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Valuation of FinTech Innovation Based on Patent Applications

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Abstract: The financial services sector, perhaps more than any other, is being disrupted by advances in technology. The purpose of this study is to provide comprehensive data and evidence on value of the FinTech innovation event. First, a text-based filtering method for identifying FinTech patent applications is provided. Using machine learning applications, innovations are classified into major technology groups. The methodology for valuation of FinTech innovation is based on data of stock price changes. To assess the value impact, Poisson flow rates and stock price movements were combined. Further, to evaluate the effect of FinTech patents on the company's value, a combination of CAR of patent application and Poisson intensities were used. Research findings provide evidence that FinTech innovations bring significant value for innovators and Blockchain being especially valuable. Such innovations as blockchain, robo-advising and mobile transactions are the most valuable for the financial sector. On one side of the spectrum, the financial industry can be affected more negatively by the innovation of nonfinancial startups that carry disruptive technology at their core. However, on the other side of the spectrum, market leaders who make significant investments in their innovations can evade most of these negative effects. This helped to form an overall view of FinTech innovations.

Keywords: FinTech innovation; valuation; patent application

1. Introduction

Recent development of FinTech raised significant interest within the financial sector and beyond. This sudden evolution and development of financial technology was welcomed by many experts, claiming that FinTech has the potential to disrupt and transform the financial sector by making it more transparent, secure and less expensive [1–3]. For the past decade, sector leaders, represented by large financial institutions, have increased their interest along with investments in FinTech innovations [4,5]. The first two quarters of 2019 raised USD 37.9 billion of global investments in FinTech [6]. According to the Harvey Nash CIO Survey, in 2019, most competitive financial institutions considered FinTech to be their major investment [7].

Despite all of this, it is currently not entirely clear how this new and fast emerging technology can influence existing financial institutions and their business models; which emerging financial technologies will prove of bearing highest value to their creators. It is expected that with the help of FinTech innovations, financial institutions will be able to lower costs and increase customer inclusion that will lead to an increase in future profits [8]. At the moment, new sector entrants are already capitalizing on the growing demand for new, more customer-centric and digitally enabled services. With key technology continuing to evolve rapidly alongside changing consumer needs, industry leaders will be forced to compete with start-ups and tech companies for the new business models. It is difficult to properly asses the circumstances without systematic data analysis on FinTech innovations.

González, Gil, Cunill and Lindahl [9] state that financial innovations increase with increasing growth of volatility among sectors more dependent on external financing, as well as with higher non-stability (growth of instability) of banks, with higher volatility of bank incomes and higher losses of banks. Beck, Tao, Chen and Song [10] presented study based on data analysis of 32 countries over the period 1996–2010. Authors pioneer in assessing the relationship between financial innovation, at one end of the spectrum, and bank growth, as well as economic growth, on the other end. Minhua and Yu [11] use a well-established event study methodology to observe average positive market reactions to announcements of financial innovation regulations, thus implying positive impacts of regulations on company's operations and refer to such an impact as an 'innovation effect'. Lerner [12] studied patenting activities of investment banks and revealed a correlation with their size. Later, he tried to take into account the features of empirical research and the fact that granted patents were rarely used. Implemented analysis focused on organizations introducing financial innovations through the study of a number of hypotheses proposed in the literature. The results showed that the generation of innovation is inversely proportional to the size of the organization, emphasizing the failure of small companies to obtain their patent rights. Schmedders and Citanna [13], studied how the coefficient of incompleteness and structural changes in the financial market affect asset price volatility.

Summarizing the extensive theoretical literature on financial innovation and patenting, main areas of scientific research can be distinguished:

- Nature and design of financial innovation;
- Adoption of financial innovations and its motives;
- Conditions of the economic environment that stimulate financial innovation;
- Effects of financial innovation on profitability and economic well-being;
- Review of financial innovation.

However, key issues regarding the characteristics of financial innovations and their distribution remain unresolved. These issues relate to the nature of financial innovation, and the mathematical basis for assessing the impact of financial innovation in the financial market. In this regard, authors attempted to create a methodology for assessing the impact of financial innovations on the financial market. The proposed model is theoretical in nature and (since empirical studies for the totality of financial innovations are not possible) shows the relationship of the elements that affect the financial market.

The aim of study is to provide comprehensive data and evidence on the value of the FinTech innovation event. In search of a reliable set of innovative measures, some scholars show that researchers used various data collection tools, ranging from unstructured interviews, in which respondents were asked to list a number of measures (important for evaluating financial innovation), to structured interviews that required the respondent to list the list of measures affecting innovative strategies [14].

This paper builds upon a number of various articles and reports. Analysis of Fintech innovation value is based on the data of stock price changes linked with patent application disclosure. Results of the study can be used for further analysis of the reaction of financial sector to the innovation.

2. Literature Review

2.1. Analysis of Key FinTech Innovations

Financial technology or FinTech is a term used to describe the impact of new technologies on the financial services industry [15]. It covers a variety of products, processes, applications and business models that intend to transform the traditional understanding and way of providing financial services [16].

According to the Financial Stability Board FSB definition, "FinTech is technology-enabled innovation in financial services that could result in new business models, applications, processes or products with an associated material effect on the provision of financial services" [17].

From the point of view of procedures, FinTech refers to new applications, processes, products or business models in the field of financial services, consisting of one or more additional financial services, provided in whole or for the most part via the Internet. Services can be provided simultaneously by various independent service providers, typically including at least one licensed bank or insurance company [18].

Based on data analysis, different reports and scholars [15,17,19], the FinTech landscape can be mapped across four broad dimensions and technologies classified into major innovations groups that are ultimately developed for the purpose of application (present or future) in financial services (Table 1):

Table 1. Key FinTech innovations transforming financial services (source: elaborated by authors, based on articles, surveys and industry reports).

		Technology Innovation	**Financial Services**
Dimension	Artificial intelligence (AI) Big Data	Machine learning (ML) Predictive analytics Data analytics	Investment advice (robo-advising) Credit decisions Asset Trading
	Distributed computing	Distributed ledger (DLT) Blockchain	Digital currencies Back-office, recording Settle payments
	Cryptography	Smart contracts Biometrics Cybersecurity	Automatic transactions Identity protection Cybersecurity
	Mobile access internet	Digital wallets Application programming interfaces (APIs) Mobile transactions Internet of things (IoT)	Crowd funding person-to-person transactions (P2P) Smartphone wallets Inter-operability and expandability

Table 1 implies all the listed innovations should be considered FinTech as their implementation lies (or is intended for) in financial services.

The study presents how FinTech innovations in all four dimensions influence value from the point of view of individual traditional companies, i.e., market leaders and competitors. Theoretical discussion implies that disruptive innovations of potential market participants can be particularly unpleasant for industry leaders who struggle to adapt to changes and focus on customers. On the other hand, market leaders can benefit from disruption, because they have more financial resources and greater economies of scale for introducing new lines of business compared to competitors [20]. Empirical tests confirm the latest predictions that the amount of resources allocated to R&D&I can increase the agility of market leaders to damage from potential external disruptive innovations.

An analysis of the value of Fintech innovations requires reliable estimates (statistical data) of their value. Research on corporate innovation states that the reaction of stock prices to patent applications can be used to examine the valuation (value) of innovations [21]. However, it is less valuable that the reaction of price to a patent publication reflects an unexpected factor: market investors can anticipate a future event and partially include this expectation in the price of the firm's shares today. Without adjusting for the rational anticipation of the abnormal reaction of stock prices to a disclosed patent application, it will not give a rational assessment of innate value of financial innovation. Previously conducted research of stock price reactions to patent applications do not take into consideration the possible expectation of investors. However, in the study of Kogan, Papanikolaou, Seru, and Stoffman [22] the value of patents using pending adjusted price responses to patent grants was evaluated. Authors state that the market can expect several future financial innovations, but in this article, we focus on the Poisson distribution.

2.2. Classification of FinTech Innovations with Machine Learning

The application of a machine-learning method was used for the purpose of classifying patent applications based on textual data. Method was applied in three steps: 1—processing of textual data of applications; 2—building sample unit; 3—training algorithm to single out categories of innovations.

Table 2 presents the results of a machine-learning method performance—neural networks (out-of-sample). Such measures as "accuracy", "precision", "recall", and a combination of the last two called "F1 score" are used to determine classification performance [23]. Neural networks method carries three layers with neurons: 1.124 in first, 286 in second and 42 in third.

Table 2. Performance of machine-learning method (source: author, based on [24]).

	Neural Network (%)
Accuracy	94.7
Precision	98.8
Recall	97.4
F1 score	98.1

Table 3 reports performance scores of five main FinTech categories that were selected during text based filtering: (0) nonfinancial innovations, (1) blockchain, (2) cybersecurity, (3) mobile transactions, (4) robo-advising, (5) IoT.

Table 3. Performance of the neural network method for sample training (created by authors).

Category	Precision (%)	Recall (%)	No. of Applications in Category	No. of Applications in Predicted Category	No. of Applications
0	98.9	97.2	517	514	44.916
1	100.0	99.5	104	112	1.446
2	97.9	97.4	269	264	5.127
3	96.3	97.1	213	214	3.165
4	97.8	97.7	91	91	1.512
5	97.6	95.3	76	77	1.251
Total:	98.1	97.4	1.270	1.270	59.417

Performance of the used machine-learning method is summarized in Table 2. This algorithm has 98.8% precision and 97.4% of recall. Column of No. of Applications presents the text-filtered set of patent applications that were assigned into each of the five categories by the used algorithm. Created sample consists of 86% of nonfinancial innovations and 14% of FinTech patent applications

3. Methodology and Data

3.1. Methodology for Assessing Worth Based on Values with Reactions of Stock Market

The worth of FinTech innovations needs to be reliably estimated to be able to carry out empirical analysis. Lately, the research literature has acknowledged that new patent values can be studied on the basis of the fluctuations of the stock prices. However, there is a catch to it, as one must take into consideration the possibility of investors anticipation of the future patent case, that might correct the company's stock price prior the patent event itself. Consequently, to evade the biased estimation of the innovation value, a rational anticipation correction has to be implemented into the model. Most studies of the stock fluctuations do not take into consideration that possible future insight of the investors anticipating the possible patenting events.

Sometimes, more than one future innovation can be anticipated by the market. Thus, it is important to be able to evaluate the value of FinTech innovations, considering the possibility of multiple innovations. We created a method, that in itself was sufficiently general while giving a possibility to be used with a wide range of data count models (i.e., Poisson, negative binominal, etc.). To simplify the process, however, the focus was on the Poisson count distribution, which is used in many studies of patenting activity such as [25].

V_0 is the company value before the patent event, V^* is the value increase caused by one patent event. The count of the patents N that will happen over a period (t, $t + T$) under our assumption is following a Poisson distribution:

$$Price(N = k|I_t) = \frac{\lambda^k e^{-\lambda}}{k!},\ k = 0, 1, 2, \ldots \quad (1)$$

Here the information set of the participants in the market is marked by I_t, at specific point in time marked by t. The time $t + T$ change value for the company is kV^* when the exact count of the patent events is k. We can express the value of the company before patent disclosure happens:

$$\overline{V}_{i,0} = V_{i,0} \sum_{k=1}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!}(kAV_i) + \lambda AV_i \quad (2)$$

If we take independency of patent events as a constant, then the event of a patent produces a conditional distribution over further patents, which is a ZTP conditional Poisson distribution:

$$Pr(N = k|N \geq 1, I_t) = \frac{\lambda^k e^{-\lambda}}{(1 - e^{-\lambda})k!},\ k = 1, 2, \ldots \quad (3)$$

So we can express the actual value of the company after the patent disclosure happens:

$$\overline{V}_{i,0} = V_{i,0} + \sum_{k=1}^{\infty} Pr(N = k|N \geq 1, I_t)kAV_i = V_{i,0} \sum_{k=1}^{\infty} \frac{\lambda^k e^{-\lambda}}{(1 - e^{-\lambda})k!}kAV_i = V_{i,0} + \frac{\lambda}{1 - e^{-\lambda}}AV_i \quad (4)$$

Following Equations (2) and (4) we can express the value increase caused by one patent event as:

$$AV_i = \frac{\Delta\overline{V}}{\frac{\lambda}{1-e^{-\lambda}} - \lambda} = \frac{e^{\lambda} - 1}{\lambda}\Delta\overline{V}_i \quad (5)$$

$\Delta\overline{V} \equiv \overline{V}_1 + \overline{V}_0$ correspond to the company value change after the patent application disclosure. In Equation (5) we made an uncomplicated calculation of the increasing value of a patent V^* using data of the observations. Mainly we could calculate the change of the market value $\Delta\overline{V}$ based on the irregular reactions of the stock prices. We could also calculate intensity parameter λ using empirical models of the patent counts, for example Hausman et al. [25].

3.2. Methodology of Assessing the Intensities of Innovations

The innovation intensity parameter λ has to be assessed as the time-variable value. To do that we used the innovator panel data from the patent filing counts and integrated it into the series of Poisson regressions. As there was a possibility of dependencies between the intensity of innovation and the specifics of the technology or the characteristics of the innovator, we constructed different combinations of the type of the technology and the innovator and we integrated them into the models separately. Total assessed count of the models was 18, which included 5 FinTech categories (15 models) and 3 models for benchmarking financial innovations that were not FinTech.

When evaluating public companies for a specific category of technology k, we used MLE (maximum likelihood estimation):

$$\begin{aligned}\log\left(\lambda_{i,k,t}\right) = \quad & a+\beta_1 Asset_{i,t}+\beta_2 R\&D\&I_{i,t}+\beta_3 R\&D\&I_{i,t-1}+\beta_4 R\&D\&I_{i,t-2} \\ & +\beta_5 R\&D\&I_{i,t-3}+\beta_5 Age_{i,t}+\beta_6 PreviousFinTech_{i,t} \\ & +\beta_6 PreviousOtherF_{i,t}+\beta_7 PreviousNonF_{i,t}+\gamma_i+\delta_t\ +\varepsilon_{i,k,t}\end{aligned} \tag{6}$$

Here t and i are, respectively, year and innovating company. In this regression total assets are $Asset_{i,t}$; *R&D&I* spendings *n* + *1* years before the present year are $R\&D\&I_{i,t\text{-}n}$; total age of the company since the founding is Age; the stock of company's FinTech applications before the t year is $PriorFinTech_{it}$; the stock of the company's nonfinancial filings before the t year is $PriorNonF_{i,t}$; the stock of company's non-FinTech financial applications before t year is $PriorOtherF_{i,t}$. Indexes γ_i and δ_t are used to express the fixed effects of innovator and year and all other non-indicator controls are expressed in natural logarithm.

For private companies the following regression is assessed:

$$\begin{aligned}\log\left(\lambda_{i,k,t}\right) = \quad & a+\beta_1 PreviousFinTech_{i,t}+\beta_2 PreviousOtherF_{i,t}+\beta_3 PreviousNonF_{i,t} \\ & +\gamma_i+\delta_t+\varepsilon_{i,k,t}\end{aligned} \tag{7}$$

Results of the Poisson regressions are represented in Table 6. As the table data suggests, more FinTech patent applications were completed by larger companies. Additionally, for the private companies, there were solid positive predictors of the innovations in FinTech in the form of company's age and amount of the prior non-FinTech applications. Further, for the individuals, the prior innovation experience in non-FinTech areas of finance was the most robust predictor of FinTech filing activity.

3.3. FinTech Innovation Patenting Data

Preparing data for the further analysis authors relied on various researches and data sources, such as open databases along with additional information processing and data matching. No commercial bulk data sources were used, therefore some limitations concerning data were necessary.

For the purpose of providing solid proof on the FinTech innovation event and value, a data set based on publically available patent applications was constructed. Patent applications were analyzed using publicly available data from World Intellectual Property Organization (WIPO) [26], European Patent Office (EPO) and Google Patents databases. This study was based on patent applications and not granted patents mainly for the reason that granting a patent takes years and FinTech is a relatively new field thus many of the patents were applied only recently.

We started by limiting the time span of patent application search to the period of 2015–2019. Which gave a search result of 1,511,546 applications. These applications were then limited to the International Patent Classification (IPC) classes "G" and "H", which were considered to potentially relate to FinTech [27]. It should be noted that not all developments relating to finance and business can be the subject of a patent [28].

Text in the abstract and description sections of patent application and information of assignees was used in order to distinguish assignees into groups of private/individual investors, private and public companies.

Due to the absence of clear and standard definitions of what explicit technologies FinTech covers, a list of terms related to finance was generated to pin down patent applications to those that represent financial services and products.

Table 4 shows main filtering (elimination) steps of applications to match specified criteria and the number of valid applications left for further analysis.

Table 4. Creating a sample for filtering patent applications (created by authors).

	Steps	Eliminated Applications	Valid Applications
1	Total number of patent applications from 2015 to [1] 2019		1,511,546
2	Eliminate applications that do not fall under the "G" or "H" classes of International Patent Classification (IPC)	790,631	720,915
3	Eliminate nonfinancial applications that do not meet the definition based on selected financial terms	731,214	59,417
4	Eliminate applications that fall under the category on "nonfinancial" after use of machine-learning algorithm	39,709	19,708
5	Eliminate applications with incomplete information	8867	10,841
6	Eliminate applications of universities, research institutes	128	10,713
7	Eliminate applications of companies that don't have public trading data	5801	4912
8	Patent applications left in the set:		4912
9	FinTech applications where the applicant is:		
	Public company		1159
	Private company		2974
	Individual		779

[1] Data from database was retrieved on November 2019. Therefore, not covering full year.

Total set of applications classified by machine learning method based on text filtering was 59,417, finance related was 19,708. From 19,708 applications, 8867 were eliminated as invalid, for the reason of missing necessary information (data). Finally, the data set was left with 4912 applications that were used for further analysis: 1159 on public companies; 2974 on private companies and 779 on individual innovators.

After application of machine learning algorithms to gathered data, the main innovations categories were distinguished: blockchain, mobile transactions, P2P, cybersecurity, IoT, data analytics and robo-advising.

In Table 5 applications are classified by different types of innovators. Data required for determining status, classification and dates were gathered from public sources. An interesting observation that can be drawn from this data is that private companies are most active and prevail in most of categories of

FinTech innovations. Public companies bring substantial contributions to innovations in robo-advising, while individuals contribute more in cybersecurity.

Table 5. FinTech patent applications by innovations applicants' type (created by authors).

Category	Individual	Public Company	Private Company
blockchain	5	94	109
cybersecurity	514	931	1.271
mobile transactions	162	88	993
robo-advising	89	17	347
IoT	9	29	254
Total:	779	1.159	2.974

It can be stated that public companies (as a group) stimulated (promoted) the introduction of only a small number of Fintech innovations.

In order to determine the value of a FinTech innovation patent application to several publicly traded companies new methodology was developed. Stock market reaction to the event of patent publication was used as basis for valuation. To understand intrinsic value of every innovation for the company, predicted count intensity and stock price change of company needed to be combined.

Such an approach gives an opportunity to determine how much companies operating in the sector of financial services tend to profit from their own FinTech innovations. Overall study shows that blockchain, robo-advisors and cybersecurity are among the innovations carrying the largest value to the companies. The developed method allowed us to determine how innovation's value impacts the financial industry using stock price data, which means it is limited to measure the effect of publicly traded companies.

Among the listed categories of FinTech, cybersecurity and mobile transactions had the largest number of innovations over the period of the historical sampling. Blockchain as a category secured its position as the fastest growing innovation in the field of FinTech. To study the consequences of introducing FinTech innovations, a methodology for evaluating financial technologies in the financial market (based on the cost of patent applications for one or more companies traded on the stock exchange) was developed.

The valuation was based on the observed reaction of the stock market to the disclosure of patent applications. It is important to note that this approach took into account market expectations regarding various types of patent applications filed by different categories of entities. Initially, the intensity of innovation was assessed using a Poisson regression model, which takes into account factors such as the type of technology, time effects and previous experience of the patent applicant. Then, for each patent application, the predicted counting intensity was combined with the movement of company stock prices to determine the implicit value of innovation for the company. Applying this approach of valuation, we analyzed the number of companies in the financial market that have benefited from their own innovations in the field of financial technology. Calculations showed that the value of FinTech innovations (i.e., the value received by innovator) in general is positive.

Further study presents how value is influenced by FinTech innovations from the viewpoint of traditional companies, i.e., market leaders and their competitors. In different studies, the presented theoretical discussions imply that disruptive innovations presented by potential market participants might be particularly unpleasant for industry leaders who find it difficult to adapt to changes and focus on customers. At the same time, industrial disruption can be potentially beneficial to market leaders, as they usually have greater economies of scale and more financial resources for introducing new lines of business, compared with competitors. Empirical tests confirm the latest predictions that market leaders' ability to evade damage from disruptive external innovations is closely related to the sum total of resources allocated for their own R&D&I.

This study complemented a significant number of studies that use patent data to study the innovative activities of companies [28,29]. Although the literature contains valuable information on innovation and corporate patenting in general, most of the previous research was based mostly on granted patent data and do not fully cover innovative activities in the field of FinTech, which actively has been carried out during recent years. Placing the main focus on patent applications in the field of FinTech innovation, we can mitigate problems of truncating data regarding patenting and provide more complete picture of the latest trends and models.

The developed model expanded on recognizing the nature of innovative events over time, which allowed us to more accurately assess the real value of such impact. In general, such approach of combining reactions of stock prices with predicted Poisson flow rates is helpful in exploring other different types of potentially recurring and to a certain extent expected phenomena, such as a reassessment of analyst estimates, the sequence of news releases by a company, or a wave of possible merges or bankruptcies.

Theoretical studies described in vast literature prove how external financial innovations can benefit or harm existing companies and how traditional companies can protect themselves from external threats by using their own innovations. It is rather difficult to test such theories because big samples of data about possible competitive threats from innovation are very difficult to obtain. This study used a new systematic data set in order to determine how innovations of potential participants can affect individual companies in the industry.

The approach presented in the article of FinTech patent applications identification and classification applying text analysis and machine learning contributes to literature that applies these methods to finance and economics. Machine learning algorithms that are used to classify texts are actually new to the financial field and can be used effectively to analyze a wide range of issues related to patent applications, legal documentation and other textual data.

3.4. Assessing the Value of Own Patent Filings

Further we evaluated the effect that owning FinTech patents has on the value of the publicly traded financial companies. To acquire this data, we used a combination of the cumulative (market-adjusted) abnormal returns (CAR) over the period of event of patent application with the Poisson intensities. We can use Equation (5)'s empirical analogue to assess the value of the innovation to the company:

$$V_{i,j,k,t}^{f\ IND} = \frac{e^{\lambda_{j,k,t}} - 1}{\lambda_{j,k,t} \times n_{k,t}} CAR_{i,t} M_{i,t} \tag{8}$$

Here the technology type of innovation is k, the company is i and the date of the publication of the innovation is t. $\lambda_{i,k,t}$ is the intensity of innovation from the Poisson regressions that was projected in Assessing the intensities of innovations Section; $n_{k,t}$ refers to a number of patents that have been disclosed on the date t by a company i; $CAR_{i,t}$ is a 4 day period calculation which starts 2 days prior the patent disclosure date t; $M_{i,t}$ refers to a company's market capitalization 5 days before the disclosure date t.

4. Results and Discussion

4.1. Results on Number of FinTech Innovation Events

This Table 6 presents Poisson regression models calculation on the number of FinTech innovation events that occur in a given time period (2015–2019). Regression is calculated for every technology category separately. Research and Development and Innovation are the company's expenditures that it spends on R&D&I before the year of patent application event. FinTech previous applications are the number of company's previous Fintech patent applications. Nonfinancial previous applications are the number of company's previous nonfinancial patent applications. All applications are counted in the same IPC "G" and "H" classes.

Table 6. Poisson count models calculated for FinTech innovations (created by authors).

Public Companies	Blockchain	Cybersecurity	Mobile Transactions	Robo-Advising	Internet of Things
Assets	0.943 **** (−0.193)	0.907 *** (−0.349)	−1.277 ** (−0.541)	−35.903 * (−20.399)	−0.355 (−0.486)
Research and Development and Innovation	0.073 (−0.304)	1.753 *** (−0.557)	−0.172 (−1.72)	59.590 ** (−29.945)	1.988 (−1.362)
Research and Development and Innovation 1	0.048 (−0.3)	−0.673 (−0.66)	1.908 (−2.245)	34.657 ** (−16.662)	3.738 (−2.336)
Research and Development and Innovation 2	−0.236 (−0.288)	0.364 (−0.662)	0.287 (−2.05)	−22.221 ** (−10.288)	−7.361 *** (−2.344)
Research and Development and Innovation 3	−0.273 (−0.248)	−0.935 * (−0.514)	−1.241 (−1.443)	29.204 ** (−14.246)	2.111 * (−1.129)
Age	−0.201 (−0.591)	−0.093 (−1.329)	−3.693 ** (−1.514)	37.648 (−139.437)	−0.295 (−2.107)
Fintech previous applications	0.111 (−0.11)	−0.092 * (−0.174)	0.244 (−0.309)	−5.566 (−3.711)	−1.126 *** (−0.339)
Nonfinancial previous applications	0.253 ** (−0.101)	0.197 (−0.176)	0.358 (−0.278)	27.971 ** (−12.487)	1.243 *** (−0.305)
Private Companies					
Age	1.145 *** (−0.166)	1.730 *** (−0.306)	3.399 *** (−0.628)	11.987 ** (−5.55)	3.547 *** (−0.725)
Fintech previous applications	−0.555 *** (−0.09)	−1.103 *** (−0.137)	−1.643 *** (−0.267)	−2.790 ** (−1.304)	−1.105 *** (−0.27)
Nonfinancial previous applications	0.619 *** (−0.101)	0.818 ** (−0.174)	0.966 *** (−0.281)	8.111 *** (−2.982)	0.867 ** (−0.369)

Data in parentheses represent robust standard errors. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

In Table 7 we see a cumulative data for private innovation values across seven different categories and five major FinTech groups, FinTech innovations and non-FinTech financial innovations. CARs for each of the five categories are provided individually. The data prove that FinTech innovations lead to a notable value for the company. For the innovator value on average is 21.5 M USD and the median reaches 41 M USD. Comparing these values to innovations that fall under the category of non-FinTech financial, a substantially lower median value is created, that is USD 2.1 M, but the average value is still similar to the value FinTech innovations. In most of the innovation types the mean CAR values are positive. The fact that median and mean values in some innovation types have opposite signs, shows the degree of substantial asymmetry in the distributions. Mobile transactions have the only negative median value. Futher, the biggest values are seen in blockchain innovation, cybersecurity and robo-advising (USD 99.4 M, USD 56.3 M and USD 52.2 M, respectively).

We use bootstrapping to evaluate the importance of the median and mean values. Bootstrapped p values for medians and means are presented in the Table 7 in parentheses. We have received results that show statistical difference of zero of the positive medians for blockchain, cybersecurity, robo-advising and IoT. Additionally, the positive median for all FinTech innovations shows high statistical significance. Thus, the statement, that FinTech innovations bear significant value to their innovators is supported by the p values in Table 7.

Table 7 presents data on the value effect for the company of selected FinTech innovation categories. Values, that are expressed in millions USD, from public company's abnormal stock returns (CAR) linked to their patent application event, are calculated according to Equation (8). CARs are calculated over the period of 2 days: starting one day before the news of patent application. Data in parentheses represent p-values for means and medians, and a bootstrapping method was used to calculate p-values.

Table 7. FinTech innovation value for the company (created by authors).

Innovation Category	CAR (%)	Mean	Median	Standard Deviation
Blockchain	0.31	62.5 (0.431)	99.4 (<0.001)	1768.50
Cybersecurity	0.47	49.2 (0.456)	56.3 (0.083)	1021.73
Mobile transactions	−0.36	−89.7 (0.385)	−18.4 (0.089)	1792.64
Robo-advising	0.29	−104.6 (0.455)	52.2 (0.011)	964.1
IoT	−0.38	−31.4 (0.611)	2.2 (0.783)	817
All FinTech Innovations		21.5 (0.483)	41.0 (<0.001)	1548.80
Non FinTech Financial Innovations		19.6 (0.564)	2.1 (0.482)	3031.20

Further we evaluate the effect that underlying technologies have on the value of FinTech innovations. For this cause multivariate regressions are used. On the first stage the goal is a mitigation of skewness and outliers in the distribution of the value. For this cause, a logarithmic transformation is applied to the estimated values:

$$V = \begin{cases} \log(1 + V^{*}); & V^{*} > 0 \\ -\log(1 - V^{*}); & V^{*} < 0 \end{cases} \tag{9}$$

Here, V is a converted value that is later used in regressions as the dependent variable. V^{*} is the estimated in Equation (8) value. Further, following form regressions are estimated:

$$V^{f\ IND}_{i,k,t} = \alpha_i + \beta' TechD_k + \Gamma' X_{i,k,t} + \varepsilon_{i,k,t} \tag{10}$$

Here $V_i{,}^{O}{}_k{,}^{W}{}_t{}^{N}$ is the value (which is log transformed) of the patent application on a date t of technology type k to a company i. *TechD* are the binary variables and express categories of different FinTech. X contains controls of company size, company age before FinTech applications, before applications in other financial areas and before nonfinancial applications in IPC "G" and "H". Company and year fixed effects, patent breadth and quality controls are also included. Nonindicator controls are expressed in natural logarithm.

Table 8 presents regression results. According to the data, the most valuable innovation categories are blockchain followed by robo-advising. These types of innovation have much more significant value compared to mobile transactions baseline. However, it can be observed that other categories are not that significantly different from mobile transactions. These data show that, regarding future cost savings in financial services, there are big potential benefits offered by blockchain technology.

4.2. Discussion

In this analysis the value of FinTech innovation was presented through a patent lens. This is a tangible measure that proves that protecting the output of companies' investment can bear positive value effect. Being an essential source of competitive intelligence, patents can help companies to withstand introduction of disruptive innovation [30]. In this paper, the focus is put on patent applications rather than on granted patents which provides more of a complete analysis of recent trends in FinTech innovation.

Table 8. Innovation category and company value of FinTech (created by authors).

Innovation Category	Value
blockchain	2.022 ** (0.652)
cybersecurity	0.245 (0.533)
mobile transactions	1.341 * (0.731)
robo-advising	1.637 * (0.731)
IoT	0.704 (0.947)

* $p < 0.10$; ** $p < 0.01$.

The method that was developed complements other researchers that used stock prices to determine the value of innovation. Presented study extends and combines reactions of stock prices with Poisson innovation intensities. It can be used to analyze different types of recurring and partially anticipated events. Approach used in this paper to identify and classify FinTech innovations using machine learning and text analysis can contribute to the economic literature. The study demonstrates a correlation between financial innovations and impact or value on the financial market.

Despite the current widespread of FinTech, the fundamental challenge that was faced analyzing FinTech innovations is that there is currently no official definition or consensus about what FinTech is and of what exact technologies or services it comprises [31].

4.3. Limitations

Patenting FinTech inventions has a number of challenges and one of the limitations is that it reflects only part of financial sectors' innovation activities as not all of them can be subject to patenting [32]. While previous researchers have focused more on the analysis of granted patents [33,34], trends on machine learning technologies and applications [35,36], the presented study is based on patent applications, mainly for the reason that granting a patent takes years and FinTech is a relatively new field, thus many of the patents were applied only recently.

The other limitation is related to the complexity of companies R&D&I expenditures that makes it hard to determine exact investments. Further research is needed for a broader understanding of FinTech innovation impact on financial sector and society.

5. Conclusions

Such an increase of interest in FinTech-powered innovation during recent years brings out the need for a deeper understanding of a potential value that these new emerging technologies can bear to their inventors. There is an increase in general understanding that patents play an important part in an organization's innovation strategy. Different sectors adopt different strategies for generating value from innovations. Currently there is an obvious difference between how financial services and technology companies perceive patents.

Analysis of valuation of financial innovation presented in this paper was based on stock price data. The developed model expanded on recognizing the nature of innovative events over time, which allowed to assess value impact more accurately. For this purpose, Poisson flow rates and stock price movements were combined, which proved to be useful exploring other partially anticipated recurring phenomena such as the sequence of company news releases and wave of mergers or bankruptcies.

The presented study provides evidence that FinTech innovations bring value to their inventors and generally are valuable to the whole financial sector. Most valuable FinTech innovations are blockchain innovation (USD 99.4 M), cybersecurity (USD 6.3 M) and robo-advising (USD 52.2 M).

On the other hand, some categories of FinTech innovation have a negative value effect on companies. Findings state that market leaders that invest in their own R&D&I, have tendency to avoid harm introduced by disruptive innovations.

For further research, the authors suggest to focus on a deeper analysis of the additional features of FinTech innovations and how they affect the value of companies in the financial sector. What is more, the conducted study can be used as basis for further research of social impact of FinTech innovation.

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