corporate governance theories to blockchain adoption. Furthermore, we explore present and future use cases and implications of blockchains in corporate governance. Using our systematic review and textual analysis, we further identify gaps and common trends between prior academic and industry literature. Moreover, for our empirical analysis, we compile a unique database of blockchain investments to forecast future investments. In addition, we explore blockchain potential in corporate governance during and post COVID-19. We find prior academic articles to mostly focus on regulation (49 studies) and Initial Coin Offerings (ICOs) (46 studies), while industry articles tend to concentrate on exchanges (10 studies) and cryptocurrencies (9 articles). A significant growth in literature is observed for 2017 and 2018. Finally, we provide behavioural, regulatory, ethical and managerial perspectives of blockchain adoption in corporate governance.

Keywords: blockchain; disruptive technology; corporate governance; corporate voting; tokenisation; smart contracts

JEL Classification: G20; G3

1. Introduction

Coined as a disruptive innovation, blockchain technology (Nakamoto 2008) has potential for creating and increasing socio-economic welfare as well as increasing the financial industry's reputation. Moreover, the use of blockchains simultaneously interacts with and challenges firms, stakeholders and financial markets. However, as identified by our study, literature solely focusing on corporate governance adoption of blockchain remains sparse. Most slightly touch on one or two applications but are primarily focused on other blockchain-related topics such as Initial Coin Offerings (ICOs) or cryptocurrencies. In addition, our study would particularly be relevant in a post-COVID-19 world, where the ability to digitally conduct business online will be paramount in the "new normal". Thus, we systematically review prior academic and industry literature for the current use of blockchains (BC) in corporate governance (CG) and regulation and link its implications to traditional theories in corporate governance. Our study identifies how academic and industry literature evolved through time and across key areas relevant to blockchain adoption in corporate governance. We further identify similarities, trends and gaps between academic and industry literature. Furthermore, we provide a behavioural, ethical and managerial perspective on blockchain adoption in corporate governance and regulation. In addition, we compile a unique empirical database and conduct an empirical analysis of blockchain and related start-up investments globally and forecast future blockchain investments. Finally, we develop a blockchain adoption framework in corporate governance.

We pose the following research questions: 1. What are the current and future use cases of blockchain applications in corporate governance? 2. What are the trends, gaps and similarities between prior industry and academic literature? 3. What are the implications of adopting blockchain in corporate governance and links to theories in prior literature? 4. What are the advantages, challenges, misconceptions and limitations for blockchain adoption in corporate governance during COVID-19 and post COVID-19? 5. What are the links between investments in blockchain internationally and future forecasts? Although there is a growing literature on the development of blockchain technology, few studies explore blockchain applications, particularly with regard to corporate governance. Our study is most related to Yermack (2017), who focuses on the impact of blockchain adoption in corporate governance on various stakeholders such as managers, small shareholders, institutional investors and other parties. Yermack (2017) finds blockchain adoption in corporate governance would result in reduced cost, increase in liquidity, transparency and bookkeeping accuracy. Our study differs from these papers and prior literature in several aspects. 1. We develop a framework for blockchain adoption in corporate governance. 2. We compare academic and industry literature to identify common trends, over- and under-explored areas and evolution of literature through time for a large sample of articles (183). 3. We provide an empirical analysis of blockchains and related start-up investments globally. 4. We link theories in corporate governance to implications from blockchain adoption. Thus, this study contributes to the behavioural perspectives and structural changes not limited to firms due to technology shocks such as blockchain but including market participants, developers and regulators alike. From a social paradigm perspective, this study would appeal to academics, industry practitioners, governments, law- and policymakers, entrepreneurs and investors of blockchains.

Selected key findings from the systematic review of 851 records and a final article sample of 183 for the sample period 2012 to 2020 include the following. We identify nine primary themes from prior literature that has some relevance to blockchain adoption in corporate governance, discussed in detail in the results (Section 5.1). On one hand, academic articles mostly focus on the regulatory theme (49 studies) and ICO theme (46 studies). On the other hand, industry articles primarily focus on exchange-related themes (10 studies) and the cryptocurrency theme (9 articles). We observe a significant interest in both academia and industry during 2017 (48 studies) and 2018 (42 studies) in aggregate. With China's renewed investments in the Blockchain-based Service Network (BSN) and COVID-19 lockdowns driving many firms towards digital transformation, interest in blockchains is most likely to further increase in 2020.

Selected findings from the textual analysis include the following: We identify that both industry and academic literature is largely concentrated around 1. Bitcoin, 2. markets, 3. technology and 4. fintech application themes. However, the industry and academic interests diverge in the following cases, where the industry focuses more on 1. privacy, 2. business and 3. global themes and academia concentrates on 1. governance, 2. networks and 3. ledger themes. Giving context to these themes from the content of these literatures enables us to observe that the industry focuses more on blockchain potential on a global scale, with business applications and features of blockchain such as privacy. Meanwhile, academic literature tends to have a narrower focus, with much concentration on exploring blockchain governance and architecture.

We compile a unique empirical database from industry data sources such as PwC, ICO insights, token data, CB Insights, Statista and Hutt Capital. Primary results from our empirical analysis for quarterly data from 2013 to 2019 includes the following. A growing linear trend is observed for investments and deal count beyond 2020, with investments and deal counts in 2020 and 2021 reaching 6.173 and 6.051 USD billion and 822 and 937, respectively, despite the COVID-19 crisis. We observe a negative correlation between European blockchain investments and Asia (largely driven by China). However, there is a strong correlation between global blockchain investments and Asia. These key results and additional results from our systematic review, textual analysis and empirical analysis are discussed in more detail in the results and discussion (Section 5).

This study is organised as follows. Section 2 provides a literature review. Section 3 outlines the research design. Section 4 discusses blockchain technology. Section 5 includes the results and discussion from the systematic review, textual analysis and empirical analysis, including the Decentralized Autonomous Corporate Governance (DACG) Framework. Section 6 outlines blockchain adoption in corporate governance, impact and present and future use cases. Section 7 identifies the governance and ethical aspects of blockchains with regard to corporate governance applications. Section 8 explores blockchain potential in corporate governance during COVID-19 and in the post-COVID-19 environment. Section 9 discusses the limitations of our study. Finally, Section 10 concludes the study.

2. Literature Review

This section provides a detailed description of corporate governance and blockchain-related corporate governance literature. The findings from the systematic review of literature are provided in the results and discussion (Section 5.1). In this study, a systematic, structured literature review is undertaken to identify sources of secondary data, the historical context and best practice comparator information. While we discuss prior research on corporate governance, our objective is not to provide an exhaustive review of every aspect of blockchains in finance or corporate governance. This study is focused on the adoption of blockchain technology on corporate governance and thus would only focus on corporate governance theories that can be affected by blockchain adoption.

2.1. Corporate Governance

One of the first definitions widely accepted of corporate governance is offered by the Cadbury (1992), where corporate governance is defined as "the system by which companies are directed and controlled". Several adaptations of this first definition have been used later by academics in corporate governance research (du Plessis et al. 2005; Monks and Minow 1995). The agency cost theories of corporate governance state that the primary goal of good governance of firms is to protect shareholders and other stakeholders from managerial discretion. The separation between ownership, control and divergent interests of different stakeholders make it necessary to adopt governance mechanisms to align stakeholders' interests (Aguilera and Cuervo-Cazurra 2009). There are multiple corporate governance mechanisms recognized by research, both internal and external (Fama and Jensen 1983; Jensen 1993). These mechanisms attempt to reduce agency costs and guarantee an efficient decision-making process that maximizes the firm's wealth (Ahlering and Deakin 2007). Amongst the internal mechanisms, the most relevant ones seem to be the shareholders' ownership structure, the board of directors and the role of compensation of directors and managers.

In addition, transaction cost theory, first initiated in Coase's (1937) paper and later theoretically described by Williamson (1996), is an interdisciplinary alliance of law, economics and organizations. This theory defines the firm as an organization consisting of people with different views and objectives. The underlying assumption of transaction theory is that firms have become so large that they in effect substitute for the market in determining the allocation of resources. In other words, the organization and structure of a firm can determine prices and production. An alternative theory in corporate governance, which is the stewardship theory, has its roots in psychology and sociology and is defined by Davis and Thompson (1994). According to this theory, stewards are company executives and managers working towards protecting and creating wealth for the shareholders. Unlike agency theory, stewardship theory stresses not the perspective of individualism, but rather the role of top management as stewards, integrating their goals as part of the organization. Another theory in corporate governance is resource dependency theory. While stakeholder theory focuses on relationships with many groups for individual benefits, resource dependency theory concentrates on the role of board directors in providing access to resources needed by the firm. Hillman et al. (2000) contend that resource dependency theory focuses on the role that directors play in providing or securing essential resources to an organization through their links with the external environment.

Finally, political theory considers the approach of developing voting support from shareholders by purchasing voting power. Hence, having political influence may direct corporate governance within the organization. Public interest is much reserved as the government participates in corporate decision-making, taking into consideration cultural challenges. The objective of this study's literature review is not to discuss the entire literature on corporate governance but to identify certain theories that may be affected by blockchain adoption in the corporate governance sphere. In Section 6, our framework and several key Tables link these theories to blockchain adoption in corporate governance.

2.2. Blockchain and Corporate Governance

The article mostly related to our study is Yermack (2017). Yermack (2017) states that blockchain adoption in corporate governance would result in greater liquidity, lower costs, accurate record-keeping and transparent ownership. As mentioned in the introduction section, our paper significantly differs from Yermack (2017) and prior literature by developing an adoption framework, conducting a systematic review of a large sample of articles, differentiating between academic and industry literature and identifying gaps and trends, and finally linking prior traditional corporate governance theories to blockchain adoption. Catalini and Gans (2016) assert that integrations of multiple ledgers of banks via blockchain would speed up processes and reduce costs. However, Cong and He (2019) find that smart contracts can lead to increased collusive behaviour among participants. Several studies explore payment system applications for blockchains (Yamada et al. 2016) based on alternate ledger designs (Badertscher et al. 2017) and smart contracts (Atzei et al. 2017). Abadi and Brunnermeier (2018) question blockchains' ability to remain cost-effective, decentralized and accurate all at once. Houy (2014) finds that transaction fees, which are the prices paid to trade a security, are directly linked to computing power of miners. Aoyagi and Adachi (2018) develop a theoretical framework to explain cryptocurrency prices based on blockchains under asymmetric information. Kim (2017) find Bitcoin transaction costs to be 2% lower relative to standard conversion rates on average. Easley et al. (2017) test transaction fee evolution by implementing a game-theoretic model and explain users' and miners' strategic behaviour. Jayasuriya and Sims (2019) explore the effects of blockchain applications in accounting and find numerous applications including triple-entry accounting, reduced earnings management, real-time auditing.

A key differentiation to be made between blockchain-based and non-blockchain-based firms is the use of cryptocurrencies or crypto tokens. These tokens may impact operational, financing and strategic aspects of firm decision making (Rohr and Wright 2017; Chen 2018; Howell et al. 2018; Liu and Wang 2019a). Entrepreneurship-based crypto tokens enable stakeholder coordination with network externalities in a single ecosystem (Li and Mann 2018; Bakos and Halaburda 2018; Sockin and Xiong 2020). Cong et al. (2020) state that blockchain features such as immutability, transparency and wealth-sharing incentivize developers, early adopters and entrepreneurs to this particular technology. Li and Mann (2018) find that as the quality of the platform improves, it attracts more users and further drives up the value of the tokens, creating positive network effects.

We identify prior literature related to ICOs. However, the objective of this study is not to review ICO literature extensively but to identify aspects relevant for corporate governance and blockchains, as detailed in the results and discussion section. ICOs are a new financing mechanism for blockchain-based ventures, especially at the early stage of development (Ante et al. 2018; Kaal and Dell'Erba 2017; Zetzsche et al. 2018; An et al. 2019; Momtaz 2019a). Chod and Lyandres (2018) state that ICOs facilitate fundraising without having to relinquish control rights by the founders. Kaal and Dell'Erba (2017) compare ICOs with initial public offerings (IPOs) and state that ICOs have significantly lower issuer fees due to the non-involvement of intermediaries such as banks. Conley (2017) and Catalini and Gans (2018) state that ICOs create more demand for tokens and increased competition among token buyers and subsequently reveal consumer value. Chemla and Tinn (2017) identify similarities of ICOs to crowdfunding, where informed investment decisions are made through the wisdom of the crowds. Adhami et al. (2018) assert that ICO whitepapers and project-related details being widely available over the Internet will reduce information asymmetry and at the same time expose entrepreneurs to a wider range of investors. Lee and Parlour (2019) argue that ICOs provide a more liquid and secondary market for tokens listed on crypto exchanges relative to venture capital and private equity investments. However, several studies such as Collomb et al. (2018), Clements (2018) and Zetzsche et al. (2018), identify regulatory arbitrage and uncertainty around regulation as ICO disadvantages. Trimborn et al. (2018) find that majority of ICOs have a fixed token supply with a single round of financing which is required to increase token price with more demand. Liu and Wang (2019b) review prior literature on ICO token construction and valuation.

Literature that analyses ICO success include (Adhami et al. 2018; Blaseg 2018; Deng et al. 2018; Feng et al. 2018; Fisch 2018; Howell et al. 2018; Rhue 2018; Zetzsche et al. 2018; Bourveau et al. 2019 and Dean et al. 2019). Several studies focus on the quality of the management team and ICO advisors as signals of project quality and success potential (Amsden and Schweizer 2018, Lyandres et al. 2019, Bourveau et al. 2019). An et al. (2019) and Howell et al. (2018) highlight the significance of the enterpreneurs' experience, and Momtaz (2020a) and Momtaz (2019c) find CEO emotion and loyalty as being significant for ICO outcomes. Another strand of ICO literature finds significant underpricing in ICOs relative to IPOs (Adhami et al. 2018; Momtaz 2018; Bourveau et al. 2019; Ofir and Sadeh 2019). Benedetti and Kostovetsky (2018) and Momtaz (2019b) state that tokens are under-priced to attract a wider investor base and to overcome information asymmetry issues related to ICOs. Furthermore, studies such as Benedetti and Kostovetsky (2018); Momtaz (2018); Felix and Eije (2019); Drobetz et al. (2019) and Lyandres et al. (2019) focus on ICO under-pricing determinants and identify investor sentiment and first-day returns as being significant for long term ICO return prediction.

2.3. Legal and Governance Aspects of Blockchains and Applications

Blockchain-based firms would be a novel institution type which may require new economic analysis and governance mechanisms. Thus, several studies highlight the importance of government oversight on blockchain adoption (Davidson et al. 2016; Yeoh 2017). Other studies identify problems with ICO bans and explore optimal ICO regulation (Robinson 2017; Barsan 2017; Chohan 2017; Kaal and Dell'Erba 2017; Li and Mann 2018; Zetzsche et al. 2018). According to Kaal and Vermeulen (2017), 25 countries are considering comprehensive cryptocurrency regulation. Such regulation is key to prevent money laundering and black-market operations (Brenig et al. 2015; Abramowicz 2016; Hardy and Norgaard 2016; Humphries and Smith 2018; Foley et al. 2019). Piazza (2017) discusses blockchain adoption in corporate governance purely from a regulatory perspective. The author surmises that due to uncertainty in regulation, Bitcoin and blockchain adoption in ownership reporting and accounting is not prudent. However, Piazza (2017) does support the adoption of blockchain as a corporate voting tool. Brainard (2016) discuss various cryptocurrency regulation and courses of action. Furthermore, another strand of studies highlights the importance of regulation coordinated within society (Atzori 2015; Hughes and Middlebrook 2015; Mills et al. 2016; Robinson 2017; Nabilou and Prum 2019). Harwick (2016) discusses cryptocurrency-related, economic barriers, legal, technical, intermediation, governance factors and solutions.

Evans (2014) analyses present cryptocurrency platforms and alternatives and highlight the need for adequate governance. Tasca (2015) provides a case for country-level governance with regard to cryptocurrencies and payment systems related to financial intermediaries. Bagby et al. (2018) propose expanded jurisdiction on cryptocurrency regulatory initiatives. Luther (2016) states a lack of government support and regulation as a key barrier for cryptocurrency prevalence and success. Barsan (2017) and Pilkington (2018) discuss ICOs in general and advocate for stringent regulation to avoid hacking similar to the decentralised autonomous organisation (DAO) hack. Zetzsche et al. (2018) provide legal recommendations that would mitigate participation risks in ICOs to investors. Kim et al. (2018) explore the cryptocurrency regulatory landscape and develop a framework for cryptocurrency valuation.

Blockchain-based regulation also involves regulation of equity crowdfunding. Zhu and Zhou (2016) explore Chinese equity crowdfunding platforms and provide blockchains as a viable solution resulting in low-cost, efficient, secure platforms requiring regulatory oversight. The next section provides a detailed description of our research design.

3. Research Design

This section firstly explains the research design for the systematic review and textual analysis and secondly provides the research design for the empirical analysis. The systematic survey and textual analysis enable us to identify the key diverse factors to be included in our framework. Our framework provides an overall picture of the many parties involved, theories from prior literature, market forces and the role of blockchain governance factors as it relates to blockchain adoption in corporate governance. Next, we hand-collect blockchain-related investment data globally and forecast future investments, deal counts and correlations among different geographic regions.

3.1. Systematic Review

As a meta-analysis method, systematic reviews are developed to explore, collect and analyse present knowledge and gaps regarding certain concepts (Briner et al. 2009). Industry and academic articles on general blockchain applications across industries and its impact have begun to proliferate in prior literature. However, each analysis in some way possesses limited scope about applications and impact on corporate governance. This proliferation further creates risks in knowledge collection and integration of findings to academics and practitioners (Briner et al. 2009). Hence, this study collates these dispersed articles in a systematic and coherent manner to identify factors relevant for blockchain adoption in corporate governance, analyse gaps, similarities and trends between the academic and industry literature and develop an adoption framework.

Given this setting, we follow (Briner and Denyer 2012) and (Moher et al. 2009) to implement a systematic literature review. The key steps are as follows. 1. Identify the motivation behind the review and formulate research questions; 2. collate the relevant articles from prior literature, conduct quality assessments and synthesise the required data; 3. carefully analyse the final sample of articles manually and through textual analysis to identify trends, gaps and similarities between academic and industry literature and to develop the framework; and 4. finally, present the findings from our review and the developed framework for blockchain in corporate governance. We construct a final sample of 183 (28 industry and 155 academic articles) articles. These articles are finalised from a preliminary search that yielded 851 articles for the sample period from 2012 to 2020. Further details about the article inclusion and exclusion criteria, search methods and keywords are described in detail in the next sub-sections.

3.1.1. Definition of Research Questions

The first stage involves motivating the study and defining the research questions. Blockchain is an ever-evolving technology and is a key part of the digital transformation process for most businesses. Hence, understanding this technology and its impact is important. However, a key part that often gets missed by most prior literature is how blockchain relates to corporate governance, its theories and implications. Furthermore, due to the proliferation of general blockchain adoption literature, it is important to conduct a systematic review to comprehend prior literature and identify insights relevant for blockchain adoption in corporate governance. To this end, the following research questions are formulated.

1: What are the present and future use cases of blockchain applications in corporate governance?

This research question identifies present and future blockchain use cases from a wide range of applications of blockchain across many industries, from general adoption articles and finance-related articles themselves.

2: What are the trends, gaps and similarities between prior industry and academic literature?

This question is formulated to obtain an overview of over- or under-explored areas and differences of interest between the industry and academic literature with regard to blockchain and corporate governance. The findings related to this research question would aid future researchers and industry practitioners to identify gaps where more research and applications are required and would promote collaborations between industry and academia.

3. What are the implications of adopting blockchain in corporate governance and linking to theories in prior literature?

Clearly identifying the impact of blockchain adoption for corporate governance is key for successful deployment and maintenance of blockchain within the finance industry. By linking existing traditional corporate governance theories to blockchain adoption, this research question aids in better understanding impacts and unintended consequences.

4: What are the advantages, challenges, misconceptions and limitations for blockchain adoption in corporate governance during and post COVID-19?

Due to lockdowns and social distancing, most businesses have been pushed for digital transformation at a faster pace, including those in the financial sector. Blockchain being one of the key fintech technologies, this research question aims to understand the advantages, limitations and barriers of adoption of blockchain in corporate governance during and post COVID-19.

5. What are the links between investments in blockchain internationally and future forecasts?

This empirical research question collates empirical data on blockchain investments from several data sources and forecasts future investments to identify future investment trends.

3.1.2. Collating Articles

This section details the steps followed for article selection. We carried out a systematic literature search in Science Direct, Business Source Premier, Scopus and Google Scholar. The article collation process involved the following steps: 1. database identification (Science Direct, Scopus, Business Source Premier and Google scholar); 2. finalising keywords and search criteria (for the preliminary search); 3. identifying the initial set of articles and analysing manually and through textual analysis; 4. constructing the final sample of articles; and 5. classifying the identified relevant articles into major themes; Science Direct, Scopus and Google Scholar were selected as suggested by finance specialist librarians at the university as being the primary databases[1] with an exhaustive list of industry and academic articles relevant to blockchain technology in finance.

The article search included several permutations of the following keywords: "finance+blockchain", "decentralised system+finance", "decentralised network+finance", "decentralised ledger+finance", "cryptocurrencies+corporate governance", "digital currencies+corporate governance", "bitcoin+corporate governance", "Ethereum+finance", "ICO+finance," "financial services+blockchain", "security+blockchain", "ethics+blockchain", "blockchain+corporate governance", "financial intermediaries+blockchain", "COVID-19+blockchain", and "regulation+blockchain" in the title, abstracts, text, and keywords fields of the search engine. Moreover, the reference list from selected articles was further analysed to identify more articles not previously captured by the search criteria (snowball effect). This preliminary search yielded 851 records in total from all the databases. These articles include peer-reviewed research articles, conference proceedings papers, consulting and professional body reports, white papers, book chapters, short notes and short surveys. Subsequently, we segregated academic and articles and constructed a final sample of 183 blockchain-related articles (28 industry and 155 academic articles), which was used in the analysis, possessing factors relevant to or that can be re-purposed for corporate governance.

1 Several search refinement features of Scopus and Science Direct are used following specific articles that might be in a grey area with regard to interest. However, for good measure we conducted a regular Google search as well and reviewed search results so as not to miss important industry reports.

3.1.3. Final Article Sample Selection

The pre-defined inclusion/exclusion criteria in Table 1 aid in constructing the final sample of articles. Several exclusion criteria are implemented prior to including the articles in the bibliographic manager. These included perusing for language, document type (notes, editorials) and further removing articles that contain no information relevant to blockchain adoption in corporate governance. In the initial stage, all articles' keywords, abstracts and introductions were assessed. Subsequently, any article that met one of the exclusion criteria was excluded. Several articles were further excluded following a full text review and being purely related to technical aspects of blockchain technology. Additional articles related to finance, corporate governance and survey methodologies are included in the reference list of the study but not included in the review analysis as they are not related to blockchain technology.

Table 1. Inclusion and exclusion criteria.

Selection Criteria		Article Description	Grey Literature (Literature Whose Relevance Is Unclear from the First Search)
Inclusion	With time-frame restrictions beginning from 2012	Peer-reviewed research articles (including articles in press), conference proceedings papers, book chapters, review papers, short surveys, serials etc.	Technical reports relating to blockchain but with factors that can be relevant or repurposed for applications in corporate governance.
		Databases used: Google Scholar, Science Direct, Business Source Premier and Scopus.	
Exclusion	Prior to importation to bibliographic manager	Non-English articles, articles with missing abstracts, notes, editorials	Generic reports related to blockchain technology without any factors relevant to corporate governance.
	During title screening	Generic articles related to the blockchain technology and/or blockchain architecture with no application possibility in finance or relevance for corporate governance.	
	During abstract screening	Software-oriented articles related to blockchain technology and not related to blockchain governance	
	During full-text screening	Articles solely addressing technical aspects of blockchain technology and not related to blockchain governance	

3.1.4. Textual Analysis and Thematic Coding

All articles in the final sample are submitted to machine-learning-based textual analysis software named 'Leximancer'. Through Leximancer, key themes and sub-themes are identified for the framework development and further differentiation between industry and academic literature. Additional factors to the framework are included by carefully reading the articles in the final sample for robustness of the results from Leximancer and to provide context to the key themes identified by the software. Thematic content analysis through Leximancer is conducted via resource maps, and detailed results are explained in Section 5.2.

Resource Maps

A resource map provides a broad view of a large amount of literature in one single graph. The size of each concept point indicates its connectedness. As the algorithm goes through the list, it will attempt to draw words as close as possible to the centre of the visualization. These key themes and sub-themes identified via the resource maps and the manual systematic review of prior literature form the foundation for our DCAG.

3.2. Empirical Data Collection and Methodology

Due to blockchain's relative novelty, its exponential development and secrecy by adoptive firms due to future profitability prospects, empirical data with regard to blockchain applications are difficult to obtain (Dapp 2014). Given this setting, for the empirical analysis, firstly, we hand-collected and compiled a unique quarterly database from 2012 to 2020 of blockchain and related start-up investments globally through historical reports from PwC, Token Data, CB Insights, ICO Insights, Statista and Hutt Capital. The future values are forecasted using a basic average linear extrapolation on past values due to the lack of a number of observations and additional data.

4. Blockchain Technology

Blockchain is just one form of the broader area of distributed ledger technology (Brainard 2016). Given the widespread use of the term "blockchain", we use that term instead of distributed ledger technology (DLT). There are two main types of blockchains: public and permissioned. On a public blockchain, such as Bitcoin, no permission is required to use or view the blockchain. The two highest-profile public blockchains are Bitcoin and Ethereum (Atzei et al. 2017). Bitcoin was the first blockchain (Nakamoto 2008). Most public blockchains are open-source, and no central authority or person runs a public blockchain. Rather, a network of peers agrees on the state of the blockchain. Newer platforms such as IOTA, Hashgraph, Holochain and Dfinity do not use a chain of blocks (Wright and De Filippi 2015). Verification on the Bitcoin blockchain is made via peers (miners). Bitcoin's blockchain is a ledger that records the number of bitcoins an entity owns in a particular wallet (Abadi and Brunnermeier 2018). It also contains a full transaction history of all transactions sent and received by that particular wallet. People or entities are not defined by their names, as they would be for a bank account; rather, public keys are used (Chen 2018). Public keys are a long string of numbers and letters. The Bitcoin blockchain records the bitcoins each public key owns. A public key, in turn, is controlled by the individual who has the private key (another long string of numbers and letters). Whoever has access to the private key is able to transfer bitcoins, highlighting the importance of the security of the private key (Atzei et al. 2017). Crucially, unlike with a password for a bank account, there is no ability to recover a lost or forgotten private key.

Miners are incentivized to perform the validation and block creation work by a block reward: a reward of bitcoin for successfully adding a block to the blockchain, plus the transaction fees from the transactions the miner includes in the block (Babich and Hilary 2019). The block reward further serves to distribute newly created bitcoin. Bitcoin is currently capped at 21 million bitcoins and it is expected that in approximately 2140, the last bitcoin will be created. Once the last bitcoin is created, miners will receive only transaction fees that are attached to transactions (Beck et al. 2018). Transactions cannot be altered after the fact, although it is possible in exceptional circumstances to make retrospective changes (DuPont 2017). Bitcoin and its proof-of-work consensus system have been criticized for their electricity use, although Vranken (2017) has questioned the estimates. Several blockchains, mindful of electricity usage, use proof-of-stake or delegated proof-of-stake, which do not expend large amounts of electricity, as nodes are chosen at random to validate transactions (Vranken 2017). For example, proof of importance consensus is used in the NEM blockchain. Permissioned blockchains, which are considered next, do not normally use proof-of-work and thus have minimal electricity requirements (Vranken 2017). Permissioned blockchains, as the name suggest, can limit who has permission to validate transactions, view the blockchain and create transactions. Permissioned blockchains are generally run by consortiums. Fewer participants translate to a permissioned blockchain that is not as decentralized as a public blockchain (Beck et al. 2017). Several public blockchains, such as Ethereum and NEM, offer permissioned versions.

4.1. Smart Contracts

Smart contracts are a set of instructions residing on a blockchain, written in computer code, and are a key aspect of harnessing blockchains' capabilities. Szabo (1994) states that a smart contract can execute the terms of a contract and is a computerized protocol. They can be used, for example, to guarantee payment by counterparties involved in a contract. Ethereum is the first blockchain to successfully employ smart contracts. The self-enforcing nature of smart contracts results in transaction costs of monitoring and enforcing adherence to rules and laws being removed (Cong and He 2019). Sisli-Ciamarra (2012) states that firm board composition may also be affected by smart contracts. Generally, firms have bankers as directors to signal financial markets' creditworthiness, and smart contract signalling may deter this need. Mik (2017) argues that smart contracts can be implemented to solve numerous legal and enforcement issues. In our opinion, applications of smart contracts in corporate finance and governance could include option exercises and other contingent claims requiring instant collateral transfer in case of default. They can also include performance-based employee compensation packages. Moreover, smart contracts alleviate agency costs in many of these scenarios in corporate governance (Yermack 2017). Finally, a firm's willingness to implement smart contracts can signal future ethical behaviour.

4.2. Decentralized Autonomous Organizations (DAO)

Organizations/firms are deemed to be a natural mechanism for conducting businesses, and this form of organization dates back to the mid-19th century (DuPont 2017). However, blockchains have the potential to transform the future organization to a digitized decentralized network of stakeholders (DuPont 2017 and Sims 2019). In our opinion, blockchains can facilitate a form of novel organization without senior management or an organizational hierarchy. Blockchains are an opportunity for new organization types to develop based on a distributed decentralized structure (Scott et al. 2017). Shermin (2017) argue that blockchains can overcome traditional principal–agent dilemmas through decentralized governance and highlight the importance of smart contracts to implement a trust regulatory system. A DAO is an amalgamation of blockchains, smart contracts and stakeholders all working together interactively. The basic rules of governance are programmed into the blockchain at setup (DuPont 2017). All stakeholders involved with the DAO will possess tokens that represent a share in the DAO's performance (similar to a share of an organisation/firm). Therefore, the fundamental profit maximisation goal of the firm can be restated as the value maximisation of the tokens for a DAO (DuPont 2017). Essentially, in our opinion, a DAO is an organisation controlled by token holders that operate on a blockchain through smart contracts. Thus, DAOs will have to be governed by laws and regulations similar to all regular firms in order to interact and conduct business in the real world. Therefore, these token holders will replace board members AND top management, where decisions would be made by token holders. Moreover, the type of token possessed by each token holder may determine the type of contract for each project within the DAO, similarly to an employee in a regular organization/firm.

5. Results and Discussion

This section firstly discusses the systematic review results, then the results from the textual analysis and DACG framework and finally moves on to the empirical results. Moreover, this section answers Research Question 2: What are the trends, gaps and similarities between prior industry and academic literature? The key findings from the systematic review section involve the identification of nine key themes with regard to prior literature, the time trends and cross-sectional distributions of these literature, common trends and over- and underexplored themes between industry and academic literature.

5.1. Systematic Literature Review Results

The study analyses 183 articles, out of which 28 are from the industry for the sample period from 2012 to 2020. By reading through prior literature, we are able to broadly classify them into the following key themes: 1. exchanges and CG, 2. corporate voting and CG, 3. practice and education of BC, 4. BC and CG, 5. regulation, 6. BC technology related to CG, 7. ICOs and crowdfunding, 8. cryptocurrencies and 9. other. The "Other" theme includes articles with a prime focus in another area than the themes identified with regard to blockchain but still having some relevant factors to draw upon for blockchain adoption in corporate governance.

Academic and Industry Article Comparison

Table 2 identifies the number of articles that focus on the key themes utilized to develop the decentralized autonomous corporate governance framework (DACGF) in this study. According to Table 2, the industry focus is primarily on the two themes of stakeholders (23 studies) and blockchain impact and value creation (20) from our DACG framework. Academic studies primarily focus on market mechanisms (60 studies) and blockchain governance (57 studies). Corporate governance emerges as an underexplored area by both academic (7 studies) and industry (1 study) literature, highlighting the importance of our study and the DACG framework. Table A1 is provided as a separate Internet Appendix A for brevity and identifies the themes from the systematic review on blockchain adoption in corporate governance among academic studies and industry articles.

Table 2. Focus counts for framework development from prior literature.

Framework	Focus on Any Factor within Theme		
Key Themes	Total	Industry Reports	Academic Studies
Corporate governance theories relevant to blockchain adoption	8	1	7
Blockchain impact and value creation	54	20	34
Stakeholders	53	23	30
Market mechanisms	74	14	60
Blockchain governance	60	3	57

Source: CB insights, PwC, ICO Insights and Token Data.

Figure 1 depicts the industry and academic article count across time, and Figure 2 provides the article count by key themes for industry and academic literature and the aggregate of both. In Figure 2, several articles from both industry and academic may overlap across several themes. Figure 2 further enables us to identify the trends, gaps and similarities between academic literature and industry reports.

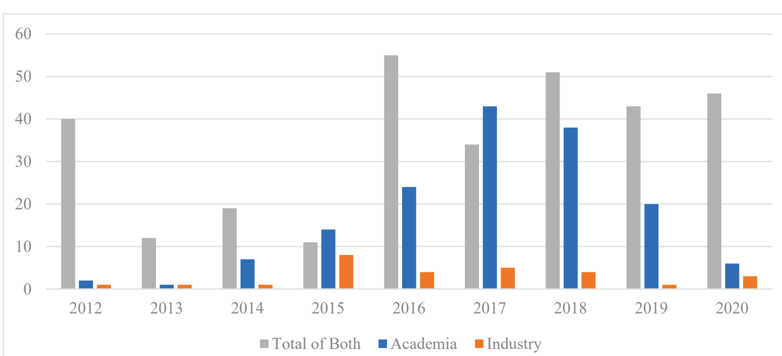

Figure 1. Year-wise article count.

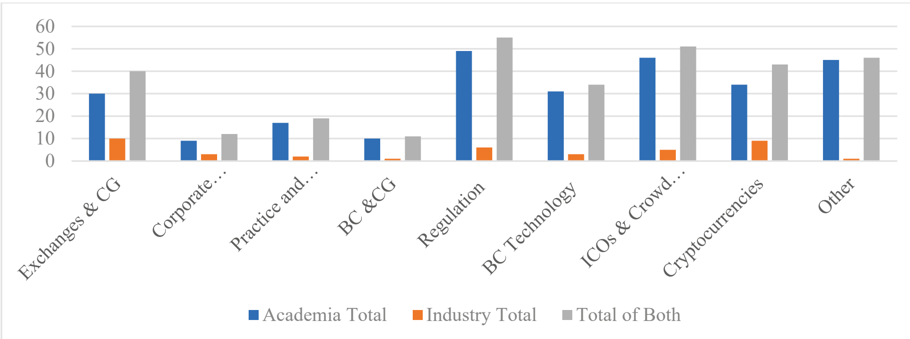

Figure 2. Topic-wise article count for academic and industry articles and total aggregate.

According to Figure 1, articles skyrocketed during 2017 and 2018 for academia, with 43 and 38 and for industry, with 5 and 4 articles, respectively. However, the year with the greatest number of articles from the industry with some relevance for corporate governance was 2015 (8 studies). This count suggests that academia seems to lag behind industry by two years in terms of blockchain articles with factors relevant for corporate governance. Due to some stringent regulatory measures and bans in 2018 in China, there is a significant decline post-2018 (Allan and Hagiwara 2018), with only 20 academic studies in 2019. This trend is likely to reverse with interest picking up due to COVID-19 and renewed interest from China. Figure 2 displays the theme-specific distribution of our sample of 183 articles. These themes are identified from our systematic review as opposed to the earlier themes mentioned that are directly from our DACG framework. According to Figure 2, academic articles mostly focus on regulation (49 studies) and ICOs (46 studies). Industry articles primarily focus on exchanges (10 studies) and cryptocurrencies (9 articles). This result is understandable, as most industry applications tend to focus on digital or cryptocurrencies and their many applications in financial services. These numbers highlight the interdisciplinary potential of blockchains across industries.

5.2. Textual Analysis

The first step in manually identifying differences, gaps and trends between academic and industry literature involves carefully reviewing the text body. However, as an additional step, these three resource maps further help to differentiate between academic and industry literature. Moreover, to develop the DACG framework, we use textual analysis to obtain a broad perspective of prior literature and industry reports. Through this, we identify the key themes and which studies are clustered around them as explained in the first part of Section 5.1.

The Map

The resource maps below provide information about the main concepts across the literature analysed and finally the similarities in the contexts in which they occur. This analysis helps us to develop our DACG framework and to identify key themes. Figure 3 shows words such that the terms that occur the most frequently are positioned centrally and are of the largest size for academic and industry literature, thus, providing an overall birds-eye view of the entire sample of 183 articles. According to the large-sized and nearby linked words, we can observe that Figure 3 identifies 1. blockchain, 2. technology, 3. markets, 4. financial, 5. shareholders, 6. transactions, 7. information and 8. transparency as key themes emerging from prior literature. By coding those themes and giving them context, we can identify that they relate to focus on blockchain technology itself: blockchains in finance and financial markets, blockchains in exchanges with links to shareholders, blockchains for payment systems with links to transactions, and finally blockchain features such as transparency and information on a blockchain. Further examples and explanations of blockchain applications are explained in Section 6.

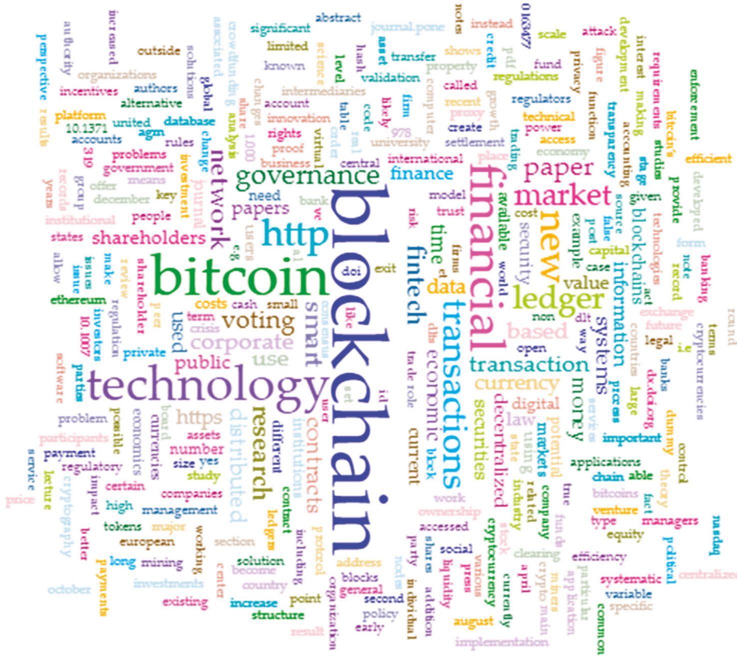

Figure 3. Resource map from textual analysis of both industry and academic literature.

Figures 4 and 5 display resource maps for academic and industry literature separately. By comparing key themes identified in Figures 4 and 5 we again explore the differences, similarities and gaps between academic and industry literature. Figure 5 depicts 1. blockchain, 2. Bitcoin, 3. technology, 4. financial, 5. transactions, 6. network, 7. fintech, 8. governance, 9. markets and 10. ledger as key themes in the academic literature. Meanwhile, Figure 5 shows 1. blockchain, 2. markets, 3. technology, 4. business, 5. global, 6. privacy, 7. Bitcoin, 8. industry, 9. transactions, 10. bank, 11. currencies and 12. fintech as key themes from industry reports. By comparing these themes, we can identify that both industry and academic literature can be largely concentrated on 1. Bitcoin, 2. markets, 3. technology and 4. fintech. This shows the preferred blockchain-based areas in Bitcoin, blockchains in markets, technology of blockchains itself and use of blockchain as a financial technology. However, the industry and academic interests diverge in the following cases: industry focuses on 1. privacy, 2. business and 3. global, and academia focuses on 1. governance, 2. networks and 3. ledger. Giving context to these themes would enable us to observe that industry focuses more on blockchain potential on a global scale, with business applications and features of blockchain such as privacy. However, the academic literature is relatively narrower by exploring blockchain governance and blockchain architecture with regard to its networks and the decentralised nature of blockchains.

Figure 4. Resource map from textual analysis of academic literature.

Figure 5. Resource map from textual analysis of industry literature.

5.3. Decentralized Autonomous Corporate Governance (DACG) Framework

In essence, blockchain is a distributed ledger (which can be open, permissioned or private) that records transactions in a permanent verifiable manner among parties efficiently. In some platforms, these tasks can be programmed to trigger transactions automatically given certain contingencies (smart contracts). With blockchain-enabled corporate governance, need for intermediaries such as brokers, banks and lawyers would be significantly reduced. Instead, stakeholders, users, organizations and blockchains would transact and communicate with each other with as little friction as possible. Such a newly digitized world of corporate governance, which may seem decades away into the future, is the daunting potential of blockchains. Moreover, due to COVID-19, that future may come more sooner than anticipated. Figure 6 outlines our DACG framework.

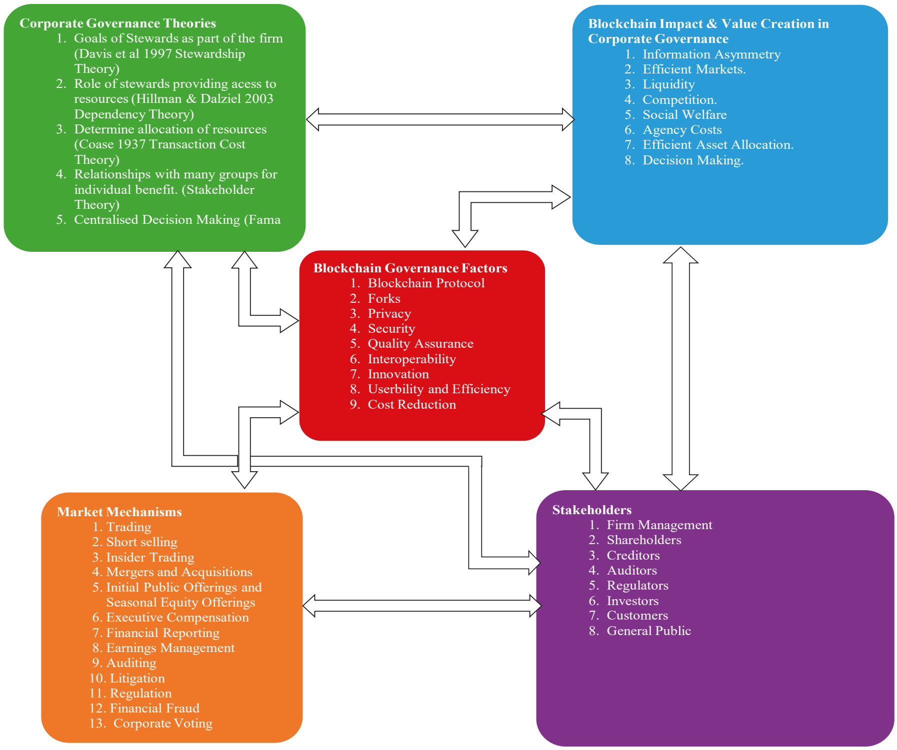

Figure 6. Decentralized autonomous corporate governance.

Key features of the blockchain technology are already deeply embedded in our economic, legal and political systems in terms of record-keeping, transactions, contracts and stakeholders. Similar to the functions in a blockchain, organizational governance and boundaries are established as is verification of ownership, identities, recordkeeping of events and interactions among stakeholders. Hence, in our opinion, application of blockchain into corporate governance is just another form of digitizing the same factors in corporate governance. However, the possibility of digitization at every level may pose several ethical, regulatory and social issues apart from key advantages. These issues and advantages are discussed in the later sections of this study. The DACG Framework is designed to help organizations and interested parties achieve clarity, ensure value from their efforts, create a clear mission, maintain scope and focus and establish accountabilities with regard to blockchain adoption in corporate governance. This section of the paper describes the key components and core factors of the DACG Framework. In essence, this framework provides an overview of blockchains, its impact and relevant corporate governance applications and theories to enable proper adoption.

5.3.1. Why Use the DACG Framework?

Most transactions of an organization revolve around the following key drivers: profit maximization, manage complexities and costs, risk management, security and privacy. All efforts of an organisation would ultimately revolve around these three core mandates. However, maintaining focus on all factors and keeping all aspects in mind may be difficult, especially when trying to explore the feasibility and potential adoption of a new technology such as blockchains. Given this setting, our framework helps interested parties and organisations to keep the bigger picture in mind. Frameworks enable us to organize how we envision and communicate about ambiguous, new and complicated concepts.

Thus, a proper framework at a higher level on the impact of blockchain adoption can provide clarity and purpose for interested stakeholders. Our framework has five main components: corporate governance theories, market mechanisms, blockchain impact, stakeholders and finally, at the centre, blockchain governance. The key themes in our framework are explained in detail below.

5.3.2. Corporate Governance Theories Relevant to Blockchain Adoption

One contribution of our study is to survey prior literature on corporate governance theories and identify theories that are related to blockchain adoption and explore their subsequent impact. Table 3 explains these theories and impact of blockchain adoption in more detail. Identification of such theories is important to fully understand the potential and implications of blockchain adoption and develop new theories related to blockchain adoption in corporate governance. To this end, we have identified these key theories in corporate governance. 1. Goals of stewards as part of the firm (Davis et al. 1997, Stewardship Theory). 2. Role of stewards providing access to resources (Hillman and Dalziel 2003, Dependency Theory). 3. Determining allocation of resources (Coase 1937, Transaction Cost Theory). 4. Relationships with many groups for individual benefit. (Stakeholder Theory). 5. Centralized decision making (Fama and Jensen 1983 Agency Costs).

Table 3. Blockchain Adoption Implications and Corporate Governance Theories.

Corporate Governance Theory	Theory Description	Blockchain Adoption Implications
	1. Shares of a corporation would be issued and held on a blockchain	
Agency costs	The primary goal of good governance in firms is to protect shareholders and other stakeholders from the managerial discretion	1. Increased transparency and subsequent reduced information asymmetry would significantly change incentives and profit opportunities for managers.
Transaction cost theory	The organization and structure of a firm can determine price and production.	1. Reduced cost and speed of execution would greatly improve liquidity, and information incorporation into asset prices would facilitate high frequency. 2. It would increase demand for investments in stocks and also create new investing strategies, objectives and dynamics. 3. The real-time archiving of trades would result in information being incorporated into prices more speedily, making markets more efficient
Stewardship theory	Stewards are company executives and managers working and protecting and making money for the shareholders.	1. It would reduce information asymmetry and would significantly change incentives and profit opportunities for institutional investors, insiders and other traders in general
Resource dependency theory	Concentrates on the role of board directors in providing access to resources needed by the firm	1. Increased transparency may change and even expand the role of shareholders in corporate governance. 2. This may also hinder the board of directors and be interrupted by shareholders with no expertise in the relevant field.
Political theory	Considers the approach of developing voting support from shareholders, rather than by purchasing voting power	
	2. Corporate Voting	
Agency costs	The primary goal of good governance in firms is to protect shareholders and other stakeholders from the managerial discretion.	1. Voters and the firm would be able to see that votes had been cast validly, but if desired, would not be able to see how particular voters voted. This in turn would greatly increase the cost and speed of voting, would increase accuracy and would reduced interference by management.
Transaction cost theory	The organization and structure of a firm can determine price and production.	
Stewardship theory	Stewards are company executives and managers working and protecting and making money for the shareholders.	1. Increased transparency and speed and reduced costs would result in more shareholder and other interested stakeholder participation. Thus, stakeholders may get involved directly in corporate governance and petition for votes on important firm decisions.
Resource dependency theory	Concentrates on the role of the board directors in providing access to resources needed by the firm.	
Political theory	Considers the approach of developing voting support from shareholders, rather than by purchasing voting power	1. Using blockchain for corporate elections and shares would make empty voting more difficult or even prevent it entirely. Smart contracts can be used so that there is a stand-down period following the transfer of a share, during which time that share has no voting rights.

5.3.3. Blockchain Impact and Value Creation

This section is an amalgamation of our identification of the bridge between prior academic research and industry reports on blockchain applications in corporate governance. This key theme was developed by identifying the characteristics, advantages and disadvantages of present and future use case applications of blockchain adoption in corporate governance through our systematic review, then linking these to value creation avenues in terms of prior academic literature and market mechanisms that are affected by blockchain adoption in corporate governance. These key factors include the following: 1. Information asymmetry—blockchain offers transparency. 2. Efficient markets—blockchain offers higher speed, efficiency, lesser agency costs and transparency. 3. Liquidity—blockchain can handle large amounts of data with ease and efficiency and more transparency. 4. Competition—blockchain allows more participation. 5. Social welfare—blockchains would result in lesser agency costs, frauds and mismanagement. 6. Agency costs—removal or reduction of agents in blockchains results in lesser agency costs. 7. Efficient asset allocation—increased speed, efficiency and transparency and more efficient markets would result in efficient resource allocation. 8. Decision-making—blockchain would result in better decision making due to lesser agency costs, more transparency and efficient markets.

5.3.4. Stakeholders

This section synthesizes the stakeholders involved in blockchain adoption in corporate governance. This identification is fundamental to the understanding and implementation of blockchain adoption with regard to corporate governance. The key factors in this section include 1. firm management. 2. shareholders. 3. creditors. 4. auditors. 5. regulators. 6. investors. 7. customers and general public.

5.3.5. Market Mechanisms

This section identifies the market mechanisms that would be affected by blockchain adoption in corporate governance. The key factors include 1. trading, 2. short selling, 3. insider trading, 4. mergers and acquisitions, 5. initial public offerings and seasonal equity offerings, 6. executive compensation, 7. financial reporting, 8. earnings management, 9. auditing, 10. Litigation, 11. Regulation, 12. financial fraud and 13. corporate voting.

5.3.6. Blockchain Governance

Finally, at the centre of the framework lies the blockchain governance section that is linked to all other sections. Without proper governance of blockchains, its adoption in any area would not be sustainable long term. Therefore, this section includes the following key blockchain governance factors: 1. blockchain protocol, 2. forks, 3. Privacy, 4. Security, 5. quality assurance, 6. Interoperability, 7. Innovation, 8. usability and efficiency and 9. cost reduction. To ensure efficient, ethical and sustainable blockchain adoption in corporate governance, it is important to understand all themes and factors identified in our DACG framework.

5.4. Empirical Analysis

This section answers Research Question 5: What are the links between investments in blockchain internationally and future forecasts? Table 4 outlines blockchain wallet users in millions with numbers increasing to 44.69 million users in the 2019 fourth quarter, showing demand interest increasing. A significant increase in users can be observed between the first and second quarter in 2019 to reflect the Bitcoin price fluctuations, trade war fears between U.S. and China and growing interest in cryptocurrencies.

From the supply side, Figure 7 depicts the number of venture rounds completed between 2017 and the end of February 2018 led or participated in by key investors in blockchain and innovative technologies. It identifies several key venture capital firms monopolising investments in blockchain technologies in financial markets. Figure 8 depicts the percentage of blockchain and related startups for several key countries between 2017 and the end of February 2018. The U.S. is leading investments in blockchain and related startups. The majority of the "other" percentage is due to China.

Table 4. Number of Blockchain Wallet users.

Year	Number of Blockchain Wallet Users in Millions
2016 Q3	8.95
2016 Q4	10.98
2017 Q1	12.89
2017 Q2	14.97
2017 Q3	17.26
2017 Q4	21.51
2018 Q1	23.95
2018 Q2	25.76
2018 Q3	28.89
2018 Q4	31.91
2019 Q1	34.66
2019 Q2	40.09
2019 Q3	42.31
2019 Q4	44.69

Source: Statista.

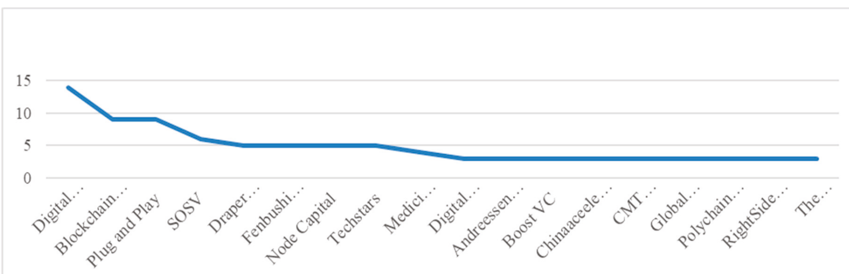

Figure 7. Venture round count completed by key investors of blockchain between 2017 and end of February 2018. Source: CB insights, PwC, ICO Insights and Token Data.

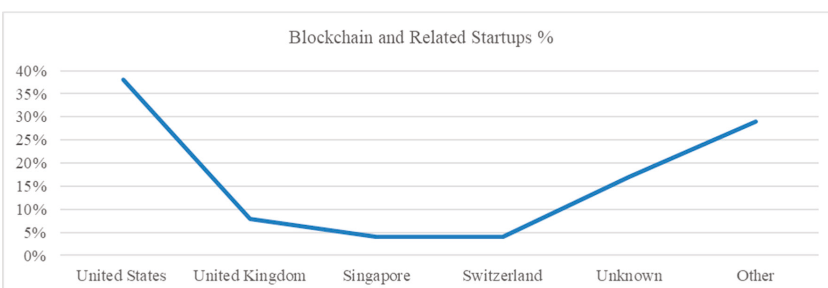

Figure 8. Percentage of Blockchain and related start-ups by geography between 2017 and end of February 2018. Source: CB insights, PwC, ICO Insights and Token Data.

Figure 9 depicts blockchain technology investment by different categories. According to Figure 9, the majority of blockchain investments are applications related to Bitcoin, with the highest and third-highest investments being in bitcoin exchanges and Bitcoin-based financial services. The second highest investment is in innovations in blockchain platforms. It is concerning to observe the low investments in blockchain big data, where developments would be made in handling the large amount of data maintained on blockchains. Figure 10 depicts the number of investments in each blockchain category. This supports the picture provided in Figure 9 with numerous Bitcoin-related applications monopolizing developments with regard to blockchain technology.

The quarterly data for the sample period 2013 to 2019, for Table 5 and Figures 11 and 12, are collected from CB insights, Hutt Capital, PwC, ICO Insights and Token Data. There is negative correlation between European blockchain investments and those of Asia (largely driven by China). Table 5 provides the correlation of investments in blockchains between global investments, U.S., Europe and Asia. There is negative correlation between European blockchain investments and those of Asia (largely driven by China). There is strong correlation between global blockchain investments and Asia showing a co-movement of optimistic sentiment in blockchains and the massive investments by China.

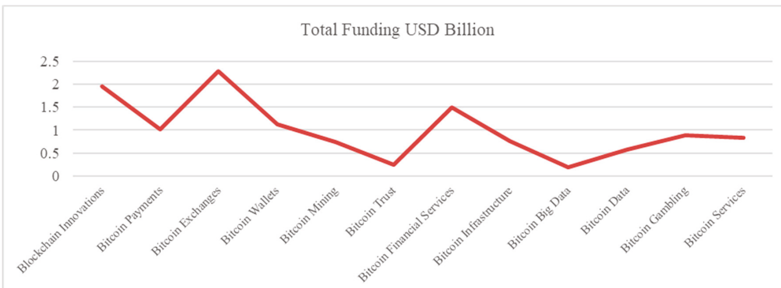

Figure 9. Blockchain Technology investment by different categories. Source: CB insights, PwC, ICO Insights and Token Data.

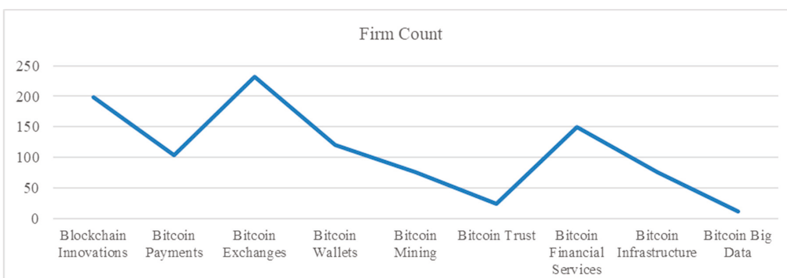

Figure 10. Number of blockchain technology deals by different categories. Source: CB insights, PwC, ICO Insights and Token Data.

Table 5. Correlations of quarterly investments in fintech between global investment, U.S., Europe and Asia from 2013 to 2019.

Region	Correlation
Global and U.S.	0.22
Global and Europe	0.20
Global and Asia	0.94
U.S. and Europe	0.11
U.S. and Asia	0.16
Europe and Asia	−0.15

Source: Calculated by the authors using CB insights, Hutt Capital, PwC, ICO Insights and Token Data sources.

We used average linear extrapolation to forecast future investments and blockchain deal counts globally. Figures 11 and 12 both exhibit a growing linear trend for investments and deal counts in 2020 and 2021, reaching 6.173 and 6.051 USD billion and 822 and 937, respectively despite the COVID-19 crisis. This is expected, as with lockdowns and social distancing measures expected to be in place for the foreseeable future, most firms are driven to digital transformations where blockchain is a key technology. In addition, with increased investment from China in the BSN and the race to implement digital currencies by central banks in several countries including the U.S., increases in blockchain investments are expected to further increase globally.

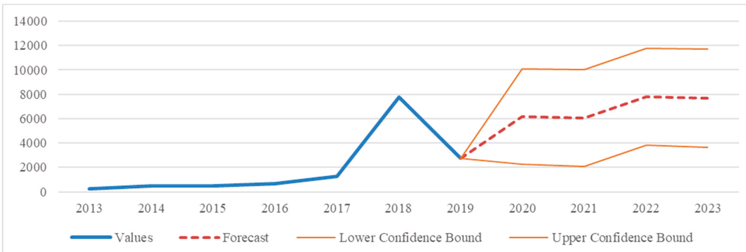

Figure 11. Venture capital investments in blockchain technology and future investment forecasts ($ million). Source: Calculated by the authors based on quarterly data from 2013 to 2019 using CB insights, Hutt Capital, PwC, ICO Insights and Token Data sources.

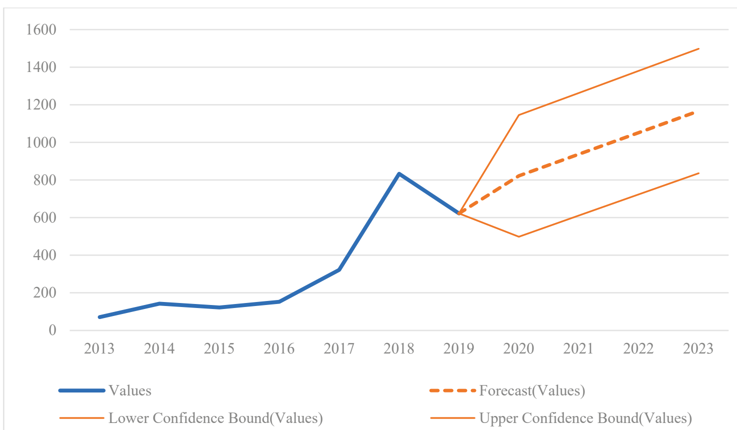

Figure 12. Number of deals by venture capital firms in blockchain technology and future deal count forecasts. Source: Calculated by the authors using CB insights, Hutt Capital, PwC, ICO Insights and Token Data.

6. Blockchain Adoption in Corporate Governance

This section answers our Research Question 1: What are the current and future use cases of blockchain applications in corporate governance? We discuss applications of blockchain by financial institutions, accounting and taxation and initial coin offerings in two other studies. The work by stock exchanges around the world on blockchain is particularly significant. They signal that tokenization of shares will occur sooner rather than later. The key implementations of blockchain in clearing houses and securities exchanges are provided in Table 6.

Moving exchanges to blockchain platforms would reduce information redundancies, costs and speed of transactions, subsequently improving performance (Mathew and Irrera 2017). However, a common risk with regard to blockchains is the issues of security of private keys (Mathew and Irrera 2017). These are proofs of ownership which can be stolen. In our opinion, multi-signature transactions where signatures of all parties are required before agreement to a transaction may circumvent this issue. Table 7 provides a summary of the implications of blockchain adoption in corporate governance to various market mechanisms and market participants based on prior literature and our opinion.

Table 6. Present Blockchain Applications in Corporate Governance.

Blockchain Application	Exchange	Year	Description and Use Case	Collaborating Tech Firm
LINQ	NASDAQ	2015	Blockchain platform for private bond and stock trade	
	Toronto's TMX Group		Blockchain platform for its Natural Gas Exchange (NGX)	
	Australian Stock Exchange (ASX)	2015	Replacing its clearing and settlement platform CHESS with blockchain technology	Implemented by Digital Asset Holdings.
	Japan Exchange Group (JPX)		Developing a blockchain platform for trading low liquidity securities	IBM
Korean Start-up Market	Korea Exchange	2017	To trade shares of start-up companies	
	India's National Stock Exchange (NSE)	2017	Conducted a blockchain trial of a KYC (know-your-customer) data protocol	
	Moscow Exchange (MOEX)		Exploring moving its National Settlement Depository (NSD) to a blockchain platform	
	Deutsche Börse and Deutsche Bundesbank	2016	Been testing blockchain platform prototypes for securities settlement	
	London Stock Exchange		Use of blockchain platforms to improve post-trade processing	
	Luxembourg Stock Exchange		Implemented a blockchain platform for a security system for digitally signed documents and related codes	
	Santiago Exchange is		Exploring blockchain technology to be applied across Chile's financial sector	IBM
	Hong Kong Exchange and Clearing (HKEX)		Enhance its post-trade infrastructure.	implemented by Digital Asset Holdings.
	the Singapore Exchange (SGX)	2018	Integrating Blockchain technology into its core infrastructure.	
	Zimbabwe Stock Exchange		Exploring adoption of blockchain technology	

Table 7. Stakeholders and Blockchain Adoption Implications in Corporate Governance.

Stakeholders	Behavioural Perspectives of Blockchain Adoption
1. Market Mechanisms	Mergers where building hostile positions for takeovers may be hindered and blockchains may become a part of takeover defence mechanisms.
2. Shareholders	Whilst shareholders might become more passive, similar to what is discussed in Grossman and Hart's (1980) free-rider problem, it is more likely that the increased transparency that blockchains offer may change and even expand the role of shareholders in corporate governance. This may also hinder board of directors' and managers' decision-making, especially if interrupted by shareholders with no expertise in the relevant field.
3. New Breed of Third-Party Identity Verification Firms	Even if aliases are used for share purchases, third parties could earn fees for ascertaining the identity of shareowners. These third parties would build upon the existing mechanisms used in financial markets to identify certain traders based on observed sequences, size and timing of trades.
4. Intermediaries and Exchanges	Blockchains could reduce settlement times to minutes if not seconds, or slightly longer if public blockchains are used, and without the need for intermediaries.
5. Insiders	Insiders'/managers' buy order trades result in significant and stronger market reactions as opposed to sell orders (Brochet (2010)). Blockchains would enable easier differentiation of informed trading, subsequently increasing the information content and absorption into asset prices.
6. Retail Investors	Blockchain, with its increased transparency and (considerably) faster execution, would be available to retail investors. The advantages previously available to institutional investors may be reduced and the playing field levelled.
7. Block Holders	The reduction in costs especially for selling shares via increased liquidity would enhance block holder exits and would increase block holders' power over managers (Edmans (2014)). The increased threat of exit by block holders would result in managers pursuing shareholder-value-maximizing projects and deter them from projects with private benefits (Admati and Pfleiderer (2009)).

6.1. Firm Share Tokenization

This article explores the effects of blockchain adoption in the corporate governance sphere such as the tokenisation of a corporation's shares. Tokenisation involves placing shares onto a blockchain and the resulting consequences and opportunities. Blockchain could provide unprecedented transparency to market participants to identify the ownership positions and transactions of debt, equity investors and insiders (managers) (Primm 2016). This would decrease moral hazard, fraud and errors by firms, exchanges and regulators alike (Kahan and Rock 2008). The tokenisation of shares allows for increased efficiency, specifically in terms of accuracy and timeliness of shareholder voting, payment of dividends and a myriad of other uses including limiting empty voting (Accenture 2017). Lee (2016) states that blockchain technology has advantages such as cost execution speed and settlement time reduction.

The ability to observe trading transactions historically, as well as in real-time, reduces information asymmetry and would significantly change incentives and profit opportunities for institutional investors, insiders and other traders in general (Primm 2016). In our opinion, securities may be designed to better utilize the ability of smart contracts to be executed autonomously. There are, however, legal issues with the tokenisation of a corporations' shares, which are not discussed in this study. Schroeder (2015) explores the legal implications of virtual assets existing on blockchains, classifying them as uncertificated securities under Article 8 of the Uniform Commercial Code. Other implications of blockchain adoption would be spillovers to mergers and acquisitions. Even market mechanisms such as mergers where building hostile positions for takeovers may be hindered, and blockchains may become a part of takeover defence mechanisms (Schroeder 2015), whilst shareholders might become more passive, similar to what is discussed in Grossman and Hart's (1980) free-rider problem. In our opinion, it is more likely that increased transparency offered by blockchains may change and even expand the role of shareholders in corporate governance.

Malinova and Park (2017) state that identifying buyers and sellers would benefit markets in general and increase market welfare. Thus, based on this argument, digital identity would be preferred over attempts to hiding identity. In the U.S., stock trades generally take approximately three business days to settle (Malinova and Park 2017). Many parties are involved in these transactions, which occur under the Depository Trust Clearing Houses' supervision. Blockchains could reduce settlement times to minutes if not seconds or slightly longer if public blockchains are used, and without the need for intermediaries (Primm 2016), thus reducing costs and commissions involved. In our opinion, significantly improved liquidity would facilitate high-frequency trading and demand for investments in stocks and create new investing strategies, objectives and dynamics.

Insiders'/managers' buy order trades result in significant and stronger market reactions as opposed to sell orders (Brochet 2010). It is our view that blockchains would enable easier differentiation of informed trading, subsequently increasing the information content and absorption into asset prices. This would be a departure from current market dynamics, where speed of bad news and good news absorption to prices is slow (Hong et al. 2000). Market makers would be able to observe all shares traded by investors. This would increase the quality of information content generated (Accenture 2017), thus leading to more efficient prices and reduced risk premiums (Edmans et al. 2016). We perceive that this would spill over to efficient resource allocation in the real economy and also better decision-making internally at firms.

6.2. Corporate Elections

Corporate elections are one of the many ways blockchains can be used in corporate governance. Current corporate elections are often conducted through proxy voting systems. Kahan and Rock (2008) find that present proxy voting systems are flawed as there are erroneous voter lists, incorrect vote tabulations and incomplete ballot distributions. Listokin (2008) identifies close elections as ending up in favor of management choices. Blockchain can be used to implement accurate proxy voting by allocating eligible voters a token or vote coin as a number that represents their voting power (Boucher 2016). Voters and the firm may observe that votes had been cast validly. However, if desired, they would not observe how particular individuals voted. In our opinion, this would greatly increase the speed of voting and accuracy and would reduce cost and interference by management. Moreover, we believe that increased transparency, speed and reduced costs would result in more shareholder and other interested stakeholder participation. Thus, stakeholders may get involved directly in corporate governance and petition for votes on important firm decisions.

6.3. Empty Voting

Empty voting involves using borrowed shares or derivative combinations to acquire voting rights on a temporary basis. This mechanism would shield the voter from being exposed to cashflow rights, monitoring or enforcement of those securities (Hu and Black 2006; Christoffersen et al. 2007). Shareholders engage in empty voting to gain immediate profits or for long-term ownership motivations. Using blockchain for corporate elections and shares would prove empty voting more difficult or even prevent it entirely (Boucher 2016). Smart contracts can be used to enforce a stand-down period following the transfer of a share, during which time the share is stripped of its voting rights. Table 3 mentioned earlier provides a summary of the implications of blockchain adoption in corporate governance. This table further links blockchain adoption to traditional corporate governance theories in academic literature.

6.4. Reg Tech and Corporate Governance

RegTech refers to digitized regulation compliance and has been prevalent since the 1990s. Growing investments in blockchain and wide adoption especially in the financial services industry have picked the interest of regulators on evaluating blockchain's potential in this sphere. Moreover, the global RegTech Market revenue is expected to reach $7.2 billion by 2023 (Infoholic Research 2018). However, the majority of existing regulation on blockchain is limited to ICOs, cryptocurrencies and very specific legal issues such as "know your client (KYC)" and "Anti-money-laundering (AML)". The role of RegTech with regard to corporate governance is very clear. Blockchains can provide enhanced security, process digitization, document tracking and internal and external management with regard to regulatory compliance (De Lis 2016). Blockchain has the capability to track and monitor compliance rates at an individual level in a relatively small amount of time. Several RegTech applications track online activities of a firm's employees (Arner et al. 2017). Subsequently, these records compiled can be used to identify adherence to firm rules and other regulations. In addition, these applications can track and monitor irregularities in documents, employee activities and create incident reports (Deloitte 2016).

7. Blockchain Governance and Ethical Aspects

Governance of blockchains is a key issue. Public blockchains are governed autonomously by software code. The code specifies inputs, the priority and timing and limits the sizes or contingencies associated with encoding every transaction into the blockchain (Atzori 2015). These parameters of governance in a blockchain are similar to the regulations specified by stock exchanges for listed firms. Most corporations that are exploring blockchain projects are using permissioned blockchains such as a permissioned version of Ethereum. However, even in permissioned blockchains, governance rules would need to be negotiated and renegotiated, similar to partnerships or other customized financial contracts (Paech 2017). Beck et al. (2018) provide an excellent discussion on blockchain governance from a DAO case study perspective. Table 8 summarizes present regulation of blockchain technology in several selected countries.

Ethical Aspects of Blockchain

A key relevance of blockchains to financial markets is its immutability (Papadopoulos 2015), thus limiting or removing a firm managements' ability to influence accounting records and other business transactions ex-post. Fraudulent activities such as using employee stock options to extract private benefits at the shareholder's expense by backdating the option date when price levels are lowest (Bray and Mathews 2011) would be mitigated by blockchain adoption. It is our view that the high level of transparency provided by blockchain would reveal more high-quality information and increased speed to shareholders. This in turn would increase firm management accountability to shareholders, regulators and other market participants. Tapscott and Tapscott (2017) argue that blockchains introduce a novel sphere of business integrity of transparency, honesty, consideration and accountability, which in turn would result in better accurate pricing of executive compensation and asset prices in general. Ultimately, blockchains may shift power from firm management towards shareholders, employees and regulators (Yermack 2017).

In addition, blockchains can help solve coordination, verification, authentication and enforcement issues. For example, extremely high transaction costs and many breaches of the law go unnoticed. Even if such breaches are identified, it is often too late, with substantial damage already ensured (Brummer 2015). Finally, in our view, an overlooked feature of blockchain is its potential in preventing wrongdoing. For example, instead of designing a regulatory system to attempt to prevent empty voting, empty voting can be prevented as follows: shares can be in effect programmed so that following the sale of a share, it is stripped of voting rights for a set period; nor would an individual be able to borrow a share and vote using that particular share.

Table 8. Global Regulation of Blockchains.

Country	Regulation
United States	Enacted state laws on smart contracts, blockchain-based digital signatures and legal admissibility of blockchain ledgers as evidence.
Russia	Announced a regulatory framework for ICOs.
France	Allows crowdfunding records to be kept on blockchain ledgers.
United Kingdom	Started to allow sandboxes for certain fintech products including blockchains.
Switzerland and Luxembourg	Announced similar sandboxing initiatives to the United Kingdom.
Australia	The International Organization for Standardization (ISO) has set up a task force working on these internal blockchain standards and also on standards about the interoperability of separate blockchains.
China	Prohibition of crypto-currencies/taskforces on blockchain.
Japan	Reports/declarations/taskforce.
India	Reports/statements of intent to regulate.
Turkey	Taskforces on blockchains.
Singapore	AML regulation on c-currencies/taskforce on blockchain.
Canada	Reports/taskforces/sandboxing.

8. Blockchain Adoption and Corporate Governance during the COVID-19 Crisis

This section answers our Research Question 4: What are the advantages of blockchain adoption in corporate governance during and post-COVID-19? With an ongoing major worldwide health outbreak challenging and disrupting firms, individuals and many social aspects, corporate governance digitalization becomes increasingly important. Blockchains can play a central role in this setting. In our opinion, blockchain technology may be used to record firm data and ensure these data sources are transparent and traceable within each firm to effectively reduce errors, processing times and smooth firm administration. Thus, blockchains would provide management with a platform, to track progress of projects in real-time, and employees can register the relevant data on to the chain securely. The data links based on transparent monitoring and increased security via blockchains would result in an increase in accountability by employees and other stakeholders linked to the firm. This would further reduce mismanagement, security risks and errors during lockdowns and working-from-home environments. Moving firms day-to-day operations and transactions onto a blockchain platform would aid in corporate boards having better oversight. With blockchain platforms updated in real time, boards would possess increased visibility of business operations and better understand the risks faced by the firm and the impact of the ever-evolving pandemic situation, thus resulting in improved day-to-day and strategic decision-making. Additionally, blockchains can facilitate efficient coordination of information sharing, planning, implementation and communication to employees and other stakeholders.

Moreover, the pandemic has highlighted the fragilities in the traditional financial markets and fiat currencies, with many advocating for digital currencies. Cryptocurrency is a key theme of blockchain applications and is relevant to corporate governance as identified by our study. Two major reasons behind this renewed interest in digital or crypto currencies stem from inflation of traditional fiat currencies and the decrease in interest rates of traditional assets such as bank deposits. Thus, the ongoing COVID-19 pandemic has accelerated the development of central bank digital currencies. For example, the People's Bank of China has already completed basic function development for a digital yuan. Moreover, the development of Blockchain-based Service Network (BSN), which is backed by an alliance of Chinese state-owned firms, government agencies, banks and technology firms further highlight the importance of corporate governance with regard to blockchains. The BSN is expected to reduce the costs of doing blockchain-based business in China by 80%. Alibaba subsidiary Ant Financial also grabbed the spotlight by announcing its new consortium chain called Open Chain. The COVID-19 outbreak is a common challenge faced by businesses across the world. Thus, blockchain can be the new tool for corporate governance to overcome this unprecedented disruption for our way of conducting business and traditional corporate governance.

9. Limitations of Our Study

This section discusses several limitations of our study. With regard to the empirical analysis section, a major limitation is the small sample period of 2012 to 2020. Most firms are secretive in their nature on investment breakdown into new technologies. Thus, it is difficult to obtain investments only relating to blockchains. Another limitation is that of sample selection bias, which can occur in systematic reviews due to distortions in the search and selection criteria. In order to overcome this issue, we used various permutations of our search topics, backtracked from key words in other survey articles on blockchain unrelated to finance and used refinements in our search databases. In addition, we further perused the reference lists of articles selected to identify relevant articles (snowball effect). Inconsistent coding of themes may be another limitation of our study. Thus, we supplemented our manual review process through textual analysis and by carefully re-assessing the articles in our final sample manually with special focus on the abstract, keywords, introduction and conclusion.

10. Conclusions

Blockchain technology has great potential to provide efficient solutions to many issues that adversely affect current systems in corporate governance. However, several issues of permissioned versus public blockchains, capital required, possibilities of hacking, lack of extensive research and understanding, to name a few, still persist. Our study differs from its contemporaries by systematically reviewing prior scattered literature, conducting a textual and empirical analysis to develop a framework for blockchain adoption in corporate governance, differentiating between industry and academic literature over time and key themes and forecasting future investments. In addition, our study provides a behavioural and ethical perspective to blockchain adoption in corporate governance. A systematic review of 851 records and a final article sample of 183 for the sample period 2012 to 2020 resulted in the identification of nine primary themes from prior literature with relevance to blockchain adoption in corporate governance. Academic articles mostly focus on regulation (49 studies) and ICOs (46 studies), while industry articles primarily focus on exchanges (10 studies) and cryptocurrencies (9 articles). Significant growth in academic and industry literature is observed for 2017 (48 studies) and 2018 (42 studies) in aggregate.

Through our textual analysis, we identified that the industry and academic literature pursue common themes, such as 1. Bitcoin, 2. markets, 3. technology and 4. fintech related to blockchain. However, their interests diverge, where industry focuses more on 1. privacy, 2. business and 3. Global, and the academia concentrates on 1. governance, 2. networks and 3. ledger. Based on our empirical analysis, we forecast investments and deal counts in blockchain for 2020 and 2021 reaching up to 6.173 and 6.051 USD billion and 822 and 937, respectively. Finally, we conclude that with regard to corporate governance, permissioned blockchains may still be used to limit transparency, yet absolute transparency may cause unwarranted shareholder panic. Thus, firms would most likely implement different accessibility levels. A key question is whether regulators should allow firms to limit transparency. Blockchains may result in better corporate governance models with higher accuracy, accessibility and efficiency, resulting in improved decision making by shareholders. Smart contracts on blockchains in the future can provide novel ways of governing corporates. However, as highlighted by this study, such progression should go hand-in-hand with the corresponding regulatory developments. Moreover, COVID-19 environment driving most firms to digital transformation including China's massive investments in Blockchain technology (BSN) and the digitalisation of the Yuan and interest in blockchains is most likely to further increase significantly in the future.

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Appendix A

Table A1. Comparison of literature between industry, academic studies and professional bodies.

	Exchanges & CG	Corporate Voting & CG	Practice and Education of BC	BC &CG	Regulation	BC Technology	ICOs & Crowd Funding	Crypto-Currencies	Other
Industry	10	3	2	1	6	3	5	9	1
Academia									
Abadi and Brunnermeier (2018)			1			1			1
Abramowicz (2016)					1			1	
Adhami et al. (2018)					1		1	1	
Aggarwal and Stein (2016)			1		1		1		
Amsden and Schweizer (2018)							1		
Aoyagi and Adachi (2018)						1		1	1
Arner et al. (2017)					1				
Ante et al. (2018)							1		
An et al. (2019)							1		
Asharaf and Adarsh (2017)						1			1
Atzei et al. (2017)						1		1	1
Atzori (2015)					1	1		1	1
Babich and Hilary (2019)						1			1
Barefoot (2015)					1				
Badertscher et al. (2017)	1					1		1	
Bagby et al. (2018)					1				1
Bakos and Halaburda (2018)							1	1	
Barber et al. (2012)						1		1	
Barsan (2017)					1				
Bebchuk and Jackson (2012)	1				1				1
Benedetti and Kostovetsky (2018)							1		
Blaseg (2018)							1		
Böhme et al. (2015)	1			1		1			
Boucher (2016)		1				1			1
Bourveau et al. (2019)	1						1	1	
Braggion et al. (2020)									
Brenig et al. (2015)					1			1	
Brainard (2016)	1				1	1			
Brummer (2015)	1				1				
Butenko and Larouche (2015)					1				
Buterin (2014)						1	1		1
Catalini and Gans (2016)	1		1						
Catalini and Gans (2018)					1			1	1
Carvalho (2020)						1			
Chemla and Tinn (2017)							1		
Chen et al. (2019)				1					1
Chen (2018)						1	1		1
Chiu and Greene (2018)							1		1
Christensen et al. (2015)						1	1		1
Chod and Lyandres (2018)			1		1		1		
Chohan (2017)					1		1		

Table A1. *Cont.*

	Exchanges & CG	Corporate Voting & CG	Practice and Education of BC	BC &CG	Regulation	BC Technology	ICOs & Crowd Funding	Crypto-Currencies	Other
Clements (2018)							1	1	
Cocco et al. (2017)			1						
Cohen et al. (2017)	1				1				
Collomb et al. (2018)							1	1	
Cong and He (2019)			1	1		1			
Cong et al. (2020)						1	1	1	
Conley (2017)							1	1	
Cortez (2014)					1				1
Da Rin and Penas (2017)									1
Dapp (2014)									1
Davidson et al. (2016)					1				
Dean et al. (2019)									1
Deer et al. (2015)									1
Filippi and Hassan (2016)					1				1
De Filippi and Wright (2018)									1
De Lis (2016)									1
Deng et al. (2018)							1		
de Reuver et al. (2018)			1						
Dierksmeier and Seele (2018)					1				
Drobetz et al. (2019)							1		
DuPont (2017)				1					
Easley et al. (2017)				1					1
Eyal and Sirer (2018)						1			1
Evans (2014)					1	1			
Fanning and Centers (2016)		1							
Feng et al. (2018)							1		
Fenwick et al. (2018)					1				1
Felix and Eije (2019)							1	1	
Fichman and Zheng (2014)			1						1
Fisch (2018)							1		
Foley et al. (2019)					1			1	
Frame and White (2014b)			1						1
Gomber et al. (2017)									1
Goldstein et al. (2019)		1							
Governatori et al. (2018)					1				
Graglia and Mellon (2018)									1
Harwick (2016)					1			1	
(Hileman and Rauchs 2017)									
Holden and Moar (2017)									1
Houy (2014)	1					1			
Howell et al. (2018)				1			1	1	
Hsieh et al. (2017)				1		1		1	
Hughes and Middlebrook (2015)					1			1	
Jayasuriya and Sims (2019)			1		1				
Kaal (2016)					1				
Kaal and Vermeulen (2017)					1				1
Kaal and Dell'Erba (2017)					1		1		

Table A1. *Cont.*

	Exchanges & CG	Corporate Voting & CG	Practice and Education of BC	BC &CG	Regulation	BC Technology	ICOs & Crowd Funding	Crypto-Currencies	Other
Kanzler (2015)	1		1						1
Kim (2017)	1								1
Kim et al. (2018)					1				
Lee (2016)	1						1		
Lee and Parlour (2019)							1		
Li and Mann (2018)							1		
Liu and Wang (2019a, 2019b)				2			2	2	
Luther (2016)					1			1	
Lyandres et al. (2019)							1		
Malinova and Park (2017)	1								
Mathew and Irrera (2017)	1								1
McWaters et al. (2016)	1	1							
Mik (2017)									1
Mills et al. (2016)					1				
Momtaz (2018)							1		
Momtaz (2019a, 2019b, 2019c)							3	1	
Momtaz (2020a, 2020b)							2		
Nabilou and Prum (2019)					1			1	
Nowiński and Kozma (2017)			1						
Ofir and Sadeh (2019)	1	1			1		1		
Paech (2017)						1			
Papadopoulos (2015)	1							1	1
Philippon (2016)									1
Piazza (2017)	1		1						
Pilkington (2018)					1				
Primm (2016)					1				1
Proskurovska and Dörry (2018)						1			
Rabah (2017)						1			
Rhue (2018)							1		
Robinson (2017)					2				
Robinson (2018)					2				
Rohr and Wright (2017)						1			1
Ron and Shamir (2013)	1							1	
Rossow (2018)									1
Scott et al. (2017)					1				
Schindler (2017)			1						
Shermin (2017)					1				
Sims et al. (2018)					1			1	
Sockin and Xiong (2020)							1	1	
Suzuki and Murai (2017)	1	1							
Tama et al. (2017)			1						
Tanaka et al. (2017)	1								1
Tapscott and Tapscott (2017)				1					
Tasca (2015)					1				
Trimborn et al. (2018)							1	1	
Tsukerman (2015)					1				
Vranken (2017)									1

Table A1. *Cont.*

	Exchanges & CG	Corporate Voting & CG	Practice and Education of BC	BC &CG	Regulation	BC Technology	ICOs & Crowd Funding	Crypto-Currencies	Other
Wang and Vergne (2017)							1	1	
Wang et al. (2016)			1			1			
White (2017)	1	1				1			
Wright and De Filippi (2015)						1		1	
Wu and Liang (2017)	1					1			
Yamada et al. (2016)	1					1		1	
Yermack (2017)	1	1	1						1
Yeoh (2017)					1				
Ying et al. (2018)	1	1							
Yli-Huumo et al. (2016)	1								
Yoo and Won (2018)	1								
Zalan (2018)	1								
Zavolokina et al. (2016)	1								
Zetzsche et al. (2018)					1		1		
Zetzsche et al. (2017)							1		
Zheng et al. (2018)									1
Zhu and Zhou (2016)					1				
Academia Total	30	9	17	10	49	31	46	34	45
Industry Total	10	3	2	1	6	3	5	9	1
Total References (Only those that fall under these classifications)	40	12	19	11	55	34	51	43	46

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Are We Ready for the Challenge of Banks 4.0? Designing a Roadmap for Banking Systems in Industry 4.0

Amir Mehdiabadi [1], Mariyeh Tabatabeinasab [2], Cristi Spulbar [3], Amir Karbassi Yazdi [4] and Ramona Birau [5,*]

[1] Department of Management, South Tehran Branch, Islamic Azad University, Tehran 1584743311, Iran; Amir.mehdiabadi@gmail.com
[2] Department of Law, Payame Noor University, Tehran 1584743311, Iran; smtn.1798@gmail.com
[3] Faculty of Economics and Business Administration, University of Craiova, Craiova 200585, Romania; cristi_spulbar@yahoo.com
[4] Young Researchers and Elite Club, South Tehran Branch, Islamic Azad University, Tehran 1584743311, Iran; st_a_karbassiyazdi@azad.ac.ir
[5] Faculty of Education Science, Law and Public Administration, Constantin Brancusi University of Targu Jiu, Târgu Jiu 210135, Romania
* Correspondence: ramona.f.birau@gmail.com; Tel.: +40-767970777

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Abstract: The purpose of the present paper is to provide an advanced overview of the practical applications of Banking 4.0 in Industry 4.0. This paper examines the technology trends in the Fourth Industrial Revolution and identifies the key indicators behind the creation of a strategic map for the fourth-generation banks and their readiness to enter Industry 4.0. This paper examines a systematic review of fully integrated Banking 4.0 and the application of the technologies of Industry 4.0 and illustrates a distinct pattern of integration of Banking 4.0 and Industry 4.0. One of the prominent features of this article is the performance of successful global banks in applying these technologies. The results showed that Banking 4.0 in Industry 4.0 is an integrative value creation system consisting of six design principles and 14 technology trends. The roadmap designed for banks to enter Industry 4.0 and how they work with industrial companies will be a key and important guide.

Keywords: technology; banking 4.0; industry 4.0; roadmap; digitalization; big data

1. Introduction

The technology landscape, which is evolving thanks to the introduction of 5G networks, has affected all sectors of the banking industry. Emerging technologies have opened the door to a range of applications and inter-industrial collaborations that were previously only imagined in dreams. New applications have changed current business models, paved the way for innovation, and created new opportunities for revenue generation.

The term "Industry 4.0" refers to the concept that technology has permeated all areas of society: production, finance, services, transportation, and communications (Cividino et al. 2019). Such developments are driven by digital integration (with devices and processes capable of transmitting and processing huge masses of data) and automation (the availability of machines capable of carrying out tasks of medium–high complexity) (Muscio and Ciffolilli 2019; Rossini et al. 2019). The pervasiveness of the Internet and smart mobile phones, along with the emergence of technologies such as the Internet of Things, biometrics, big data, advanced analytics, artificial intelligence, blockchain, etc., has created an organizational focus on designing and developing pre-designed products and services, and personalized and customized services are provided for each customer. One of the industries that have changed a lot as a result of the advancement of technology is the banking industry, but it seems that these changes continue. “The development of technology has revolutionized all industries in the world, and the banking industry is no exception,” Banker (2019) wrote in a recent report.

Some researchers suggested that the notion of Industry 4.0 supposes blurring the differences between the work of people and the work of machines (Ślusarczyk 2018). Lu (2017) argued that the concept of Industry 4.0 can be summarized as an integrated, adapted, optimized, service-oriented, and interoperable manufacturing process that is correlated with algorithms, big data, and advanced technologies. The Fourth Industrial Revolution, also known as Industry 4.0, provides smart, efficient, effective, individualized, and customized production at reasonable cost (Erol et al. 2016). According to Stock and Seliger (2016), the concept of Industry 4.0 includes three fundamental dimensions of integration: (1) the horizontal integration across the entire value creation network, (2) vertical integration and networked manufacturing systems, and finally (3) end-to-end engineering across the entire product life cycle.

Today, a significant portion of bank customers are young people and middle-aged people who have different expectations and preferences than the previous generation. Meeting these expectations and preferences is no longer possible with existing banking models, and it will only be possible with the use of fourth-generation tools, technologies, and mechanisms. Entering Industry 4.0 has two distinct natures: first satisfying new needs through new products and processes, and second, higher productivity thanks to the implementation of process innovations (Zambon et al. 2019). Entering the new generation of customers into the marketplace and doing business in this revolution requires a thorough rethinking of existing banking services and products. Productivity enhancement, innovative products, speedy transactions seamless transfer of funds, real-time information system, and efficient risk management are some of the advantages derived through the technology in banks (Saravanan and Muthu Lakshmi 2016).

The current global economy is constantly changing, so innovation and technological development are key issues in the context of a sustainable approach. Industry 4.0 should be perceived as a great opportunity due to its new technologies. Moreover, Ślusarczyk (2018) argued that the main objective of Industry 4.0 is to achieve a higher level of operational effectiveness and productivity, and simultaneously a higher level of automation. Certain researchers also suggested that the four major pillars of Industry 4.0 are the following: Internet of Things (IoT), Industrial Internet of Things (IIoT), cloud-based manufacturing, and smart manufacturing, which contribute significantly to the metamorphosis of the manufacturing process into a completely digitized and intelligent process (Vaidya et al. 2018). Companies are interested in meeting their customers’ needs, but also in obtaining useful information from them, which can be used for innovation (Nethravathi et al. 2020).

Remarkably, Industry 4.0 needs its banking system. The use of Industry 4.0 technologies for digitizing assets, creating a digital identity, providing special offers to customers, offering customization, etc., is one of the most central strategies of Banking 4.0. For example, South Korea currently has the third-largest cryptocurrency market after Japan and the United States, and Shinhan Bank, South Korea’s second-largest bank, has recently joined KT Corp, the second largest provider of services, and the country’s telecommunications has cooperated. The subject of this collaboration has been the development of a block chain-based platform. For a long time, it was the banking industry that decided how to interact and provide customer service. In Generation Banking, the optimal combination of interaction is determined by the customer. As a result, banks need to fundamentally reconsider their business model.

According to an IBM World Business Partner in Taiwan, the company is ready to enter the era of Bank 4.0 (IBM Business Partner Directory 2018). Accordingly, banks will be set up to provide an integrated system that will improve mobile banking by providing solutions to help facilitate the automation of banking processes. In classifying the evolution of the bank over the past few decades, the Internet has helped Banking 1.0 to grow into Banking 2.0, and with the rapid rise of smartphone popularity, Banking 3.0 has come to life. Now, the third generation bank is moving forward to Banking 4.0, but not because of new inventions, but because of the maturity and growth of new technologies such as artificial intelligence and virtual reality systems and voice recognition, which together make a powerful team for better banking services and solving modern problems. Banks are globally readjusting their business strategies toward e-banking in order to achieve rapid growth in financial development (David and Kaulihowa 2018). E-banking represents an innovative process by which a customer performs banking transactions electronically without having to physically enter a bank or financial institution (Simpson 2002). Banking 4.0 provides its customers with personalized, integrated, and customized experiences that are transforming customer interactions with the bank. Becoming a Bank 4.0 means providing a convincing presentation of both customer experience and performance experience based on open, flexible, and integrated architecture.

Jack Ma (who is the founder of the e-commerce platform Alibaba) founded MyBank four years ago. The bank has introduced a new era of offering services to small and medium-sized enterprises (SMEs). In recent years, MyBank has loaned 2 trillion yuan to 16 million small and medium-sized Chinese companies. This is done by real-time data and 3000-variable risk-based credit management models. In addition to the advantages of the MyBank lending system, transactions are carried out at a high rate. Loan applications are processed and approved within 3 minutes. Now, compare this technology trend in MyBank with the 30-day time required by traditional banks! The difference is extremely obvious and indisputable, and the gap can no longer be covered by traditional banking.

Due to the high volume of data collected by Alibaba and other related e-commerce platforms, it uses the business information and social credit rating of potential customers with their consent. Capgemini (2017a) argued that high-class BigTechs such as Google, Facebook, Apple, and Amazon imposed a very high upper limit on the customer expectations using superior personalized and digital customer interactions. As a result, this amount of big data and analytics makes it easier for small and medium-sized companies to approve loans and, of course, pay less ineffective loans. These are loans that are spent for non-strategic and non-practical purposes. MyBank says it has been able to lend to SMEs up to four times more than traditional banks. However, traditional banks reject about 80% of SMEs' lending applications due to insufficient credit or data.

Industry 4.0 provides competitive advantages based on advanced technologies and practices for companies in the manufacturing industry. Having a deep understanding of the particularities of Industry 4.0 is a prerequisite for the development of the strategic and technological roadmap in bank 4.0. Therefore, the present study first examines the technologies used in Industry 4.0 and examines them as applied examples in prestigious banks in the world. Then, by integrating the views, we present an applied model of the fourth generation banking approach in the context of Industry 4.0. Finally, a clear roadmap for achieving fourth-generation banking has been formulated. Figure 1 shows the research plan. So, the researchers are asking three main questions:

1. Is it necessary for the banking sector to join Banking 4.0?
2. In practice, is there an interaction between Industry 4.0 and Banking 4.0 within the organizations?
3. Is it possible to develop a codified roadmap for entering Industry 4.0?

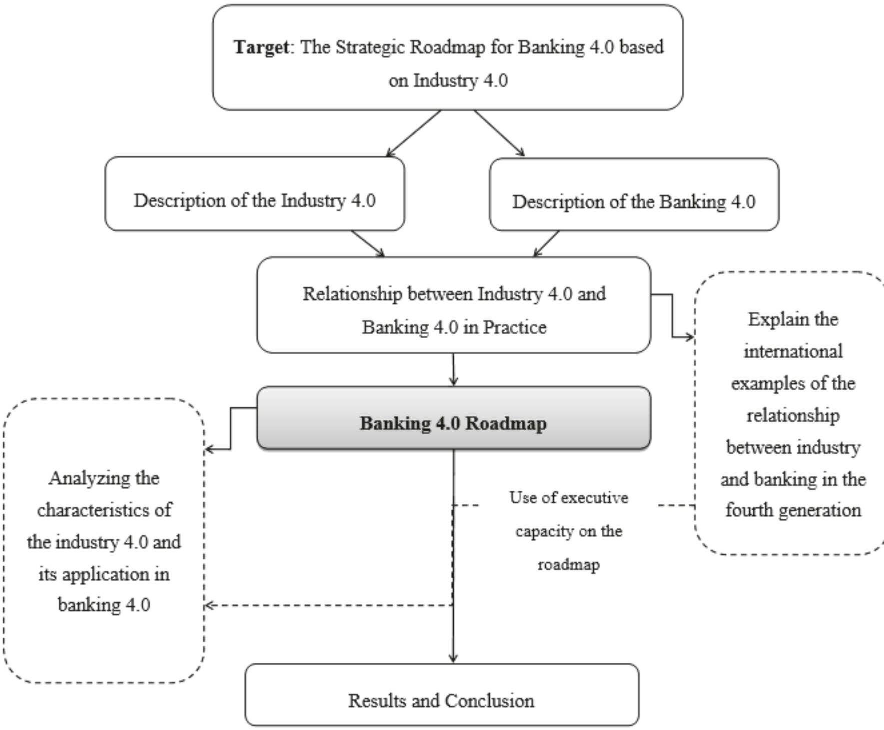

Figure 1. Research plan. Source: Own contribution of the authors.

2. Literature Review

2.1. Industry 4.0

Our current business environment is radically changing, and the increasingly demanding and rapidly changing customer needs are the underlying reason that has driven industry revolutions at different periods (Mohamed 2018). These revolutions have brought to the world drastic changes in diverse areas, posed huge challenges for industries and manufacturers, led to massive innovations and transformations, and remarkably affected people's way of life (Huang 2017). Industry 4.0 is also known as the Digital Revolution or the Fourth Industrial Revolution. The First Industry Revolution encompasses the use of the steam engine in manufacturing facilities, followed by the introduction of electrically powered mass production (Second Industry Revolution) (Pagliosa et al. 2019). The Third Industry Revolution corresponds to the use of electronics and information technology (IT) to automate manufacturing (Kagermann et al. 2013). I4.0, deemed as the Industry 4.0, focuses on the digitalization of all physical assets and the massive integration of value chain participants (PwC 2017) (see Figures 2 and 3).

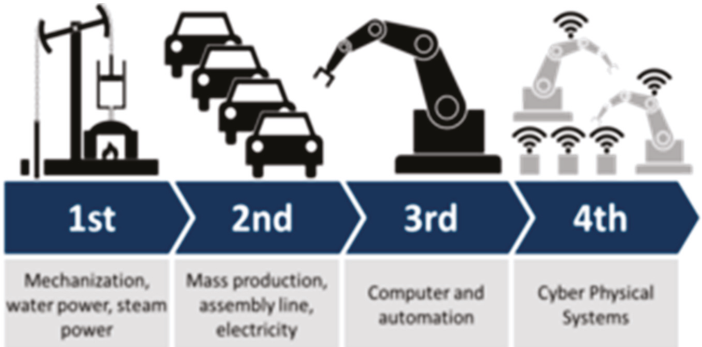

Figure 2. Through the industry revolutions. Source: Own contribution of the authors.

Figure 3. The Concept of the Fourth Industry Revolution. Source: Own contribution of the authors.

There are various definitions for Industry 4.0 considering that many researchers and practitioners define this term according to their level of understanding and unique perspective. There are also inter-relating terms such as IoT, Cyber-Physical Systems (CPS), Smart Systems, Digitalization, and Digital Factory (Khan and Turowski 2016).

Certain researchers define Industry 4.0 as the concept of automation and data exchange in the manufacturing technologies, which enables the use of Internet of Things (IoT), Cyber–Physical Systems (CPS), big data analytics, cloud computing, and cognitive computing, with the main goal of achieving a higher level of progress (Herčko et al. 2015). Other researchers suggested that the crown jewel of Industry 4.0 is the networking of smart digital devices with products, tools, robots, and people based on intelligent factories (Mekinjić 2019).

Moreover, I4.0 is the latest trend when it comes to automation and data exchange in production systems (SCOOP 2017; CNI, National Confederation of Industry 2016). The adoption of technologies, such as CPS, big data, and IoT provides relevant information and creates new possibilities for process improvement (Bohács et al. 2013; Schuh et al. 2017). In addition, one of I4.0's main advantages is the ability to adapt quickly to volatile demand scenarios and products with short life cycles (Sanders et al. 2016). According to Tamás and Illés (2016), I4.0 has generated important changes in production systems and created demand for new jobs. Recent research on this subject indicates a lack of studies about the impact of I4.0 on manufacturing environments (Zuehlke 2010; Landscheidt and Kans 2016; Gjeldum et al. 2016; Xu and Chen 2016; Martinez et al. 2016; Sanders et al. 2016; Kolberg et al. 2017; Santorella 2017).

Agrawal et al. (2017) argues that Industry 4.0 can be identified as an emerging platform of technologies that revolutionize the rate of productivity per employee while reducing the cost of controlling and compliance incurred by corporations. According to Berger (2017), Industry 4.0 provides flexibility to the production processes; thus, it helps to create products that are tailored to the target segment while satisfying personalized needs through a low marginal cost. Vaidya et al. (2018) discusses the challenges incorporated with the applications of Industry 4.0, namely, intelligent decision making and negotiation mechanism, high-speed networking protocols, manufacturing specific big data and analytics, system modeling and analysis, cyber security, modularized and flexible physical artifacts, investment, etc. Lu (2017) mentions that Industry 4.0 creates a value-added integration horizontally and vertically in the manufacturing processes. Thus, horizontal integration was done through value creation modules from the material flow to the logistics of product life cycle, whereas the vertical integration through product, equipment, and human needs with different aggregation levels of the value creation and manufacturing systems.

2.2. Banking 4.0

Today, the rate of technological change in the banking sector and the entire economic ecosystem is extremely high. These changes have a significant impact on the dynamism of individuals and the socio-political community that no one could have imagined. Increasing data usage, machine learning based on artificial intelligence, the Internet of Things, and digital technologies play an important role in this process.

Banking 1.0 is what we call banking, and this is the same traditional banking that services are provided at certain times in the branch. The contemporary banking theory argues that commercial banks, composed with other financial mediators, are essential in the distribution of wealth in the economy (Bhattacharya and Thakor 1993). Then came the introduction of technologies such as the Internet and some Banking 2.0 services that were slowly pushing banking out of the branches. This is possible with the advent of ATMs and card readers, since we are witnessing the formation of off-branch services at different times. This period began in 1980 and lasted until 2007. With the advent of self-service banking, things have changed, and we have come to realize that banking can also be portable, which is Banking 3.0 (It is related to the supply and expansion of mobile services. These services may be provided on a smartphone platform or even portable card readers. This period lasted from 2007 to 2015), but banking 4.0 is a major transformation that will live with you (Figure 4). Topics such as intelligence, sharing, and evolutionary computing are discussed.

Harjanti et al. (2019) argued that digital transactions necessitate an improved banking experience, so the banking industry also conducts experiments by applying innovative technology in order to support mobility and increase transaction speeds and efficiency for its customers. Some previous studies suggested that the highest dilemma for the current banking system is to explain the high costs of branch banking but also to obtain an increase in profitability as branch-driven revenue growth (Capgemini 2012). According to Athanasoglou et al. (2006), the size of banks contributes to recognizing possible economies or diseconomies of scale in the banking area considering cost differences, products, and risk diversification.

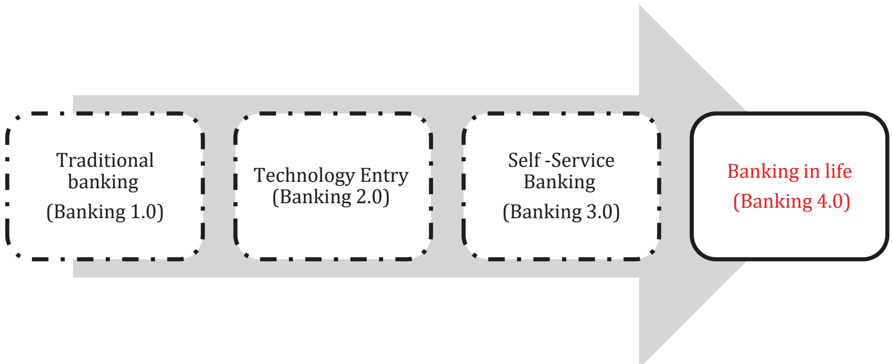

Figure 4. The banking revolution. Source: Own contribution of the authors.

The banking system represents a fundamental pillar of the economic growth and macroeconomic stability, especially in the context of globalization. However, the evolution of the banking sector in each country is affected by continuous changing dynamics of the international banking architecture and financial environment (Spulbar and Birau 2019b). Nowadays, a company or startup can provide banking services by providing financial technology (FinTech)-based applications. The use of artificial intelligence and intelligent, cognitive, and voluntary algorithms has entered banking in this period). The banking sector has been immensely benefited from the implementation of superior technology during the recent past almost in every nation in the world. Productivity enhancement, innovative products, speedy transactions, the seamless transfer of funds, real-time information system, and efficient risk management are some of the advantages derived through the technology (Saravanan and Muthu Lakshmi 2016). The new era of financial deregulation is supported by the revolution in information and communication technology, which helps banks ensuring innovation in their products and services at competitive prices (Turk Ariss 2008).

Maturity models offer a complex guidance to define, assess, and evaluate the progress of the current state of the banking sector in its journey of Industry 4.0. (Bandara et al. 2019). Other researchers developed a maturity model using the existing model of Software Process Improvement and Capability Determination (SPICE) considering only two main dimensions, i.e., capability dimension and aspect dimension (Gökalp et al. 2017).On the other hand, the technology acceptance model is generally considered as the most influential theory in IT and information systems (Benbasat and Barki 2007).

The paradigm shift from the concentrated market structure under financial repression to the competitive framework under financial liberalization has laid down the foundation for the emergence of private and foreign banks originally in developed countries and afterward in developing countries (Sohrab Uddin and Sohel 2018). Today, a significant portion of bank customers are young people and middle-aged people who have different expectations and preferences than the previous generation. Meeting these expectations and preferences is no longer possible with existing banking models and will only be possible with the use of fourth generation tools, technologies, and mechanisms.Banks can no longer begin their design with business goals and market share, but they need to know how to get their attention and preferences without directly interacting with the customer, thereby achieving business goals.Based on the definition of Temenos (2018), properly digitizing, or in other words Banking 4.0, means "Experience-Driven Banking" capability that requires coverage of both "Customer Experience" and "Execution Experience"(see Figure 5).

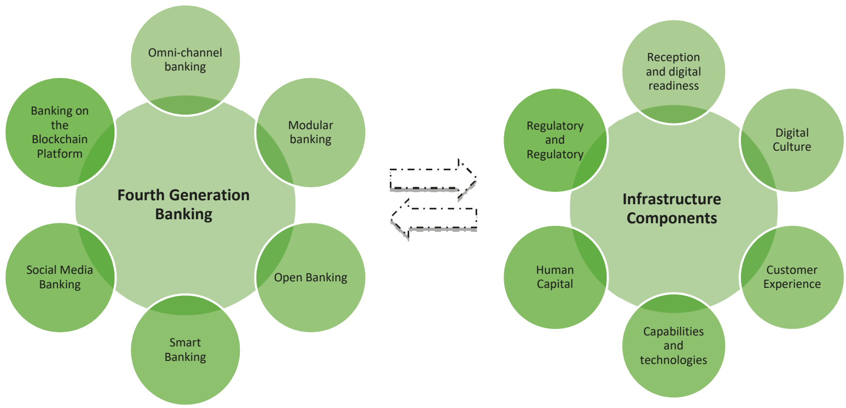

Figure 5. The relationship between Banking 4.0 and infrastructure. Source: Own contribution of the authors.

Industry 4.0 needs its own banking structure. Industries 4.0 are largely international in scope, and customers from all over the world choose them. A radical change in the marketing and segmentation of banking customers makes it unique for each customer. There seems to be only one type of banking, and that is proprietary banking in a new way. With the development and maturation of technologies such as the Internet of Everything (IoE) (by creating a connected network of people, processes, data, objects, etc.), Internet of Value, blockchain technology, cloud technology, advanced robotics, virtual reality, 3D printing, miniaturization of sensors, and the exponential development of emerging technologies and innovations are coming across completely different generations of banking.

Certain researchers provide a Maturity Model to assess the level of readiness in adapting to Industry 4.0 of the banking sector, which includes the following maturity levels, i.e., Initial, Managed, Defined, Established, and Digital Oriented (Bandara et al. 2019).

2.3. The Relationship between Industry 4.0 and Banking 4.0 in Practice

2.3.1. Replacing Banks with Organizations and Institutions

Heffernan (2005) considers that banks represent financial firms, offering loan and deposit products on the market and catering to the changing liquidity needs of their consumers, such as borrowers and depositors. However, banks hope that by improving the level of technology and technological development, they will be able to provide more services to customers at a higher rate and have greater transparency in this process. The establishment of an efficient and solid banking system is an important prerequisite for sustainable economic growth (Spulbar and Birau 2019a). A significant part of the bank's resources each year are spent securing the system and complying with other principles approved by the world's financial system, and it is in this environment that financial institutions grow. Institutions that are responsible for providing services to the people but do not comply with the cumbersome rules of the banking system in the countries. Since these financial institutions spend a large portion of their financial resources on upgrading their financial and banking technologies, the efficiency of these institutions is higher, and they can be more creative with the tools available. Therefore, in the next 5 years, banks can be considered the financial and economic body of large countries, but small and medium-sized financial institutions are responsible for the micro-tasks of the banking system, and more people will be in contact with these institutions.

2.3.2. Advantages and Disadvantages of FinTech Development in Banking

FinTech has found a broader meaning day by day and now plays its role as a disruptor of order in various parts of the financial and monetary system, including micro payments, money transfer, lending, comparison and online sales of various types of insurance policies, capital increase, and asset management. It has even been recognized in the formation of new paradigms such as the Bitcoin currency. The industry has expanded the number of online solutions in the above fields to the extent that it has become one of the most important threats to traditional banking and portfolio management. In addition, today, FinTech is seen as a good platform for implementing ideas based on the sharing economy and crowdfunding. That is why Ernst and Young (2016) cited consumers' main reasons for accepting FinTech's solutions: easy account opening (43.3%), more attractive rates/costs (15.4%), access to various products and services (12.4%), better online experience and performance (11.2%), better service quality (10.3%), more innovative products than products available in traditional banks (5.5%), and a higher level of trust than traditional solutions (1.8%). They also remove barriers that prevent consumers from accepting FinTech solutions: the lack of knowledge of Fintech products and services (53.2%), lack of needing to use them (32.3%), Prefer to use traditional financial service providers (27.7%), Not being aware of how to use them (21.3%), not trusting them (11.2%), and Fin-techs have been used in the past, but they don't want to use them again (0.8%). Instead of attacking each other, banks and FinTech are increasingly partnering with each other (see Figure 6).

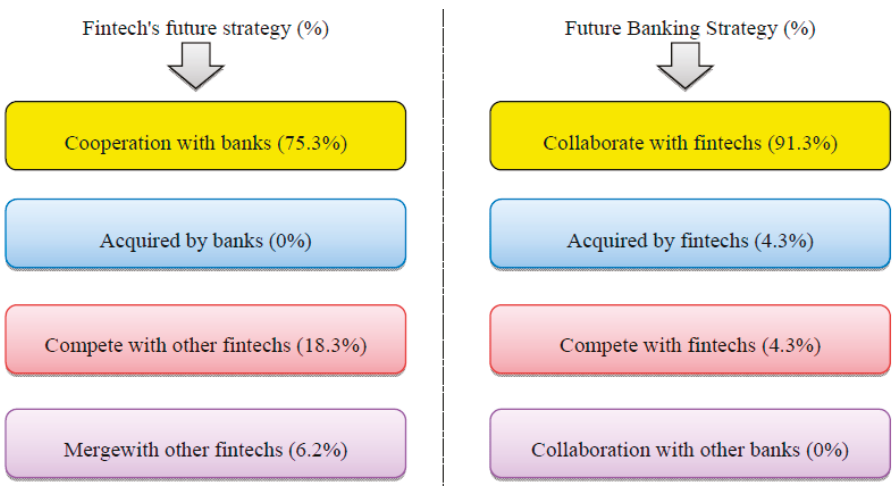

Figure 6. The future strategy of banks and financial technology (FinTech). Source: Capgemini Financial Services Analysis (Capgemini 2017a).

2.3.3. JAK Bank: Interest-Free Banking

Looking at the outside world, we will see that the government, non-governmental public institutions, military institutions, philanthropists, and even in some cases the private sector have established banks that bear a strong resemblance to what we call Islamic banking. Nonprofits need bank accounts to collect revenues used in moving the nonprofit's mission forward. A nonprofit is a corporation given "exempt organization" status by the Internal Revenue Service. Banks usually follow the same rules for opening and maintaining accounts as they do with for-profit organizations with some variations. Individual banks and individual nonprofits may have their own rules and regulations for added security (Leonard 2019). Unity Trust Bank, Meezan Bank, and JAK Bank are examples of nonprofit banking that have taken steps toward fourth-generation banking goals.

The JAK bank was started in 1930 following a massive recession in Denmark (Ielasi and Vichi 2013). Unemployment and high interest rates at the time led farmers to form a co-operative in one year. This cooperative was named in honor of the three founders of classical economics, JAK: Jord (Land), Arbejde (Work Force), and Kapital (Capital). JAK's members concluded that earning profits was the main cause of economic instability and, as a result, inflation and unemployment. So, they started three nonprofit projects to demonstrate the idea of nonprofit loans. JAK Bank may be the first nonprofit bank in the world (Williams and Anielski 2004). A membership of approximately 39,000 (as of December 2015) dictates the bank's policies and direction. The Board of Directors is elected annually by members, who are each allowed only one share in the bank. The JAK Members Bank does not offer any interest on saved money. All of the bank's activities occur outside of the capital market, as its loans are financed solely by member savings. JAK Bank differs significantly from other banks in the following areas, as shown in Table 1.

Table 1. JAK Bank differences.

Difference	JAK Bank	Other Banks
Customers	Partner-centric, joint venture, one-vote-one-share model	Based on customer-centric model and activity sharing
Bank system	A fully savings-based system, loans are based on savings. On the other hand, loans are fully backed by member savings	Partial storage system; when a loan is granted, new money enters the bank through retained earnings. The loan is not backed by other investors. Only a small amount of the required loan is protected by the private bank. Of course, under the supervision of the central bank. Money saving in private banks in the United States is between 1% and 3%.
Loans	Loans are offered on the basis of deposit and member capacity, and the sole purpose is to repay the loan	Loans are repaid on the basis of the customer's credit value, and loan repayments include the principal and interest of the money.
Interest on loans	Interest is not credited, but the price of executive services is reviewed annually	All loans and credits accrue interest.
Interest on deposits	For deposits, interest is not paid, but concessions are granted equal benefits	The deposits accrue interest, but it is not so high.
Investor Profits	JAK Bank does not operate similar toother banks. Does not even benefit from the loans	Other banks obtain a return on their investment based on value and profitability results, which is used to pay employees and so on.

Source: (Williams and Anielski 2004).

The global crisis and the inability of the conventional banking system to prevent and deal with it, on the one hand, and the relative stability of Islamic banking in the face of this crisis, on the other, have attracted the attention of financial and banking experts and policymakers on Islamic banking. However, Islamic banks have many similarities with conventional banking in the type of transactions and services they provide, so that sometimes these similarities are questioned. Thus, these banks follow the principles and rules, the correct and complete observance of which leads to the stability of the banking system and the fair distribution of income throughout the economy. According to the doctrine of the Islamic Economic Sector, although human beings are free to design financial contracts, invent production methods, and organize economic activities, this freedom is within the limits set for justice and public welfare.

The main similarity between Islamic banking and JAK is the lack of interest. In fact, they both share an ideology. The only difference in religion (fighting corruption, usury, and the spiritual upliftment of man) is that it affects Islamic banking (Hyder 2013). Ahmad (2000) Islamic banking policy that is also in line with JAK principles: (1) the need for spiritual and moral awakening; (2) the rediscovery of the importance of physical and human capital information and the production of real services and goods; (3) a market economy with social responsibility, (4) moral commitment, and the positive role of government. The following Table 2 shows the main differences between Islamic Banking and JAK.

Table 2. Main differences between Islamic Banking and JAK.

The Main Criteria	Islamic Banking	JAK
Ownership	The shareholders own the bank	Members own the bank
Taking Part	Shareholders participate by sharing capital	Members, especially the borrowers, contribute capital
Main Products	Profit and loss sharing, joint venture, leasing	Savings and lending
Attributes	Spirituality, ethics, rationality and philanthropy	Economic freedom, justice, democracy, shared responsibility, and no interest
The Cost of Loans	No interest	No interest
Marketing	Using experienced media similar to traditional banks	Selective and informative, regular efforts to train members and customers of the bank
Vision	Borrowers have to make long-term savings	Borrowers do not have to make long-term savings

Source: Own contribution of the authors.

It is clear that bankinginterest rates cause unemployment, poverty, and social harm. In 1931, JAK members concluded that profit was the main cause of economic instability, resulting in high inflation and unemployment. So, they started profit-free projects to show that the idea of profit-free loans is coming true. High interest rates mean the rising cost of goods and services in all production and trading activities associated with lending. In the face of such price increases, industries are forced to (1) decrease wages or dismiss part of staff; (2) increase the price of their goods or services and; (3) increase the production of your goods or services by producing them on a large scale, in whichcosts are staggering and economical in scale.

2.3.4. Atom Bank and Gobank: Branchless Banking (BB)

Atom Bank is the first bank in the United Kingdom to be established based on BB and mobile application architecture (Atombank 2016a, 2016b). In order to achieve better customer service, the specialized focus of the branch staff and cutting costs is a convenient and cost-effective way. BB requires changes inside and outside the bank branches so that the role of the physical branches will not be the same as before, and out-of-the-box changes require up-to-date technology and the use of payment tools such as the Internet, telephony, mobile, ATM, POS, VTM, etc. (Dzombo et al. 2017). BB involves the delivery of financial services outside conventional bank branches, using retail agents or other third-party intermediaries as the principal point of contact with customers, and use of technologies such as card-reading point-of-sale (POS) terminals and mobile phones to transmit transaction details (CGAP 2011).

Banks are being innovative, largely due to intense competition, and they are therefore at the forefront of new developments, not only in banking but also in wider financial markets (Faure 2013). The BB concept began in South America, specifically in Brazil and Mexico (CGAP 2008). Based on early experiences, BB has made a significant contribution toward financial inclusion in developing countries. Most financial service providers collaborate and use partnerships with businesses that have a substantial local retail presence as a key competitive strategy (CGAP 2008).

Delloite (2012) believes that this type of banking is one of the distribution channel strategies used to provide financial services.BB enables customers to reduce costs through instant access. This model of banking to organizations reduces the costs associated with conducting low volume transactions as well as the costs associated with physical presence. There are two main advantages of this type of banking nowadays: first, diversifying services and adapting to market needs, and second, responding to market-created needs (Delloite 2012).

In addition, in many different parts of the world, the development of BB has been emphasized in various ways (CGAP 2010). In Brazil, private and state-owned banks provide services through micro agents such as supermarkets, pharmacies, post offices, and lottery shop. These agents are called "banking correspondents". Municipalities in Brazil belong to this category. In January 2006, The Central Bank of India issued guidelines for banks to use micro agents. The ICICI Bank in India is one of them. In South Africa, BB through micro agents is only permitted for approved financial institutions. ABSA and MTN banks are examples of this type of banking. In the Philippines, since the year 2000, mobile telecom operators and smartphones have been offering BB services. Safaricom in Kenya, a wholly owned subsidiary of Vodafone and a pioneering operator, offers its M-Pesa account to its customers who can fill or empty the account in ways similar to those in mobile electronic money. Gobank is another one of the best and most practical examples of offshore banking that has been launched solely for Americans (GoBank 2016). Go Bank is a real bank that works entirely on mobile. There are five important reasons that drive customers to this type of banking in the US: quick inventory checking, online check-in, money transfer, an extensive ATM network, and security.

2.3.5. Financial Technology (FinTech)

Financial technology (FinTech) is recognized as one of the most important innovations in the financial industry and is evolving at a rapid speed, which is driven in part by the sharing economy, favorable regulation, and information technology (Lee and Shin 2018). FinTech systems provide new and advanced business models such as crowdfunding, P2P, and B2B using disruptive technology, and as a consequence, the traditional banking business model faces a major challenge (Dasho et al. 2017). The progress of FinTech is defined as an uninterrupted process during which finance and technology have evolved together based on rapidly developing technology (Arner et al. 2015). FinTech promises to reshape the financial industry by cutting costs, improving the quality of financial services, and creating a more diverse and stable financial landscape. After all, it can be perceived as a FinTech revolution. According to PwC (2017), 83%of financial institutions believe that various aspects of their business are at risk to FinTech startups. Figure 7 presents the five components of the FinTech ecosystem.

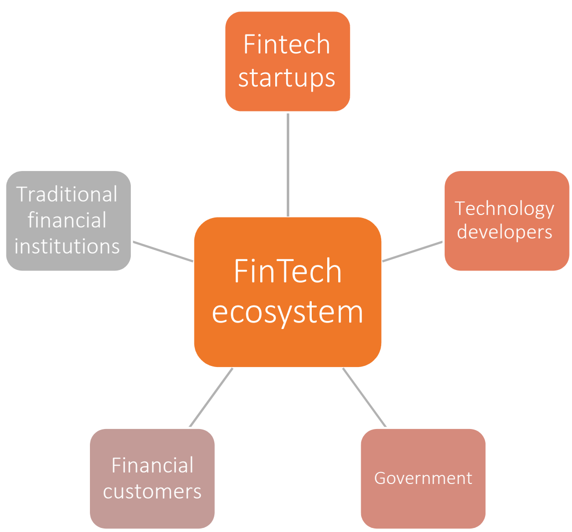

Figure 7. The five elements of the FinTech ecosystem. Source: Lee and Shin (2018).

- **FinTech startups** (e.g., payment, wealth management, lending, crowdfunding, capital market, and insurance FinTech companies);
- **Technology developers** (e.g., big data analytics, cloud computing, cryptocurrency, and social media developers);
- **Government** (e.g., financial regulators and legislature);

- **Financial customers** (e.g., individuals and organizations);
- **Traditional financial institutions** (e.g., traditional banks, insurance companies, stock brokerage firms, and venture capitalists).

At the center of the ecosystem are FinTech entrepreneurial organizations that represent the Industry 4.0 in a very good way. The core of these organizations in Industry 4.0: innovation in payment, wealth management, lending, financial aggregation, capital markets, lower operating cost insurance, targeting the niche market, and providing personalized services in facing traditional companies. Figure 8 shows the investment in FinTech companies from 2010 to 2017.

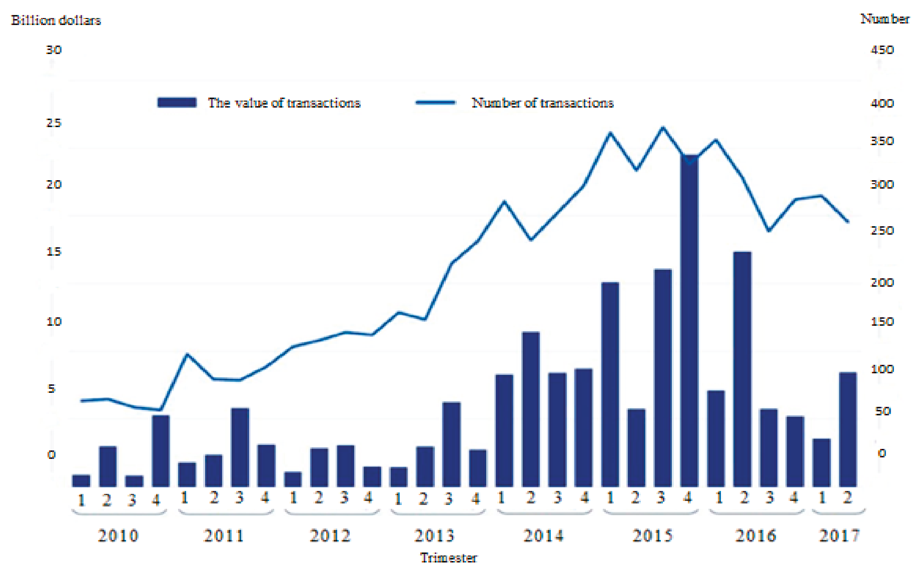

Figure 8. Investing in FinTech companies. Source: (KPMG 2017).

As a result, venture capitalists have invested more than $12 billion in FinTech startups over the past five years. In Figure 9, you can see the list of companies in the field of FinTechnologies up to Year 2017 that have become Unicorn companies (with a market value of $1 billion).

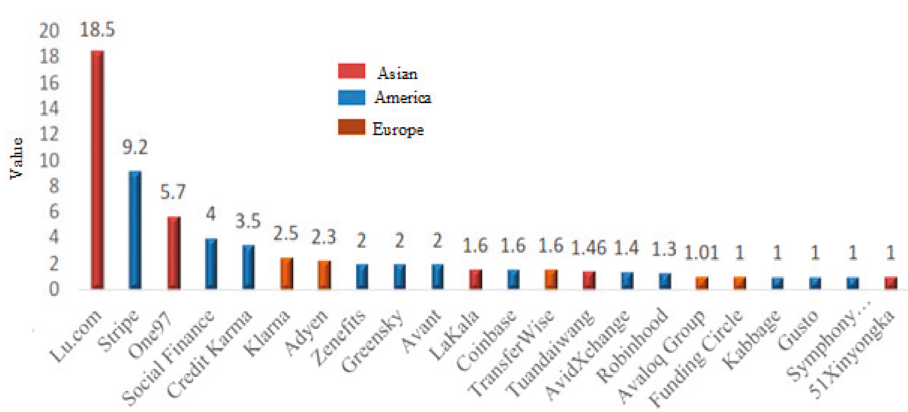

Figure 9. Unicorn companies. Source: (KPMG 2018).

Certain researchers stated that the FinTech structure of business is digital-based financial services that range from payment systems, banking services, insurance services, loans, and fund collections, to mere advice or learning to the public through digital media (Koesworo et al. 2019).

2.3.6. Open Banking (OB): APIs and Fidor Bank

OB is a newly emerging and rapidly developing area in financial systems (Open banking homepage 2018). The focus is on sharing data using the Open Application Programming Interfaces (Apiacademy homepage 2018). Applications that collect banking data from different institutions through API (application program interface) and present them on a single platform can be developed. APIs or application program interfaces are sets of rules that functions (applications) that can follow to communicate with each other and act as an interface between different applications. In addition to other benefits and advantages, APIs also save on costs; APIs can be used to implement app data from one app to another on a platform or service in a relatively inexpensive and simple way. The technology also adds value to the services provided. These applications can be developed by the in-house software developers as well as by the developers from outside of the organization (Kandırmaz and Tiryaki 2018). Customers can make better decisions by monitoring all their financial information in a single application (Figure 10).

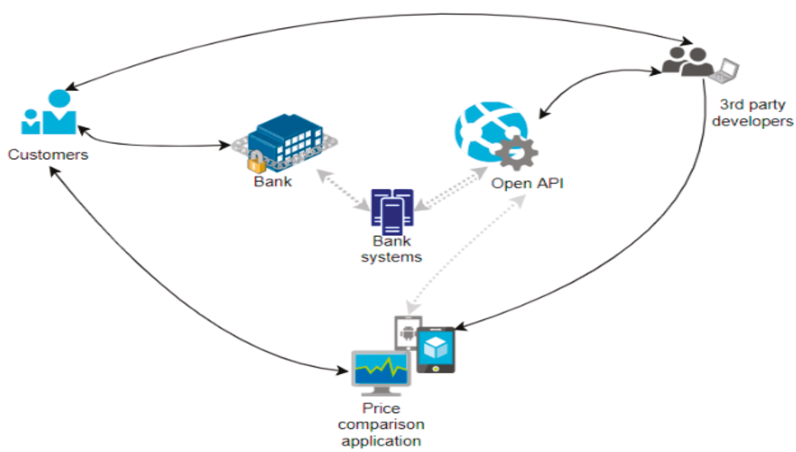

Figure 10. The structure of open banking (OB). Source: (Kandırmaz and Tiryaki 2018).

OB has enabled the organizations of Industry 4.0 to disclose data, algorithms, and processes through application programming interfaces and to generate new revenue streams. AnOB model also presents new opportunities for product creation and distribution (Figure 11). In the approach of Industry 4.0, the banking industry has made major changes by involving a large number of partners who are able to incorporate themselves into the product development process. In this new approach, the importance of APIs is emphasized.

Fidor Bank, given its relatively long focus on providing APIs, has significant experience developing revenue streams around API-based businesses. Figure 12 shows the benefits of implementing banks APIs. While the bank often earns its income through the community-banking model, net interest income, fees, and commissions, about one-third of its revenue comes from activities that provide open APIs and white-label (a product or service that is manufactured by one company but re-marketed by another company, as if it were made by a second company) solutions. Fidor Bank is growing as much as its white-label partnerships, the revenue generated by shared revenue streams will grow, and partners will expand their businesses.

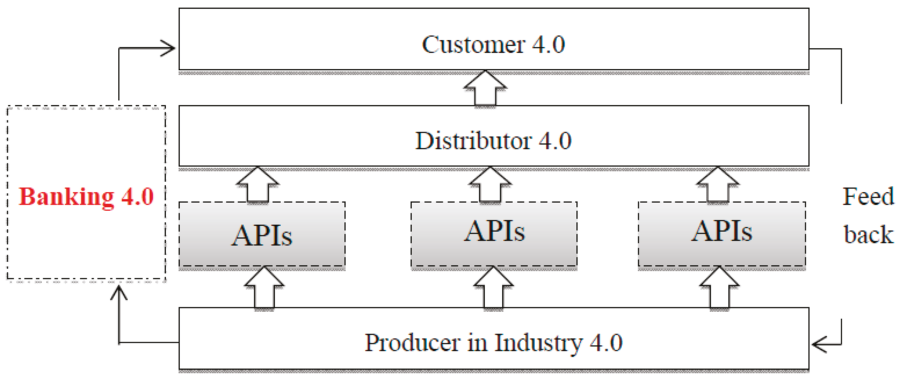

Figure 11. The role of application programming interfaces (APIs) in Industry 4.0. Source: Own contribution of the authors.

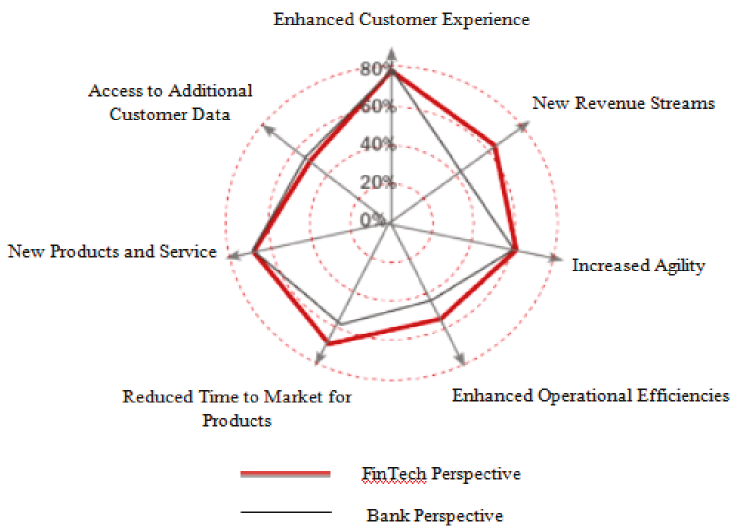

Figure 12. Benefits of implementing banks' APIs. Source: Capgemini (2017b) Retail Banking Executive Interview Survey, Capgemini Global Financial Service.

OB and BB are both on the path to fourth-generation banking development. The difference is that having open APIs, in particular, enables banks to collect operational data from a variety of sources, including customer buying habits, financial requirements, and risk appetite. Therefore, banks can offer products and services to customers with different tools and channels. However, banks also need to provide personalized services and products to different audiences through different channels. To this end, banks will work with FinTech to design a variety of products from platforms and tools, which will greatly improve product distribution. Therefore, in BB, by maximizing the potential of information and communication technology to customers without visiting the branch, through customer distribution and the supply of products and services with the same platforms and tools, customer satisfaction increases.

2.3.7. Omni-Channel (O-C): Disney Company and Starbucks

The O-C approach can be seen as the evolution of the multi-channel and having its origins in the retail industry (Rosman 2015). According to the multi-channel view, the customer gets a diverse experience across channels and acts as an integrator of information, whereas the O-C view focuses on bridging the gaps between different channels with the aim to provide a consistent and seamless customer experience (Rosman 2015; Saghiri et al. 2017). Based on this, three key principles or factors of O-C can be defined as follows: (1) seamless interaction between the channels (i.e., seamless transition to a second channel, enabling continuation of what was already started in the first channel), (2) optimization across channels (i.e., designing tasks and functionalities for different devices adapted to their unique context and strengths), and (3) consistent experience across channels (e.g., presentation and language or that task models are found consistent over different devices) (see McKinney 2014; Rosman 2015).

It should be noted in the first place that the concept of the O-C is in fact an organizational strategy. The O-C concept is not limited to banks and financial institutions, but it can be applied to any business dealing with customers (Figure 13).

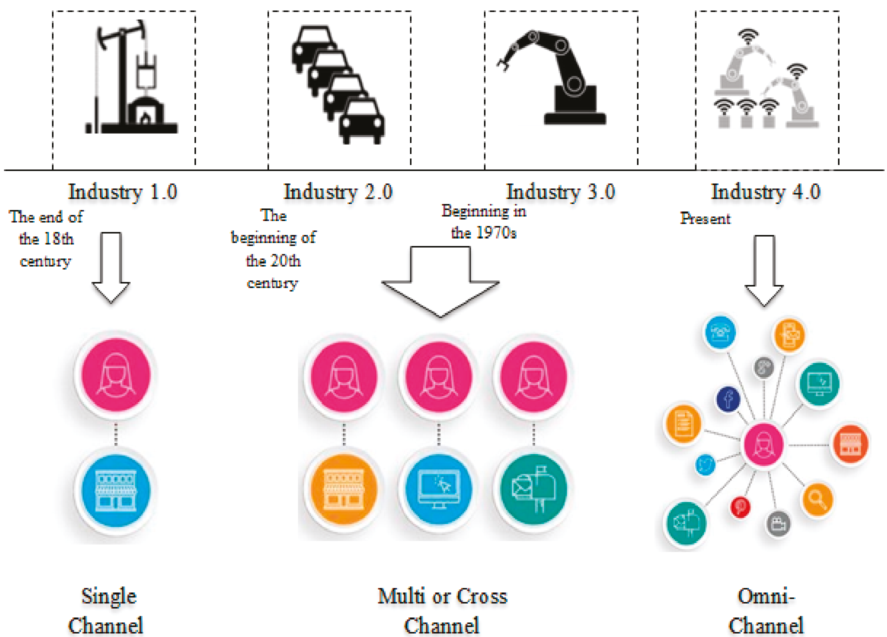

Figure 13. The relationship of communication channels in the Industry Revolution. Source: Own contribution of the authors.

According to Figure 10, in Industry 4.0, where human resources face plenty of new technologies, sensitivity, creativity, and communication in enterprises should be improved (Lee et al. 2018). Industry 4.0 is based on the unique involvement of human resources in the use of technology. All previous revolutions were limited only to increasing efficiency through the use of modern work methods and technical inventions. Currently, ensuring comprehensive integration of the human and technological sphere requires profound changes in the social sphere—also among employees of enterprises (Jasińska and Jasiński 2019). The following are the types of communication channels simultaneously with the developments of the Industry Revolution:

Single Channel: The most primitive way of connecting businesses with customers has been around for centuries. In this way, customers are connected to the business in only one way, mainly through physical communication (shop, bank branch, insurance office, etc.).

Multi-Channel: In this way, businesses can communicate with customers in several ways or ports, but each of these ports is completely independent of the other ports. The emergence of electronic tools such as phones, mobile phones, and computers has greatly helped to expand this way of communication, as most businesses today use the multi-channel method to communicate with their customers. In the case of banks and financial institutions, the advent of systems such as ATMs, telephone banks, internet banking, mobile banking, etc., has practically led to the relationship of customers with banks in a multi-channel manner.

Cross-Channel: This is a higher level of multi-channel mode. As stated in the multi-channel method, each communication port is completely independent of the other ports and virtually a single client is seen as a separate and separate identity in each port. In contrast, in the cross-channel approach, each customer has a single identity that is recognized in all ports with the same identity. It should be noted that in the cross-channel method, communication ports are still independent of each other.

Omni-Channel: In this case, not only does the customer have a single identity across all ports, but virtually all ports see it as a unified system. In the O-C style, customer communication is performed seamlessly, anytime, anywhere on all devices. In this way, the customer and the activities he/she does are central to the way the services are provided to him/her. Accordingly, the service to each customer is personalized based on the activities he has done on all ports. As a result, it not only responds to the customer's explicit requests, but also their interests and implied needs.

The most important difference between multi-channel and O-C is that multi-channel puts the brand at the center of the strategy and sends a similar message to customers on all communication channels. However, omni puts the customer channel at the center of the strategy. In this way, the message that is to be sent to the customer changes and will be appropriate to the way the customer interacts with other communication channels. So, the five main features of the O-C in Banking 4.0 are:

- Port uniformity
- Integration of ports versus independent ports
- Customer-centric versus bank-centric
- Interaction versus transaction
- Guessing customer needs versus making requests

Technically, in order for an O-C-based architecture to meet these needs, it needs to take advantage of new technologies such as responsive design. Big data, NoSQL database, data mining, data analysis, etc., which emerged in Industry 4.0. For instance, a NoSQL (originally referring to "non SQL" or "non-relational") database provides a mechanism for storage and retrieval of data that is modeled in means other than the tabular relations used in relational databases.

- **Disney Company:** Disney is one of the companies that has good communication with customers by using the O-C concept. It is based on fiction and creative stories, and it is no wonder that in the real world, it also uses creative ways to omni-channel. Disney paid close attention to details and made it possible to access all parts of the website via mobile. After logging in, the user can plan each minute of the trip through the app. Visitors can follow the park through the app, the location of all sights, and the length of time they need to queue. Users also get their rooms through the app and charge all the purchases they make to room service. All Disney communication channels are interconnected and provide a good user experience.
- **Starbucks:** Starbucks is another brand that has made good use of the omni-channel concept. Starbucks has branches in most cities around the world and provides a good customer experience.Each time a user pays his account via bank or mobile card, the purchase points he has are added to his account. The Starbucks app also introduces the nearest branch to the user

and prepares the coffee by the time the user arrives. Users can also view the new coffee list in the menu and be informed of the song played in each branch (Starbuck works with many companies. Playing all kinds of music and having a lot of branches around the world has made customers understand different pleasures. So, customers can choose their Starbucks according to the music played). Surely every user after experiencing such features will become a permanent customer of the brand.

2.3.8. Robotics in Banking

Robotics is revolutionizing the way lots of banking and finance companies do business through something called robotic process automation (RPA). According to Romao et al. (2019), RPA represents the use of software with artificial intelligence (AI) and machine learning capabilities in order to drive high-volume, repeatable tasks that previously required only humans to perform. It is essentially a virtual workforce based on software that frees up human employees to focus on less tedious tasks that only humans do well. For example, PayPal and credit institutions also use robots to provide services to their customers. PayPal uses the robot to transfer money from person to person on its own program. PayPal also interacts with robots from companies such as Uber. MasterCard has also built a robot for its customer service department as well as for its Masterpass application. Bank of America has also created a robot on Facebook for its cardholders. Robotic process automation is a quick and simple way for banks to automate a wide range of processes (Mlađenović 2018):

- Secure efficient interaction between different systems, thus eliminating the need for employees to manually source data
- Upgrade middle and back-office processes (faster execution, fewer errors)
- Speed up the processing of big data
- Free up employees to focus more on clients and provide a better customer experience
- Reduce time-to-market and total cost of ownership (TCO)
- Simplify regulatory compliance with greater transparency
- Pave the way for a new wave of transformation toward 100% digital banking.

3. Banking 4.0 Roadmap in Industry 4.0

It is imperative to create a roadmap for Banking 4.0 in Industry 4.0. While technology acts as an empowering factor for banks to move in the right direction, it has also led to the growth of non-traditional companies in Industry 4.0. Companies use technology to provide simple, easy, convenient, and affordable financial products and services to customers. Since the emergence of the technologies of Industry 4.0 has had a significant impact on both industry and financial services, there has been a growing trend in the banking industry that focuses on innovation using these new technologies.

Figure 14 shows the most important components of the Fourth Industrial Revolution and its relationship to fourth-generation banking. There is a great deal of ambiguity about the definition of IoT, as each stakeholder has defined it according to its user (Atzori et al. 2010). IoT refers to IIoT in the Fourth Industrial Revolution, which deals with industrial applications of IoT (Wang et al. 2016a). Physical objects can work through IoT to communicate with each other and to better coordinate decision making (Al-Fuqaha et al. 2015).

Internet of Services (IoS) refers to the purposeful use of new value creation methods through PaaS (Product-as a-Service) business models (Ghobakhloo 2018, p. 919). IoS provides the technology makers with the technological infrastructure needed to provide services and provide customers with continuous communication and increased competitiveness (Becker et al. 2014). The transformation of humans and their devices into active elements on the Internet is called a complex social and technical system called IoP (Internet of People) (Conti et al. 2017). The existence of the social devices (SDs) and People as a Service (PeaaS) constitutes the necessary infrastructure for IoP. The development of IoT, which is of great interest to researchers today, is called the Internet of Data (IoD) (Fan et al. 2012). Paying attention to the means of transmitting, storing, and processing data in the IoT environment where a lot of data is generated is one of the tasks of IoD (Anderl 2014).

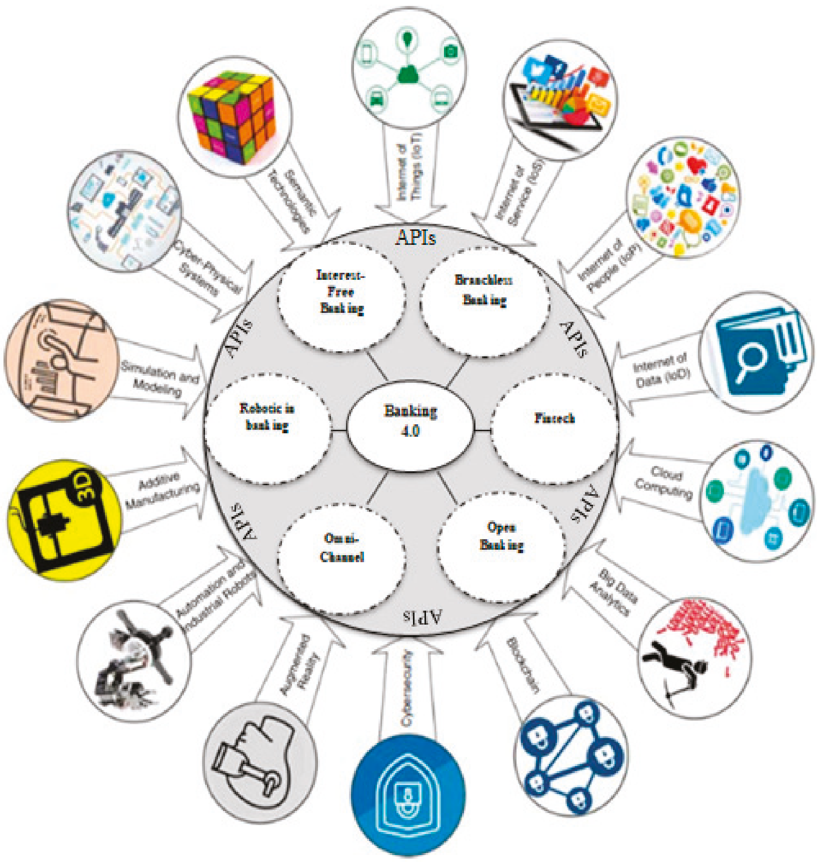

Figure 14. Design principles of Banking 4.0 in Industry 4.0. Source: Own contribution of the authors.

Although cloud computing is not a new concept, there is no single definition for it yet (Ghobakhloo 2018, p. 920). The concept has expanded into the world of technology through the development of hardware, technology and computing, and the provision of services over the Internet (Oliveira et al. 2014). Using this concept has created a variety of applications, including web-based management dashboard and cloud-based collaboration, and it enables the integration of distributed manufacturing resources and the establishment of a collaborative and flexible infrastructure across geographically distributed manufacturing and service sites (He and Xu 2015). In fact, the concept of cloud structures will generate subsequent structures (Ooi et al. 2018).

The concept of big data has been in technology and industry for many years (Ghobakhloo 2018). Srivastava and Gopalkrishnan (2015) argued that big data has recently unlocked secrets of money movements, helped prevent major disasters and thefts, but also understand consumer behavior. For instance, the core idea of business intelligence (BI) is to recognize the behavior of the customer and to predict their purchase pattern for improvement of the business considering that building strong customer relationships is very important for companies (Nethravathi et al. 2020). Consequently, this approach benefits the banking sector, considering the flexibility and easiness of extracting useful information for the interest of their consumers. However, organizations are analyzing data to maintain good survival and make effective decisions in times of crisis as well as market competition (Hu et al. 2014). For example, big data analytics helps companies improve their performance, monitor the status of competitors in the industry, develop customized products, and take preventive measures to prevent crashes. They can also make the production chain and operations easier and more transparent (Babiceanu and Seker 2016; Wang et al. 2016b). Analyzing this type of data enables traditional organizations to better plan the future and use the results to increase system efficiency and efficiency (LaValle et al. 2011). On the other hand, customers' buying behavior could be accurately researched in the actual market place, rather than in surveys and samples (Hawaldar et al. 2019).

Blockchain has many capabilities and is based on emerging financial currencies such as bitcoin and Ethereum (Ghobakhloo 2018). This technology is also known as distributed ledger technology. By providing transparent, secure, reliable and fast solutions, blockchain provides special conditions for public or private organizations (Underwood 2016). The application of this technology is crucial in the Fourth Industrial Revolution because the use of countless smart devices around the world makes it possible to perform transparent, secure, fast, and flawless transactions without human interference in the IoT environment (Devezas and Sarygulov 2017; Sikorski et al. 2017). Blockchain activity is not just about financial services, but any kind of digital activity developed in the Fourth Industrial Revolution based on automation. The activity that this concept offers is in fact leading the organizations and creating a trusted, independent relationship between smart factories, suppliers, and customers.

The type of technology that enables organizations to graphically visualize the real environment in the Fourth Industrial Revolution is Augmented Reality (AR) (Yew et al. 2016). The development of software and hardware applications has led AR to act in various industrial processes and products as a guide in describing, planning, and monitoring real-time performance, error detection and recovery, and various training strategies (Doshi et al. 2017; Khan et al. 2011). The search for industrial reality also shows that manufacturing organizations use AR to support employee training programs, task simplification, control, and product design (Elia et al. 2016).

Today's organizations are turning to the use of robots due to the increasing use of automation. The use of robots is essential for world-class organizations because of the benefits such as increased efficiency and quality, increased reliability and waste reduction, the better utilization of resources, and increased competitiveness (Ghobakhloo 2018; Esmaeilian et al. 2016). The importance of cybersecurity in the Fourth Industrial Revolution was high because no organization was safe from cyber threats. Threats of recent years include The Stuxnet. Malware created a serious threat to nuclear power plants by slowing down the speed of centrifuges. There is no doubt that in the Fourth Industrial Revolution, the issue of cybersecurity and privacy for organizations and individuals is a challenge (Thames and Schaefer 2017). It is essential to create some sort of industrial integration in the chain through the Internet. Obviously, the more links there are, the more information security and transparency they will have (Mehnen et al. 2017).

One of the things that created a trusting relationship between financial organizations in the Fourth Industrial Revolution is 3D printing technology (Ghobakhloo 2018). This technology enables organizations to generate prototypes and conceptual designs that create and play an important role in simplifying activities and increasing their speed (Gilchrist 2016). The Fourth Industrial Revolution has brought organizations and customers together so that customers can come into their organization, even at home, at night, or even while swimming, and do different things. Simulation and modeling techniques have been developed to improve economic designs and evaluate their performance in the real world (Kocian et al. 2012). These concepts are needed in smart factories to evaluate the actual performance of machines, products, and employees (Rüamann et al. 2015). Simulation and modeling not only enable manufacturers to detect errors in the early stages, they also avoid significant costs and irreparable damage to the organization (Gilchrist 2016).

CPS is a suite of state-of-the-art technologies that are capable of interconnecting physical assets and computing operations (Lee et al. 2015). CPS is controlled by computer-based algorithms and integrated with its users over the Internet. The CPS also plays a human role in everything that is capable of computing, networking, and physical processes (Gilchrist 2016). Another important component of the Fourth Industrial Revolution that can be a common standard for information exchange is semantic technologies (Janev and Vraneš 2011). Semantic technologies achieve a high level by offering an abstraction layer above existing IoT technologies and infrastructure that connects data, content, and processes. Importantly, the IIoT lacks universal protocols for integrating machines and does not have the various components of smart factories to achieve a single user (Thuluva et al. 2017). In such circumstances, utilizing the integration of the semantic web with Web of Things (WoT) technologies can provide a definite framework. This feature facilitates the interoperability of assets and services as well as the way in which heterogeneous components are communicated in the Fourth Industrial Revolution.

Industry 4.0 needs its own banking. Industry 4.0 is largely international in scope and customers from all over the world choose it. A radical change in the marketing and segmentation of banking customers makes it unique for each customer (Figure 15). In the short term, the fourth-generation banking strategies must first be identified in the context of the Fourth Industrial Revolution. It is necessary to set a timetable for developing the infrastructure and creating user relationships. A specific management team can be appointed in this regard. In the medium term, it is necessary to carefully monitor the timing of all aspects of the strategic plan. The Digital Acceptance and Readiness Program, Human Capital, Digital Culture, Regulatory, Capabilities and Technologies, and Networking should be delivered to the Fourth Industrial Revolution in accordance with the world schedule.

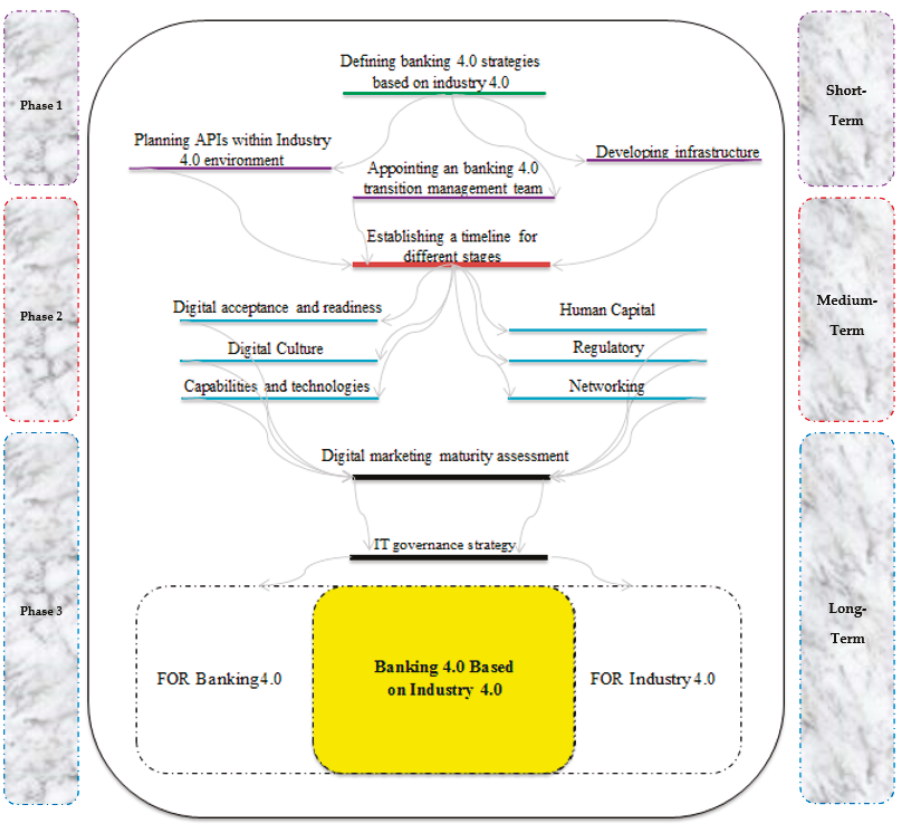

Figure 15. The strategic roadmap for Banking 4.0 based on Industry 4.0. Source: Own contribution of the authors.

In the long run and after achieving short and medium-term goals, the two goals of digital marketing maturity assessment and IT governance strategy will be provided for fourth-generation banking.

4. Results

We are at a time when exciting things are happening in the banking industry. Non-stop technology is advancing, providing opportunities for institutions through which they can expand their services and eliminate traditional financial services altogether. These state-of-the-art technology networks will provide the opportunity to meet customer needs instantly and intelligently through various channels. This will be achieved when new strategies for computing and storage are explained, advanced analysis is performed, cyber security capabilities are upgraded, and a completely new perspective for banking services is outlined. Which technology has the greatest potential for the Industry 4.0 in Banking 4.0? The exact answer to this question is not clear, but there is no order in the application of the introduced trends, but it is these organizations that must prioritize and allocate the necessary capital to implement each of them. There are so many opportunities, and any passivity or desire to stay calm will put a high risk on the organization.

Banking and payment services must move toward the formation of a fully intelligent network. Overall, improving the customer experience, using artificial intelligence, the emergence of databases, the use of identification algorithms, the use of machine learning methods, and data analysis are among the features of the new generations of banking. However, the important thing is that digital technologies have made major changes in banking. Traditional banks are migrating more digital services to digital channels every day. Customer preference for the increased convenience and availability of services is also strongly aligned with this change and gives it more acceleration. This has led to a change in the structure of the distribution network of banks, and in addition to reducing the need for physical branches, it has also changed the function and mission of branches. However, evidence from international banks and even some traditional industries shows that non-alignment with digital and technological developments, while reducing profitability and value creation, will also jeopardize the survival of these institutions. Today, banking is a cascade of multiple technologies, rules and regulations, and demographic factors that cut the length and breadth of its value chain. These factors affect the way businesses are run by banks, so that common banking practices are not enough to meet growing customer expectations as well as improve profitability. Therefore, the factors influencing the evolution of the banking industry can be divided into two main categories: business developments and technical developments. In the area of business developments, new non-bank actors in the form of FinTech or startups have disrupted the banking business and impaired the role of intermediaries in banks. However, in the technical sector, the emergence of new technologies such as blockchain, robotics, etc., has had a significant impact on the performance of the banking industry.

5. Conclusions

Banks and FinTechs have been working for years to find common ground. The FinTechs have stepped in to gain market share and have been successful in injecting new concepts into banking. However, they ran into trouble when they tried to get a large scale of banks to be able to process and reach more customers. Banks initially looked at the FinTechs with skepticism and distrust, but since then they have praised their entrepreneurial approach. Undoubtedly, due to the existence of old systems and cultural frustration with risking within banks, FinTechs have breathed new life into the banking system. Both sides (banks and FinTechs) have increasingly come to the conclusion that by combining and synergizing their strengths, they can create value.

Banks need to change the way they think about the past and keep up with the advances in technology. Besides, the first thing they need to focus on is improving and providing services from the customer's point of view so that they can create the key factor of customer experience in the best way. Therefore, the basis for valuing fourth-generation banks is based on the creation of cooperation between the bank and customers. Finally, banks need to work closely with technology and knowledge-based companies to introduce new operating methods. Banks will be very similar to technology companies, and they desperately need to work with these companies to accelerate the process of transformation and business transformation. From the point of view of Industry 4.0, a successful economy has the most assets, activities, and focus in digitizing its assets. The experience of using technology is very new, even in the world.

However, the most important limitations of the research are the limitations of technology and culture, as well as the type of vision of customers regarding the nature of banking. A study of the structure of various industries and the lack of attention to the necessary infrastructure for the development of technologies required by Banking 4.0 in different countries shows that more studies should be done on the use of emerging technologies in various banking and industrial sectors.

Future researchers are also advised to identify and prioritize the following: (1) the pathology of various emerging technologies in Banking 4.0 in terms of legal and regulatory structures and (2) the indicators of Industry 4.0 to enter Banking 4.0.

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Jump Driven Risk Model Performance in Cryptocurrency Market

Ramzi Nekhili [1,*] and Jahangir Sultan [2]

1 Department of Accounting and Finance, Applied Science University, East Al-Ekir 5055, Bahrain
2 Department of Finance, Bentley University, Waltham, MA 02452, USA; jsultan@bentley.edu
* Correspondence: ramzi.nekhili@asu.edu.bh; Tel.: +973-39477694

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Abstract: This paper aims at identifying a validated risk model for the cryptocurrency market. We propose a stochastic volatility model with co-jumps in return and volatility (SVCJ) to highlight the role of jumps in returns and volatility in affecting Value-at-Risk (VaR) and Expected Shortfall (ES) in cryptocurrency market. Validation results based on backtesting show that SVCJ model is superior in terms of statistical accuracy of VaR and ES estimates, compared to alternative models such as TGARCH (Threshold GARCH) volatility and RiskMetrics models. The results imply that for the cryptocurrency market, the best performing model is a stochastic process that accounts for both jumps in returns and volatility.

Keywords: stochastic volatility with co-jumps; threshold GARCH; RiskMetrics; validation; cryptocurrency market

JEL Classification: C22; G11; G12

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1. Introduction

Forecasting volatility is pivotal for developing accurate and realistic risk management models that perform well in good times and in bad. An accurate volatility forecast depends on the assumptions made by the analyst and selection of proper statistical models that can provide a parsimonious representation of the stylized features of the data. When risk management fails, the blame is squarely placed on risk models. According to Bernanke (2008), "Those institutions faring better during the recent turmoil generally placed relatively more emphasis on validation, independent review, and other controls for models and similar quantitative techniques. They also continually refined their models and applied a healthy dose of skepticism to model output". Hence, a crucial task facing a risk manager is to make sure the models are tested, back-tested, and validated to minimize expected losses.

Academics, practitioners, and regulators have commonly used risk models that were deemed sophisticated in terms of forecasting risk. For instance, JPMorgan and Bank of America use historical simulation to estimate their trading risk. Others rely on volatility forecasting models such as GARCH family models, exponentially moving average, JPMorgan's RiskMetrics, and extreme value theory models. In this respect, academics provided various results of the reality checks of these models and suggested different versions of the GARCH volatility models by alternating between Normal, Student-*t*, and Skewed-*t* distributions in an attempt to better capture tail events and asymmetry of the data generating process (see, for example, Bauwens and Laurent (2005), Danielsson and Morimoto (2000)). Other scholars suggested hybrid models combining, for instance, filtered historical simulation with GARCH models or assuming different error terms in the models. Nevertheless, such models require assumptions about the stochastic processes of the underlying asset prices that are subject to validation failure either because of misspecification or the latent characteristic of the parameters, especially during economic downturns.

On a more macro level, it is now evident that the importance of risk models remains fundamental for capital requirements as imposed by the Basel regulations. Decision-makers rely on these risk models as long as they have passed some validation criteria adopted by financial institutions and regulatory authorities. Three critical model-failures have been noted in the literature—1992 Deutsche Bank loss of $500 million, the 1998 collapse of Long Term Capital Management (LTCM), and the 2012 "London Whale"[1] debacle of JPMorgan Chase & Co. For the Deutsche bank loss, the culprit was the assumption of flat volatility to price options and, in the case of the LTCM debacle, the blame was placed on the model's use of Gaussian copula and the assumption of no contagion (Jorion 2000).[2] Finally, the 2012 loss of $6.2 billion, due to a spreadsheet error in calculating Value-at-Risk (VaR) and operational risk at JPMorgan Chase, highlights why it is important to validate risk models.[3]

In light of some of these historical data, it is fitting that scholars shifted their approach to stochastic volatility risk models, postulating that volatility is driven by its own stochastic process that accounts for jump dynamics in the returns rather than skewness or excess kurtosis. Such an approach, when pitted against other risk models, outperformed both in and out-of-sample backtesting results (see, for example, Maheu and McCrudy (2005), Su and Hung (2011), and Ze-To (2012)). Their results supported a consensus that jumps are causing extreme value in returns and taking them into consideration provides better VaR forecasts for long and short positions at lower and higher VaR levels. Though such models were successfully validated, they accounted for jumps in the return series and not in volatilities. In addition, many of these risk models were validated in a portfolio context, and little has been done with individual assets with a stochastic model that accounts for both jumps in returns and volatilities (see, for example, Eraker et al. (2003)).

The challenge, therefore, is to identify the best risk model that has passed some validation criteria using risk measures such as VaR and Expected Shortfall (ES), which remain the building-block of market risk regulations. One typical means for identification of the best risk forecast model is by analyzing violation ratios, which is better known as backtesting. Although some scholars argue that risk model choice is the least concern for decision-makers (see, for example, Danielsson et al. (2016)), the scenario takes a different path when dealing with individual financial assets and considering economic events affecting financial markets.

Risk validation in any financial asset that trades on organized platforms is critical for national and international regulatory bodies that are entrusted with providing a safe and sound financial environment for financial transactions. To this extent, investor safety is paramount for an assessment of risks of cryptocurrencies so that proper regulatory controls, if needed, can be designed and implemented. The popular media have declared the cryptocurrencies as some of the most volatile assets in the financial market worldwide. Such assertions must be validated using appropriate econometric risk models that incorporate stylized features of the market to understand the evolution of risk and the factors that are responsible for it. Most importantly, the structure of the market, transaction costs, market microstructure, price formation, and the volatility should be studied within an appropriate risk model. For the emerging cryptocurrencies market where governmental oversight and regulatory structure is still evolving, model risk due to wrong assumptions can lead to wrong conclusions and incorrect policy implementation.

Overall, cryptocurrencies have taken place in the financial markets and in portfolio management. They may be useful in risk management and ideal for risk-averse investors in anticipation of negative shocks to the market. They are also considered as investment assets useful for portfolio diversification and hedging against movements in other financial assets such as commodities. To sum up, for an

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1 The term "London Whale" was based on the enormous size of the bet on credit default swaps made by the London office of the bank's risk management division.

2 In addition, the LTCM model made several critical mistakes, including assuming that returns were normally distributed, and the time period to establish the risk parameters was rather short. See Jorion (2000) for more.

3 Interestingly, JPM CEO Jaime Dimon had initially described the problem as "a tempest in a teapot".

investor trying to manage tail risk in cryptocurrencies, choosing an appropriate model is critical for forecasting volatility.

This paper aims at exclusively identifying a risk model that is valid for the cryptocurrency markets. It also attempts to build up on the consensus that cryptocurrencies exhibit extreme volatility that needs to be properly quantified for risk management purposes. The existing literature suggests that both stochastic volatility and jumps in returns in the equity market are important components of the returns. Hence, we consider theoretical and applied return models that require the specification of a stochastic volatility component. The model that we select accommodates the persistence in volatility, and volatility of a jump to address the unpredictable and large movements in the price process. In essence, our objective is to examine if jumps in returns and volatility can help us predict tail risk and expected shortfall more accurately. Furthermore, it also is important to determine if jumps in returns and volatility can help us accurately predict and manage expected losses from investing in cryptocurrencies. This particular focus on the volatility structure of the cryptocurrency market is incomplete in the literature.

Our risk model validation approach starts with a nonparametric test to detect jumps in the dynamics of the price process in the cryptocurrency market. Next, we introduce the price dynamics as inputs in a stochastic model that allows for jumps in both returns and volatility, as well as their correlation. We call this the Stochastic Volatility with Co-Jumps (SVCJ) model. We further study how such a model could be appropriate for risk measurement and compare its Value-at-Risk and Expected Shortfall predictions with competing models that are frequently applied to financial time series. Backtesting criteria are implemented to test the statistical accuracy of the models, followed by an examination of the statistical significance of the differences between the models.

Our results suggest that no one model universally fits all cryptocurrencies. We find that there are jumps in the returns and volatility of returns in the cryptocurrency market, though jump probability estimates vary across currencies. We find evidence of the leverage effect where volatility has an asymmetric response to good news and bad news. Both the SVCJ and TGARCH models produce accurate forecasts of tail risk and Expected Shortfall (ES) better than the popular RiskMetrics model. Finally, the strongest result in the paper is that the proposed SVCJ model produces lower economic losses than the TGARCH and RiskMetrics models. This implies real savings for an investor for dealing with capital losses for investing in the cryptocurrency market.

The paper proceeds as follows. In Section 2, we discuss the proposed stochastic volatility model with jumps and leverage. In Section 3, we offer empirical results. The final section concludes the paper.

2. Methodology

An understanding of the volatility process of financial assets is necessary for investors to manage risks of investing in financial markets. Equally important is that regulators have a more informed view of the underlying volatility structure of these assets so that appropriate regulatory policies can be designed to attract investors and potential new issuers. To this extent, it is important to examine if assets have time varying volatility, jumps, autocorrelation, extreme risk, and how the volatility process responds to good news and bad news in the markets. These issues have been investigated in the literature individually in a disparate manner when they should be addressed simultaneously in an integrated model to allow interaction among these volatility parameters (see Ardia et al. (2019), Barivera et al. (2017), and Segnon and Bekiros (2019), and references therein). Hence, we adopt a model that can capture quick and persistent movements of the conditional volatility of returns as in Eraker et al. (2003), which was an implementation of the model with jumps in both returns and volatility by Duffie et al. (2000). Such models showed that, with jumps in returns and jumps in stochastic volatility, the performance is better than competing models with different specification of the volatility process. A number of papers have examined equity price models with jumps in returns and stochastic volatility (see, for example, Bakshi et al. (1997), Andersen et al. (2002), and Pan (2002)) and made it clear that both stochastic volatility and jumps in returns are important components of the time series properties of financial assets.

Let us begin by defining $logP_t$ as the logarithmic price process with V_t as the stochastic variance. Both processes are assumed to have a continuous path or happen to be discontinuous with the occurrence of at least one jump:

$$\begin{aligned} dlogP_t &= \mu dt + \sqrt{V_t} dW_t^X + J^X dZ_t^X \\ dV_t &= \kappa(\theta - V_t)dt + \sigma_V \sqrt{V_t} dW_t^V + J_t^V dZ_t^V, \end{aligned} \tag{1}$$

where the stochastic volatility V_t has parameters κ and θ that are the mean reversion rate and mean reversion level, respectively. W^X and W^V are correlated standard Brownian motions with $\text{Cov}(dW_t^X, dW_t^V) = \rho dt$. $Z_t^X = Z_t^V$ are contemporaneous jump arrivals in both prices and volatility and are assumed to follow a Poisson process with constant intensity λ. σ_V represents the volatility of volatility and measures the variance responsiveness to diffusive volatility shocks.

Because data are observed in discrete time, it is common to use an Euler discretization of the continuous time process in Equation (1). Assuming a time discretization of one day ($dt = 1$) and $X_t = logP_t - logP_{t-1}$, the discrete model, labeled SVCJ, becomes:

$$\begin{aligned} X_t &= \mu + \sqrt{V_{t-1}}\epsilon_t^X + J_t^X Z_t^X \\ V_t &= \kappa(\theta - V_{t-1}) + \sigma_V \sqrt{V_{t-1}}\epsilon_t^V + J_t^V Z_t^V \end{aligned} \tag{2}$$

where J_t^X and J_t^V are the correlated jump sizes with $J_t^V \sim exp(\mu_V)$ and $J_t^X | J_t^V \sim N(\mu_X + \rho_J J^V, \sigma_X^2)$, and ϵ_t^X and ϵ_t^V are standard normal random variables with correlation ρ. We note that, when $\rho_J = 0$ and $\mu_V = 0$, the model turns to a stochastic volatility with jumps of Bates (1996), and, when $\rho_J = 0$, $\mu_V = 0$, $\lambda = 0$, $\mu_X = 0$, and $\sigma_X = 0$, the model is a stochastic volatility of Heston (1993).

We use a likelihood-based framework for estimating multivariate jump-diffusion models using the Markov Chain Monte Carlo (MCMC) method. This method is based on Bayesian modeling that requires using a likelihood, a priori distribution, and a posteriori distribution. Prior distributions are required for the initial volatility state, V_0, and for all parameters governing the dynamics of the volatilities. Moreover, the prior contains information about both the parameters and the structure of the latent processes: the stochastic specifications of the jump sizes, and jump times. As in Eraker et al. (2003), the priors are always consistent with the intuition that jumps are "large" and infrequent. More specifically, we choose a prior that places low probability on the jump sizes being small, say less than one percent, and a prior that places low probability on the daily jump probability being greater than 10 percent. In this paper, we generate results with priors.

Next, the forecastability of the SVCJ model is compared to commonly adopted alternative volatility models within the popular GARCH family. For this and to be in line with the stylized facts that financial time series have leptokurtosis, heavy tail, and autocorrelation, we impose volatility dynamics within the universe of GARCH specifications. We choose the TGARCH specification of Glosten et al. (1993) is due to its ability to capture the so-called leverage effect, the tendency of volatility to increase more with negative news rather than positive news. Brownlees and Engle (2012) argued that this volatility model has superior forecasting performance than other known volatility models[4]. The model takes into consideration any presence of autocorrelation of order p and is presented as follows:

[4] Other volatility forecasting models would include ARCH, GARCH, I-GARCH, GARCH-M, GJR-GARCH, and TARCH, for example. However, it is very tough to generalize the statement because results from the above models may vary due to differences in assets, data, and time period under study. See, for example, Ali (2013).

$$
\begin{aligned}
X_t &= a_0 + \sum_{j=1}^{p} a_j X_{t-1} + u_t \\
\sigma_t^2 &= \omega + \alpha u_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}^- + \beta \sigma_{t-1}^2,
\end{aligned}
\tag{3}
$$

with $u_t \sim D(0, \sigma_t^2)$ representing independent and identically distributed shocks with zero mean and time-varying variance, and $I_{t-1}^- = 1$ if $u_t < 0$, and zero, otherwise. In this model, the parameters α and β are respectively the ARCH and GARCH coefficients, and the parameter γ captures the leverage effect of the returns. In line with the stylized facts observed in the cryptocurrency market (see for example Chan et al. (2017), Caporale and Zeokokh (2019), and Ardia et al. (2019)) and, because there is a large departure of the cryptocurrencies returns from normality, we allow for the distribution D of shocks to follow a Student-t or skewed Student-t with ν degrees of freedom.

We explore whether the forecasts generated from the two models are able to provide an investor with a valid tool to hedge risk. Therefore, we derive VaR and ES using the simulated volatility series when fixing the parameter estimates produced by the models. An n-day τ% VaR is defined as

$$
\text{VaR}_t^\tau(X) = \inf\{x \mid Pr(X_t < -x) \le \tau\}, \tag{4}
$$

and, once X is below VaR_τ, we define

$$
\text{ES}^\tau(X) = \frac{1}{\tau}\int_0^\tau \text{VaR}_u(X)du. \tag{5}
$$

To concentrate on a specific return bracket, we adopt a non-parametric technique based on Filtered Historical Simulation of Barone-Adesi et al. (1999) to simulate 5000 returns' paths from both the SVCJ and the AR(2)-TGARCH (1,1)$\sim t$ models. For the latter, we first standardize returns by quantiles and volatility estimates and then generate returns' paths serving as the basis for calculating VaR and ES.

Next, we evaluate the accuracy of each model through backtesting the estimated VaR and ES. The backtesting relies on comparing the risk measures estimated by the models under analysis with the actual trading results. The cases in which the actual loss exceeds the VaR estimate are called exceptions. According to Christoffersen (1998), the exception sequence is defined as:

$$
I_t^\tau = \begin{cases} 1, \text{if } X_t < -\text{VaR}_t^\tau & \text{violation occurs} \\ 0, & \text{otherwise} \end{cases} \tag{6}
$$

for $t = T+1, \ldots, T+n$, where T is the number of return observations used to estimate the VaR of the day $T+1$, and n is the number of one-step-ahead estimates of that risk measure included in the test. Consequently, Christoffersen's conditional coverage test (LR_{cc}) for VaR backtesting consists of determining whether the probability of occurrence of an exception, $p = Pr[X_t < \text{VaR}_t^\tau]$ is significantly different from the defined τ (unconditional coverage test LR_{uc}) and whether the exception sequence is serially independent (independence test LR_{ind})[5]. The likelihood ratio statistics for the test of correct conditional coverage is defined as:

$$
LR_{cc} = 2\ln\left[(1-\pi_{01})^{n_{00}}\pi_{01}^{n_{01}}(1-\pi_{11})^{n_{10}}\pi_{11}^{n_{11}}\right] - 2\ln\left[(1-\tau)^{n_0}\tau^{n_1}\right] \tag{7}
$$

where n_0 and n_1 are respectively the number of 0s and 1's in the indicator series, n_{ij} is the number of observations with value i followed by value j in the I_t^τ series. The value $i, j = 0$ denotes no violation, while $i, j = 1$, denotes the opposite. The series I_t^τ are assumed to be a first-order Markov process

[5] The probability of an exception does not depend on the previous day's outcome.

with transition probabilities $\pi_{ij} = \frac{n_{ij}}{\sum_j n_{ij}}$[6]. The likelihood function LR_{cc} follows a $\chi^2_{(2)}$ and tests the independence of exceedance (loss) across time periods. If the sequence of losses is independent, then $\pi_{01} = \pi_{11} = p$. Hence, this test can reject a model that generates too many or too few violations.

Given that VaR passes this test, we then proceed with backtesting the excess loss component, $L = \mathrm{ES}^\tau - \mathrm{VaR}^\tau$, using the McNeil et al. (2005) 'zero mean test' and the bootstrap method of Efron and Tibshirani (1994), which requires no assumption on the distribution of $S = (L - \mathrm{ES}^\tau)1_{L>\mathrm{VaR}^\tau}$.

Lastly, we test the superiority of a model vis-à-vis a competing model with respect to the loss function of Angelidis et al. (2004) and using Sarma et al. (2003) 'zero median test'. The loss function is defined as:

$$C_t = \begin{cases} (X_t - (-\mathrm{VaR}_t^\tau))^2, & \text{if violation occurs} \\ \left(q_\tau[X_t]_{T+1}^{T+n} - (-\mathrm{VaR}_t^\tau)\right)^2, & \text{otherwise} \end{cases} \tag{8}$$

where $q_\tau[X_t]_{T+1}^{T+n}$ is the quantile of the out-of-sample returns used for backtesting. At each time t, C_t increases either by excess loss, if a violation occurs, or by the difference between VaR_t^τ forecast and the future quantile. It follows that choosing the best accurate model i over model j, which will minimize the total loss $\sum_{t=1}^T C_t$, can be decided by testing the hypothesis that the median of the distribution $B_t = C_{it} - C_{jt}$ is equal to 0. Here, B_t is known as the loss differential between model i and model j at time t, and a negative value indicates the superiority of model i over j. This loss function is of practical interest to investors seeking to reduce market risk and avoiding allocating more money than needed.

3. Data and Empirical Results

In this section, we describe the details of the procedures for the comparison of the previously discussed risk models for the matter of validation, and, for a better understanding of our results, we divide this section in three parts. In the first part, we describe the stylized facts of the sample and conduct preliminary diagnostics. The second part presents the details of the in-sample estimation of the risk models, namely SVCJ, TGARCH, and RM. In the third part, we evaluate the out-of-sample forecasting ability of the models in terms of VaR and ES, and then perform backtesting for validation purposes.

3.1. Data

Over the last few years, the most important aspect of cryptocurrencies which has gained prominence in the media is the realized market volatility. To be fair, the media's infatuation with cryptocurrencies is manifested in the actual market data. Between 26 April 2013 and 16 May 2019, the daily average return from the largest cryptocurrency Bitcoin (BTC) was 0.3% with 4.34% standard deviation. There were 174 days with daily returns falling by more than 5%, and 178 days with daily returns increasing by more than 5%. The maximum daily return during this period was 43.58% (19 November 2013) and the largest one-day change was –23.43% (12 December 2013). On 18 December 2017, the market cap for BTC was $320 billion and the price soared to $19,783 (17 December 2017). One year later, the market cap for the currency declined to $63 billion (28 December 2018). As of this writing (23 May 2019), BTC had a market cap of $138.5 billion. Such large, unprecedented swings in the market value can be terrifying for some investors, while others see opportunities. In more recent days, however, there is a lot more emphasis on avoiding volatility and promoting the stability of the cryptocurrencies to bring some sense of calm in the market. For example, companies like Google, IBM, and Facebook[7] have announced their plans to introduce newer coins and each one is claiming that their currency will be a more stable asset than the others (Forbes, 16 April 2019).

[6] $\pi_{01} = Pr[I_t^\tau = 1 \mid I_{t+1}^\tau = 0)$, and $\pi_{11} = Pr[I_t^\tau = 1 \mid I_{t+1}^\tau = 1]$.
[7] In fact, Facebook is planning to introduce a cryptocurrency, appropriately named as 'Stablecoin' for its "WhatsApp" platform.

We use daily prices of seven successful[8] cryptocurrencies: Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Stellar (XLM), Monero (XMR), Dash (DASH), and Bytecoin (BCN), all collected from cryptocompare.com[9]. The data span the period 5 August 2014 to 24 March 2019, with a total of 1693 daily observations. Table 1 reports the summary statistics including the mean, standard deviation, minimum, maximum, skewness, kurtosis, and the p-values of the Ljung–Box test for first-order autocorrelation for all cryptocurrencies. Ripple has the highest mean of 0.24% and Bytecoin has the highest standard deviation of 11.44%. All cryptocurrencies display excess kurtosis and the Ljung–Box test shows that data exhibit first and second-order autocorrelation except for Stellar at the 5% confidence level.

Table 1. Descriptive statistics of daily log-returns of cryptocurrencies.

	Mean	StDev	Min	Max	Skewness	Kurtosis	AR1	AR2
BTC	0.010	0.166	−0.146	1.788	3.609	22.78	0.091	0.117
XRP	0.037	0.355	−0.309	6.190	5.546	65.93	0.421	0.048
LTC	0.016	0.248	−0.136	4.789	9.196	130.18	0.880	0.766
XLM	0.015	0.213	−0.206	3.808	5.532	68.53	0.037	0.039
XMR	0.007	0.134	−0.147	1.306	2.998	15.12	0.733	0.423
DASH	0.012	0.175	−0.196	1.595	2.705	12.23	0.671	0.180
BCN	0.009	0.163	−0.157	3.049	6.775	95.30	0.234	0.117

Data spans from 5 August 2014 until 24 March 2019. AR1 and AR2 display the p-values of the Ljung–Box for autocorrelation of first and second order. p-values below the 1% significance level indicate rejection of the null hypothesis of no autocorrelation.

3.2. In-Sample Estimation

Table 2 provides posterior summaries for parameter estimates from the stochastic volatility with co-jumps (SVCJ) model for all cryptocurrency series. For the MCMC framework, there were 10,000 iterations with a burn-in of 2000 iterations to minimize the influence of the initial values. The initial values were as follows: $\mu \sim N(0,1)$, $\kappa \sim N(0,1)$, $\kappa\theta \sim N(0,1)$, $\rho \sim u(-1,1)$, $\sigma_V^2 \sim IG(2.5, 0.1)$, $\mu_X \sim N(0,100)$, $\rho_J \sim N(0,4)$, $\sigma_X^2 \sim IG(5,20)$, $\mu_V \sim G(20,10)$, and $\lambda \sim B(2,40)$. The SVCJ model appears to be an ideal candidate for the cryptocurrencies, as indicated by the low MSE. The results show that the jump intensity λ is significant for all cryptocurrencies and is high for XRP and LTC, respectively 10.6% and 9.3%, and low for BCN and BTC, respectively 2.5% and 3.8%. The jump correlation ρ_J is insignificant for all cryptocurrencies, similarly to the findings of Eraker et al. (2003) with stock prices.

The results also show a positive correlation, ρ, between the Brownian motions of returns and volatility for all cryptocurrencies except for XRP and DASH, where it is negative. This shows that a negative shock to returns increases volatility, and we can infer that the leverage effect contributes to the effectiveness in fitting the volatility of cryptocurrency returns. Figure 1 displays the jumps in returns and volatility for selected cryptocurrencies with high and low intensity of jumps. XRP and LTC have high intensity, and BTC and BCN have low intensity jumps.

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8 Our sample of cryptocurrencies captures market dynamics for various market capitalizations, ranging from high to low. Among the largest market caps (22 May 2019), we have Bitcoin ($136.13 billion) and XRP ($15.88 billion), in the middle market cap category, we have Litecoin ($5.44 billion), and Bytecoin ($0.169 billion) represents the small market cap category.

9 It is important to acknowledge that there are significant differences in the quality of data that are available at multiple sites including CoinAPI, Cryptodatadownload, Cryptocompare, Coinmarketcap, and Coingecko. According to Alexander and Dakos (2019), some of these data are traded prices while others are non-traded prices issued by the exchanges, leading to questionable results in empirical studies.

Table 2. Parameter estimates of stochastic volatility with co-jumps (SVCJ).

	BTC	XRP	LTC	XLM	XMR	DASH	BCN
μ	0.023	−0.042	−0.003	−0.046	−0.009	−0.020	−0.032
	(0.007)	(0.023)	(0.009)	(0.016)	(0.018)	(0.014)	(0.042)
κ	0.088	0.162	0.055	0.309	0.356	0.188	0.108
	(0.003)	(0.016)	(0.002)	(0.006)	(0.015)	(0.005)	(0.230)
θ	0.091	0.314	0.165	0.168	0.132	0.186	0.505
	(0.009)	(0.025)	(0.010)	(0.012)	(0.016)	(0.016)	(0.138)
μ_X	−0.002	−0.003	0.004	0.003	0.001	0.000	0.002
	(0.031)	(0.050)	(0.040)	(0.030)	(0.030)	(0.028)	(0.048)
σ_X^2	2.37	1.83	7.05	1.92	1.92	1.51	1.76
	(0.068)	(0.065)	(0.105)	(0.065)	(0.067)	(0.050)	(0.062)
λ	0.038	0.106	0.093	0.050	0.061	0.079	0.025
	(0.007)	(0.017)	(0.010)	(0.009)	(0.012)	(0.011)	(0.011)
μ_V	0.732	2.509	1.079	3.787	1.583	1.796	2.747
	(0.110)	(0.383)	(0.107)	(0.531)	(0.240)	(0.224)	(11.747)
σ_V	0.011	0.029	0.010	0.041	0.034	0.021	0.162
	(0.003)	(0.008)	(0.002)	(0.007)	(0.011)	(0.004)	(0.046)
ρ	0.012	−0.016	0.002	0.006	0.005	−0.020	0.007
	(0.021)	(0.041)	(0.026)	(0.023)	(0.023)	(0.022)	(0.040)
ρ_J	0.000	0.003	0.001	0.000	0.001	0.001	0.000
	(0.001)	(0.013)	(0.024)	(0.005)	(0.012)	(0.010)	(0.001)
MSE	0.854	0.853	0.869	0.837	0.878	0.853	0.826

Parameter estimates of SVCJ model are displayed along with the posterior means and the posterior standard deviations (in parentheses). The posterior sampling was carried out with 10,000 MCMC iterations and 2000 burn-in iterations.

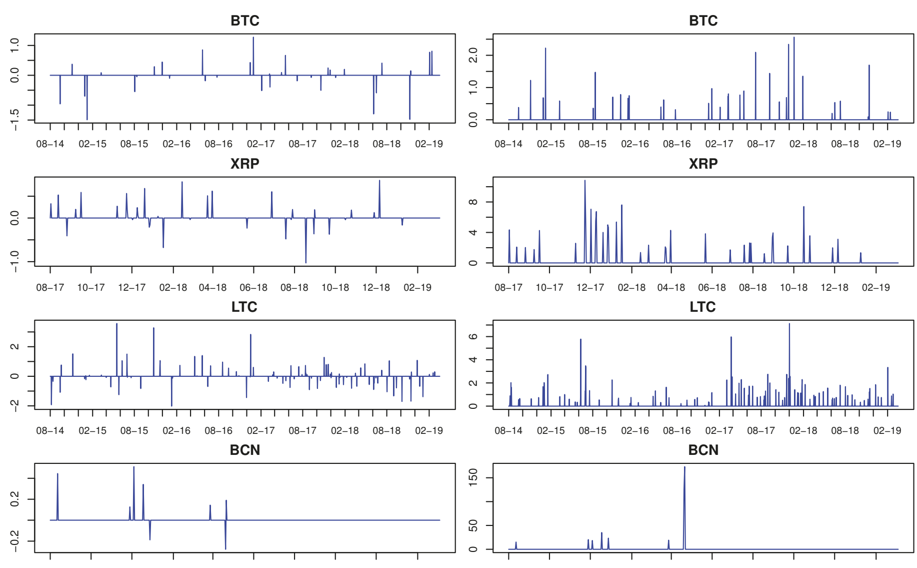

Figure 1. Jumps in returns (**left columns**) and jumps in volatilities (**right columns**).

We have also estimated several AR(2) return models with various volatility specifications namely, asymmetric GARCH, IGARCH, TARCH, and GJR-GARCH, and by alternating between Student-*t* and Skewed Student-*t* errors. Table A1 (see Appendix A) displays the estimation results of these models for the cryptocurrencies. Each model was ranked on the basis of the log-likelihood function (higher the better) and the AIC (lower the better). Overall, the TGARCH with skewed *t*-distributed errors turns out to be the best volatility fitting model for the cryptocurrencies considered in this paper. These results contradict the findings of Chan et al. (2017) that IGARCH and GJR-GARCH models provide the best fits for the most popular and largest cryptocurrencies.

Table 3 summarizes these results by reporting the AR(2)-TGARCH(1,1)∼Skewed *t* estimated parameters. The parameters α and β, which represent short-run dynamics, are all significant for all cryptocurrencies. This suggests that the volatility is intensively reacting to market movements and that shocks to the conditional variance take time to die out. The leverage effect γ is statistically significant for all series except for XRP, DASH, and BCN. There were no remaining autocorrelations in both the standardized residuals and the squared standardized residuals.

Table 3. Parameter estimates of AR(2)-TGARCH(1,1)∼Skewed *t* volatility model.

	BTC	XRP	LTC	XLM	XRM	DASH	BCN
a_0	0.093	−0.117	**0.046**	−0.098	0.218	0.103	**0.308**
	(0.040)	(0.041)	(0.054)	(0.040)	(0.106)	(0.069)	(1.002)
a_1	−0.055	−**0.098**	−0.081	−0.157	−0.053	−0.062	−0.235
	(0.018)	(0.028)	(0.022)	(0.041)	(0.025)	(0.020)	(0.026)
a_2	−0.061	−0.042	−0.072	−0.048	−**0.027**	−0.064	−**0.036**
	(0.024)	(0.025)	(0.021)	(0.019)	(0.023)	(0.017)	(0.143)
ω	0.066	0.632	0.125	0.474	0.569	0.448	0.794
	(0.032)	(0.201)	(0.059)	(0.158)	(0.177)	(0.130)	(0.244)
α	0.271	0.634	0.421	0.271	0.193	0.268	0.167
	(0.061)	(0.139)	(0.095)	(0.054)	(0.035)	(0.042)	(0.039)
β	0.852	0.620	0.859	0.775	0.794	0.755	0.810
	(0.020)	(0.053)	(0.021)	(0.043)	(0.038)	(0.038)	(0.038)
γ	−0.136	−**0.061**	−0.169	−0.222	−0.183	**0.066**	−**0.197**
	(0.071)	(0.064)	(0.087)	(0.089)	(0.093)	(0.073)	(0.161)
Shape	2.473	2.383	2.117	2.852	3.487	3.246	3.398
	(0.218)	(0.026)	(0.038)	(0.244)	(0.371)	(0.313)	(0.363)
Skewness	0.930	1.057	1.056	1.145	1.104	1.118	1.078
	(0.027)	(0.026)	(0.028)	(0.033)	(0.036)	(0.035)	(0.117)
LogLikelihood	−3315.8	−3757.8	−3586.5	−4230.5	−4321	−4064	−4735.8
AIC	5.007	5.672	5.419	6.389	6.523	6.138	7.151

Summary of the estimation results of the AR(2)-TGARCH(1,1)∼Skewed *t* for the cryptocurrencies. Standard errors are in parentheses and bold indicates insignificance at 5% and 1% levels.

The estimated volatility from these three distinctly different models are reported in Figure 2 for BTC, as an example. A visual examination shows that the volatility graphs are markedly different across models. The SVCJ model produces the smoothest plot because it includes all parameters of the volatility series. The plots generated from the remaining models are substantially jagged and show significant structural breaks, which can impede our estimation of tail risk.

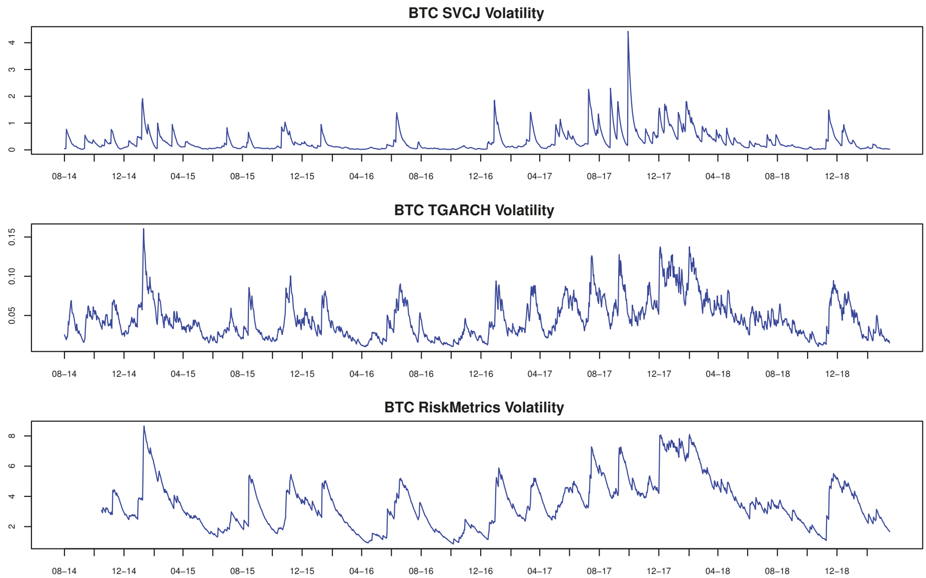

Figure 2. Estimated Volatility from SVCJ, TGARCH, and RiskMetrics Models

3.3. Out-of-Sample Validation

We proceed with an out-of-sample comparison of the risk measures and forecasting ability of the two models, SVCJ and TGARCH. Our benchmark model is the RiskMetrics (RM) of J.P.Morgan (1996). The risk measures VaR and ES were estimated with a rolling window of $T - 365 = 1328$ daily log-returns, and the remaining 365 days (24 March 2018 to 24 March 2019) are kept for out-of-sample forecasts and accuracy checks. We then simulate 5000 returns paths from both models. For the AR(2)-TGARCH(1,1)$\sim$Skewed t model, we used the Filtered Historical Simulation by first extracting the standardized residuals using the volatilities to form a new set of innovations, which are then utilized to obtain the conditional mean. For each return, these steps are repeated recursively to obtain different simulated pathways, with 5000 draws from the standardized residuals to generate 1328 (same as in-sample size) replicates of the returns.

Table 4 reports the out-of-sample backtesting results. The Christoffersen (1998) conditional coverage test confirms that the two models SVCJ and TGARCH accurately forecast the VaR as the p-values are greater than 5%. There is an exception for XRP where TGARCH performs better for 1% VaR. Although the RiskMetrics model displays forecasting accuracy, it occasionally fails to perform accordingly for LTC and XLM cryptocurrencies. Speculative investors taking either a long or short position in a cryptocurrency can generate accurate VaR forecasts using these two models.

Table 4. Value-at-Risk backtesting results.

	SVCJ			TGARCH			RM		
	LR_{cc}	VaR (%)	ES (%)	LR_{cc}	VaR (%)	ES (%)	LR_{cc}	VaR (%)	ES (%)
1% Level									
BTC	0.660	6.89	9.41	0.499	9.23	13.96	**0.017**	8.91	13.24
XRP	**0.047**	11.34	16.74	0.993	9.62	12.36	0.476	12.90	19.53
LTC	0.177	11.45	17.05	0.407	12.74	19.80	**0.017**	11.72	19.00
XLM	0.053	15.99	22.43	0.408	10.13	12.60	**0.047**	14.38	21.35
XMR	0.289	10.76	15.13	0.289	10.94	14.67	0.940	15.11	21.96
DASH	0.083	9.42	13.67	0.452	11.91	15.85	0.256	13.57	19.77
BCN	0.098	17.79	24.78	0.365	18.10	20.75	0.630	24.62	37.38
5% Level									
BTC	0.401	2.49	5.09	0.998	4.38	7.52	0.181	4.67	7.55
XRP	0.623	4.34	8.65	0.499	4.85	7.70	0.913	6.94	11.07
LTC	0.446	5.04	9.10	0.842	5.74	10.25	**0.001**	5.88	10.06
XLM	0.239	5.38	11.57	0.457	5.17	7.87	0.150	7.99	12.40
XMR	0.296	3.49	7.89	0.159	5.94	8.96	0.163	8.37	12.94
DASH	0.404	3.66	7.13	0.235	6.78	9.85	0.649	7.54	11.69
BCN	0.050	5.75	12.61	0.348	10.20	14.50	0.256	13.02	21.04

Christofersen's test p-values and average values of the VaR and ES forecasts are displayed under SVCJ, AR(2)-TGARCH(1,1)∼Skewed t, and RiskMetrics (with a decay factor of 0.94). Bold p-values below 5% rejects the null hypothesis of correct exceedances and independence of violation sequences, and hence represents inaccurate VaR estimates.

Given the accuracy of the models, Table 5 reports the zero mean test of excess loss provided that the model first passes the test for VaR. The results indicate that the predictive power of SVCJ model is better than TGARCH and RM models at the 5% level (many of the p-values are less than 5%). One possible explanation of such a finding is that TGARCH and RM models' forecasting have less significant gains over the forecasts of the SVCJ model. This particular evidence supports our prior that accounting for jumps in returns and volatility is a reason for the SVCJ model's superior predictive power.

Table 5. Expected Shortfall backtesting results.

	1% Level			5% Level		
	SVCJ	TGARCH	RM	SVCJ	TGARCH	RM
BTC	0.334	0.798	Fail	0.137	0.610	0.703
XRP	Fail	0.999	0.999	0.701	0.871	0.708
LTC	0.996	0.999	Fail	0.881	0.998	Fail
XLM	0.685	0.999	Fail	0.984	0.940	0.390
XMR	0.753	0.509	0.923	0.281	0.788	0.896
DASH	0.539	0.533	0.920	0.000	0.982	0.234
BCN	0.546	0.865	0.957	0.571	0.971	0.907

Results of the zero mean test for the excess loss, provided that the model generates accurate VaR estimates. p-values are reported at 1% and 5% risk levels for the cyptocurrencies. p-values below 5% indicate inadequacy of the model for estimating ES.

Table 6 summarizes the test of the best performing model with respect to the quantile loss function of Angelidis et al. (2004). For each cryptocurrency and confidence level, we present the loss differential B and the p-values of the zero median test of Sarma et al. (2003). When p-values are less than 5%, it implies that two competing models are significantly different from each other in terms of estimating risk. The opposite implies that the two competing models are not significantly different from each other, with respect to the quantile loss function. Hence, regulators and risk managers remain indifferent between these two models. The results suggest that, at the 5% level, the SVCJ model is better than TGARCH and RiskMetrics models because it produces lower economic losses. At the 1% level, some of the results show that a risk manager is indifferent between the models for VaR estimation. For instance, for Bitcoin and Stellar, SCVJ and TGARCH models are not significantly different from each other, with respect to the quantile loss function. For the same cryptocurrencies, these two models are performing better than the RiskMetrics model. Therefore, as far as loss is concerned, a risk manager would prefer either SVCJ or TGARCH model over RiskMetrics.

Table 6. Quantile Loss Function test for the best model for VaR estimates

	SVCJ vs. TGARCH		**SVCJ vs. RM**		**TGARCH vs. RM**	
	B	***p*-Value**	**B**	***p*-Value**	**B**	***p*-Value**
1% Level						
BTC	277	1.0000	SVCJ		TGARCH	
XRP	TGARCH		RM		4	0.0000
LTC	155	0.0023	SVCJ		TGARCH	
XLM	287	1.0000	SVCJ		TGARCH	
XMR	176	0.2480	100	0.0000	8	0.0000
DASH	147	0.0001	105	0.0000	56	0.0000
BCN	234	1.0000	162	0.0159	12	0.0000
5% Level						
BTC	93	0.0000	209	0.9975	147	0.0001
XRP	86	0.0000	85	0.0000	2	0.0000
LTC	131	0.0000	112	0.0000	157	0.0034
XLM	185	0.6030	SVCJ		TGARCH	
XMR	95	0.0000	27	0.0000	0	0.0000
DASH	77	0.0000	40	0.0000	46	0.0000
BCN	130	0.0000	96	0.0000	43	0.0000

B statistic and *p*-values, at 1% and 5% risk levels are reported for the cyptocurrencies. *p*-values below 5% indicate that the difference in the performance of models is significant. If one model fails the previous backtest, we then report the other prevailing model.

Overall, as noted earlier in Table 5, there is a gap between the quantities of risk measured by VaR and ES at the 1% and 5% confidence levels. This suggests that ES gives a more accurate measure of risk than the traditional VaR measure. This finding seems to support the recommendation from the Basel Committee on Banking Supervision (2013) that banks use ES in lieu of VaR, and that there should be a recalibration of the confidence level for consistency and accuracy of the risk measure. In terms of the forecast accuracy, our results show that SVCJ and TGARCH generate better forecasts at the 1% level then RM. This evidence clearly supports the notion that fat-tailed volatility models can predict risk more accurately than non-fat-tailed models. In summary, the combination of jumps in returns and volatility in a stochastic model yields the most accurate VaR forecasts for the majority of the cryptocurrencies studied in this paper.

4. Conclusions

It is now a widely accepted view that risk models should account for the stylized facts of the data in order to be successfully validated. Estimating risk was mainly performed on many financial asset markets but not on the emerging cryptocurrency market, which has been proven to be extremely volatile. Typical volatility models may not adequately provide an accurate representation of the cryptocurrencies volatility process for successful risk management purposes. In particular, risk models must be able to capture the cryptocurrencies volatility process that includes stochastic volatility, persistence in volatility, and jump process. All these stylized features are critical for capturing unpredictable and large movements in the price process and for accurately predicting tail risk and expected shortfall. There is limited research on this topic despite the fact that investors are exploring how cryptocurrencies can be integrated into a portfolio along with other traditional assets such as stocks, bonds, currencies, and commodities. Choosing a proper model that provides a parsimonious representation of the distribution of the return-generating process is the first step.

In this paper, we identified risk models for the cryptocurrency market and evaluated their performance for validation purposes. We evaluated models based on stochastic volatility with co-jumps in returns and volatility (SVCJ), threshold GARCH volatility (TGARCH), and RiskMetrics. Backtesting methods using the conditional and unconditional coverage were performed to test the validity of the models, and the regulatory loss function was applied to choose the most accurate model.

The validation results reveal that, although the models considered in this paper are effective for fitting the cryptocurrency returns, the SVCJ model more accurately forecasts risk in a VaR and ES sense, and the reality check proves its superiority over TGARCH and RiskMetrics models. Therefore, incorporating jumps in the cryptocurrency volatility model improves the forecasting ability of risk in terms of VaR and ES. This is important for risk-averse investors and for speculative investors who are particularly interested in hedging their risk in a VaR sense. It is, therefore, recommended to use a model that accounts for jumps, leptokurtosis, and leverage effects when dealing with cryptocurrency market data. Such a model improves risk forecasting in terms of VaR and Expected Shortfall.

The results in this study have several implications for applying the SVCJ model to other assets including commodities, foreign currencies, and stock market indices, especially in times of stress. The global financial market has seen unprecedented volatility in recent days, given falling oil prices and concerns related to the COVID-19 pandemic. It would be interesting to see if such wild swings in the market can be studied using the SVCJ model to incorporate the co-jumps in returns and volatility affecting the measurement of VaR and Expected Shortfalls in the contagion like period that we now have. We leave that for a future study.

Author Contributions: R.N. collected the data, carried the statistical analysis, and drafted the manuscript. J.S. carried the literature review and helped with the discussion. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Volatility estimates.

	GARCH $\sim t$	**GARCH** $\sim$ **Skewed** t	**IGARCH** $\sim t$	**IGARCH** $\sim$ **Skewed** t	**TGARCH** $\sim t$	**TGARCH** $\sim$ **Skewed** t	**GJR-GARCH** $\sim t$	**GJR-GARCH** $\sim$ **Skewed** t
Bitcoin (BTC)								
a_0	0.191 (0.048)	0.140 (0.058)	0.191 (0.048)	0.140 (0.057)	0.175 (0.032)	0.093 (0.040)	0.197 (0.050)	0.149 (0.056)
a_1	−**0.021** (0.026)	−**0.021** (0.026)	−**0.022** (0.026)	−**0.021** (0.026)	−0.051 (0.023)	−0.055 (0.018)	−**0.031** (0.031)	−**0.032** (0.027)
a_2	−0.043 (0.025)	−0.044 (0.025)	−0.043 (0.025)	−0.044 (0.025)	−0.059 (0.014)	−0.061 (0.024)	−0.048 (0.023)	−0.050 (0.025)
ω	0.205 (0.090)	0.210 (0.089)	0.203 (0.077)	0.207 (0.077)	0.063 (0.030)	0.066 (0.032)	**0.169** (0.175)	0.173 (0.085)
α	0.171 (0.024)	0.173 (0.024)	0.171 (0.023)	0.173 (0.023)	0.254 (0.053)	0.271 (0.061)	0.195 (0.032)	0.197 (0.030)
β	0.827 (0.025)	0.825 (0.025)	0.828 (NA)	0.826 (NA)	0.857 (0.021)	0.852 (0.020)	0.839 (0.049)	0.837 (0.027)
γ					−0.141 (0.073)	−0.136 (0.071)	−0.073 (0.041)	−0.073 (0.032)
shape	3.385 (0.240)	3.401 (0.242)	3.377 (0.191)	3.393 (0.193)	2.517 (0.216)	2.473 (0.218)	3.417 (0.284)	3.441 (0.246)
skewness		0.951 (0.030)		0.951 (0.030)		0.930 (0.027)		0.951 (0.030)
LogLikelihood	−3333.9	−3332.6	−3333.7	−3332.4	−3315.8	−3313.3	−3331.4	−3330.2
AIC	5.035	5.034	5.033	5.033	5.009	5.007	5.033	5.032
Ripple (XRP)								
a_0	−0.256 (0.067)	−0.161 (0.083)	−0.256 (0.067)	−0.162 (0.082)	−0.220 (0.054)	−0.117 (0.041)	−0.250 (0.068)	−0.156 (0.083)
a_1	**0.001** (0.028)	**0.001** (0.029)	**0.001** (0.028)	**0.001** (0.028)	−**0.011** (0.028)	−**0.098** (0.028)	**0.004** (0.028)	**0.005** (0.028)
a_2	−0.040 (0.023)	−**0.035** (0.025)	−0.040 (0.022)	−**0.035** (0.025)	−0.047 (0.017)	−0.042 (0.025)	−0.041 (0.023)	−**0.035** (0.025)
ω	1.940 (0.776)	1.843 (0.766)	1.932 (0.671)	1.834 (0.663)	0.617 (0.196)	0.632 (0.201)	2.033 (0.806)	1.933 (0.808)
α	0.375 (0.072)	0.364 (0.073)	0.374 (0.071)	0.364 (0.072)	0.640 (0.140)	0.634 (0.139)	0.425 (0.092)	0.411 (0.095)
β	0.623 (0.080)	0.634 (0.081)	0.624 (NA)	0.635 (NA)	0.625 (0.051)	0.620 (0.053)	0.615 (0.081)	0.627 (0.084)
γ					−**0.055** (0.064)	−**0.061** (0.064)	−0.083 (0.041)	−0.077 (0.032)
shape	3.025 (0.184)	3.036 (0.187)	3.023 (0.152)	3.034 (0.154)	2.370 (0.163)	2.383 (0.165)	3.014 (0.184)	3.021 (0.187)
skewness		1.062 (0.032)		1.062 (0.032)		1.057 (0.026)		1.062 (0.032)
LogLikelihood	−3778.7	−3776.7	−3778.6	−3776.6	−3759.5	−3757.8	−3778.1	−3776.2
AIC	5.705	5.704	5.704	5.702	5.678	5.672	5.706	5.705

Table A1. *Cont.*

	GARCH $\sim t$	GARCH $\sim$ Skewed t	IGARCH $\sim t$	IGARCH $\sim$ Skewed t	TGARCH $\sim t$	TGARCH $\sim$ Skewed t	GJR-GARCH $\sim t$	GJR-GARCH $\sim$ Skewed t
Litecoin (LTC)								
a_0	−**0.027** (0.034)	**0.043** (0.055)	−**0.027** (0.044)	**0.043** (0.055)	−**0.028** (0.040)	**0.046** (0.054)	−**0.021** (0.044)	**0.054** (0.055)
a_1	−0.084 (0.024)	−0.083 (0.022)	−0.084 (0.022)	−0.083 (0.022)	−0.086 (0.021)	−0.081 (0.022)	−0.086 (0.022)	−0.083 (0.022)
a_2	−0.057 (0.021)	−0.076 (0.021)	−0.075 (0.021)	−0.076 (0.021)	−0.071 (0.021)	−0.072 (0.021)	−0.075 (0.021)	−0.074 (0.020)
ω	0.181 (0.087)	0.182 (0.085)	0.179 (0.081)	0.180 (0.081)	0.126 (0.058)	0.125 (0.059)	0.139 (0.070)	0.146 (0.071)
α	0.115 (0.027)	0.115 (0.020)	0.116 (0.018)	0.116 (0.019)	0.448 (0.066)	0.421 (0.095)	0.139 (0.024)	0.143 (0.026)
β	0.883 (0.036)	0.883 (0.020)	0.883 (NA)	0.883 (NA)	0.859 (0.021)	0.859 (0.021)	0.900 (0.017)	0.900 (0.017)
γ					−0.158 (0.086)	−0.169 (0.087)	−0.083 (0.023)	−0.086 (0.024)
shape	2.677 (0.119)	2.679 (0.118)	2.670 (0.075)	2.672 (0.075)	2.102 (0.006)	2.117 (0.038)	2.639 (0.114)	2.631 (0.114)
skew		1.063 (0.030)		1.063 (0.030)		1.056 (0.028)		1.067 (0.031)
LogLikelihood	−3610.6	−3608.4	−3610.4	−3608.1	−3588.6	−3586.5	−3604.0	−3601.5
AIC	5.452	5.450	5.450	5.448	5.420	5.419	5.444	5.441
Stellar (XLM)								
a_0	−0.407 (0.089)	−**0.162** (0.111)	−0.407 (0.089)	−**0.162** (0.111)	−0.385 (0.074)	−0.098 (0.040)	−0.384 (0.090)	−**0.140** (0.113)
a_1	−0.156 (0.028)	−0.162 (0.028)	−0.156 (0.028)	−0.162 (0.028)	−0.157 (0.025)	−0.157 (0.041)	−0.154 (0.028)	−0.156 (0.028)
a_2	−0.061 (0.025)	−0.056 (0.024)	−0.061 (0.025)	−0.056 (0.024)	−0.062 (0.028)	−0.048 (0.019)	−0.057 (0.025)	−0.050 (0.025)
ω	3.069 (1.197)	3.046 (1.101)	3.057 (1.127)	3.037 (1.071)	0.490 (0.179)	0.474 (0.158)	3.395 (1.246)	3.377 (1.174)
α	0.272 (0.058)	0.267 (0.056)	0.272 (0.055)	0.268 (0.051)	0.305 (0.065)	0.271 (0.054)	0.341 (0.080)	0.332 (0.080)
β	0.726 (0.058)	0.731 (0.052)	0.727 (NA)	0.731 (NA)	0.760 (0.048)	0.775 (0.043)	0.711 (0.056)	0.718 (0.051)
γ					−0.195 (0.086)	−0.222 (0.089)	−**0.106** (0.074)	−**0.097** (0.073)
shape	3.073 (0.215)	3.090 (0.224)	3.069 (0.167)	3.086 (0.170)	2.738 (0.225)	2.852 (0.244)	3.043 (0.217)	3.046 (0.224)
skew		1.141 (0.039)		1.141 (0.039)		1.145 (0.033)		1.138 (0.039)
LogLikelihood	−4243.1	−4235.6	−4243.1	−4235.5	−4237.9	−4230.5	−4241.9	−4243.5
AIC	6.405	6.395	6.404	6.394	6.399	6.389	6.405	6.395
Monero (XMR)								
a_0	−**0.064** (0.127)	**0.153** (0.154)	−**0.067** (0.126)	**0.152** (0.155)	−**0.021** (0.127)	0.218 (0.106)	−**0.031** (0.130)	**0.183** (0.156)
a_1	−0.044 (0.025)	−0.044 (0.024)	−0.044 (0.026)	−0.044 (0.026)	−0.054 (0.027)	−0.053 (0.025)	−0.044 (0.026)	−0.043 (0.028)
a_2	−**0.024** (0.026)	−**0.023** (0.026)	−**0.024** (0.026)	−**0.023** (0.025)	−**0.031** (0.026)	−**0.027** (0.023)	−**0.024** (0.025)	−**0.021** (0.026)
ω	3.852 (1.275)	3.633 (1.232)	3.810 (1.271)	3.570 (1.228)	0.601 (0.181)	0.569 (0.177)	3.838 (1.265)	3.655 (1.235)
α	0.235 (0.053)	0.224 (0.051)	0.244 (0.042)	0.236 (0.042)	0.199 (0.036)	0.193 (0.035)	0.265 (0.064)	0.255 (0.063)
β	0.754 (0.042)	0.762 (0.042)	0.755 (NA)	0.763 (NA)	0.785 (0.039)	0.794 (0.038)	0.756 (0.042)	0.764 (0.042)
γ					−0.185 (0.094)	−0.183 (0.093)	−**0.076** (0.058)	−**0.072** (0.056)

Table A1. *Cont.*

	GARCH $\sim t$	GARCH $\sim$ Skewed t	IGARCH $\sim t$	IGARCH $\sim$ Skewed t	TGARCH $\sim t$	TGARCH $\sim$ Skewed t	GJR-GARCH $\sim t$	GJR-GARCH $\sim$ Skewed t
shape	3.420 (0.365)	3.486 (0.374)	3.358 (0.254)	3.395 (0.264)	3.432 (0.365)	3.487 (0.371)	3.448 (0.371)	3.503 (0.378)
skew		1.094 (0.039)		1.094 (0.039)		1.104 (0.036)		1.094 (0.039)
LogLikelihood	−4324.1	−4320.9	−4326.7	−4322.9	−4324.1	−4321.0	−4323.2	−4320.1
AIC	6.527	6.524	6.533	6.529	6.526	6.523	6.527	6.524
Dash (DASH)								
a_0	−**0.057** (0.094)	**0.166** (0.116)	−**0.057** (0.044)	**0.166** (0.166)	−**0.089** (0.063)	0.103 (0.069)	−**0.074** (0.095)	**0.144** (0.116)
a_1	−0.058 (0.028)	−0.049 (0.028)	−0.057 (0.028)	−0.049 (0.028)	−0.061 (0.024)	−0.062 (0.020)	−0.058 (0.027)	−0.052 (0.027)
a_2	−0.055 (0.026)	−0.055 (0.026)	−0.055 (0.026)	−0.055 (0.026)	−0.065 (0.020)	−0.064 (0.017)	−0.054 (0.026)	−0.055 (0.026)
ω	2.779 (0.814)	2.616 (0.770)	2.777 (0.809)	2.615 (0.770)	0.481 (0.140)	0.448 (0.130)	2.680 (0.788)	2.486 (0.734)
α	0.290 (0.058)	0.275 (0.056)	0.291 (0.045)	0.276 (0.043)	0.292 (0.047)	0.268 (0.042)	0.244 (0.054)	0.227 (0.051)
β	0.708 (0.045)	0.723 (0.043)	0.708 (NA)	0.723 (NA)	0.741 (0.040)	0.755 (0.038)	0.711 (0.044)	0.725 (0.042)
γ					−0.141 (0.073)	−0.136 (0.071)	−0.073 (0.041)	−0.073 (0.032)
shape	3.313 (0.293)	3.342 (0.309)	3.309 (0.226)	3.336 (0.292)	3.147 (0.296)	3.246 (0.313)	3.367 (0.292)	3.419 (0.310)
skew		1.127 (0.039)		1.127 (0.039)		1.118 (0.035)		1.129 (0.039)
LogLikelihood	−4071.2	−4065.3	−4071.2	−4070.6	−4069.1	−4064.0	−4070.3	−4064.3
AIC	6.145	6.139	6.145	6.140	6.145	6.138	6.146	6.139
Bytecoin (BCN)								
a_0	−**0.015** (0.147)	**0.184** (0.180)	−**0.011** (0.145)	**0.199** (0.182)	**0.049** (0.147)	**0.308** (1.002)	−**0.009** (0.149)	**0.203** (0.183)
a_1	−0.221 (0.028)	−0.220 (0.028)	−0.221 (0.028)	−0.220 (0.028)	−0.240 (0.027)	−0.235 (0.026)	−0.221 (0.028)	−0.219 (0.028)
a_2	−**0.034** (0.026)	−**0.033** (0.026)	−**0.034** (0.025)	−**0.034** (0.026)	−**0.038** (0.025)	−**0.036** (0.143)	−**0.034** (0.026)	−**0.033** (0.026)
ω	8.810 (2.772)	8.472 (2.630)	8.972 (3.038)	8.589 (2.891)	0.829 (0.255)	0.794 (0.244)	8.795 (2.754)	8.496 (2.610)
α	0.199 (0.052)	0.193 (0.050)	0.242 (0.045)	0.237 (0.044)	0.169 (0.034)	0.167 (0.039)	0.205 (0.059)	0.207 (0.059)
β	0.759 (0.046)	0.764 (0.044)	0.757 (NA)	0.762 (NA)	0.806 (0.039)	0.810 (0.038)	0.760 (0.045)	0.765 (0.043)
γ					−**0.159** (0.120)	−**0.197** (0.161)	−**0.016** (0.066)	−**0.033** (0.064)
shape	3.290 (0.336)	3.345 (0.350)	3.045 (0.198)	3.075 (0.204)	3.346 (0.340)	3.398 (0.363)	3.294 (0.337)	3.351 (0.352)
skew		1.065 (0.034)		1.064 (0.034)		1.078 (0.117)		1.067 (0.035)
LogLikelihood	−4737.8	−4735.9	−4738.3	−4736.5	−4738.3	−4735.8	−4737.8	−4736.8
AIC	7.151	7.149	7.150	7.149	7.153	7.151	7.152	7.152

Estimation results of various GARCH volatility models with t and Skewed t errors for the cryptocurrencies are reported in this Table. For each parameter, we report the standard errors in parentheses and bold indicates insignificance at 5% and 1% levels. Higher LogLikelihood and lower AIC indicate the best fit model for cryptocurrencies.

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Article

Decentralized Finance (DeFi) Projects: A Study of Key Performance Indicators in Terms of DeFi Protocols' Valuations

Dominik Metelski [1,*] and Janusz Sobieraj [2]

[1] Department of International and Spanish Economics, Faculty of Economics and Business Sciences, University of Granada, 18071 Granada, Spain
[2] Department of Building Engineering, Warsaw University of Technology, 00-637 Warsaw, Poland
* Correspondence: dominik@correo.ugr.es

Abstract: Decentralized finance (DeFi) protocols use blockchain-based tools to mimic banking, investment and trading solutions and provide a viable framework that creates incentives and conditions for the development of an alternative financial services market. In this respect, they can be seen as alternative financial vehicles that mitigate portfolio risk, which is particularly important at a time of increasing uncertainty in financial markets. In particular, some DeFi protocols offer an automated, low-risk way to generate returns through a "delta-neutral" trading strategy that reduces volatility. The main financial operations of DeFi protocols are implemented using appropriate algorithms, but unlike traditional finance, where issues of value and valuation are commonplace, DeFis lack a similar value-based analysis. The aim of this study is to evaluate relevant DeFi performance metrics related to the valuations of these protocols through a thorough analysis based on various scientific methods and to show what influences the valuations of these protocols. More specifically, the study identifies how DeFi protocol valuations depend on the total value locked and other performance variables, such as protocol revenue, total revenue, gross merchandise volume and inflation factor, and assesses these relationships. The study analyzes the valuations of 30 selected protocols representing three different classes of DeFi (i.e., decentralized exchanges, lending protocols and asset management) in relation to their respective performance measures. The analysis presented in the article is quantitative in nature and relies on Granger causality tests as well as the results of a fixed effects panel regression model. The results show that the valuations of DeFi protocols depend to some extent on the performance measures of these protocols under study, although the magnitude of the relationships and their directions differ for the different variables. The Granger causality test could not confirm that future DeFi protocol valuations can be effectively predicted by the TVLs of these protocols, while other directions of causality (one-way and two-way) were confirmed, e.g., a two-way causal relationship between DeFi protocol valuations and gross merchandise volume, which turned out to be the only variable that Granger-causes future DeFi protocol valuations.

Keywords: decentralized finance; DeFi; blockchain technology; total value locked; TVL; gross merchandise volume; panel data analysis; granger-causality

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1. Introduction

Despite the widespread use of the internet over the past 30 years and its numerous applications, it has definitely not lived up to the expectations in terms of the development of the financial industry, especially considering the dynamics of change versus technological progress (Abdulhakeem and Hu 2021; Harwick and Caton 2020). Moreover, despite widespread access to the internet, there are still about 1.7 billion people in the world who are bank-excluded, i.e., have no access to bank accounts at all. At least that is what a report by the World Bank Group says (Abdulhakeem and Hu 2021). Even with a relevant number of innovative institutions such as investment banking and fintechs, the biggest shortcoming of the financial sector remains its heavy concentration and centralization.

A breakthrough in this regard—raising hopes for a progressive decentralization of the entire financial system—only came with the development of blockchain technology and the innovations associated with this revolutionary technology (Sobieraj 2019; Abdulhakeem and Hu 2021). It should be emphasised that blockchain itself as a technology enables peer-to-peer transactions without intermediaries and any centralization (Swan 2015; Sobieraj 2019; Saengchote 2021; Almeida and Gonçalves 2022; Xu and Xu 2022).

With the development of the Blockchain, an entire ecosystem of financial applications has also emerged, built on the Blockchain network, using crypto tokens and smart contracts, and offering transparent financial services without intermediaries (Caldarelli and Ellul 2021; Grassi et al. 2022). This entire ecosystem has been named DeFi, from decentralized finance (Stepanova and Eriņš 2021). DeFi implies that financial services should be provided by users themselves to other users (Schueffel 2021). In short, this is made possible by using software components for a decentralized peer-to-peer system on the blockchain (Schueffel 2021). As Zetzsche et al. (2020) note, DeFi protocols and platforms are some of the most widely discussed new technological developments in global finance today. They are trustless and based on transparent solutions (Caldarelli and Ellul 2021). Saengchote (2021) notes that the existence of DeFi protocols offers many advantages. One of the most valuable, in his opinion, is composability, i.e., that different protocols can freely interact with each other to form new services.

This study addresses some basic metrics that allow DeFi protocols to be compared in terms of their basic analytical performance. One of these metrics is the Total Value Locked (TVL), which defines the DeFi market and indicates how much money is locked in a given DeFi protocol. Since there are different types of DeFi protocols in the DeFi market (e.g., decentralized exchanges, lending protocols, asset management, etc.), TVL represents different things for different types of DeFis. To illustrate what exactly TVL is, it is therefore useful to use a concrete example. Assuming that we are referring to lending protocols, the TVL associated with such DeFi platforms can be explained as the funds held as collateral for the loans taken out. More precisely, it is the total value of DeFi tokens staked on the blockchain as collateral.

The design of the study is very simple. We examine the relationship between DeFi protocol valuations and a whole set of financial metrics (variables) commonly used to compare the performance of these protocols. In reviewing the literature (Table A1 in Appendix A), there are not that many studies that address this issue. Admittedly, there are quite a number of studies on the emerging DeFi market. However, they mostly address the same, highly theoretical issues, i.e., the challenges, benefits and potential of the DeFi ecosystem (Abdulhakeem and Hu 2021; Werner et al. 2021; Calcaterra and Kaal 2021; Makarov and Schoar 2022), primitives, types of operational protocols and safety (Werner et al. 2021; Sun et al. 2021; Kitzler et al. 2021; Caldarelli and Ellul 2021), problems and risks associated with the formation of DeFi markets (including market manipulation, distorting incentives, excessive short-termism, Ponzi schemes and money laundering) (Chohan 2021; Schär 2021; Sun et al. 2021; Caldarelli and Ellul 2021; Bekemeier 2021), comparisons between the DeFi market and the CeFi market (Qin et al. 2021b), and inefficiencies of the DeFi market (Momtaz 2022). There are also few studies that rely on robust statistical models, and those that have been conducted relate exclusively to the most popular performance indicator, namely TVL (as if this were the only indicator that tracks the performance of DeFi protocols), alternatively to investor attention (Corbet et al. 2022; Şoiman et al. 2022) or to the association of the performance of DeFi protocols with traditional cryptocurrencies (Corbet et al. 2021; Dahlberg and Dabaja 2021; Maouchi et al. 2022; Schär 2021; Şoiman et al. 2022; Yousaf et al. 2022). There is also a study that refers to the returns of DeFi protocols (Şoiman et al. 2022). The literature also contains very focused studies that address specific issues related to DeFi protocols, such as the study on the nature of user behavior (Green et al. 2022) or the studies on explosive dynamics (Corbet et al. 2021; Wang et al. 2022). In contrast, there is a distinct lack of research addressing the issue of protocol valuation and how it depends on relevant financial variables. Indeed, Kaal et al. (2022) and Brucker (2022) point to the lack of such studies and the need for research to better understand digital asset valuations, including DeFi protocols in particular. Our study attempts to fill this gap. More specifically, the study examines how the valuations of individual DeFi projects depend on their TVL and a number of other important metrics characterizing individual DeFi projects, such as protocol revenue, total revenue, gross merchandise volume, and DeFi tokens' inflation factor, etc.

Furthermore, the study shows a difference between different DeFi protocols' classes (i.e., decentralized exchanges, lending protocols and asset management). Finally, the study also highlights some similarities between DeFi and conventional finance—in terms of the relevant valuation metrics considered in this study (and their counterparts in traditional finance). This knowledge leads to a better understanding of DeFi markets that are only in their early stages of emergence. We note that there is a lot of research on DeFi, but there is a lack of solid, model-based econometric research explaining the specificity and relevant properties of this market from a financial analysis perspective.

As for the contribution, the study shows that there are a number of different metrics that go beyond the most well-known TVL. Knowing these metrics allows for a better understanding of the DeFi market and a more in-depth evaluation of DeFi protocols. In the article, we analyze the valuations in the context of these metrics and provide a set of definitions. Among other things, we point out that besides TVL, another metric that seems to be widely underestimated is gross merchandise volume (GMV), which is the total value of sales and has gained popularity in the analysis of internet companies and especially e-commerce platforms (Yan et al. 2017; Prokhorova 2020; Sharma 2021). We also note that there are several categories of DeFi protocols that differ from each other. For example, they show different tolerance to changes in TVL (which is shown in a simple experiment where valuations are regressed on TVL values). All in all, the work is quantitative in nature and in it we use different research methods (correlation analysis, Granger-causality, and panel data analyses) that lend themselves to the analysis of associations between the type of data used in the study.

The structure of this article is as follows. First, we provide an overview of the literature to date, outlining the current state of academic knowledge on decentralized finance. We then present a methodology and model that explains the relationship between the valuations of DeFi protocols. Finally, we describe the results obtained, provide a discussion, and present conclusions from the conducted research.

2. Characteristic of the DeFi Market

There is currently a growing global interest in the digital economy, with a particular focus on blockchain technology. Decentralized finance is one of the leading current trends related to blockchain technology (Stepanova and Eriņš 2021). DeFi offers exciting possibilities, i.e., it consists of many highly interoperable protocols and applications. The advantage of DeFi over traditional finance of centralised finance (CeFi) is that all transactions can be independently verified by anyone due to the easy accessibility of data to users. DeFi platforms work as decentralized applications with smart contracts implemented on the blockchain (distributed ledger technology). As an emerging technology, they have the potential to disrupt the entire financial sector in the future (Şoiman et al. 2022). Schär (2021) sketched a picture of the DeFi market with a special focus on the opportunities this market offers and the potential risks of the DeFi ecosystem. According to the author, the DeFi market currently has a niche character, but could offer a more transparent, open and stable financial infrastructure in the future due to some of its specific features, i.e., easy accessibility, transparency, efficiency, and composition.

The decentralized nature of smart contract applications (based on distributed ledgers) provides these systems with a properly managed settlement layer. DeFi's blockchain-based ecosystem architecture enables the creation of many innovative products, e.g., decentralized equivalents of traditional financial instruments, but also completely novel instruments that did not exist before. Examples include decentralized stablecoins, flash loans (Qin et al. 2021a; Chohan 2021), autonomous liquidity pools (Schär 2021; Borisov 2022) or atomic swaps (Tefagh et al. 2020; Reiter 2022). All this makes the potential of DeFi enormous. For example, flash loans are a unique concept related to blockchain and DeFi, offering the ability to borrow hundreds of millions of dollars without putting up any collateral. However, the caveat (limitation) is that such an operation (transaction) must be completed in a single block. This gives an opportunity to borrow unlimited funds, provided that such a flash loan is repaid immediately after all sets of operations have been completed in one full transaction.

Below is a diagram of the layers of the DeFi market (also known as the DeFi stack), which gives a better understanding of the nature of this market (see Figure 1).

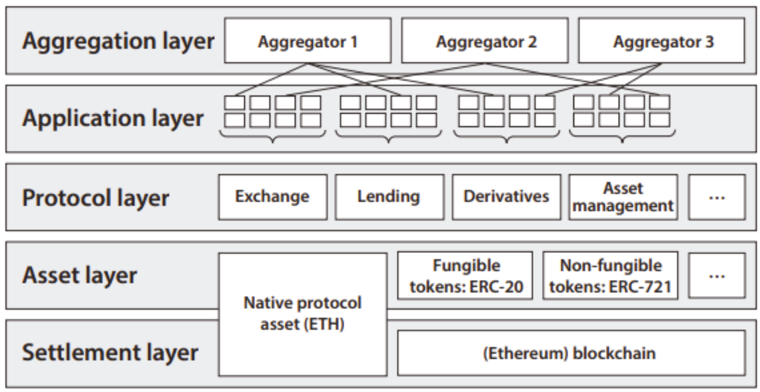

Figure 1. DeFi stack.

It is also worth pointing out some significant risks and weaknesses associated with DeFi technology. There are at least several of them. The most serious relate primarily to the safety of users of this technology, with unintended use and the oracle problem (Caldarelli and Ellul 2021) cited among the greatest threats. The latter is a problem arising from the system's reliance on external data sources to properly update smart contracts (e.g., clearing issues). These problems are discussed in great detail in the work of Caldarelli and Ellul (2021), among others. In the same vein, Chohan (2021) points to a number of problems associated with the emergence of the DeFi sector, namely various types of security risks that prevent the wider adoption of DeFi, such as distorting incentives, market manipulations, Ponzi schemes or money laundering practices. One such Ponzi scheme turned out to be the Terra-LUNA project, which collapsed spectacularly in just one week in early May 2022. The crypto community is still struggling with the aftermath of the billion-dollar collapse of Terra LUNA. Within a week, around $45 billion of the market capitalization of UST and Luna was completely wiped out of the market.

It is important to note that the empirical research and literature on DeFi is not yet as extensive as that on cryptocurrencies. However, there are some interesting studies that deserve to be mentioned. For example, Gudgeon et al. (2020) have presented evidence of the inefficiency of DeFi tokens in relation to their liquidity, market efficiency and interest rates. Werner et al. (2021) characterize the DeFi market in the context of operational protocol types, its overall ecosystem primitives and its security concerns. Zetzsche et al. (2020) have analyzed the development potential of the DeFi market in relation to its security, threats, risk control and regulatory needs. The authors emphasize the need for efficient design of regulatory issues, which in their view should include their embedding in the DeFi protocols themselves, i.e., through algorithmization in smart contracts. According to these authors, the biggest threat to the DeFi market is the risk that the traditional form of accountability will be challenged by decentralization, potentially compromising the effectiveness of enforcement of traditional financial regulations. Harwick and Caton (2020) note that if decentralized, autonomous finance is to be taken seriously in the financial world, it must begin to integrate identity with the real world.

Among the benefits that DeFi protocols can offer are, for example, a much wider range of financial services, lower costs of the services offered, as well as the business model itself, which operates at a lower operating cost, and finally the obtaining of greater privacy (Şoiman et al. 2022). DeFi offers easy access to services (pseudo-anonymity). Furthermore, it makes use of multiple technological layers (Katona 2021). Stepanova and Eriņš (2021) provided an overview of the capabilities, advantages and disadvantages of DeFi projects/protocols, analyzing and discussing the 12 most popular DeFi applications, and relying on the TVL metric.

For a more detailed characterization of the DeFi market, it is worth reaching for the work of Harwick and Caton (2020), Schär (2021), Stepanova and Eriņš (2021), Zetzsche et al. (2020), among others. In terms of the technology itself and business models, DeFi protocols are based on smart contracts and implement decentralized management. What is also important is that DeFi platforms use multiple technology layers, which provides opportunities to easily combine existing applications and create new innovative solutions (Katona 2021; Popescu 2020; Şoiman et al. 2022). Şoiman et al. (2022) note that DeFi tokens share a number of similarities with ICO tokens and, like the latter, can serve many different functions depending on the needs of the platform, e.g., they can be traded on platforms, held for profit, but they can also provide access to various products or services. The functions of DeFi platforms (protocols) can be very complex and play different roles, e.g., they offer the possibility to trade digital assets, lend digital tokens and earn interest, trade derivatives, buy insurance and more (Coinbase 2022). An important and growing application of DeFi protocols are stablecoins, which are tokens that attempt to tie their market value to an external reference asset, such as fiat currencies. Examples of such stablecoins are Tether (USDT), USD Coin (USDC), Dai (DAI), Binance USD (BUSD), Pax Dollar (USDP), TrueUSD (TUSD), and Digix Gold Token (DGX).

Examples of the different roles/functions that DeFi protocols can fulfil are (1) utility tokens that provide access to platform services and can be used to regulate payments for services offered on such DeFi platforms (such utility tokens are payable in relation to such services); (2) governance tokens (examples are year.finance or Maker Protocol) that allow users to benefit from the development of the platforms. Such tokens are similar to equity shares in public companies; (3) stablecoins, whose price is linked to other more stable currencies; (4) liquidity provider tokens (LPTs), which increase the liquidity of decentralized exchanges (DEXes); and (5) collateral tokens, which facilitate transactions in lending protocols. These can be stablecoins, for example, but also LPTs or even non-fungible tokens (NFTs).

Qin et al. (2021b) point out that unlike traditional finance, in the case of DeFi, the blockchain technology (on which DeFi is based) ensures an adequate integrity, transparency and control of the entire system. In contrast to conventional cryptocurrencies such as Bitcoin or Ethereum, which are touted as alternative money and payment solutions, DeFi protocols offer an alternative to banking and investment services (Zetzsche and Anker-Sorensen 2021; Şoiman et al. 2022). Aramonte et al. (2021) point out the differences between DeFi and traditional finance. More specifically, DeFi protocols are different in terms of the functionalities they offer. DeFi operates on different principles than traditional finance, including the use of digital collateral instead of physical collateral (Aramonte et al. 2021). Digital assets used as collateral in DeFi protocols include cryptocurrencies such as Bitcoins, Ethereum or Non-Fungible Tokens (NFTs). DeFi market participants who use their funds in lending protocols can book interest gains and, in return, borrowers can reinvest borrowed assets in other platforms and projects (Corbet et al. 2021). Furthermore, Qin et al. (2021b) and Saengchote (2021) highlight another important feature of DeFi, namely the significantly higher returns on financial assets that DeFi protocols offer.

It is also worth noting that not everyone shares the optimism related to DeFi development. For example, Momtaz (2022) examined the efficiency and role of intermediation in a large segment of DeFi, with particular attention to the theory of search. More specifically, to search-related frictions, which, according to this theory, offset to some extent the efficiency gains attributed to lower transaction costs through blockchain and smart contracts. Viewed through the lens of Walrasian equilibrium, search constraints in the DeFi market reduce society's wealth by almost half, which is why DeFi appears to be relatively inefficient, according to the authors.

3. Empirical Background

In-depth econometric analyses arising from robust models provide great opportunities to assess the relationships between different types of data. In the case of DeFi, unfortunately, there is a lot of data available, while there are few such studies. For example, Corbet et al. (2021) examined DeFi markets for explosive dynamics (bubbles), relying on the Supremum Augmented Dickey-Fuller (Sobieraj and Metelski 2021) and the modified Hacker-Hatemi-J Wald method, as well as the Diebold-Yilmaz return and volatility spillover analysis. Interestingly, their results showed the presence of bubbles in the valuations of DeFi protocols in Q3 2021, while it is worth noting here that the TVL peak in the DeFi market was reached in early December 2021. A similar study was later conducted by Wang et al. (2022) and also showed the existence of bubbles in the DeFi market. Thus, it can be seen that SADF and GSADF tests for price exaggeration (explosiveness) detection can serve as a tool to effectively monitor this market. In another study, Corbet et al. (2022) used the Mackey-Glass causality test and Markov regime switching vector autoregression analysis to investigate what drives DeFi prices and the impact of investor attention. Green et al. (2022) used survival analysis, more specifically Kaplan-Meier survival curves and Cox hazard regression, to assess usage and risk patterns within the AAVE protocol, which is one of the largest lending protocols within DeFi.

Interestingly, regarding the specifics of the bubbles in DeFi tokens, Corbet et al. (2021) have shown that they are self-generated and that the catalyst for their acceleration is associated conventional cryptocurrencies, mainly Ether and Bitcoin. On the other hand, an analysis of the comovement between DeFi tokens and cryptocurrencies has shown that DeFi tokens should not be placed in the same asset class as conventional cryptocurrencies. In this context, they are a separate asset class (Maouchi et al. 2022; Corbet et al. 2021; Schär 2021; Şoiman et al. 2022; Yousaf et al. 2022), although they are strongly linked to cryptocurrencies. The study by Corbet et al. (2021) also shows that, given the returns and volatility, it is not the leading cryptocurrencies Bitcoin and Ethereum, but rather Chainlink (LINK) and Maker (MKR) that have a significant impact on DeFi tokens and contribute to bubbles in this market.

Zmaznev (2021) investigated the negative impact of regulatory uncertainty shocks on the TVL in DeFi smart contracts using a structural VAR model. Overall, the response is negative for the leading DeFi categories (decentralized exchanges, lending protocols). However, the author emphasises that uncertainty contributes to the TVL in derivatives and payment protocols.

As with traditional cryptocurrencies (Bitcoin, Ethereum), the extremely dynamic development of the DeFi market in its initial phase was influenced by the so-called network effect (i.e., the capture of user acceptance) (Liu and Tsyvinski 2021; Cong et al. 2021; Ante 2020; Şoiman et al. 2022). Typically, network effects consist of an exponential growth of people joining a particular protocol, making a particular DeFi token more useful and valuable. Each additional user of DeFi tokens makes them more valuable to all other players at a rapid pace (Alabi 2017; Wheatley et al. 2019).

Another study worth mentioning is the work of Şoiman et al. (2022), who conducted an analysis of the determinants of DeFi market returns. In their study, they considered four important factors that can affect the returns of this market, namely (1) the relationship of DeFi tokens to the cryptocurrency market, (2) network factors, (3) investor attention, and (4) the TVL-to-market valuation ratio. The study by Şoiman et al. (2022) highlights the importance of TVL, which is a measure of the amount of funding allocated to DeFi projects, while illustrating the extent of the growth and performance of this market.

4. Total Value Locked

Total value locked is the value of assets deposited in a project's smart contracts (Zakieh et al. 2022). In addition to the valuations themselves (i.e., the capitalization of individual projects and the market as a whole), TVL is one of the cryptocurrency indicators that DeFi market investors use to evaluate the projects they put their money into (Zmaznev 2021). The fact of the matter is that funds are invested in different DeFi protocols for a variety of purposes, including staking, liquidity pools, and lending. According to Xu and Xu (2022), the exponential growth of TVL in DeFi protocols shows that there is a bright future for automated financial services. The TVL is specifically brought up as a comprehensive metric for DeFi protocols, as it directly reflects the financial side of services as well as their usage (Zmaznev 2021).

Saengchote (2021) sheds light on what DeFi Total Value Locked (TVL) could really measure and illustrates the complexity of DeFi analysis and market monitoring. The author notes that TVL is calculated as the market value of tokens deposited/locked in the system and is therefore highly dependent on token prices. Therefore, the relationship of this variable to valuations is expected to be relatively strong. Şoiman et al. (2022) refer to TVL as a certain unique variable that is specific to the DeFi market, as it is an indicator of the growth and success of that market. In simple terms, it corresponds to the amount of committed funds in DeFi protocols. According to the empirical evidence presented by these authors, TVL seems to be the most important variable for this market, followed by transactions (investor attention) and network effects. Some interesting remarks on TVL can also be found in the work of Stepanova and Eriņš (2021). According to Maouchi et al. (2022), TVL can be used to evaluate DeFi tokens and monitor this market. It is therefore worth taking a closer look at this variable and evaluating its historical performance.

The sharp downward trends in the cryptocurrency markets that have emerged in the second quarter of 2022 have led to decentralized finance seeing a very dramatic decline in TVL. A major impetus that accelerated this trend was the price collapse of the major cryptocurrencies Bitcoin and Ethereum below the level of 50% of their peak values reached in the first half of 2022. The slump in the market for the leading cryptocurrencies also led to declines in the DeFi market. As a result, the TVL across all decentralized financial protocols has fallen by 50% in a relatively short period of time. It should be noted that in early May 2022 (i.e., before the actual crash of the entire cryptocurrency market, which coincided with the collapse of Terra-LUNA project), the TVL in all DeFi protocols was estimated to be around \$200 billion. At that point, it was difficult to even speak of a crash, as the historical TVL for this market reached \$252 billion in December 2021. The sequence of events was as follows. In the last week of April there was a drop of about \$20 billion in DeFi's TVL. However, the real crash began on 9 May 2022. From then on, it took only 3 days (until 11 May 2022) for the TVL of the entire DeFi market to shrink by another \$30 billion to \$150 billion. And yet this was only the beginning. In the weeks that followed, further declines occurred, for a total of an additional \$40 billion in TVL. This development shows how high the risk is when investing in DeFi markets at this early stage of their development (see Figure 2).

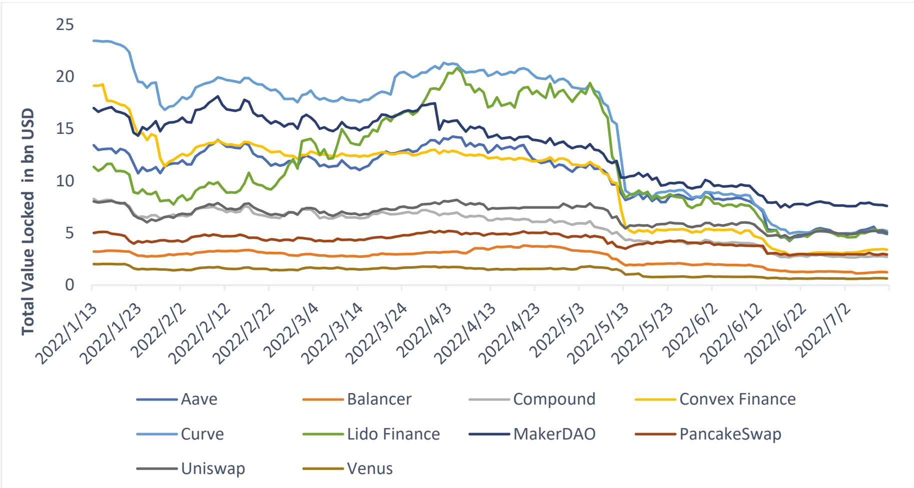

Figure 2. Top 10 dapps based on daily total value locked. Source: own elaboration.

5. Data and Methodology

5.1. Data Collection

We collected information on 30 DeFi tokens using data from the defillama, tokenterminal and dappradar databases (tokenterminal.com, defillama.com and dappradar.com websites accessed on 15 July 2022). Table 1 shows the exact names of the DeFi types and protocols examined. Defillama and Tokenterminal are the most complete data aggregators collecting important metrics for DeFi platforms and financial data for DeFi protocols. From the above databases, we have extracted data on key DeFi performance metrics, i.e., market capitalization, TVL, protocol revenue, total revenue, gross merchandise volume, and the inflation factor of DeFi protocols.

Table 1. DeFi protocols used in this study.

Decentralized Exchanges	Lending Protocols	Asset Management
Uniswap	Aave	Convex Finance
Synthetix	MakerDAO	Lido Finance
Loopring	Compound	Yearn.Finance
PancakeSwap	Abracadabra Money	Yield Guild Games
Curve	Centrifuge	Fei Protocol
1inch	Liquity	Ribbon Finance
Osmosis	Venus	Rari Capital
Maiar	Maple Finance	Enzyme Finance
0x	TrueFi	Alchemix Finance
SushiSwap	Homora	Harvest Finance

Source: own elaboration.

The study investigates the relationships between different variables related to DeFi protocol assessments. To this end, we have used several research methods that are appropriate for investigating relationships between data of this type, namely causality analysis and a panel regression study, which is underpinned by the fact that the study examines longitudinal data and thus both cross-sections and time series. The causality study shows how knowledge about individual variables enables the assessment of the interaction between variables, but can also be used to predict future valuations. In causality analysis, the interaction between variables can be determined. While x determines y, y can determine x. In panel regression analysis, there is a one-sided interaction.

The data used in the study refer to the period between 11 January and 8 July of 2022. The advantage of choosing such a data window is that the results provide a better answer to the question of how to mitigate the decline in valuations during the bear market. One of the ways to do this is to control the supply of tokens, which should be more tightly controlled by an appropriate inflation factor. But of course there are a number of other factors that could be considered. One such factor could be the investment strategies of the protocols themselves. A good example is Umami Finance, a protocol that is pioneering the mass adoption of DeFi with its growing ecosystem of professional, regulatory-compliant DeFi products tailored to the institutional market (Umami Documentation 2022). The Umami team is building a suite of rigorously tested, highly scalable vaults that generate sustainable returns on key crypto assets (e.g., $USDC, $ETH and $BTC). Umami's goal is to establish decentralized, permissionless smart contracts as the foundation of the global financial system and enable financial autonomy for investors around the world. The Umami Finance protocol pays out a portion of the return to market participants who stake their governance tokens. In short, the Umami Protocol uses a delta-neutral strategy where it earns returns on both long and short positions (Umami Documentation 2022). It is expected to be able to generate returns between 15–35% while remaining delta neutral. For historical comparison, as far as Umami Finance is concerned, its non-native treasury assets were worth $5.6 m in February 2022, and by the end of May 2022 they had fallen to $5.4 m (a drop of $0.2 m), a decline of 3.5%. It is also important to note that the broader market has fallen by 30% over the same period. This means that in a declining market, the US Treasury was able to generate enough returns and fees to reward the protocol token holders, cover its operating costs and still outperform the broader market.

Table 2 below shows the variables used in the study and their descriptions.

Table 2. Variables used in the study and their description.

Variable	Description
Valuations (VAL)	The valuation of defi protocols is equal to the number of tokens in circulation multiplied by the token price. Kaal et al. (2022) and Brucker (2022) point out the lack of studies dealing with the valuation of digital assets, especially with regard to DeFi protocols.
Total Value Locked (TVL)	Total value locked refers to the amount of user funds deposited in a DeFi protocol. This indicator assesses the total value of assets deposited in a single DeFi project or in all DeFi protocols (usually expressed in US dollars). DeFi assets include rewards and interest derived from typical services such as lending, staking and liquidity pools in the form of smart contracts. In staking, for example, TVL allows investors to select the DeFi platforms with the highest rewards. More specifically, the TVL in DeFi's staking protocols represents the amount of assets deposited by liquidity providers. By the end of 2021, TVL had reached a value of approximately $250 billion globally, an increase of more than 600-fold in a 2-year period during which the DeFi market grew from $400 million TVL to the aforementioned $250 billion. With the growing popularity and value of DeFi in the cryptocurrency space, TVL has become an important metric for investors to assess whether the entire DeFi ecosystem or a single protocol is safe and worth investing in. First of all, it is important to stress that capital is required for DeFi protocols to work. DeFi market participants usually deposit their capital as collateral for loans or liquidity pools. This in turn leads to subsequent returns on DeFi protocols and benefits for investors and end users. The rising TVL of a particular DeFi protocol is an indicator of its increasing popularity and thus its liquidity and utility. These factors contribute to the success of such a protocol. With higher committed capital in DeFi protocols, their participants receive more significant rewards and revenues. In contrast, an outflow of funds (i.e., a lower TVL) means that fewer funds are available and therefore lower revenues are generated. With new protocols emerging in the DeFi space all the time, it can be difficult for end users to determine the exact TVL of the entire market and the investment prospects for a particular DeFi protocol. However, there are platforms that monitor the money flows in DeFi protocol smart contracts on the blockchain (e.g., DefiLlama or DeFi Pulse). They are able to display TVLs by extracting the total balance of all DeFi chains together or of each individual platform. Based on the TVL indicator, investors and DeFi market participants can look for safer protocols that have a more consolidated market position due to the high value of the funds deposited in them (e.g., one can assume that only those protocols whose TVL exceeds $1 billion are worth investing in, which should be a safe assumption). A sufficiently high TVL indicator is an indication that the DeFi protocol is trustworthy, which usually goes hand in hand with a relatively high demand for a particular DeFi platform and should also be reflected in an experienced development team and a valuable business model underlying the entire project. All of these factors should attract more participants and investors and thus contribute to the growth of the TVL project.

Table 2. *Cont.*

Variable	Description
Protocol Revenue (PR)	Protocol revenue is equal to the amount of revenue that is distributed to tokenholders. Put differently, DeFi protocols' revenues show the amounts of money the protocols generated for its users and token holders.
Total Revenue (TR)	Total revenue is equal to total fees paid by the users. It is calculated over a given time period. For example, daily total revenue for a given day is equal to the fees paid during that day (24 h). More importantly, protocol revenue and total revenue has different economic meanings for token holders. While the former only includes revenue paid to the protocol and/or its token holders, the latter also includes revenue taken by supply-side participants such as makers or liquidity providers. That is to say that supply-side revenue is equal to the amount of revenue a DeFi project pays to its supply-side participants. An example of the supply-side participants are liquidity providers who are given a number of liquidity provider tokens (LPTs) when they deposit their cryptocurrency in a DeFi pool. LPTs are returned to the DeFi system when a liquidity provider wishes to withdraw their deposited coins.
Gross Merchandise Volume (GMV)	In addition to the above indicators, another indicator that helps in analyzing the growth of DeFi businesses is the gross merchandise value (GMV). GMV is most commonly used to assess online businesses, and has particularly gained popularity in relation to e-commerce businesses (Yan et al. 2017; Prokhorova 2020; Sharma 2021). Sharma (2021) defines GMV as an indicator used in online retailing to indicate a total sales dollar value for merchandise sold through a particular marketplace over a certain period. The GMV is particularly useful in analysing the growth potential of DeFi projects/applications/protocols. The popularity of the DeFi sector is clearly reflected in the growth of the number of new DeFi projects and the volume of TVL deposited in these protocols. Interestingly, the indicator is very popular with marketplaces that are directly or indirectly involved in online trading. In its simplest form, the GMV is defined as the total value of sales in a given period. Thanks to the GMV, internet companies whose business model is to sell to non-business customers can compare their value in a given period with the corresponding periods in the past. The indicator makes it possible to estimate the growth of their business over time (for a given time horizon). Investors can also compare companies with a similar business profile in a fairly simple way thanks to the GMV. Naturally, the higher the value of the index, the greater the DeFi protocol. From an investor's point of view, the GMV enables the selection of business projects with higher growth potential and the estimation of the growth of financial results in the future. In addition, the GMV indirectly shows who is the leader in a particular niche. The higher the value, the better known a particular project is among consumers/users. And every market leader receives a bonus because of its size. Therefore, it has to spend relatively little on marketing because it has a large base of customers/users and a high level of awareness. Therefore, it can do its business cheaper (due to lower costs). So although the GMV only shows gross revenue, it can also indirectly tell us which project may have lower costs.
Inflation Factor (INF)	The inflation factor reflects the dilution of the market capitalization in circulation of a given DeFi protocol. One of the key factors that crypto market traders consider when making investment decisions is the inflation rate of the native token or coin for a particular protocol/project. The inflation rate is therefore an important issue when it comes to the supply and demand of DeFi (cryptocurrencies) tokens. When the supply of a token exceeds the demand for it, the line of least resistance for the price of that cryptocurrency will point downwards, leading to a price decline in the market. In other words, the inflation rate should be considered as the rate at which the supply of a particular token in circulation changes. For example, if the inflation rate is 5%, this means that 5% more tokens have entered circulation. The reasons for the increase in the number of tokens in circulation can be different, e.g., rewards, staking or minting. The number of tokens in circulation can also decrease, e.g., due to lost keys or burning. It is worth noting that in the early stages of development of some crypto projects, the associated inflation can have a positive effect (as was the case for Bitcoin in its early years). However, from a logical point of view, it is the low inflation rate that should be better perceived by participants in this market, as it naturally leads to less pressure on the buy side (the traditional law of supply and demand and scarcity of goods applies here). In the early stages of a project development, the inflation rate can remain at a relatively high level. This was the case, for example, with Bitcoin itself, where inflation was high in the first years after the digital currency appeared on the market (in 2012 it was even over thirty per cent, but halved already by the following year). In general, the inflation rate indicator is calculated as follows: Inflation Rate % $= (\text{Supply}_t/\text{Supply}_{t-1}) - 1$.

Source: own elaboration.

Tables 3–5 show some descriptive statistics for different classes of DeFi protocols (lending protocols, decentralized exchanges and DeFi apps).

Table 3. Descriptive statistics for the lending protocol class of tokens.

Lending	Total Lending Revenue	Aave Dominance	Median Lending Revenue	Median Lending P/S Ratio
	$1.25b	+43.6%	$736.44k	17.2x

Note: Total Lending Revenue—total borrowing interest generated by listed lending protocols; Dominance—the leading lending protocol's share of total borrow interest; Median Lending Revenue—the median of total borrowing interest generated by listed lending protocols; Median Lending Price to Sales (P/S) ratio—median of P/S ratio of listed lending protocols. Source: own elaboration.

Table 4. Descriptive statistics for the decentralized exchanges class of tokens.

Exchange	Total Exchange Revenue	Uniswap Dominance	Median Exchange Revenue	Median Exchange P/S Ratio
	$5.80b	+41.4%	$3.87m	14.6x

Note: Total Exchange Revenue—total trading fees generated by listed exchanges; Dominance—The leading exchange's share of total trading fees; Median Exchange Revenue—Median of total trading fees generated by listed exchanges; Median Exchange P/S ratio—Median of P/S ratio of listed exchanges. Source: own elaboration.

Table 5. Descriptive statistics for the DeFi class of tokens.

DeFi	Total DeFi Revenue	Uniswap Dominance	Median DeFi Revenue	Median DeFi P/S Ratio
	$13.14B	+25.7%	$6.33m	13.4x

Note: Total DeFi Revenue—Total revenue generated by listed DeFi protocols; Dominance—the leading DeFi protocol's share of total transaction fees; Median DeFi Revenue—median of total revenue generated by listed DeFi protocols; Median DeFi P/S ratio—Median of P/S ratio of listed DeFi protocols. Source: own elaboration.

Table 6 shows similar statistics for the conventional blockchain class. It is worth noting that most DeFi protocols are based on the Ethereum blockchain.

Table 6. Descriptive statistics for the blockchain class of tokens.

Blockchain	Total Blockchain Revenue	Ethereum Dominance	Median Blockchain Revenue	Median Blockchain P/S Ratio
	$20.12b	+76.3%	$3.87m	7559.8x

Note: Total Blockchain Revenue—total transaction fees generated on listed blockchains; Dominance—the leading blockchain's share of total transaction fees; Median Blockchain P/S ratio—median of total transaction fees generated by listed blockchains; Median DeFi P/S ratio—median of P/S ratio of listed blockchains. Source: own elaboration.

5.2. Methodology

Since the study aims to examine the relationship between the DeFi Protocol valuations and a number of financial variables that can be used to represent and justify the performance of this market, it is assumed that both Granger causality analysis and panel data analysis are methods commonly used to assess the relationship between different variables. Panel data analysis is a widely used statistical method for analysing two-dimensional (i.e., cross-sectional and time-series) data. In the empirical part, valuations are estimated using panel regressions. More specifically, DeFi protocols are represented as panels and subsequent days as time. The pooled OLS specification assumes that there is no heterogeneity between different DeFi projects, which is expressed by using the following equation:

$$Val_{it} = \alpha + \beta X'_{it} + e_{it} \tag{1}$$

where Val_{it} denotes the valuation corresponding to each of the projects and is log-linearized to adjust for disparities, to better explore their dynamic properties and simplify the calculations (Metelski and Mihi-Ramirez 2015). In other words, i = 1,2, . . . , 30 refers to the number of individual projects recorded in the database, and t = 11 January 2022. . . 8 July 2022 refers to consecutive days. The term α is the common intercept, X' is the vector with the predicting variables, which means that a specific set of control variables is used to obtain the results. The same predictors are used in all models, i.e., total value locked (tvl), protocol revenue (pr), total revenue (tr), gross merchandise volume (gmv), inflation factor (inf). Moreover, the term e_{it} included in the model presented above is the error term. The specification FE with fixed individual effects is expressed by the following equation:

$$Val_{it} = \alpha_i + \beta X'_{it} + e_{it} \tag{2}$$

where α_i represents the fixed effects of each DeFi protocol. It controls for heterogeneity between different DeFi protocols. The difference between the FE specification and the OLS model is that the former, unlike the latter, reflects DeFi protocols' effects, which are reflected in the term α_i. Therefore, α_i can be viewed as the ignorance about all of the other systematic factors that predict DeFi projects' valuations, other than X'.

In the study, we will also conduct a correlation analysis and check whether there are causal relationships between the variables under study. To this end, we conduct Granger causality and Granger causality reversal tests. For a more detailed explanation of the Granger causality method, see the work by Metelski and Mihi-Ramirez (2015).

6. Results

As mentioned earlier, for the analysis, we use daily data from the first two quarters of 2022 (between 11 January and 8 July), specifically data on circulating market capitalization (val) (response variable) and the total value locked (tvl) and a whole host of other variables, i.e., protocol revenue (pr), total revenue (tr), gross merchandise volume (gmv), and inflation factor (inf) (explanatory variables) for 30 different DeFi protocols studied (i.e., Uniswap, Synthetix, Loopring, PancakeSwap, Curve, etc.). The study examines the relationships between the data and, in particular, explores how the TVL and the rest of the explanatory variables affect the valuations of these protocols. In other words, the panel regression analysis aims to provide evidence that helps to better understand what drives DeFi valuations in relation to some intrinsic characteristics and informative metrics of the DeFi protocols. We tested all correlation coefficients (for each pair individually) and found that all corresponding p-values were less than 0.05 (see Figures 3 and 4). This is an indication that the correlation estimates between the variables studied are statistically significant. For example, the correlation between the valuation of the DeFi protocols and their respective TVLs is 0.6080682, and this is a statistically significant result (Pearson t-test value = 52.639, df = 4723, p-value < 2.2×10^{-16}) (see Figure 3 below). However, it must be taken into account that we are dealing with a time series, so the reliability of such tests is weaker than with cross-sectional data.

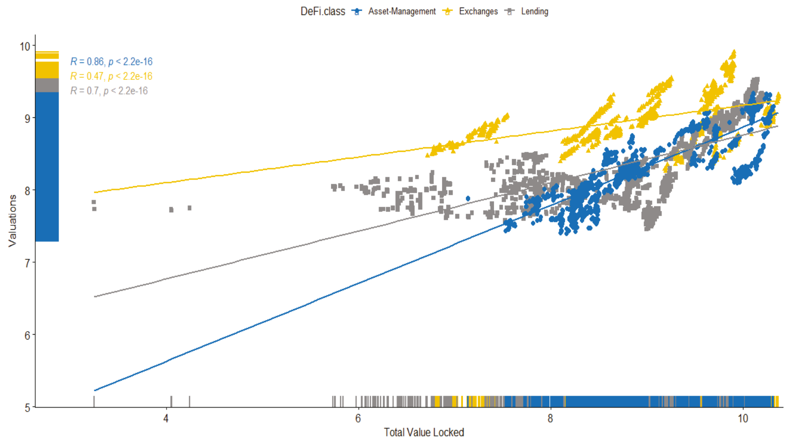

Figure 3. Correlations between Valuations and TVLs for 3 different DeFi classes' protocols. Note: All data logarithmized. Source: own elaboration in R-Studio.

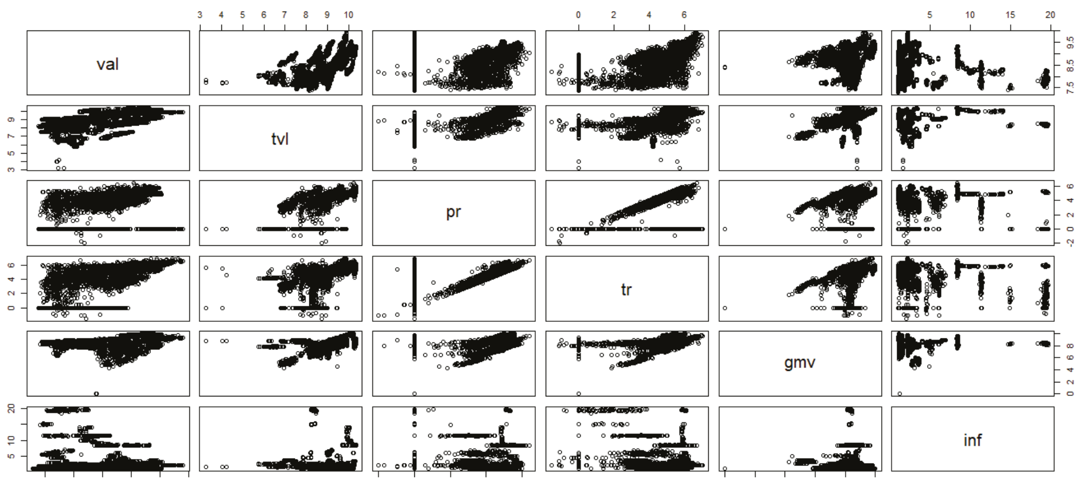

Figure 4. Pairwise Correlations for the Variables Used in the Study. Source: own elaboration in R-Studio.

Interestingly, for the different classes of DeFi protocols, we can see that the relationships between the valuations of these protocols and their TVLs vary (this can be seen in the elasticities of the regression lines shown in Figure 3 above). In general, the steepest regression line is for the "Asset Management" class and the flattest for the 'Decentralized Exchanges" class. It is thus clear that the TVL is relatively more important for "Asset Management" protocols, which seems logical in that the performance of these protocols is much more dependent on the funds under management. To understand this better, an analogy can be drawn with mutual funds, whose valuations depend to a much greater extent (than e.g., other companies in the financial industry) on the amount of capital under management. In general, the value of a fund is determined by its net asset value (NAV), which is equal to the total value of assets minus the total value of liabilities. Moreover, assets under management (AUM) represent the total market value of investments, which depends on the flow of funds entrusted by investors. On the other hand, AUM determines the level of asset management fees, which influence the valuations of these funds (Boudoukh et al. 2004).

However, the pairwise correlations between the variables studied do not suggest causality. Based on the above results, it is difficult to give a clear answer as to whether TVL and other exogenous variables cause an increase in DeFi valuations, which would confirm our research hypotheses that DeFi valuations are dependent on TVL, total revenue, and gross merchandise volume—which might be perceived as proxies reflecting the success of the DeFi protocols. There is much evidence to suggest that this may be the case. The results of the correlation coefficients give an indication that this is indeed the case. To be sure, we use the Granger causality test to assess the causal relationships between the variables under study (Thurman and Fisher 1988; Metelski and Mihi-Ramirez 2015). This can help us understand whether some of the explanatory variables provide statistically significant information about future DeFi valuations. The results of the Granger causality tests suggest that knowledge of DeFi valuations (as measured by daily circulating market capitalization) is useful in predicting future values of the TVL in these protocols [F = 5.6021, Pr(>F) = 0.009755]. As it turns out, of all the explanatory variables included in the study, only the Gross Merchandise Volume can be useful in predicting the future valuations of the DeFi protocols [F = 2.6968, Pr(>F) = 0.04435]. All tested relationships are listed in Table 7.

Table 7. Pairwise Granger causality tests.

Dependent Variable	Hypothesis Tested:	F-Statistic	*p*-Value
VAL	TVL: there is a unidirectional relationship (VAL⇒TVL)	5.1128	0.001566 **
	PR: there is a unidirectional relationship (VAL⇒PR)	5.556	0.0008394 ***
	TR: there is a unidirectional relationship (VAL⇒TR)	27.354	$<2.2 \times 10^{-16}$ ***
	GMV: there is a bilateral relationship (VAL⇔GMV)	2.6968; 13.749	0.04435 *; 6.531×10^{-9} ***
TVL	PR: there is a unidirectional relationship (TVL⇒PR)	18.321	8.4×10^{-12} ***
	TR: there is a bilateral relationship (TVL⇔TR)	4.6502; 31.471	0.003005 **; $<2.2 \times 10^{-16}$ ***
	GMV: there is a unidirectional relationship (TVL⇒GMV)	17.384	3.385×10^{-11} ***
PR	TR: there is a bilateral relationship (PR⇔TR)	9.3282; 11.368	3.819×10^{-6} ***; 2.008×10^{-7} ***
	INF: there is a unidirectional relationship (PR⇒INF)	3.4802	0.01525 *
TR	GMV: there is a unidirectional relationship (TR⇐GMV)	3.7378	0.01071 *
	INF: there is a unidirectional relationship (TR⇐INF)	3.4491	0.01592 *

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05. Source: own elaboration.

The results of the Granger causality tests show the most likely direction of the relationships between the variables. Thus, the results suggest that DeFi protocols' valuations drive the change in TVL and in other pivotal variables such as protocol revenue and total revenue, and gross merchandise volume. TVL, on the other hand, drives protocol revenue, total revenue, and gross merchandise volume. This could suggest that at this early stage of the DeFi market's development, increased valuations are attracting new users and liquidity providers to these protocols, which translates into an increase in the total revenue from these protocols, and also an increase in payments to token holders in the form of protocol revenue, which further pulls in new users and new capital (in the form of staking and yield farming). As for the relationships between DeFi protocols' valuations and the other explanatory variables, the bilateral relationship was only demonstrated for one variable, namely gross merchandise volume. This type of data analysis allows for a better understanding of the relationships that exist between the variables.

In general, a higher TVL of DeFi protocols means greater liquidity, popularity and, at the same time, usability—an indication of the success of DeFi projects. When the TVL increases, it means that more capital is committed to DeFi protocols, which translates into significant benefits and revenues for participants in these protocols. Lower TVLs, on the other hand, mean less availability of funds (liquidity pools) and thus lower revenues from these protocols.

To better explain the assessment of the association of DeFi protocols' valuations with other variables studied, we also conducted a short panel regression analysis, the ordinary least squares (OLS) and fixed effects model specifications.

The results of the FE model specification can be found in Table 8. We omit the results of the OLS model specification because the F-test showed that it is inferior to the results of the FE specification (F = 713.02, df1 = 19, df2 = 3174, p-value < 0.000000000000022; alternative hypothesis: significant effects). All variables were log transformed (Metelski and Mihi-Ramirez 2015). The logarithmic transformation of the variables in the model has some important advantages. In general, a regression model without transformation has unit changes between the explanatory and response variables, where a unit change in an independent variable coincides with a constant change in the dependent variable. Taking the logarithm of one or both variables, the case changes from a unit change to a percentage change (Metelski and Mihi-Ramirez 2015).

Table 8. Fixed Effects panel regression model.

Predictor	Estimate	Std. Error	*t*-Value	Pr(>|t|)
Total Value Locked	0.3886304	0.0102634	37.8655	<0.00000000000000022 ***
Protocol Revenue	−0.0193467	0.0047426	−4.0793	0.00004628 ***
Total Revenue	0.0168036	0.0041144	4.0841	0.00004534 ***
Gross merchandise volume	0.1757711	0.0103339	17.0092	<0.00000000000000022 ***
Inflation factor	−0.0192243	0.0017573	−10.9399	<0.00000000000000022 ***
Total Sum of Squares:	138.75			
Residual Sum of Squares:	75.903			
R^2/R^2 adjusted	0.45293/0.44897			
F-statistic: 525.57 on 5 and 3174 DF, p-value: < 0.000000000000000222				

Note: Signif. codes: 0 '***' 0.001. Source: own elaboration.

As far as the modelling assumptions are concerned, a number of tests were carried out to verify that the model used is robust and reliable. In particular, the Breusch-Pagan LM test of independence (chi2(171) = 191.56, Pr = 0.1344) indicates that there is no cross-sectional dependence in the model. As for heteroskedasticity, the modified Wald test (since the best model specification turned out to be the one with fixed effects) confirms that no heteroskedasticity problem was found in the model (Prob > chi2 > 0.05 [chi2 (19) = 27.09, Prob > chi2 = 0.10257]). With regard to the analysis of stationarity, a Fisher's test was performed (which assumes under the null hypothesis that all series are non-stationary; H0: all panels contain unit roots and the alternative assumes that at least one series in the panel is stationary). The results confirm stationarity (i.e., inverse chi-square(60) P = 91.6689, p-value = 0.0052, and since the p-value is less than 0.05, we reject H0). As for the analysis of the cointegration test, it is assumed that researchers conduct cointegration tests when time series are non-stationary to determine whether they have a stable, long-term relationship. Since we are dealing with already transformed data and stationarity in the model, there is no need to conduct a cointegration test analysis. Furthermore, the F-test of overall significance shows that the variation in the dependent variable (the valuations of the DeFi protocols) is explained by the independent variables (jointly). In other words, the regression model is a better fit than a model that does not contain independent variables. The F-test is used to test the overall significance of the multiple regression by determining whether the variation in the dependent variable (DeFi protocols' valuations) is explained by the independent variables. It is also worth noting that the goodness of fit (Adjusted $R^2 = 0.44897$) indicates that almost 45% of the variability in the valuations of the DeFi protocols (endogenous variable) is explained by the explanatory (exogenous) variables—which seems to be an indication of a good model.

From the results, it can be concluded that TVL, Total Revenue, and Gross Merchandise Volume have a positive impact on the valuations of DeFi protocols. All beta coefficient estimates for these variables are positive and statistically significant. It should be noted that the influence of the variable TVL on DeFi protocols' valuations is the largest. These results find a logical explanation as we are dealing with proxies for the performance of DeFi protocols. This is because the more resources that go into these DeFi protocols, the better it is for their valuations (which means that higher valuations are justified). Since the TVL reflects the value of funds paid into the smart contracts of these protocols, higher numbers usually mean higher valuations for these protocols. In turn, the gross merchandise volume is equal to the total value of sales. It has a different meaning for the different classes of DeFi protocols. For decentralized exchanges it is the total trading volume, for lending protocols it is the total borrowing volume and for asset management it is the total trading volume of their product. Total revenue, in turn, is the total fees paid by users of DeFi protocols. It is calculated over a certain period of time. Thus, the daily total revenue for a given day corresponds to the fees paid on that day. The protocol revenue and the inflation factor, on the other hand, show a negative association with DeFi protocols' valuations, for which there is also a logical explanation. This is because the protocol revenue is equal to the amount of revenue distributed to DeFi token holders. The protocol revenue can therefore be understood in a similar way to the dividends that a public company distributes to its shareholders. In the case of DeFi protocols, the capital paid out is the capital flowing out of the protocol. The inflation factor, on the other hand, reflects the dilution of the valuations, i.e., it has a similar meaning to the issuance of new shares in traditional companies. Even for a typical equity company, an increase in the number of shares in circulation usually has a negative impact on the valuation.

7. Discussion

The emergence of DeFi in 2020 has brought with it the possibility of new forms of investment. From a financial perspective, this is positive as DeFi can help diversify and complement traditional portfolios by seeking returns that are independent of traditional asset classes such as equities and bonds, and by reducing overall sensitivity to traditional markets (Yousaf and Yarovaya 2022). In particular, some DeFi protocols offer an automated, low-risk way to generate returns with a "delta-neutral" trading strategy that reduces volatility. On the other hand, DeFi represents a completely new field and therefore requires an unconventional view when measuring performance. It is worth noting that there are no comprehensive studies (robust model-based econometric analyses) in the literature that justify the evaluation of DeFi protocols in the context of some specific metrics of a financial nature. The need for such studies has been highlighted by Kaal et al. (2022) and Brucker (2022), among others. One performance metric that is becoming increasingly popular among DeFi investors is TVL, a cryptocurrency indicator to assess the total value of all assets (funds) deposited in DeFi protocols (TVL can be reported for a single DeFi protocol, but can also be aggregated and reported as a value for all protocols). According to Zmaznev (2021), TVL reflects the financial side of DeFi services and their use and is therefore a suitable metric for assessing DeFi protocols. However, it should be noted that DeFi assets are not homogeneous, but are composed of different classes of contributed funds in DeFi protocols, i.e., they include liquidity pools as well as interest or different types of rewards resulting from the services offered in DeFi protocols, such as loans, stakes, or the aforementioned liquidity pools locked in smart contracts. In terms of stakes, the TVL metric should be interpreted as the amount of assets deposited by liquidity providers in DeFi protocols. Such a metric makes it easier to compare different DeFi protocols to select those that offer the highest returns in terms of annual percentage yields (APYs). Of course, it is not possible to flawlessly rank individual protocols (e.g., based on their TVLs), and therefore the demise of a DeFi protocol that offers high staking premiums while having a high TVL cannot be ruled out. An example of this is the recent quick total failure of Terra (LUNA), which allowed up to 20% APY through stakes. TerraUSD (UST) was a stablecoin hosted by the Terra network that became the second blockchain with the highest TVL after Ethereum in the second quarter of 2022 (Azar et al. 2022).

Typically, TVL can be used to assess whether an individual DeFi protocol is sound and worth investing in. As a rule of thumb, determining the value of TVL sometimes requires more sophisticated mathematics than taking into account all deposits, withdrawals and determining the actual amount held in a DeFi protocol and deposited in smart contracts. The TVL is also affected by the value of the native token and the fiat currency in which it is denominated. Therefore, the TVL changes when these values change. An increase in the value of a DeFi token therefore leads to an increase in its TVL (Saengchote 2021). The TVL is important from the perspective of DeFi protocols because it is their lifeblood and enables them to operate; without deposited capital, in the form of smart contracts, DeFi protocols could not function. In this context, the TVL can be interpreted as an early indicator of the potential gains of DeFi protocols as well as the benefits to participants and investors in these protocols.

In addition to TVL, this study also considers metrics such as protocol revenue, total revenue, gross merchandise volume and the inflation factor. Each of these metrics is important in its own way (in the context of the DeFi assessment) from the perspective of both project teams and investors. However, if one takes protocol revenue and total revenue, for example, it is interestingly difficult to find broader definitions for these terms that explain how the two metrics differ. It turns out that the difference between them is significant. First of all, protocol revenue and total revenue have different economic meanings for token holders. Protocol revenue includes only the revenue paid to the owners of the protocol and/or its token holders, while total revenue also takes into account the revenue of supply-side participants. Supply-side participants, for example, can be defined as liquidity providers who receive a certain number of liquidity provider tokens (LPTs) when they deposit their cryptocurrency into the DeFi pool. What the policy of each DeFi protocol is in terms of revenue generated depends largely on the individual strategies of those protocols. The design teams of the DeFi protocols are staffed by the respective strategists and project managers who develop the financial and marketing policies implemented in the smart contracts. These policies define, among other things, the strategy plans for issuing additional tokens (minting, burning), payouts, rewards, etc. It is in this context that the inflation factor variable, which was included in our study (and whose broader definition is included in Table 2), should be understood. In fact, all these points are interlinked and form part of complex DeFi protocol strategies. A number of complex factors such as adding new tokens or removing them, involving market participants in the development of DeFi platforms by issuing governance tokens (Şoiman et al. 2022), offering high rewards for providing liquidity (to attract capital to the protocol so that the whole project gains momentum)—these are all elements of complex system dynamics that ultimately lead either to the success or failure of the project. In the case of Terraform Labs, the company behind Terra USD (UST) and Terra (LUNA), their flawed adoption led to the collapse of the entire project. It is therefore worth highlighting and analyzing these problems. By clearly pointing them out, we also see the value and contribution of this study.

The results also show that GMV has a significant Granger effect on DeFi protocol valuations, implying that there is some kind of interaction between the two variables. In practise, this can be seen as a kind of relationship between variables, where each of the variables under consideration influences the other reciprocally. This confirms that the

GMV is particularly useful as an indicator for analyzing the growth potential of DeFi projects/applications/protocols. This indicator makes it possible to estimate the performance of DeFi protocols' business models over time. Simply put, DeFi market participants can use the GMV indicator to easily compare protocols with a similar business model. Obviously, the higher the value of the indicator, the greater the DeFi protocol. From the investor's perspective, the GMV enables the selection of business projects with higher growth potential and the estimation of the growth of financial performance in the future. In addition, the GMV indirectly shows who is the leader in a particular niche. The higher the value, the better known a project is among its participants/users. In the context of the DeFi protocols and the results of the study (both the causality analysis and the panel regression analysis), it can be assumed that the GMV is strongly undervalued in contrast to the TVL. The causality analysis suggests that GMV is the only variable that Granger-causes future DeFi protocol valuations.

In contrast, the results of the panel regression analysis study show that the beta coefficients of the variables protocol revenue, total revenue and inflation rate are small and therefore these variables have low predictive power (compared to TVL and GMV), although on the other hand, the direction of these relationships suggests that slightly higher valued projects are those that distribute less revenue to their token holders and control their token supply in circulation more restrictively. It is likely that in the early stages of development of these projects, retained revenues may have a positive impact on subsequent valuations. In the early stages of project development (presumably to maximize the network effect), distribution to supply-side participants in the form of liquidity pools might make more sense from the perspective of the project teams behind the development of the DeFi protocols.

As a future research direction, it might be interesting to link DeFi protocol valuations to the treasury metric (which is the value of project funds held in the chain and includes the value of unallocated governance tokens). The value of the treasury can be seen as an indicator of the financial strategies of each protocol, which of course are also related to the reward distribution policy. This would make it possible to examine the correlation between the distribution policy of the rewards and the overall strategies of the individual protocols.

8. Conclusions

The study is based on a dual quantitative methodology (panel data analysis + Granger causality) and analyzes the valuations of 30 selected protocols representing three different classes of DeFi projects (i.e., decentralized exchanges, lending protocols and asset management) in terms of their relevant performance metrics. More specifically, the study shows how the valuations of DeFi protocols depend on key financial variables that represent their performance, such as total value locked, protocol revenue, total revenue, gross merchandise volume and inflation factor.

The study shows the results of the pairwise Granger causality tests for all variables and the results of the fixed effects panel regression model. The panel data analysis provides evidence that all five explanatory variables examined influence DeFi protocol valuations (TVL, total revenue and gross merchandise volume—positively; protocol revenue and inflation factor—negatively). Considering that for each explanatory variable studied there is a specific counterpart in the world of traditional finance (e.g., TVL corresponds to assets under management, total revenues to corporate profits, protocol revenues to the share of profits paid to investors, etc.), one can conclude that DeFi protocols' valuations follow very similar laws to those of traditional finance. As for the Granger causality tests, it could not be confirmed that future valuations of DeFi protocols can be effectively predicted based on knowledge of the TVLs of these protocols, while other directions of causality (unilateral and bilateral) were confirmed, e.g., a causal bilateral relationship between valuations of DeFi protocols and gross merchandise volume. As for the Granger causality tests, knowing the causal relationships between the variables (see Table 7) can serve to better understand the interdependencies between all variables.

Also, assessing of the correlations between valuations and TVLs for three different classes of DeFi protocols shows that the strongest relationship between DeFi protocol valuations and their respective TVLs is reported for asset management protocols and the weakest for decentralized exchanges (DEXes). In general, the steepest regression line is for the "Asset Management" class and the flattest for the "Decentralized Exchanges" class. It is thus clear that the TVL is relatively more important for "Asset Management" protocols, which seems logical since the performance of these protocols depends much more on the funds under management. To understand this better, an analogy can be drawn with mutual funds, whose valuations depend to a much greater extent (than for other companies in the financial sector, for example) on the amount of capital under management.

In summary, the study firstly confirms the relevance of the relationship between TVL and the performance of DeFi protocols (their valuations). TVL is the most popular indicator for evaluating DeFi projects. The panel analysis study confirms the strongest association of this indicator with valuations themselves, which should not surprise anyone. After all, TVL is considered the lifeblood of DeFi protocols, and without deposited capital, DeFi protocols could not thrive. Moreover, the idea of liquidity pools and yield farming is to offer often unimaginably high returns (over certain, usually short periods of time) in order to attract investors' attention (which can be interpreted as the cost of promoting the projects). On the other hand, the bicausal relationship between TVL and DeFi protocol valuations could not be confirmed. Second, the study highlights the need to consider metrics other than TVL, investor attention or associations with the classic cryptocurrency market (such as Bitcoin or Ethereum) when evaluating DeFi protocols (or selecting appropriate protocols in an investment context).

Third, the paper clarifies some DeFi-related definitions (for the metrics on which the study is based) that are also not found in the literature. While one can read about the GMV indicator in the context of some internet projects (mainly e-commerce) (Yan et al. 2017; Prokhorova 2020; Sharma 2021), few know that it can also be effectively used to evaluate DeFi protocols as an indicator (as confirmed by the results of our study and both Granger causality and panel data analysis). We also clarify the differences between protocol revenues and total revenues by justifying their relevance (importance) from the perspective of investors/market participants and DeFi protocol design teams. In particular, in the context of the latter (i.e., the design teams), we highlight that these issues form an important part of the design strategies they develop, which are later implemented in smart contracts.

Fourth, the study highlights the importance of controlling the supply of tokens in the investment policy of project development teams, while also pointing out that this is an important issue for participants in this market—and is not always perceived negatively. Very often, the additional supply of tokens is linked to the participation of users and market participants in the development of the protocols themselves (through governance tokens). Again, much depends on the strategy of a protocol and it is impossible to determine conclusively whether this will have a positive or negative impact on the future of the projects themselves. Often the performance of two projects with similar initial conditions will be different.

Fifth, the diversity of the DeFi market (which is not homogeneous) is explained in the paper. Within this market, there are different categories of business models, including decentralized exchanges, lending protocols and asset management protocols. In a simple experiment, shown in Figure 3, we can see that the sensitivity of valuations to inflows and outflows of funds is different for the different categories of DeFi protocols. This is reflected in the different elasticities of the regression lines (reflecting valuations regressed on the TVL values). As it turns out, the steepest regression line is for the Asset Management class and the flattest for the Decentralized Exchanges class. It is clear, then, that the TVL is relatively more important for the "Asset Management" protocols.

Finally, the practical application of the findings presented in this paper is that they contribute to a better understanding of what drives DeFi protocol valuations and what indicative performance metrics to look for. In other words, the paper contributes to systematizing knowledge about the determinants of DeFi protocol assessments. A fairly extensive literature review presented in the paper provides a better understanding of the importance of DeFi protocols as an alternative to traditional finance. Drawing on the literature on the subject, we identify a number of potential determinants of DeFi protocol assessments and investigate their relevance and robustness using two different scientific methods. The article can therefore be seen as a contribution to the broader debate on the valuation of DeFi protocols in the context of financial markets and the value of the assets these protocols represent. The empirical evidence and some conclusions presented in the article can be useful for both theorists and practitioners of the DeFi market.

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Appendix A

Below, in the form of Table A1, we give an overview of the most relevant studies dealing with DeFi protocols.

Table A1. Important works/studies dealing with DeFi protocols/project subject.

Authors	Subject
Abdulhakeem and Hu (2021)	Analysis of the DeFi market potential.
Werner et al. (2021)	Analysis of the DeFi ecosystem—primitives, types of protocols and security.
Chohan (2021)	Identification of key themes accompanying the emergence of the DeFi sector.
Qin et al. (2021b)	Comparison of DeFi and CeFi markets in terms of legal, economic and security aspects.
Meyer et al. (2021)	A systematic review of the literature on the fragmented field of DeFi studies.
Momtaz (2022)	Study on the effectiveness and role of intermediation in the large DeFi segment.
Jensen et al. (2021)	Taxonomic overview of agents, drivers and risks. Analysis of key market categories and applications of DeFi applications. Identification of key risk groups for potential DeFi market players (stakeholders).
Schueffel (2021)	An overview of the specificities (special features) of the DeFi market compared to traditional finance.
Caldarelli and Ellul (2021)	Analysis of the security of the DeFi ecosystem and in particular the oracle problem in DeFi.
Grassi et al. (2022)	An assessment of the role of financial intermediation in light of DeFi.
Wronka (2021)	An analysis and assessment of the new challenges posed by the emergence of DeFi (particularly in in relation to combating financial fraud in the DeFi ecosystem).
Schär (2021)	Analysis of the opportunities and potential risks associated with the DeFi ecosystem.
Calcaterra and Kaal (2021)	The role of finance in the development of decentralized systems.

Table A1. *Cont.*

Authors	Subject
Kitzler et al. (2021)	A study of the composition of protocols of decentralized finance. It shows the interplay (interaction) between DeFi protocols and associated smart contracts from a macroscopic perspective. The study provides a better understanding of financial products and assesses the systemic risk of the DeFi market.
Momtaz (2022)	Analysis of the role of intermediation in the efficiency of decentralized finance (DeFi) markets.
Xu and Xu (2022)	A study of business models of various DeFi protocols—in particular decentralized exchanges (DEXs), loanable funds protocols (LFPs) and yield aggregators.
Mohan (2022)	A study of the organisation of the DeFi market, including how automated market makers (AMMs) operate.
Bartoletti et al. (2021)	An overview of open challenges and opportunities for formal methods in DeFi. DeFi Theory.
Bekemeier (2021)	An analysis of the systemic risk of the DeFi ecosystem.
Saengchote (2021)	Analysis of stablecoin flows between DeFi protocols and evidence of DeFi's profit-chasing behaviour.
Makarov and Schoar (2022)	The modus operandi and mechanics of the new DeFi architecture. Potential benefits and challenges in the development of the DeFi market.
Sun et al. (2022)	Analysis of decentralized governance solutions (using MKR, DAI and Etherem as examples). The impact of centralized governance on a range of factors including finance, trading, exchange, network metrics and market sentiment.
Sun et al. (2021)	Security risks. A systematic way to find vulnerabilities in DeFi projects. Verification of financial models from smart contracts.
Şoiman et al. (2022)	Analysis of the DeFi market returns and valuations.
Piñeiro-Chousa et al. (2022)	Analysis of the relationship between returns on DeFi tokens, other traditional investments and user-generated content.
Wang et al. (2022)	Testing the existence and dates of price bubbles in the DeFi and NFT markets with the use of the SADF and GSADF tests.
Zmaznev (2021)	The impact of regulatory uncertainty shocks on total value locked in DeFi smart contracts.
Corbet et al. 2022	A comparative assessment of the factors influencing DeFi token prices.
Green et al. (2022)	An insight into user behaviour patterns and risk within the AAVE lending protocol. Survival analysis of DeFi lending protocols to discover and characterise user behaviour.
Maouchi et al. (2022)	A study of digital asset bubbles amid the COVID -19 pandemic (using a sample of 9 DeFi tokens). Signs of DeFi and NFT-specific bubbles in 2020 and 2021.

Source: own elabrotation.

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FinTech Entrepreneurial Ecosystems: Exploring the Interplay between Input and Output

Ekaterina Koroleva

Graduate School of Industrial Economics, Peter the Great St. Petersburg Polytechnic University, 195251 St. Petersburg, Russia; koroleva_ev@spbstu.ru

Abstract: This paper aims to examine the interplay between the attributes of the FinTech ecosystem (input) and productive entrepreneurship (output) in Russian regions. A survey was used to gather data from FinTech representatives in ten selected regions located in Russia. The acquired responses allowed measuring the FinTech ecosystem attributes by calculating the FinTech ecosystem index. Correlation analysis was used to analyse the association between the FinTech ecosystem index and productive entrepreneurship, as measured by the number of FinTechs. Data envelopment analysis was used to determine regions with more productive entrepreneurship given the ecosystem attributes. The FinTech ecosystem index defines a similar environment in the analysed regions for financial sector entrepreneurship. The regions have high values of physical infrastructure, demand, and talent, while new knowledge and networks appear as weaknesses. Still, Moscow has the highest and Chelyabinsk the lowest FinTech ecosystem index. There appears a positive link between FinTech ecosystem attributes and productive entrepreneurship. The Moscow and Chelyabinsk regions are also revealed as the regions that effectively create an environment for productive entrepreneurship from the position of the Fintech ecosystem index. This study contributed to the existing literature by measuring FinTech ecosystem attributes and productive entrepreneurship, investigating the relationship between them and determining the territories with productive entrepreneurship. It also contributed to Russian FinTech literature by being the first to measure the environment for financial sector entrepreneurship.

Keywords: FinTech; entrepreneurial ecosystem; input and output layers; attributes; productive entrepreneurship

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1. Introduction

An entrepreneurial ecosystem is a dynamically balanced system consisting of interdependent subjects and an entrepreneurial environment (Lu et al. 2021). Its input layer is based on attributes—conditions that allow or restrict entrepreneurship (Stam 2018). Productive entrepreneurship forms the output of an entrepreneurial ecosystem (Stam 2015). It refers to the innovation activity of entrepreneurs that contributes to the commercialisation of new ideas and knowledge and leads to economic growth in a certain territory (Aidis 2005; Acs and Szerb 2007).

The entrepreneurial ecosystem approach has gained prominence among scholars and practitioners in understanding an environment for productive entrepreneurship (Feld 2020; Szerb et al. 2019). However, the link between ecosystem attributes and productive entrepreneurship remains relatively unclear (Nicotra et al. 2018). Understanding this link is important to ensure the most favourable conditions for developing productive entrepreneurship, which can lead to economic growth in a particular territory.

This paper focuses on FinTech ecosystems (FEs); they are considered a type of entrepreneurial ecosystem that supports the development of FinTech companies (FinTechs), which are high-growth companies that disrupt or contribute to the provision of traditional financial services (Laidroo et al. 2021). FEs are characterised by the proliferation of FinTechs

(Alaassar et al. 2021), which are often presented by start-ups and apply innovation in the financial sector. In the first half of 2019, 48 FinTech unicorns, start-ups valued at over USD 1 billion, accounted for 1% of the global financial industry (CBInsights 2019). This emphasises the high entrepreneurial activity in a FinTech ecosystem (FE) and allows one to perceive it as an entrepreneurial ecosystem.

Previous studies on FEs have either analysed the interplay between its actors (Hendrikse et al. 2020; Lee and Shin 2018; Yazici 2019) or focused on measuring their attributes (Ernst and Young 2014; Findexable 2021; Gagliardi 2018; Laidroo et al. 2021; Sinai Lab 2020). The disadvantage of most suggested measurement tools is that they focus on official statistics or the views of experts. The early stages of an FE's development and a lack of accumulated statistics (Diemers et al. 2015) have led to not including significant attributes or relying on a mix of information covering different territory levels. In addition, the number of studies is focused on the risks related to FinTechs (Vasenska et al. 2021; Morales et al. 2022) or the efficient use of digital technologies (Popova 2021; Lewandowska et al. 2021).

Nevertheless, to our knowledge, there is no measurement tool for FE attributes based on a survey that would allow us to aggregate the opinions of the FinTech community about the entrepreneurship environment in the financial sector. This study attempts to fill these gaps in the context of Russian regions.

Therefore, the goal of the study is measuring FE attributes and productive entrepreneurship, investigating the relationship between them and determining territories with more productive entrepreneurship.

The context of Russia is an interesting case for investigation for the following reasons. In 2021, Russia emerged as a TOP-20 country in the Global FinTech Index, rising 13 positions from the previous year (Findexable 2021). Russia has also been ranked in the TOP-3 countries for applying innovative solutions in the financial sector (Kuhn 2021). According to Ernst and Young (2019), the FinTech Adoption Index in Russia amounted to 82% in 2019, exceeding the global average rate. The above-mentioned achievements indicate that Russia has cultivated a favourable climate for FinTech development.

In this study, we developed a survey tool for measuring FE attributes: the FE index. This index extends previous conceptual and empirical work on entrepreneurial and FE ecosystems (Feld 2020; Isenberg 2011; Neck et al. 2004; Spigel 2017; Stam and van de Ven 2019; Szerb et al. 2019; Findexable 2021; Sinai Lab 2020; Laidroo et al. 2021). Two approaches—additive and multiplicative—were used to calculate the FE index.

There is no consensus in the ecosystem literature on the level of analysis—city, region, country, or other levels. This study is based on the regional level, like other empirical research on ecosystems (DeFries and Nagendra 2017; Leendertse et al. 2021; Stam 2018). The suggested tool for measuring FE attributes was tested for 10 Russian regions where most FinTechs are located.

The FE index recognises a similar environment in the analysed regions for financial sector entrepreneurship. These regions have high estimates of physical infrastructure, demand, and talent. New knowledge and networks appear to be this environment's weak sides in terms of financial sector entrepreneurship. Among these regions, Moscow has the most favourable environment for entrepreneurship in the financial sector. Such attributes as finance and leadership mostly determine Moscow's superiority over other regions. At the same time, the Chelyabinsk region has the lowest FE index value.

The correlation analysis showed a positive link between FE attributes and productive entrepreneurship, as measured by the number of FinTechs. Data envelopment analysis (DEA) indicated territories with productive entrepreneurship. With the additive FE index, Moscow was recognised as a region that has effectively created an environment for productive entrepreneurship. Regarding the multiplicative FE index, the Chelyabinsk region achieved the best results. The contrary results can be explained by the features of the FE index calculation and highlight the importance of choosing an adequate measure of FE attributes. The results of the DEA analysis also indicate that the physical infrastructure and demand in Russian regions are underutilised by entrepreneurs. In addition, the results highlight finance, intermediate services, and formal institutions as attributes maximally used by entrepreneurs and require additional attention from policymakers for entrepreneurship development. Improving the understanding of FE attributes and their links to productive entrepreneurship would benefit both policymakers and entrepreneurs.

This paper contributes to the literature on entrepreneurial ecosystems (Stam 2018; Stam and van de Ven 2019; Mateos and Amorós 2019; Villegas-Mateos 2020; Leendertse et al. 2021) by supporting a positive link between an ecosystem's attributes and productive entrepreneurship. Based on this link, this current research provides a tool for identifying territories with productive entrepreneurship.

This paper contributes to the FinTech literature in several respects. It extends the literature on measuring FE attributes (Ernst and Young 2014; Gagliardi 2018; Findexable 2021; Sinai Lab 2020; Alaassar et al. 2021; Laidroo et al. 2021) by developing a survey-based approach. It also contributes to the FinTech literature in Russia (Kleiner et al. 2020; Koroleva et al. 2021; Vaganova et al. 2020) by being the first to measure FE attributes.

This article is structured as follows. The theoretical and empirical backgrounds are summarised in Section 2. The methodology and data are presented in Section 3. Section 4 concentrates on the results of this study. Finally, Section 5 provides a discussion and conclusion.

2. Literature Review

2.1. Entrepreneurial and FinTech Ecosystems

Several studies (Spigel 2017; Stam 2015) indicate that an entrepreneurial ecosystem approach can be used for synthesising academic research on entrepreneurship and its regional developments. This approach supposes the analysis of two main layers: the attributes of an ecosystem (input) and productive entrepreneurship (output). The connection between attributes and productive entrepreneurship is difficult to explain due to their interdependence. Attributes influence productive entrepreneurship, but over time, output also feedbacks into input (Stam 2015).

The main challenge in identifying attributes arises from entrepreneurial ecosystems' diverse origins and complexity (Spigel 2017). Although there is no universal approach to classifying the attributes of entrepreneurial ecosystems, different scholars and practitioners have attempted to create classifications and tools for measuring them. Table 1 summarises the classifications of entrepreneurial ecosystem attributes found in the literature. The relevant articles were collected from the 2004–2020 Scopus database using the keywords 'attributes of entrepreneurial ecosystem' and 'elements of entrepreneurial ecosystem'.

Table 1. Overview of entrepreneurial ecosystem attributes.

Research	Formal Institutions	Entrepreneurship Culture	Physical Infrastructure	Demand	Networks	Finance	Leadership	Talent	New Knowledge	Intermediate Services
Stam (2015); Stam and van de Ven (2019); Leendertse et al. (2021)	+	+	+	+	+	+	+	+	+	+
Szerb et al. (2019)	+	+	-	-	+	+	+	+	+	-
Nicotra et al. (2018)	+	+	-	-	+	+	-	+	+	+
Spigel (2017)	+	+	+	-	+	+	+	+	+	+
Liguori et al. (2018); Isenberg (2011)	+	+	+	-	+	+	+	+	-	+
Cohen (2006); Neck et al. (2004)	+	-	-	-	+	+	-	+	-	+

Note: + means the research includes the attribute and - means that it does not include it.

The comparison of entrepreneurial ecosystem attributes was based on Stam's (2015) model because it provides the most comprehensive view of an entrepreneurial ecosystem, including institutional arrangements and resource endowment elements. This model consists of 10 attributes: formal institutions, entrepreneurship culture, networks, physical infrastructure, finance, leadership, talent, new knowledge, demand, and intermediate services.

Formal institutions reflect the regulation and role of the government in ecosystem formation. Entrepreneurship culture characterises the value of entrepreneurship. It consists of an entrepreneur's innovativeness, willingness to take risks, self-organisation, and motivation. Physical infrastructure includes transport and digital infrastructure, which support the development of entrepreneurship. Demand reflects the readiness of customers to buy products or use services. Networks reflect collaboration between actors and their readiness for equal dialogue. Finance reflects access to different financial resources. Leadership characterises actors taking a leadership role in an entrepreneurial ecosystem. Talent covers the labour market and higher education. This represents the availability of highly qualified training of entrepreneurs or specialists in the market who support entrepreneurs in the process of starting a business. R&D investments are included in the attributes of the entrepreneurial ecosystem as new knowledge. Intermediate services characterise support by informal institutions, such as incubators or accelerators. In this paper, we also relied on Liguori et al. (2018) while developing a survey covering FE attributes.

Most attempts to measure FE attributes have been made by analytical companies. Sinai Lab (2020) created the Global FinTech Hub Index as an expansion of applying another index—the China FinTech Hub Index. This index is based on three perspectives, enterprise, consumer, and government, and ensures the cross-comparability of data from different countries. The Global FinTech Index (Findexable 2021) consists of three metrics, the number of FinTechs, the number of unicorns, and the environment, and ignores quality information about FE attributes. The developers of this index explained the choice of metrics using their own and their partners' experiences. According to Ernst and Young (2014), it is adequate to highlight four main FE attributes—talent, capital, policy, and demand—and estimate them from the opinions of experts. The report by Gagliardi (2018), based on 15 interviews with renowned experts, followed FE attributes: demand drive, systemic linkages, and regulatory oversight.

Practitioners' indices determine an FE's key attributes. First, it is an activity of formal institutions. Developing FinTech-friendly regulations and special state programmes contributes to developing entrepreneurship in the financial sector. Then, demand reflects the popularity of FinTech services among customers. Finance, talent, and networks are used at least once in calculating corresponding indices. Nevertheless, the indices suffer from a lack of theoretical background and are based on developers' experience. This means that indices may ignore the significant attributes and complexity of a FinTech ecosystem. A lack of accumulated statistical resources leads to basing these indices on a mixture of information covering different territories (country versus region).

Academics have suggested alternative approaches to measuring FE attributes. Based on the ecosystem index by Stam and van de Ven (2019), Laidroo et al. (2021) developed the additive FE index at the country level. We highlight the importance of IT infrastructure and FinTech regulation and reveal these elements as separate attributes of an FE. The disadvantage of this index is the unequal weight of the attributes. To our knowledge, no further attempts have been made to measure FE attributes.

A healthy entrepreneurial ecosystem generates productive entrepreneurship as an output. The term productive entrepreneurship lacks a single agreed-upon definition. Productive entrepreneurship reflects any activity that contributes to the net output of an economy. For Aidis (2005), this refers to innovative actions that result in an economically productive business. Acs and Szerb (2007) emphasise that productive entrepreneurship enables the creation and commercialisation of valuable knowledge.

Considering these definitions, it is possible to determine the main characteristics of productive entrepreneurship. First, productive entrepreneurship contributes to economic growth, including job creation. Then, it generates innovation. Finally, it is a way of commercialising new ideas and knowledge. In the framework of this current research, productive entrepreneurship is understood as an innovation activity that contributes to the commercialisation of new ideas and knowledge and leads to economic growth in a certain territory. In Section 3.2 of this paper, a measure of productive entrepreneurship is suggested based on the proposed definition.

2.2. Developing the Conceptual Framework

In line with previous research, applying the ten attributes of an entrepreneurial ecosystem may require adjustments when considering an FE (see Table 2).

Table 2. Attributes of an FE.

Attribute	Description
Formal institutions	The extent to which a government supports the FinTech activity
Entrepreneurship culture	The extent to which entrepreneurship is valued
Physical infrastructure	The extent to which potential customers of FinTech services have access to the internet
Demand	The extent to which potential customers adopt FinTech services
Networks	The extent of communication between actors within the FE framework
Leadership	Leadership that guides and directs collective action
Talent	The extent of individuals with skills adequate for FinTech development
Finance	The amount of capital invested in FinTechs
New knowledge	Investments in new knowledge
Intermediate services	The supply and accessibility of intermediate business services

The classification of FE attributes includes the attributes mentioned in previous research and ensures a comprehensive FE view.

Formal institutions identify the rules of organising a business and of government supporting FinTech entrepreneurship. The FinTech sector is connected to applying innovations, which are often restricted by compliance with certain regulations (Bromberg et al. 2017). Entrepreneurship culture covers the propensity for entrepreneurship, including its popularity and the attitudes of the society. It is also based on the history of successful FinTechs, among other aspects. It can provide benefits and resources for potential entrepreneurs regarding how to best organise a business in the FinTech sector. Physical infrastructure reflects the possibility of customers receiving FinTech services, which require the use of web resources. This would be impossible without the creation of certain physical infrastructure. Demand is critical to the health of any sector, especially the nascent FinTech sector (Ernst and Young 2014), and is identified by customers' readiness to use FinTech services.

Spigel (2017) insisted on the different emphases of actors and their roles in an ecosystem framework. However, it is necessary to ensure equal access to actors and terms for a network to develop entrepreneurship in the financial sector (Brush et al. 2019). Leadership guides collective action (Stam and van de Ven 2019) and identifies trends in the financial sector. This leadership is critical in building and maintaining a healthy ecosystem (Feldman 2014). The ease of creating a team to start a FinTech project or to find a suitable candidate for an employment vacancy also contributes to developing entrepreneurship in the financial sector. Talent emphasises the relevance of the availability of potential employees with suitable IT and business skills and adequate experience in the financial sector.

Within an FE, access to financing is a critical attribute that ensures the growth of individual companies and the entire industry. That is why it is relevant to develop bank credits and alternative financing (e.g., venture capital, business angels, etc.). To apply innovative solutions, it is necessary to invest in and develop them. Therefore, new technological knowledge is highlighted as one FE attribute. Intermediate services include support from informal institutions, such as incubators and accelerators. Organisations create accelerator programmes and coworking spaces (Block et al. 2018). They also connect investors to promising FinTechs, which broadens their financing possibilities (Alaassar et al. 2021).

2.3. Level of Analysis

There is no consensus in the entrepreneurial ecosystem literature regarding the level of analysis of entrepreneurial ecosystems—city, region, country, or other levels. Relevant boundaries of an entrepreneurial ecosystem are difficult to identify due to their openness. Each attribute of an ecosystem can have its own boundaries (Leendertse et al. 2021). Government support is limited by the governmental level (i.e., municipal, regional, or national). The development of physical infrastructure is identified by localities. The training of qualified personnel for entrepreneurship depends on an educational institution's location. New knowledge can be identified by the location of the innovation centres.

Kuckertz (2019) distinguished between the administrative, spatial, and conceptual boundaries of an entrepreneurial ecosystem. DeFries and Nagendra (2017) insisted on the necessity of going beyond administrative boundaries to involve stakeholders in an entrepreneurial ecosystem. Leendertse et al. (2021) focused on the analysis of entrepreneurial ecosystems at the regional level (i.e., between the municipal and national levels). However, entrepreneurs' activities are not restricted by cities or regions and can go beyond a specific country. Entrepreneurs can also be actors in several entrepreneurial ecosystems or connectors of ecosystems on a global scale (Malecki 2011). Nevertheless, ecosystem management is place-based (Roundy et al. 2018), which is why, in the framework of this current research, the defining of entrepreneurial ecosystem boundaries is possible.

Experience in measuring FE attributes also shows different levels of analysis. Laidroo et al. (2021) concentrated on the country level. Ernst and Young (2014) and Sinai Lab (2020) focused on the city level. Findexable (2021) published the Global FinTech Index on two levels simultaneously: country and cities.

In this current study, the theoretical background is the entrepreneurial ecosystem approach. Based on the results of highly cited research on entrepreneurial ecosystems (DeFries and Nagendra 2017; Leendertse et al. 2021; Stam 2018), we focused on a regional-level analysis of FEs.

3. Data and Methodology

3.1. Initial Data

In the framework of this research, a FinTech is defined as a company that contributes to the provision of financial services and has generally innovative information technology elements in its activities. It can be an independent or bank-owned company. To measure FE attributes and productive entrepreneurship and investigate the relationship between them, it was necessary to collect data on FinTechs in Russian regions. To collect data on companies, different official data sources were analysed (e.g., banks' and accelerators' websites, media)[1]. As a result, a list of 332 companies was compiled and registered in 2020 in a certain region of Russia. The distribution of FinTechs across the Russian regions is presented in Table 3.

FinTechs' uneven regional distributions may indicate different stages of development and distribution of FinTech services. To achieve the goal of this research, 10 identified regions were selected for further analysis. Based on Stam's (2015) model, the data on FE attributes were collected mostly via an online survey and covered the conceptual framework developed earlier. The focus group for the survey comprised FinTech owners, board members, or executives. Table 4 presents empirical indicators of each attribute, source, and scale.

Table 3. The distribution of FinTechs across Russian regions.

Region	FinTechs	
	Number	Share (%)
Moscow	272	81.93
St. Petersburg	16	4.82
Republic of Tatarstan	6	1.81
Sverdlovsk region	5	1.51
Novosibirsk region	4	1.20
Nizhny Novgorod region	3	0.90
Perm region	3	0.90
Voronezh region	3	0.90
Chelyabinsk region	3	0.90
Rostov region	3	0.90
Other regions	14	4.22
Total:	332	100.00

Table 4. Indicators for measuring the FE Index.

Attribute	Empirical Indicator	Source	Scale
Formal Institutions	Presence of special FinTech programs	Survey	1 to 5 (best)
	FinTech-friendly regulatory legislation	Survey	1 to 5 (best)
Entrepreneurship culture	Risk-taking	Survey	1 to 5 (best)
	Doing business	Survey	1 to 5 (best)
Physical infrastructure	Companies using the internet (as % companies)	Official statistics of regions	0 to 100 (best)
	Internet users (as % population)	Official statistics of regions	0 to 100 (best)
Demand	Using the Internet for financial transactions (companies)	Official statistics of regions	0 to 100 (best)
	Using the Internet for financial transactions (population)	Official statistics of regions	0 to 100 (best)
Networks	Dialogue between actors	Survey	1 to 5 (best)
	Equal terms of competition	Survey	1 to 5 (best)
Leadership	Initiative of entrepreneurs	Survey	1 to 5 (best)
	Presence of leadership	Survey	1 to 5 (best)
Talent	Ease of creating a team	Survey	1 to 5 (best)
	Ease of finding an employee	Survey	1 to 5 (best)
Finance	Access to information about financing possibilities	Survey	1 to 5 (best)
	Ease of access to financing	Survey	1 to 5 (best)
New knowledge	R&D cooperation	Survey	1 to 5 (best)
		Survey	1 to 5 (best)
Intermediate services	Availability of incubators and accelerators	Survey	1 to 5 (best)
	Availability of advisers	Survey	1 to 5 (best)

The initial idea was to develop the FE index based only on the survey results. After designing the draft survey, a pre-test was performed on five respondents to define any inadequate and potentially ambiguous expressions. Most respondents reflected that they were not competent in assessing demand and physical infrastructure. Therefore, information on these attributes was added from official statistics. Data collected from official statistics reflected the situation in specific regions at the end of 2021. The final survey questionnaire and its correspondence to empirical indicators and sources are presented in Appendix A.

Google Forms was used as the main survey platform. The survey was carried out from May to August 2021 by representatives of Russian FinTechs. Links to the online questionnaire were sent to FinTechs via email or by mobile application in the framework of the conference TechWeek (31 May–2 June 2021). Suitable emails were determined based on the data presented on the companies' web pages or were found via personal contacts. The first email was followed by two to three reminders.

As a result, the dataset includes 137 responses: 100 from Moscow, 10 from Saint Petersburg, 5 from the Sverdlovsk region, 4 from the Novosibirsk region, 3 from each the Republic of Tatarstan, Nizhny Novgorod, Perm, Voronezh, Chelyabinsk, and Rostov regions. For Moscow, St. Petersburg, and the Republic of Tatarstan, the survey covered part of FinTechs' population. This is explained by the large number of FinTechs in the regions, which led to the necessity of assessing the severity of the sampling bias. For other regions, the survey covered all representatives of FinTechs.

To assess the severity of sampling bias, the representativeness of the sample was tested using a chi-square test statistic and two indicators: the type of FinTech owner and Skolkovo membership. Skolkovo is an innovation centre that aims to develop technology entrepreneurship and research in Russia. To benefit from Skolkovo, FinTechs aim to be a member of the innovation centre. The choice of indicators is explained by the availability of relevant information. In the case of the presence of several types of owners in one company, all were included in a further analysis. Therefore, the number of owners can be greater than the number of FinTechs.

It was necessary to test whether the distribution of FinTechs in the sample was the same as in the original sample. These and further calculations were carried out in the STATA. The results of the chi-square test are presented in Table 5.

Table 5. Comparison of sample and original distributions.

	Moscow		
The owner of FinTechs	Observed	Expected	Pearson
Bank	38	29	1.671
Individual	53	46	1.032
Company (not bank)	17	20	−0.671
VC fund	7	6	0.408
	Pearson chi2 test (3) = 4.4750 Pr = 0.215		
FinTech is a member of Skolkovo	Observed	Expected	Pearson
Yes	15	17	−0.485
No	85	83	0.220
	Pearson chi2 test (1) = 0.2835 Pr = 0.594		
	St. Petersburg		
The owner of a FinTech	Observed	Expected	Pearson
Bank	0	0	-
Individual	7	10	−0.949
Company (not a bank)	4	2	1.414
VC fund	2	3	-0.577
	Pearson chi2 test (3) = 3.233 Pr = 0.199		
FinTech is a member of Skolkovo	Observed	Expected	Pearson
Yes	4	3	0.577
No	6	7	−0.378
	Pearson chi2 test (1) = 0.4762 Pr = 0.490		
	Republic of Tatarstan		
The owner of FinTech	Observed	Expected	Pearson
Bank	0	0	-
Individual	3	3	-
Company (not bank)	1	1	-
VC fund	1	1	-
	Pearson chi2 test (3) = 0.0000 Pr = 1.000		
FinTech is a member of Skolkovo	Observed	Expected	Pearson
Yes	1	1	-
No	2	2	-
	Pearson chi2 test (1) = 0.0000 Pr = 1.000		

Insignificant *p*-values (Pr) in all cases imply that the distribution of the sample accords with the analysed regions' population statistics.

3.2. Methodology

This section is structured according to the goal of the study. First, the author suggests the approaches of measuring the FE attributes and productive entrepreneurship. Then, the tool of evaluating the association between the identified indicators is discussed.

3.2.1. Calculating the FE Index

To map FE attributes, the FE index was constructed. This index compares different regions and ranks them in terms of a set of indicators. The algorithm for constructing the FE index was developed based on existing studies (Stam 2018; Stam and van de Ven 2019; Leendertse et al. 2021; Laidroo et al. 2021) and by considering the limitations of the developed measures of ecosystem attributes.

Constructing the FE index included five main stages. The first step was to calculate the average value of the empirical indicators measured by the survey. According to the information presented in Table 4, the scales of the indicators differed. The second step was to normalise the scales of the indicators. To index formalisation, it was necessary to ensure equal weight (Leendertse et al. 2021). Therefore, indicators from official statistics were adapted to a Likert scale (from 1 to 5 (best)).

The third step was the reduction of FE indicators to a comparable value. This was achieved by normalising the average value of each indicator to 1 (Stam 2018). This means that indicators in the regions performing below average have a value below 1, while indicators performing better than average have a value above 1. The fourth step consisted of ensuring the same weight of attributes in the FE index. Each ecosystem attribute was represented by two indicators. The same number of indicators for each attribute ensures the same weight in the FE index. In future research, the weighing methodology may change based on the opinions of experts or the professional community.

Finally, the value of the attributes was summed into one index. The index value remained close to 10. This means that the regions performing on average for all scoring attributes had an index value of 10. Regions performing higher than average for all scoring attributes had an index value greater than 10, while regions performing lower than average for all scoring attributes had an index value lower than 10.

Stam (2018) also analysed complex interactions among entrepreneurial ecosystem attributes and suggested calculating a multiplicative ecosystem index. This leads to index values with a much larger variation. In this research, two approaches to calculating the FE index were also used. The suggested approach overcame the limitations of previous measures of ecosystem attributes via these aspects.

First, the survey-based approach provided the opportunity to represent the opinions of many representatives of FinTechs. As a result, the data gathered better describe an ecosystem's attributes (Mathers et al. 1998). To assess the severity of sampling bias, the representativeness of the sample was tested using the chi-square test statistic with different criteria. The survey-based approach ensured the comparability of the collected data using the same questions in the same way. Second, the survey-based approach allowed for the collection of data within a particular territory and avoided the use of information from different territory levels to assess the attributes of ecosystems at a certain level. The normalisation of the scales of the indicators ensures their equal weight-to-index formalisation.

3.2.2. Indicating the Productive Entrepreneurship

There is no universal measure of productive entrepreneurship. The literature review by Nicotra et al. (2018) revealed three approaches to measuring entrepreneurship: gross-based, assumption-based, and performance-based. Gross entrepreneurship focuses on the net entry of regional indicators. For example, Piergiovanni et al. (2012) analysed the growth of companies in specialised industries. Carree and Thurik (2008) focused on changes in labour productivity at the regional level. The assumption-based approach to productive entrepreneurship focuses on the survival of start-ups. Coad and Rao (2008) indicated that innovation-based start-ups are more survival-oriented than not. Thus, innovation-based start-ups can be a possible indicator of productive entrepreneurship.

Performance-based productive entrepreneurship focuses on the number of high-growth start-ups as an indicator. According to Acs and Szerb (2007), high-growth start-ups play a special role in contributing to the economic growth of territories. Leendertse et al. (2021) suggested focusing on the number of gazelles—companies that increase their revenue by at least 20%, starting from a revenue base of USD 1 million. Acs et al. (2017) insisted on using a stronger term: the number of unicorns.

Measuring productive entrepreneurship in Russian regions is not an easy task. The official statistics of Russian regions do not allow diversification of indicators—labour productivity or gross regional product—depending on a specific industry (including FinTech). There are also no unicorns in Russia (Stas 2021). We also found no gazelles in the Russian regions. Based on an assumption-based approach to productive entrepreneurship, the number of FinTechs is identified as a possible measure. Thus, FE attributes were measured by the FE index, and productive entrepreneurship by the number of FinTechs.

3.2.3. Testing the Association between the FE Index and Productive Entrepreneurship

To analyse the links between the indicators, a correlation analysis was conducted on a dataset of 10 Russian regions. This was selected partly because correlation analysis was the most common tool used in previous studies (Stam 2018; Stam and van de Ven 2019). However, the small sample size reduced the relevance of the regression analysis.

DEA was used to estimate the efficiency of Russian regions using FE attributes in productive entrepreneurship. This method was originally developed for the efficiency measurement of different units and is widely used in the context of entrepreneurship (Lafuente et al. 2018; Pandey 2018). DEA is a nonparametric approach based on linear programming that determines the efficiency level for each unit in a sample. The efficiency level of the decision-making units (DMUs) was identified in comparison with the best unit in the sample by deriving the compared efficiency. DEA calculates a single relative ratio for each DMU in a sample by comparing input and output information.

In the context of this current research, the DMU was a particular region in Russia, the input was the value of the FE index, and the output was the number of FinTechs. The main advantage of DEA is its ability to compare diverse and heterogeneous inputs–outputs simultaneously, with no assumption about the data distribution (Lee and Ji 2009). The number of DMUs should be not less than the multiplication of the numbers of outputs and inputs and not less than three times the sum of the numbers of outputs and inputs (Cooper et al. 2007). Therefore, the DEA analysis based on 10 regions in Russia was considered fair. The DEA efficiency value ranged from 0.0 to 1.0. Regions with a DEA efficiency value equal to 1.0 were considered effective. Regions with an efficiency value lower than 1.0 were considered ineffective.

Two types of DEA are widely used by researchers. They are input-oriented (focused on the minimisation of input information) and output-oriented (focused on the maximisation of output information) analyses. In the framework of this research, the DEA model was oriented towards the output. Policymakers and entrepreneurs aim to engage in a created environment by maximally developing entrepreneurship in a region.

DEA allows for determining slacks (Sharma et al. 2009), represented by the magnitude of inefficiency in particular inputs. Due to slacks, we additionally analysed the separate attributes of FEs and indicated ones that used inefficiency in a certain Russian region.

4. Results

4.1. The FE Index

Based on the algorithm discussed in Section 3.2, the distribution of the average values of FE attributes (normalised to one scale) in Russian regions is presented in Appendix B.

In the analysed regions, the attributes' values are distributed similarly. This indicates a similar approach to creating an environment to develop entrepreneurship in the financial sector. The regions have high-quality physical infrastructures. Ninety percent of the population (or companies) in the Russian regions has access to the internet. This means that around 90% of the population or companies are potential customers of FinTech services. This number is comparable to the value of the 2019 FinTech Adoption Index in Russia. According to Ernst and Young (2019), 82% of people have used FinTech services.

Physical infrastructure influences customers' adoption of FinTech services and customers' related demands. In the case of Russian regions, demand achieves sufficiently high evaluations. It reflects a significant portion of customers, including companies, who use the internet for financial transactions. The attribute talent evaluated highly. If the founders of FinTechs do not have adequate knowledge, they will need a team of experts with such knowledge to support the launch of a FinTech (Koroleva et al. 2021). A high score for this attribute means that the representatives of FinTechs do not encounter the problem of finding experts with knowledge supporting a FinTech's launch in Russian regions.

New knowledge and networks are recognised as the weak sides of the environment for entrepreneurship in the financial sector. According to the opinions of FinTech representatives, organisations are not investing enough in R&D. The application of innovative solutions is associated with difficulties in legislation and the risk of customers' negative attitudes towards a service (Arner et al. 2017; Chuang et al. 2016). Therefore, companies are not very interested in scientific developments and prefer to suggest services based on proven solutions.

In addition, an ecosystem's actors have unequal access to the financial sector. The feature of FinTech development in Russia is the superiority of banks and the state (Stas 2021). Currently, the focus of the Central Bank of Russia is to create an infrastructure environment (e.g., remote identification, a fast payment system, etc.) that would provide equal access and ensure competition for each FE actor. However, despite the Central Bank's efforts, evaluations of networks remain low.

Intermediate services (support of incubators, accelerators, or other advisers) receive high evaluations in Moscow, St. Petersburg, and the Republic of Tatarstan. Most intermediate services in Russia are in innovation centres. A significant share of FinTechs that participated in the survey were Skolkovo members. Perhaps such high values are due to this aspect.

In comparison with other regions, Moscow has high values in leadership. This can be explained by the location of the Central Bank of Russia and most cluster organisations in the financial sector. Moscow also has a sufficiently high evaluation of access to finance. Generally, alternative financing has not developed in Russia compared to other countries (Lyasnikov et al. 2017). Nonetheless, Moscow is more attractive for FinTech entrepreneurship than other regions. Most exhibitions and competitions for obtaining additional financial resources are held in Moscow. Therefore, for FinTechs, it is easier to acquire information about possible financing and to participate in competitions there. Finance and leadership mostly determine Moscow's superiority over other regions.

With the implementation of the proposed algorithm, the following results were obtained with the additive FE index (see Figure 1).

Moscow, St. Petersburg, and the Republic of Tatarstan perform better than the average for most attributes and had an index value higher than 10. The Novosibirsk and Nizhny Novgorod regions have FE index values of around 10 (9.73 and 9.6, respectively). Other regions performed lower than average for most attributes and had an index value below 10.

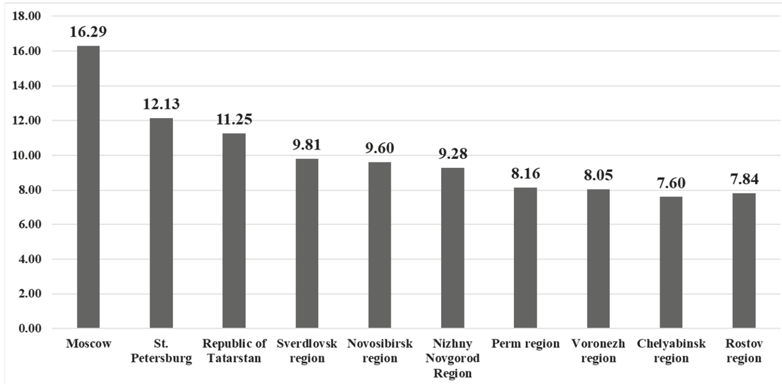

Figure 1. Additive FE index for Russian regions.

The maximum ranges of attribute evaluations are in intermediate services, finance, and formal institutions. This highlights the differences in access to finance, local and state programmes, and support from intermediate business services in the regions. Demand and physical infrastructures varied the least and achieved high evaluations. This shows the relevance of internet access and customers' readiness to use FinTech services in all Russian regions.

The disadvantage of the additive FE index is that attributes with above-average evaluations have a stronger effect on the index than do attributes with below-average values. Supporting Stam (2018), the results of the calculation of the multiplicative FE index are presented in Figure 2. The multiplicative FE index has a variation much larger than the additive index.

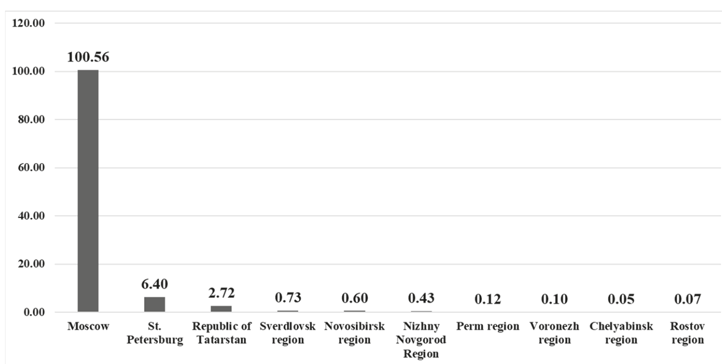

Figure 2. Multiplicative FE index for Russian regions.

As expected, the multiplicative FE index highlights a significant gap in all attributes of Moscow from other regions but does not contradict the conclusions drawn from the additive FE index. Considering the complex and nonlinear relationship between an entrepreneurial ecosystem's attributes (Stam 2018), we support that the multiplicative index is superior to the additive index.

4.2. Relationship between FE Attributes and Productive Entrepreneurship

To test the link between FE attributes and productive entrepreneurship, a correlation analysis was conducted (see Table 6).

Table 6. Relation between FE attributes and productive entrepreneurship.

Correlation Coefficient	Additive FE Index	Multiplicative FE Index
Number of FinTechs	0.85 ***	0.99 ***

Note: *** $p < 0.001$.

Both FE indices were positively and statistically correlated significantly with the number of FinTechs. This result supports the positive association between FE attributes (input) and productive entrepreneurship (output).

Applying DEA allows for defining Russian regions with productive entrepreneurship, considering the value of the FE index. The results are presented in Table 7.

Table 7. Identification of efficient Russian regions, comparing values of the FE index with productive entrepreneurship.

Region	Additive FE Index		Multiplicative FE Index	
	Rank	Efficiency Value	Rank	Efficiency Value
Moscow	1	1.000	8	0.049
St. Petersburg	2	0.079	9	0.046
Republic of Tatarstan	3	0.032	10	0.040
Sverdlovsk region	4	0.031	6	0.125
Novosibirsk region	5	0.025	7	0.121
Nizhny Novgorod region	10	0.019	5	0.126
Perm region	9	0.022	4	0.445
Voronezh region	8	0.022	3	0.543
Chelyabinsk region	6	0.024	1	1.000
Rostov region	7	0.023	2	0.785

Using different approaches to calculate the FE index led to opposite results. This can be explained by differences in the initial data. Moscow has a 1633.16 times higher multiplicative FE index value than the Chelyabinsk region and a 2.12 times higher value with the additive FE index. Such a huge difference in measuring the environment for entrepreneurship in the financial sector led to contrary results and highlights the importance of choosing adequate measures for FE attributes.

The results based on the additive index indicate that Moscow is the region that effectively creates an environment for productive entrepreneurship. The results of the multiplicative index rank the Chelyabinsk region as the most efficient. Recall that this region received the lowest FE index value. The recognition of a region as effective means that it makes the most of the environment created in the region for productive entrepreneurship in the financial sector.

The DEA analysis, by additionally calculating slacks, revealed attributes with enough high value and that are underutilised by entrepreneurs in their activities within the framework of the financial sector. The results are presented in Table 8.

Table 8. The slack of inefficient Russian regions.

	Formal Institutions	Entrepreneurship Culture	Physical Infrastructure	Demand	Networks	Leadership	Talent	Finance	New Knowledge	Intermediate Services
Moscow	-	-	-	-	-	-	-	-	-	-
St. Petersburg	0.03	0.03	0.04	0.04	0.05	0.01	0.04	-	0.03	0.03
Republic of Tatarstan	0.01	0.02	0.03	0.03	0.03	-	0.02	0.01	0.03	0.03
Sverdlovsk region	0.02	0.02	0.05	0.05	0.03	0.02	0.03	0.02	0.04	-
Novosibirsk region	0.01	0.04	0.03	0.03	0.02	0.02	0.03	0.01	0.02	-
Nizhny Novgorod region	0.01	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.01	-
Perm region	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01	-
Voronezh region	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.01	-
Chelyabinsk region	0.01	0.01	0.03	0.03	0.02	0.01	0.01	0.01	0.01	-
Rostov region	0.02	0.02	0.04	0.04	0.02	0.02	0.02	0.01	0.03	-

In the context of Russian regions, physical infrastructure and demand are attributes underutilised by entrepreneurs in their financial sector activities. The insufficient use of attributes is explained by the insufficient development of other attributes. This was also visible in Spigel (2017), who showed a significant dependence between attributes in an ecosystem.

Finance, intermediate services, and formal institutions are identified as attributes maximally used by entrepreneurs and require additional attention from policymakers for developing entrepreneurship. This partly supports the conclusions made earlier in the results of analysing the FE index. In Russian regions, alternative finance (e.g., venture capital, business angels, etc.) is poorly developed. Most FinTechs are financed by their owners (Koroleva et al. 2021). Intermediate services are located mostly near innovation centres. Therefore, support from incubators or accelerators is accessible only to members of these centres. Formal institutions highlight the necessity of developing FinTech-friendly legislation and special state programmes. Thus, improving the understanding of FE attributes and their links to productive entrepreneurship could benefit policymakers and entrepreneurs.

5. Conclusions and Discussion

This paper provides evidence of the relationship between FE attributes and productive entrepreneurship in regions of Russia. We propose a survey-based tool for measuring the attributes of FEs that seems to properly capture underlying phenomena. This approach expands the application of Stam's (2015) model and Liguori et al.'s (2018) perceptual measure to FEs in terms of measuring attributes. The suggested approach provides the opportunity to represent the opinions of many FinTech representatives. A survey-based approach allows for the consideration of FEs' uniqueness and remains flexible in terms of covered territory.

The creation of a favourable environment for entrepreneurship had a positive association with productive entrepreneurship in the financial sector of Russian regions. In addition, the DEA analysed the regions with productive entrepreneurship, based on the results of measuring FE attributes. These results can help policymakers and entrepreneurs understand the strengths and weaknesses of a certain region's environment and use them to accelerate business activity in the financial sector. The results of the DEA analysis support Spigel (2017) in matters of the interdependence of an FE's attributes and highlight the need for more balanced development of an entrepreneurial environment in the financial sector.

This paper extends the literature on measuring FE attributes (Ernst and Young 2014; Gagliardi 2018; Findexable 2021; Sinai Lab 2020; Alaassar et al. 2021; Laidroo et al. 2021) by developing a survey-based approach. It also contributes to FinTech research in Russia (Kleiner et al. 2020; Koroleva et al. 2021; Vaganova et al. 2020) by being the first to measure FE attributes in regions of Russia. The approbation of the algorithm determines a similar approach for creating an environment to develop entrepreneurship in the financial sectors of different regions. The regions have sufficiently developed physical infrastructures and high demand for FinTech services. New knowledge and networks were defined as weak aspects of the entrepreneurial environment in Russia's financial sector. It is also possible to highlight the unbalanced development of FE attributes throughout the regions.

This paper contributes to the literature on entrepreneurial ecosystems (Stam and van de Ven 2019; Mateos and Amorós 2019; Villegas-Mateos 2020; Leendertse et al. 2021) by analysing the link between ecosystem attributes and productive entrepreneurship and by suggesting a tool for revealing effective regions in the context of FE attributes and productive entrepreneurship. This allows us to determine the attributes that are underutilised or not sufficiently developed to contribute to entrepreneurs' activities.

Our results have limitations. The analysis was based on a relatively small number of regions in one period. To arrive at more robust findings, this analysis should be repeated in multiple periods. This would deliver more data points of FE index values and productive entrepreneurship and allow for feedback effects of productive entrepreneurship on FE attributes. The analyses should also be repeated in other contexts, potentially estimating different relationships between FE attributes and productive entrepreneurship. The approbation of a developed survey-based approach was realised at the regional level. However, it can be debated whether regional borders provide the most adequate boundaries for FEs. Boundaries are almost always arbitrary, likely somewhere between the municipal and national levels (Stam 2018; Stam and van de Ven 2019; Leendertse et al. 2021).

Despite these limitations, and due to the increasing role of FinTechs, this paper provided a unique example of measuring FE attributes based on the survey approach, understanding the link between attributes and productive entrepreneurship, and indicating territories that effectively use a created environment to develop entrepreneurship in the financial sector.

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Appendix A. Indicators and Questions in the Questionnaire

Empirical Indicator	Claim	Scale	Source
Presence of special FinTech programs	The local government has programmes in place to help new FinTechs, such as with training programmes or special grants.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Liguori et al. (2018)
FinTech-friendly regulatory legislation	There is clear progressive regulatory legislation that supports FinTech activity in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Pollari (2017)
Risk-taking	The social values and culture of the region encourage entrepreneurial risk-taking.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Doğan (2016)
Doing business	It is relatively easy to start a business, including in the region's financial sector.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Feld (2020)
Dialogue between actors	The actors of an FE aim to communicate with each other on controversial issues in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Hendrikse et al. (2018)
Equal terms of competition	The actors of an FE compete on equal terms in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Brush et al. (2019)
Initiative of entrepreneurs	The social values in the region encourage FinTech founders' self-sufficiency and personal initiatives.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Liguori et al. (2018)
Presence of leadership	There is a certain leader who guides and directs collective action in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Lobo et al. (2016)
Ease of creating a team	It is easy for FinTechs to create a team of individuals with knowledge supporting its launch in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Koroleva et al. (2021)
Ease of finding an employee	It is easy for FinTechs in the region to find an employee to fill an open position.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Kuzmina-Merlino and Saksonova (2018)
Access to information about financing possibilities	Information on what funding programmes are available for FinTechs is easily accessible.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Liguori et al. (2018)
Ease of access to financing	Local individual investors in the region are willing to financially support FinTechs.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Liguori et al. (2018)
R&D cooperation	Financial organisations have cooperative agreements in R&D with other actors in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Cassiman and Veugelers (2002)
	Financial organisations invest in R&D in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Cassiman and Veugelers (2002)
Availability of incubators and accelerators	Local organisations (e.g., incubators and accelerators) are active in supporting FinTechs.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Liguori et al. (2018)
Availability of advisers	Professional services (e.g., lawyers and accountants) for FinTechs are readily available in the region.	1—completely wrong; 2—wrong; 3—rather yes than no; 4—true; 5—absolutely true	Liguori et al. (2018)

Appendix B. The Distribution of the Value of FE Attributes in Russian Regions

Attribute	Empirical Indicator	Moscow	St. Petersburg	Republic of Tatarstan	Sverdlovsk Region	Novosibirsk Region	Nizhny Novgorod Region	Perm Region	Voronezh Region	Chelyabinsk Region	Rostov Region	Mean
Formal institutions	Presence of special FinTech programs	3.78	2.30	2.00	1.40	1.33	1.66	1.33	1.33	1.00	1.00	1.71
	FinTech-friendly regulatory legislation	2.36	1.90	1.00	1.33	1.25	1.00	1.00	1.00	1.00	1.33	1.32
Entrepreneurship culture	Risk-taking	3.72	2.60	2.67	2.20	2.75	2.66	2.33	1.66	1.33	2.00	2.39
	Doing business	3.11	2.50	2.00	2.20	2.50	2.00	1.33	1.00	1.00	1.33	1.90
Physical infrastructure	Internet users (companies)	4.92	4.66	4.91	4.74	4.50	4.73	4.52	4.74	4.62	4.68	4.70
	Internet users (population)	4.60	4.48	4.38	4.30	4.20	3.89	4.07	3.77	4.24	4.35	4.23
Demand	Using the Internet for financial transactions (companies)	4.36	3.96	3.35	3.52	3.40	3.58	3.48	3.55	3.55	3.74	3.65
	Using the Internet for financial transactions (population)	4.51	4.46	4.28	4.12	4.21	3.99	3.87	3.97	4.09	4.17	4.16
Networks	Dialogue between actors	3.01	2.70	3.00	1.60	1.75	1.00	1.33	1.66	1.66	1.33	1.90
	Equal terms of competition	2.06	1.90	1.67	1.80	1.50	1.66	1.00	1.66	1.33	1.00	1.56
Leadership	Initiative of entrepreneurs	3.88	2.80	2.67	2.40	2.25	2.66	1.66	1.33	2.00	2.33	2.40
	Presence of leader	4.78	2.40	1.33	3.00	2.50	2.33	2.00	1.66	1.66	1.66	2.33
Talent	Ease of creating the team	4.73	3.10	3.00	3.20	3.25	3.00	2.33	2.00	2.33	2.00	2.89
	Ease of finding employee	3.13	3.20	2.33	2.60	2.25	2.66	1.66	2.00	1.33	1.66	2.28
Finance	Access of information about financing possibilities	3.12	1.70	1.67	1.60	1.25	1.33	1.00	1.33	1.00	1.00	1.50
	Ease of access to financing	2.92	1.70	1.33	1.40	1.50	1.50	1.60	1.33	1.33	1.00	1.56
New knowledge	R&D cooperation	3.10	1.80	2.33	1.40	1.50	1.50	1.66	1.33	1.33	1.33	1.73
		2.03	1.90	2.00	1.80	1.50	1.00	1.33	1.33	1.00	1.66	1.56
Intermediate services	Availability of incubators and accelerators	4.81	2.80	3.67	1.25	1.75	1.66	1.66	1.66	1.33	1.00	2.16
	Availability of advisers	4.70	3.80	3.33	1.40	1.25	1.66	1.33	1.33	1.33	1.00	2.11

Note

1 Main data sources are Rusbase (https://rb.ru/fintech/ (accessed on 31 July 2021)), FintechLab (http://list.FinTech-lab.ru/ (accessed on 1 August 2021)), and FinTech Association (https://www.fintechru.org/ (accessed on 1 August 2021)).

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FinTech Companies: A Bibliometric Analysis †

Gencay Tepe [1,*], Umut Burak Geyikci [1] and Fatih Mehmet Sancak [2]

[1] Faculty of Business, Manisa Celal Bayar University, 45140 Manisa, Turkey; umutburak.geyikci@cbu.edu.tr
[2] Dikkan Group, 35730 Izmir, Turkey; fatih.sancak@dikkan.com
* Correspondence: gencay.tepe@cbu.edu.tr; Tel.: +90-236-201-39-25

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Abstract: The financial-technology industry has recently attracted the attention of many sectors. The financial-technology industry designs new and unusual technological financial services in many areas. It combines technology with finance and provides an alternative to the traditional financial system. In the scope of this study, 636 publications were obtained from Scopus. Various tools, such as Microsoft Excel for frequency analysis, and VOSviewer for data visualization, were used. The open-source codes used for bibliometric analysis through the R Studio program were developed by the authors and used for citation-metrics analysis. The main aim of this study was to find out the most influential studies and authors and to reveal the distributions and impacts of publications in the FinTech area between 2015 and 2021 from the Scopus database. The results indicate that the most influential journal is Sustainability Switzerland, and the most cited author is Gomber et al. Additionally, Rabbani has the most publications, while China has emerged as the most productive country. On the other hand, this study found that FinTech research clustered in four areas. These areas are computer science, business management, economics, and social sciences. This FinTech study examines financial services, financial access, and financial technology, where FinTech is at the center. It also focuses on cryptocurrency, bitcoin, and smart contracts where the blockchain is at the center. The results reveal a systematic map of existing studies. Further, the study plays a guiding role in future research.

Keywords: FinTech; financial technology; blockchain; financial information systems

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1. Introduction

Although it only entered the literature five years ago, FinTech has been studied a lot. It refers to companies and Finance 4.0 that create financial technologies at the highest level. Globally, FinTech is being implemented rapidly in human life in recent years.

Of recent FinTech studies, some focus on all aspects of the issue in general (e.g., Arner et al. 2016; Zalan and Toufaily 2017; Dospinescu et al. 2021), while others examine more-specific aspects. These include studies related to banks and traditional financial institutions (Kotarba 2016; Buchak et al. 2018; Hu et al. 2019), venture capital, cryptocurrencies, and blockchain (Kaplan and Lerner 2016; Ante et al. 2018; Gozman and Willcocks 2019; Kim et al. 2018; Ji and Tia 2021; Mora et al. 2021), insurance (Yan et al. 2018b; Stoeckli et al. 2018), and asset management (Rogowski 2017; Dugast and Foucault 2018). While each study adds an important perspective on the subject, a bibliometric analysis can provide a broader perspective and assessment than has been the case for studies thus far.

A network analysis carried out through bibliometric analysis defines new areas and information on the subject more strongly. It can also identify research groups and researchers to show how various areas of thought have emerged. Finally, it can identify leading and influential researchers in these research groups, identify different and new issues addressed by these influential researchers, and identify areas of study related to these new issues.

This study provides a detailed and comprehensive analysis by identifying researchers and publications with high influence in this pool, starting with 401 studies focusing on future-oriented FinTech applications. Various performance indicators were calculated for the bibliometric analysis. The formulization of the methods used was encoded by the authors on an R-based basis using the R Studio 1.2 program. The data processed through the program were then handled with Gephi 0.8.2 and VOSviewer 1.6.11 programs for visualization and mapping purposes to obtain the final outputs.

FinTech, which is short for financial technology, has spread rapidly worldwide, although its importance varies from country to country depending on the level of economic development and market structure (Berkmen et al. 2019). The concept, which originated in the early 1990s, currently refers to a rapidly evolving process in financial services (Arner et al. 2017; Hochstein 2015). FinTech describes companies offering financial services using modern creative technologies that *"attract customers with products and services that are more user-friendly, efficient, transparent and automated than those currently available"* (Dorfleitner et al. 2017, p. 5). FinTech firms cannot be defined within legal parameters because they operate in different business lines and models, and a wide range of industries, from crowdfunding to credit providers, cryptocurrencies to angel-investment networks.

FinTech has developed through three basic stages (Arner et al. 2017). The first phase resulted from surplus production and technological innovations brought about by the industrial revolution with the use of the first simple abacuses. After the mid-1800s, the invention of the telegraph (Nicoletti 2017), and telegraph communication and intensive trade between countries, enabled financial transactions to be made on a global scale using technology (Standage 2013). From 1866 to 1967, the financial services industry was heavily connected with technology but remained largely analog. This period is called FinTech 1.0.

Developments in digital technology between 1967 and 2008, known as FinTech 2.0, enabled financial-services technologies to switch from analog to digital and become globalized. For example, Barclay's Bank was the first to introduce automatic teller machines (ATMs) in 1967 (Nicoletti 2017), while electronic payment systems significantly changed the financial structure, making money transfers between banks and countries quite easy. In 1975, the Basel Committee was established to reduce the risks of interbank money transfers, with new rules to regulate relations between international banks (History of the Basel Committee 2019).

In terms of what consumers expect from a bank, e-banking/m-banking, the possibility of performing ATM cash transactions, customer service, ease of use, and the volume of information on the card have become very important (Dospinescu et al. 2019). On the other hand, rapidly developing financial integration that connected global markets marked a new era, FinTech 3.0, after 2008, especially with the introduction of the Internet, when Wells Fargo presented the first internet-banking experience, and startups and technology companies began offering financial products and services directly to businesses and consumers (Arner et al. 2016). These FinTechs considerably damaged the profitability of the banking sector (Zalan and Toufaily 2017).

While we currently still live in FinTech 3.0, a future upgrade to FinTech 4.0 will happen. Arner et al. (2017) even claim that FinTech 4.0 arrived in 2018, thanks to applications such as the Internet of things, big data, artificial intelligence, and cloud computing.

Figure 1 shows how FinTech is segmented into four fundamental sectors (Dorfleitner et al. 2017). Financing is the segment that provides funding for individuals or organizations through crowdfunding and credit and factoring. Crowdfunding usually involves raising small amounts of money from large numbers of people via the Internet or social media. The most important feature is the setting of the deadline. If the target amount cannot be reached within the specified period, the operation is canceled (Lee and Kim 2015). Credit and factoring are the processes by which FinTech firms provide financing to individuals or companies cheaply and quickly by automating transactions in collaboration with banks. The second main sector, asset management, includes services such as social trading, Robo-advice, personal financial management (PFM), and investing and banking. The third sector, payment, refers to national and international payment transactions. These include virtual payment methods, such as cryptocurrencies and blockchains, which are used as alternatives to conventional monetary transactions. Finally, other FinTechs cannot be classified within the first three traditional banking functions. These include insurance, search engines, comparison sites, technology, IT, and infrastructure.

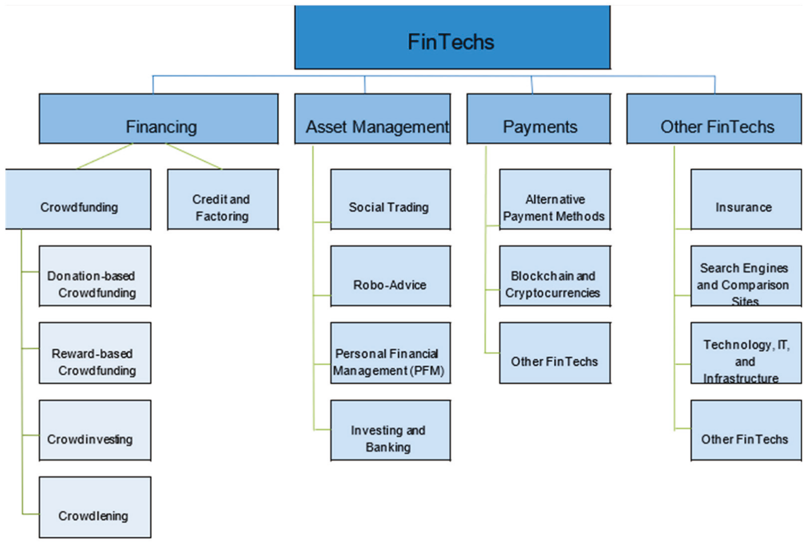

Figure 1. FinTech Segmentations. **Source:** Dorfleitner et al. (2017), cited by Al-Ajlouni and Al-Hakim (2018).

The term bibliometric was first used in the Journal of Documentation (Fairthorne 1969). Bibliometrics (sometimes called scientometrics) involves quantitative analysis, which is the main tool of science. It provides a statistical analysis of data, such as how frequently journal articles are cited. Comparisons can be made across countries and research branches. While bibliometric analyses are becoming increasingly popular, their novelty means that there are no studies yet that directly investigate FinTech. Only two (Milian et al. 2019; Wu 2017) have used the word FinTech in their titles. However, they did not exclusively focus on it. Instead, their analyses drew on the following segments: payments, deposit, and landing, insurance, capital raising, investment management, and market provisioning. A few bibliometric studies have focused on individual segments within FinTech, such as crowdfunding (Martínez-Climent et al. 2018; Blasco-Carreras et al. 2015; Blažun Vošner et al. 2017), payments (Karafiloski and Mishev 2017; Cao et al. 2017; Dabbagh et al. 2019; Zheng et al. 2018; Merediz-Solà and Bariviera 2019; Liu 2016), asset management (Yan et al. 2018a), and other financing functions (Kumari and Sharma 2017; Cancino et al. 2017).

2. Research Method

The basic aim of a bibliometric analysis is to collect previous literature and related topics on the research subject to form objective findings that can be tested and replicated. It aims to both categorize previous studies and offer a rigorous methodological examination of the research results. To show that the study adds new information to the literature, the results should be defined in accordance with the research questions.

Research Questions

In the present study, FinTech-related publications and researchers were subjected to structural categorical analysis. Following Milian et al. (2019), the following two basic research questions with three sub-questions and two others, a total of seven, were addressed.

RQ1. How has the literature developed between 2015 and 2021?

RQ1.1. What are the most influential studies and authors?
RQ1.2. What are the main studies in FinTech?
RQ1.3. What are the distributions and impacts of publications over time?

To respond to RQ1, it is necessary to group the important studies, identify the relationships between them, and categorize them within the framework of current studies. This leads to the second question:

RQ2. What are the important topics in the FinTech literature?

In responding to this question, Lotka's Law and Bradford's Law, which are classics in bibliometric analysis, were assessed for their compatibility with the data.

RQ3. Are the results compatible with Lotka's Law?
RQ4. Are the results compatible with Bradford's Law?

3. Sampling and Methodology

Bibliometric analysis was used to determine the scope of the scientific FinTech literature. The bibliometric analysis used in this research is a very detailed and comprehensive analysis technique in this field.

Bibliometric Analysis

The bibliometric analysis identifies the most prolific countries and universities, and the most influential authors, studies, and journals. The FinTech and bibliometric analysis dataset for the study was taken from Scopus. While Web of Science was also scanned, it was excluded from the evaluation because it provided considerably fewer studies than Scopus. The bibliometric analysis technique aimed to reveal the evolution of the FinTech research literature in terms of RQ1.1, RQ1.2, and RQ1.3, specifically the most influential articles, authors, and topics.

Many factors can be examined in bibliometric analysis. However, the analysis to be performed must be suitable for the purpose. The present study followed the method proposed by Cadavid Higuita et al. (2012), Albort-Morant and Ribeiro-Soriano (2016), and Martínez-Climent et al. (2018). In this method, the indicators are divided into three types: quantity, quality, and structural indicators (Martínez-Climent et al. 2018). (1) Quantity indicators contain numerical data for the area to be analyzed. (2) Quality indicators show the academic impact of publications. (3) Structural indicators reveal the relationships between publications.

Social network analysis is used for measuring both quality and structural indicators. In social network analysis, the network consists of nodes connected through networks (Wasserman and Faust 1994). This determines the centrality of each author by the number of connections they make with other members of the network. Centrality has three main principles: degree, closeness, and betweenness (Freeman 1979, cited by Milian et al. 2019). Centrality degree indicates how many co-publications an author has. Betweenness measures the number of times a node captures the shortest route between two other nodes, and thus shows the binding role that the author plays among other authors. Farness is the sum of the shortest distance of one node from other nodes while proximity is the opposite of farness. The greater the degree, the less the total distance from one node to all other nodes (Milian et al. 2019). Authors with high proximity reach new information faster and spread their ideas more quickly.

RQ2 addresses the issue of which topics FinTech researchers focus on while Lotka's Law (Lotka 1926), which measures authors' scientific productivity, was addressed through RQ3. According to Lotka's Law, the number of authors contributing to the literature with n number of studies is $1/n^2$ of the number of authors contributing to the literature with a single study.

RQ4 assesses Bradford's Law (Bradford [1929] 1985), which determines the distribution of references to journals. According to this law, a bibliographic study on any subject will show that there is a small core group of journals that publishes a third of all articles in this field. A second, larger group of journals publishes the next third while the biggest group of journals publishes the remainder.

4. Findings

This section presents the results, periods, publications, authors, and other information of the analyses.

A total of 636 publications were scanned in Scopus for academic papers on FinTech (including journal articles, conference papers, books, and book chapters). Figure 2 specifies the number of publications found by years.

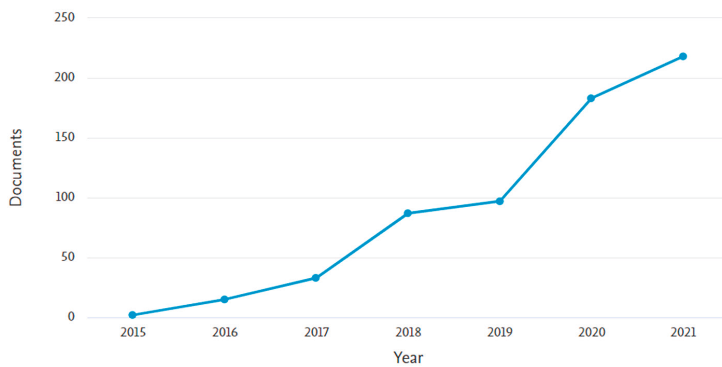

Figure 2. Publishing trend in FinTech. Note(s): This figure represents the publication trend of academic papers on FinTech between 2015 and 2021. The data were retrieved from the Scopus database using the keyword "FinTech".

Figure 2 shows that FinTech has grown geometrically since 2015 when it first emerged as a concept. The papers were written by 1445 different authors from 387 different journals and books. In the scanned sources, the average citations per document were 7.52, the number of documents per author was 0.44 while the collaboration index was 2.75.

Table 1 shows which ten universities had the most affiliations of FinTech authors. Universities in Asian countries have contributed the most (6 of the top 10). Table 1 also shows total production (TP), total citations (TC), and citations per publication (CPP).

Table 1. Top 10 university affiliations by documents.

No	University	TP	TC	CPP	h-Index
1	Bina Nusantara University	16	30	1.88	3
2	Amity University	11	8	0.72	2
3	The University of Sydney	10	181	18.1	3
4	UNSW Sydney	9	191	21.2	4
5	Ahlia University	9	18	2	3
6	Soongsil University	8	110	13.75	3
7	Universitas Indonesia	8	12	1.5	2
8	Singapore Management University	7	244	34.85	4
9	Universidad Anáhuac México	7	0	0	0
10	Kingdom University	6	55	9.17	4

Note(s): This table was created with a dataset from Scopus via Excel.

Figure 3 shows which 10 institutions sponsored the most FinTech papers.

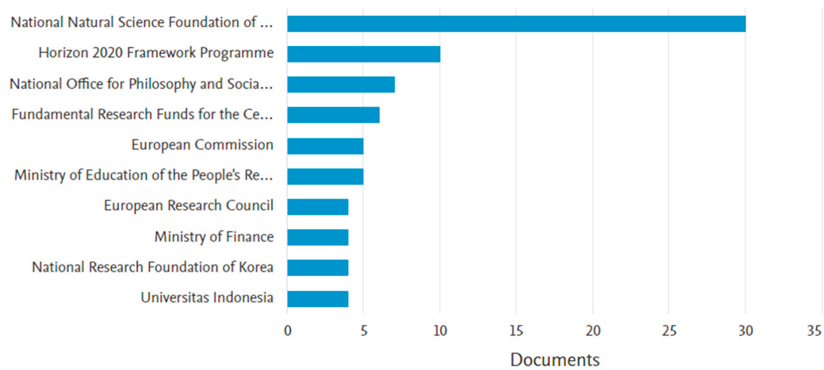

Figure 3. Top 10 funding sponsors of documents. Note(s): This figure represents the 10 institutes that sponsored the most academic articles on FinTech between 2015 and 2021. The data were taken from the Scopus database using the keyword "FinTech".

Figure 4 shows the geographical locations of all contributing countries, with the number of publications decreasing from dark to light blue, while grey indicates no contribution. China, the USA, and the UK have the highest contributions.

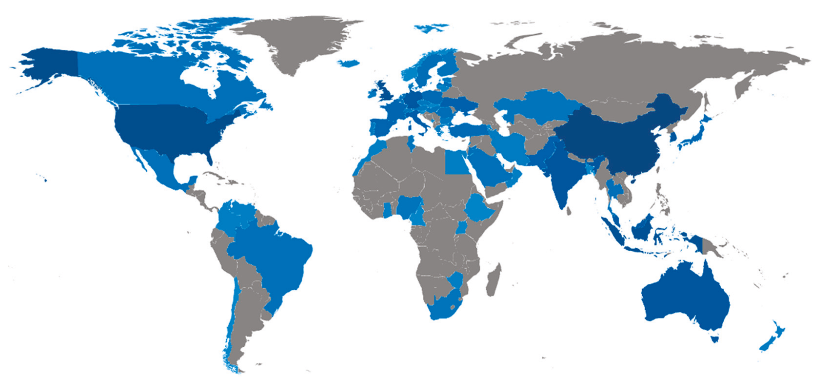

Figure 4. Geographical locations of contributing countries. Note(s): This figure was created with a dataset from Scopus via R Studio.

Figure 5 shows the country collaboration map. UK authors have 59 joint publications with authors in other countries, including 7 with Chinese authors, 6 with Australian authors, and the remaining 46 collaborations with authors in 25 different countries. The UK is followed by the US with 54 collaborations, China with 52, Australia with 43, and Singapore with 18.

Table 2 lists the 10 most productive journals. The journals that are not in the field of Finance and Entrepreneurship were excluded from the analysis results. At the top, Sustainability Switzerland has the most publications on FinTech, and a TC value of 96, whereas the second-ranked, Lecture Notes in Computer Science including subseries, has a TC value of 40. Despite only ranking tenth, Industrial Management and Data Systems has the highest CPP value at 33.2, and Financial Innovation has the second-highest CPP value at 15.28.

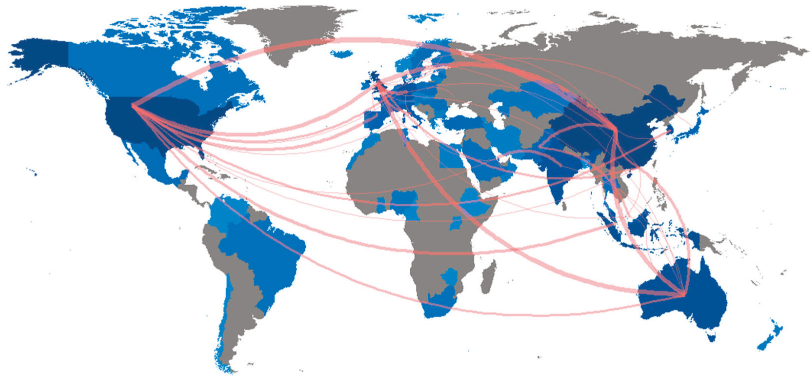

Figure 5. Country collaboration map. Note(s): This figure was created with a dataset from Scopus via R Studio.

Table 2. Most-productive journals.

No	Journals	TP	TC	CPP	h-İndex
1	Sustainability Switzerland	15	96	6.4	5
2	Lecture Notes in Computer Science including subseries	8	40	5	1
3	Journal of Open Innovation: Technology, Market, and Complexity	8	33	4.12	3
4	Finance Research Letters	8	32	4	2
5	Perspectives In Law, Business and Innovation	8	0	0	0
6	Financial Innovation	7	107	15.28	4
7	Impact Of Financial Technology (Fintech) on Islamic Finance and Financial Stability	7	6	0.86	2
8	Palgrave Studies in Democracy, Innovation, and Entrepreneurship for Growth	7	0	0	0
9	ACM International Conference Proceeding Series	6	20	3.3	3
10	Industrial Management and Data Systems	5	166	33.2	4

Note(s): This table was created with a dataset from Scopus via Excel.

As the most productive country, China has 87 publications, 745 citations, and 8.56 citations per publication. Six of the top ten are Asian countries, two are European, while Australia represents Oceania. The most productive countries all have h-index values of 4 or above (Table 3).

Table 3. Most-productive countries.

No	Countries	TP	TC	CPP	h-Index
1	China	87	745	8.56	13
2	United States	84	1415	16.84	18
3	United Kingdom	67	615	9.18	12
4	Indonesia	49	137	2.79	7
5	South Korea	41	673	16.41	12
6	Australia	41	416	10.14	8
7	India	36	57	1.58	4
8	Germany	31	762	24.58	10
9	Malaysia	25	87	3.48	6
10	Singapore	21	287	13.6	7

Note(s): This table was created with a dataset from Scopus via Excel.

4.1. Author Influence

Table 4 shows which authors have been most prolific. Authors with four or more publications between 2015 and 2021 are listed in Table 4. Rabbani, with the most publications, has a TC score of 55. Tan, who is in second place, has a TC score of 105. More than half of Rabbani and Khan's citations are self-citations. Muthukannan has the lowest CPP score, which indicates a weak correlation between that author's large number of publications and their impact factor.

Table 4. The top 10 contributing authors' number of published articles and self-citations.

No	Authors	TP	TC	CPP	h-Index	Self-Citations
1	Rabbani, M.R.	6	55	9.16	4	26
2	Tan, B.	5	105	21	2	9
3	Wójcik, D.	5	19	3.8	3	5
4	Muthukannan, P.	5	8	1.6	2	1
5	Hornuf, L.	4	156	39	3	9
6	Jagtiani, J.	4	89	22.25	3	3
7	Gozman, D.	4	65	16.25	2	6
8	Wonglimpiyarat, J.	4	52	13	3	0
9	Khan, S.	4	42	10.5	3	22
10	Ashta, A.	4	39	9.75	3	9

Note(s): This table was created with a dataset from Scopus via Excel.

Table 5 shows which authors received the most citations by year. Table 4 above shows citations based on total publications, whereas Table 5 shows the most citations received by one study. The 10 authors with the most citations had 1342 citations in total, with an average of 134.2 citations each.

Table 5. Most-cited authors.

	Publications/Year	<2017	%	2017	%	2018	%	2019	%	2020	%	2021	%	Total
1	Gomber et al. (2018)	0	0%	0	0%	8	3%	43	20%	62	29%	101	47%	**214**
2	Lee and Shin (2018)	0	0%	0	0%	7	3%	30	14%	82	40%	85	41%	**204**
3	Gomber et al. (2017)	0	0%	1	5%	19	11%	31	17%	58	33%	65	37%	**174**
4	Gabor and Brooks (2017)	0	0%	7	4%	19	13%	28	19%	33	22%	59	40%	**146**
5	Buchak et al. (2018)	0	0%	0	0%	1	1%	15	13%	30	25%	71	60%	**117**
6	Gai et al. (2018)	0	0%	0	0%	9	8%	32	28%	32	28%	40	35%	**113**
7	Schueffel (2016)	0	0%	3	3%	16	15%	16	15%	34	33%	34	33%	**103**
8	Leong et al. (2017)	0	0%	2	2%	9	9%	21	21%	34	35%	32	33%	**98**
9	Haddad and Hornuf (2019)	0	0%	0	0%	0	0%	6	6%	34	36%	54	57%	**94**
10	Shim and Shin (2016)	1	1%	5	6%	10	12%	18	22%	22	28%	24	30%	**79**

Note(s): This table was created with a dataset from Scopus via Excel.

Figure 6 shows the frequency of citations of individual articles. The size of each node indicates the number of citations. The most-cited authors were Gomber et al. (2018), Lee and Shin (2018), Gomber et al. (2017), Gabor and Brooks (2017), Buchak et al. (2018), Gai et al. (2018), Schueffel (2016), Leong et al. (2017), Haddad and Hornuf (2019), and Shim and Shin (2016).

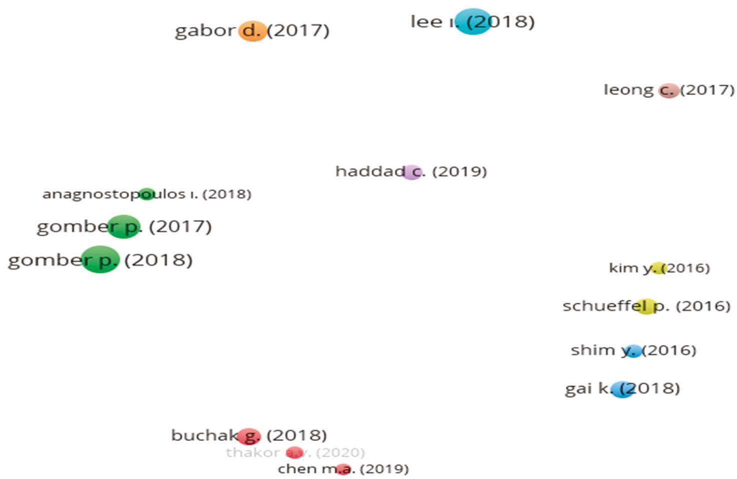

Figure 6. Frequency of citations of publications (Fractionalization). Note(s): This figure was created with a dataset from Scopus via VOSviewer.

4.2. Centrality of Publications

Bibliometric analysis can also determine the relationship between publications. Node sizes are determined by the number of citations and a network is created by attributing the degree of the node to each citation. The size of the node indicates the degree of centrality. The links show the direction of information flow of direct citations between nodes from the former to the new. Node tags include the degree of total centrality as well as definitions of publications. Figure 7 presents the network structure for nodes with a degree of centrality of more than 10.

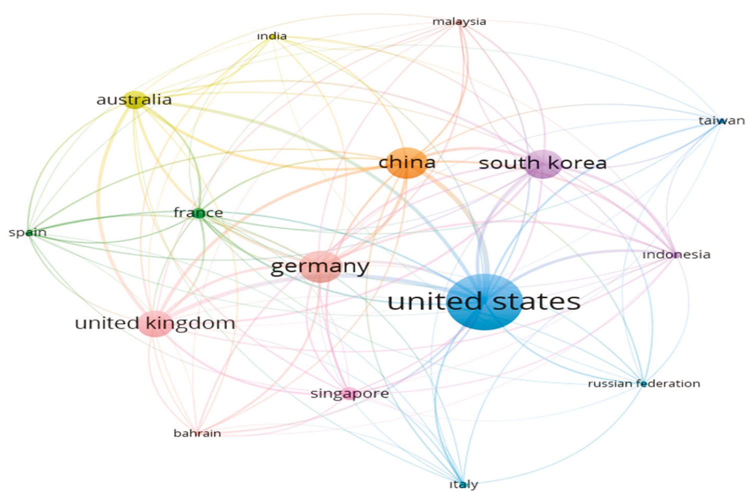

Figure 7. Network visualization of the centrality of countries' citations. Note(s): This figure was created with a dataset from Scopus via VOSviewer.

4.3. Centrality of Keywords

Figure 8 shows the network of keywords. The lines connecting the nodes represent the relationship between the most commonly used keywords in the articles in the study. These can be grouped into four sets: financial technology, China, financial services, and blockchain. On the left, crowdfunding, blockchain, and machine learning appear to be grouped around FinTech. The high frequency of these terms shows the interest and up-to-datedness of the researchers.

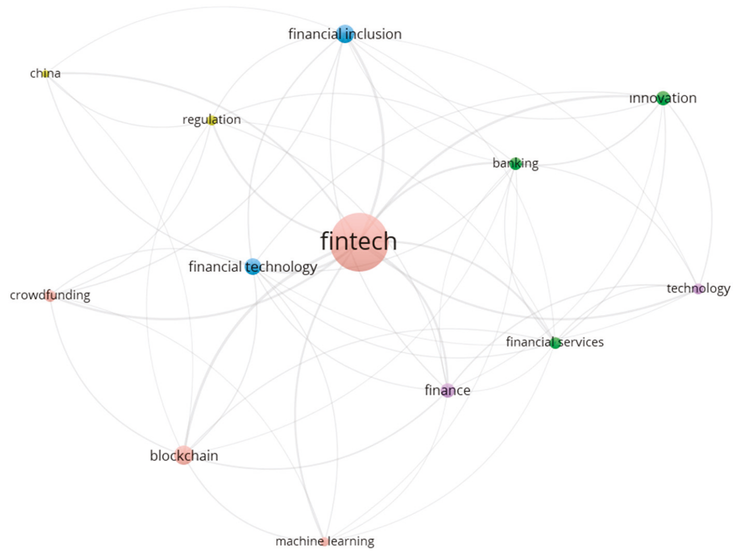

Figure 8. Network visualization of the centrality of keywords. Note(s): This figure was created with a dataset from Scopus via VOSviewer.

Regarding the distribution of the scientific fields that the sampled studies come from, business management comes first with 22.7%, followed by computer science with 18.2%, economics (16.7%), and social sciences (13.3%). Thus, a variety of disciplines are conducting research into FinTech (Figure 9).

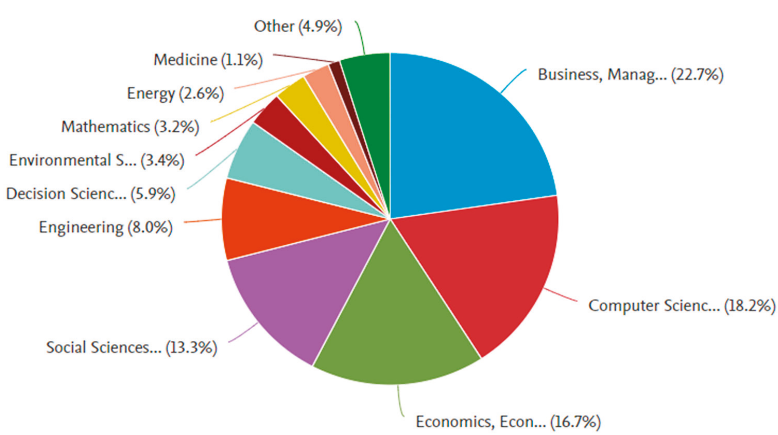

Figure 9. Distribution of disciplines for studies of FinTech. Note(s): This figure represents the distribution of disciplines in FinTech studies between 2015 and 2021. The data were taken from the Scopus database using the keyword "FinTech".

Figure 10 shows the betweenness centrality, which measures the number of times a node intersects the shortest path between two other nodes. This indicates an author's importance in connecting with other authors (Milian et al. 2019). The minimum number of citations in the figure is 10. Of the 60 sampled publications, 21 with links to each other were mapped, with a centrality between 0 and 10. Gomber et al. (2018), Shim and Shin (2016), and Schueffel (2016) have the highest centrality.

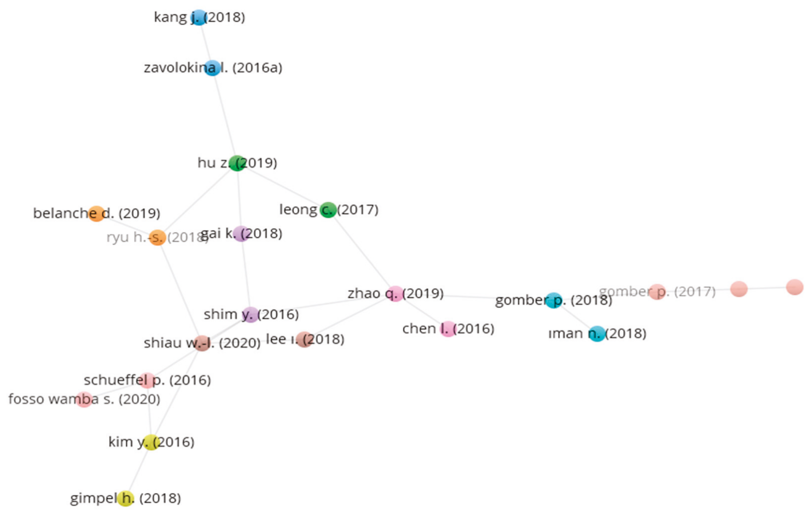

Figure 10. Intermediation as betweenness centrality. Note(s): This figure was created with a dataset from Scopus via VOSviewer.

4.4. Lotka's Law

Lotka's Law (Lotka 1926) predicts the number of publications published by each author in a particular field. That is, 60% of the authors will write one article, 15% will write two, 7% will write three, 4% will write four, etc. Figure 11 presents the results for papers on FinTech alongside the predicted distribution according to Lotka. It shows that 88.6% of authors have just one publication, 7.6% have two, and 2.5% have three. This indicates that FinTech authorship does not currently comply with Lotka's Law. The dashed line in the graph represents the graph that should be according to Lotka's Law.

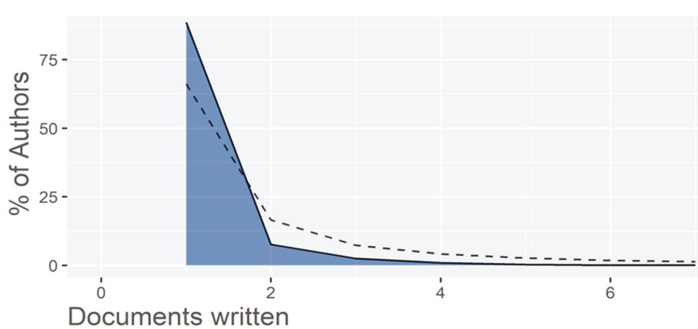

Figure 11. Lotka's Law of productivity, and actual authorship distribution. Note(s): This figure was created with a dataset from Scopus via R Studio.

4.5. Bradford's Law

Bradford's Law (Bradford [1929] 1985) measures whether journals have a core effect by dividing the journals in a specific field into three groups as outlined earlier. In the present study, 636 studies were published by 387 different journals and books. As Figure 12 shows, 40 journals and books accounted for 212 papers, 148 journals and books published 215 papers, and 199 journals and books published 209 articles. This suggests that FinTech research publishing is in line with Bradford's Law.

Figure 12. Bradford's Law of core publications and actual distribution by publications. Note(s): This figure was created with a dataset from Scopus via R Studio.

5. Results and Discussion

RQ1. How has the literature developed over time?

This question was answered by sub-questions RQ1.1, RQ1.2, and RQ1.3.

RQ1.1. What are the most influential studies and authors?

When the publications in 2018 are examined in Table 5, Gomber et al. (2018) with 47%, Lee and Shin (2018) with 41%, Buchak et al. (2018) with 60%, and Gai et al. (2018) with 35% received the most citations for 2021, while Gomber et al. (2017) with 37%, Gabor and Brooks (2017) with 40%, Haddad and Hornuf (2019) with 57%, and Shim and Shin (2016) with 30% received the most citations again in 2021. As the subject is still very new, researchers' interest is increasing continuously as indicated by the growing number of citations.

Gomber et al. (2018), Lee and Shin (2018), Gomber et al. (2017), and Gabor and Brooks (2017) all received at least 140 citations during the review period. Gomber et al. (2018) reported that the long-standing dominance of leading companies is at risk because they cannot effectively connect with the FinTech revolution. They presented a new FinTech-innovation-mapping approach that enables the assessment of the degree of changes and transformations in four financial services areas: operations management in financial services, technological innovations, multiple innovations, and issues related to investments. Lee and Shin (2018) examined FinTechs from a historical perspective and focused on various FinTech business models and investment types with their game-changing features. Gomber et al. (2017) introduced the institutions related to the digital finance cube, which includes three basic dimensions of digital finance and FinTech, related business functions, applied technologies, and technological concepts. Gabor and Brooks (2017) examined the increasing importance of digital-based financial inclusion in the form of development interventions through FinTechs, government agencies, and other organizations. They concluded that FinTech-philanthropy development (FPD) creates ecosystems that map, expand, and monetize digital footprints. They also noted that the vision of the irrational client combines behavioral economics with predictive algorithms to accelerate access to finance and monitor adherence to them, while the digital revolution proposes new forms of profiling with financial(ized) inclusion that makes poor households new generators of financial assets.

RQ1.2. What are the main studies in FinTech?

As shown in Figure 6, Buchak et al. (2018) was one of the most influential works, followed by Gomber et al. (2018), Lee and Shin (2018), and Gomber et al. (2017). Buchak et al. (2018) studied how two forces, regulatory differences and technological advantages, contributed to this growth, due to the fact that shadow-bank market share in residential-mortgage origination nearly doubled from 2007 to 2015, with particularly dramatic growth among online "FinTech" lenders. Gai et al. (2018) surveyed FinTech by collecting and reviewing contemporary achievements that theoretically proposed a data-driven FinTech framework. The survey included five technical topics: security and privacy, data techniques, hardware and infrastructure, applications, and management and service models. They demonstrated the basics of creating active FinTech solutions. Schueffel (2016) offered a definition that is distinct as well as succinct in its communication, yet sufficiently broad in its range of application. Leong et al. (2017) examined the development of a FinTech company that gives micro-lending to university students in China. They showed how digital technology offers a firm strategic capability, how an alternative credit score can be calculated with unconventional data, and how financial coverage of market segments that are not previously covered can be realized. Haddad and Hornuf (2019) investigated the economic and technological determinants inducing entrepreneurs to establish ventures with the purpose of reinventing FinTech and found that the more difficult it is for companies to access loans, the higher is the number of FinTech startups in a country. Shim and Shin (2016) used Actor–Network Theory (ANT) to conduct a multi-level analysis of the historical development of China's FinTech industry as a stepping stone for investigating the interaction between it and the emerging social and political context. They also discussed policy implications of China's FinTech industry, focusing on the state's changing role in driving the growth of the national sector inside and outside.

RQ1.3. What are the distributions and effects of publications over time?

The sample included 636 studies focusing on FinTech applications, by 1445 different authors, from 387 different journals and books. The journals and books with the most publications (see Table 2) were as follows: Sustainability Switzerland with 15 publications, Perspectives in Law, Business and Innovation with 8 publications, and Impact of Financial Technology (Fintech) on Islamic Finance and Financial Stability with 7 publications. The top 10 journals and books include Industrial Management and Data Systems with 33.2 CPP, Financial Innovation with 15.28 CPP, Lecture Notes in Computer Science including subseries with 5 CPP, Journal of Open Innovation: Technology, Market, and Complexity with 4.12 CPP, and Finance Research Letters with 4 CPP. Thus, despite the novelty of this field, there are already many periodicals regularly publishing research on FinTech.

RQ2. What are the important topics in the FinTech literature?

Figure 9, which was developed according to Figure 8, showed the research disciplines of the sampled articles and the relationships between the most-frequently used words. The most common keywords in the papers were financial technology, blockchain, financial services, and financial inclusion. These keywords most often appeared in business-management sources (22.7%), followed by computer science (18.2%), economics (16.7%), and social science (13.3%). Thus, these four disciplines account for approximately 71% of all publications on FinTech, which indicates that this field is currently confined to a few disciplines rather than being evenly dispersed across many.

From the analysis of the relationships between groups in the coding scheme, a framework has emerged for the literature summary, whose main axis is the FinTech activity sector, as shown in Figure 8. FinTech is most strongly connected to financial inclusion, China, and financial services, whereas blockchain has more connections with bitcoin, cryptocurrency, and smart contracts. Figures 8 and 9 formed the main backbone of the analysis for addressing RQ2.

RQ3. Are the results compatible with Lotka's Law?

Unsurprisingly, the vast majority of authors (88.6% of 1445) have just one publication, since FinTech has only recently entered the literature. Lotka's Law, however, predicts that only 60% of authors should have a single publication. Similarly, while 7.6% of authors examined had two publications, Lotka's Law predicts this should be around 15%. While just 2.5% of authors had three publications, Lotka's Law predicts 7%. Consequently, the distribution of authorship in FinTech does not conform to Lotka's Law.

RQ4. Are the results compatible with Bradford's Law?

Bradford's Law predicts that publications can be divided into three groups according to diminishing impact. The 40 journals that constitute the first group of publications in the study published 212 publications, 148 journals in the second group published 215, and 199 journals published 209 articles. The results of the study show that the first few journals published a third of the studies, followed by a large group that published the second third, and the largest number of journals published the remaining third. Thus, the distribution of publications by journals on FinTech is in line with Bradford's Law.

6. Conclusions

This study contributes to the understanding of the FinTech research phenomenon in five different ways in the scope of 636 publications obtained from Scopus between 2015 and 2021. First, FinTechs, which are increasingly influential globally, are also increasingly attracting attention in the scientific literature. Despite this growing interest, the research areas of publications on FinTechs are still not fully determined. The scarcity of mapping studies on FinTechs, as well as the lack of systematic reviews, suggests the need for a comprehensive analysis. The present study reveals the rapidly increasing interest in FinTech over the past six years as reflected in 636 publications from 387 journals and books predominantly representing four academic disciplines: business management, computer science, economics, and social science.

Second, this study identified the sub-topics and trends in publications on FinTechs along two axes. The first is financial services, financial inclusion, and financial technologies, where FinTech is centered. The access of investors and researchers to financial services, their involvement in financial business and transactions, and the use of financial technology are issues that have a significant impact on society. Research on the subject also shows that people of all levels are influenced by FinTech applications represented by these concepts and that traditional applications are quickly losing ground to FinTech applications. The second axis concerns the links to FinTech of cryptocurrency, bitcoin, and smart contracts, with blockchain as the hub. These new technological tools, in which information security is crucial, play an important role in making the individual and society freer. These technologies also demonstrate important security and privacy requirements that are needed in commercial life by opening the way for unmediated secure trade.

Thirdly, in order to make a complete definition of FinTech, this study investigated whether there is a consensus regarding the framework needed to describe FinTech. Research indicates the existence of a structure in which internet-based financial work and transactions can be conducted securely and privately, that facilitates access to information and finance, and that replaces the traditional financial structure with innovative companies.

Fourth, the study assessed the contributions and support of universities to academic research on FinTech. Universities in Asian countries receive more sponsorship and produce more articles, although their impact scores are lower. While the US and Europe have higher impact scores due to their current superiority in science and technology, Asian countries, especially China, are now focusing heavily on the issue and want to capture the trend of development in this area. The US leads in international cooperation between academics researching FinTech, followed by China, the United Kingdom, and Australia.

Fifth, while the distribution of authorship in this field conflicts with Lotka's Law, Bradford's Law was supported. The results of the study show that the first few journals published a third of the studies, followed by a large group that published the second third, and the largest number of journals published the remaining third. Given that FinTech is a very new field, it is possible that patterns of research publications will converge more with these laws in the future.

This study reflected the opinions and practices of all segments of FinTech research, as it included a wide range of articles, from traditional financial institutions to the FinTech ecosystem. As with similar studies adopting such a broad framework, however, the present study has limitations due to databases and search directories. The fact that databases such as Web of Science and ScienceDirect are not included in the study is a research limitation. In future studies, it is recommended to conduct comparative studies between Scopus, Web of Science, and ScienceDirect databases to expand the literature. The studies sampled here were also unique as they are some of the first in the field. This study examined research publications on FinTech based on four main research questions, which made it possible to deepen the study. FinTech research is predominantly conducted within business management, computer science, economics, and social science, thus paving the way for more in-depth research in these areas. In addition, several issues emerged that need to be examined more deeply, particularly FinTech's relationship with financial inclusion and financial services, and Blockchain's relationship with cryptocurrency and smart contracts. Examining these relationships to reveal their strength, causes, and effects would fill an important gap in the literature.

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Adverse Selection in P2P Lending: Does Peer Screening Work Efficiently?—Empirical Evidence from a P2P Platform

Yao Wang * and Zdenek Drabek

Institute of Economic Studies, Faculty of Social Sciences, Charles University, Opletalova 1606/26, 110 00 Prague, Czech Republic; zdenek.drabek1@gmail.com
* Correspondence: 73645327@fsv.cuni.cz; Tel.: +420-776502469

Abstract: The rapid development of online lending in the past decade, while providing convenience and efficiency, also generates large hidden credit risk for the financial system. Will removing financial intermediaries really provide more efficiency to the lending market? This paper used a large dataset with 251,887 loan listings from a pioneer P2P lending platform to investigate the efficiency of the credit-screening mechanism on the P2P lending platform. Our results showed the existence of a TYPE II error in the investors' decision-making process, which indicated that the investors were predisposed to making inaccurate diagnoses of signals, and gravitated to borrowers with low creditworthiness while inadvertently screening out their counterparts with high creditworthiness. Due to the growing size of the fintech industry, this may pose a systematic risk to the financial system, necessitating regulators' close attention. Since, investors can better diagnose soft signals, an effective and transparent enlargement of socially related soft information together with a comprehensive and independent credit bureau could mitigate adverse selection in a disintermediation environment.

Keywords: credit analysis; microfinance; fintech; decentralized finance; P2P; soft information

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1. Introduction

Peer-to-peer (P2P) lending has passed the shakeout period and entered a steady growth period. Its development experience can provide valuable inspiration for current market players. The fast development of disintermediated online lending in the past decade, while providing convenience and efficiency, also generates significant concealed credit risk for the financial system (Huang 2018). For example, due to the fragile auditing process and high default rate, in August 2018, the Chinese P2P market ushered in its consolidation period and experienced a reduction of 42% in P2P platforms when 168 platforms ended operation. Even after the Interim Administrative Measures for the Business Activities of P2P Lending Information Intermediaries was established, the default rate in the P2P industry was still at a high level (You 2018). According to (Gao et al. 2021), Chinese P2P lending platforms have an astonishing default rate of 87.2%, based on data available in 2019. Thus, questions are generated. Does disintermediation really provide more efficiency to the lending market, or does it actually add unforeseen credit risk to the system? Does peer screening work efficiently? This paper used a large dataset with 251,887 loan listings from the pioneer P2P lending platform RenrenDai to investigate the efficiency of the credit-screening mechanism under a disintermediated environment by comparing the performance of loan funding signals and repayment determinants.

A group of scholars (Dorfleitner et al. 2016; Santoso et al. 2020; Liao et al. 2015; Lin et al. 2013; Pötzsch and Böhme 2010; Khan and Xuan 2021) attempted to investigate the determinants of credit rationing in the field. However, the findings in the literature regarding the determinants of loan application success and repayment behavior were inconsistent. Moreover, due to data limitation, the analyses of the default determinants were insufficient. The purpose of our paper was, therefore, to contribute to the literature that explores the determinants of the loan application's performance and the default behavior of the online P2P lending platform. More importantly, the comparison of the results can provide evidence for our research question: Does the peer screening mechanism in the P2P platform efficiently diagnose the signals provided by the borrowers in their loan applications? Due to limitations in the repayment history data, no similar study has been performed using an emerging-market dataset. The only reference is (Iyer et al. 2016), who explored the question by using a Prosper dataset and US credit bureau data. However, this paper did not go deeper and explore the specific determinants which resulted in the misspecification. Our paper will fill this gap and also enrich the literature for emerging markets. We used the dataset from P2P pioneer RenrenDai to test our hypothesis. We divided the information provided by the borrowers into two categories: hard (financial) information and soft (social) information. Our findings showed that the hard (financial) indicators were given great importance when lenders were deciding whether to lend money. However, hard information was either unimportant or even acted in the opposite direction when it came to predicting the repayment behavior of a borrower. Meanwhile, soft information had much less inconsistency in the two models. This proved the existence of a TYPE II error in the investors' decision-making process, which indicated that the investors were predisposed to making inaccurate diagnoses of signals, and gravitated to borrowers with low creditworthiness while inadvertently screening out their counterparts with high creditworthiness. Due to the growing size of the fintech industry, this may pose a systematic risk to the financial system, necessitating regulators' close attention. Since, in contrast to hard financial-based signals, investors can better diagnose the soft signals, this implies enlarging socially related soft signals, and the building up of a comprehensive credit bureau could mitigate the adverse selection in a disintermediation environment.

The paper is divided into five sections. In the literature review, we provide an overview of the existing literature concerning the determinants of loan application success and loan defaults in the P2P market. We compare inconsistencies to find the gaps, then we define our scope. In Section 3, general information about the dataset will be introduced, and our model and the descriptive summary of the chosen variables will be presented. In Section 4, the results of the model are analyzed in detail. Finally, we conclude and discuss the policy implications in the discussion and conclusions section.

2. Literature Review

In the 1950s and 1960s, (Arrow 1964; Debreu 1959) were the first to explore optimal contracts under uncertainty, and laid the foundation for contract theory. In the late 1960s and 1970s, Gorge Akerlof, Josef Stiglitz, and Michal Spence formed the incentive theory as a branch of contract theory, and introduced the concepts of "hidden information" and "hidden actions". The asymmetric information problem under the incentive theory has been prolongedly discussed in modern contract economies. Credit rationing (Stiglitz and Weiss 1981) and information signaling (Spence 1973) were the two major branches of the discussion.

One major class of the contracting problem lies in hidden information, which is also regarded as adverse selection. It describes a situation in which one party to the contract has private information that the other does not. When the contract is made by the party that lacks private information, the uninformed party needs to screen the information possessed by the informed party. This is the so-called screening problem. If the contract is offered by the informed party, it is a signaling problem, since the informed party can signal the information they have through the type of contract offered. (Akerlof 1970) used the automobile market as an example to explain the situation in which one party has private information, and regards the second-hand automobile market as a market for "lemons", since the seller has private information about the condition of the car, and thus they have the incentive to sell cars of below-average-quality. Therefore, the entire market quality has been dragged down, but due to the asymmetric information, the buyer can only bargain according to the average price, so would only like to buy lower-quality cars, which results in above-average-quality cars exiting the market. This situation, when low-quality products replace high-quality products, resulting in the entire market quality declining, is so-called adverse selection. In the loan market, this refers to a situation in which high-risk borrowers are usually those who are most eagerly looking for money, and most likely to obtain the loan. Thus, how to mitigate adverse selection and how to efficiently use signals to screen the borrower becomes a crucial and heated discussion topic. Credit appraisal is the application of screening in the financial market; the borrower has private information about the quality of the project and the incentives of paying back. Our research investigated the efficiency of the screening mechanism in online lending and a possible approach for improvement.

Empirical research concerning credit analysis in peer-to-peer lending can be divided into two groups. One is targeted at analyzing the trust of the lenders. This research area studies how lenders screen borrowers, or what the determinants are for the success of loan funding. The other trend investigates the borrower's repayment behavior, which indicates their creditworthiness; in other words, the potential factors that may signal the possibility of default.

From the perspective of lenders, according to (Debreu 1959), "The role of soft information in trust building: Evidence from online social lending" is representative of the literature analyzing lenders' trust. Data was used from Germany's largest P2P platform, Smava, to analyze trust-building between borrowers and lenders. The interest rate was used as a proxy for trust level. They introduced the concept of soft information as the personal information the borrower was willing to disclose. The results showed that communicating personal information increased lenders' trust, but the impact was small and limited to educational and professional information. In addition, if the borrower used statements aimed at arousing pity, they were given a higher interest rate, indicating a loss of trust. (Herzenstein et al. 2008), on the other hand, more comprehensively summarized the determinants of success in P2P lending into several groups: demographic characteristics, including gender, race, and marital status; financial strength, including credit ratings from credit bureaus, debt ratio, and house ownership; effort indicators, i.e., the effort to increase reputation, mainly through group activity and loan description; and loan decision variables, i.e., the loan features, such as amount, interest rate, and duration. Their results showed that all variables representing financial strength had a significant influence on funding success except house ownership, which was insignificant. Credit ratings from A to E were all positively related to success, except high-risk grading, but debt-to-income ratio was negatively related to success. Results for demographic characteristics showed that women were more likely to receive funding, which was opposite to expectations; marital status was not significant in the decision to grant a loan. African Americans; racial identity had a negative effect on loan funding success. The effort to include a picture had no significant influence on success, but the effort to join in group activity and give a loan description had a positive effect.

Besides these two representative works which summarized the determinants of success in funding applications, a large group of researchers examined the impact of a specific screening variable on the success of the loan application. (Barasinska and Schäfer 2014) analyzed the impact of gender on the possibility of successful funding on German P2P platform Smava; (Gonzalez and Loureiro 2014) and (Pope and Sydnor 2011) analyzed whether a profile picture would influence funding success; similarly, (Duarte et al. 2012) analyzed appearance and funding success; (Greiner and Wang 2009), (Herrero-Lopez 2009), and (Lin et al. 2013) focused on the impact of social capital on loan success; (Wang et al. 2019) led the analysis of the impact of video information on loan success. Researches in this field provided evidence of the screening determinants from the lender's perspective, but lack the comparison with the borrower's repayment behavior. This may be due to data limitation, but without this comparison we cannot diagnose the efficiency of these determinants. Looking from the lender's perspective can only provide information about the lenders' preference but cannot show whether these preferences correctly recognized the borrower's creditworthiness. Our research is based on the determinants previous studies provided, but in addition we compared the results with the borrowers' repayment behavior to explore the real efficiency of the screening mechanism of the lenders.

From the perspective of borrowers, (Santoso et al. 2020) used data from three Indonesian P2P platforms to analyze the determinants of loan interest rates and default status. As an inconsistency in the existing literature, they also observed that factors such as age and gender have different results on three different platforms. The paper investigated the relationship of the chosen determinants with default probability and the loan interest rate. However, they did not link these two results together and further investigate the phenomenon behind and the origin of the problem. Our paper's target is to fill this gap and analyze whether borrower signals are correctly diagnosed by lenders. (Dorfleitner et al. 2016) studied the effect of soft factors derived from descriptive text on the probability of successful funding and probability of default on two European P2P lending platforms. Their results showed that typos, text length, and keywords evoking positive emotions are significantly related to funding success but have no impact on default probability. Their research provided the first evidence of linguistic factors in credit analysis; however, they only focused on linguistic factors and did not further investigate the misdiagnosis of other soft factors when comparing lenders' judgment and borrowers' real behavior.

The first paper that touched on the efficiency of the lenders' diagnosis is that of (Iyer et al. 2016) in the 2016 paper, "Screening peers softly: Inferring the quality of small borrowers", they used the advantage that they had acquired the true credit scores of the borrowers from the credit bureau while the lenders on the prosper platform only had information about the credit grading. As a predictor, they used the final interest rate collected by the borrower to assess whether the lenders on the platform would use the details available to assess the borrower's true credibility. The results showed that, within one credit category, the lenders were able to infer one-third of the variation in creditworthiness that was captured by credit scores. Their results also suggested that, on top of the traditional financial factors, non-standard "softer" information was also used in analyzing the borrower's credit risk, especially for lower credit rating borrowers. Although the paper diagnosed the fact that lenders on the platform had one-third of the ability to infer the real creditworthiness of the borrower, it also indicated that misspecification existed since only one-third had been captured which implied that two-thirds hadn't. This paper opened the first debate on whether the usage of soft information would compensate for the traditional credit analysis model and add more choice for credit model development after the 2008 financial crisis. However, this paper did not delve into the specific determinants which resulted in the misspecification. Our paper is an extension of that of (Iyer et al. 2016), whereby we provide empirical evidence for the misspecification of the lenders' screening mechanism in P2P lending.

We further compared the literature on these two trends, and found inconsistent results for the same variable in different models; for example, gender was insignificantly correlated with success in (Pötzsch and Böhme 2010) but significantly correlated with success in (Zhang et al. 2017), (Herzenstein et al. 2008) and (Pope and Sydnor 2011). At the same time, female gender was shown to be positively related to default in (Santoso et al. 2020) but negatively related to default in (Ge et al. 2017) and insignificantly related in (Pope and Sydnor 2011). Moreover, the results of (Dorfleitner et al. 2016) showed that typos, text length, and keywords evoking positive emotions were significantly related to funding success but had no impact on default probability. People who mentioned education in their loan descriptions were more likely to obtain loans (results significant), but mentioning education was shown to be insignificant in predicting default. However, in (Liao et al. 2015), people with higher degrees of education had a lower probability of default (significant) but were not more likely to get funding (insignificant). In (Freedman and Jin 2008), mentioning education in loan descriptions had an insignificant influence on funding success but people who did so were significantly less likely to default. Mentioning car ownership was not significantly related to success but was significantly and positively related to default. In addition, mentioning family was significantly and positively related to success but also significantly and positively related to default. Due to these inconsistencies, we doubt whether investors can truly diagnose the credit signals given by borrowers. If there are misdiagnoses, which factors resulted in these mismatches?

Thus, we come up with our hypothesis:

Hypothesis 1: *Investors on the P2P platform can correctly diagnose the credit signals the borrower provide and efficiently screen out low credit borrowers;*

Hypothesis 2: *Investors can more efficiently diagnose hard financially related signals than soft socially related signals.*

3. Data, Model and Variables

The data we used is from one of the world's pioneer P2P platforms, RenrenDai, which was established in 2010. By October 2016, the total amount of its transactions exceeded 21.2 billion yuan. The platform targets microloans, 71,000 yuan being the average loan amount. The platform consisted of 251,887 listings from 2010 to 2014. Borrowers fill out a loan application online to be published on the website. Peer investors conduct their own credit analyses and choose which loans to invest in. The funding process is completed when the entire loan amount has been filled by investors. Like crowdfunding, a single loan may have multiple investors. Thus, among the total listings, only 65,394 loans were funded. The borrowers can repay the loan in full or in monthly installments until it matures. Among the funded loans, 50,819 loans are still in the repayment process and 14,575 loans have reached maturity. In the finished loans, 13,901 loans completed the repayment process while the other 674 defaulted, representing a relatively modest default rate of about 4.2%. Detailed variable descriptions are presented below.

Since the dependent variable is binary, we use the logit model to test the determinants of loan funding and default in P2P lending. Our models are presented below:

Model I:

$$\text{Logit}\left(\text{Funded}_i\right) = \beta_0 + \beta_1 Hard\ Informtion_i + \beta_2\ Soft\ Informtion_i + \propto Control\ Variables_i + \varepsilon \tag{1}$$

Model II:

$$\text{Logit}\left(\text{Default}_j\right) = \beta_0 + \beta_1 Hard\ Informtion_j + \beta_2\ Soft\ Informtion_j + \propto Control\ Variables_j + \varepsilon, \tag{2}$$

The dependent variable for Model I, the funding probability model, is a dummy variable which equals 1 when the loans have been successfully funded, otherwise 0.

Model II is the default predicting model; the dependent variable default represents whether the loan has been repaid completely without delay. 1 represents 'defaulted'; 0 represents 'repaid'.

All the chosen hard and soft information variables are listed in Appendix A, Table A1. All the chosen variables are based on the references from the literature review. We used financially related information, income level and collaterals as the hard information. Socially and psychologically related information such as age, gender, loan description, marital status, educational level and social media information are used as the soft information. Loan features are used as the control variables.

The hard information is represented by key financial determinants that indicate the wealth and solvency of the borrower. They are the four key fundamental financial indicators that are available in our dataset: monthly income, home ownership, car ownership and existing mortgage loans. Car and home ownership are dummy variables, with 1 indicating 'ownership' and 0 indicating 'none'. We include verification of income in the model to certify accuracy.

As soft information is difficult to measure, proxies must be employed. Table 1 summarizes the proxies used in our model. Our approach to soft data is similar to that in the literature: we employ education duration (e.g., (Liao et al. 2015)), age (e.g., (Gonzalez and Loureiro 2014)), and gender (e.g., (Gonzalez and Loureiro 2014; Barasinska and Schäfer 2014; Ravina 2019; Pope and Sydnor 2011)). We also employed the length of the loan purpose statement as a linguistic indicator, as suggested by (Lin et al. 2013; Kim et al. 2020).

Since social impact has been proved to be a significant factor on loan success by (Greiner and Wang 2009; Herrero-Lopez 2009; Lin et al. 2013), we used the verification data from Weibo (the largest Chinese social network) as our indicator of social impact. If an applicant's social network was verified, it is represented as "1", otherwise "0".

Profile photos were shown to influence the funding success in (Pope and Sydnor 2011) study. Since the profile photos on Renrendai.com were not always real pictures of the applicants, we chose video verification as the picture indicator's proxy. During the verification process, borrowers must video themselves holding their ID cards and reading a statement accepting general rules and conditions from Renrendai.com as part of the verification procedure, and then upload the video with their loan application. If the applicant accepted video verification, this is recorded as a "1," otherwise it is reported as a "0".

The expansion of mobile services is a fundamental component of Fintech 2.0, and mobile usage data is the preferred verification tool for Fintech firms, particularly big data firms. Since mobile numbers were introduced to China's real-name system, allowing tracking and verifying of real cellphone users, it has become a critical source for anti-fraud efforts. Furthermore, one of the most powerful indicators of default in the consumer finance market is mobile usage behavior. As a result, we included a variable for mobile verification in our model. This is also a dummy variable: "1" means verified, "0" means not verified.

Based on (Nigmonov et al. 2022) and (Khan and Xuan 2021), we included the interest rate, the length of the loan, and the amount of the loan. The average interest rate is 14.9%, and the highest interest rate is 24.4%. The average amount is 60,637.93 yuan. Since the amount is quite large, we used the log of amount as the proxy to normalize the distribution. The loan term is from 1 month to 36 months. The average term is 16 months.

We summarize the descriptive statistics of all the independent variables in Table 1 below.

Table 1. Descriptive Summary of Independent Variables.

Variable	Observation	Mean	Std.Dev.	Min	Max	Median	First Quartile	Third Quartile
Income	222,757	4.064	1.281	1	7	4	3	5
Car verified	251,842	0.042	0.200	0	1	0	0	0
House verified	251,842	0.044	0.206	0	1	0	0	0
Mortgage loan	251,842	0.134	0.341	0	1	0	0	0
Description	251,842	184.488	101.908	0	367	165	88	276
Age	251,842	31.334	7.688	1	86	29	26	35
Gender	251,842	0.163	0.370	0	1	0	0	0
Marriage	251,842	0.492	0.500	0	1	0	0	1
Education	236,656	14.081	1.755	12	19	15	12	15
Mobile verified	251,842	0.048	0.213	0	1	0	0	0
Weibo verified	251,842	0.031	0.174	0	1	0	0	0
Video verified	251,842	0.042	0.199	0	1	0	0	0
Interest	251,842	14.936	3.550	3	24.4	15	13	16
Amount	251,830	10.186	1.350	6.908	14.914	30,000	10,000	62,200
Term	251,842	16.333	10.676	1	36	12	6	24

4. Results

Table 2 shows the logit regression results for Model I and Model II. The results show that income has a positive relationship with success since we take the mean group 4 as the reference group. Income groups lower than 4 are less likely to receive loans, while groups higher than 4 are more likely than the average group to have loans funded. This reflects the common sense of peer investors, who believe higher income means better solvency and more trustworthiness. This is consistent with most of the research in the field such as (Pötzsch and Böhme 2010). However, the default results suggest that this is not the case: the lower income group is negatively correlated to default, thus they actually have lower default possibility (e.g., income groups 2 and 3), while the high income group can default more (e.g., income groups 6 and 7 are more likely to default than income group 4). This may be because borrowers have the intention to lie about their income to create a more trustworthy image to the lenders. However, the lenders did not recognize the risk of the fake information. Moreover, the value of the income verification has not been recognized: the high verified income group has a lower default probability. Nevertheless, compared to income group 4, investors give more loans to income group 3 than groups 5,6,7, which is evidently a TYPE II error that provides loans to those with lower creditworthiness. This results from the misdiagnosis signals from income. This also implies the necessity of key information verification on the P2P platform. Since there is no credit rationing process on the platform, the judgment is purely based on unprofessional lenders. The validity of the information provided on the platform becomes critical.

Table 2 presents the logit regression results for the funding probability model and default prediction model with coefficient and robust standard errors in brackets.

Table 2. Comparison of Logit Regression Results for Funding Probability and Default Predicting Model.

	(1)	**(1)**
VARIABLES	**Funded**	**Default**
Hard Information Variables 1. Income verified	2.832 ***	0.596 **
	(0.0629)	(0.232)
1. Income group 1	−0.668 ***	−0.874
	(0.105)	(1.086)
2. Income group 2	−1.660 ***	−0.604 *
	(0.0821)	(0.344)
3. Income group 3	−0.394 ***	−0.168
	(0.0191)	(0.134)
5. Income group 5	0.155 ***	−0.360 **
	(0.0232)	(0.168)
6. Income group 6	0.382 ***	0.233
	(0.0282)	(0.148)
7. Income group 7	0.475 ***	0.261 *
	(0.0323)	(0.156)
Income verified#1.Income group 1	0	0
	(0)	(0)
Income verified#2.Income group 2	1.136	2.803 ***
	(0.738)	(0.882)
Income verified#3.Income group 3	0.434 ***	0.471
	(0.0903)	(0.329)
Income verified#5.Income group 5	−0.308***	−1.156 **
	(0.106)	(0.580)

Table 2. *Cont.*

	(1)	(1)
VARIABLES	**Funded**	**Default**
Income verified#6.Income gorup 6	−0.606 ***	−1.744 ***
	(0.116)	(0.584)
Income verified#7.Income gorup 7	−1.172 ***	−2.233 ***
	(0.117)	(0.577)
Car verified	0.448 ***	−0.394 ***
	(0.0440)	(0.110)
Home verified	0.0795	0.348 ***
	(0.0529)	(0.122)
Mortgage Loan	−0.311 ***	−0.409 *
	(0.0231)	(0.216)
Homeverified#1Mortgage loan Soft Information Variables	0.240 ***(0.0779)	−0.179(0.276)
Loan description	0.0130 ***	−0.00603 ***
	(9.02×10^{-5})	(0.000549)
Age	0.0653 ***	−0.00531
	(0.00103)	(0.00625)
Gender	0.274 ***	−0.274 **
	(0.0183)	(0.129)
Marriage	0.345 ***	−0.203 *
	(0.0167)	(0.104)
Educational	0.0763 ***	−0.120 ***
	(0.00441)	(0.0167)
Mobile verified	−0.515 ***	−0.486 ***
	(0.0432)	(0.131)
Weibo verified	0.605 ***	−0.627 ***
	(0.0492)	(0.151)
Video verified	2.522 ***	1.007 ***
Control Variables	(0.0423)	(0.120)
Interest	−0.304 ***	0.195 ***
	(0.00352)	(0.0138)
Amount	−0.304 ***	0.0349
	(0.00817)	(0.0452)
Term	0.113 ***	0.0117 **
	(0.000935)	(0.00579)
Constant	−2.150 ***	−3.159 ***
	(0.110)	(0.603)
Pseudo R2	0.5883	0.1674
Observations	222,437	14,566
Time & Regional Fixed Effect Control	No	No

Heteroscedasticity-Robust, standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The numbers associated with the variable 'income' refer to income groups. The sample includes 7 income groups.

After comparing the logit regression results from both models, we can see that, except car ownership, all other hard information variables have either opposite results when compared to each other or different significance levels.

The median income group 4 is used as the reference variable, revealing that lower-income groups (1,2,3) are less likely to receive loan funding compared to the median income group (4), whereas higher-income groups (5,6,7) were more likely to be funded. The funding probability model shows interesting results, in which the interaction effect of verified income and declared income elicit opposite results. Surprisingly, higher-income groups are less preferred by the investor. Combined with the results of the default predicting model, we find that verified higher-income groups show lower default probability. However, higher-income groups without income verification demonstrate a higher probability of default. The implication may be that people in higher-income groups are more inclined to be dishonest regarding their incomes. In Table 3, we further analyzed the distribution of the income verification, the results showing that the income verification percentage increases along with the increase of income levels. Applicants in income groups 1 and 2 are very unlikely to verify their income, the verification percentage being only around 0.3%. On the other hand, the high-income groups all have a verification percentage above 14%. However, as we can see from the regression results, investors are less willing to lend to verified high-income groups than the average income group, although verified high-income groups have a lower probability of default. But investors are more willing to lend to unverified high-income groups, who actually have a higher probability of default. This induces TYPE II errors among the investors, since they cannot diagnose the income verification in high-income groups as a positive signal of creditworthiness and lend more funds to those who have a higher probability of default.

Table 3 shows the distribution of the verified income group and the percentage it occupies of the total application according to income group.

Table 3. Verified Income Distributions.

Income Group	Verified	Total	Percentage
1	4	1231	0.32%
2	20	7190	0.28%
3	5641	82,862	6.81%
4	8057	65,763	12.25%
5	4597	31,046	14.81%
6	3178	19,863	16.00%
7	2133	14,802	14.41%
Total	23,630	222,757	10.61%

Lenders tend to prefer borrowers with fixed assets such as houses or cars. However, only car ownership is seen to be a significant indicator of reduced probability of default. House ownership is unable to secure loan payment, a finding that is in consonance with that of (Jiménez and Saurina 2004) research, in which loans with collateral are often linked to higher default rates. Additionally, since loans in the P2P market are usually small-sized, this makes a car easier to monetize, whereas the process of realizing a house for loan repayment is more time-consuming and complicated, compared to smaller assets. As far as the mortgage loan is concerned, investors prefer borrowers without any debt. However, the default model is suggestive of the fact that the probability of default is lower for people with mortgage loans. This could be attributed to the fact that people with mortgage loans are more concerned about their creditworthiness.

For soft information, mobile verification exhibits the opposite result in the logit regression. It is negatively correlated to funding probability, but also negatively correlated to default. This means that borrowers who have mobile verification are less likely to default but are also less likely to get the loan funded. From Table 4, we can see that the percentage of mobile verified in successful loans (4.77%) is much less than in defaulted loans (17.87%).

Additionally, the percentages of successful and non-default mobile and video verified loans differentiated substantially. Successful mobile verified loans represent 26.6% of all verified loans, among which only 3.9% defaulted. This is lower than the total default rate of 4.6%. This substantiates a positive relationship of the verified mobile with the high creditworthiness of the borrowers. However, lenders cannot effectively diagnose the signal and categorize the borrowers by this feature.

The phenomenon of non-financial information can improve the prediction model and can sometimes even outperform financial information in predicting default, which has been proved by (Fernando et al. 2020) and (Bhimani et al. 2013) using business loans. Now we add further evidence from the microfinance dataset.

Table 4 shows the distribution of the mobile verification in funded and not funded loans, and in default and defaulted loans.

Table 4. Mobile Verification Distribution List.

Mobile Verification	**Funded**		
	0	**1**	**Total**
0	172,187	67,650	239,837(95.23%)
1	8815	3190	12,005(4.77%)
Total	181,002	70,840	251,842(100%)
Mobile Verification	**Default**		
	0	**1**	**Total**
0	11,398	573	11,971(82.13%)
1	2503	101	2604(17.87%)
Total	13,901	674	14,575(100%)

The video verification also showed opposite results in the Logit regression comparison, which is consistent with (Duarte et al. 2012), where borrowers' willingness to show their appearance does not indicate that they have higher creditworthiness. However, most of the lenders attach great trust to video verification since the indicator is significantly correlated to loan success. As shown in Table 5, in contrast to mobile verified, 61.29% of video verified loans succeed in funding, while 8.2% defaulted, which is 3.6% higher than the total default rate of 4.6%. This may be due to the fact that borrowers that bear higher risk are willing to offer more information, indicating a classic adverse selection case and a TYPE II error existence.

Table 5 shows the distribution of video verification in funded and not funded loans, and in default and defaulted loans.

Table 5. Video Verification Distribution List.

Video Verification	**Success**		
	0	**1**	**Total**
0	176,955	64,433	241,388(85.85%)
1	4047	6407	10,454(4.15%)
Total	181,002	70,840	251,842(100%)
Video Verification	**Default**		
	0	**1**	**Total**
0	8878	223	9101(62.44%)
1	5023	451	5474(37.56%)
Total	13901	674	14,575(100%)

We can also see from the significance level of the variables that all the hard information is significant in the funding probability model except house ownership, but becomes less significant when it comes to the default predicting model. However, this phenomenon does not exist in soft information variables, as the results of soft information are more consistent in both models. This suggests that lenders were less capable if diagnosing the signals from hard information compared to soft information.

From our regression results, we can see that investors were not able to effectively diagnose most of the useful information from the signals provided by borrowers provide, especially from hard financially related signals. This indicates that investors on the P2P platform may have lacked the financial literacy regarding credit appraisal. Their biased investment decisions may have created credit risk to the disintermediated financial system. On the other hand, the P2P investors react surprisingly well to soft signals. They correctly diagnosed the effect of age, gender, educational level, marital status, and social media on creditworthiness. This has important policy implication - in a financial environment with a weak credit bureau and limited financial literacy, soft information may even performs better on credit screening. Adding more socially related soft information into the credit rationing model could mitigate adverse selection in disintermediated financial institutions.

5. Discussion and Conclusions

This paper examines whether online P2P investors can accurately and effectively diagnose signals of creditworthiness during their decision-making process. According to our findings, the TYPE II errors exist in the investors' decision-making process. Comparisons of the signs used in determining both loan defaults and loan funding show that the investors were predisposed to making inaccurate diagnoses of signals and gravitate to borrowers with low creditworthiness, while inadvertently screening out their counterparts with high creditworthiness.

This particularly happens with hard financially based signals. Specifically, signals such as income and property ownership were insignificant or typically provided contradictory guidance in terms of default. However, investors have allocated disproportionate weights to this in the decision-making process of loan funding. Surprisingly, rather than hard financial signals, investors were more adept at diagnosing soft social signals. That is, all directions of soft signals in the loan funding process were found to be accurate reflections in the default prediction model with the exception of softer signals such as video and mobile verification. These results suggest that soft social information can be a compensatory solution when hard information is not solid enough. The absence of solid credit bureau is typically the main problem for developing countries in credit appraisal, and as our results show, soft information can provide an alternative solution in credit analysis to this problem. Due to data limitations, our soft information is restricted to social identity information. However, with artificial intelligence and machine learning development, softer information relevant to social behavior such as social networks and mobile usage behavior can provide more comprehensive angles of credit analysis in microfinance and deserve further research.

Our paper clearly demonstrated the existence of the TYPE II errors in the disintermediated lending market, indicating a high potential credit risk in financial markets. Due to the growing size of the Fintech industry, this may pose systematic risk to financial systems, requiring regulators' close attention. In addition, we believe the problem of misidentification of credit worthiness signals can be alleviated by a sophisticated and independent credit bureau and increasing public financial literacy. Meanwhile, expanding the use of social soft information could also mitigate adverse selection in the disintermediated financial institutions. And this process must be accompanied by establishing a transparent and effective oversight over the use of soft information in order to avoid abuse.

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Appendix A. List of Variables

Table A1. Description of independent variables.

Variables	Description
Hard Information	
Income level	Category variable: Monthly income of the borrower (1~7) Group 1: <1000 yuan Group 2: 1001~2000 yuan Group 3: 2000~5000 yuan Group 4: 5000~10000 yuan Group 5: 10,000~20,000 yuan Group 6: 20,000~50,000 yuan Group 7: >50,000 yuan
Income verification	Dummy variable: income is verified-1; is not verified-0
Home ownership verification	Dummy variable: ownership is verified-1; is not verified-0
Car ownership verification	Dummy variable: ownership is verified-1; is not verified-0
Mortgage loans	Dummy variable: the borrower has a mortgage loan-1; doesn't have a mortgage loan-0
Soft Information	
Loan description	Length of the loan description
Age	Age of the borrower
Gender	Dummy variable: female-1; male-0
Marital status	Dummy variable: married-1; otherwise-0
Educational level	Years of education
Weibo verification	Dummy variable: the social network is verified-1; is not verified-0
Mobile verification	Dummy variable: the mobile number is verified-1; is not verified-0
Video verification	Dummy variable: finished the video verification-1; otherwise-0
Loan features	
Interest	Interest rate of the loan in percentage
Term	Length of the loan in months
Amount	Amount of the loan, used log of amount as the proxy

Appendix B. Robustness Check

Since the dataset is from 2010 to 2014, the change in macroeconomic environment in these years may influence the decisions of the investors and the behavior of the borrowers. As China has 36 different regions, regional differences may be found in financial behavior. Thus, we added region and year dummy variables into the model to control the fixed effect of time and region.

The loan application distribution by region and year are listed in Tables A2 and A3 accordingly.

Table A2. Loan Application Distribution by Region.

	Freq.	Percent	Cum.
Unwritten	35,686	14.17	14.17
Beijing	7421	2.95	17.12
Shanghai	9794	3.89	21.01
Shenzhen	232	0.09	21.10
Guangzhou	3030	1.20	22.30
Tianjin	11	0.00	22.31
Hongkong	16	0.01	22.31
Guangdong	26,806	10.64	32.96
Jiangsu	14,645	5.82	38.77
Shandong	19,649	7.80	46.57
Zhejiang	13,424	5.33	51.90
Henan	9821	3.90	55.80
Sichuan	9295	3.69	59.49
Hubei	9430	3.74	63.24
Hunan	8482	3.37	66.61
Hebei	8005	3.18	69.78
Fujian	13,535	5.37	75.16
Anhui	6520	2.59	77.75
Liaoning	8794	3.49	81.24
Shanxi (NW)	5150	2.04	83.28
Jiangxi	3845	1.53	84.81
Chongqing	7636	3.03	87.84
Guangxi	4834	1.92	89.76
Yunan	3450	1.37	91.13
Neimenggu	2344	0.93	92.06
Heilongjiang	3347	1.33	93.39
Shanxi (N)	3684	1.46	94.86
Jilin	3707	1.47	96.33
Guizhou	3204	1.27	97.60
Xinjiang	1370	0.54	98.14
Gansu	2231	0.89	99.03
Hainan	1066	0.42	99.45
Ningxia	764	0.30	99.76
Qinghai	331	0.13	99.89
Xizang	266	0.11	99.99
Taiwan	17	0.01	100.00
Total	25,1842	100	

Table A3. Loan Application Distribution by Year.

	Freq.	Percent	Cum.
2010	1009	0.79	0.79
2011	14,509	11.33	12.12
2012	12,771	9.97	22.09
2013	48,751	38.07	60.17
2014	51,006	39.83	100.00
Total	128,046	100.00	

The regression result with region and year dummy is presented in Table A4. The results are in line with original regression, in that most of the hard information variables have opposite results in the two models while most of the soft variables have consistent results. This proves the existence of TYPE II errors in the investors' decision-making process.

Table A4. Robustness Test with Region and Year Dummy.

	(1)	(1)
VARIABLES	**Funded**	**Default**
Hard Information Variables 1. Income verified	3.064 ***	−0.0189
	(0.0811)	(0.303)
1. Income group 1	−0.355 ***	−0.793
	(0.136)	(1.029)
2. Income group 2	−0.878 ***	−0.522
	(0.0987)	(0.366)
3. Income group 3	−0.291 ***	−0.241 *
	(0.0260)	(0.140)
5. Income group 5	0.200 ***	−0.265
	(0.0318)	(0.175)
6. Income group 6	0.436 ***	0.260 *
	(0.0387)	(0.157)
7. Income group 7	0.654 ***	0.258
	(0.0441)	(0.165)
Income verified#1.Income group 1	0	0
	(0)	(0)
Income verified#2.Income group 2	−0.728	0
	(1.214)	(0)
Income verified#3.Income group 3	0.340 ***	0.582
	(0.118)	(0.439)
Income verified#5.Income group 5	−0.312 **	−1.412 *
	(0.132)	(0.848)
Income verified#6.Income group 6	−0.657 ***	−2.729 **
	(0.142)	(1.077)
Income verified#7.Income group 7	−1.137 ***	−3.127 ***
	(0.150)	(1.061)
Car verified	0.485 ***	−0.394 ***
	(0.0478)	(0.121)
Home verified	0.250 ***	0.341 ***
	(0.0559)	(0.130)
Mortgage Loan	−0.188 ***	−0.258
	(0.0328)	(0.224)
Homeverified#1Mortgage loan Soft Information Variables	−0.0247 (0.0850)	−0.360 (0.289)
Loan description	0.0124 ***	−0.00571 ***
	(0.000120)	(0.000592)
Age	0.0596 ***	−0.00799
	(0.00142)	(0.00671)
Gender	0.247 ***	−0.303 **
	(0.0249)	(0.135)

Table A4. *Cont.*

	(1)	(1)
VARIABLES	**Funded**	**Default**
Marriage	0.325 ***	−0.243 **
	(0.0225)	(0.112)
Educational	0.0484 ***	−0.170 ***
	(0.00621)	(0.0269)
Mobile verified	−0.553 ***	−0.537 ***
	(0.0470)	(0.144)
Weibo verified	0.506 ***	−0.402 **
	(0.0536)	(0.163)
Video verified	2.206 ***	1.106 ***
Control Variables	(0.0460)	(0.133)
Interest	−0.306 ***	0.223 ***
	(0.00480)	(0.0156)
Amount	−0.448 ***	0.0772
	(0.0124)	(0.0519)
Term	0.102***	0.00808
	(0.00134)	(0.00708)
Constant	2.138 ***	−2.628 ***
	(0.224)	(0.849)
Pseudo R2	0.6102	0.2029
Observations	118,203	13,987
Time & Regional Fixed Effect Control	Yes	Yes

Heteroscedasticity-Robust, standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To control for multicollinearity, we analyzed the variance inflation factors (VIF) of our chosen variables. The results[1] show that all the independent variables' VIFs are within 2 and with an average of 1.27. In other words, the variance of the estimated coefficients is inflated with very low factors and within a reasonable rule-of-thumb of 10. For verification, we also calculated the square root of VIF, the R square for the correlation between the given independent variable and the rest of the independent variables, and the tolerance indicators, which are computed as 1- R square. The results prove the non-existence of multicollinearity.

Note

1 We checked the variance inflation factor, the R square for the correlation between the given independent variable and the rest of the independent variables, and the tolerance indicators for each independent variable. The results show that all variables have VIFs lower than 2, R square less than 0.2, and tolerance less than 1.

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Information Disclosure in China's Rising Securitization Market

Xueer Chen and Chao Wang *

Faculty of Law, University of Macau, Macau, China; yb67214@connect.um.edu.mo
* Correspondence: chaowang@um.edu.mo

Abstract: E-commerce and FinTech are currently booming in China. The growing consumer market is accompanied by internet finance, by which consumers can easily borrow money from financial institutions online. As a result, the growing risks of financial institutions are of concern to the government and regulatory bodies. Consequently, the securitization market in China is seeing rapid growth that could affect financial stability. Applying FinTech and emerging technologies in securitization might be an effective way to protect against these risks. This paper studies the question of whether China needs a higher standard of information transparency in order to protect against its risks against the background of digital transformation. We analyzed the determinants of securitization in the Chinese banking sector, relying on data on banks for two periods: pre-2017Q4 and post-2017Q4. The main findings of the paper demonstrate that the application of FinTech in China's banking industry resulted in less information asymmetry. The risk exposure was the most significant determinant in general. Higher risk exposures increased securitization transaction volumes, which reflects securitization with adverse selection problems between the originator and investors. Liquidity and profitability, as important determinants indicating the moral hazard problem, also affected securitization pre-2017Q4, but liquidity and profitability were found to be unimportant determinants after the application of FinTech (the post-2017Q4 period). Moreover, this study finds that the effects of the adverse selection and moral hazard problems varied in different types of banks. Overall, our findings suggest that the Chinese securitization market needs a higher standard of information transparency.

Keywords: FinTech; information asymmetry; adverse selection; moral hazard

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1. Introduction

E-commerce and FinTech are currently booming in China. The growing consumer market is accompanied by internet finance, by which consumers can easily borrow money from financial institutions through online platforms. As a result, the growing risks of the financial institutions are of concern to the government and regulatory bodies. Consequently, the securitization market in China has grown rapidly in recent years. Securitization in China has experienced a great increase since 2014, and it is now the second-largest securitization market in the world (Hogan Lovells 2019). The main reason for this rapid growth is the simultaneous release by the China Banking Regulatory Commission (CBRC) and the China Securities Regulatory Commission (CSRC) of documents to implement a reform that replaced the approval system for asset securitization with a filing system (Tang et al. 2017). Due to financial disintermediation and the need for central banks to establish interest rate corridors, commercial banks are increasingly enriching their asset allocation choices, which also influence the investment in securities (Huang et al. 2019). In 2019, the total volume of ABS issued in China reached USD340 billion, marking a 16.69% increase compared with 2018. The total outstanding volume of ABS by the end of 2019 stood at USD566 billion, a 27% increase compared with 2018 (Phua 2020). The remarkable growth of securitization in China is similar to that in the United States before the global financial crisis of 2007–2009. The securitization market in the United States also experienced rapid growth before the global financial crisis from 2007 to 2009. Many commentators cite the remarkable growth of securitization in the United States as a major contributor to the ensuing crisis. Part of the argument is that securitization creates an additional layer of information asymmetry in the origination of a loan, which results in adverse selection, moral hazard problems, and thus higher default rates. China's securitization market, as mentioned, has also experienced remarkable development. The question of whether securitization affects the financial stability in China has yet to be answered and is a growing concern for authorities. The answer might depend on the standard of information transparency, and a high degree of information transparency will always benefit an authority's monitoring activities and help to protect investors.

One of the effective ways to improve the standard of information transparency is to apply FinTech and emerging technologies in the securitization market against the background of the digital transformation of banking. Due to the new digital giants in China—Alibaba and Tencent—and the COVID-19 pandemic, traditional Chinese banks have tended to increase their focus and efforts on digital transformation. For example, some of these traditional banks have leveraged FinTech and emerging technologies, such as machine learning, artificial intelligence, big data, cloud computing, and blockchain, to shape their operating model enterprise-wide. Machine learning and artificial intelligence have had a strong impact on credit risk management, which can be used to deal with the problems of information asymmetry (Mhlanga 2021). According to Deloitte's (2018b) report, cloud computing, big data, artificial intelligence, and blockchain technology entered the stage of comprehensive application in the banking industry in 2018, and "FinTech", "Inclusive Finance", and "Asset Management" have become key words in many banks' annual reports. FinTech and emerging technologies have also been applied in the securitization market to enhance its standard of information transparency. More specifically, all loan data can be placed on a blockchain. Those loan data thus become immutable and are time-stamped on a verifiable audit trail (Structured Finance Industry Group & Chamber of Digital Commerce 2017). Blockchain technology could be used to automatically share and analyze data in line with regulatory requirements; underlying loans, for example, could be easily and automatically matched against the securitization's proposed structure, thus making compliance easier (Sindle et al. 2017).

It is currently unclear whether the digital transformation of banking can reduce the impact of information asymmetry and whether information transparency regulations are sufficient for the supervision of securitization or the need to leverage FinTech and emerging technologies. Thus, this study aims to answer the following question: Does China need a higher standard of information disclosure to protect against its risks? To answer this research question, we examined the potential moral hazard and adverse selection problems in securitization and compared those problems in two periods. The first period is pre-2017Q4 and the second period is post-2017Q4. Post-2017Q4 represents the stage of FinTech's comprehensive application in the banking industry.

The moral hazard and adverse selection problems can be tested by the motivations for the securitization of loans. More details and reasons can be found in Section 2. The original research on the determinants of the securitization of loans emerged during the 1980s, when a strand of U.S. research studied loan sales, an instrument that is similar to loan securitization (Giddy 1985; Pavel 1986; Pavel and Phillis 1987). Giddy found that capital requirement is an important determinant for loan sales. Pavel and Phillis (1987) proved that securitization provides a means of reducing a bank's credit risks. After the global financial crisis of 2007–2009, research in this area resurfaced. The starting research was on the determinants of European banks' engagement in loan securitization (Bannier and Hänsel 2008). They examined firm-specific and macroeconomic factors that drive financial institutions' decisions to engage in loan securitization transactions. Bank size, credit risk, liquidity, and performance are the four main factors of load securitization transactions in European banks. Two similar papers then reported an empirical study on Italy and Spanish loan securitization markets, respectively (Affinito and Tagliaferri 2010; Cardone-Riportella et al. 2010). The result of the study from Affinito and Tagliaferri (2010) is similar to that of Bannier and Hänsel. However, Cardone-Riportella et al. (2010) claimed that liquidity and performance are the only two decisive factors in securitization. Credit risk is not the main determinant. Acharya et al. (2013) also found that risk exposure failed to promote increased securitization growth, which means that banks were securiting without transferring the risk to investors. Recently, the topic on the determinants of loan securitization in European banks was studied again (Farruggio and Uhde 2015), and the determinants of loan securitization in the pre-financial crisis and the post-financial crisis were compared. The determinants of loan securitization changed remarkably over the pre-crisis and crisis periods.

In accordance with these recent journals, (1) the first contribution of this paper is to study the determinants that drive securitization in the Chinese banking section. Markets in different regions and countries reflect the varying outcomes of securitization determinants. The determinants of securitization in China might be quite distinct from previous research. This paper compares the determinants in different types of bank, and how securitization in these various types of banks are affected by the determinants. (2) Additionally, this study proposes and explains why the four determinants mentioned above can be used to examine the problems of information asymmetry in securitization. Specifically, a securitization determinant study reflects not only the motivation of securitization in the banking section, but also the financial stability. Financial stability is influenced by information asymmetry. Information asymmetry is reflected by moral hazards and adverse selection. Moral hazards and adverse selection are tested by the four determinants. After examining how these four determinants are related to the moral hazard and adverse selection problems in securitization, we can then assess whether current information transparent standards are sufficient for securitization development in China. (3) Finally, this study investigates the effect of FinTech in China's banking sector by comparing the change in securitization determinants in the two periods.

Summarizing our results, we find that the risk exposure is the most significant determinant, followed by liquidity and profitability before the comprehensive FinTech application in China. After that, risk exposure is still the motivation of securities issuance, but there is no evidence that liquidity and performance can promote loan securitization transactions. Capital requirement could be the motivation for securities issuance in commercial banks. Additionally, by comparing the outcomes of the determinants at two stages, this study finds that the application of FinTech can reduce information asymmetry in the securitization market dramatically, especially for moral hazards. However, we still cannot fully reject the influence of banks' incentives on risk transfers to outside investors after a comprehensive FinTech application. Therefore, the answer to the research question is that China still requires a higher standard of information disclosure to protect against its risks. The remainder of the paper is organized as follows: Section 2 provides the theoretical background and summarizes earlier empirical evidence on securitization determinants, followed by the theories of adverse selection and moral hazards. In Section 2.3, we will explain how those securitization's determinants are linked to adverse selection and moral hazards. Subsequently, Section 3 presents the empirical methodology, a data description, and variable definitions and empirical models. Empirical results are presented in Section 4, where both univariate analysis and multivariate analysis are given. According to the empirical results, Section 5 will discuss the findings and link them to the adverse selection and moral hazard problems. Section 6 will provide corresponding recommendations. Section 7 concludes.

2. Theoretical Foundation

2.1. Determinants of Loan Securitizations

The research addressing the reasons for securitizations includes the need for new sources of funding (liquidity), credit risk management (risk exposure), the search for new profit opportunities (regulatory capital arbitrage), and performance.

2.1.1. Liquidity

The first reason to securitize an asset is an alternative source of funding. Banks can transform loans into cash by the securitization mechanism (Kothari 2002). This mechanism is typically related to 'true sale' transactions when a bank transfers parts of loan portfolios to SPV (Special Purpose Vehicle) and in turn receives liquidity from the issuance of loan-backed securities by the vehicle (Farruggio and Uhde 2015). In this way, banks can acquire alternative funding resources in a new way beyond traditional equity, as well as debt financing. Thus, securitization makes banks less vulnerable to liquidity shocks.

The empirical evidence clearly shows that the liquidity effect is a significant determinant for loan securitization in European markets. Cardone-Riportella et al. (2010) found that liquidity is one of the main factors that drives securitization in Spain according to a sample of 408 observations in the pre- and post-financial crisis. The same conclusion can be found in Italy during the period from 2000 to 2006 (Affinito and Tagliaferri 2010). Similarly, Bannier and Hänsel (2008) found that low liquidity triggered securitization issuances from 17 European countries between 1997 and 2004.

2.1.2. Risk Exposure

Securitization enables banks to lower risk exposure through credit risk transfers. It is related to 'true sale' transactions and the 'bankruptcy-remoteness' principle. When a bank transfers parts of loan portfolios to SPV, the corresponding loans are also removed from the bank's balance sheet, and the underlying assets from the bank are isolated. After that, investors do not have any claims against the bank's assets once a default or bankruptcy occurs. The 'true sale' transaction and the 'bankruptcy-remoteness' mechanism allow credit risk sharing with investors, and banks do not have obligations to maintain value and reap the excess returns. The risk exposure is distributed by securitization rather than held by one bank, which minimizes the financial distress cost. Early theoretical journals proved that securitization provides a means of reducing a bank's credit risks by this mechanism (Greenbaum and Thakor 1987; Pavel and Phillis 1987). However, in some cases, credit risks are difficult to transfer out of banks, because the originator generally retains the first-loss tranche (low- or zero-rated securities). This means that risks inherent to the securitized assets are considered in the banks but off-balance sheet (Calomiris and Mason 2004; Higgins and Mason 2004). The other problem is that the transfer of low-quality loans to SPV could lower a bank's reputation, and only those banks with reputational advantages can repeatedly enter the securitization market and place multiple transactions (Ambrose et al. 2005).

Corresponding to the theoretical predictions, the empirical evidence is ambiguous. Some empirical studies, including those of Minton et al. (2004) and Bannier and Hänsel (2008), show that credit risk exposure is important for banks' securitization decisions, while other empirical evidence indicates that, compared with risk transfers, issuing banks prefer to retain low-risk loans in their portfolio and remove high-risk loans from the balance sheet to build their reputation (Altunbas et al. 2010; Ambrose et al. 2005; Albertazzi et al. 2015).

2.1.3. Regulatory Capital Arbitrage

Banks can reduce regulatory capital via securitization because of the different capital requirements between the bank's assets on the balance sheet and those within the first-loss piece. Under the First Basel Capital Accord (Basel I), because the amount of required regulatory equity capital was comparably low when securitizing banks' assets, banks were able to provoke arbitrage profit by keeping the largest part of default risks (e.g., corporate and retail loans) within the first-loss piece rather than keeping them on banks' balance sheets (Ambrose et al. 2005; Calomiris and Mason 2004). However, before the financial crisis of 2007–2009, the Basel commitment required a higher standard regarding regulatory capital to improve financial stability (Basel II), and this resulted in fewer opportunities of regulatory capital arbitrage. Basel II follows a 'substance over form principle', which more precisely determines the required regulatory capital for all retained tranches of a securitization (Blum 2008) and strongly stimulates incentives to transfer subordinated tranches and the first-loss piece to external investors (Farruggio and Uhde 2015).

The empirical evidence on the regulatory effect is also ambiguous. There is no strong evidence indicating an opportunity to realize regulatory capital arbitrage spur securitizations in U.S. banks from 1993 to 2002 (Minton et al. 2004). By contrast, other U.S. securitization market research yielded different outcomes by employing 112 financial institutions from 2001 to 2005 (Uzun and Webb 2007). Ambrose et al. (2005) provide a similar conclusion and noted that securitization is driven by regulatory capital arbitrage.

2.1.4. Performance

Apart from the factors discussed above, performance is another determinant of securitization because of the accounting benefits, intermediation profit, and higher liquidity. First, securitization allows banks to acquire accounting benefits when the book value is less than the market value of the loans, and an overvaluation of the retained interest is carried at a fair market value in the case of securitizations (Niinimaki 2012). Moreover, banks can acquire an intermediation profit via the specific design in terms of securitization loans rather than long-term warehousing (Duffie 2008). Additionally, Lockwood et al. (1996) suggest that cash inflows from securitization can be used to retire existing debt, which in turn reduces interest expenses and increases reported earnings. In spite of those potential benefits, the downsides of securitization should not be forgotten, including the fixed costs of setting up an SPV and a potential reduction in the flow of tax benefits when the assets are kept on the balance sheet and financed with debt (Calmès and Théoret 2010).

Empirical studies show the ambiguous outcomes of bank performance. Cardone-Riportella et al. (2010) presented supporting theoretical arguments indicating that more efficient and larger banks securitize their loans more frequently and may issue greater transaction volumes. On the other hand, Affinito and Tagliaferri (2010), based on a study of Italy, concluded that less capitalized and riskier banks with less liquidity are more likely to securitize their loans. Bannier and Hänsel (2008) showed that bank efficiency and size might be important determinants of securitization, while their results reveal that less profitable banks have much greater incentives to securitize their loans.

2.2. Securitization and Information Asymmetries

2.2.1. Asymmetric Information in Securitization

Information asymmetry is a condition wherein one party in a relationship has more or better information than another (Bergh et al. 2018). Information about securities' intrinsic values is asymmetric, due to the long chain of structures inherent in the securitization process, resulting in a loss of information about the quality of the underlying loans (Gorton 2009). In addition, 'marketing-to-market' is not feasible in the securitization market; in such cases, valuations often involve 'marketing-to-model', which does not reflect a true market price and is associated with information asymmetry (Dowd 2009). Generally, sellers have better information about the deteriorating quality of loans than potential buyers, because most sellers (dealers) are either fully integrated or partially integrated by engaging in some process of the securitization chain; in addition, by owning an originator, sellers also have information on the quality of the originations, since the gains to acquiring better information on the quality of securities are perceived to be small, and consideration to potential buyers is not needed to value the underlying collateral in the securities. Frequently, buyers take the simpler approach of using credit agency ratings or standard copula models, which do not value the underlying securities directly (Beltran et al. 2017).

2.2.2. Adverse Selection in Securitization

Information asymmetries are hard to avoid in the securitization market and will contribute to adverse selection and moral hazard problems. The adverse selection problem appears when two (or more) individuals are about to contract on a trade and one of them happens to have more information than the other(s). Seminal contributions were made by Akerlof (1970), Spence (1978), and Rothschild and Stiglitz (1976), applying adverse selection to the product, labour, and insurance market, respectively. They stated that the information-advantaged individuals always hide key information and mislead other individuals' decisions, which could result in a threat to information-disadvantaged individuals' benefits and even drive market prices down. For example, buyers might not be able to distinguish between a high-quality car (a 'peach') and a low-quality car (a 'lemon'), while the seller knows what he/she holds. If the buyer is only willing to pay a fixed price for a car at the fair value (p_{avg}), the seller will sell 'lemons' out (since $p_{lemon} < p_{avg}$) and hold 'peaches' (since $p_{peach} > p_{avg}$). Eventually, the number of 'lemon' sellers increases, and 'peach' sellers tend to leave the market, which would drive high-quality cars from the market and contribute to a market collapse (Akerlof 1970).

Banking and financial institutions are associated with adverse selection in the securitization market because of information asymmetries. According to the 'market for lemons' theory, the sellers (originators) with an information advantage will sell inferior-quality or low-quality loans to their potential buyers (investors) but retain the high-quality loans on their balance sheet via securitization. In the empirical research, the commercial mortgage-backed security (CMBS) market in the U.S. was shown to be consistent with theoretical predictions of a lemon discount; after controlling for observable determinants of loan pricing, conduit loans enjoyed a 34-basis-point pricing advantage over portfolio loans (An et al. 2011). On the contrary, some empirical evidence reflects that some financial institutions aim to build their reputation for not selling lemons to the securitization market. Lenders typically obtain soft and hard information to evaluate the credit quality of a borrower (Petersen 2004; Agarwal and Hauswald 2010). Soft information compared with hard information cannot be credibly transmitted to the market when loans are securitized. Banks securitize loans that have a relatively low amount of soft information (Drucker and Puri 2009), meaning banks retain low-default-risk loans in their portfolios. Likewise, collateralized loan obligations, as a kind of securitization, also prove that adverse selection problems in corporate loan securitizations are less severe than commonly believed (Benmelech et al. 2012). Unlike the aforementioned studies, Agarwal et al. (2012) found that the securitization strategy (adverse selection or not) of lenders changes with the financial environment; specifically, banks generally sold low-default-risk loans into the market but retained high-default-risk loans in their portfolios before the financial crisis, while most banks in financial crisis showed a pattern of adverse selection.

2.2.3. Moral Hazard in Securitization

On the other hand, a situation in which information asymmetry occurs after an agreement is obtained between individuals is called a moral hazard. The term "moral hazard problem", by extension, has been applied to the principal agent problem (Stiglitz 1989). Mirrlees (1999), Holmström (1979), and Grossman and Hart (1983) have made key contributions to this area. They found that, once the contract has been signed, the agent takes advantage of hidden action and hidden information and can take more risks, because the principal bears the cost of the risks. For example, once a car insurance contract is signed, the insurance company (the principal) observes whether or not the driver is careful enough, and the driver (the agent) might not drive carefully because the insurance company bears the cost of the accident (Mirrlees 1999). A moral hazard also affects securitization market risks once the information asymmetry between lenders and securitization issuers (SPV) increases. When the lending bank sells loans, the bank no longer bears the full cost of default and thus will choose to screen the borrower less than the efficient amount; the moral hazard problem can arise if securitization issuers are naive about lender screening (Dell'Ariccia et al. 2008; Mian and Sufi 2009).

According to the empirical studies, Keys et al. (2008) found that securitization under a moral hazard leads to lax screening, which is consistent with the theoretical result. Specifically, they stated that mortgage purchasers follow a 'rule of thumb' in deciding which loans to purchase: for exogenous reasons, they are willing to buy mortgage loans given to the borrowers with Fair Isaac Corporation scores (FICO scores) above 620. However, the default ratio of borrowers with scores higher than 620 is higher than that of borrowers with scores below 620. This is strong evidence that securitization does result in lax screening by lenders. However, Bubb and Kaufman (2014) re-examined the credit score cut-off evidence with a new dataset and through a theoretical lens that assumes rational equilibrium behaviors in comparison with moral hazards in the securitization market.

2.2.4. Adverse Selection and Moral Hazard and Financial Stability

Both adverse selection and moral hazards in securitization affects financial stability and even leads to significant consequences. Adverse selection does not affect the financial market under normal economic conditions; however, as the price falls with an economic downturn, the impacts of adverse selection—an increase in uncertainty of asset value, a flight to liquidity, and a miss assessment of systemic risks (Kirabaeva 2010)—are identified by investors. Buyers (buyer panic) are afraid to invest in overpriced assets ('lemons'), which results in trading in those assets that may diminish or halt altogether. Moreover, overpriced assets lose their ability to serve as collateral for other transactions, which contributes to a credit crunch (Kirabaeva 2011). The moral hazard is the other important factor that affects financial stability. Under the 'Originate-to-Distribute' model, investors bear bank risks via buying banks' securitization, which often leads to socially excessive risk-taking (e.g., lax screening) (Dowd 2009).

2.3. The Relationship between Determinants and Adverse Selection and Moral Hazard

Based on Section 2.1, loan securitization determinants are liquidity, credit risks, regulatory capital arbitrage, and performance. Each factor reflects the different potential benefits and risks for both securitization sellers and buyers. Summarizing Section 2.2, sellers have more information about the quality of underlying loans than the potential buyers, which could result in adverse selection and moral hazards. This paper considers the adverse selection in securitization that is reflected in credit risk transfers. The bank, as the originator, knows more about the quality of underlying loans than investors. When a securitization transaction involves information asymmetry, banks transfer low-quality loans to SPV and sell them to investors with overvalued prices. With regard to moral hazards, banks that securitize their loan will generate higher profitability because investors bare those risks.

This paper aims to determine whether securitization leads to adverse selection and moral hazards through studying the determinants of securitization in the banking sector. The securitization mechanism is divided into two sections in Figure 1. Adverse selection is reflected on the right side of the figure. It mainly occurs between the originator and investors. If securitization is used as a way to transfer credit risks, a large amount of low-quality loans move into SPV and are then sold to investors. Thus, the risk exposure determinant reflects the motivation of risk transfers and is used to examine adverse selection in securitization transactions. The moral hazard is shown by whether or not banks change their behaviors and their willingness to take risks, which occurs between borrowers and banks. Liquidity, regulatory capital arbitrage, and performance can be used to examine moral hazards. These different determinants show a bank's behavioral change and change in potential risks. When securitization is used to increase bank liquidity, it might result in lax screening. If regulatory capital arbitrage drives bank securitization, banks tend to hold less capital as a cushion against asset malfunction. Improving profitability via securitization will suffer from the fixed costs of setting up an SPV and a potential reduction in the flow of tax benefits.

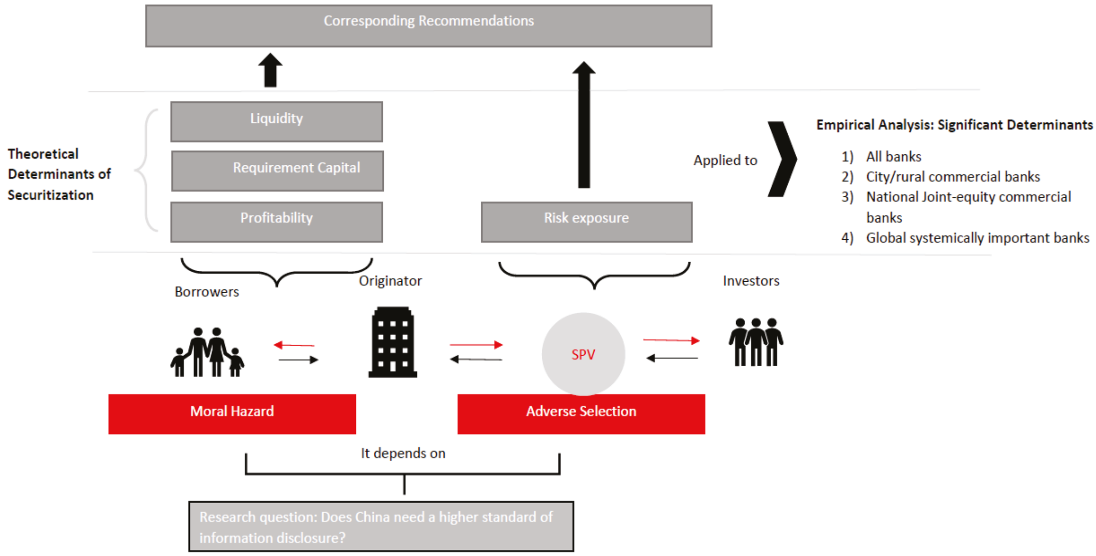

Figure 1. Framework of the study.

3. Material and Methods

3.1. Data Repository

There are 67 banks that have issued securitized securities in China since 2005 to 2017Q4, and only 35 banks that have issued these securities more than twice before 2017Q4. The remaining 32 banks have only issued once, and their securitization transaction volume is lower, so they were not included in this study. After 2017Q4, seven more commercial banks issued securities. The final dataset refers to the above 35 banks from 2007Q4 to 2017Q4 (quarterly) and 42 banks from 2007Q4 to 2021Q2 (quarterly). Data on securitization were drawn from the China Securitization Analytics website and Wind. Other data related to financial statements were collected from Bloomberg, Wind, and annual reports.

3.2. Definition of Variables

3.2.1. Explanatory Variables

The bank-specific variables used in our models are based on the literature review. The main regressors in this study include liquidity, risk exposure, capital requirement, and performance. We describe each variable and its expected effect in the following. Variable definitions and a summary of expected relationships are given in Tables 1 and 2.

Liquidity

Following discussions in earlier research, this study considers two variables as proxies of the liquidity factor.

(1) Net Loans/Deposits and Short-Term Funding (ND ratio): this ratio analyses the liquidity assets of a bank. Net loans are the total loans without the loan loss reserve. The higher the net loans, the lower the liquid assets.
(2) Liquid Assets/Deposits and Short-Term Funding (LD ratio): this is the ratio of the value of the liquid assets (easily converted to cash) to the short-term funding plus deposits. Liquid assets include cash, cash collaterals, and due from banks. Deposits and short-term funding here include total customer deposits (current, saving) and short-term borrowings and repos.

According to the previous studies, because securitization involves a bank transforming its illiquid assets into liquid ones, one will expect a bank to be more predisposed to securitize part of its loan portfolio when its liquid assets are restricted. Therefore, liquid assets/deposits and short-term funding are expected to be positively related to the liquidity of a bank, while net loans/deposits and short-term funding are negatively related to it. Overall, the liquidity effect should be negative, since this paper expects weak banks to have greater incentive to be active in the securitization market.

Risk Exposure

This paper includes two proxies for the credit risk exposure—the loan loss reserves/total loans ratio and the impaired loans/total loans ratio.

(3) *Loan Loss Reserves/Total Loans* (LL Reserves): This ratio estimates the quality of loans. Loan loss reserves cover a number of factors related to potential losses containing bad loans, customers defaults, and the renegotiated terms of loans that incur less often than previously estimated. Thus, the larger amount of loan loss reserves means a lower loan quality.
(4) *Impaired Loans/Total Loans* (IT ratio): This measures the amount of total impaired loans (as a percentage). The lower impaired loans/total loans ratio corresponds to a better loan quality.

This study assumes that a bank with high credit risks suffers higher financial stress costs and therefore tries to address non-performing loans by securitization rather than by holding them on the balance sheet. Thus, banks with a higher credit risk exposure will securitize a large part of their assets.

Table 1. Variable definitions and expected relationships.

Symbol	Description	Measurement	Expected Relationship
Dependent Variable			
Transaction volumes_total assets	Securitization transaction volumes	Securitization transaction volumes divided by bank total assets *	
Independent Variable			
Liquidity	Liquidity of a bank	Liquid Assets/deposits and short-term funding ratio plus net loans/deposits and short-term funding ratio *	+
Risk exposure	Bank's credit risk exposure	LL reserves ratio plus impaired loans/total loans ratio *	+
Capital requirement	Bank regulatory capital	Tier one ratio plus equities/assets ratio *	-
Performance	Performance of bank	Cost-to-income ratio plus return on assets ratio *	?

* Data source: independent variable data are from Bloomberg, banks' financial reports, and Wind; the transaction volume data is from the China Securitization Analytics website and Wind.

Capital Requirement

With respect to the regulatory capital arbitrage hypothesis, this paper uses two proxies for measuring the capital cushion against asset malfunction.

(5) *Total Equities/Total Assets* (TETA ratio): this ratio measures the amount of protection afforded to a bank by the amount of equity invested in the bank. Since equity is a basic cushion against asset malfunction, a higher equity-to-asset ratio means that the entity acquires the greater protection.
(6) *Capital Adequacy Ratio* (Tier One Capital Ratio): this ratio measures a bank's capital adequacy. It is the total capital adequacy ratio under the Basel standards. Under

the requirement of Basel III, the minimum tier one was increased to 6%: 4.5% of the common equity tier one (CET1) plus 1.5% of an additional tier one (AT1). According to regulations in China, the minimum tier one capital requirement for systemically important financial institutions is 9.5%, and that for non-systemically important financial institutions is 8.5%.

In line with theoretical arguments, we expect that banks in general holding less regulatory capital will suffer from the pressure of regulatory compliance. Poorly capitalized banks may be generally more prone to realize regulatory capital arbitrage through securitization.

Table 2. Variable definitions and expected relationships.

Symbol	Description	Measurement	Expected Relationship
Dependent Variable			
Transaction volume_total assets	Securitization transaction volumes	Securitization transaction volumes divided by bank total assets *	
Independent Variable			
Net_loans_D&ST_funding	Bank's net loans to deposits and short-term funding ratio	Book value of bank's net loans divided by total deposits and short-term funding quarterly *	+
Liquidity_assets_D&ST_funding	Liquidity assets to deposits and short-term funding ratio	Cash and cash equivalents of banks divided by total deposits and short-term funding quarterly *	-
Loan_loss_reserves_total_loans	Creditors budget as an allowance for bad loans to total loans ratio	Book value of a bank's loan reserves divided by total loans *	+
Impaired_loans_total_loans	Impaired loans to total loans ratio	Book value of a bank's impaired loans divided by total loans *	+
Total_equities_total_assets	Total equities to total assets ratio	Ratio of total equity divided by total assets *	-
Tier_one	Tier one ratio	Core capital divided by total assets *	-
Cost_to_Income	Cost-to-income ratio	Bank total cost divided by total income *	?
Return_on_assets	Total return on total assets ratio	Bank's return on assets ratio *	?

* Data source: independent variable data are from Bloomberg, banks' financial reports, and Wind; the transaction volume data is from the China Securitization Analytics website and Wind.

Performance

The cost-to-income ratio and the return on assets ratio are used to monitor the effect of performance.

(7) *Cost to Income Ratio* (CIR ratio): this ratio is also called the efficiency ratio and indicates the amount of operating expenses as a percentage of the operating revenue. This ratio reviews how efficiently a bank is being run; a high CIR ratio reflects low efficiency and poor performance.
(8) *Return on Assets* (ROA ratio): this ratio shows how profitable a bank is relative to its total assets.

It is difficult to expect how performance affects securitization. Previously published studies have not yielded conclusive results in terms of performance.

Dependent Variable

To control for the bank size effect of the dependent variables, the securitization transaction volume is scaled by the entity's total assets. The sample was collected from 35 securitizing banks, and their total transaction volume is around CNY 1.2 trillion.

3.3. Empirical Model

This paper employs fixed effects and random effects estimation methods on panel data in order to compare the determinants of banks' engagement in loan securitizations pre- and post-2017 in China. Panel data (also called longitudinal data) embodying information across both time series and cross sections (entities) are multi-dimensional (Diggle et al. 2002). The sample of this study comprises panel data on 35 banks across 7 years and 42 banks across about 11 years for analysis. There are broadly two classes of panel estimator approaches, fixed effects and random effects models, that can be employed in this research. These two models are normally employed to obtain a function that predicts whether an observation belongs to a particular group or when trying to analyze the influence of a series of independent variables on the dependent variable (in our case, the three bank-specific determinants that may influence the amount of securitization). The unobserved variables can have any associations with the observed variables in the fixed effects model, while the unobserved variables are assumed to be uncorrelated or more strongly statistically independent than all of the observed variables in a random effects model. It is difficult to determine whether or not the unobserved variables in this case are statistically independent of the four bank characteristics. To determine the appropriate model, we used the Hausman test. If the probability in the Hausman test is larger than or equal to 0.95 and less than or equal to 1 ($0.95 \leq$ Prob. ≤ 1), it is suggested that the error term is not correlated with the independent variables, the hypothesis is not rejected, and the random effects model should be applied for an analysis. By contrast, if the probability is too low, the unobserved variables are related to the observed variables, and a fixed effects model will be acceptable.

The empirical models are as follows:

$$\begin{aligned}(\text{Transaction} \quad & \text{volumes/totalassets})_{i,t} \\ &= \beta_0 + \beta_1(\text{liquidity ratio})_{i,t-1} + \beta_2\ (\text{credit risk ratio})_{i,t-1} \\ &+ \beta_3(\text{capital adequacy ratio})_{i,t-1} + \beta_4(\text{performance ratio})_{i,t-1} + \varepsilon_{i,t-1}\end{aligned} \tag{1}$$

$$\begin{aligned}(\text{Transaction} \quad & \text{volumes/totalassets})_{i,t} \\ &= \beta_0 + \beta_1(\text{netdeposit/depositand S.T funding})_{i,t-1} \\ &+ \beta_2\ (\text{liquidityassets/depositand S.T funding})_{i,t-1} \\ &+ \beta_3(\text{loan lossreserves/totalloan})_{i,t-1} + \beta_4(\text{impairedloans/totalloan})_{i,t-1} \\ &+ \beta_5(\text{capital adequacy ratio})_{i,t-1} + \beta_6(\text{equities/assets})_{i,t-1} + \beta_7(\text{CIR})_{i,t-1} \\ &+ \beta_8(\text{ROA})_{i,t-1} + \varepsilon_{i,t-1}\end{aligned} \tag{2}$$

Here, (Transaction Volumes/Total Assets) $_{i,t}$ is the dependent variable. β_0 is a common intercept that is the same for all cross-section units and over time. $\varepsilon_{i,\ t-1}$ is the cross-sectional error term. Decisions of securitization issuances are according to published financial statements. Since the securitization transaction volume is not synchronous with the current financial statement data, this paper expects that the securitization transaction volume/total assets is related to the explanatory variables at $t-1$ (a quarterly ago). The variables in Equation (1) are calculated according to the above settings. The independent variable liquidity ratio is made up of a liquid assets/deposits and short-term funding ratio and a net loans/deposits and short-term funding ratio (see Table 1). The other three independent variables' calculations are the same as those for the liquidity ratio, which are the sum of two corresponding proxies. Equation (2) can provide a more intuitive analysis of these variable formations.

4. Results

4.1. Univariate Analysis

4.1.1. By Bank Type

For the study of how bank-specific determinants drive loan securitization in the whole banking industry and in different types of banks, the sample is divided into four types of bank. First, the whole sample is divided into policy banks and commercial banks (see Table 3). Policy banks in China are responsible for financing economic and trade development and state-invested projects according to policy (Turner et al. 2012), namely the China Development Bank, the Import and Export Bank of China, and the Agricultural Development Bank of China. However, China has approved further reforms to those banks (State Council 2015). The remaining banks are commercial banks. The main difference between these two types of banks is that policy banks provide services for policy-related lending, while commercial banks aim to pursue higher profits.

Table 3. Specific kinds of banks.

Bank Type	Description
(A) Whole bank	Whole banks are composed of policy banks and commercial banks.
(1) Policy banks	These banks, according to the policy, are responsible for financing economic and trade development and state-invested projects.
(2) Commercial banks	These banks, according to the market, provide services such as accepting deposits, providing business loans, and offering basic investment products.
(B) Commercial banks	Commercial banks are composed of city/rural commercial banks, national joint-equity commercial banks, and global systemically important banks.
(3) City/rural commercial banks	These banks only focus on specific rural regions and cities (small and medium-sized banks).
(4) National joint-equity commercial banks	These banks are able to operate in the whole country (medium-sized and large banks).
(5) Global systemically important banks	These banks are financial institutions whose distress or disorderly failure would cause significant disruption to the wider financial system and economic activity (super large banks).

Source: (A) Whole banks = policy banks + commercial banks. (B) Commercial banks = city/rural commercial banks + national joint-equity commercial banks + global systemically important banks.

Commercial banks are further divided into two kinds of bank according to asset scale, namely, city/rural commercial banks and national commercial banks. City/rural commercial banks' assets are much smaller than the other two types of bank and are only found on the basis of urban credit cooperatives (KPMG 2017a), while national commercial banks are able to operate across the country and have assets that are larger than those of city/rural commercial banks.

4.1.2. Independent Variable Comparison

Comparing independent variables of different types of banks can give us their specific characteristics. This paper finds that policy banks have less liquidity and profitability; correspondingly, commercial banks have a greater advantage in these two areas. Studying commercial banks further shows that large-scale banks present less liquidity, lower credit risks, and more adequate regulatory capital for whole periods.

(1) Policy banks versus commercial banks

The most significant differences between policy banks and commercial banks are in liquidity and performance, especially liquidity (see Tables 4 and 5). The average liquidity ratio of policy banks can be around five times higher than that of commercial banks (364.4% versus 77.1%). The gap of the liquidity ratio became even wider after 2017, and the average performance between policy banks and commercial banks changed significantly. Variable risk exposure and regulatory capital were similar.

Table 4. Bank-specific determinant variable comparison (pre-2017Q4).

Symbol	Policy Banks	Commercial Banks	City/Rural Commercial Banks	National Commercial Banks
Dependent Variable (Mean)				
Transaction volumes_total assets	0.0016	0.0035	0.0078	0.0015
Independent Variable (Mean)				
(1) Liquidity	3.644	0.771	0.698	0.807
(2) Risk exposure	0.036	0.036	0.047	0.031
(3) Regulatory capital	0.154	0.166	0.157	0.169
(4) Performance	1.197	1.407	1.325	1.477

Data were collected from Bloomberg, Wind, the banks' financial reports, and the China Securitization Analytics website.

Table 5. Bank-specific determinant variable comparison (post-2017Q4).

Symbol	Policy Banks	Commercial Banks	City/Rural Commercial Banks	National Commercial Banks
Dependent Variable (Mean)				
Transaction volumes_total assets	0.0014	0.0028	0.0064	0.0015
Independent Variable (Mean)				
(1) Liquidity	9.911	0.924	0.843	0.954
(2) Risk exposure	0.047	0.043	0.043	0.044
(3) Regulatory capital	0.142	0.175	0.167	0.178
(4) Performance	1.648	0.812	0.812	0.812

Data were collected from Bloomberg, Wind, the banks' financial reports, and the China Securitization Analytics website.

In order to investigate liquidity further (see Tables 6 and 7), the liquidity variables were divided by (1) net loans/deposits and short-term funding (the ND ratio) and (2) liquid assets/deposits and short-term funding (the LD ratio). The ND ratio of policy banks is much higher than that of commercial banks (315.6% versus 51.7%), which indicates paradoxically that the loans provided by policy banks are around three times greater than their own deposits and short-term funding, which could result in poor liquidity. Even though policy banks on average acquire more liquidity assets compared to commercial banks (48.8% versus 25.2%), they still struggle with poor liquidity because of the massive amount of loans. After 2017Q4, the liquidity issue of policy banks was more serious. The ND ratio of policy banks was about 12 times higher than that of commercial banks.

Table 6. Bank-specific determinant variable comparison (pre-2017Q4).

Symbol	Policy Bank	Commercial Banks	City/Rural Commercial Bank	National Commercial Banks
Dependent Variable (Mean)				
Transaction volumes_total assets	0.0016	0.0035	0.0078	0.0015
Independent Variable (Mean)				
(1) Net_loans_D&ST_funding	3.156	0.517	0.442	0.548
(2) Liquidity_assets_D&ST_funding	0.488	0.252	0.256	0.259
(3) Loan_loss_reserves_total_loans	0.027	0.029	0.036	0.026
(4) Impaired_loans_total_loans	0.009	0.007	0.012	0.005
(5) Total_equities_total_assets	0.063	0.064	0.061	0.065
(6) Tier_one	0.081	0.101	0.096	0.104
(7) Cost_to_Income	0.441	0.411	0.423	0.394
(8) Return_on_assets	0.757	1.012	0.930	1.083

Data were collected from Bloomberg, Wind, the banks' financial reports, and China Securitization Analytics website.

Both (7) the cost-to-income ratio and (8) the return on assets (ROA) ratio were used to measure bank performance. The difference in the performance ratios between the policy banks and commercial banks is mainly caused by the ROA rather than the cost-to-income ratio. The cost-to-income ratio of the two types of bank are similar (44.1% in policy banks versus 41.1% in commercial banks). However, the cost-to-income ratio of policy banks became much higher than that of commercial banks after 2017Q4, which means that policy banks have higher operating costs. However, the mean of the ROA of commercial banks is much higher than that of policy banks. The ROA of commercial banks is 1.012, which is about 25% higher than that of policy banks. The high ROA of commercial banks reflects that commercial banks have a greater advantage in profitability than policy banks. This also indicates the different operating visions of these two types of bank; policy banks are for policy-related lending, while commercial banks pursue higher profitability.

Table 7. Bank-specific determinant variable comparison (post-2017Q4).

Symbol	Policy Bank	Commercial Banks	City/Rural Commercial Bank	National Commercial Banks
Dependent Variable (Mean)				
Transaction volumes_total assets	0.0014	0.0028	0.0064	0.0015
Independent Variable (Mean)				
(1) Net_loans_D&ST_funding	9.5876	0.7674	0.6825	0.7980
(2) Liquidity_assets_D&ST_funding	0.3239	0.1571	0.1600	0.1560
(3) Loan_loss_reserves_total_loans	0.0138	0.0139	0.0120	0.0146
(4) Impaired_loans_total_loans	0.0327	0.0295	0.0308	0.0290
(5) Total_equities_total_assets	0.0700	0.0688	0.0656	0.0699
(6) Tier_one	0.0720	0.1066	0.1009	0.1086
(7) Cost_to_Income	1.6408	0.8058	0.8052	0.8060
(8) Return_on_assets	0.0071	0.0064	0.0068	0.0062

Data were collected from Bloomberg, Wind, the banks' financial reports, and the China Securitization Analytics website.

(2) (City/rural commercial banks versus national commercial banks

Commercial banks are a large part of our sample, which were divided into two types and analyzed further. On average, commercial banks with larger-scale assets presented less liquidity, lower credit risks, more adequate regulatory capital, and better performance before 2017Q4 (see Tables 6 and 7). However, the city/rural commercial banks had an advantage in credit risks over national commercial banks after 2017, which improved their performance.

The ratios employed to measure the bank's credit risks are (3) loan loss reserves/total loans (the LL ratio) and (4) impaired loans/total loans (the IT ratio). National commercial banks had a greater advantage in credit risk management compared with city/rural commercial banks before 2017. The LL ratio and the IT ratio of the city/rural commercial banks were much higher than those of the national commercial bank, which was as high as 3.6%. This indicates that banks with a larger scale are better at risk management. However, the LL ratio of the national commercial banks increased significantly and became much higher than that of the city/rural commercial banks, which caused those banks to lose their advantage in risk management.

Both the CIR and ROA variables, as banking efficiency or performance measures, show that the city/rural commercial banks' performance was worse (43.4% and 101%) than that of the national commercial banks during the first period. Hence, banks with large-scale assets tend to have better performance. However, the profitability of both kinds of bank changed after 2017Q4, and their profitability tended to be similar.

4.1.3. Univariate Analysis

The previous analysis is based on part of an independent variable comparison. This section analyzes how those characteristics affect their securitization (dependent variables).

(1) Policy banks versus commercial banks

The securitization transaction volume of commercial banks is much higher than that of policy banks for the two periods. The mean percentages of the transaction volume to total assets are 0.35% and 0.28% for the commercial banks, as opposed to 0.16% and 0.14% for the policy banks (see Tables 6 and 7). The previous section shows that liquidity and performance are the two major different variables between policy banks and commercial banks for the whole period. Therefore, the liquidity and performance of banks might be two significant determinants that affect loan securitization. Entities resorting to securitization are net borrowers of funds in the interbank market and are seeking to improve its financial position.

Comparing (1) the ND ratio, (2) the LD ratio (liquidity measures), (7) the CIR, and (8) the ROA (performance measures), with higher liquidity and performance, banks acquire securitization issuances. The other two determinants, risk exposure and regulatory capital, also reflect the relationship with bank loan securitization. Risk exposure and regulatory capital are positively related to securitization transaction volume, even though their effects are limited.

(2) City/rural commercial banks versus national commercial banks

The transaction volume to the total assets in commercial banks increased with their decreasing asset scale for the whole period, even though the amount of securitization issuance rose with a larger asset scale. The percentages of the transaction volume to the total assets regarding city/rural commercial banks was the largest (0.78% and 0.64%), much larger than those of national commercial banks (0.21% and 0.15%).

The previous section indicates that liquidity and performance are also significantly different variables for the two types of bank. Thus, this paper considers the difference in the securitization transaction volume to the total assets because of the important liquidity and performance before 2017Q4. After that, the liquidity and regulatory capital were the two significantly different variables, so the motivations for the securitization of commercial banks changed. Improving liquidity and regulatory capital arbitrage is expected to be the motivation of securitization after 2017Q4. The subsequent analysis will confirm whether this variable is statistically significant in the model.

4.2. Multivariate Analysis

4.2.1. Groups of Bank Samples

This paper focuses first on regression on all bank levels, followed by research on types of bank. The sample of banks is divided into three main groups, namely, (1) whole banks, (2) commercial banks, and (3) national commercial banks (see Table 8). Whole banks consist of all banks (policy banks and commercial banks); commercial banks are composed of city/rural commercial bank and national commercial banks. The national commercial banks are the last group studied.

Table 8. Types of bank group.

Types of Bank Group	Description
(A) Whole bank	Whole banks = policy banks + City/Rural commercial bank + National commercial banks
(B) Commercial bank	Commercial banks = City/Rural commercial bank + National commercial banks
(C) National commercial bank	National commercial bank

4.2.2. Results of Four-Variable Regression

This paper examines four variables using a fixed effects model and a random effects model. According to the Hausman test, the probability of all results are lower than 95%, which means that the composite error term is correlated with all of the explanatory variables. Thus, a fixed model is more appropriate. The following analysis is based on the results of the fixed effects model (see Tables 9–12).

Table 9. Regression results of four variables in $t-1$ (pre-2017Q4).

	All Banks		All Commercial Banks		National Commercial Banks	
	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model
(1) Liquidity ($t-1$)	−0.001 ***	−0.001 ***	−0.010 *	−0.009 *	−0.003	−0.002
	(−3.375)	(−3.375)	(−1.911)	(−1.810)	(−1.243)	(−0.927)
(2) Risk_Exposure ($t-1$)	0.174 ***	0.174 ***	0.157 ***	0.162 ***	−0.001	0.016
	(−5.072)	(−5.072)	(−6.608)	(−6.826)	(−0.019)	(−0.385)

Table 9. *Cont.*

	All Banks		All Commercial Banks		National Commercial Banks	
	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model
(3) Capital_Requirement ($t-1$)	−0.011	−0.011	0.004	−0.001	−0.027 ***	−0.020 ***
	(−0.659)	(−0.659)	−0.227	(−0.051)	(−2.802)	(−3.104)
(4) Profitability ($t-1$)	−0.0002	−0.0002	0.001	0.002**	0.001 **	0.0005
	(−0.010)	(−0.010)	(−0.835)	(−2.03)	(−2.117)	(−0.657)
Constant	0	−0.0003	0.003	0.002	0.007 *	0.006
	(−0.094)	(−0.095)	(−0.703)	(−0.408)	(−1.75)	(−1.623)
Observation	129	129	118	118	87	87
Adjusted R-squared	0.441	0.432	0.46	0.449	0.219	0.173
Hausman Test Prob.		0		0		0.006

Data were collected from Bloomberg, Wind, the banks' financial reports, and the China Securitization Analytics website; *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10. Regression results of four variables in $t-1$ (post-2017Q4).

	All Banks		All Commercial Banks		National Commercial Banks	
	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model
(1) Liquidity ($t-1$)	0	0	0.001	−0.001 ***	−0.001	−0.001 ***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
(2) Risk_Exposure ($t-1$)	−0.024 *	−0.026 *	−0.051 **	−0.051	−0.038 ***	−0.033
	(−0.024)	(−0.026)	(0.021)	(0.020)	(0.014)	(0.013)
(3) Capital_Requirement ($t-1$)	−0.002	0.002	0.004	0.007	0.006	−0.001
	(−0.002)	(0.002)	(0.008)	(0.007)	(0.005)	(0.005)
(4) Profitability ($t-1$)	0	0	0.001	0.001 **	0	0
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Constant	0.004 ***	0.005 ***	0.003	0.006	0.003 **	0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Observation	387	387	362	362	266	266
Adjusted R-squared	0.01	0.01	0.7649	0.029	0.001	0.043
Hausman Test Prob.		0.47		0.01		0.01

Data were collected from Bloomberg, Wind, the banks' financial reports, and the China Securitization Analytics website; *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 11. Regression results of eight variables in $t-1$ (pre-2017).

	All Banks		All Commercial Banks		National Commercial Banks	
	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model
(1) Net_loans_D&ST_funding ($t-1$)	−0.001 **	−0.001 **	−0.015 **	−0.013 ***	−0.001	0.00006
	(−2.214)	(−2.553)	(−1.907)	(−2.125)	(−0.372)	−0.022
(2) Liquidity_assets_D&ST_funding ($t-1$)	−0.003	−0.004	0.001	−0.0003	−0.001	−0.001
	(−1.123)	(−1.280)	−0.431	(−0.096)	(−0.184)	(−0.427)
(3) Loan_loss_reserves_total_loans ($t-1$)	0.109 ***	0.116 ***	0.111 ***	0.115 ***	−0.039	−0.021
	−4.394	−4.64	−4.878	−5.334	(−0.960)	(−0.510)
(4) Impaired_loans_total_loans ($t-1$)	0.366 ***	0.367 ***	0.302 ***	0.303 ***	0	0.011
	−6.418	−5.982	−5.425	−5.49	(−0.003)	−0.235
(5) Total_equities_total_assets ($t-1$)	0.028	0.056	0.120 *	0.142 **	−0.122 **	−0.101 ***
	−0.642	−1.197	−1.851	−2.184	(−2.630)	(−2.708)
(6) Tier_one ($t-1$)	−0.048	−0.062 **	−0.041	−0.046*	0.023	0.019 **
	(−1.656)	(−2.266)	(−1.559)	(−1.935)	−1.578	−2.189
(7) Cost_to_income ($t-1$)	0.001	0.001	0.001	0.001	0.001	0.001
	−0.646	−0.831	−0.809	−0.725	−0.889	−1.56
(8) ROA ($t-1$)	0.003 *	0.003 **	0.003 *	0.002	0	−0.001
	−1.789	−2.376	−1.872	−1.539	−0.298	(−0.575)
Constant	−0.001	−0.001	−0.002	−0.002	0.008 **	0.007 **
	(−0.391)	(−0.463)	−0.492	−1.539	−2.138	−2.192
Observation	129	129	118	118	87	87
Adjusted R-squared	0.499	0.49	0.519	0.518	0.39	0.247
Hausman Test Prob.		0.000		0.000		0.011

Data were collected from Bloomberg, Wind, the banks' financial reports, and the China Securitization Analytics website; *t*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 12. Regression results of eight variables in $t-1$ (post-2017).

	All Banks		All Commercial Banks		National Commercial Banks	
	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model	Fixed Effects Model	Random Effects Model
(1) Net_loans_D&ST_funding ($t-1$)	0.000	0.000	0.001	−0.003	−0.001	0.001
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)
(2) Liquidity_assets_D&ST_funding ($t-1$)	0.002	0.002	0.008	0.011 **	−0.002	−0.001
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(−0.001)
(3) Loan_loss_reserves_total_loans ($t-1$)	−0.049 *	−0.043 *	−0.036	−0.011	−0.002	−0.001
	(−0.049)	(−0.043)	(0.030)	(0.028)	(0.021)	(−0.001)
(4) Impaired_loans_total_loans ($t-1$)	−0.003	−0.007	−0.041	−0.065	−0.106 ***	−0.097 ***
	(−0.003)	(−0.007)	(0.045)	(0.042)	(0.031)	(−0.097)
(5) Total_equities_total_assets ($t-1$)	−0.039 *	−0.027	−0.029	0.02	−0.043 ***	−0.048 ***
	(−0.039)	(−0.027)	(0.029)	(0.026)	(0.022)	(−0.048)
(6) Tier_one ($t-1$)	0.028 *	0.022 *	0.031 **	0.017	0.024 **	0.017*
	(0.028)	(0.022)	(0.015)	(0.014)	(0.010)	(0.017)
(7) Cost_to_income ($t-1$)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
(8) ROA ($t-1$)	0.044	0.087	0.022	0.054	−0.068	−0.046
	(0.044)	(0.087)	(0.046)	(0.045)	(0.032)	(−0.046)
Constant	0.004 ***	0.005 ***	0.000	0.003	0.005 ***	0.004 ***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
Observation	386	386	361	361	265	265
Adjusted R-squared	0.763	0.037	0.770	0.061	0.356	0.098
Hausman Test Prob.		0.000		0.000		0.005

Data were collected from Bloomberg, Wind, the banks' financial reports, and the China Securitization Analytics website; t-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

(A) All banks

Liquidity and risk exposure were the two important determinants of securitization in China's banking sector before 2017Q4, showing a confidence level of more than 99%. Compared with liquidity, risk exposure presents more a significant effect on loan securitization transaction volume, because the probability of securitizing increases given more variation in the dependent variable. When a bank's risk exposure increased by one unit, the probability that a bank will opt for securities increased by 17.4% when the other variables were held constant. Risk exposure had a positive effect on securitization. The liquidity effect on loan securitization was limited. A one-unit liquidity change only resulted in a 0.1% securitization transaction volume adjustment. The higher risk exposure motivated banks to issue more loan securities. Additionally, banks with a lower liquidity could raise liquidity and funding via securitization.

Risk exposure was an important determinant for securitization only after 2017Q4, showing a confidence level of more than 90%. When a bank's risk exposure increased by one unit, the probability that a bank will opt for securities increased only by 2.4% when the other variables were held constant, which is much lower than that before 2017Q4. Additionally, improving liquidity was not a determinant of securitization for all banks.

(B) Commercial banks

Consistent with all banks, liquidity and risk exposure were still the two important determinants of the loan securitization transaction volume. The risk exposure ratio was significant at a 99% confidence interval and with an obvious effect on the securitization transaction volume (a one-unit risk exposure rise corresponds to a 15.7% change in securitization transaction volume). Liquidity was only in the 90% confidence interval, so it is not as important as risk exposure.

The motivation for commercial banks' securitization issuance was similar to the other banks. Risk exposure was the only determinant after 2017Q4.

(C) National commercial banks

The determinants of securitization in national commercial banks were completely different from the previous two groups before 2017Q4. Capital requirements and profitability were two important determinants in this group. Capital requirements, compared with performance, was more significant with respect to securitization. When a bank's regularity capital decreased by one unit, the probability that a bank would opt to securitize increased by 2.7%. With a lower regularity capital, the banks acquired a higher securitization transaction volume, which could reflect securitization as a way to search for new profit opportunities. The profitability variable was statistically significant, indicating that banks are using securitization to raise their performance, but its effects on national commercial banks are limited (only a 0.1% regression coefficient).

However, capital requirements and profitability were not the determinants of securitization after 2017Q4. The table shows that risk exposure was still the determinant for national commercial banks, which was significant at a 99% confidence interval.

4.2.3. Results of Eight-Variable Regression

In Tables 11 and 12, as with the four-variable regression analysis, both the random effects approach and the fixed effects approach were applied in this regression. According to the Hausman test probability, the fixed effects model is valid.

To further confirm the findings, eight-variable multivariate analysis was conducted. Each determinant was evaluated by two proxies, introduced in the methodology section. If both of two variables were in a confidence interval greater than 90%, the determinant was considered to drive securitization issuances. Additionally, if only one variable was statistically significant in relation to the transaction volume, its influence on securitization was concluded.

(A) All banks

Liquidity and risk exposure were the main drivers of loan securitization in the Chinese banking sector, which is basically consistent with previous results, but performance was also a significant driver of securitization in the eight-variable regression before 2017Q4. Specifically, (3) the LT ratio and (4) the IT ratio as risk exposure measures were statistically significant. The coefficients of (3) the LT ratio and (4) the IT ratio were 10.9% and 36.6%, respectively, and appear to exert the most influence on the probability that a bank opts to securitize, compared to the other variables. (1) The ND ratio as a proxy of liquidity indicates statistical significance at the 5% level. While the liquidity effect was limited, the one-unit ND ratio rise only improved securitization truncation volume by 0.1% in all banks. Even though this regression result indicates that securitization can be used as a way to improve a bank's performance, the coefficient of this ratio is too small, so its effect is limited. (8) The ROA ratio variable as a profitability measure is the least statistically significant determinant among the four basic determinants proposed in the literature.

After 2017Q4, reducing capital requirement and risk exposure was the main determinate for the whole banks. Specifically, (4) the LT ratio was statistically significant, but the coefficients of that ratio were much lower than that before 2017Q4. Both (5) the TETA ratio and (6) the ROA ratio are related to loan securitization issuance. However, they are both significant at a 90% confidence interval.

(B) Commercial banks

In the group of commercial banks, all four determinants affected loan securitization before 2017Q4 but to varying extents. Risk exposure, compared with the other determinants, was the most significant for securitization. Two variables, (3) the LL ratio and (4) the LT ratio, presented statistical significance at the 99% confidence level. The coefficients of both ratios were also the highest compared to the other variables—11.1% and 30.2%, respectively. Liquidity was the second most significant determinant. (1) The LD ratio measuring liquidity was related to loan securitization. These two determinants are consistent with the four-variable regression. The capital requirement and performance were statistically significant, which also motivates banks to securitize part of its portfolio, but not as significant as risk exposure and liquidity. (6) The tier one ratio (capital requirement measures) and (8) the ROA ratio (profitability measures) were statistically significant, but only in the 90% confidence interval, so they were the least statistically significant. This might explain why neither of them were significant in relation to loan securitization in the four-variable regression. The coefficient value of (8) ROA (performance proxy) was close to zero. Using securitization as a mechanism for improving a commercial bank's performance does not seem to be very efficient.

The motivation for the securitization issuance of commercial banks was only regulatory capital arbitrage after 2017Q4. Reducing risk exposure and increasing liquidity and performance were no longer determinants of securitization issuances. (6) The tier one ratio (capital requirement measures) was statistically significant but only in the 95% confidence interval.

(C) National commercial banks

Regularity capital was the only driver of securitization activities in national commercial banks. (5) The TETA ratio measuring capital requirement was the only variable with statistical significance. Profitability was an important determinant for securitization in the four-variable regression, but (7) the CIR and (8) ROA variables measured as bank profitability did not reach statistical significance in the eight-variable regression. This leads to a new conclusion: Regulatory capital, rather than performance, is the only determinant that appears to exert the most influence on loan securitization. National commercial banks could lower their regularity capital (regulatory capital arbitrage) via securitization. Interestingly, risk exposure was no longer a significant determinant for a bank's securitization decisions in the national commercial banks. This is completely different from all other banks.

Risk exposure was the other determinant of securitization issuance after 2017Q4. The risk exposure and regularity capital were two main drivers of securitization activities in national commercial banks. Specifically, (4) the IT ratio, measured as a bank's risk exposure, reached statistical significance at the 99% confidence level. (7) The CIR and (8) ROA variables were also statistically significant.

In summary, the results of the eight-variable regression are basically consistent with the four-variable regression, but they also revealed some new important determinants for securitization. Specifically, securitization transaction was motivated by both risk exposure and liquidity, risk exposure especially in the first period, but was still motivated by risk exposure after 2017Q4. However, the eight-variable regression shows that performance was another significant determinant for securitization, even though its effects were limited before 2017Q4.

4.3. Results of Varying Types of Banks

4.3.1. Derivations from Regression Results

The above findings only reflect how these determinants affect securitization decisions in varying bank groups, but it is difficult to indicate how determinants influence varying types of banks, not including national commercial banks. This can be safely deduced by comparing different bank groups (see Table 13). Specifically, city/rural commercial banks can be deduced through a comparison of the *p*-value and coefficients of commercial banks and national commercial banks. For example, if the former regression probability of a hypothesis variable (*p*-value) (commercial banks) is higher than that of the national commercial banks, national commercial banks can be considered to have contributed to an increased *p*-value. If the variable regression probability is the same or similar, their coefficients will be compared and their influence inferred. Policy banks are also analyzed according to this methodology.

Table 13. Types of bank.

Kinds of Banks	Derivation from Regression Results
(1) National commercial banks	National commercial banks = (C) National commercial banks
(2) City/rural commercial banks	City/rural commercial banks = (B) Commercial banks − (C) National commercial banks
(3) Policy banks	Policy banks = (A) Whole banks − (B) Commercial banks

4.3.2. Derivations from Four-Variable Regression

(1) National commercial banks

National commercial banks and their change were analyzed in the four-variable regression section, so we do not need to compare and discuss their important determinants. Liquidity was the only determinant before 2017Q4, but risk exposure became the main motivation for securitization issuance after 2017Q4.

(2) City/rural commercial banks

In city/rural commercial banks, liquidity and risk exposure were the main determinants for securitization before 2017Q4. As per the previous analysis, capital requirement was the only significant determinant in national commercial banks. In other words, liquidity and risk exposure were not related to national commercial banks' securitization. However, these two variables were statistically significant in all commercial banks. This implies that city/rural commercial bank liquidity and risk exposure are related to the dependent variable and result in the statistical significance of all commercial banks.

However, liquidity and risk exposure were not the drivers of loan securitization issuance after 2017Q4. The *p*-value of national commercial banks was in the 99% confidence interval, which was higher than that of commercial banks (in the 95% confidence interval). This implies that city/rural commercial banks have no motivations for securitization issuance.

(3) Policy banks

Liquidity and risk exposure were significant determinants motivating policy banks' securitization before 2017Q4. The risk exposure *p*-value in the all-bank regression was in the 99% confidence interval, and this was found for the national commercial banks as well. Thus, their coefficients were further compared. The coefficient of risk exposure variables in all banks was higher than that of all commercial banks (17.4% versus 15.7%). The risk exposure of the policy banks could influence their securitization decisions and raise the corresponding coefficient in the all-bank regression. The regression probability of liquidity in all banks is higher than that in all commercial banks. Thus, the liquidity of policy banks was also a significant determinant for their securitization transaction and improved the probability in the all-bank regression.

However, it is hard to infer specific drivers by comparing *p*-values of the commercial bank group and the all-bank group. Due to the lower *p*-value of the all-bank group, we inferred that there is no motivation for securitization issuance. This outcome is the same in the case of rural/city commercial banks.

4.3.3. Derivation from Eight-Variable Regression

(1) National commercial banks

More detail about national commercial bank securitization determinants can be found in Section 4.2.3.

(2) City/rural commercial banks

Liquidity, risk exposure, and profitability are three important determinants for securitization transaction volume in city/rural commercial banks. This is because these three determinants are not statistically significant in the former group but present contrary outcomes in the commercial bank group. The statistical significance comes from the effect of city/rural commercial banks. The (5) TETA ratio is also statistically significant in the sample of commercial banks. However, its *p*-value is lower than that of the national commercial bank group, confirming that capital requirement is a significant determinant in city/rural commercial banks.

Only the regulatory capital arbitrage is inferred to have been an important determinant after 2017Q4. The (5) TETA ratio was also statistically significant in the sample of commercial banks and is the same as that of the national commercial banks in the 99%

confidence interval. The coefficient was higher than that of the commercial bank group, which could imply that regulatory capital arbitrage was the main motivation for city/rural commercial banks to issue securities.

(3) Policy banks

Risk exposure was inferred to have been an important determinant in policy banks before 2017Q4. The (1) ND ratio (liquidity measures), the two variables (3) and (4) of risk exposure, and (8) the ROA ratio (profitability measures) were statistically significant in all banks, but the regression coefficients of (1) and (8) were smaller or equal to the former groups, which makes it difficult to prove that liquidity and profitability were two important determinants of policy bank securitization issuance. The *p*-values of variables (3) and (4) of all banks were the same as those of the commercial bank group. Although the coefficient of (3) was lower than that of the sample of commercial banks (10.9% versus 11.1%), the coefficient of (4) in the sample was much higher than that of the commercial bank sample (36.6% versus 30.2%). Therefore, the effect of risk exposure in all banks was greater than that of the commercial bank group. The risk exposure affected policy bank securitization and improved the corresponding coefficient.

Risk exposure and regulatory capital arbitrage were inferred to be two main determinants in policy banks after 2017Q4. Regarding risk exposure, (3) the LT ratio was statistically significant in the 90% confidence interval in the all-bank group, but there was no statistical significance in the commercial bank group. We conclude that national policy banks contributed to an increased *p*-value. In the same way, it can also be inferred, by comparing (5) TETA ratios, that the regulatory capital arbitrage was the other main determinant.

5. Discussion

5.1. Discussion of Results

This paper investigates what drives bank securitization in China and compares determinants before and after 2017Q4. Generally, the paper shows that, before 2017Q4, a bank was more likely to issue securities if the bank's credit risk exposure, its liquidity, and its performance were higher. A bank's credit risk was still a main driver of securitization issuance volume. The regulatory capital arbitrage also influenced securitization decisions. However, the liquidity and performance were not determinants of securitization issuance after 2017Q4. Specifically, credit risk exposure was the most significant determinant compared to the other two. The main motivation of bank securitization could have been credit risk transfers, followed by increased liquidity and improved profitability. Interestingly, capital requirement—or, more precisely, (5) the total equities to total assets and (6) the tier one ratio—did not seem to influence banks' securitization decisions very strongly before 2017Q4. However, these two variables were statistically significant with respect to securitization issuance after 2017Q4. Liquidity—or, more precisely, (1) net loans to deposits and short-term funding and (2) liquidity assets to deposits and short-term funding—did not seem to influence banks' securitization decisions very strongly. (5) The cost-to-income ratio and (6) the return on assets also did not seem to influence banks' securitization decisions strongly after 2017Q4.

The paper also shows that the four determinants in different types of banks display different propensities toward securitization activities in the two periods. To differentiate motivations of securitization between the varying types of banks, this paper looks particularly at the varying types of bank groups in more detail. Before 2017Q4, two types of bank group (the commercial bank group and the national commercial bank group) were used in the empirical models. The findings indicate that risk exposure was still the most important determinant, which is the case in all banks. The (3) loan loss reserves to total loans and (4) the impaired loans to total loans, measuring credit risk exposure, presented statistical significance in the group of commercial banks. Additionally, credit risk exposure affected bank securitization more obviously—the coefficients of (3) and (4) were much higher than those of the other determinants. The second important determinant that drives banks' securitization was liquidity. (1) The net loans to deposits and short-term funding were statistically significant with respect to securitization transaction volumes, except in the group of national commercial banks. However, because the *p*-values and coefficients of the liquidity variables were lower than those of risk exposure, the liquidity determinant was not as important. The profitability determinant also drove securitization transactions in all commercial banks but was less important than the above two determinants, which is shown by the lower *p*-values of profitability. Consistent with the results of all banks, the capital requirement determinant was considered the least important determinant. It is only related to securitization issuance in the group of national commercial banks. After 2017Q4, the all-bank group and the national commercial bank group were the only two groups that issued their securities because of the risk exposure. However, the capital requirement determinant was found to be related to securitization issuance in the group of all banks.

Risk exposure is the most important determinant for bank securitization, by bank group analysis and by different types of bank analysis, for the whole period. Higher credit risks in a bank has motivates a larger part of an asset-securitized portfolio, and these securitized assets are more likely to be low-quality or impaired loans. This is because the bank is able to decrease stress costs and improve risk management when it removes these low-quality or impaired loans from the balance sheet via securitization transactions and shares those credit risks with investors. Thus, these findings are indicative that securitization is mainly used as a risk transfer. Liquidity was the second most important determinant before 2017Q4, but it was not the determinant after 2017Q4. The use of securitization is regarded as a mechanism in the search for liquidity and, therefore, as a source of additional financing. In this way, banks can newly acquire alternative funding resources and be less vulnerable to liquidity shock. The other important determinant is profitability. The first period indicates that securitization was used as a way to improve performance. Generally, that performance mainly came from intermediation profits via a specific design of securitization loans or by raising cash inflows to retire existing debts that could reduce interest expense. However, improving a bank's performance via securitization issuance could be more difficult after 2017Q4. The capital requirement did not seem to influence banks' securitization (except national commercial banks in the first period), but this changed after 2017Q4. It can be stated that regulatory capital arbitrage hampered by the regulatory scheme was difficult to apply in the securitization market, but that has changed in the last three years.

5.2. Determinants, Adverse Selection, and Moral Hazards in Chinese Banking

5.2.1. Adverse Selection

The risk exposure determinant, measuring the quality of loans, can be used to test adverse selection problems. These problems are mainly concerned with securitization transactions between the originator and investors. Generally, the originator has more and superior information about the underlying assets than investors. If a securitization transaction involves serious information asymmetry, where the investor is not clear about the underlying quality of an asset, the securitization originator can move low-quality loans into SPV and sell them to investors. Thus, the quality of underlying assets is key in studying adverse selection problems. If large amounts of low-quality underlying assets are moved from banks and sold to investors, investors are more likely to buy 'lemons' from an originator, resulting in adverse selection problems. Based on the background of banking in China as well as our regression results, this paper shows that the securitization transactions made in this setting are related to adverse selection problems for the following reasons.

(1) Writing off non-performing loans, asset management companies (AMCs), 'debt-to-equity' swaps, and non-performing loan (NPL) securitization are four main ways to tackle non-performing loans in China. They are allowed and supported in banks in China; however, the effects of those approaches in practice are questioned.

The traditional way to tackle non-performing loans is writing them off. This approach is widely used with lower non-performing loans, but it is at the expense of banks' net profits and decreases the bank's profitability.

AMCs are another way to tackle NPLs. They acquire distress debt from banks and then progressively restrict and repack those acquisitions in the flowing. The four major AMCs play a critical role in tackling NPLs (Deloitte 2018a). Building on this, recent reforms allow AMCs, with 35 currently in operation, to take on bad debt. They also permit AMCs to sell bad debt to third-party investors rather than simply acting as warehouses for NPLs (Foreign and Commonwealth Office 2017). However, there are signs that those corporations rely heavily on bank loans to finance their purchases in order to expand their scale; given the circular relationship with the banks, some local AMCs are simply perpetuating loans to zombie firms (Foreign and Commonwealth Office 2017). The effects of AMCs are doubtful; those credit risks might be moved from balance sheets but essentially are not eliminated and could even increase risk exposure.

'Debt-for-equity' swaps were initiated by the State Council in 2016 to replace bad loans with an equity stake in the relevant companies, becoming another solution to China's cooperation debts. In theory, debt-for-equity swaps could act as a relatively growth-friendly route to incorporate deleveraging that can decrease the problems of corporate debt problems (Martin 2016). In other words, 'debt-to-equity' swaps aim to decrease high corporate leverage and lower debt risks directly, which could indirectly lower banks' credit risks. However, in practice, 'debt-to-equity' swaps face implementation risks, because banks are compelled to swap bad loans for equity to keep failing 'zombie' companies alive (Fitch 2016). In addition, the 'debt-for-equity' swap scheme is unlikely to reach a scale at which it addresses corporate sector leverage in a meaningful way, given the lack of investor interest and the capital constraints of banks (Nolet and Wong 2017). If 'debt-to-equity' swaps cannot deal with high leverage and NPLs efficiently for corporations, then this approach indirectly fails to decrease NPLs in banks.

With the diversification of underlying assets in terms of securitization, non-performance loan securitization has become a new way to deal with NPLs. The mechanism is similar to loan securitization, but the underlying assets are replaced by non-performing assets. In this way, more investors participate in the market to help optimize non-performing assets and increase banks' non-performance asset disposal (KPMG 2017b). However, the high risks of these underlying assets could affect the confidence of investors. In order to overcome this issue (Daniel et al. 2016), banks tend to retain large amounts of high risk tranches. Thus, the high cost of NPL securitization could make tackling credit risks difficult.

(2) The official data from CBRC and other financial institution estimations jointly indicate that credit risks in the banking context in China have been boosted in the past few years, and the financial system is on a dangerous trajectory. If the approaches of tackling non-performing loans are less efficient as discussed above, banks will be encouraged to transfer their risks via loan securitization directly.

Even though exposure to credit risks slowed down after 2016 (KPMG 2017a), NPLs have increased extraordinarily in recent years with the slowdown of the Chinese economy. According to the information disclosed by the CBRC, the various loan balance of commercial banks' asset portfolios was RMB 98.029 trillion at the end of 2017, representing an increase of RMB 11.121 trillion compared to the end of 2016. The NPL ratio is as high as 1.74% and has risen extraordinarily since 2012 (DBS 2018). However, foreign institutions have estimated that the NPL ratio would be much higher than is indicated by the official data. Fitch (2017) estimated that the NPL ratio could be in a range from 15% to as much as 21%, equivalent to around 11–20% of China's economy. The IMF (2016) estimated a similar ratio, i.e., a total debt at risk, based on individual firm level data on interest coverage ratios and liability ratios, at 15%.

The high NPLs result in increased stress costs and a threatened stability. However, securitization with 'true sale' transactions and the 'bankruptcy-remoteness' mechanism provide banks with credit risk transfer opportunities. Generally, because of the market mechanisms in securitization, such as lender reputation concerns, the lenders retain high-default-risk loans in their portfolio; while financial risks grow, lenders change dramatically and retain low-default-risk loans in their portfolios (Agarwal et al. 2012). Thus, when banks are under pressure of high credit risks, they are more likely to share large amounts of low-quality loans via securitization.

It can be summarized that NPLs have increased dramatically in the past few years, but approaches tackling NPLs in practice are doubtful. With a rising risk exposure without efficient methods to tackle risk, high-risk exposure could motivate banks to transfer credit risks from balance sheets via loan securitization directly. In addition, our study indicates that risk exposure presents statistical significance in relation to securitization transaction volume. Higher credit risks in banks drive larger amounts of loan securitization. As mentioned previously, the quality of underlying assets is key to studying adverse selection problems. We conclude that banks tend to pack those low-quality assets from their portfolios and move to SPV to protect themselves against high credit risks. Once a large amount of low-quality or low-performance loans are packaged without efficient information disclosure, investors are more likely to buy low-quality securitizations. This will hurt investor protections and even drive the securitization market down. There are consequences of adverse selection in securitization.

5.2.2. Moral Hazards

In this paper, liquidity, profitability, and capital requirement determinants are used to study moral hazards in bank securitization. Moral hazards are mainly concerned with the relationship between borrowers and banks (originators) or the bank itself. They mainly show that banks use securitization to take on more risks. Specifically, once a bank's risks are incurred by investors without enough information to supervise the bank's operations, the bank will take more risks, which results in financial instability. We found, by comparing two periods' securitization determinants, that moral hazards tended to decrease because these three determinants had a lower influence on securitization issuance. Before 2017Q4, liquidity contributed to serious moral hazard problems in securitization, while the profitability and capital requirement determinants presented a lower association to such problems. However, the capital requirement presented a greater association to moral hazard problems after 2017Q4.

Liquidity

Liquidity is considered an important determinant contributing to moral hazard. Moral hazards in securitization with regard to liquidity are mainly present in lax screening by lenders. Securitization is used to increase bank liquidity according to multiple variable analysis. Banks can acquire additional and sufficient liquidity through securitization. Sufficient liquidity generally encourages banks to offer a larger amount of loans to borrowers and pursue higher profitability. The supply of loans is increased, while the demand is unchanged, and lax screening by lenders can stimulate a higher demand for loans. Lax screening also increases a bank's financial risks and results in the instability of the financial system, especially for so-called 'too-big-to-fail' financial institutions. Additionally, the regulatory scheme also encourages banks to provide more loans to support economic development. The regulatory authorities (China Banking and Insurance Regulatory Commission) released a regulatory scheme aiming to ease the higher amount of liquidity. The specific operation is the relaxation of their bad loans to a range of 120–150% from the current minimum of 150% (WSY 2018). This move can help commercial banks improve their capability in guarding against liquidity risks, serve the real economy, and maintain the safe, stable operation of the banking system (Xinghua 2018). Clearly, banks with the encouragement of a liquidity regulatory scheme lead to large amounts of liquidity from banks to support economic devolvement. This could result in lax screening to a certain degree. We conclude that, before 2017Q4, banks were able to acquire sufficient liquidity and encourage borrowers to take larger loans and that they were more likely to lax-screen borrowers and even offer loans to ineligible borrowers. Therefore, if authorities are not able to acquire enough information to supervise efficiently, lax screening would lose control.

However, Chinese authorities, over the three years prior to the study period, asked banks to restrict the loan supply, especially property loans, to ward off an economic bubble. Banking regulators paid attention to the rebound of the proportion of property loans among their new loans (Nasdaq 2021). Lax screening by lenders decreased under prudential supervision. We inferred that such regulators reduce moral hazards in securitization.

Profitability

Profitability is not associated with moral hazards in securitization, because profitability fails to drive securitization under our analysis. Even though profitability presents statistical significance in relation to securitization transaction volumes in the majority of banks, the correlation coefficient values are almost zero, which reveals that their effects are limited. This could be explained by that fact that securitization can increase liquidity, lower credit risks, and improve risk management, which can improve performance jointly but not directly. In addition, the tax standard of securitization in China is not mature enough, which is reflected by the lower tax incentives and limits the ways in which performance can be improved via securitization. Before the tax reform, securitization generated taxation problems that did not fully reflect the tax neutrality principle (Liang 2015). The pilot program for replacing the business tax with a value-added tax (VAT) abolished the business tax in 2016. However, how the application of a VAT affects the securitization is still ambiguous, because it is not relevant to purely domestic securitization transactions (Phua 2020). Therefore, we conclude that it is difficult for banks to improve their profitability via securitization transactions due to the tax issue and to take more risks. The profitability determinant cannot result in moral hazards in securitization transactions.

Capital Requirement

The capital requirement is not related to moral hazards either. The capital requirement presents no statistical significance in relation to securitizations, which means that most banks do not use loan securitization to save on regulatory capital. This is because the Basel II framework under the 'standardized approach' no longer allows for regulatory capital arbitrage. Basel III, which could further enhance the capital regulation, was scheduled to be introduced from 2013 to 2019 (Financial Stability Board 2018). We consider regulatory capital arbitrage to be the main relation between regulatory authorities and banks. Those financial institutions seeking new opportunities of regulatory capital arbitrage might never come to an end, but it has become harder to continue with the maturity of regulations. Regulatory capital arbitrage is difficult to apply in loan securitization. Less regulatory capital could not result in moral hazard problems in securitization transactions before 2017Q4. However, banking regulators in China intensified capital rules in the three years prior to that; for example, banks that failed to comply with capital adequacy requirements by the end of 2010 in terms of the amount of capital they had to hold against their loans were punished, with limits on market access and so on (McMahon 2009). Chinese regulators also drafted tougher capital rules for China's too-big-to-fail banks, seeking to curb risks (Bloomberg 2021). Regulatory capital arbitrage might have been applied in securitization transactions under the pressure of stricter capital requirements after 2017Q4.

6. Recommendations

This paper aims to examine adverse selection and moral hazards by examining the determinants of securitization in China and then to answer the main research question: Does China need a higher standard of information transparency to protect against its risks? The findings show that securitization involved both adverse selection and moral hazard problems before 2017Q4, but the digital transformation of banking reduced those issues after 2017Q4. Generally, adverse selection, compared with moral hazards, is more serious. Even though digital transformation reduced information asymmetry significantly, adverse selection and moral hazards still affected the loan securitization market and its stability. Thus, China still needs a higher standard of information transparency to protect against these risks. The recommendations according to this paper's findings are as follows:

(1) The first recommendation regards the adverse selection problem. The standard of information transparency in terms of the underlying assets should be further improved, particularly for the quality of underlying assets. According to our empirical study, risk exposure is the most significant determinant for securitization, which shows that securitization is mainly used as a way to transfer credit risks to investors. As the operating model of banks tends to change from an 'originate-to-hold' to an 'originate-to-distribute' model, risk exposure can be shared with securitization investors to lower bank risks, but investors' benefits should also be protected. It is essential to guarantee that investors are informed about the corresponding price and risks of their investments. A regulatory scheme should require originators to disclose more information in terms of the underlying assets for investors to reduce information asymmetry.
(2) Securitization also involves moral hazards, which is reflected in the regulatory capital arbitrage. The second recommendation is a regulatory scheme that requires banks to disclose more information about regulatory capital arbitrage and the relative shadow banks.
(3) We also found that, even though securitization involves both adverse selection and moral hazards, their effects are different in different types of bank. Thus, our third recommendation is that a regulatory scheme should require varying standards of information disclosure according to the type of banks. National commercial banks should disclose more information because national commercial banks evidenced serious moral hazard and adverse selection problems after 2017Q4. Credit risks were highest in the commercial bank group, but they did not excel in terms of performance, which also indicates that protecting these risks is more difficult. Relatively speaking, policy banks and city/rural commercial banks are not expected to need as high a standard as the other two types of banks.
(4) This paper also indicates, via a comparison of two periods, that digital transformation resulted in lower information asymmetry and higher financial stability. Even though digital transformation reduces adverse selection and moral hazards in banking, it still affects securitization. The last recommendation is to apply blockchain in securitization to further enhance their information transparency.

7. Conclusions

In summary, by comparing two periods, FinTech applications in the banking industry could result in lower information asymmetry. However, moral hazard and adverse selection problems still affect the securitization market, which could affect financial stability. Thus, China needs a higher standard of information transparency.

The moral hazard and adverse selection problems were tested by studying the determinants of loan securitization in China's banking sector. Specifically, risk exposure was the main determinant of securitization issues over the whole period, which means that the adverse selection problem might affect the securitization market. This result is similar to that of studies by Minton et al. (2004) and Bannier and Hänsel (2008). Liquidity and performance were considered to test moral hazards, and they were less statistically significant with respect to securitization issuance after 2017Q4. However, the capital requirement could be a main determinant of securitization. This conclusion is similar to that of studies by Uzun and Webb (2007) and Ambrose et al. (2005).

In order to protect against adverse selection and moral hazards, China needs a higher standard of information transparency. First, since adverse selection in securitization mainly affects risk transfer, information disclosure should focus more on the underlying assets to ensure that investors know what they are investing in and that they are willing to pay corresponding prices and bear the corresponding risks. The second recommendation regards moral hazards, which are mainly reflected in the capital requirement. Information disclosure should correspond more to regulatory capital arbitrage. The third is that a regulatory scheme of information disclosure should be diversified according to the varying types of bank. The last recommendation is to apply blockchain in securitization to further enhance their information transparency.

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Did Financial Consumers Benefit from the Digital Transformation? An Empirical Investigation

Soojin Park [1], Prida Erni Kesuma [1] and Man Cho [2,*]

1 KEPCO International Nuclear Graduate School (KINGS), 658-91 Haemaji-ro, Seosaeng-Myeon, Ulju-gun, Ulsan 45014, Korea; sugini1144@gmail.com (S.P.); prida.erni@gmail.com (P.E.K.)
2 KDI School of Public Policy and Management, 263 Namsejong-ro, Sejong-si 30149, Korea
* Correspondence: mancho@kdischool.ac.kr; Tel.: +82-10-5312-2990

Abstract: This study aimed to test, through empirical investigation, how the rapid advancement of digital transformation (DT) has impacted the price of financial services. To this end, we compiled a set of macro-level indicators on the aggregate outcomes of the financial services sector in Korea over the last three decades and conducted an analysis to gauge the effects of DT on the country using those indicators. Using the ARDL-ECM (autoregressive distributed lag error-correction model), we show that, over time, the unit cost of financial intermediation in Korea has tended to move in tandem with the growth in economic output, although the profit portion of the unit cost has not exhibited a long-term relationship with the GDP trend. The long-term effect of the DT trend is negative (i.e., cost-saving) for labor input, capital expenditure, and the total unit cost of financial intermediation, which are all shown to be statistically significant. Consequently, we conclude that DT contributed to enhancing consumer benefit, mainly by achieving the operational efficiency of labor and capital, from 1990 to 2019 in Korea. From a policy perspective, our finding implies that DT-driven innovation in the sector can benefit financial customers if excessive levels of profit are restrained through market competition.

Keywords: digital transformation; financial consumer protection; financial operational efficiency; error-correction model (ECM); financial consumer policies

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1. Introduction

It is well established that there is generally an endogenous, or mutually reinforcing, relationship between financial development and economic growth (King and Levine 1993; Rajan and Zingales 1998; Manning 2003; Pagano and Pica 2012). Additionally, as in the case of many emerging-market countries, the financial sector in Korea has played a direct role in promoting socio-economic growth, as is evidenced by the various credit programs during the high-growth period of the 1970s to the 1990s. Meanwhile, starting in the 1980s, various financial liberalization measures were implemented, which were accelerated after the Asian financial crisis (AFC) in 1997–1999. As a consequence, the sector has grown substantially since the AFC in terms of both size and diversity.

However, whether growth in the financial sector in Korea has contributed to key macroeconomic outcomes in any meaningful fashion, such as in industrial productivity or income inequality, has rarely been examined.

Philippon (2015, 2016) reported that that the financial services sector in the US has been overpriced since the early 1980s, as evidenced by its realized per-unit cost of providing the service continuously exceeding the projected optimal level. In addition, studies argue that the disruptive innovations in the sector introduced by digital transformation, often labeled as FinTech, can contribute to enhancing the operational efficiency of existing financial institutions.

At a global level, there have been two interrelated mega-trends during the last two decades that are making a profound impact on the financial services sector in most countries. First, there has been a rapid advancement of digital transformation (DT) in delivering various types of financial services, often referred to as FinTech (or financial technology), which encompasses areas such as P2P lending and crowdfunding, online payments, cryptocurrencies, robo-advisors, InsurTech, and RegTech[1]. Second, there have been growing legal and regulatory efforts to protect consumers in the financial markets, as evidenced by such legislations as the *Dodd–Frank Wall Street Reform and Consumer Protection Act* of 2010, as well as those "good" practices suggested by (G20/OECD/INFE 2017; Organization of Economic Cooperation and Development (OECD) 2019; The World Bank 2012; and Cho and Park 2021).

Given these ongoing trends, this study aims to tackle two particular research questions. First, what impact does this trend of digital transformation (DT) have on aggregate (or macro-level) outcomes of the financial services sector in Korea as a whole? Second, what implications can we draw from the findings of the macro-level analysis? More specifically, we would like to look at how the per-unit price of financial services has been changed, in a similar vein to the analysis performed by Philippon (2015), and to further investigate whether the DT trend has made any significant impact on price changes. This study focuses on the financial market of Korea during a period when both rapid DT and financial market strengthening occurred. This study on Korea, where rapid DT and financial market deepening occurred during the observation period, may provide a different view of the labor efficiency of the financial industry from that of the US, which was investigated by Philippon (2015). More importantly, Korea's case may shed light on the impact of DT on the efficiency gains in the financial industry, which may provide policy implications for other emerging markets.

To this end, we compiled a set of indicators of the aggregate outcomes of the financial services sector in Korea during the last three decades and used the correlation estimate as a proxy for the country's DT trend. In so doing, the method put forth by Philippon (2015, 2016) was employed, which involved computing the unit cost of financial intermediation, i.e., an aggregate cost of providing the service during a given time period divided by the total monetary value of the financial service at the end of the period. We also attempted to contribute to the literature by breaking down the unit cost into its sub-components—labor cost, capital expenditure, and profit elements—and used those sub-categories in our empirical analysis. For the empirical analysis, we used the ARDL-ECM (autoregressive distributed lag error-correction model) to investigate the short- and long-term effects of digital transformation on three specific variables related to providing financial services: labor cost, capital expenditure, and total cost.

Our empirical results show that, over time, the unit cost of financial intermediation in Korea has tended to move in tandem with the growth in economic output, although the profit portion of the unit cost did not exhibit a long-term relationship with the GDP trend. Furthermore, the long-term effect of the DT trend is negative (i.e., cost-saving) for labor input, capital expenditure, and the total unit cost of financial intermediation, which is shown to be statistically significant. Consequently, we show that DT has contributed to an enhancement in consumer benefit, mainly by achieving the operational efficiency of labor and capital in Korea.

Through these findings, we aim to contribute to measuring the social cost of financial services and analyzing the impact of DT on the financial industry, which relates to financial consumer protection from an economic perspective. It could also provide a sound basis for establishing financial consumer policy and international comparisons.

The rest of the paper consists of the following sections: Financial Sector Development and Digitalization (Section 2), Valuing the Financial Services Sector in Korea (Section 3), Empirical Test and Results (Section 4), and Conclusions (Section 5).

2. Financial Sector Development and Digitalization

A well-functioning financial services sector is crucial, both in the micro sense of consumer welfare and in the macro sense of economic and social development (Odedokun

1996). There is generally an endogenous, or mutually reinforcing, relationship between financial market development and economic growth; that is, a positive association between the size of private credit and the GDP growth rate is fairly well established and is more pronounced in developing countries than in developed ones (King and Levine 1993; Rajan and Zingales 1998; Manning 2003; Pagano and Pica 2012). In addition, an inverse U-shaped relationship between economic growth and the ratio of private credit to GDP has also been documented, implying that the strengthening of the financial market can have a detrimental effect on growth after a certain threshold (e.g., 100% of the ratio of private credit to GDP as reported), possibly due to an overinvestment in a sector that is generally viewed as a less productive segment of the economy (Cecchetti and Kharroubi 2012; Arcand et al. 2012; Cournède and Denk 2015).

Since the recent financial crisis, there has been debate in the literature that the price of financial services has been too high vis à vis its direct input costs, and that the operational efficiency thereof should be substantially enhanced. In particular, Philippon (2015, 2016) estimated the unit cost of providing financial intermediation in the US and documented that the sector has been too expensive since the early 1980s, and that, as a remedy for the efficiency gain, the disruptive innovations introduced by the FinTech industry can contribute to restoring the efficiency of the sector by posing heightened competition and contestability to existing financial institutions. As a related point, there has also been argument for more innovative and specialized business models in the financial services sector, including a "narrow banking" model, for which FinTech is viewed as a potential driver (Pennachi 2012; Chamley et al. 2012; Cochrane 2014). In this study, we examine the price dimension of financial intermediation, i.e., whether or not service providers (financial consumers) have increased service charges (pay) too much (following the same inquiry posed by Philippon 2015), which is a macro-level financial consumer issue.

From an emerging-market perspective, the financial services sector in Korea has strengthened as aggregate economic output has grown since the 1960s. To illustrate this, the three key service sectors for financial consumers—banking, insurance, and investment—have all exhibited steady growth along with the growth[2] in GDP. However, the growth in the financial services sector after the AFC, in terms of both size and diversity, has not contributed to macroeconomic outcomes, such as increasing industrial productivity or narrowing societal income and wealth inequality (Cho et al. 2017).

Another relevant trend in Korea to note is digital transformation (DT). Unlike in the US and several other advanced economies, where information and communications technology (ICT)-driven innovations in the financial sector started in the 1990s and have been showing a continuous pattern ever since, FinTech and other innovative financial services in Korea are more recent and discrete with an abrupt and rapidly increasing pattern. However, this DT-driven financial innovation appears to be similar between Korea and other countries.

In particular, Cho (2021) summarizes four main social outcomes from tech-based financial intermediation. First, thanks to much cheaper, faster, and more convenient intermediation based on the internet or mobile platforms, FinTech service providers have greatly enhanced the efficiency of financial intermediation (International Monetary Fund (IMF) 2017; Buchak et al. 2017; Fuster et al. 2018; Frost et al. 2019; Jagtiani and Lemieux 2019; Organization of Economic Cooperation and Development (OECD) 2019). Second, FinTech can also lead to over-leverage for some consumer segments (Chava and Paradkar 2018; DiMaggio and Yao 2018). Third, regarding financial inclusion, FinTech service providers tend to serve those borrowers with low credit scores or thin filers (i.e., those consumers with no or low records of financial transactions) more often, and their lending activities penetrate those areas with fewer bank branches per capita, as well as those where the local economy is not performing well (Jagtiani and Lemieux 2019; De Roure et al. 2021). Fourth, FinTech service providers are shown to be reducing the effect of information asymmetry between borrower and lender by collecting and utilizing various types of soft data for ex ante credit evaluation for financial consumers (Lin et al. 2013; Iyer et al. 2016; Puri et al. 2017; Hildebrand et al. 2017; Freedman and Jin 2017; Berg et al. 2018). Lastly, those BigTech-affiliated financial service providers can contribute to the macroeconomy in two main ways: by imposing competition and contestability on existing financial institutions and by increasing the factor productivity of the firms within a BigTech-driven innovation ecosystem (Citi Global Perspectives and Solutions 2018; Frost et al. 2019). In addition, a number of recent studies have documented the effects of the FinTech services sector on various micro-aspects of the financial services sectors, e.g., on the financial behavior of individual investors in the COVID-19 era (Priem 2021), on collaborative consumption behavior in the technology-driven sharing economy (Graessley et al. 2019), on green financial behavior and the transition to a low-carbon economy (Ionescu 2020b, 2021a, 2021b), and on data aggregation and the provision of FinTech infrastructure (Ionescu 2020a).

In an aggregate sense, digital technologies can have both positive and negative effects on efficiency in the finance sector through various channels. For example, Le et al. (2021) showed that the expansion of FinTech credit may serve as a wake-up call to the banking system and thus make a positive impact, even though FinTech credit tends to be more developed in countries with less efficient banking systems.

As an initial observation, the DT-driven financial innovations in Korea appear to be making an impact on the existing financial institutions already. As shown in Figures 1 and 2, the extent of digital transformation in the banking sector is increasing in Korea: bank branches and ATM per capita are declining, while mobile and internet accounts are increasing.

Figure 1 shows that the number of physical bank branches declined from 1.82 per million adults in 2011 to 1.55 per million adults in 2017. It also shows that the number of ATM machines decreased from 28.8 per million adults in 2012 to 27.2 per million adults in 2016. Conversely, mobile and internet banking accounts soared from 20,463 per million adults to 28,251 per million adults in 2015. The two figures demonstrate a clear trend of digital transformation in the finance sector.

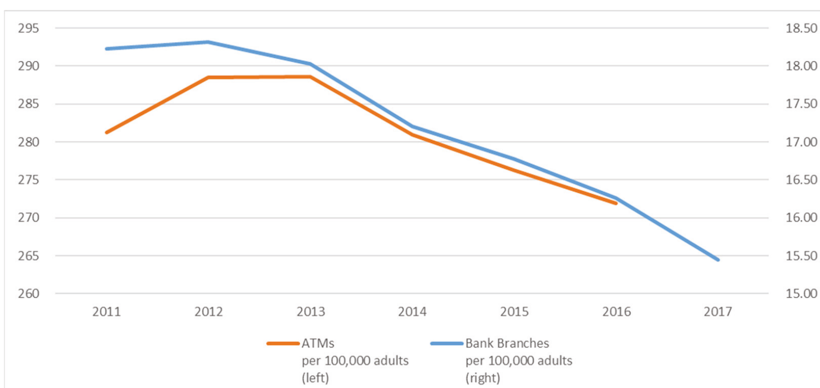

Figure 1. Number of bank branches and ATMs, Korea (2011–2017). Source: (The World Bank 2019).

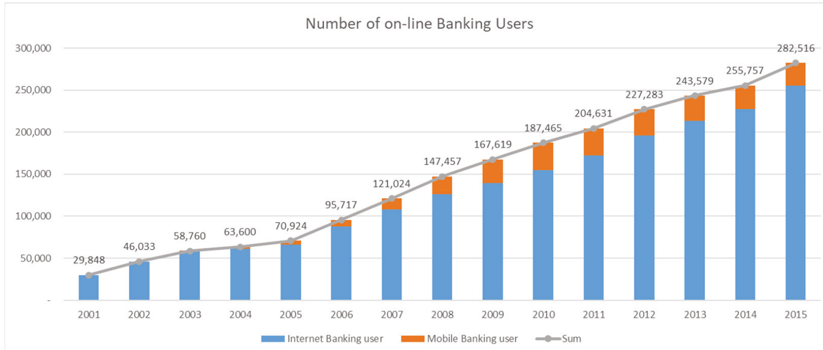

Figure 2. Number of online banking accounts (per 100,000 adults), Korea (2001–2015). Note: The number is counted based on registered accounts. One person may have multiple accounts that are each counted separately. Source: (Bank of Korea 2021).

3. Valuing the Financial Services Sector in Korea

3.1. Cost of Financial Intermediation

Financial consumers pay the user cost of finance for financial services. The total user cost comprises the return to saver and the cost of financial intermediation (Philippon 2015). The return to saver is the capital cost of the financial services industry and the cost of financial intermediation, which is a net value add of the financial industry. Conceptually, the cost of financial intermediation is a net cost that a society pays for consuming financial services. The cost of financial intermediation is distributed as a wage, capital expenditures ("Capex" hereafter), and profit. Thus, from the input perspective, the net value add of the financial industry ("*VAF*" hereafter) is composed of the four components below:

$$VAF = L + K + Y + T, \tag{1}$$

where L = labor cost, K = operating Capex, Y = profit, and T = tax, and the "operating capital expenditures (K)" does not include a return to saver (capital cost for intermediation).

We established *VAF* data from 1990 to 2019 based on the National Accounts produced by the Bank of Korea (BOK). All monetary values were converted into 2015 prices by the producer price index.

3.2. Intermediated Asset and Unit Cost of Intermediation

The quantity of financial services was measured by the year-end stock of intermediated assets in the financial industry. We included the total credit created by the financial industry and the stock market cap. The total amount of created credit was measured by total liquidity (L) minus M1 monetary supply, as below:

$$Intermediated\ Asset = (L - M_1) + S, \tag{2}$$

where L = total liquidity, M_1 = M_1 money supply, and S = stock market cap.

Intermediated assets have increased faster than GDP growth, reaching 3.52 times the GDP in 2019 from 1.31 times in 1990. As a trend to illustrate this, Figure 3 shows the total value of financial intermediation, which is the size of total intermediated assets as a multiple of GDP.

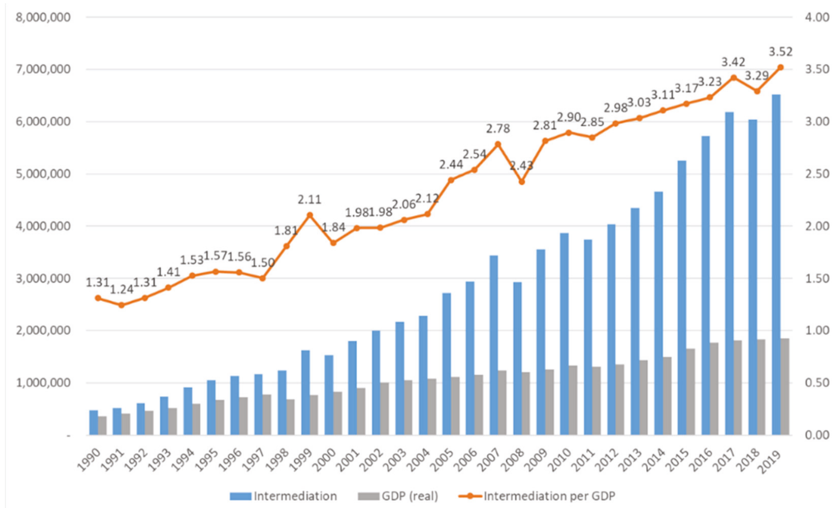

Figure 3. Intermediated asset over GDP. Source: (Bank of Korea 2020; The World Bank 2021).

Finally, we established the unit cost of intermediated asset data from 1990 to 2019 by dividing the *VAF* by the intermediated asset. The unit cost of intermediated asset (*UCIA*) is the consumer cost of using one unit of intermediated asset:

$$Unit\ Cost\ of\ Intermediated\ Asset\ (UCIA) = \frac{VAF}{Intermediated\ Asset} \tag{3}$$

The *UCIA* decreased from 3.38% in 1990 to 1.76% in 2019. We broke down the portion of *UCIA* into labor cost (L), Capex (K), and profit (Y) as illustrated in Figure 4. The labor cost per intermediated asset continuously decreased, whereas the profit per intermediated asset stayed around 0.976% on average. It was found that the decrease in financial services cost, measured by *UCIA*, was mainly due to a decrease in the unit cost of labor per intermediated asset from 1990 to 2019. In contrast, the profit per intermediated asset was comparatively stable, even with a downward shift after 2011. From the analysis of Philippon (2015), the ratio of intermediated asset over GDP in the US was around 2.9–4.1 after 1990, which is higher than that of Korea (1.31–3.52 times). Yet, the *UCIA* in the US was around 1.8–2.2% after 1990, which is slightly lower than that of Korea (1.76–3.38%). Furthermore, it tends to decline from 1990 onwards, a trend which is similar in both economies.

We further checked the number of employees in the financial industry from 1990 to 2018. No trend exists, but there is a shape of periodical fluctuation. We observed that the wage, *VAF*, and profit per employee continuously increased. In particular, the intermediated asset per employee significantly increased from 1.07 billion in 1990 to 8.63 billion in 2018. These results are consistent with the continuous decrease in labor cost per intermediated asset as discussed above. Thus, we found that the savings in the *UCIA* were mainly caused by the operational efficiency of labor. Additionally, the unit cost of operating Capex per *UCIA* decreased, even though the portion is small. We will test whether the operational efficiency gains of these two factors are caused by digital transformation in the finance sector in Korea.

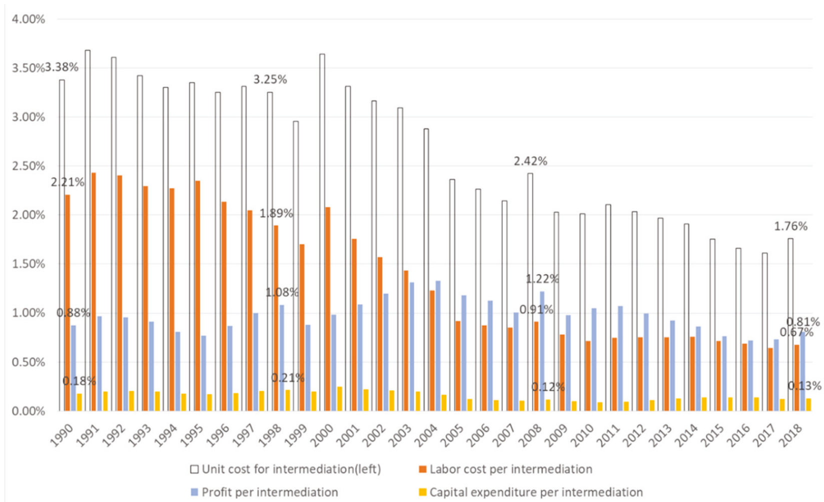

Figure 4. Unit cost per intermediated asset by components. Source: Author compilation quoted in (Bank of Korea 2020; Korea Statistics Information System (KSIS) 2021).

3.3. Digital Transformation in Finance Sector

We collected the data related to digital transformation in the finance sector from internet and mobile bank accounts, the number of which have increased rapidly since the early 2000s. During this process, we were confronted with the problem that the data have not existed for a long enough period to study. Therefore, we selected a percentage of internet users as a variable proxy for internet and mobile bank accounts to explain the degree of digital transformation in the finance industry, as there is a high degree of correlation: the correlation between internet users and the number of internet bank accounts is 0.8837, and the correlation between internet users and the number of mobile bank accounts is 0.8911.

3.4. Digital Transformation and Unit Cost of Intermediation

Before the empirical investigation, we visualized the trends in digital transformation, measured by the percentage of internet users, and compared them with the *UCIA*. The *UCIA* decreased rapidly from 2000 to 2005, during which period the percentage of internet users increased greatly, as can be observed from the graphs in Figure 5.

Figure 5 illustrates that the percentage of internet users rose sharply from 1999 and then stabilized from 2005. This trend is highly correlated with Figure 2, except for the difference in timing. It makes sense that the supply of the internet in Figure 5 precedes the distribution of internet and mobile banking in Figure 2. The *UCIA* rose once in 2000 and continued to decrease from 3.64% to 1.76% until 2018.

In the next section, we will test whether digital transformation caused the operational efficiency of the financial industry, either in labor or capital. If it is proved that an efficiency gain was achieved through digital transformation, we will further investigate whether the operational efficiency gain was delivered to financial customers. This will mean that the efficiency gain was not exclusively enjoyed by stakeholders as a form of profit.

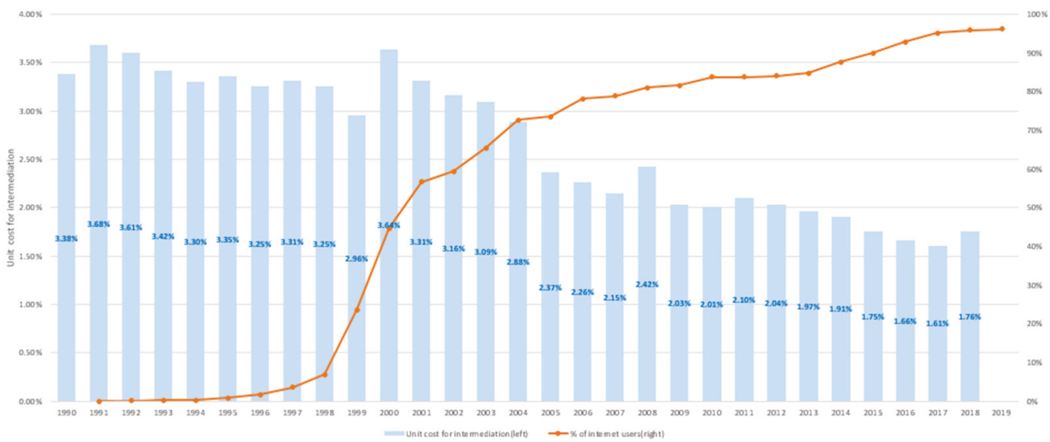

Figure 5. Impact of digital transformation and unit cost for intermediation. Source: Author compilation quoted in (Bank of Korea 2020; Korea Statistics Information System (KSIS) 2021).

4. Empirical Test and Result

4.1. Testing Methodology

We found a non-stationary distribution issue, which may cause spurious regression, when we performed the augmented Dickey–Fuller test. Therefore, we decided to use an ARDL (autoregressive distributed lag)-based error-correction model (ECM). The ECM is useful, as it includes an error-correction term, thus allowing non-stationary variables (Engle and Granger 1987; Hassler and Wolters 2006).

For the purpose of applying the ARDL-ECM, we tested the existence of a long-run cointegration relationship based on the "bounds test" (Pesaran et al. 2001): the OLS (Ordinary Least Squares) estimators of short-run parameters are asymptotically normal, and the corresponding estimators are consistent if the regressors are I (1) processes and asymptotically normally distributed, regardless of the order of integrations. Pesaran et al. (2001) suggested asymptotic critical values of band from all regressors being purely I (0) to all regressors being purely I (1). Later, Narayan (2005) studied the corresponding critical values for various sample sizes, including small samples. We selected three variables (*UCIA*, labor cost per intermediated asset, and Capex per intermediated asset) that showed long-term cointegration with digital transformation in the financial industry, which was measured by a proxy variable of the percentage of internet users. In addition, the optimal lags of the variables were determined based on the AIC (Akaike information criterion).

We used the ARDL-ECM (autoregressive distributed lag error-correction model) to investigate the short- and long-term impact of digital transformation on (Model 1) labor costs for financial services, (Model 2) capital expenditure for financial services, and (Model 3) costs for financial services (Pesaran and Shin 1999).

$$\Delta y_t = C - (1-\theta)(y_{t-1} - \alpha - \beta x_{t-1}) + \sum_{m=1}^{p} \gamma_m \Delta y_{t-m} + \sum_{n=0}^{q} \delta_{n+1} \Delta x_{t-n} + v_t, \quad (4)$$

where adjustment = $-(1-\theta)$; long-term relationship = β; short-term relationship = δ_{n+1}; and $0 < \theta < 1$.

After the modeling, we performed the Durbin–Watson and Breusch–Godfrey tests to check the serial correlation. We also utilized the White test to check for heteroskedasticity issues. The above three models were selected from a number of trials to meet the assessment criteria. Finally, we checked the stability of our models based on the cumulative sum of squares (CUSUMQ) in residuals (Brown et al. 1975; Stamatiou and Dritsakis 2014).

4.2. Data and Statistics

The Table 1 represents a summary of the variables used for the empirical test.

Table 1. Variable descriptions.

Name of Variables	Mean	Description	Unit
VAF	Value add in finance industry	Value add of financial industry * selected from national accounts of Korea	billion Korea Won
Labor	Labor cost	Labor cost among *VAF*, selected from national accounts of Korea	billion Korea Won
Profit	Profit	Profit among *VAF*, selected from national accounts of Korea	billion Korea Won
Capex	Capital expenditure	Capital expenditure among *VAF*, selected from national accounts of Korea	billion Korea Won
Tax	Tax	Tax among *VAF*, selected from national accounts of Korea	billion Korea Won
GDP_growth	GDP growth rate	GDP growth rate in Korea (year to year)	percent
Empl	Number of employees	Thousand number of employees in financial industry of Korea	thousand people
Wage	Total wage of financial industry	Total sum of wages in financial industry of Korea	billion Korea Won
Intermedi	Intermediated asset of financial industry	Scale of financial services, measured by the liquidity aggregate (L) minus monetary base (M0) plus market cap of stock in Korea	billion Korea Won
Internet	Number of internet banking users	Thousand people of internet banking users in Korea	thousand people
Mobile	Number of mobile banking users	Thousand people of mobile phone banking users in Korea	thousand people
user_internet	Percentage of internet users	Percentage of internet users in Korea	percent

(*) Financial industry includes banks, stocks, insurance, and other financial services companies. Note: all monetary values are converted into 2015 value, based on the producer's price index of Korea.

The Table 2 shows the basic statistics of our data. We used interpolation for the missing years.

Table 2. Basic statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
cost_intermedi	29	2.6810	0.7122	1.61	3.64
labor_intermedi	29	1.4041	0.6773	0.64	2.34
capex_intermedi	29	0.1596	0.0470	0.08	0.24
user_internet	30	54.0933	38.1594	0.00	96.20
gdp_grow	30	5.1833	3.4747	−5.10	11.50
internetb	15	52,792.93	31,511.59	10,918	109,760
wage_empl	29	42.3806	10.6291	23.53	59.53

Note: cost_intermedi = consumer cost per unit of intermediated asset (*VAF*/Intermedi); labor_intermedi = labor cost per unit of intermediated asset (Labor/Intermedi); capex_intermedi = capital expenditure per unit of intermediated asset (capex/Intermedi); user_internet = percentage of internet users; gdp_grow = growth rate of GDP; internetb = number of internet banking users; wage_empl = average wage per employee in financial industry.

4.3. Test Result

First, we performed the DF-GLS (Dickey-Fuller with Generalized Least Squares method) unit root test with the four main variables: percentage of internet users (user_internet), labor cost per intermediated asset (labor_intermedi), capital expenditure per intermediated asset (capex_intermedi), and *UCIA* (cost_intermedi). As expected, we confirmed that all four variables are not stationary, as they are time-series data.

Second, we selected candidate variables and formulated ARDL (p, q) models by OLS to obtain the optimal lag orders p and q of Equation (4) based on the AIC model selection criteria. In addition, we performed a bounds test, where it was assumed that the model comprised both I (0) and I (1) variables, and two levels of critical values were obtained. The procedure was to test the joint significance of the lagged levels of the variables. The null hypothesis of no cointegration was rejected if the F-statistic was higher than the critical value of I (0) and I (1) regressors and the t-statistic was smaller than the critical value of I (0) and I (1) regressors. We selected three dependent variables that showed a long-term correlation with the degree of digital transformation[3] (measured by "user_internet").

The selected variables, optimal lag orders, and bound test results for three models are summarized in Table 3.

Table 3. Lag orders and result of bounds test for the selected dependent variables.

Model #	Dependent Variable	Independent Variable	Selected Lag Orders (p, q)	Bounds Test	
				F-Test Result	*t*-Test Result
1	labor_intermedi	user_internet	(2, 3)	6.507 **	−3.314 **
2	capex_intermedi	user_internet	(2, 3)	6.233 **	−3.522 **
3	cost_intermedi	user_internet	(1, 3)	10.050 ***	−4.444 ***

Note: **, *** represent significance levels at 5%, and 1%, respectively.

Once the existence of long-term autocorrelation was checked, we estimated three ARDL-ECMs. The first model tested the effect of digital transformation (user_internet) on the labor efficiency gains (labor_intermedi). The test result is summarized in Table 4.

Table 4. Model 1—impact of digital transformation on labor cost efficiency gains.

D.labor_Intermedi VARIABLES	Adjustment	Long Run	Short Run
LD.labor_intermedi			0.614 ***
			(0.141)
D.user_internet			0.0153 ***
			(0.00354)
LD.user_internet			−0.00787
			(0.00551)
L2D.user_internet			0.0102 *
			(0.00507)
L.labor_intermedi	−0.433 ***		
	(0.131)		
user_internet		−0.0168 ***	
		(0.000920)	
Constant			0.933 ***
			(0.296)
Observations	26	26	26
R-squared	0.747	0.747	0.747

Note 1. Standard errors in parentheses: *** $p < 0.01$, * $p < 0.1$. Note 2. D = first difference operator, L = lagged variable.

The error term ($-(1-\theta)$) from Equation (4) determines how quickly the long-term equilibrium is restored, and the estimated result should exist between -1 and 0. As expected, the coefficient of error (adjustment) term was estimated at –0.433 and was statistically significant under the 99% confidence level. The coefficient of the long-term relationship (β) from Equation (4) was estimated at –0.0168 under the 99% confidence level. We found that, if the percentage of internet users increases by 1%p, the labor cost per intermediated asset decreases by 0.0168%p, ceteris paribus. We conclude that digital transformation in the finance sector caused the operational efficiency of labor, resulting in savings of labor cost per intermediated asset from a long-term perspective in Korea.

The second model tested the effect of digital transformation (user_internet) on the operational capital cost efficiency gains (capex_intermedi). The test result is summarized in Table 5.

Table 5. Model 2—impact of digital transformation on operational capital cost efficiency gains.

D.capex_Intermedi VARIABLES	Adjustment	Long Run	Short Run
LD.capex_intermedi			0.538 ***
			(0.159)
D.user_internet			0.00203 ***
			(0.000702)
LD.user_internet			−0.000755
			(0.000826)
L2D.user_internet			0.00163 *
			(0.000805)
L.capex_intermedi	−0.450 ***		
	(0.128)		
user_internet		−0.000955 ***	
		(0.000152)	
Constant			0.0852 ***
			(0.0242)
Observations	26	26	26
R-squared	0.634	0.634	0.634

Note 1. Standard errors in parentheses: *** $p < 0.01$, * $p < 0.1$. Note 2. D = first difference operator, L = lagged variable.

The coefficient of adjustment (error) term was estimated at –0.450 and was statistically significant under the 99% confidence level. The coefficient of the long-term relationship (β) from Equation (4) was estimated at –0.000955 under the 99% confidence level. The test results showed that if the percentage of internet users increases by 1%p, the operational capital expense per intermediated asset decreases by 0.000955%p, ceteris paribus. We conclude that digital transformation in the finance sector also enhanced the operational efficiency of capital and resulted in savings in operational capital cost per intermediated asset from a long-term perspective in Korea.

The third model tested the effect of digital transformation (user_internet) on the *UCIA* (cost_intermedi). The test result is summarized in Table 6. The *UCIA* is the sum of unit cost of labor, operational capex, and profit per intermediated asset. Furthermore, it measures the consumer cost paid for financial services. We performed this test separately from the above two to check whether the operational efficiency gains achieved from digital transformation was ultimately delivered to consumers as a reduced service cost.

Table 6. Model 3—impact of digital transformation on financial services cost.

D.cost_Intermedi VARIABLES	Adjustment	Long Run	Short Run
D.user_internet			0.0246 *** (0.00616)
LD.user_internet			−0.00157 (0.00797)
L2D.user_internet			0.0168 ** (0.00744)
L.cost_intermedi	−0.498 *** (0.112)		
user_internet		−0.0180 *** (0.00131)	
Constant			1.643 *** (0.383)
Observations	26	26	26
R-squared	0.624	0.624	0.624

Note 1. Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$. Note 2. D = first difference operator, L = lagged variable.

The coefficient of error adjustment term was estimated at –0.498 and was statistically significant under the 99% confidence level. The coefficient of the long-term relationship (β) from Equation (4) was estimated at –0.018 under the 99% confidence level. The test results showed that if the percentage of internet users increases by 1%p, the unit cost of intermediated asset decreases by 0.018%p, ceteris paribus. We conclude that digital transformation in the finance sector ultimately resulted in a decrease in the unit cost of financial services per intermediated asset from a long-term perspective in Korea. From Equations (1) and (3), the *UCIA* can be rephrased as below:

$$UCIA = \frac{L}{Intermediated\ Asset} + \frac{K}{Intermediated\ Asset} + \frac{P+T}{Intermediated\ Asset} \quad (5)$$

From the above two test results, the long-term cost efficiency gains of labor ($\frac{L}{Intermediated\ Asset}$) was measured as 0.0168%p, and that of capital expenditure ($\frac{K}{Intermediated\ Asset}$) was measured as 0.000955%p. The sum of these two estimations equals 0.01775%p, which is close to the third test result of 0.018%p. With Equation (5) and the three test results, we conclude that the operational efficiency gains in both labor and operational assets, achieved from digital transformation, are ultimately delivered to consumers as a reduced service cost in Korea. Another important consideration is the role of profit per intermediated asset. The above result was partly due to the comparatively stable level of profit per intermediated asset, which shared 0.000245%p of a comparatively small portion of efficiency gains.

The long-term impact on financial services is estimated at a 0.018%p decrease, which is similar to the sum of savings in labor cost and capital expenditure. The costs for financial services comprises labor cost, capital expenditure, profit, and tax. It is estimated that digital transformation saved 0.0169%p of labor costs and 0.000955%p of capital expenditure, measured as a ratio to unit cost for intermediation. The cost for financial services also follows the trend of GDP growth in Korea. However, we found that financial industry profits, measured as financial mediation, did not have a long-term relationship with digital transformation.

In summary, our empirical results show: over time, the unit cost for financial services moves in tandem with the trend in GDP growth in Korea, although the profit portion of the cost did not have a long-term relationship with the DT trend; the DT trend saves 0.0168%p of labor costs, and 0.000955%p of capital expenditure, measured as a ratio to unit cost for intermediation; and the long-term impact of the DT trend on total service cost is estimated to be a 0.018%p decrease, which is similar to the sum of savings in labor cost and capital expenditures.

4.4. Robustness Check

We checked the existence of a serial correlation issue through the Durbin–Watson and Breusch–Godfrey tests with three models. We also performed the White test to check for heteroskedasticity issues. The results suggest that three models do not have serial autocorrelation or heteroskedasticity issues, as summarized in Table 7.

Table 7. Diagnostic test results.

Tests	Model 1		Model 2		Model 3	
	Test Value	Decision	Test Value	Decision	Test Value	Decision
Durbin–Watson (d-statistic)	1.9073	No autocorrelation	1.997	No autocorrelation	1.8520	No autocorrelation
Breusch–Godfrey LM test (Prob > chi2)	0.9072	No serial correlation	0.7529	No serial correlation	0.3095	No serial correlation
White test (Prob > chi2)	0.4076	No heteroskedasticity	0.4070	No heteroskedasticity	0.6799	No heteroskedasticity

Lastly, once the three ARDL-ECMs were determined, the cumulative sum of squares (CUSUMQ) in recursive residuals was plotted to assess the parameter stability (Brown et al. 1975; Stamatiou and Dritsakis 2014). As can be seen from the Figures 6–8, the graphs of statistical CUSUMQ are within the critical values at the 5% significance level, which means that all the coefficients in the three models are stable. All three models proved to be stable within 5% of the upper and lower bounds. The results are illustrated as follows.

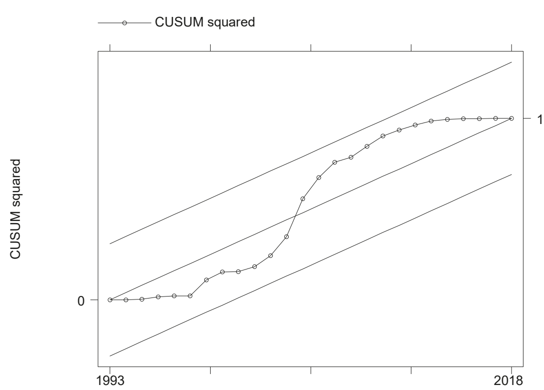

Figure 6. CUSUMQ for Model 1.

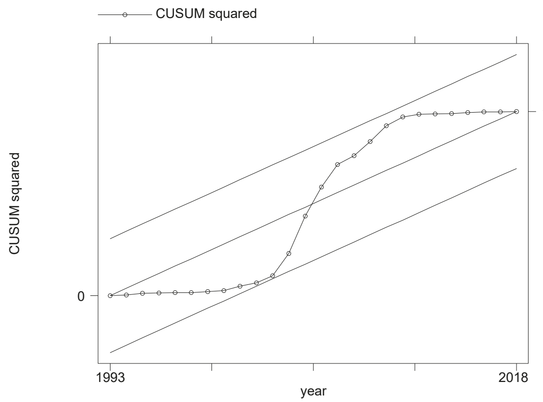

Figure 7. CUSUMQ for Model 2.

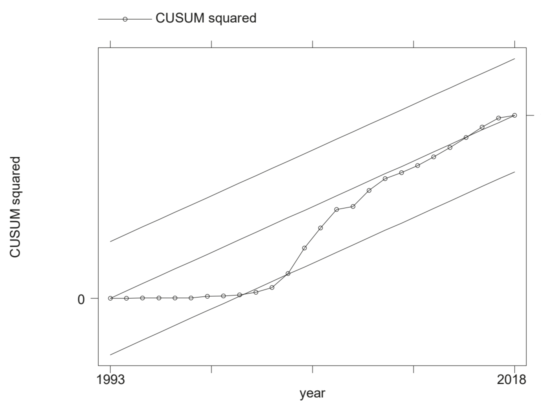

Figure 8. CUSUMQ for Model 3.

4.5. Discussion and Policy Implication

It was observed that in Korea, from the late 1990s to 2000s, the saved operating cost per unit of financial intermediation, achieved through digital transformation (DT), was used for a reduction in consumer fees rather than increasing the industry's profit or wage per intermediated asset. We conclude that digital transformation (DT) in the nation has contributed to a decreased financial services cost and has resulted in improved consumer benefit.

In fact, the total number of employees in the Korean financial industry fluctuated during our analysis window, and the wage per employee constantly increased. On the other hand, the amount of intermediated asset served by one employee increased far more quickly than the increase in salary per person, resulting in a decrease in labor cost per intermediated asset, which is measured by *UCIA*.

This result is surprising, as Philippon (2015, 2016) maintained that the wage level in this industry in the US is much higher than in other industries and the gap is widening. The *UCIA* in Korea (3.38%) was higher than in the US (2.2%) in 1990, but it decreased dramatically to 1.75%, which is close to that of US in 2015 (approximately 1.8%). Our study shows that, while the recent literature documents a high and rising cost of financial intermediation in the US and in other countries, the consumer cost per financial intermediation has constantly improved over time in Korea.

From a financial policy perspective, our study may provide a possible direction for where the efficiency gains from innovative DT could be used to reduce the customer cost while constantly increasing the labor wage per person in the finance sector. However, it can only be achieved when the excessive level of profit is constrained, either by market competition or through intervention from the authorities. In addition, financial authorities may leverage the ongoing trend of digital transformation (DT) as a driver of efficiency gain in the financial services sector as a whole, which could be promoted via various means of incentives to the service providers.

5. Conclusions

This study aimed to empirically investigate the interrelationship between digital transformation in the financial services sector and financial consumer benefit by utilizing a set of aggregate outcomes indicators of the financial services sector in Korea. The main findings are that, over time, the unit cost for financial intermediation in Korea has tended to move in tandem with the growth in economic output, although the profit portion of the cost has not exhibited a long-term relationship with the GDP trend. Furthermore, the long-term effect of the DT trend is negative (i.e., cost-saving) for labor input and capital expenditure, which are shown to be statistically significant, and, as a consequence, its impact on the total intermediation cost is also positive and statistically significant.

The main implication of our empirical findings is that, while the recent literature documents a high and rising cost of financial intermediation in the US and in other countries, the financial services sector in Korea is seemingly different from those countries, in that we did not find evidence that the cost of intermediation in the country is excessive in comparison with those countries, as well as over time within the country.

In addition, the ongoing trend of digital transformation appears to be working as a driver of efficiency gain in the financial services sector as a whole. From a financial consumer perspective, these outcomes should be viewed as positive as the price of the service is not overly expensive, and the data and ICT-driven innovations in the sector are also working in their favor. From a policy perspective, our findings imply that DT-driven innovation in the sector can work in the customer's favor if the excessive level of profit is restrained through market competition.

As to future research topics, we note several issues to be tackled going forward. First, the more specific welfare implications of DT, as discussed in Section 2, could be theoretically and empirically examined, e.g., intermediation efficiency via internet- or mobile platform-based services, the financial inclusion effects across consumer segments or geographical areas, and the BigTech-driven innovation effects along with the appropriate regulatory regimes for them. Second, the interplay between digital technologies and specific financial products, and their welfare implications, could be further analyzed. For example, a change in the shares of certain financial products may have affected the change in *UCIA* in Korea during our test period, along with the efficiency gains through digital transformation. In particular, the rapid growth in the residential mortgage lending sector, which is based on standardized lending products, may have enhanced operational efficiency, and could be specifically examined in future research. Third, the length of the time series data in our research was short, and a similar empirical investigation with more extended time series data could also be performed, for Korea as well as for other countries. International comparative studies in that vein would also contribute to the compilation of a set of meaningful KPIs (Key Performance Indicators) for assessing the progress of DT in those countries.

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Notes

1. See Cho (2021) for a survey on the social effects of the FinTech sector.
2. The size of household lending as a % of GDP has grown from 3.6% in 1975 to 99.1% in 2018; the size of insurance and pensions together has increased from 1.3% to 78.2% during the same period; and the total capitalization in the stock market has risen from 100% in 1997 to 1400% in 2018.
3. We selected the percentage of internet users as a proxy measure for the number of internet banking users and the number of mobile phone banking users as the latter two variables provide too short a period for analysis. The correlation measured between the percentage of internet users and the number of internet banking users is 0.883, and that between the percentage of internet users and the number of phone banking users is 0.891.

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Fintech Credit and Bank Efficiency: International Evidence

Tu D. Q. Le [1,2,*], Tin H. Ho [1,2], Dat T. Nguyen [2,3] and Thanh Ngo [4,5]

1 Institute for Development and Research in Banking Technology, University of Economics and Law, Ho Chi Minh City 700000, Vietnam; tinhh@uel.edu.vn
2 Vietnam National University, Ho Chi Minh City 700000, Vietnam
3 School of Finance and Banking, University of Economics and Law, Ho Chi Minh City 700000, Vietnam; datnt20704@sdh.uel.edu.vn
4 School of Aviation, Massey University, Palmerston North 4442, New Zealand; t.ngo@massey.ac.nz
5 University of Economics and Business, Vietnam National University, Hanoi 10000, Vietnam
* Correspondence: tuldq@uel.edu.vn

Abstract: The expansion of fintech credit around the world is challenging the global banking system. This study investigates the interrelationships between the development of fintech credit and the efficiency of banking systems in 80 countries from 2013 to 2017. The findings indicate a two-way relationship between them. More specifically, a negative relationship between bank efficiency and fintech credit implies that fintech credit is more developed in countries with less efficient banking systems. Meanwhile, a positive impact of fintech credit on the efficiency of banking systems suggests that fintech credit may serve as a wake-up call to the banking system. Therefore, fintech credit should be encouraged by the authorities around the world.

Keywords: fintech credit; banking efficiency; data envelopment analysis; structural equations model; GMM

JEL Classification: E51; G23; O31

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1. Introduction

The literature documents that the financial sector is the backbone of any economy. Since the rapid development of financial technology, a new relationship between banks and capital markets has evolved. Capital markets and banks are viewed as competing sources of financing, since one sector develops at the expense of the other (Allen and Gale 1999), but these intermediaries can also be considered complementary to each other (Song and Thakor 2010). Recently, Ngo and Le (2019) demonstrated the existence of a two-way nexus between the capital market and the banking system. This study, therefore, revisits the causal relationship between the recent development of fintech credit platforms and the banking system.

The global credit markets have experienced an undergoing transformation in which new digital lending models (i.e., peer-to-peer (P2P)/marketplace lending and invoice trading) have grown in many countries. Following Claessens et al. (2018), fintech credit is defined as all types of credit facilitated for both consumers and businesses by online platforms rather than conventional banks or lending institutions. Fintech credit models were initially established based on decentralized platforms in which individual lenders or institutional investors select potential borrowers or projects to advance in a specific framework (Jagtiani and Lemieux 2019). The detailed description of big tech credit models is out of the scope of this study but was comprehensively discussed by Cornelli et al. (2020). Previous lessons emphasize that an excessive expansion of credit can trigger a financial crisis and severe recession in an economy (Aliber and Kindleberger 2015). Since the growth of fintech credit is very rapid and has become more economically relevant, there is an urgent need for an adequate assessment of this aspect.

Several studies investigating the determinants of fintech credit have found that fintech credit is more developed in countries where banking intermediation and banking coverage are lower (Cornelli et al. 2020). A general conclusion is that fintech credit seems complementary rather than a substitute for the banking system (Claessens et al. 2018), and more especially promoting access to credit for underserved segments and financial inclusion (Oh and Rosenkranz 2020). However, Tang (2019) suggested that P2P lending platforms in the US serve as substitutes for bank lending regarding infra-marginal bank borrowers, while acting as complements in terms of small loans. This partly confirms the early findings of De Roure et al. (2016), who found that P2P lending substitutes the banking sector for high-risk consumer loans, and those of De Roure et al. (2018), who presented further evidence in favor of such bottom fishing. Furthermore, Yeo and Jun (2020) proved that bank stability is not affected by P2P lending, as these platforms operate in the low-credit segment.

Our study contributes to the literature in several ways. Empirical studies on fintech credit are scarce due to data unavailability. Prior studies commonly investigated the determinants of fintech credit development when controlling several aspects of banking regulation. Additionally, few theoretical and empirical works using proprietary P2P lending data have attempted to examine the impact of P2P lending on bank lending in several borrowers' segments. These studies, however, may provide an incomplete picture of the causal relationship between the development of fintech credit and banking systems. For instance, when the banking system is less efficient because of either implementing an inappropriate procedure to assess the credit quality of borrowers or underserving consumers in remote regions where there is limited bank access, this would encourage a shift towards online lending platforms. Meanwhile, fintech credit platforms could also reduce the issue of asymmetric information via their screening and evaluating practices, especially by offering investors more information about the risk of a potential loan and other characteristics of prospective borrowers. Consequently, this may reduce the necessity of the banking system. We also contend that the growth of fintech credit may serve as a wake-up call for the banking systems, as they may respond to the greater pressure caused by these platforms by enhancing their efficiency. The efficiency of the banking system is defined as its ability to produce the existing level of outputs with minimal inputs, i.e., input-oriented DEA efficiency (Coelli et al. 2005). This study is the first attempt to examine the interrelationships between fintech credit and bank efficiency using a two-stage framework in 80 countries from 2013 to 2017. In the first stage, banking efficiency scores are estimated by DEA with the use of financial ratios, as proposed by Ngo and Le (2019). Those efficiency scores are then linked with the growth of fintech credit, as measured by the natural logarithm of the volume of fintech credit per capita in the second stage using the Generalized Method of Moments estimator in a simultaneous equations model (SEM). This thus would help to shed light on the interrelationships between them so that some recommendations on fintech credit can be drawn.

In what follows, Section 2 provides a brief literature review regarding the interrelationships between fintech credit and bank efficiency. Section 3 presents the data and the methodology used in this study. Section 4 discusses the empirical findings while Section 5 concludes.

2. A Brief Literature Review

The literature can be divided into two strands. The first strand focuses on the relationship between the emergence of financial technology (fintech) firms and the banking system. Several studies argued that fintech competitors generating new business models with the use of big data may disrupt conventional banks, although banks are gradually adapting to digital finance (Vives 2017). One of the potential advantages of new competitors is to provide digital services that attract the younger generation, due to more convenience and better ease of use (Deloitte 2015). Therefore, the development of fintech credit was a potential threat to the banking system. However, in the case of high switching costs, a bank that faces difficulty in distinguishing old from new customers may act as a quiet fat cat, because it needs to secure the profitability derived from its huge client base. This thus may permit fintech firms to enter the market and serve unbanked people or/and technology-savvy customers. This may be true for the case of P2P lending platforms, where they utilize advanced technology based on a large amount of information from social media that may mitigate adverse selection and moral hazard issues. Therefore, the partnership between a new entrant and incumbent seems to be the most appropriate. Vives (2017) further emphasized that this strategy is more relevant to regulatory arbitrage, given that the regulation on fintech credit is less strict. On the other hand, banks may prefer barriers to new entrants. In the case of payment segments where fintech firms may rely on the payment infrastructure of the incumbents to provide complementary or differentiated services, these incumbents have more incentives to increase the costs of entrants.

Although empirical studies on the impact of fintech credit on the banking system are limited, they show mixed findings. Buchak et al. (2018) found that the most vulnerable are US rural commercial banks that gradually lost lending volumes to fintech credit, especially personal loans, and that tend to lend to riskier borrowers, while the lending volumes of urban commercial banks are not affected. In the same vein, P2P lending platforms may substitute bank lending volumes in terms of infra-marginal bank borrowers in the US (Tang 2019) or high-risk consumer loans in Germany (De Roure et al. 2016). However, others showed opposite findings. Tang (2019) also showed that P2P lending serves as a complementary for the banking system regarding small loans. The positive relationship between fintech and banking sector development may be because fintech firms focus on serving niche segments such as either low-cost services or unbanked people or high quality of services that could meet consumers' needs regarding accessibility, customization, and speed based on the analysis of a large amount of information on personal data (Navaretti et al. 2017). Therefore, the banking system may not be disrupted by the evolution of fintech credit (Siek and Sutanto 2019; Yeo and Jun 2020). A recent study by Sheng (2021) even demonstrated that fintech can enhance the overall supply of bank credit to small and medium enterprises but this impact varies between small and large banks.

In the second strand, the impact of the banking system on fintech credit is focused on. Given the presence of fintech credit in the marketplace, incumbent banks may respond to it in several ways, such as cooperating with new entrants, acquiring them partially or completely, or competing with them directly. These strategies depend on whether an investment would make a firm more competitive or more vulnerable in the competitive market. A conceptual framework of Bömer and Maxin (2018) proposes that the fintech–bank partnership allows fintech firms to sell their products and services by using different label approaches. Thus, banks may improve fintech's profitability. Only a few studies on the factors affecting the development of fintech credit consistently show that fintech credit is more developed in markets where there is a low level of banking coverage (Claessens et al. 2018; Cornelli et al. 2020) and a less competitive banking system (Le 2021).

In sum, several studies investigate a one-way relationship between the banking system and the development of fintech credit or the impact of fintech credit on bank lending. A study by Ngo and Le (2019) indicated the existence of interrelationships between financial development and banking efficiency. Given the emergence of fintech credit in the financial market, our study is the first attempt to examine whether a two-way relationship between fintech credit and bank efficiency exists.

3. Data and Research Methodology

3.1. Data

Our data were gathered at an aggregate or national level. More specifically, data used in DEA analysis were extracted from the Financial Development and Structural Dataset (Beck et al. 2000), while those used in SEM analysis were mainly collected from the database provided by Cornelli et al. (2020), who provided an update on the Global Alternative Finance Database. The database is held at the Cambridge Centre for Alternative Finance

(CCAF). Other macroeconomic variables were extracted from the World Development Indicators (World Bank 2017). Initially, a total of 203 banking systems in the Financial Development and Structural Dataset were considered in our initial sample. We then excluded those for which fintech credit data (either the volume of fintech credit or the volume of fintech credit per capita) were unavailable. After matching these datasets, we arrived at an unbalanced dataset of 80 countries from 2013 to 2017, as presented in Table A1 in Appendix A.[1]

3.2. First Stage: Estimating the Efficiency of Banking Systems

The literature suggests that bank efficiency can be calculated by using either a non-parametric method (i.e., DEA) or a parametric approach (i.e., stochastic frontier analysis (SFA)) (Berger and Humphrey 1997; Boubaker et al. 2020). However, Liu et al. (2013) showed that DEA was used as the main methodology among 3134 non-theoretical research papers, among which banking studies accounted for the highest proportion. DEA was thus selected in our study, since it works well with a small sample size and is also less prone to specification errors than SFA—and therefore is more flexible (Reinhard et al. 2000).

Furthermore, the DEA method has also received much attention in studying the efficiency of firms in financial services such as stock markets, insurance, pension funds, mutual funds, risk tolerance, and corporate failure prediction (Boubaker et al. 2018, 2021; Paradi et al. 2017; Vidal-García et al. 2018).[2]

In DEA, the efficiency of a bank/banking system, or the so-called Decision-Making Unit (DMU), is estimated as its ability to transform inputs into outputs. A DMU is efficient if it either utilizes the fewer inputs to produce a given set of outputs (input-oriented) or if it can produce the most outputs from the given set of inputs (output-oriented). In our efficiency estimations, an input-oriented DEA model is used because a banking system may find it easier to manage its inputs rather than outputs in a more competitive market (Ngo and Le 2019).

For a set of n DMUs (j = 1, ... , n) each using s inputs x_i (i = 1, ... , s) to produce m outputs y_r (r = 1, ... , m), based on the constant-returns-to-scale model introduced by Charnes et al. (1978), Banker et al. (1984) proposed the variable-returns-to-scale (VRS) DEA model to estimate the efficiency score of the j_0-th DMU as

$$\begin{aligned}
&EF_{j_0} = max_{u,v,u_0} \sum_{r=1}^{m} u_r y_{rj_0} - u_0 \\
&\text{Subject to} \\
&\textstyle\sum_i^s v_i x_{ij_0} = 1,\ \forall \text{i, j} \\
&\textstyle\sum_r^m u_r y_{rj_0} - u_0 - \sum_i^s v_i x_{ij_0} \le 0,\ \forall \text{i, r, j} \\
&u_r,\ v_i\ \ge\ \varepsilon,\ \forall \text{i, r} \\
&\quad u_0 \text{ is unconstrained in sign}
\end{aligned} \tag{1}$$

where u and v are the weights of the outputs and inputs, respectively.

Following Ngo and Le (2019), the whole banking system of an economy is treated as a single DMU in the VRS DEA model with indices for the inputs and outputs as measured at the aggregate level. Note that the efficiency scores of DMUs derived from the DEA approach are affected by the selection of inputs and outputs. The literature suggests that the choice of inputs and outputs is determined based on three main approaches, including the intermediation approach and production approach and the revenue (or value-added) approach (Drake et al. 2006; Ho et al. 2021; Le and Ngo 2020). In our study, the intermediation approach was adopted, since it is more appropriate to examine the whole banking system. Accordingly, the entire banking system of a nation was considered an intermediary between depositors and borrowers. That means any banking system tends to utilize deposits and overhead costs to provide credits to the private sector and increase its earnings (Ngo and Le 2019). Hence, the input-oriented DEA model was used to estimate the technical efficiency of the banking systems regarding pursuing this objective.

Similar to Ngo and Le (2019), our inputs included the ratio of total bank deposits to GDP (*DEPOSIT*) and the ratio of total bank overhead costs to total assets (*LABOR*), whilst outputs consisted of the private credit to GDP as a share of GDP (*CREDIT*) and the ratio of net interest revenue to interest-bearing assets (*NIM*). Note that because of substantially missing data on other input and output variables (the ratio of non-performing loans to total loans, the ratio of bank capital to total assets, returns on assets, and returns on equity), a set of two inputs and two outputs was used. Given that our sample ranged from at least 50 countries in 2013 up to 80 countries in 2017, the use of a set of two inputs and two outputs was consistent with the DEA literature (Ngo and Le 2019). Because the DEA calculation is year-based, and we did not examine the productivity change over time, the unbalanced data did not affect our analysis.

Table 1 presents the descriptive statistics of inputs and outputs used in DEA analysis. There appears to be little change in the costs (*LABOR*) and profitability (*NIM*) of banking systems over the examined period. When observing *DEPOSIT*, there was an increasing trend in the first three years and then a decrease in the latter period. However, the opposite phenomenon was observed in the case of *CREDIT*. This perhaps may reflect the growth of fintech credit platforms in providing financial solutions and services, which gradually increases the market share of lending. Additionally, a high standard deviation of these variables suggests that large volatilities and scale differences exist among our selected banking systems. This further demonstrates the appropriate use of VRS DEA to examine the scale effect.

Table 1. Descriptive statistics of the inputs and outputs used in DEA analysis.

Year	2013	2014	2015	2016	2017
No. Obs	50	59	66	75	80
			DEPOSIT		
Mean	52.96	63.61	63.23	60.35	62.24
STD	44.02	57.41	54.95	42.27	51.05
			LABOR		
Mean	3.75	3.18	3.56	3.4	3.56
STD	2.69	2.24	4.13	3.53	2.7
			CREDIT		
Mean	67.47	60.12	61.25	59.58	61.34
STD	113.68	47.09	46.83	40.88	42.001
			NIM		
Mean	4.86	4.12	3.86	4.09	4.92
STD	3.27	2.88	2.83	2.99	3.91

Sources: Authors' calculation based on Beck et al. (2000).

3.3. Second Stage: The Interrelationship between Banking Efficiency and Fintech Credit

Most empirical studies examine the determinants of either banking efficiency (Manlagnit 2015) or fintech credit (Claessens et al. 2018; Cornelli et al. 2020). Additionally, several studies used bank-level data to investigate the interrelationship between banking efficiency and other environmental factors (Le 2018), while others used cross-country data to investigate the two-way linkage between capital market development and banking efficiency (Ngo and Le 2019). As explained above, fintech credit is more likely to expand in economies where banks do not meet the demand for banking products/services, while fintech credit may serve as a wake-up call to banking systems. Taken together, we further investigate the interrelationship between fintech credit and bank efficiency, since the one-way investigation may suffer from simultaneous bias. Because a structural equations model

(SEM) can offer a set of interrelated questions in a single, systematic, and comprehensive analysis (Gefen et al. 2000), the following SEM is proposed:

$$LNFINCAP_{i,t} = \alpha_1 + \beta_1 EF_{i,t} + \beta_2 GDPCAP_{i,t} + \beta_3 GDPCAP2_{i,t} + \beta_4 REGFIN_{i,t} + \beta_5 MOBILE_{i,t} + \beta_6 BRANCH_{i,t} + \beta_7 GDPGR_{i,t} + \varphi_{i,t} \tag{2}$$

$$EF_{i,t} = \alpha_2 + \gamma_1 LNFINCAP_{i,t} + \gamma_2 LERNER_{i,t} + \gamma_3 CONCEN_{i,t} + \gamma_4 RS_{i,t} + \gamma_5 GDPGR_{i,t} + \gamma_6 INF_{i,t} + \omega_{i,t} \tag{3}$$

where *LNFINCAP* and *EF* are the two endogenous variables. $EF_{i,t}$ represents the banking efficiency in economy *i* at time *t* and ranges from 0 to 1, deriving from the first stage, whilst $LNFINCAP_{i,t}$ is measured by the natural logarithm of the volume of fintech credit per capita in economy *i* at time *t*.[3]

Following Claessens et al. (2018) and Cornelli et al. (2020), the development of fintech credit is associated with a country's level of economic and financial development (*GDPCAP*, the gross domestic product per capita), fintech regulation (*REGFIN*, a dummy variable that takes a value of 1 if an explicit regulation of fintech credit was in place in a country, and 0 otherwise), mobile phone subscriptions (*MOBILE*, mobile phone subscriptions per 100 persons), the density of the bank branch network (*BRANCH*, a number of bank branches per 100,000 adults), and a country's economic growth (*GDPGR*, the GDP growth rate). Because *GDPCAP* is likely to be a proxy for many factors relating to a country's stage of development, a positive impact of *GDPCAP* on *LNFINCAP* is expected. We further included *GDPCAP2*, a squared GDP per capita to capture possible non-linearity in this relationship. When a fintech regulation (*REGFIN*) is introduced, this may further foster the development of fintech credit because of more trust towards new intermediaries regarding the supply of funds from investors. Additionally, most fintech credit platforms have apps on mobile devices, intending to improve their convenience for users. Thus, an increase in mobile phone subscriptions (*MOBILE*) may promote the development of fintech credit. Furthermore, economic growth (*GDPGR*) may increase demand for financial products and services, and borrowers may seek credit from different sources of funds with better prices. This, therefore, increases the development of fintech credit. When traditional lending providers are limited to offering their financial products and services during economic downturns, this creates an opportunity for the expansion of fintech credit.

Following Phan et al. (2016) and others, banking efficiency is associated with banking competition (*LERNER*, the Lerner index of the banking sector mark-ups), market concentration (*CONCEN*, the ratio of three largest banks' assets to all commercial banks' assets), and banking regulation (*RS*, a regulatory stringency index for the banking sector), economic growth (*GDPGR*, the GDP growth rate), and inflation (*INF*, the inflation rate). The information generation hypothesis suggests a negative impact of competition on banking efficiency (Marquez 2002). Greater competition may reduce banks' capability of gathering information and increase the probability of adverse borrower selection. Consequently, this results in lower banking efficiency. The quiet life hypothesis proposes that market concentration (or market power) impacts banking efficiency negatively because it permits banks to enjoy a 'quiet life'—reducing the bank manager's efforts to minimize their bank's inefficiency (Berger and Hannan 1998). Empirical studies show mixed findings (Le and Ngo 2020; Phan et al. 2016). Moreover, Manlagnit (2015) documented conflicting findings regarding the relationship between banking regulation and banking efficiency in prior studies using bank-level data. We, however, used aggregate data to control for this relationship. Last, the effect of macroeconomic conditions such as economic growth and inflation was also considered. Table A2 in Appendix A provides a summary of variables used in SEM with their definitions and expected signs.

Moreover, Table A3 in Appendix A presents descriptive statistics of variables used in SEM analysis. There appears to be an increasing trend in *LNFINCAP* and *LNALTERCAP* from 2013 and 2017, which reflects the rapid penetration of fintech and big tech firms in lending markets. The growth of fintech credit platforms is further facilitated by the increasing use of mobile phones (*MOBILE*) and a reduction in the number of bank branches (*BRANCH*).

We test for heteroscedasticity using a two-step Breusch–Pagan test when one or more regressors are endogenous. Firstly, each of the two equations with pooled OLS with robust standard errors is run. Thereafter, Breusch–Pagan tests are performed. The results show that *p*-values of Equations (2) and (3) are 0.00 and 0.02, respectively, suggesting high heteroscedasticity.

From Equations (2) and (3), the error terms $\varphi_{i,t}$ and $\omega_{i,t}$ may be related because the same data are used. If unaccounted for, the simultaneous equation bias from these equations can result in inconsistent and biased estimators. These errors are simultaneously correlated, as they include the impact of factors that may be omitted. Because the banking systems' operation is homogenous in many ways, the impact of the omitted factors on the relationship between fintech credit and banking efficiency for one country may be similar to that for another. If this is true, these errors account for similar effects and will be correlated. To address this issue and control for heteroskedasticity and arbitrary autocorrelations, the panel Generalized Method of Moment (GMM) (Baltagi 2008) was used. The GMM estimator is more efficient than other conventional estimators such as fixed or random effects when a serial correlation exists or when the assumption on the strict exogeneity of regressor is false (Wooldridge 2001). Since the SEM framework effectively controls for the endogeneity and the GMM estimator generates efficiency gains when endogenous explanatory regressors are present, all estimations in our results were run with the use of the GMM estimator, which utilizes the interactions among the innovations in Equations (2) and (3). We further used the Newey and West (1987) method to control for heteroskedasticity and arbitrary autocorrelations when estimating Equations (2) and (3). Because the Newey–West method involves an expression in the squares of the residuals which is analogous to White's formula, these estimates contain White's correction. When the context of time series is considered, Newey–West standard errors are robust to both arbitrary heteroskedasticity and arbitrary autocorrelation. Therefore, our study used the SEM with GMM estimator combined with the Newey–West method to examine the interrelationships between fintech credit and banking efficiency. This approach was also used by several other studies, such as Nguyen (2012), Le and Pham (2021), and Le (2020), among others.

4. Results

4.1. The Analysis of the Efficiency of Banking Systems around the World

The average efficiency scores (*EF*) of global banking systems ranged from 0.738 (i.e., 26.2% inefficient) to 0.808 (i.e., 19.2% inefficient), as indicated in Figure 1. A modest decrease in the technical efficiency of the banking systems around the world over the examined period may reflect the consequence of the global financial crisis of 2007–2008 and the European debt crisis. Additionally, there appears to be a slight reduction in scale efficiency (SE), from 0.91 in 2013 to 0.897 in 2017, implying a more competitive environment of the global banking system. In contrast to a slight reduction in banking efficiency, the volume of fintech credit significantly increased over the studied period.

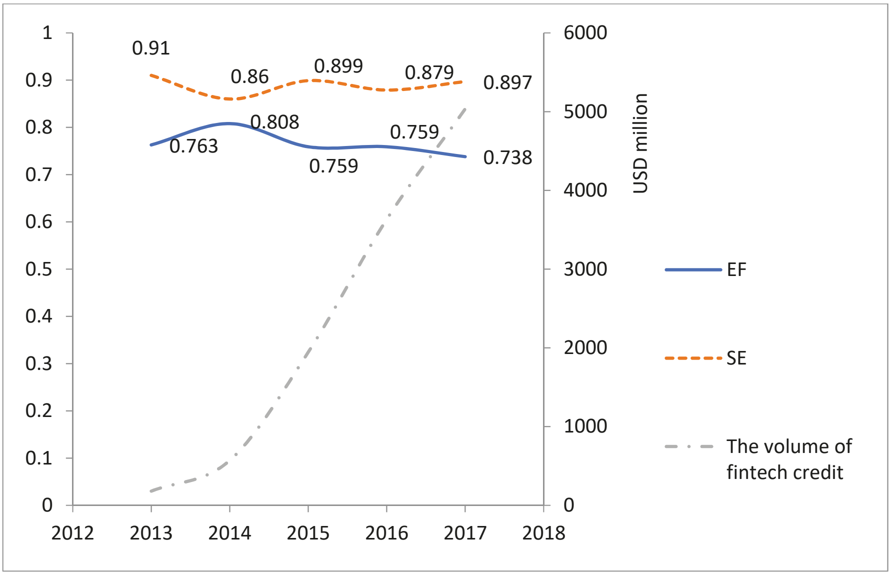

Figure 1. The evolution of banking efficiency (**left** axis) and the volume of fintech credit (**right** axis).

4.2. The Interrelationships between Fintech Credit and Banking Efficiency

Table A4 in Appendix A describes the correlation matrix of the variables used in SEM. At first glance, *EF* is negatively related to *LNFINCAP* and positively associated with *LNALTERCAP*. Additionally, there appear no significant correlations between the explanatory variables used in each equation. Nonetheless, the intertemporal relationship between *EF* and *LNFINCAP* can only be examined by using the SEM analysis.

Table 2 shows that the *p*-value of the Hansen test is statistically not significant, and thus the null hypothesis cannot be rejected. This means no evidence of over-identifying restrictions in SEM analysis with the use of the GMM estimator. Alternatively, all conditions for the moments are met and the instruments are accepted.

For the determinants of fintech credit development (Part 1 of Table 2), *EF* is significantly and negatively associated with *LNFINCAP*, suggesting that the less efficient the banking system in a country is, the more developed its fintech credit is. This somewhat supports the early findings of Cornelli et al. (2020), who found that fintech credit is more developed where the level of bank intermediation of deposits to loans is lower. *LNFINCAP* is also significantly and positively related to *GDPCAP*, implying that fintech credit is more developed in nations where there is a greater level of economic and institutional development. However, the coefficient of *GDPCAP2* is negative and significant, suggesting that this positive link becomes less crucial at greater levels of development. Nonetheless, this confirms the findings of Cornelli et al. (2020) and Claessens et al. (2018). Furthermore, a positive coefficient estimate on *REGFIN* demonstrates that the growth of fintech credit is rapid in a country where there is an explicit fintech credit regulation. This is comparable with the findings of Rau (2020), who demonstrated that the introduction of an explicit legal framework significantly boosts crowdfunding volume.

Additionally, *BRANCH* impacts *LNFINCAP* negatively, supporting the view that fintech credit serves either in underbanked regions or in the low-credit market segment (Yeo and Jun 2020) as a complement to conventional bank credit (Cornelli et al. 2020). This finding is also comparable with the use of agency banking. Nonetheless, we do not find any significant evidence that fintech credit is affected by economic growth (*GDPGR*) or mobile phone subscriptions (*MOBILE*).

Table 2. Results of second-stage SEM analysis.

Part 1. Equation (2) of SEM **Dependent Variable: LNFINCAP** **Independent Variables**	**Coefficient**	**Standard Error**	***t*-Statistic**
Constant	−0.553	1.095	−0.505
EF	−2.944 **	1.285	−2.291
GDPCAP	0.152 ***	0.027	5.702
GDPCAP2	−0.001 ***	0.0003	−3.509
REGFIN	0.791 **	0.378	2.093
MOBILE	−0.005	0.005	−1.089
BRANCH	−0.021 *	0.012	−1.815
GDPGR	−0.01	0.046	−0.212
No. Obs		330	
J-Statistics (*p*-value)		0.158	
Part 2. Equation (3) of SEM **Dependent Variable: EF** **Independent Variables**	**Coefficient**	**Standard Error**	***t*-Statistic**
Constant	0.585 ***	0.115	5.101
LNFINCAP	0.022 **	0.01	2.222
LERNER	0.295 ***	0.071	4.168
CONCEN	−0.0002	0.001	−0.335
RS	0.05	0.149	0.332
GDPGR	−0.001	0.004	−0.177
INF	0.021 ***	0.003	7.932
No. Obs		330	
J-Statistics (*p*-value)		0.158	

Notes: *LNFINCAP*, the natural logarithm of the volume of fintech credit per capita; *EF*, efficiency score of the individual banking system as derived from VRS DEA estimation; *GDPCAP*, the GDP per capita; *GDPCAP2*, the squared term of GDPCAP; *REGFIN*, a dummy variable that takes a value of 1 for a country where an explicit fintech credit regulation is in place, and 0 otherwise; *MOBILE*, the mobile phone subscriptions per 100 persons given the mobile-based nature of most fintech credit platforms; *BRANCH*, the number of bank branches per 100,000 adult population; *LERNER*, the Lerner index of the banking sector mark-ups in an economy; *CONCEN*, the ratio of three largest banks' assets to all commercial banks' assets; *RS*, a regulatory stringency index for the banking sector of an economy; *GDPGR*, the economic growth rate; and *INF*, the inflation rate. The table contains results estimated using a simultaneous equations model (SEM) with the GMM estimator and the Newey–West method. *EF* and *LNFINCAP* represent the two endogenous variables in SEM. *, ** and *** denote the two-tail significance at the 10%, 5%, and 1% levels, respectively.

For the determinants of banking efficiency (Part 2 of Table 2), a positive coefficient estimate on *LNFINCAP* suggests that fintech credit may serve as a wake-up call for the banking system. New credit activities provide financial services in which lenders and borrowers conduct transactions directly without the need for the intermediation of traditional financial institutions. The banking systems may respond to the increasingly competitive environment caused by the rapid expansion of fintech credit platforms by improving their efficiency. Learning from fintech credit platforms, the banking systems may utilize the application of emerging technologies in the banking industry (i.e., artificial intelligence technology, blockchain technology, cloud computing technology, big data technology) to their operating activities. In this sense, Cheng and Qu (2020) highlighted that the development of bank fintech is more likely to reduce credit risk for Chinese commercial banks. Additionally, *LERNER* is positively and significantly associated with *EF*, suggesting that the efficiency of the banking system is improved with a less competitive banking system. Therefore, this supports the view of the information generation hypothesis as proposed by Marquez (2002). Furthermore, a positive impact of *INF* on *EF* suggests that future movements in inflation are fully anticipated by the banking systems, and thus this increases their profits. This is consistent with prior studies such as Demirgüç-Kunt and Huizinga (1999). Finally, we do not find any significant evidence that bank efficiency is influenced by market concentration, economic growth, and regulatory stringency for the banking system.

In sum, the findings suggest that there is a two-way relationship between fintech credit development and banking efficiency. Similar to the findings of Cornelli et al. (2020), the depth of fintech credit is more likely associated with a reduction in banking efficiency. Meanwhile, an expansion of fintech credit may serve as a wake-up call to the banking systems and perhaps place competitive pressure on them to improve their operations to remain a viable competitor.

4.3. Robustness Checks

For robustness, we first replace fintech credit with total alternative credit as measured by a sum of fintech credit and big tech credit (*LNALTERCAP*), as shown in Table 3. In contrast to prior studies such as Cornelli et al. (2020) and Claessens et al. (2018), we do not report the results of big tech credit as a dependent variable in SEM with the GMM estimator because of the smaller number of countries and years in which big tech credit is present. The number of observations for big tech credit only accounts for 14.84% of the total observations.

Table 3. Results of second-stage SEM analysis using an alternative measure of fintech credit.

Part 1. Equation (2) of SEM Dependent Variable: LNALTERCAP Independent Variables	**Coefficient**	**Standard Error**	***t*-Statistic**
Constant	−0.149	0.662	−0.225
EF	0.368	0.818	0.45
GDPCAP	0.082 ***	0.013	6.178
GDPCAP2	−0.001 ***	0.0002	−3.840
REGFIN	0.352 *	0.209	1.687
MOBILE	−0.003	0.002	−1.955
BRANCH	−0.019 ***	0.006	−3.387
GDPGR	0.009	0.023	0.377
No. Obs		330	
J-Statistics (*p*-value)		0.135	
Part 2. Equation (3) of SEM Dependent Variable: EF Independent Variables	**Coefficient**	**Standard Error**	***t*-Statistic**
Constant	0.551 ***	0.131	4.197
LNALTERCAP	0.04 **	0.017	2.356
LERNER	0.280 ***	0.067	4.166
CONCEN	0.0001	0.001	0.246
RS	−0.002	0.142	−0.017
GDPGR	0.001	0.004	0.288
INF	0.018 ***	0.002	8.351
No. Obs		330	
J-Statistics (*p*-value)		0.135	

Notes: *LNALTERCAP*, the natural logarithm of the volume of total alternative credit per capita; *EF*, efficiency score of the individual banking system as derived from VRS DEA estimation; *GDPCAP*, the GDP per capita; *GDPCAP2*, the squared term of *GDPCAP*; *REGFIN*, a dummy variable that takes a value of 1 for a country where an explicit fintech credit regulation is in place, and O otherwise; *MOBILE*, the mobile phone subscriptions per 100 persons given the mobile-based nature of most fintech credit platforms; *BRANCH*, the number of bank branches per 100,000 adult population; *LERNER*, the Lerner index of the banking sector mark-ups in an economy; *CONCEN*, the ratio of three largest banks' assets to all commercial banks' assets; *RS*, a regulatory stringency index for the banking sector of an economy; *GDPGR*, the economic growth rate; and *INF*, the inflation rate. The table contains results estimated using a simultaneous equations model (SEM) with the GMM estimator and the Newey–West method. *EF* and *LNALTERCAP* represent the two endogenous variables in SEM. *, ** and *** denote the two-tail significance at the 10%, 5%, and 1% levels, respectively.

Part 2 of Table 3 confirms the positive impact of total alternative credit on banking efficiency, while the development of total alternative credit is not affected by the banking efficiency, as indicated in Part 1 of Table 3. This insignificant impact can be explained by the fact that big tech firms have operated in different countries, and thus may go beyond the capacity of domestic controls to capture the global nature of big tech business models.

Big tech firms often have a wide range of business lines, in which lending accounts for only one (often small) part. However, the volume of big tech credit is usually large (i.e., this was at least twice as large as fintech credit in 2019) (Cornelli et al. 2020). The advantage of using large volumes of information allows big tech firms to effectively measure the loan quality of potential borrowers based on a large existing and cross-border user base, given the application of advanced technology in lending segments. Additionally, big tech firms may focus on serving potential borrowers who have already been existing customers in their ecosystem.

Following the classification by Cornelli et al. (2020), we also divide our sample into two groups, including developed and non-developed economies. Although the results cannot be reported here but are available upon request, the findings show that a two-way relationship between fintech credit and banking efficiency still holds for the case of non-advanced economies. Again, this confirms our above findings. When observing advanced economies, there appears only a one-way negative impact of fintech credit on banking efficiency, suggesting that fintech credit tends to substitute for the banking system. This is because more developed economies will have a higher demand for credit from firms and households, and thus, these potential borrowers tend to switch to new intermediaries. The advantages of fintech credit and big tech credit are comprehensively discussed by Cornelli et al. (2020) and Claessens et al. (2018). However, these findings need to be cautiously interpreted because of the small sample size used in SEM with the GMM estimator (i.e., there are only 92 observations in the case of developed economies).

Furthermore, we use the natural logarithm of the volume of fintech credit as an alternative measure of fintech credit. A positive impact of fintech credit on banking efficiency still holds, while the relationship in the other direction is insignificant. Additionally, we replace *REGFIN* with other variables that reflect countries' institutional characteristics (i.e., barriers to entry, as expressed by the ease of doing business variables, and investor disclosure and efficiency of the judicial system). For the ease of doing business, we used score starting a business (overall), score-time (days), score-paid-in minimum capital (% of income per capita), and score-cost (% of income per capita). For the investor protection and judicial system, we used the extent of disclosure index, trial, and judgment (days), enforcement of judgment (days), and enforcement fees (% of claim). All indicators were collected from the World Bank Ease of Doing Business database. We ran each indicator individually to avoid multicollinearity issues. The findings indicate a two-way relationship between fintech credit and banking efficiency, although the reports are not presented but are available upon request. Nonetheless, our above findings are confirmed.

5. Conclusions

This study investigates the causal relationship between fintech credit and banking efficiency in 80 countries from 2013 to 2017 using a two-stage framework. In the first stage, DEA with the use of financial ratios was employed to estimate the efficiency of the banking systems around the world. In the second stage, the GMM estimation in SEM was used to examine the above interrelationship. The findings of the first stage show that the average efficiency scores of these banking systems are relatively low, suggesting that there is still room for them to improve.

Importantly, the findings of the second stage indicate that there is a negative relationship between banking efficiency and fintech credit, while greater fintech credit can promote banking efficiency. Additionally, a negative relationship between the density of bank branch networks and fintech credit suggests that fintech credit serves underbanked regions. Our findings further emphasize that fintech credit is more developed in economies where explicit fintech regulation is present. Therefore, the implementation of a legal framework regarding fintech credit is very important for the development of fintech credit. Additionally, our findings reemphasize the significance of monitoring and anticipating the movement of the inflation rate is very important to enhancing the efficiency of the banking system. All in all, promoting fintech credit would bring about mutual benefits, including

(1) addressing the unbanked or low-credit segments that banking systems do not serve, and (2) enhancing the efficiency of the banking systems.

This study has some limitations. We could not extend the choice of variables in our DEA model nor incorporating the country-fixed effect variables in our SEM analysis due to data limitations. Future research may extend the data so that a balanced panel could be obtained to examine the efficiency and productivity changes over time of the banking systems. Additionally, future studies are encouraged to use different DEA models under the different assumptions in the first stage. For the second stage SEM analysis, the impact of big tech credit on banking efficiency should be considered in future studies when the relevant data are more widely available.

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Appendix A

Table A1. The list of countries included in our sample.

United Arab Emirates	France	Malaysia	Senegal
Argentina	Ghana	Mozambique	El Salvador
Austria	Guatemala	Nigeria	Togo
Australia	Hong Kong	Netherlands	Thailand
Belgium	Indonesia	Norway	Turkey
Burkina Faso	Ireland	New Zealand	United Republic of Tanzania
Bulgaria	Israel	Panama	Uganda
Burundi	India	Peru	United States of America
Brazil	Italy	Philippines	Uruguay
Côte d'Ivoire	Jordan	Pakistan	Viet Nam
Chile	Japan	Poland	South Africa
China	Kenya	Portugal	Zambia
Colombia	Cambodia	Paraguay	Bolivia
Czech Republic	Korea	Russian Federation	Cameroon
Germany	Lebanon	Rwanda	Costa Rica
Denmark	Lithuani	Saudi Arabia	Georgia
Ecuador	Latvia	Sweden	Zimbabwe
Estonia	Madagascar	Singapore	
Egypt	Mali	Slovenia	
Spain	Myanmar	Slovakia	
Finland	Mexico	Sierra Leone	

Table A2. A summary of variables used in SEM and their expected signs.

Variables		Definitions	Expected Signs	Sources
LNFINCAP	The development of fintech credit	The natural logarithm of the volume of fintech credit per capita	±	Cornelli et al. (2020) and CCAF
EF	Bank efficiency	Efficiency score of the individual banking system as derived from Data Envelopment Analysis under variable returns to scale assumption	±	The Financial Development and Structural Dataset
GDPCAP	a country's level of economic and financial development	The gross domestic product per capita	+	World Bank
REGFIN	Fintech regulation	A dummy variable that takes a value of 1 for a country where an explicit fintech credit regulation is in place, and 0 otherwise	+	Rau (2020)
MOBILE	Mobile phone subscriptions	Mobile phone subscriptions per 100 persons	+	World Bank
BRANCH	The density of bank branch network	The number of bank branches per 100,000 adult population	±	World Bank
LERNER	Banking competition	The Lerner index of the banking sector mark-ups	±	World Bank and Igan et al. (forthcoming)
CONCEN	Market concentration	The ratio of three largest banks' assets to all commercial banks' assets	±	The Financial Development and Structural Dataset
RS	Banking regulation	A regulatory stringency index for the banking sector	±	World Bank
GDPGR	Economic growth	The GDP growth rate	±	World Bank
INF	Inflation	The inflation rate	±	World Bank

Table A3. Descriptive statistics of variables used in the second-stage analysis.

	2013		2014		2015		2016		2017	
	Mean	**STD**	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**	**Mean**	**STD**
LNFINCAP	−2.31	2.14	−2.26	2.6	−1.36	2.56	−0.5	2.39	−0.18	2.55
LNALTERCAP	1.19	3.03	1.77	3.28	2.49	3.64	3.31	3.37	4.31	3.02
GDPCAP	19.17	16.68	23.15	19.91	23.71	19.78	22.31	18.79	22.5	19.06
GDPCAP2	639.16	775.57	925.07	1270.4	946.89	1283.16	845.54	1229.45	864.56	1274.52
REGFIN [1]	0.14	0.35	0.17	0.38	0.19	0.4	0.24	0.43	0.29	0.45
MOBILE	99.22	34.36	108.97	37.33	112.7	35.6	112.8	31.13	116.07	34.13
BRANCH	16.47	15.99	17.57	15.5	17.49	14.97	17.97	14.59	15.94	12.44
LERNER [2]	0.28	0.09	0.3	0.14	0.29	0.13	0.31	0.15	0.31	0.15
CONCEN	63.14	18.32	63.28	18.93	62.48	17.22	60.5	15.55	60.21	17.26
RS [3]	0.72	0.08	0.73	0.09	0.73	0.08	0.73	0.09	0.64	0.09
GDPGR	4.12	3.67	3.75	2.42	3.12	4.65	3.05	2.18	3.84	1.94
INF	4.19	4.69	3.46	4.35	2.94	4.6	3.43	5.05	3.92	4.84

Notes: The dependent variable was winsorized at the 1% and 99% levels. [1] *REGFIN* is obtained from Rau (2020). [2] *LERNER* was collected from the World Bank data. However, the data over the period 2015–2017 were obtained based on the estimates of Igan et al. (forthcoming). [3] *RS* is constructed by Navaretti et al. (2017) from the World Bank database.

Table A4. Correlation matrix between variables used in this study.

	1	2	3	4	5	6	7	8	9	10	11
1. LNFINCAP	1										
2. LNALTERCAP	0.8 ***	1									
	(22.08)										
3. EF	−0.03	0.04	1								
	(−0.48)	(0.64)									
4. GDPCAP	0.52 ***	0.48 ***	−0.07	1							
	(10.34)	(9.21)	(−1.25)								
5. GDPCAP2	0.43 ***	0.39 ***	−0.02	0.93 ***	1						
	(8.09)	(7.12)	(−0.37)	(43.74)							
6. BRANCH	0.26 ***	0.22 ***	−0.18 ***	0.49 ***	0.29 ***	1					
	(4.6)	(3.87)	(−3.06)	(9.37)	(5.12)						
7. MOBILE	0.29 ***	0.25 ***	−0.07	0.59 ***	0.48 ***	0.32 ***	1				
	(5.04)	(4.43)	(−1.25)	(12.17)	(9.09)	(5.65)					
8. LERNER	0.08	0.07	0.22 ***	0.13 **	0.27 ***	−0.05	0.14 **	1			
	(1.3)	(1.26)	(3.81)	(2.14)	(4.68)	(−0.91)	(2.4)				
9. CONCEN	0.19 ***	0.06	−0.04	0.28 ***	0.28 ***	−0.01	0.12 **	−0.01	1		
	(3.24)	(1.08)	(−0.66)	(4.89)	(4.98)	(−0.19)	(2.03)	(−0.12)			
10. GDP	−0.12 **	−0.1 *	0.04	−0.22 ***	−0.11 *	−0.28 ***	−0.24 ***	0.08	−0.2 ***	1	
	(−2.05)	(−1.72)	(0.63)	(−3.78)	(−1.89)	(−4.99)	(−4.16)	(1.38)	(−3.49)		
11. INF	−0.43 ***	−0.32 ***	0.36 ***	−0.45 ***	−0.35 ***	−0.38 ***	−0.35 ***	0.02	−0.12 **	0.04	1
	(−8.07)	(−5.64)	(6.55)	(−8.38)	(−6.34)	(−6.86)	(−6.32)	(0.34)	(−1.99)	(0.67)	

Notes: *t*-statistics are shown in parentheses, *, ** and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

Notes

1 It is important to note that the data on fintech credit provided by Cornelli et al. (2020) and CCAF were available from 2013 to 2018, while the data used to estimate efficiency scores of banking systems were available until 2017. Therefore, our sample period of 2013–2017 was selected to maintain our observations as many as possible.

2 DEA techniques have been extensively used in finance studies. For more details, please see Boubaker et al. (2015) and Kaffash and Marra (2017).

3 Since the number of countries is relatively high, compared to the number of observations, we did not use the country fixed-effect dummy variables in our models. In addition, the inclusion of several country-specific regressors prevents us from using a set of country dummies. To be specific, we controlled for differences in the examined countries in terms of their banking competition (*LERNER*), market concentration (*CONCEN*), banking regulation (*RS*), fintech regulation (*REGFIN*) as well as other institutional characteristics (for robustness checks). We believe that any country-level differences should be accounted for in the robustness testing.

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Review

Taxing the Digital Economy through Consumption Taxes (VAT) in African Countries: Possibilities, Constraints and Implications

Favourate Y. Mpofu

School of Accounting, Auckland Park, University of Johannesburg, P.O. Box 524, Johannesburg 2006, South Africa; fmpofu@uj.ac.za

Abstract: Owing to the Fourth Industrial revolution and digital transformation, the digital economy has grown substantially globally and in Africa. Despite the positive outcomes such as advancements in technology, improvements in business models and expansion in digital financial inclusion, negative implications include the erosion of tax bases due to the invisible nature of digital transactions. Although the digital economy is one of the biggest and quickest growing sectors in the African continent, its contribution to tax revenue is negligible. Developed and developing countries are grappling to find effective ways of mobilizing revenues from this hard to tax economy. African countries have turned to digital services taxes, value added taxes and withholding taxes in a bid to collect revenue from the digital economy to broaden their tax bases. There is intense debate among policymakers, governments, development bodies and tax bodies on the most effective way to tax the digital economy. Through a conceptual analysis based on a critical review of the literature, this article contributes to the ongoing debate by assessing the possibilities and constraints of taxing the digital economy in Africa using value added tax (VAT). The paper reviewed 55 articles, most of them current, published between 2014 and 2022, reflecting embryonic nature of the subject area. The findings on the opportunities include the existence of VAT regulation, increased revenue mobilization and efficiency gains, while challenges include ambiguities in legislation, capacity constraints and tax knowledge gaps. The implications of using VAT to collect tax from the digital economy encompass increased cost of digital services, decreased access, increased inequality and impediment on employment creation, poverty reduction, digital financial inclusion, and the realization of the sustainable development goals.

Keywords: VAT; digital economy; taxation; consumption tax; constraints

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1. Introduction

The digital economy has grown dramatically worldwide, leading to the emergence of new business transactions and the growth in e-commerce and online transactions. Digitalization of the economy is viewed as a propeller for growth, innovation as well as societal change and connectivity (Organization for Economic Co-operation and Development (OECD) (2020); Schiavone Panni 2019). Despite the advantages linked to the expansion of the digital economy, several challenges have also originated. Key areas of the economy such as industries, entrepreneurial development, innovation and technology, fiscal policy and taxation have faced problems emanating from the substantial growth of the digital economy (Ahmed and Gillwald 2020). Simbarashe (2020, p. 178) asseverates, "Among these, tax implications of the digitalized economy are perhaps the most urgent issue for policymakers, governments, civil societies and international organizations". Taxation is a not only a revenue generation problem but also a development issue, a regulation matter, a financial inclusion concern and a topic that touches on the fulfilment of the United Nations (UN) Sustainable Development Goals (SDGs).

The change in business models and the widening of global digitalization has enabled MNEs and other ordinary companies to penetrate global tax jurisdictions where they only have markets but no physical presence (Kelbesa 2020; Munoz et al. 2022). These companies have managed to generate profits in ways, which have challenged the existing international tax laws' adequacy in handling and tapping tax revenue from the digital economy (OECD 2019, 2020). The African continent is not immune to these challenges (Kirsten 2019; Latif 2019, 2020; African Tax Administration Forum (ATAF) (2019a), 2019b). The digital economy has led to a consequential digital presence and investments by digital MNEs such as Amazon, Google, Netflix, Facebook, and Uber. Most African revenue authorities and their governments have started to take a special interest in how to mobilize revenue from the seemingly intricate digital economy.

MNEs had been previously operating in these market jurisdictions such as Africa, but their activities have immensely increased in breadth, scope, and intensity. The widening of the activities is due to the expansion in digital transformation, together with the advancement in communication and information technology (Akpen 2021; Bunn et al. 2020; Deloitte 2020a; Simbarashe 2020). Digitalization has brought significant modification to the way businesses conduct their activities and transactions as well as to tax administration. The changes in the business world and the fact that they now lean more on digitalization was fueled by the COVID-19 pandemic. This accordingly calls for changes to be incorporated in regulation, infrastructural development, tax policy construction and tax administration.

The invisibility and borderless feature of digital transactions makes levying and collecting taxes on them a formidable task for all economies (both developed and developing) and more so in African countries where tax administration capacities are weak, coupled with underdeveloped technologies as well as resources constraints. Identifying digital businesses, determining the scope of their activities, tracing their revenues, gathering, and verifying information that leads to the determination of tax liability is difficult for countries in general (Lowry 2019) and more challenging for African countries (Santoro et al. 2022; Simbarashe 2020).

While revenue authorities continue to face the revenue collection predicaments emanating from the growing presence of the digital economy, digital transformation continues to heighten innovation and the emergence of complex business models. Tax administration in Africa remains unclear on the most effective and efficient way to tax the digital economy, yet the challenges arising from novel technologies and intricate business models continue to mount, increasing the likelihood of tax revenue leakages. Digital transformation has indeed raised questions on whether the current international tax legislation remain applicable and adequate for tax revenue mobilization in this globalized and digitally transformed business environment. The current legislation includes the OECD transfer pricing guidelines and UN guidelines on transfer pricing (TP) as well as various unilateral TP rules (arm's length principle). While considerable efforts have been made to regulate base erosion and profit shifting (BEPS) through BEPS projects (Simbarashe 2020), OECD TP guidelines (Kabala and Ndulo 2018) and ATAF guidelines on intangibles (ATAF 2020), the key challenges in taxing the digital economy have remained insufficiently addressed (Ahmed and Gillwald 2020; Kelbesa 2020; Rukundo 2020). The BEPS Inclusive Framework on BEPS and on Addressing the Challenges in the Taxation of the Digital Economy discussions have been ongoing, and the implementation of the negotiations have been delayed to the frustration of member countries, with some of these countries resorting to enacting their own individual tax rules on the digital economy. Divergent views have emerged among member nations. In relation to the OECD consensus-based rules, ATAF, on behalf of African countries, has posed questions on the effectiveness and inclusiveness of the proposed provisions and pillars guiding the envisaged implementation (Becker 2021). The thorny areas revolve around the applicability of OECD guidelines in the African contexts. Firstly, the issues of the effectiveness of international digital services tax rules in curbing tax avoidance and evasion by MNEs in Africa. Secondly, how the consensus-based rules take into consideration the shortcomings of African tax administration authorities and other resource constraints. These issues raise concern on whether the playing field is level when viewed in the context of developed and developing country perspectives.

From the extant literature, African countries have moved towards finding their own ways to tax digital income. Some have introduced new direct digital taxes that are akin to corporate tax rates (Tunisia, Zimbabwe, Kenya, and Nigeria) (Becker 2021), others have used withholding taxes while others have expanded their consumption taxes or VAT regimes (Zimbabwe, South Africa) (Simbarashe 2020). These methods are not without their fair share of challenges and shortcomings. Firstly, with direct taxes, the difficulty lies in the establishment of the taxable nexus in accordance with the existing international tax laws. For example, the physical permanent establishment or the adequate physical presence. Secondly, digital MNEs such as Amazon, Facebook, Netflix, YouTube, and Twitter can engage in aggressive BEPS due to the mobility and intangibility of their assets. With the shift of the economy from the brick-and-mortar nature of businesses to the novel digital commercialization, BEPS is likely to broaden. Africa must find a suitable and efficient way to tax the digital economy.

Taxation of the digital economy remains explored to a limited extent due to its infancy. While some studies have focused on the need to tax the digital economy (de Lima Carvalho 2020; Ismail 2020; Schiavone Panni 2019) and some on the challenges of taxing the economy (Gulkova et al. 2019; Ndajiwo 2020; Saint-Amans 2017; Turina 2020), the methods of taxing the digital economy both direct and indirect remain comparatively unassessed. This paper focuses on the use of indirect or consumption taxes to tax the digital economy, the possibilities of effective revenue mobilization, constraints, and other associated ramifications. This study makes two vital contributions. Firstly, to the academic body of knowledge and literature on the taxation of the digital economy in general and specifically to using VAT to mobilize revenue from this economy. As highlighted previously, there is a paucity of literature that evaluates taxation of the digital of the economy using VAT in Africa. This study gives a comprehensive insight into the VAT legislation and administration that is still in its nascent stages of development and implementation in the digital economy in Africa. While Simbarashe (2020) gave an overview of the VAT legislation adopted by African countries in response to the growth of the digital economy, the authors did not conceptually analyze the practicability of administering the regulations, and the possible constraints and implications that can be encountered. Secondly, through a conceptual analysis of the VAT legislation and its applicability to the digital economy and by unpacking the likely pros and cons of VAT administration in this economy, the paper makes a practical contribution to policy formulation. Taxation is not only about collecting revenue but also about driving growth in the economy, encourage usage of goods and services as well stimulating international trade and investments. Therefore, by unpacking the key strengths of the VAT policy, the legislative shortcomings and possible areas of improvement, this paper helps inform future VAT policy amendments and new policy designs in African countries.

This paper found out that the VAT legislation with respect to taxing the digital economy was not fully developed in most African countries and that in some cases key terms and provisions of the VAT Acts were not clearly explained. The paper also found out that VAT is a cost that increases the prices of digital services and products, thus unfavorably affecting their usage. For example, if VAT is levied on services such as mobile money services, internet data, mobile phones and other digital products, this would affect usage, profitability of companies, corporate tax revenue, digital financial inclusion, and the fruition of the SDGs.

Having given the background of the conceptual analysis in this section, the next section explains the methodology employed to gather relevant literature upon which the evaluative review was conducted to generate insights on VAT administration in the digital economy, the possible opportunities, challenges, and implications associated with the VAT legislation enforcement. Section 3 covers the conceptual analysis conducted to unpack and analyze the VAT regulation in Africa's digital economy by focusing on selected

African counties. Section 4 articulates the implications and recommendations for future VAT policy construction and amendments in relation to the digital economy. Section 5 gives the conclusion, recommendations, limitations, and areas of further research.

2. Review Methodology

This article discusses the use of consumption taxes to mobilize revenue from the digital economy in Africa, mainly focusing on VAT. A critical qualitative literature review approach was adopted. The researcher conducted an evaluative analysis and interpretive critique of legislation documents, policy briefs and other previous literature to conceptualize the views of various researchers in relation VAT legislation in the digital economy. The researcher sought to give an analysis on the VAT regulation, the possible benefits, and challenges as well as implications of tax revenue mobilization in the digital economy using VAT in Africa. As proclaimed by Snyder (2019), a critical review of the literature enables researchers to gather relevant literature, discuss it, appraise, comment on it, and synthesize it. This equips researchers to give a comprehensive picture of the subject area. A critical literature review aids researchers in drawing out divergent and converging views on the subject area as well as identify research gaps, policy gaps and methodological gaps that could be explored further by future researchers (Mpofu 2021b; Paré et al. 2015; Snyder 2019). In evaluating the literature, the researcher in this case was able to draw out controversial areas such as the ambiguities in definitions such as place of supply and electronic services in the VAT legislation.

The researcher reviewed documentation on the VAT legislation towards taxing the digital economy in African countries. The documentation reviewed includes VAT Acts from the different African countries, especially those that have put the VAT legislation in place to tax the digital economy (Zimbabwe, South Africa, Angola, and Cameroon, among others). The article also assessed policy briefs released by accounting firms such as Deloitte, PWC and KPMG, among others, on VAT legislation on digital services. These were complemented by an examination of documents from tax bodies such as ATAF, developmental bodies such as the OECD and working papers from developmental research bodies such as the Institute of Development Studies (IDS) and the International Centre of Tax and the Development (ICTD) and other similar bodies. This was in addition to the review of previous studies on the taxation of the digital economy using indirect taxes, consumption taxes or VAT in Africa. The literature search was carried out through the Google scholar search engine. The search provided only a few papers, with most of them focusing on South Africa, which has been taxing the digital economy since 2014 using VAT legislation. To buttress the literature, the researcher used forward and backward snowballing to search for the more recent and previous works of the authors of the relevant articles, respectively. This yielded a few other articles. In total, 55 articles were reviewed. Therefore, to increase the diversity of the sources and make the review more meaningful, the researcher used a combination of the resources mentioned above (peer reviewed journal articles, policy briefs, working papers from development bodies and discussion papers from accounting firms). This was to overcome the limitation of the scarcity in literature linked the novel nature of the issue of taxing the digital economy in Africa. Data were reviewed until the saturation point was achieved, this being the point where further reviewing did not reveal any novel information other than what was already established (Sebele-Mpofu 2020b).

Thematic analysis was employed to present and discuss the findings of review. This was in line with the advantages of thematic analysis expounded by Braun and Clarke (2006, 2019). Data were presented in accordance with the key focal objects of the research, that is, the possibilities, constraints, and possible implications of the use of consumption taxes (VAT) to tax the digital economy. The main themes were further split into subthemes guided by the facts that emerged from the review. Accordingly, sources used were also referenced both in-text and in the reference list to enhance the traceability, confirmability, and trustworthiness of the research.

3. VAT Administration on the Digital Economy in Africa

This section presents a conceptual analysis based on an evaluative review of the literature on VAT administration and taxing the digital economy in Africa, focusing on opportunities, constraints, and implications. The sections guiding the analysis focus on VAT legislation, possibilities of mobilizing revenue from the digital economy using VAT and the challenges to effective VAT administration in the digital economy as well as the implications of levying VAT on digital transactions.

3.1. Consumption Taxes and Digital Economy Taxation

The broadening of the VAT legislation, especially the term 'electronic services', included anything ranging from software to advertising. As an output from the Global Forum on VAT set by the OECD in 2012, in September 2016 the OECD released guidelines to help countries to curb tax avoidance in the digital sector (Deloitte 2020b). These guidelines incorporated the destination principle to make non-residents service providers in market jurisdictions (country where consumers or users of the digital services are) liable for VAT in the market jurisdictions. Foreign digital service providers were obliged to register for VAT or appoint to registered domestic representative to do so on their behalf; this makes tax compliance and enforcement problematic (TaxWatch 2021).

VAT is normally referred to as a destination-based or consumption tax chargeable on a consumer. VAT is a broad-based tax levied on the consumption of goods and services (Beebeejaun 2020; Kruger and Moss-Holdstock 2014; Rooi 2015). The seller is the one who normally collects the tax. VAT is often applied on the price. VAT is a major fountain of tax revenue for most governments globally. In Africa, VAT is argued to contribute approximately 30% of national revenues (TaxWatch 2021).

The characteristics of VAT include: (1) Applicable to transactions on or the supply of goods and services; (2) calculated as a proportion of the price charged for the sale of goods; (3) chargeable at each stage of production or distribution; and (4) input tax (VAT) can be claimed. The mechanics of VAT computation are such that businesses can claim input tax that they have incurred in making taxable supplies (Lowry 2019; Russo 2019). For example, a company that sells clothing adds VAT/Goods and Services Tax (GST) to the prices of the clothes they manufacture and sell (output VAT). The company also buys a car for its sales and distribution. The purchase of the car would attract VAT (input VAT). Therefore, to arrive at the VAT payable or refundable the calculation is as follows: Output VAT-Input VAT = VAT payable or refundable.

Therefore, having explained the mechanics of VAT, the next sections look at the use of VAT in mobilizing revenue from the digital economy in international forum (briefly) (Section 3.1.1) and in Africa (Section 3.2).

3.1.1. The Application of VAT Regulation in the Digital Economy and the International Tax Platform

The unprecedented growth in digital activities globally motivated countries and international development bodies and tax bodies to explore possible ways to tap tax revenues from this novel economy. One such possible approach was the application of VAT legislation to the digital economy. Debates surround the adequacy and effectiveness of VAT regulation in fostering tax compliance and productive revenue mobilization at minimal administration and compliance costs. In most countries, VAT was never levied on digital transactions due to the absence of physical presence, hence significant revenues were being lost. This placed domestic companies supplying electronic services in an unfavorable position, since in incorporating the legal obligation to charge VAT to their consumers, their prices increased (Beebeejaun 2020; Lowry 2019; Munoz et al. 2022). Furthermore, the disadvantaged position was compounded by the registration and administration burdens, the VAT assessment, collection, and remittance costs as well as filling procedures. The OECD taskforce made recommendations to guide countries to build a fair and level taxation playing field and to protect the individual countries' ability to levy VAT. Four ways of collecting VAT are recommended. Firstly, the traditional VAT collection approach, where the assessment for VAT is carried out at the border. Secondly, the vendor collection method, whereby non-resident foreign companies are responsible for the imposition, collection, and remittance of VAT to the market jurisdiction (destination principle). Thirdly, the intermediary collection method, that is, using intermediaries to collect VAT on behalf. Lastly, the reverse charge mechanism (Beebeejaun 2020). The destination principle which is adopted by most countries (South Africa, Mauritius, Indonesia, Kenya, Zimbabwe, and Cameroon) is argued to provide certainty and predictability in revenue mobilization through VAT.

3.2. Consumption or Indirect Taxes and Taxation of the Digital Economy in Africa

Resources mobilization from the digital economy is essential for post COVID-19 pandemic national reconstruction (Onuoha and Gillwald 2022), as economic activity was adversely affected. Revenue mobilization declined, and public expenditure immensely widened as countries committed substantial resources to fighting the pandemic. The situation is more precarious in Africa where revenue mobilization is generally weak, and countries are often faced with budget deficits (Mpofu 2021a; Sebele-Mpofu 2020a). Intangible assets have gained a significant role in the digital economy, with MNEs gaining a greater share of their value creation from intangible assets. These assets include intellectual property, trademarks and copyrights that are easily and invisibly shifted across borders and that are difficult to value for TP due to lack of comparables. TP abuse becomes easy in this case, siphoning Africa of millions needed to fund health, security, education, infrastructural development, and economic growth (Sebele-Mpofu et al. 2021b; United Nations Conference Trade and Development (UNCTAD) (2020)). The debate in relation to VAT and the digital economy revolve around the opportunities, constraints, and implications. There is on-going discussion globally and in Africa specifically on whether or not to tax the digital economy and if so, using what method or tax head and at what rates. Table 1 provides an insight into the VAT provisions, collection mechanisms and tax rates used by some selected African countries. Table 1 foregrounds the overview of indirect taxes towards taxing the digital economy in Africa. The table gives a synopsis of selected countries' VAT provisions and the effective dates of legislation implementation.

Table 1. Summary of VAT regulations in selected African Countries.

Country	Legal/Statutory Provisions	Effective Date	Reference(s)
Algeria	On 12 December 2019, the country broadened its VAT legislation to incorporate sales of digital services, which are liable to a downward revised rate of 9%. The law remains silent on the registration provisions for non-resident providers No VAT liability threshold.	1 January 2020	(Bunn et al. 2020; Kelbesa 2020; Simbarashe 2020)
Kenya	From September 2013, Kenya levied VAT on digital services provided by foreign suppliers to the country 'residents. Kenya broadened its indirect tax policy in 2019 to include sales generated through digital sales markets, making VAT chargeable on these sales. Furthermore, the country widened the provisions for self-assessment under VAT.	1 January 2020	(Kapkai et al. 2021; Sigadah 2018; Simbarashe 2020; TaxWatch 2021)
Cameroon	The country introduced VAT on digital services. The provisions are such that the sale of goods and services to both businesses and individuals shall be VAT chargeable. All operators of e-platforms must register o VAT in relation to each transaction.	17 January 2020	(Simbarashe 2020; TaxWatch 2021)
Ghana	In 2013, Ghana put in place VAT regulations that if non-resident vendors selling/providing services to customers in Ghana should register for VAT. Threshold: GH 200,000 (estimated 25,000).	1 January 2014	(Simbarashe 2020; TaxWatch 2021).

Table 1. *Cont.*

Country	Legal/Statutory Provisions	Effective Date	Reference(s)
Zimbabwe	The company put in place legislative requirements for non-resident vendors of television, radio and other digital services to customers or users in Zimbabwe to register, collect and remit VAT.	January 2020	(Becker 2021; Deloitte 2020a; KPMG 2020; Simbarashe 2020)
Tanzania	The country's tax rules require non-resident provers of business to customers of telecoms services and e-commerce services to be registered for VAT.	1 July 2015	(Liganya 2020; Price Waterhouse Coopers 2020; Simbarashe 2020)
Uganda	The country's revenue authority (Uganda Revenue Authority) released a public notice requirement for non-resident vendors or providers of digital services to customers in Uganda to register for VAT and collect the Tax.	1 July 2018	(Simbarashe 2020)
South Africa	South Africa had initially enacted VAT legislation in 2013 and the regulations became effective in 2014. These regulations were broadened in 2019 with broader definition for electronic services. The country's VAT legislation requirement is that foreign providers of digital services must register as VAT vendors, collect VAT at a rate of 15% and remit it. The registration threshold was stipulated to be ZAR 1 million.	January 2019	(Kabwe and van Zyl 2021; Van Zyl 2014; Van Zyl 2013; Stephanus P. Van Zyl and Schulze 2014)
Angola	VAT rules were drafted in October 2019, which became effective in January 2020, providing that digital service suppliers must register with the country's revenue authority (Angolan Tax Authority) or appoint a local agent to collect and remit VAT in Angola.	January 2020	(Simbarashe 2020)
Morocco	The country's tax code provides that any service rendered or used using within the Moroccan territory is liable to the country's VAT at a rate of 20% that is applicable to digital services.	2019	(Simbarashe 2020)
Nigeria	Section 10 of (Nigeria's VAT Act 1993), No 102 provides that non-resident firms conducting business in Nigeria must register for tax, using the address of the person of whom the company has a standing contract. Accordingly, the non-resident company shall include tax charge on its invoice and the recipient of the service shall remit the tax to the Federal Inland Revenue Services (FIRS) in the currency of the whole transaction.	2020	(Ahmad et al. 2021)
Malawi	VAT on internet service was re-introduced in July 2013 at a threshold of MWK 10M (estimated at f 9.500).	2013	(TaxWatch 2021)

Author's Compilation from Various Sources.

From Table 1, it is evident that many African countries must formulate legislation to tax the digital economy through VAT/ GST. The VAT regulations presented in Table 1 require non–resident digital firms to register for VAT or to appoint a domestic representative to do so on their behalf. Despite the enactment of the new VAT on digital taxation laws or the widening of existing regulations to encompass the digital services, non-compliance by digital MNEs operating in Africa such as Facebook, Amazon, Netflix, and Google among others is still high and problematic (Simbarashe 2020; TaxWatch 2021).

African countries are losing a lot of revenue from the non-taxation of digital transactions. Initially, the South Africa VAT regulation on digital transactions was introduced in 2014 to cover a smaller section of electronic services; the definition was widened on 1 April 2019 to encompass electronic services provided by electronic communication or electronic agents or through the internet (Beebeejaun 2020; Bowmans 2020). Between 2014 and 2019, South African Revenue Authority Services (SARs) revenue authorities collected more than ZAR 600 million/year and an estimated ZAR 3 billion (USD 215 million) within the 5 years, (TaxWatch 2021). With the broadening of the VAT legislation in 2019 to include all electronic sectors, the SARs might improve revenue generation significantly. Discussions on the most effective way to mobilize tax from the digital economy have revolved around the superiority of VAT over Digital Services Taxes (DSTs) and the appropriateness of using VAT/GST to collect tax from the digital economy.

3.3. Benefits for Taxing the Digital Economy in Africa Using VAT

Ndajiwo (2020), while focusing on Ghana, Kenya, Rwanda, Senegal, and Uganda, expostulates that these African countries have an opportunity to mobilize taxes through VAT due to its comparative administrative ease. The researcher adds that the fact that VAT legal frameworks are already in existence, in contrast to the recently enacted DSTs, is an opportunity to exploit VAT in taxing the digital economy. Russo (2019) describes VAT as a low hanging fruit and that VAT ensures neutrality in taxation of foreign and local companies. For example, in South Africa, the VAT threshold of ZAR 1 million is applicable to both domestic and foreign companies, thus ensuring equity and neutrality in the treatment of companies. Ahmad et al. (2021) asserts that those who advocate in favor of consumption taxes submit that they promote investment and savings, thus promoting efficiency in the economy. On the other hand, critics claim that consumption taxes negatively affect the poor as they commit the greater portion of their income to financing necessities, therefore regressively affecting them, as VAT does not consider the ability to pay. VAT is also criticized for shifting the incidence of the tax burden to consumers (Ahmad et al. 2021; Kim 2020; Russo 2019). This section explores the possibilities and advantages of employing VAT in taxing the digital economy.

3.3.1. Superiority of VAT to Turnovers

Russo (2019) argues that VAT is more appropriate for taxing digital services than DSTs and posits that VAT is superior to corporate taxes on efficiency grounds. (Russo 2019) points to three important positive effects of VAT: (1) VAT does not lead to a distortion in business decision for example production, supply, and usage; (2) uniformity—VAT does not differ based on the total companies in the supply chain, not cascading; (3) effectiveness. Turina (2018) argues that modifying the VAT legislation to cover digital services is a more appropriate option and economically superior option to mobilize tax revenue from the digital economy compared to DSTs and withholding taxes. It is easy for businesses (digital services consumers) to account for VAT from the supplier through the reverse charge mechanism for Business-to-Business (B2B) interactions. It is quite challenging and not viable for Business to Customer (B2C) interactions. Difficulties in enforcing compliance are alluded to in some African countries (Nigeria, Kenya and Rwanda) (TaxWatch 2021). Despite acknowledging the possible superiority of consumption taxes, efficiency advantages and the fact that they circumvent tax cascading, it is important to note that there is ongoing argumentation regarding the conception of value creation in the digital taxes discussion (Kennedy 2019; Kim 2020; Lowry 2019). Stakeholders disagree on what constitutes value creation and how the value is created or added and by who (corporates or users).

3.3.2. Efficiency

Adhikari (2016) alludes to significant support for VAT-driven efficiency gains. While consumption taxes such as VAT are efficient and administrable, income taxes promote equity. Consumption taxes have the ability to avoid the dead weight loss of taxation, and to enable significant savings by individuals as well as investment and capital formation, and consequently higher economic productivity enhances efficiency (Kim 2020). In terms of administrability, those in favor of consumption taxes point to reduced complexity as a strength of these taxes. Researchers point out that despite the ease of administration, VAT passes the tax burden to consumers, thus making them regressive and violating the fairness and equity canons of taxation (Kim 2020; Lowry 2019). Researchers disagree on the regressive effects of VAT, with the OECD (2014) concluding from a study of 38 countries, that in 20 of these OECD countries, consumption taxes that encompassed excise and VAT, were nearly proportional or moderately progressive when evaluated for expenditure as opposed to income.

3.3.3. Creation of a Competitive E-Commerce Environment

Where African countries apply uniform registration thresholds for VAT registration for both domestic and foreign companies, equity, fairness, and neutrality are ensured, as discriminatory policies are avoided. The principles of an ideal tax policy emphasize the need for equity in tax policy and accordingly as outlined in tax morale literature (Luttmer and Singhal 2014; Sebele-Mpofu 2021), tax morale increases if taxpayers perceive that they are treated fairly, thus increasing voluntary tax compliance. Owing to the infant nature of the VAT legislation on the digital economy and the difficulties in enforcement due to lack of power by the revenue authorities and their commissioner generals to do so across territorial borders (Kabwe and van Zyl 2021), voluntary tax compliance is key. The fair digital taxation environment can indirectly encourage investment in the digital services sector, novel technological advancements, economic growth, digital financial inclusion, and fruition of the SDGs, such as gender equality (SDG5), decent work and economic growth (SDG8) and responsible consumption and production, (SDG12) among others.

3.3.4. Increased Tax Revenue Mobilization

Tax revenue mobilization is described as a stable, reliable, and predictable way of generating revenue for developing countries (Mpofu 2021c; Sebele-Mpofu 2021). African countries rely considerably on taxation for domestic revenue mobilization, the tax prominent heads being VAT and corporate tax. VAT is said to contribute around 30% or more towards African countries' overall tax revenue (TaxWatch 2021). Therefore, employing VAT to tax digital services could increase domestic revenue. Taxation is both a financing and development matter, therefore improved revenue prospects would lead to improved government funding as well as expenditure on education, health, security, infrastructure, and general economic development. Ultimately, increased government funding would lead to the realization of SDGs such as reduced poverty (SDG1), zero hunger (SDG2), good health and wellbeing (SDG3) and reduced inequalities (SDG10) among others.

3.4. Constraints to Effectively Taxing the Digital Economy in Africa Using Consumption Taxes

Non-tax compliance by digital or tech giants as they fail to collect VAT leading to large sums of revenue going uncollected negatively affects economic growth in African countries. Digital MNEs are failing to collect the VAT from their African customers and remit it to African companies (TaxWatch 2021). Therefore, they are contravening the African countries' VAT or GST in some jurisdictions. Different challenges are affecting the applicability and effectiveness of VAT legislation in taxing the digital economy globally and these might apply to the African countries, but they also vary considerably due the developed and developing country context differences. These variations could lie on administration and enforcement capacities, the state of development of VAT legislation, political power differences and clarity in legislation. Convergences on these challenges could be on the intangibility or borderless nature of digital services, as well as the ambiguities in key definitions. Janse van Vuuren (2019) and Rukundo (2020) allude to administrative challenges and increases in compliance and administrative burdens including costs. While assessing VAT legislation on the digital economy in Nigeria, Etim et al. (2020) point to the following challenges: outdated VAT legislation, poor legislation implementation, infrastructural gaps, technology, intricacies of digital transactions and the possibility of double taxation. Hadzhieva (2019) and Simbarashe (2020) posit that foreign companies raise concerns about the inconsistency in VAT legislation, the absence of double taxation agreements which compounds uncertainty and administrative responsibility, as well as advancing the probability of double taxation. This section discusses the challenges faced by African countries in the administration of VAT regulations on digital services despite the existence of legislation as set out in Table 1.

3.4.1. Invisible or Borderless Nature of Digital Transactions

VAT is exigent to apply to digital transactions. Contrary to the situation with the importation of tangible goods, where it is easy to levy tax, the intangibility and invisibility of digital services makes it challenging for tax authorities to enforce VAT on their importation, as they cannot be subjected to border checks (Kennedy 2019; Lowry 2019; Ngeno 2020; Kapkai et al. 2021). It might be challenging to collect VAT from companies with insignificant or minimal presence in market jurisdictions (Kennedy 2019).

3.4.2. Ambiguities in VAT Legislation Provisions

The TaxWatch (2021) points out that some digital MNEs such as Google, Microsoft and Facebook stated that they were complying with VAT legislation in some African countries where the legislation was clear and, in some countries, they failed to comply because the legislation was unclear. According to Kabwe and van Zyl (2021) ambiguities crystallize themselves around key definitions of important terms such as digital services, electronic services, 'supply' of digital services as well as the 'place' of supply. To levy VAT on a transaction, it must be initially demonstrated that the goods or services supplied fall within the purview of the VAT Act or legislation. The articulation of fundamental definitions becomes crucial in this regard.

- Definitions of Digital Services and Electronic Services

In some African countries, the definition of what constitutes digital services or electronic services is lean and fraught with vagueness. Kabwe and van Zyl (2021) assert that most of the VAT legislation and even that targeting the digital economy has not been regularly amended or updated in line with technological advancements, digital transformation, and the continuously evolving and emerging novel as well as complex business models. Most of the regulation has remained static and lagging technological developments in the digital economy. For example, in South Africa, the regulation remained static from promulgation in 2014 until 18 March 2019 when they were revised, and the revision became effective on 1 April 2019 (5 years after initial formulation and implementation). The revision was aimed to make the definition of electronic services expansive to give leeway for amendment in response to changes in business digital environment and advances in technological activities (Kabwe and van Zyl 2021). In Table 1, it is evident that countries such as Ghana and Malawi have not updated their VAT regulations despite the dynamism of the digital economy.

- Supply of Digital Services

For example, while focusing on South Africa, Kabwe and van Zyl (2021) allude to the fact that the VAT Act does not spell out distinct place of supply guidelines or what constitutes a supply. The place of supply must be derived from interpreting Section 7(1) of the South African VAT Act (the charging section) and Section 14 of the same Act (the section provides for the reverse charge framework). In the South African VAT Act, the definition of digital services is broad, and the Act defines these services as those outlined by the Minister of Finance in the legislation. Different international jurisdictions as well as African jurisdictions adopt different definitions for digital services and there are variations on the list of those that levied VAT. According to Kabwe and van Zyl (2021, p. 505) "the lack of international coordination and cooperation regarding a uniform definition of digital goods has resulted in a lot of confusion and uncertainty for foreign businesses". The complex and cumbersome rules will discourage digital MNEs from supplying customers in some tax jurisdictions. The variations in VAT regulations also make it difficult for foreign digital companies to comply, as they must familiarize themselves with VAT legislation in all countries they supply with digital services. The uncertainty in VAT regulations can have potentially pervasive effects on international trade, economic development, digital transformation, digital financial inclusion, and the accomplishment of the UN Sustainable Development Goals (SDGs) in developing countries and Africa is no oddity.

- Place of Supply

In some African countries, the VAT legislation on how to ascertain the place of supply is not clearly articulated. For example, Kabwe and van Zyl (2021) posit that South Africa's new expanded rules have increased the interpretation conundrum of the use and consumption principle in establishing the place of supply. The place of supply definition remains unclear and not definitive. Furthermore, the researchers state that the all-inclusive definition given by the VAT Act does not differentiate between B2B and B2C, yet the OECD calls for a clear distinction between the two in both explication and treatment. Most African countries employ and lean on the destination principle as the rationale to impose VAT, implying the taxation of an economic activity is dependent on where the service is consumed and used. Despite the destination principle seeming to be clear, it is generally complicated for revenue authorities to determine that a supply of services happened within their country. Therefore, ascertaining the place of supply is pivotal to the administration and enforcement of VAT legislation on digital services. There are times where it is easy to employ the use and consumption principle to identify the place of supply and instances where the place of supply cannot be easily identified, meaning proxies must be applied. The problem is that the VAT legislation does not articulate possible proxies or alternative rules for identifying the place of supply if the use and consumption principle is inadequate in addressing the situation. Citing Rooi (2015), Kabwe and van Zyl (2021, p. 508) portend that "if the place of supply is unidentifiable, then it becomes impractical, ineffective and inefficient to implement the relevant legislation". In South Africa, the link between enterprise and place of supply also poses challenges. Though broad and encompassing even foreign companies that supply services to South Africa on a regular basis (deemed to be carrying on an enterprise), the problem arises where the provider of digital services cannot be linked to any physical presence in the world but conducts his business activities in the cloud (Kabwe and van Zyl 2021). Therefore, with the absence of transparent and decisive 'place of supply' provisions, it is challenging to assign the transaction to a particular sovereignty, and to require them to account for VAT.

3.4.3. Complexity of Some of the Provision of the VAT Legislation

The complexity of tax legislation has a negative influence on tax administration, enforcement, and compliance (Liganya 2020; Mpofu 2021a). The TaxWatch (2021) points to a lack of simplified registration rules affecting VAT compliance in Nigeria. The report further alludes to difficulties for digital suppliers with no physical presence to comply with VAT regulations, as they might not be keen to register for VAT. The report also points out that in Senegal, the challenge is that the country has no system in place for digital services suppliers to remotely register for VAT in Senegal while they are in their foreign domiciles. In Tanzania, Liganya (2020) also alludes to the complexity of tax legislation, coupled with the lack of awareness as well as the lack of clarity in the legal and regulatory framework for taxing the digital economy. Therefore, there is a need for a simplified registration and compliance regime for foreign companies to register and collect VAT at a rate equal to the rate used for domestic companies. In South Africa, Kabwe and van Zyl (2021), raise the issue of residency, which is used as proxy in the determination of whether the transaction was supplied to South Africa and hence liable for VAT, where the place of supply rules are not sufficient or distinctive enough to support the taxing of the transaction. The researchers argue that while the VAT Act provides three conditions for deemed residency determination, it is not clear on who is responsible for establishing the residence of the person receiving electronic services. These conditions include the residence of recipient in South Africa, payment of the transaction originating in South Africa and the business address or residential address of the customer being in South Africa) (Van Zyl 2014; Van Zyl and Schulze 2014). It is as if the foreign company is saddled with this responsibility. This seemingly brings unwarranted administrative responsibility on foreign companies. This complexity seems to contradict OECD guidelines that encourage clarity and simplicity in the construction of tax rules to allow for easy comprehension of the provisions of the Act, how to account for a transaction, when and how to do so as well as the likely consequences of not complying. The adequacy and accuracy of the three conditions in determining residency remains debatable. Many questions arise regarding scenarios where the foreign company fails to identify all the three conditions provided by the Act. The conditions or proxies are much wider in developed country legislation, such as that of Australia. These include the recipient's bank address, the recipient's billing address, the recipient's IP address, the user's fixed land line via which the service in question was provided with and other additional commercially applicable information (Kabwe and van Zyl 2021). Perhaps African countries can assess some of these proxies and their relevance to their contexts to tighten the legislative provisions to minimize disputes and ambiguities.

3.4.4. Registration

There are different provisions in the African countries referring to who must register for VAT. For example, in Zimbabwe, the Act refers to a registered operator who must levy and collect tax on goods and services supplied in the furtherance of trade, and in South Africa, a vendor must charge and collect VAT on goods and services supplied by a vendor in furtherance of his enterprise. There is sometimes confusion on who has the ultimate responsibility to register for VAT. In some instances, the responsibility falls on the foreign entity and in some cases the local customer or user of services (reverse charge mechanism).

3.4.5. Administration, Monitoring and Enforcement Challenges

These are divided into administrative challenges and monitoring and enforcement challenges for easier discussion.

- Administrative Constraints

According to Rukundo (2020) and Sigadah (2018), administrative constraints should never be overlooked. Despite the VAT legislation provisions, online advertising companies are not complying. The researchers further allude to the fact that African revenue authorities are resource repressed, face capacity challenges and have feeble legal and administrative frameworks. The countries also face problems in accessing data and enforcing legal tax obligations on foreign companies (Mpofu 2021b; Sebele-Mpofu et al. 2021a). For example, according to The TaxWatch (2021), Kabwe and van Zyl (2021) and Bunn et al. (2020), despite African countries having put in place and announced the legislative conditions for digital MNEs to register for VAT, no notice has been taken of these. Political power imbalances are also at play causing administrative and compliance challenges. The TaxWatch (2021) point out the discriminatory treatment of the African continent, which could be linked to the absence of an opportunity to offset input tax against output tax. For example, VAT collected by Google in the UK is offset against input VAT charges for purchases of taxable supplies from the UK. VAT-free sales become preferable for digital MNEs when dealing with African countries, as they reduce the cost to users or customers, thus increasing sales. The segregated treatment is even evident on different African countries. For example, Google charged VAT for South African accounts, while for other African countries, they argued that the consumers in these other countries should self -assess to pay VAT through reverse charge method (TaxWatch 2021). With respect to Facebook, African countries with Facebook invoices that are inclusive of VAT include South Africa, Cameroon, and Zimbabwe. Cameroon and Zimbabwe invoices started reflecting the VAT charges recently.

MNEs tend to argue that African countries' legislation on VAT is not clear; this is despite the African countries having put the regulations in place, the policy briefs that are released by large Accountancy firms (such as Deloitte, KPMG, and Price Waterhouse Coopers (PWC)) and other development bodies on recent development in legislation in Africa. The lack of clarity in legislation concerns might hold water to some extent, but to a greater extent, political and trade power imbalances (near monopoly) could be the main reason for non-compliance.

- Monitoring and Enforcement Challenges

The lack of clarity in VAT legislation aiming to tax the digital economy is a concern in African countries. In Tanzania, Liganya (2020) alludes to the fact that legislation outlining how e-commerce transactions should be taxed is not clear. With specific reference to South Africa, Kabwe and van Zyl (2021, p. 516) raise thought-provoking concerns portending "Currently, there are no provisions in the VAT Act that enable SARs to monitor the compliance of foreign businesses. Moreover, there are currently no provisions in place within the VAT Act that impose penalties on foreign suppliers of "electronic services" in event of non-compliance". The other African countries are no exception to this. Ngeno (2020) and Kapkai et al. (2021) allude to enforcement challenges in Kenya. Even though the noncompliance penalties and interest thereon applicable to VAT defaulters in general is applicable, the Commissioner generally is not granted additional extra-jurisdictional power to collect unpaid taxes and accompanying penalties as well as interest. With no information exchange treaties and multilateral treaties in place, extra-territorial enforcement of VAT legislation becomes difficult if not impracticable. While Tax Commissioner Generals in African countries with VAT legislation on digital services are theoretically empowered to impose penalties for failure to register for VAT on foreign companies supplying digital services in African countries, the practicality of enforcing these penalties remains doubtful. According to Kabwe and van Zyl (2021) under these circumstances, the only reason that could compel foreign companies to comply with VAT legislation on digital services is the need to protect their names and avoid reputational damages for failure to comply. This is not something that African revenue authorities can rely on to foster compliance. It is something that they have no control over.

3.4.6. Lack of Knowledge and Awareness

There is lack of knowledge and awareness regarding taxes directed towards the taxation of the digital economy, including both DSTs and VAT in African countries, perhaps due to the infancy of regulations. The dearth of tax knowledge affects both tax administrators and taxpayers (Mpofu 2021a). Articulating this challenge with respect to South Africa, Kabwe and van Zyl (2021) state that the reverse charge framework is a fall-back option, in cases where a foreign company registered for VAT does not collect VAT from a South African customer. SARs normally reverts to the customer to claim the VAT not collected and paid, because in terms of the Act, the customer must self-assess. SARs officials seemed not to be aware of the reverse mechanism assessment (Kabwe and van Zyl 2021). In some cases, foreign companies are not aware of the VAT legislation on digital services. This signals the need for effective communication and dissemination of information as well as taxpayer education programs. Without adequate knowledge and awareness, in both B2B and B2C scenarios, the taxpayer may fail to account for VAT due to ignorance or perceptions that it is a burdensome, time-consuming and unnecessary. Revenue authorities in Africa lean more on the honesty of consumers when it comes to the reverse charge framework (Van Zyl and Schulze 2014). This is a weakness in legislation; otherwise, there must be a legal provision in the Act to enforce compliance with specific reference to the reverse charge apparatus. There is indeed a likelihood that a substantial number of B2C transactions escape the VAT legislation. Revenue authorities might consider them insignificant; they might not be substantial when viewed individually, but might be material when aggregated, thus leading to the erosion of the tax base in African countries.

4. Implications and Recommendations for Future VAT Policy in Africa with Respect to the Digital Economy

This section discusses the implications of employing VAT as a tax revenue mobilization tool in African countries and discusses possible suggestions for ameliorating VAT administration and its effectiveness at tapping tax revenues from the digital economy.

4.1. Implications

Several implications could be attributed to the implementation of VAT legislation in taxing the digital economy. These ramifications must be effectively assessed in conjunction with the possible constraints as well as the likely opportunities and advantages of applying VAT legislation to the digital economy. Etim et al. (2020) submit the following possible consequences of applying VAT legislation: increased administration and compliance costs, negative effects on other government policies and tax heads, heightened tax evasion and resistance to policy and increased tax burden for consumers. The application could further lead to a reduction in consumption, change in consumption patterns, modifications to the market structure and increased uncertainty for the future growth of the digital economy (Guyu 2019; Munoz et al. 2022).

Katz (2015), while focusing on Gabon, pinpointed problems that could possibly emanate from charging tax on the digital economy. These challenges were explored from the perspectives of telecommunications and e-service providers and consumers. Katz (2015) drew four major conclusions. Firstly, from the consumers' point of view, digital taxes heighten the affordability challenges in the adoption of technology as the tax cost increases the price. The increase in the prices of digital services could negatively affect not only affordability but access and usage. This could affect the growth and profitability of small telecoms business, ultimately affecting the tax heads such as income tax (both corporate and pay as you earn (PAYE)), leading to a fall in tax revenues. VAT could also affect startups and small and medium enterprises as well as self-employment. Overall, this affects employment creation; more so in African countries such as Zimbabwe, Kenya, Nigeria, and South Africa where unemployment is high among youths and these youths have been exploiting the digital space to engage in self-employment. For example, Isiandinso and Omoju (2019) and Etim et al. (2020) cited the Nigerian Investment Promotion Commission table that Nigeria was envisaged to generate USD 88 billion and create over 3 million by the year 2021. Zimbabwe is argued to have the second biggest informal economy in the world which, contributes approximately over 60% of GDP (Medina and Schneider 2018). As of December 2019, Kenya's internet penetration was approximated at 89.5% (Kapkai et al. 2021). If all these projections and statistics are anything to go by. The affordability constraints of digital services could further perpetuate unemployment, poverty, and inequality, leading to a failure to attain the UN SDGs and indirectly crippling digital financial inclusion efforts.

Secondly, even though consumption taxes can be pushed to consumers, the responsibility to account for and pay VAT rests with the digital or e-service providers who may in turn be faced with a decrease in infrastructural investment. This could arise if taxes lead to a reduction in the total amount accessible for capital expenditure. Thirdly, taxes result in taxation asymmetry between global digital providers in the digital sector. For example, companies such as Amazon, Netflix, Google, and Facebook are taxed on online advertising, whereas other online advertising companies and social networks fall outside the ambit of digital taxation. Lastly, the origination of manipulative tax avoidance schemes lead to revenue leakages and losses in market jurisdictions when digital MNEs engage in tax avoidance and evasion measures that result in base erosion and profit shifting (BEPS) (Katz 2015). Chang (2019) states that 80% of Netflix revenues is attributable to international subscribers. While citing Statista (2020a, 2020b), Beebeejaun (2020) states that Facebook made USD 18.7 billion from advertising in the first quarter of 2020 and Google generated USD 160 billion. They also made 74 billion for the year 2019 from advertisements. Beebeejaun (2020) states that some of these digital MNEs engage in BEPS-shifting behavior by shifting profits to tax havens to the detriment of market jurisdictions where these profits are generated. Concerns regarding usage reduction, market distortions and possible negative impacts on economic growth were also proclaimed by Becker (2021), Kennedy (2019), Lowry (2019) and Munoz et al. (2022).

In addition, some researchers have criticized digital taxes for impeding the adoption of novel technologies and this may curtail economic growth and development, negatively affecting financial inclusion and the realization of the SDGs (Munoz et al. 2022, Kearney 2014;

Becker 2021). Youssef et al. (2021) emphasizes the role of technology and the digital economy on entrepreneurial development. The researchers posit that digital technologies are playing a fundamental role in the transformation of the global economy, especially the modification of entrepreneurship activities and processes. Levying VAT on digital services and products affects the adoption and usage of technologies, thus negatively affecting entrepreneurial development.

Kearney (2014) alludes to a negative correlation between taxation of wireless services providers' prices and the growth in the 3G internet penetration in emerging market countries. Affirming this, Beebeejaun (2020) states that taxes may disincentivize the provision of broadband mobile network in ways that are detrimental to strategic public policy construction and planning. Domus et al. (2017) and Kapkai et al. (2021) raise the possibility of double taxation implications arising from taxing services such international roaming that could possibly give rise to VAT in the home country and the foreign country visited.

The lack of clarity in VAT legislation, especially in the definition of key terms could be a weakness for most African countries' VAT legislation on the taxation of digital services that can exploited by MNEs to evade taxes or even those expected to account for VAT through the reverse charge mechanism. In addition, the fact that the place of supply rules must be inferred from reading certain sections of the Statutes in isolation or in conjunction with others is problematic in itself. While referring to South Africa, Kabwe and van Zyl (2021) affirm this. The researchers adduce that deducing the place of supply by a combined reading of the charging provision (Section 7(1) of the South African VAT Act and Section 1, which defines vendor, electronic services, and enterprise as well as Section 14, which outlines the place of supply, is confusing for foreign digital services suppliers who are not conversant with South African laws. This could lead to companies genuinely failing to comply out of ignorance or lack of understanding of VAT legislation in African countries, noncompliance due to legislation complexity (unintentional) and not outright tax invasion (Mpofu 2021c). While in terms of the law, ignorance is no defense, Kabwe and van Zyl (2021) asseverate that complexity and lack of clarity in the structure of the VAT legislation on digital transaction could be a vital factor in non-compliance with the tax legislation and an increase in the administrative burdens for tax authorities. Sometimes, revenue authority officers must grapple with numerous calls and emails seeking clarification on the ambiguous areas in legislation, thus leading to frustration and, at times, their seemingly uncooperative nature.

Practical and Policy Implications for the Results

The implications discussed above, and the results of the study point to gaps in three areas. These areas are: (1) the level of development of VAT legislation towards taxing the digital economies; (2) VAT legislation implementation and administration; and (3) the evaluative analysis of the possible negative externalities or consequences of the VAT policy on the digital economy and the economy at a large in African countries.

The first gap suggests that African governments and policy would need to reassess and further develop their VAT legislation to cover the current crevices as they open loopholes for abuse. For effective enforcement, legislation must be free from ambiguities and vague provisions as these provide ammunition for taxpayers to avoid taxes, manipulate tax laws to their advantages or even successfully argue their cases in the court of law. All this happens to the detriment of effective domestic revenue mobilization, yet taxes contribute significantly to total national revenue in African countries.

Regarding the second gap, addressing the implementation challenges would equip both the revenue authorities and taxpayers to ensure effective VAT administration, enforcement, and compliance. Lastly, with respect to the third gap, it is key to evaluate policy, both proposed and current, in terms of the cost and benefit analysis, the negative externalities, strengths and weaknesses and the impact on the economy. Tax policy requires governments to continuously evaluate, adjust, and re-adjust in relation to the outcomes of the evaluation to ensure efficiency and effectiveness as well as adherence to other canons of taxation.

Tax policy must be able to address other functions of tax policy and not blindly focus on revenue generation.

4.2. Recommendations

This section addresses recommendations derived from the review and Figure 1 foregrounds the discussions. Figure 1 makes suggestions related to the VAT legislation construction, implementation, and administration as well as areas to focus on in reducing the negative implications on the digital economy and other sectors of the economy.

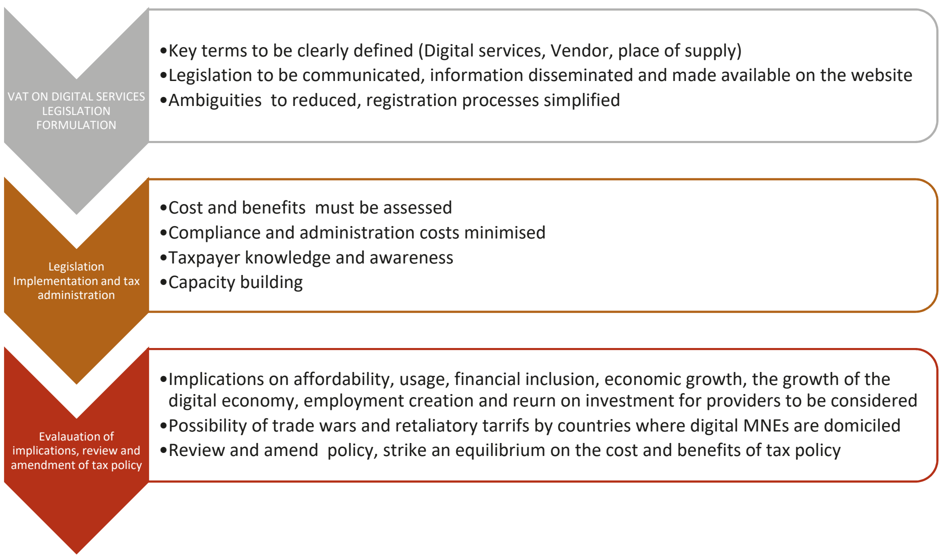

Figure 1. Summary of Recommendations to improving VAT legislation with respect to the digital economy. Source: Author's Compilation.

4.2.1. Full Development of VAT Legislation, Clarity in Definitions, Continuous Revisit and Amendment of VAT Legislation

The researcher acknowledges that most of the tax legislation towards mobilizing revenue from the digital economy is still its nascent stages and is still being developed; therefore African countries are encouraged to work tirelessly towards ironing out the shortcomings. The countries must bring clarity in critical definitions and find ways of effectively communicating the legislation to foreign companies that supply digital services. Key definitions such as digital services, electronic services and place of supply must be clearly defined to enhance the transparency and simplicity of VAT on digital services regulation. Alternative treatment of the place of supply or the possible proxies for establishing it where it is not easy to apply the use and consumption principle must be provided for in regulation. Therefore, tax law should not be static because the business environment evolves, and taxpayers are always devising new ways to avoid and evade tax. Tax law and, in this case, tax legislation on digital transactions should be updated regularly to keep abreast with developments in the digital sector and changes in technology.

4.2.2. Cooperation, Collaboration and Learning from One Another by African Countries

Researchers such as Kabwe and van Zyl (2021) call for international cooperation and consensus on an acceptable or universal definition on the definition of digital services. This article reiterates this call, acknowledging that to apply the registration measures, and administer and enforce VAT legislation on digital transactions on a unilateralism basis is challenging if not nearly impossible. International coordination and cooperation are key. This has been affirmed by several researchers who urge African countries to join, critique and contribute on international platforms on matters that concern them (Ahmed et al. 2021; Ahmed and Gillwald 2020; Onuoha and Gillwald 2022). Rukundo (2020, p. 22) specifically states, "African countries should participate in global debates through regional and international organizations, pushing for reform and for the development of international tax rules that consider their interests as source or market jurisdictions". While acknowledging the importance of their participation, it is important to note that African countries negotiate from a politically, economically and resource-disadvantaged or weak position.

This article also encourages African countries to work on a continental or regional definition for digital services, electronic services, and place of supply to reduce the complexity of VAT regulation on digital services. African countries should also learn from the mistakes and successes of each other and other developed countries and use the lessons drawn to improve their own digital tax legislation. For example, to limit the inundation with queries and questions, SARs inaugurated a Frequently Asked Question (FAQ) section on the revenue services' website in July 2019. This section is regularly updated. This is a worthwhile development that other African countries could draw on and improve, especially in the context of concerns regarding the ease of accessing the section and navigation raised by Kabwe and van Zyl (2021). Affirming the need for African countries to cooperate sincerely and effectively, Onuoha and Gillwald (2022, p. 20) state: "This will require close collaboration and synergies between the relevant regional institutions on the continent, including economic blocs, the AfCFTA and the ATAF secretariats, in the evolution of policy process that allows African countries to debate issues between themselves without fragmentation, and as a first chance of effectively negotiating their way out of the current North–South hegemony".

The idea is for the African nations to strongly influence tax policy as a unified front and to ensure MNEs pay taxes in the country where the revenue was generated (market jurisdictions).

4.2.3. Capacity Building, Training, Information Dissemination

Revenue authorities need to build capacity to tax the digital economy, train officers and disseminate information to stakeholders on the new or expanded VAT legislation targeting the digital economy. The invisible nature of the digital economy requires revenue authorities to capacitate their workforce with technical skills and knowledge to match this intricate sector. It is also vital for revenue authorities to be capacitated with financial resources so that they invest in digital and technological infrastructure that is current to be able to tap revenue from the sector. The audit departments in revenue authorities must be equipped to use technology to follow the digital footprints of transactions if tax compliance is to be effectively monitored and enforced. African nations could perhaps share technical resources and expertise through trainings and seminars conducted through ATAF or by seconding personnel to revenue authorities that have been using VAT to tax the digital economy for some time, such as SARs or other more developed economies.

4.2.4. Cost and Benefit Analysis

African governments are encouraged to do a cost and benefit analysis in relation to possible digital tax revenue mobilization and the likely creation of taxing distortions, before constructing a relevant indirect (VAT) system. Policymakers must consider the trade-off on revenue mobilization and other costs. Tax systems must build efficiency and reduce the cost of collection, guard against over-taxation and minimize the possible adverse consequences. It is crucial for governments to strike an equilibrium between collecting tax revenue from the digital economy and other important functions of taxation in the economy such as promoting economic growth, redistributing resources, and fulfilling the SDGs such as reducing inequalities, eradicating poverty, creating decent jobs, providing reliable health services and affordable education. Considering these other roles of taxation, governments must assess how levying VAT will affect these other roles and make evidence-based decisions. Tax policy construction must always strive to adhere to the principles of taxation such as economy, equity, simplicity, convenience, economy, neutrality, efficiency, transparency, and effectiveness.

5. Conclusions

As the digital economy continues to grow, technology continues to advancing and business models continue to evolve, a new set of challenges for tax administrators will continue to emerge. Revenue authorities must come to reality with the continuous growth of the digital economy and find ways of productively taxing the sector, otherwise significant tax revenue will go untapped. This would be a challenge for African countries that rely heavily on taxes such as corporate tax and VAT to fund government expenditure. The article concludes that revenue collection from the digital economy in African countries remains a formidable task. The issue of which is the most effective method or tax head to use to tax the digital economy remains hotly contested among stakeholders such academics, governments, and tax authorities. While the review revealed some opportunities and strengths of using VAT, challenges and weaknesses were also evident. This points to perhaps the need for future empirical research in countries that have implemented DSTs policy and the VAT policy to evaluate each policy and even make a comparative analysis of the performance of the tax heads (VAT and the DSTs or turnover taxes). This article recommends the need for policymakers to improve on the legislative transparency and clarity of VAT legislation, improve on administration capacity and collaborate on both continental and international levels to build a strong VAT policy and improve administration and enforcement. Since this article is a review article that is based on a review of secondary literature and previous studies, the discussions and findings might be subjective as their foundation is based on the work of others. Secondly, as the conceptual analysis is qualitative in nature, perhaps future researchers could focus on empirical research on the subject area and employ primary data or a quantitative approach. Studies based on literature reviews such as this one rely on secondary data as opposed to primary data to base their findings on, and therefore this is a limitation for this study. Further studies could focus on conducting empirical assessment of the application of VAT legislation in taxing the digital economy in Africa.

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