Journal of
Risk and Financial Management

MDPI

Article

The Impact of Digital Transformation on Performance: Evidence from Vietnamese Commercial Banks

Trang Doan Do [1], Ha An Thi Pham [2], Eleftherios I. Thalassinos [3] and Hoang Anh Le [4,*]

[1] Faculty of Economics, Binh Duong University, No. 504 Binh Duong Boulevard, Hiep Thanh Ward, Thu Dau Mot City 820000, Vietnam; doantrang.bolt@bdu.edu.vn
[2] Faculty of Finance and Banking, Van Lang University, 69/68 Dang Thuy Tram Street, Ward 13, Binh Thanh District, Ho Chi Minh City 700000, Vietnam; an.pth@vlu.edu.vn
[3] Faculty of Maritime and Industrial Studies, University of Piraeus, 185-33 Piraeus, Greece and Faculty of Economics, Management and Accountancy, University of Malta, 2080 Msida, Malta; thalassinos@ersj.eu
[4] Institute for Research Science and Banking Technology, Banking University HCMC, No. 36 Ton That Dam Street, Nguyen Thai Binh Ward, District 1, Ho Chi Minh City 700000, Vietnam
* Correspondence: anhlh_vnc@buh.edu.vn

Abstract: The role of digital transformation in creating value for commercial banks has been interesting to researchers for a long time. While many commercial banks have significantly investigated digital transformation, researchers and managers have still met many difficulties examining the distribution of digital transformation to business performance. This paper aims to evaluate the impact of digital transformation on Vietnamese commercial banks' performance by different sizes, from there proposing policy implications of digital transformation to improve the banking performance. To achieve this goal, we used a quantitative research method. Specifically, we applied the GMM system (SGMM) of Blundell and Bond for the data of 13 joint-stock commercial banks in Vietnam in the period from 2011 to 2019. Then Bayesian analysis is performed to test the robustness of the models estimated by the SGMM method. The result shows that the digital transformation has a positive impact on the performance of Vietnamese commercial banks. Besides, we also find that the larger the banks, the greater the positive impact of digital transformation on bank performance. Therefore, the efficiency of digital transformation depends on a bank scale.

Keywords: Bayes; DEA; digital transformation; performance

Citation: Do, Trang Doan, Ha An Thi Pham, Eleftherios I. Thalassinos, and Hoang Anh Le. 2022. The Impact of Digital Transformation on Performance: Evidence from Vietnamese Commercial Banks. *Journal of Risk and Financial Management* 15: 21. https://doi.org/10.3390/jrfm15010021

Academic Editor: Thanasis Stengos

Received: 27 November 2021
Accepted: 5 January 2022
Published: 7 January 2022

1. Introduction

The Fourth Industrial Revolution has created a driving force for the application of technology in business activities. With the strong development of high-speed internet, cloud computing, and blockchain technology, the Industrial Revolution 4.0 is changing the way businesses operate, the way they do business, and the behavior of consumers (Tan et al. 2021). Traditional businesses are being transformed to online, what is known as digital transformation.

Digital transformation represents a change in the activities of individuals and businesses through the application of digital technology to create major improvements in business, personal experience, and new business models (Abdulquadri et al. 2021). A more specific definition of digital transformation is mentioned in Vial (2019). Specifically, digital transformation is a process that aims to improve an entity by making significant changes to its properties through a combination of information, computing, communication, and connectivity technologies (Vial 2019). This definition shows that digital transformation can significantly change the business activities of enterprises by applying modern technologies. Therefore, changing and diversifying the operating methods of businesses is understandable since the concept of digital transformation was proposed.

The change and diversification of business activities due to digital transformation is taking place strongly in the banking sector. Besides, the issue of digital transformation in business activities in commercial banks is receiving a lot of attention from researchers, policymakers, and companies (Lee and Shin 2018). The digital transformation in commercial banks is the integration of digital technology into all banking areas, fundamentally changing the way commercial banks operate and provide value to customers such as developing financial and banking software, digital banking, mobile banking solutions, fintech, etc., be able to meet the demand of customer about the interest rate liberalization, big data, mobile finance, risk management, internet finance and customer relationship management (Ortaköy and Özsürünç 2019; Chen and Zhang 2021). This is also a culture change that requires the commercial bank to constantly challenge, experiment, and succeed or fail.

The COVID-19 pandemic made 2020 a difficult year for the banking and financial sector worldwide. However, this pandemic also plays a key role to enhance the digital transformation faster for all industries, including the financial and banking sector: the "work from home" movement forces us to change the new ways of working and requirements to new digital services, such as the ability to access to financial support quickly, has become imperative. The financial sector around the world has created rapid and positive change for customers through digital transformation using intelligent technologies such as robotic process automation (RPA), learning machine to anti-money laundering (AML), know your customer (KYC), as well as RegTech to reduce compliance risk (Schueffel 2017). The digital transformation in financial banking services is focused on customer services to meet the expectation of customers to emerging services, market transparency, and diverse customer requirements.

With the advantages that digital transformation brings to commercial banks as described above, researchers believe that digital transformation can really help increase the performance of commercial banks. According to research about testing efficiency of transactions of commercial bank distribution channels in the period from 2012 to 2015, the number of customers had counter transactions at banking branches in the UK decreased by 30%. Compared between 1992 and 2013, the number of transactions made by banking tellers in the US decreased by 45% (Jatic et al. 2017). Another research found that the Turkish banking sector was inefficient in the 2000s, and 23.6% of annual variable costs could be minimized using the existing technological opportunities (Kasman 2002). According to research conducted by Kenya, with adopting innovation, new trends, automatic risk management, the new generation of digital business analysis in the banking sector in recent years has archived very high performance. In this research, there is a negative relationship between mobile, Internet, and ATM channels and the cost to income ratio, a measure of business performance (Moffat 2017). Similarly, another research demonstrates a positive relationship between technical development in the USA banking system and banks' business performance, particularly in reducing expenses and increasing revenue due to applying novel technical development (Berger 2003). In general, studies have confirmed that technological innovation ensures the growth and viability of current banks.

However, in some countries, digital transformation in commercial banking has still met many difficulties, especially in small commercial banks. Digital transformation requires capital and development level of science and technology and requires the development of infrastructure, technology, and workflow in the direction that everything moves into online and industrialized models.

Therefore, this paper aims to evaluate the impact of digital transformation on Vietnamese commercial banks' business performance by various scales, suggesting some digital transformation policies to improve Vietnamese commercial banks' performance. Compared with previous studies, the research has made the following new contributions:

Firstly, the results show that digital transformation (CDS) has a positive effect on the performance of Vietnamese commercial banks with a statistical significance of 1%. This confirms that digital transformation has had a positive impact on the performance of Vietnamese commercial banks. In addition, the interaction between digital transformation and the size of the bank (CDS*QM) has a positive effect on the performance of Vietnamese commercial banks, with a statistical significance at 1%. This confirms that the larger the scale of commercial banks, the more digital transformation will positively impact the performance of these commercial banks. Or the effectiveness of digital transformation depends on the size of commercial banks and is consistent with the research hypothesis. In fact, it is easier for larger banks to adopt new technology because of the necessary resources, skills, commitment, and the proper understanding of technical digital opportunities (Giotopoulos et al. 2017).

Second, the research has suggested policy implications for commercial banks and regulatory agencies in Vietnam. Banks of all sizes face technological challenges. Small banks often have to depend on IT application providers because they do not have the same financial capacity as large banks. Besides, the lack of IT-qualified staff is also a significant challenge for small commercial banks in Vietnam. Therefore, small commercial banks need to balance the budget for the implementation of digital technology applications and have a good preparation of human resources capable of data management, security, and software development.

2. Literature Review

Performance is a widely used concept in the socio-economic field. Bank performance is considered as the level of success that banks achieve in allocating input resources to optimize output, reflecting the level of use of resources (human, resources, material resources, capital) to achieve defined goals (Bikker and Bos 2008; Ahmed et al. 2021). As described in the introduction, digital transformation has an impact on business processes, changing the way banks do business. Digital transformation is acting as a factor that helps to reshape the traditional interaction between customers and banks (Taiminen and Karjaluoto 2015). Especially, customers have the right to access into dozen communication channels to actively and easily interact with the banks and other customers via online customer care services (Verhoef et al. 2019). Most importantly, digital transformation helps banks to serve many different customers at the same time, helping to improve the bank's business performance. Besides, the employee's working processes are digitized, saving human resources and transaction execution time (Zhai et al. 2022). Thus, digital transformation will help the bank on the one hand increase output (increasing the number of customers), on the other hand, help the bank reduce input costs (reduce the number of employees, the time to make transactions). Therefore, one would expect to find a positive impact of digital transformation on bank performance. In this study, we propose the following research hypotheses:

Hypothesis 1 (H1). *Digital transformation has a positive impact on the performance of Vietnamese commercial banks.*

However, empirical studies have shown conflicting results on this link. Specifically, the debate about the link between digital transformation in banks and bank's performance stems from the "profitability paradox" found by Beccalli (2007). Using the sample of 737 European banks over the period 1995–2000, Beccalli (2007) did not find a significant relationship between digital transformation and bank's performance. This finding is supported by Martín-Oliver and Salas-Fumás (2008), a study examining the impact of investments in information technology (IT) and advertising on the output and profits of Spanish banks over the period 1983–2003. Most recently, the findings of Xin and Choudhary (2019) also showed similar results to Beccalli (2007). Specifically, their findings suggest that increased IT investment does not always lead to increased profits. The cause of these results may be due to the roles of digital transformation in the performance of large-size companies (Pramanik et al. 2019). The previous studies found that SMEs are facing the increasing difficulties in applying new technology due to a lack of necessary resources, skills, commitments, and knowledge about digital opportunities (Giotopoulos et al. 2017). Overcoming these difficulties requires SMEs to build different capacities. Some possibilities (for example, perceiving, searching, and collecting suitable digital knowledge) are located in SMEs' business people or executive teams. Ability to perceive new digital opportunities, change the interaction way with clients, and create value that requires changes in procedures, current resources, or building new possibilities. However, the use of technology will be a difficult issue. It requires the changes of overview and management to archive new possibilities about organization and promotion. These factors make the role of applying digital transformation to company performance changing by scale.

Hypothesis 2 (H2). *Digital transformation has different levels of impact on performance among Vietnamese commercial banks of different sizes.*

3. Methodology

This study was conducted according to the procedure shown in Figure 1.

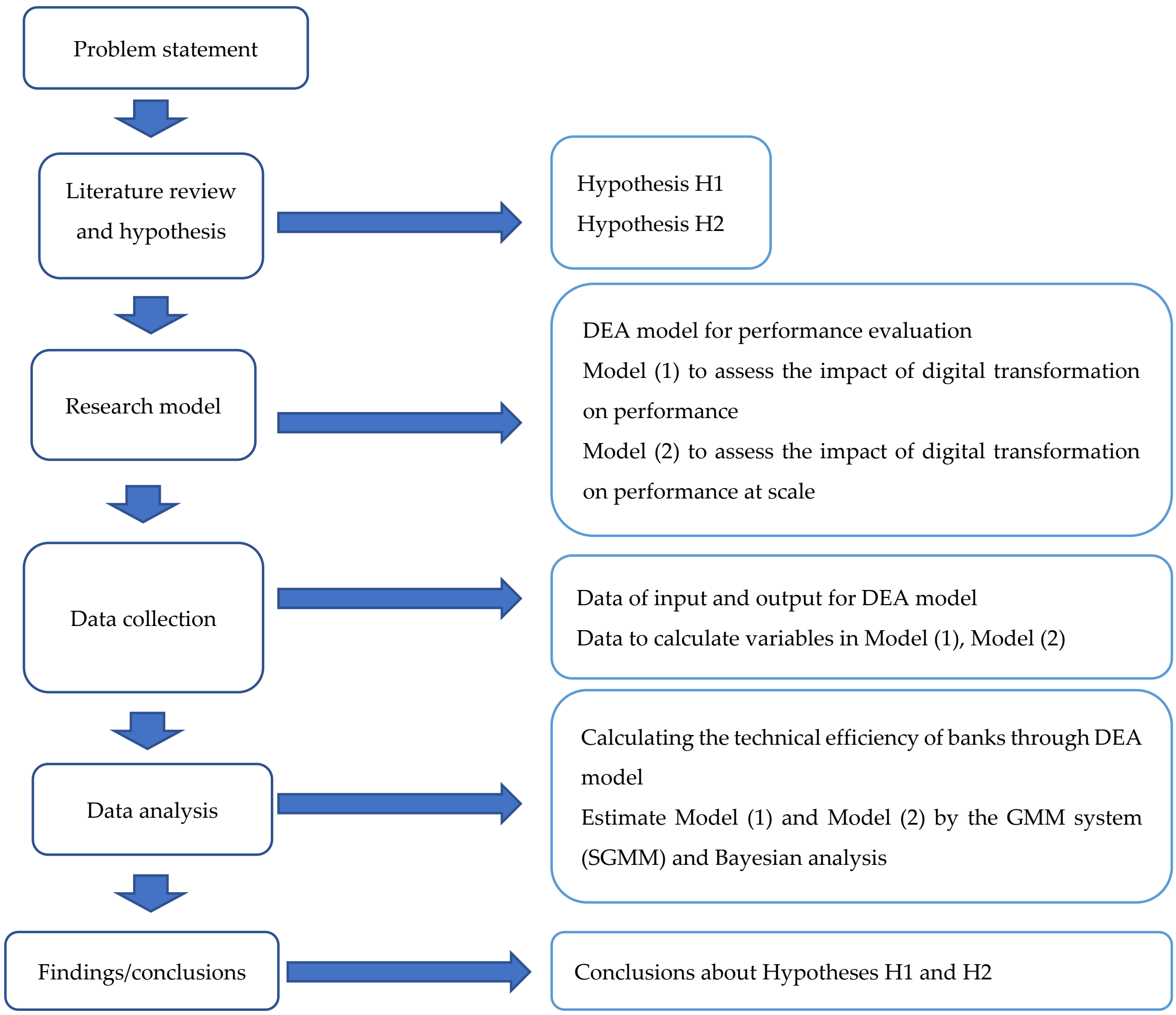

Figure 1. Research methodology scheme.

3.1. Research Model

The method of this paper is based on the backgrounds of Solow neutral technical progress, technical acceptance model (TAM), diffusion of innovation theory (DIT), and resource-based theory (RBT). In addition, reference to some recent research of Ho and Mallick (2006); Casolaro and Gobbi (2007); Lin (2007); Nyapara (2013); and San and Heng (2011), we propose a model with Solow neutral form:

Solow neutral is technical progress that enhances the use of capital with a given ratio of L and K. Solow neutral can be included in the production function as follows:

$$Yt = f(At, Kt, Lt), \text{ with At is the technical progress factor}$$

Corresponding to the capital factor (K) expresses through the variables such as capital scale, the returns to capital rate.

Corresponding to technical factor (A) is informative technology (IT). This is the main variable of the model.

In this theoretical model, A only affects L directly but not K. Therefore, assuming that the labor factor is fixed, the variables related to the labor factor will not be mentioned in this paper.

This paper, in turn, evaluates the impacts of digital transformation on the performance of commercial banks through two models.

The first model (1) independently tests the impact of digital transformation on the performance of commercial banks through variable CDS_{it}

$TE_{it} = \beta_0 + \beta_1 TE_{it-1} + \beta_2 CDS_{it} + \beta_3 QM_{it} + \beta_4 GDP_t + \beta_5 NHD_{it} + \beta_6 TD_{it} + \beta_7 TK_{it} + \beta_8 INF_t + u_{it}$ (1)

The second model (2) tests the impact of digital transformation on the performance of commercial banks through variable CDS_{it} $*QM_{it}$ as follows:

$TE_{it} = \beta_0 + \beta_1 TE_{it-1} + \beta_2 CDS_{it} *QM_{it} + \beta_3 GDP_t + \beta_4 NHD_{it} + \beta_5 TD_{it} + \beta_6 TK_{it} + \beta_7 INF_t + u_{it}$ (2)

where: it: bank i in year t; TE: performance of commercial banks; CDS: rate of technology investment; QM: commercial bank size, GDP: economic growth (the increase of gross domestic products over the years); NHD: number of operating years of a bank; TD: loan balance over the total asset (representing for credit activity scale); TK: liquid asset over the total asset (representing for liquidity risk); INF: annual inflation rate.

3.2. Data

Data to calculate input and output variables in the DEA model and the variables in Model (1) and Model (2) are collected from the audited annual financial statements of 13 Vietnamese commercial banks. The financial statements of each bank are collected for the period from 2011 to 2019. We selected these 13 commercial banks based on the availability of data to calculate the variables in Model (1) and Model (2). Besides, these 13 commercial banks are also the first banks to implement digital transformation.

Regarding the representativeness of the sample for the population, according to the State Bank of Vietnam statistics, as of 31 December 2018, the total number of commercial banks is 35, of which there are 31 joint-stock commercial banks, and 4 commercial banks with 100% state capital. Total assets of 13 commercial banks used in this research account for approximately 61% of the total assets of commercial banks. Thus, the sample size ensures the representativeness of commercial banks in Vietnam. In addition, the data of Vietnam's macro variables such as economic growth and inflation are collected from the World Bank data in the period from 2011 to 2019.

3.3. Estimation Method

To evaluate the impact of digital transformation on the performance of commercial banks, first, we measure the performance of commercial banks by the data envelopment analysis method (DEA). In which, the performance of commercial banks is measured by technical efficiency (TE). Then, we used the GMM system (SGMM) and Bayesian analysis to estimate Model (1) and Model (2). The impact of digital transformation on the performance of commercial banks is assessed through the parameters of the estimated models.

3.3.1. Methods of Measuring the Performance of Commercial Banks

This paper evaluates the performance of Vietnamese commercial banks in the period from 2011 to 2019. We measure the performance of Vietnamese commercial banks by the data envelopment analysis method (DEA) proposed by Charnes et al. (1978) and Banker et al. (1984). An important issue in applying the DEA method to the evaluation of the operational performance of commercial banks is the building of models of input and output variables to suit the business characteristics of commercial banks. Reviewing different studies in the world, the author uses the revenue and cost approach but still reflects the nature of commercial banks as financial intermediaries, raising capital and using capital for currency trading, payments to entities in the economy, so the selected inputs and outputs include:

Input variables: Input includes 03 variables representing the input resources of a commercial bank, such as mobilized capital, labor, facilities, and technical equipment. These variables are quantified by costs during the operation, including:

- Interest expense (X1): includes interest expense and equivalents representing the capital element in the input of commercial banks. The bank mainly uses customers' deposits, including savings and other deposits, issues valuable papers, etc., and has to pay interest on this mobilized capital.
- Salary cost (X2): the cost paid to employees representing the labor factor in the input of commercial banking activities.
- Other expenses (X3): non-interest expenses excluding staff costs representing the elements of equipment, technical facilities, etc.
- Output variables: the output includes two variables reflecting the business performance of a commercial bank:
- Interest income (Y1): income from credit activities and equivalents.
- Other income (Y2): including service income and other operating income

We measure each bank's efficiency once, so 13 optimizations are required, one for each bank to be evaluated. Let any j-th bank to be evaluated on any trial be designated as $bank_o$ where o ranges over 1, 2, . . . , 13. We use the data envelopment analysis method (DEA) to obtain values for the input "weights" v_i (i = 1, 2, 3) and the output "weights" u_r (r = 1, 2) as variables.

$$\max_{v,u} TE_o = \frac{u_1 Y_{1o} + u_2 Y_{2o}}{v_1 X_{1o} + v_2 X_{2o} + v_3 X_{3o}}$$

subject to

$$\frac{u_1 Y_{1j} + u_2 Y_{2j}}{v_1 X_{1j} + v_2 X_{2j} + v_3 X_{3j}} \leq 1 \ (j = 1, 2, \ldots, 13)$$

$$v_1, v_2, v_3 \geq 0$$

$$u_1, u_2 \geq 0$$

Efficient banks will have a technical efficiency TE of 1. Conversely, banks with a technical efficiency TE less than 1 are inefficient banks.

3.3.2. Method to Estimate the Impact Model of Digital Transformation on the Performance of Vietnamese Commercial Banks

To examine the impact of digital transformation on the performance of Vietnamese commercial banks, we use the quantitative method. The model is based on the knowledge foundation of Solow neutral technical progress, the technical acceptance model (TAM), diffusion of innovation theory (DIT), and resource-based theory (RBT). In addition, we make reference to some recent research of Ho and Mallick (2006), Casolaro and Gobbi (2007), Lin (2007), Nyapara (2013), and San and Heng (2011). Because the research data is panel data with 13 Vietnamese commercial banks from 2011 to 2019, we choose the estimation method for the GMM system (SGMM) of Blundell and Bond (1998).

An issue with the estimation method is the robustness of the model. Because the regression coefficients of variables in a model are changed in value as the number of observations changes, then conclusions drawn from the estimation results may be affected.

In this paper, due to the objective limit about sample data for estimation by SGMM, the result about the relationship between variables can be affected. To correct this shortcoming as such as further consolidate the estimators, we use the Bayesian method to test the robustness of the model.

The Bayesian method is derived from the following conditional probability:

$$p(A|B) = \frac{p(B|A)p(A)}{p(B)}$$

where $p(A|B)$: posterior probability, need to find the probability that Hypothesis A is true given the collected data; $p(B|A)$: the reasonableness of the data (likelihood), the probability of data collection under the condition that Hypothesis A is true; $p(A)$: prior probability, the probability that Hypothesis A we believe to be true before data collection; $p(B)$: constant, probability of data; A, B are random vectors.

In Bayesian analysis, the β_i parameters in the Model (1) and Model (2) are random vectors. Bayesian analysis determines the posterior distribution of these parameters based on the combination of the given data and the a priori distribution. Each posterior distribution describes the probability distribution of a parameter in the model. Therefore, the inference results about the β_i parameters in Model (1) and Model (2) based on posterior distributions will be more general.

$$\text{Posterior distribution} \propto \text{Likelihood function} \times \text{Prior distribution}$$

In Bayesian analysis, two important issues that need to be identified are the prior distribution and the sampling algorithm.

- The prior distribution

There are different types of a prior distribution, informative and non-informative, that can be used to generate a posterior distribution. Prior information of the parameters is an important factor in Bayesian inference. The prior distribution contains information about previously observed parameters. If the data are large enough, the prior distribution will have little effect on the posterior distribution. Conversely, when the data are too small, the prior distribution will play an important role in the posterior distribution.

In this research, because the purpose of performing Bayesian analysis is to test the robustness of the models estimated by the SGMM method, the prior distributions of the coefficients β_i will be determined by normal distributions. Specifically:

$$\beta_i \sim \text{normal}\left(\hat{\beta}, \hat{\sigma_\beta}^2\right)$$

where $\hat{\beta}$ is the value of the regression coefficient obtained from the SGMM method; $\hat{\sigma_\beta}$ is the standard deviation of the regression coefficients obtained from the SGMM method.

- The sampling algorithm

Among the MCMC methods, the Metropolis–Hastings method is very commonly used. This method was first introduced by Metropolis et al. (1953). Later, Hastings (1970) developed a more efficient algorithm.

In this research, we use the Metropolis–Hastings sampling algorithm to generate MCMC (Markov chain Monte Carlo) chain with a size 42,500, and remove 2500 at the burn-in stage. The MCMC sample size will be 40,000.

4. Empirical Result

4.1. Estimating Performance of Commercial Banks

The result of DEA analysis of commercial banks is presented in Table 1.

Table 1. The result of DEA analysis of commercial banks' performance.

Bank	2011	2012	2013	2014	2015	2016	2017	2018	2019
ACB	0.9061	0.9168	0.8673	0.8052	0.8413	0.8787	0.9401	0.8869	0.8502
BIDV	0.8657	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
CTG	0.9475	0.9302	0.9377	0.9274	0.9475	0.8841	0.9516	0.9231	1.0000
EIB	0.9503	1.0000	0.9507	0.8580	0.8591	0.8661	0.8328	0.7784	0.8275
HDB	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MBB	1.0000	1.0000	1.0000	1.0000	1.0000	0.9953	0.9557	1.0000	1.0000
NCB	0.8443	0.8281	0.8890	0.9293	1.0000	0.8853	0.9395	0.8019	0.8986
SHB	0.8867	0.9221	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
STB	0.9019	0.9185	0.9107	0.9121	0.8371	0.7423	0.8483	0.7801	0.7626
TCB	0.9615	0.9157	0.8510	0.9048	0.9925	1.0000	1.0000	1.0000	1.0000
TPB	1.0000	1.0000	1.0000	0.9668	0.9983	0.9189	0.9537	0.8799	0.9522
VCB	1.0000	1.0000	1.0000	1.0000	1.0000	0.9767	0.9957	1.0000	1.0000
VPB	0.8335	0.9295	0.8675	0.8729	0.9314	1.0000	0.9356	1.0000	1.0000

Source: calculated from STATA 16 software.

In the period 2011–2019, the performance of Vietnam commercial banks has continuously fluctuated over the years. The average technical efficiency of Ho Chi Minh City Development joint stock commercial banks (HDB) reaches the maximum level of one. In contrast, the average technical efficiency of Saigon Thuong Tin Commercial joint stock bank (STB) is the lowest at 0.8460 (see Table 2).

Table 2. Result of DEA analysis of commercial banks.

Bank	Technical Efficiency (TE)		
	Mean	Max	Min
ACB	0.8770	0.9401	0.8052
BIDV	0.9851	1.0000	0.8657
CTG	0.9388	1.0000	0.8841
EIB	0.8803	1.0000	0.7784
HDB	1.0000	1.0000	1.0000
MBB	0.9946	1.0000	0.9557
NCB	0.8907	1.0000	0.8019
SHB	0.9787	1.0000	0.8867
STB	0.8460	0.9185	0.7423
TCB	0.9584	1.0000	0.8510
TPB	0.9633	1.0000	0.8799
VCB	0.9969	1.0000	0.9767
VPB	0.9301	1.0000	0.8335

Source: calculated from STATA 16 software.

4.2. The Estimation Result of the Effect of Digital Transformation on the Performance of Vietnamese Commercial Banks

We use STATA software with balanced panel data of 13 Vietnamese commercial banks in the period from 2011 to 2019 to estimate Model (1) in Section 3 by using the SGMM method. The estimation result of the model is represented in Table 3.

The estimation result in Table 3 finds the p-value of AR(1) test is less than the significant level of 10% and the p-value of AR(2) test is greater than the significant level of 10%. Therefore, the model has the first order autocorrelation but no second order autocorrelation in its residual. In addition, the Hansen test of the model has a p-value greater than the significant level of 10%, which means the instrumental variables in the model is suitable. On the other hand, the p-value of the F test is less than the significant level of 1%, said that the model is suitable. Table 3 also shows that another constraint of the SGMM method satisfied is that number of instrumental variables does not exceed the number of the observation group. Thus, the model ensures reliability for analysis.

Table 3. The Estimation result of Model (1).

TE	Coefficient	Std. Error	*t*-Statistic	$p > t$
L.TE	0.4835 *	0.2347	2.06	0.062
TD	−0.5692	0.5087	−1.12	0.285
GDP	1.1174	2.1773	0.51	0.617
INF	−0.0126	0.4533	−0.03	0.978
CDS	0.5766 ***	0.1291	4.47	0.001
QM	−0.0567	0.0634	−0.90	0.387
TK	−0.9302 **	0.3671	−2.53	0.026
NHD	0.0052 **	0.0023	2.31	0.040
_CONS	1.8013	1.0188	1.77	0.102
AR (1) *p*-value		0.032		
AR (2) *p*-value		0.240		
Hansen *p*-value		0.162		
Number of groups		13		
Number of instruments		13		
Second stage F-test *p*-value		0.000		

The result of estimating the effect of digital transformation on the performance of Vietnam commercial banks by the SGMM method. Dependent variable TE represents the performance of Vietnam commercial banks by the SGMM method. Variable CDS donates for the digital transformation of banks. AR (1) and AR (2) *p*-values are *p*-value of the first order and second order autocorrelation tests of residual. Hansen *p*-value is the *p*-value of the Hausen test about the fitness of instrumental variable in the model. The second stage F-test *p*-value is the *p*-value of the F test about the fitness of the model. ***; **; * significant level respectively 1%; 5% and 10%. Source: calculated from STATA 16.0 software.

The estimation result of the effect of digital transformation on the performance of Vietnamese commercial banks finds that the regression coefficient of variables TK and NHD are statistically significant at 5%, the regression coefficiency of variable CDS is statistically significant at 1% and the regression coefficiency of variable L. TE is statistically significant at 10%. Especially, variable TK measured by the liquid assets on total assets represents for liquidity risk has a negative effect on the performance of Vietnamese commercial bank. The year of operation variable (NHD) positively impacts the dependent variable, implying that the longer a bank has a history of operation, the better its performance will be.

Digital transformation variable (CDS) has a positive impact with a significant level of 1%, said that Digital transformation positively affects the performance of Vietnamese commercial banks and suitable to Hypothesis H1. This finding is consistent with Solow's traditional economic theory that recognizes the importance of changing and innovating technology as the main driving force of economic growth and operation of commercial banks. This result is also supported by the empirical studies of Taiminen and Karjaluoto (2015); Verhoef et al. (2019); Bresciani et al. (2018). Digital transformation has revolutionized the business process of commercial banks, creating a relationship between clients and other related partners, enhancing business model innovation, and creating value for customers, saving cost, labor, and capital, thereby increasing the performance of commercial banks. However, bank scale (QM) is not statistically significant in the regression model shows that the bank scale does not affect the performance of commercial banks in the data sample.

4.3. Result of Estimating the Effect of Digital Transformation on the Performance by the Scale of Vietnamese Commercial Banks

We use STATA software with balanced panel data of 13 Vietnamese commercial banks in the period from 2011 to 2019 to estimate Model (2) in Section 3 by using the SGMM method. The estimation result of the model is represented in Table 4.

Table 4. The estimation result of Model (2).

TE	Coefficient	Std. Error	*t*-Statistic	*p* > t
L.TE	0.6403 ***	0.1385	4.62	0.001
TD	−0.7742 **	0.3362	−2.30	0.040
GDP	0.8492	1.5312	0.55	0.589
INF	−0.0176	0.3664	−0.05	0.962
CDS*QM	0.0228 ***	0.0066	3.48	0.005
NHD	0.0031 *	0.0016	1.96	0.074
TK	−0.7261 **	0.2766	−2.62	0.022
_CONS	0.7454	0.2961	2.52	0.027
AR (1) *p*-value		0.043		
AR (2) *p*-value		0.336		
Hansen *p*-value		0.134		
Number of groups		13		
Number of instruments		13		
Second stage F-test *p*-value		0.000		

The result of estimating the effect of digital transformation on the performance of Vietnam commercial banks by the SGMM method. Dependent variable TE represents the performance of Vietnam commercial banks by the SGMM method. Variable CDS donates for the digital transformation of banks. AR (1) and AR (2) *p*-values are *p*-value of the first order and second order autocorrelation tests of residual. Hansen *p*-value is the *p*-value of the Hausen test about the fitness of instrumental variable in the model. The second stage F-test *p*-value is the *p*-value of the F test about the fitness of the model. ***; **; * significant level respectively 1%; 5% and 10%. Source: calculated from STATA 16.0 software.

The estimation result in Table 4 finds the *p*-value of AR(1) test is less than the significant level of 10% and the *p*-value of AR(2) test is greater than the significant level of 10%. Therefore, the model has the first order autocorrelation but no second order autocorrelation in its residual. In addition, the Hansen test of the model has a *p*-value greater than a significant level of 10%, which means the model's instrumental variables are suitable. On the other hand, the *p*-value of the F test is less than the significant level of 1%, said that the model is suitable. Table 4 also shows that another constraint of the SGMM method satisfied is that number of instrumental variables does not exceed the number of the observation group. Thus, the model ensures reliability for analysis.

The estimation result of the effect of digital transformation on the performance by the scale of Vietnamese commercial banks finds that the regression coefficiency of variables TD and TK are statistically significant at 5%, the regression coefficiency of variable CDS*QM is statistically significant at 1%. The regression coefficient of variable L.TE is statistically significant at 10%. Especially, the liquid assets on total assets variable (TK) representing liquidity risk and the loan balance on total assets variable (TD) donating for the scale of credit activities have a negative effect on the performance of Vietnamese commercial banks. The year of operation variable (NHD) has a positive impact on the dependent variable, and this result is consistent with Model (1).

The digital transformation by scale (CDS*QM) has a positive effect with a significant level of 1%. This affirms that the larger scale of banks is, the more positive effect of digitalization on the performance of these banks will be. Or the efficiency of digital transformation depends on bank scale and suitable to Hypothesis H2. In fact, the larger banks with scale are the fewer difficulties that they have to face in applying new technology due to necessary resources, skills, commitments, and right knowledge about digital technological opportunities (Giotopoulos et al. 2017). In small and medium commercial banks, a number of possibilities (for example, limited financial resources, searching and selecting digital sources that are suitable for existing conditions; small market share makes revenue not enough to compensate for investment costs in IT and engineering machinery that are too large for digital transformation to make a profit) are difficult barriers in the application of digital transformation into business processes.

4.4. The Result of Testing the Robustness of Model (1)

Based on the result of analyzing the effect of digital transformation on the performance of commercial banks, we continue testing the robustness of estimators by the Bayesian method. The model is estimated as follows:

$TE_{it} = \beta_0 + \beta_1\,TE_{it-1} + \beta_2\,CDS_{it} + \beta_3 QM_{it} + \beta_4\,GDP_t + \beta_5\,NHD_{it} + \beta_6\,TD_{it} + \beta_7\,TK_{it} + \beta_8\,INF_t + u_{it}$ (1)

The prior distributions are used for the regression coefficients base on the estimation result of the most suitable method, the SGMM model. Particularly:

$$\beta_2 \sim \text{normal}(0.5766, 0.1291 \times 0.1291)$$

In this research, we use the Metropolis–Hastings algorithm to create the MCMC chain (Markov chain Monte Carlo) with size 42,500, remove 2500 in the burn-in phase, MCMC sample size will be 40,000. The result of model estimation by the Bayesian method is shown in Table 5.

Table 5. The estimation result of Model (1) by the Bayesian method.

TE	Mean	Std. Dev.	MCSE	Median	Equal-Tail [95% Cred. Interval]	
TE.L1	0.3876	0.0986	0.0014	0.3872	0.1971	0.5812
TD	0.0443	0.0960	0.0017	0.0444	−0.1437	0.2352
GDP	−2.1579	1.7874	0.0678	−2.1477	−5.7194	1.3203
INF	−0.2883	0.3312	0.0057	−0.2868	−0.9417	0.3577
CDS	0.2811	0.0838	0.0065	0.2767	0.1222	0.4643
QM	−0.0015	0.0196	0.0006	−0.0015	−0.0404	0.0371
TK	0.0029	0.1257	0.0029	0.0034	−0.2475	0.2485
NHD	0.0028	0.0024	0.0002	0.0027	−0.0020	0.0078
_CONS	0.5783	0.3125	0.0098	0.5786	−0.0345	1.1997
U0:sigma2	0.0101	0.0068	0.0003	0.0083	0.0029	0.0278
sigma2	0.0018	0.0003	0.0000	0.0018	0.0013	0.0025

Source: calculated from STATA 16.0 software.

The result of Bayesian analysis shows the average value of 40,000 regression coefficient estimators of digital transformation variable (CDS) is 0.2811 with a positive sign. In addition, the 95% confidence interval of this regression coefficient is (0.1222; 0.4643), said that the value of this regression coefficient is in the positive value domain. Besides, in Figure 2, the MCMC chain test result of the regression coefficient of the digital transformation variable (CDS) finds that the MCMC chain is converging. Trace chart says that the MCMC chain has no trend. The estimators distribute thickly into a horizontal line fluctuating around the mean value of 0.2811. The autocorrelation chart shows a decreasing correlation to 0. The distribution chart of coefficient estimators of digital transformation variable (CDS) has a normal distribution. The density functions of an MCMC half-chain, front, back, and overall are nearly identical. Thus, the results of Bayesian analysis show the regression coefficient of the digital transformation variable (CDS) is reliable.

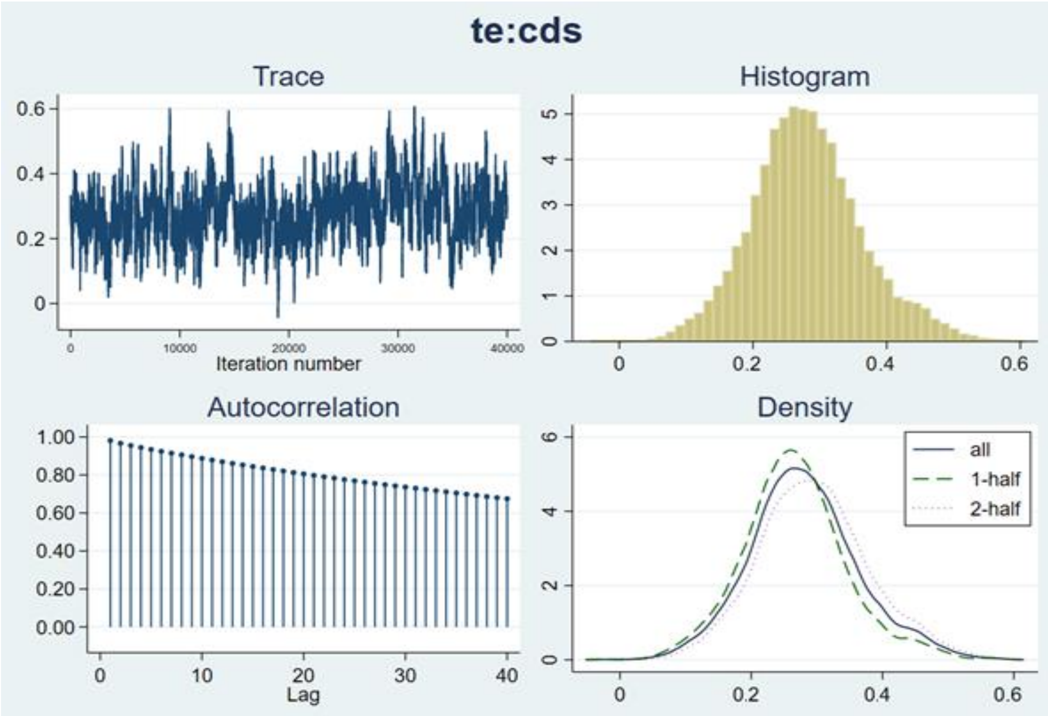

Figure 2. The result of testing the convergence of the MCMC chain corresponding to the regression coefficient of the digital transformation variable (CDS). Source: calculated from STATA 16.0 software.

4.5. The Result of Testing the Robustness of Model (2)

Based on the result of analyzing the effect of digital transformation on the performance by the scale of commercial banks via Model (2), we continue testing the robustness of estimators by the Bayesian method. The model is estimated as below:

$TE_{it} = \beta_0 + \beta_1\ TE_{it-1} + \beta_2\ CDS_{it}\ {}^*QM_{it} + \beta_3\ GDP_t + \beta_4\ NHD_{it} + \beta_5\ TD_{it} + \beta_6\ TK_{it} + \beta_7\ INF_t + u_{it}$ (2)

The prior distributions are used for the regression coefficients base on the estimation result of the most suitable method, the SGMM model. Particularly:

$$\beta_2 \sim \text{normal}(0.0228,\ 0.0066 \times 0.0066)$$

In this research, we use the Metropolis–Hastings algorithm to create the MCMC chain (Markov chain Monte Carlo) with size 42,500, remove 2500 in the burn-in phase, MCMC sample size will be 40,000. The result of model estimation by the Bayesian method is shown in Table 6.

The result of Bayesian analysis shows the average value of 40,000 regression coefficient estimators of digital transformation by scale variable (CDS*QM) is 0.0112 with a positive sign. In addition, the 95% confidence interval of this regression coefficient is (0.0036; 0.0192), said that the value of this regression coefficient is in the positive value domain.

Besides, in Figure 3, the MCMC chain test result of regression coefficient of digital transformation by scale variable (CDS*QM) finds that the MCMC chain is converging. The trace chart says that the MCMC chain has no trend. The estimators distribute thickly into a horizontal line fluctuating around the mean value of 0.0112. The autocorrelation chart shows a decreasing correlation to 0. The distribution chart of coefficient estimators of digital transformation by scale variable (CDS*QM) has a normal distribution. The density functions of an MCMC half-chain, front, back, and overall are nearly identical. Thus, the results of Bayesian analysis show the regression coefficient of digital transformation by scales variable (CDS*QM) is reliable.

Table 6. The estimation result of Model (2) by the Bayesian method.

TE	Mean	Std. Dev.	MCSE	Median	Equal-Tail [95% Cred. Interval]	
TE.L1	0.4013	0.0981	0.0014	0.4011	0.2092	0.5935
TD	0.0469	0.0977	0.0015	0.0462	−0.1410	0.2397
GDP	−1.9975	1.5149	0.0609	−1.9996	−4.9824	0.9885
INF	−0.2670	0.3263	0.0040	−0.2669	−0.9095	0.3758
CDS*QM	0.0112	0.0040	0.0002	0.0111	0.0036	0.0192
TK	0.0289	0.1238	0.0026	0.0273	−0.2113	0.2730
NHD	0.0019	0.0019	0.0001	0.0019	−0.0020	0.0057
_CONS	0.5576	0.1365	0.0022	0.5582	0.2894	0.8252
U0:sigma2	0.0072	0.0046	0.0002	0.0060	0.0022	0.0192
sigma2	0.0019	0.0003	0.0000	0.0018	0.0014	0.0026

Source: calculated from STATA 16.0 software.

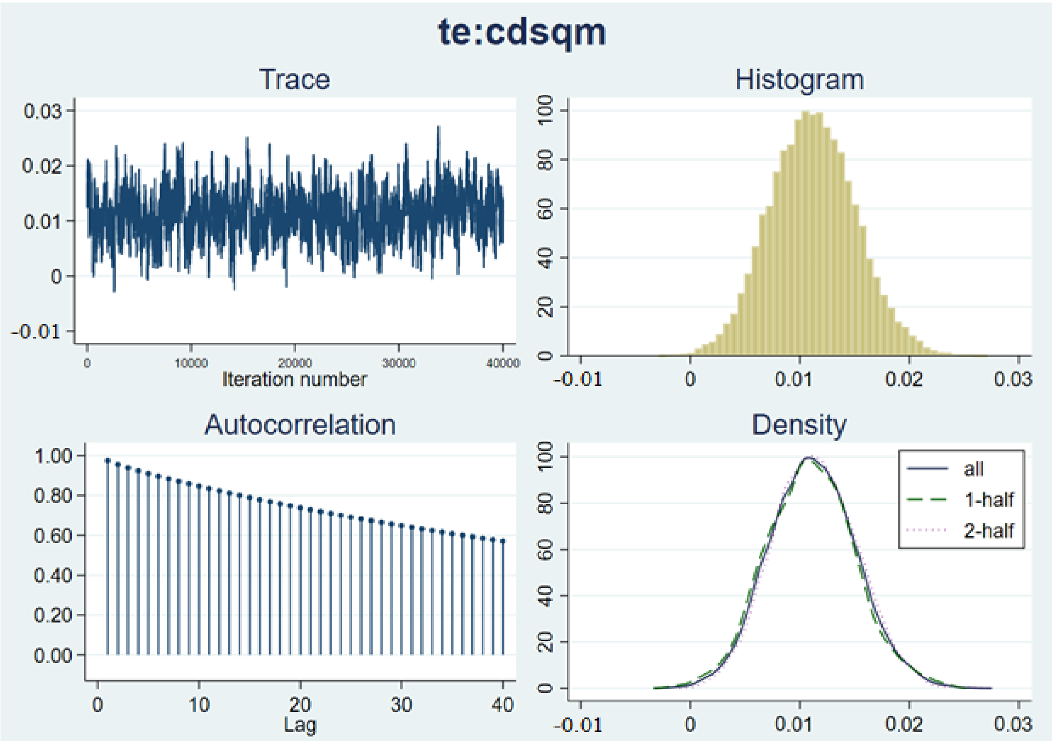

Figure 3. The result of testing the convergence of the MCMC chain corresponding to the regression coefficient of digital transformation by scale variable (CDS*QM)**.** Source: calculated from STATA 16.0 software.

5. Conclusions

The estimation result shows digital transformation variable has a positive impact with a significant level of 1%, said that the digital transformation positively affects the performance of Vietnamese commercial banks. However, the bank size (QM) is not statistically significant, showing that the bank scale does not affect the performance of Vietnamese commercial banks in the data sample. The digital transformation by scale (CDS*QM) positively affects a significant level of 1%. This affirms that the larger scale of banks is, the more positive effect of digitalization on the performance of these banks will be, or the efficiency of digital transformation depends on the scale of commercial banks.

Finally, from the perspective of the policy distribution, the paper proposes the related solutions for commercial banks and other management authorities through some comments and reviews to make policy recommendations. The banks with small or large sizes all face different technological challenges. Small banks tend to depend on low-cost IT suppliers simply because they do not have enough financial and technological capabilities to successfully take over technology applications similar to the large banks and lack a comprehensive IT workforce. Therefore, the small commercial banks need to balance their budgets to deploy the technology applications as well as a human resource with a capacity of data management, security, software development.

Although the research objective has been achieved, we believe that there are still other control variables that can be added to the model. Therefore, future studies can base on the research scope, specific conditions, to add other control variables to more fully assess the impact of digital transformation on the performance of commercial banks. Besides, expanding the sample size in future studies also makes the research results more reliable.

Author Contributions: E.I.T. conceived the idea, wrote the introduction. H.A.L. and H.A.T.P. wrote the literature review, and the methodology. T.D.D. wrote empirical results, and conclusion. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

References

Abdulquadri, Abdulazeez, Emmanuel Mogaji, Tai Anh Kieu, and Nguyen Phong Nguyen. 2021. Digital transformation in financial services provision: A Nigerian perspective to the adoption of chatbot. *Journal of Enterprising Communities: People and Places in the Global Economy* 15: 258–81. [CrossRef]

Ahmed, Shakeel, M. E. Majeed, Eleftherios Thalassinos, and Yannis Thalassinos. 2021. The Impact of Bank Specific and Macro-Economic Factors on Non-Performing Loans in the Banking Sector: Evidence from an Emerging Economy. *Journal of Risk and Financial Management* 14: 217. [CrossRef]

Banker, Rajiv D., Abraham Charnes, and William Wager Cooper. 1984. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science* 30: 1078–92. [CrossRef]

Beccalli, Elena. 2007. Does It Investment Improve Bank Performance? Evidence from Europe. *Journal of Banking and Finance* 31: 2205–30. [CrossRef]

Bresciani, Stefano, Alberto Ferraris, and Manlio Del Giudice. 2018. The management of organizational ambidexterity through alliances in a new context of analysis: Internet of Things (IoT) smart city projects. *Technological Forecasting and Social Change* 136: 331–38. [CrossRef]

Berger, Allen N. 2003. The Economic Effects of Technological Progress: Evidence from the Banking Industry. *Journal of Money, Credit, and Banking* 35: 141–76. [CrossRef]

Bikker, Jacob A, and Jaap W. B Bos. 2008. *Bank Performance: A Theoretical and Empirical Framework for the Analysis of Profitability, Competition and Efficiency*. London; New York: Routledge.

Blundell, Richard, and Stephen Bond. 1998. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics* 87: 115–43. [CrossRef]

Casolaro, Luca, and Giorgio Gobbi. 2007. Information technology and productivity changes in the banking industry. *Economic Notes* 36: 43–76. [CrossRef]

Charnes, Abraham, William W. Cooper, and Edwardo Rhodes. 1978. Measuring the Efficiency of Decision-Making Units. *European Journal of Operational Research* 2: 429–44. [CrossRef]

Chen, Shengqi, and Hong Zhang. 2021. Does digital finance promote manufacturing servitization: Micro evidence from China. *International Review of Economics & Finance* 76: 856–69. [CrossRef]

Giotopoulos, Ioannis, Alexandra Kontolaimou, Efthymia Korra, and Aggelos Tsakanikas. 2017. What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. *Journal of Business Research* 81: 60–69. [CrossRef]

Hastings, W. Keith. 1970. Monte Carlo sampling methods using Markov chains and their applications. *Biometrika* 57: 97–109. [CrossRef]

Ho, Shirley J., and Sushanta K. Mallick. 2006. *The Impact of Information Technology on the Banking Industry: Theory and Empirics*; London, UK: Queen Mary, University of London. Available online: http://webspace.qmul.ac.uk/pmartins/mallick.pdf (accessed on 10 November 2021).

Jatic, Sead, Milena Ilić, Lidija Miletić, and Aca Marković. 2017. Strategy of Swiss Banking Sector towards Digitalization Trends. *International Journal of Economics and Law* 61: 61–72.

Kasman, Adnan. 2002. Cost Efficiency, Scale Economies, and Technological Progress in Turkish Banking. *Central Bank Review* 1: 1–20. Available online: https://core.ac.uk/download/pdf/6462856.pdf (accessed on 10 November 2021).

Lee, In, and Yong Jae Shin. 2018. Fintech: Ecosystem, business models, investment decisions, and challenges. *Business Horizons* 61: 35–46. [CrossRef]

Lin, Bou-Wen. 2007. Information technology capability and value creation: Evidence from the US banking industry. *Technology in Society* 29: 93–106. [CrossRef]

Martín-Oliver, Alfredo, and Vicente Salas-Fumás. 2008. The output and profit contribution of information technology and advertising investments in banks. *Journal of Financial Intermediation* 17: 229–55. [CrossRef]

Metropolis, Nicholas, Arianna W. Rosenbluth, Marshall N. Rosenbluth, and Augusta H. Teller. 1953. Equation of State Calculations by Fast Computing Machines. *Journal of Chemical Physics* 21: 1087–92. [CrossRef]

Moffat, Leon. 2017. The Relationship between Technological Advancements and Operational Efficiency of Commercial Banks in Kenya. Master's thesis, School of Business, University of Nairobi, Nairobi, Kenya.

Nyapara, Emanuel O. 2013. The Relationship between Information Communication Technology Usage on Efficiency among Commercial Banks in Kenya. Doctoral dissertation, University of Nairobi, Nairobi, Kenya. Available online: http://erepository.uonbi.ac.ke/handle/11295/59626 (accessed on 1 November 2021).

Ortaköy, Selman, and Zehra Özsürünç. 2019. The Effect of Digital Channel Migration, Automation and Centralization on the Efficiency of Operational Staff of Bank Branches. *Procedia Computer Science* 158: 938–46. [CrossRef]

Pramanik, Himadri Sikhar, Manish Kirtania, and Ashis K. Pani. 2019. Essence of digital transformation—Manifestations at large financial institutions from North America. *Future Generation Computer Systems* 95: 323–43. [CrossRef]

San, Ong Tze, and Teh Boon Heng. 2011. Capital Structure and Corporate Performance of Malaysian Construction Sector. *International Journal of Humanities and Social Science* 1: 28–36.

Schueffel, Patrick. 2017. Taming the Beast: A Scientific Definition of Fintech. *Journal of Innovation Management* 4: 32–54. [CrossRef]

Taiminen, Heini Maarit, and Heikki Karjaluoto. 2015. The usage of digital marketing channels in SMEs. *Journal of Small Business and Enterprise Development* 22: 633–51. [CrossRef]

Tan, Nguyen Ngoc, Huynh Thi Tuyet Ngan, Nguyen Son Hai, and Le Hoang Anh. 2021. The Impact of Digital Transformation on the Economic Growth of the Countries. In *Prediction and Causality in Econometrics and Related Topics*. Edited by Nguyen Ngoc Thach, Doan Thanh Ha, Nguyen Duc Trung and Vladik Kreinovich. ECONVN 2021. Studies in Computational Intelligence. Cham: Springer, vol. 983. [CrossRef]

Verhoef, Peter C., Thijs Broekhuizen, Yakov Bart, Abhi Bhattacharya, John Qi Dong, Nicolai Fabian, and Michael Haenlein. 2019. Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research* 122: 889–901. [CrossRef]

Vial, Gregory. 2019. Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems* 28: 118–44. [CrossRef]

Xin, Mingdi, and Vidyanand Choudhary. 2019. IT Investment under Competition: The Role of Implementation Failure. *Management Science* 65: 1909–25. [CrossRef]

Zhai, Huayun, Min Yang, and Kam C. Chan. 2022. Does digital transformation enhance a firm's performance? Evidence from China. *Technology in Society* 68: 101841. [CrossRef]