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The Impact of Fintech Startups on Financial Institutions' Performance and Default Risk

Abstract

We examine the impact of fintech start-ups on the performance and default risk of traditional financial institutions. We find a positive relationship between fintech start-up formations and incumbent institutions' performance for the period 2005–2018 and a large sample of financial institutions from 87 countries. We further analyze the link between fintech start-up formations and the default risk of traditional financial institutions. Fintech start-up formations decrease stock return volatility of incumbent institutions and decrease the systemic risk exposure of financial institutions. The findings indicate that legislators and financial supervisory authorities should closely monitor the development of fintech start-ups, because fintechs not only have a positive effect on the financial sector's performance but also can improve financial stability relative to the status quo.

JEL-Codes: K000, L260, O300.

Keywords: fintech, bank performance, default risk, financial stability.

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1. Introduction

The rise of financial technology (fintech) has received considerable attention from academics, practitioners, and regulators. The recent hype about fintech is due to the development and deployment of novel technologies such as artificial intelligence, big data, cloud computing, machine learning, blockchain, and other technologies that have the potential to revolutionize the financial sector, which was historically considered among the most traditional and conservative sectors in the economy. The Financial Stability Board of the Bank for International Settlements defines fintech as "as 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" (European Banking Authority, 2017, p. 7). Fintech innovations have emerged in many of the traditional value-adding sections of a universal bank, including financing, asset management, payment services, and others (Dorfleitner et al., 2017). Fintech start-ups not only challenge traditional financial institutions by providing cheaper, faster, and easier access to financial services but also potentially foster the transformation and innovation activities of incumbent institutions (Milian et al., 2019; Di et al., 2021; Panos and Wilson, 2020; An and Rau, 2021). However, little is known about how fintech start-ups affect the traditional financial sector.

A core function of financial institutions is the intermediation of financial resources (Merton, 1992). Yet the financial crisis of 2007–2008 created a credit crunch (Campello et al., 2010; Campello et al., 2011; Cowling et al., 2012), which resulted in financial constraints of many small and medium-sized firms (Mc Cahery et al., 2015). Economic output declined sharply, and unemployment rates increased worldwide (Daly et al., 2012; Bruno et al., 2014). Moreover, bank customers lost their confidence in many of the traditional financial institutions, which in some regions resulted in bank runs, such as that of British Northern Rock in 2008. This fragile environment provided the ground for novel products and services of fintech start-ups, which started with a clean slate and did not need to overcome a history of failure and excessive risk-taking. As a result of consumers' distrust in banks, marketplace lending has become more prevalent (Saiedi et al., 2020). In particular, banks' misconduct is related to the emergence of the United States (U.S.) online lending market (Bertsch et al., 2020). Moreover, research indicate that fintech start-ups have the potential to better address information asymmetries (Lin et al., 2013; Ge et al., 2017; Xu and Chau, 2018), because they leverage additional information about borrowers from the Internet, thereby enabling them to receive credit for the first time and, in some cases, at cheaper rates (Serrano-Cinca et al., 2015; Iyer et al., 2016; Jagtiani and Lemieux, 2019). Services provided by fintech start-ups also include algorithm-based investment advice, mobile banking services, instant online and mobile payment infrastructure, innovative risk management systems, and cost-efficient foreign exchange services (Haddad and Hornuf, 2019). The increasing prevalence of fintech start-ups and the potential pressure they put on incumbent firms raise the question of how fintech start-ups affect the performance and risk-taking of traditional financial institutions.

Research has often argued that fintech start-ups do not fully comply with financial regulation and engage in regulatory arbitrage using existing legal exemptions (Hornuf and Schwienbacher, 2017; Buchak et al., 2018; Cumming and Schwienbacher, 2018), which might consequently undermine financial stability (Fung et al., 2020; Li et al., 2020; Vučinić, 2020). Because financial stability has a direct impact on economic growth, scholars have investigated financial institutions' default risk and the conditions under which this risk led to subsequent financial turmoil (Beck et al., 2006; Acharya and Naqvi, 2012; Diamond and Rajan, 2012). Fintechs can, for example, affect systemic risk through their increasing interconnectedness with traditional financial institutions and a lax supervision by authorities (BIS, 2017). By contrast, new business models that are uncorrelated with traditional financial institutions can also reduce systemic risk in the financial industry. To the best of our knowledge, empirical research has not yet examined the systemic risk of traditional financial institutions resulting from fintech start-up formations. In this article, we therefore raise the question: Does the emergence of fintech start-ups affect systemic risk of traditional financial institutions?

The empirical literature on financial innovation in general and the interaction between traditional financial institutions and fintechs in particular is still scarce. Lerner (2002) and Miller (1986) measure financial innovation by the filing of financial patents and show that it has been increasing since the late 1970s. The quality of financial patents and financial innovations, however, was often low (Lerner et al., 2016). Scott et al. (2017) show that the financial industry traditionally invested a large share of expenses in information technology (IT), reaching around one-third of all expenses in the early 1990s. In particular, early on, the financial industry employed computers. However, only a few financial innovations (e.g., automated teller machines) have led to considerable changes in financial institutions and their business models (Merton, 1995). Whether fintechs affect incumbents' ability to innovate and consequently perform is still an open question.

A related article to ours focusing on bank–fintech alliances is that of Brandl and Hornuf (2020), who run a bank–fintech network analysis for Germany and find that bank–fintech relationships are often product-related. They argue that this form of alliance is due to fintechs' development of an algorithm or software, the value of which can only be determined when the software has been adapted more thoroughly to customer needs. Hornuf et al. (2020) refine these findings by analyzing bank characteristics associated with bank–fintech alliances. They hand-collect data for the largest banks from Canada, France, Germany, and the United Kingdom and provide detailed evidence that banks are more likely to form alliances with fintechs when they pursue a well-defined digital strategy and/or employ a chief digital officer. Furthermore, they find that banks more often invest in small fintechs but often build product-related collaborations with larger fintechs, which is in line with predictions from incomplete contract theory (Grossman and Hart 1986; Aghion and Bolton 1992). Phan et al. (2020) investigate a sample of 41 Indonesian banks. They find that fintechs negatively predict bank performance and argue that fintechs substitute for traditional banks by providing less expensive and more efficient services

In this article, we collected data for 8,092 financial institutions and 12,549 fintech start-ups from 87 countries to assess the effect of fintech start-ups on the performance and default risk of traditional financial institutions. Our results indicate a positive and significant impact of fintech formations on financial institutions' performance. An increase of fintech start-up formations is associated with an increase of incumbent institutions' performance. Our findings also suggest that fintech formations decrease stock return volatility and financial institutions' exposure to systemic risk. These findings might be of interest to academics, practitioners, and regulators alike, especially as the fintech sector is steadily growing and becoming increasingly integrated with the traditional economy and incumbent financial institutions (Li et al., 2020).

The remainder of the article proceeds as follows. Section 2 summarizes the literature and introduces our hypotheses. Section 3 describes the data and introduces the variables used in the quantitative analysis. Section 4 presents the descriptive and multivariate results. Section 5 provides a discussion and conclusion of our study.

2. Literature and hypotheses

A wealth of literature has investigated the performance of financial institutions. In the past decade, research has examined the determinants of financial institutions' performance, analyzing how firms address corporate governance issues (Aebi et al., 2012; Peni and Vähämaa, 2012; Zheng and Das, 2018), master the diversification of their business activities (Berger et al., 2010; Brahmana et al., 2018; Chen et al., 2018; Kim et al., 2020), deal with external regulation (Naceur and Omran, 2011; Psillaki and Mamatzakis, 2017), react to monetary policies (Mamatzakis and Bermpei, 2016; Gambacorta and Shin, 2018), deal with the legal and institutional framework (Kalyvas and Mamatzakis, 2017; Bitar and Tarazi, 2019; El Ghoul et al., 2021), generate intellectual capital (Talavera et al., 2018; Nawaz, 2019; Adesina, 2021), and engage in shadow banking activities (Tan, 2017; Lin et al., 2018). Given the all-embracing and massive development of the fintech sector in the past decade, it seems worthwhile also to investigate how fintech start-up formations affect financial institutions' performance.

Consumer theory stipulates that new products or services, such as those developed by fintech start-ups, act as either complements to or substitutes for existing products or services (Aaker and Keller, 1990; Frank, 2009). The products and services that fintech start-ups offer are more likely to benefit traditional financial institutions if they are complements but threaten incumbent institutions' performance if they are substitutes (Kaul, 2012). While fintechs have the potential to develop revolutionary business models, collaborations between banks and fintechs have most often been evolutionary in nature (Bhalla, 2019). Thus, existing products or services have merely been enhanced, with innovations rarely replacing existing ones (Merton, 1995). For example, invoice trading and factoring always existed, but the innovation of fintechs was to scale these services down and offer them to small and medium-sized enterprises (Dorfleitner et al., 2017).

Most research concludes that IT is beneficial for incumbent institutions because it helps reduce transaction costs, thereby improving service quality, optimizing business structure, and promoting business transformation and upgrading (Shu and Strassmann, 2005; Lapavitsas and Dos Santos, 2008; Martín-Oliver and Salas-Fumás, 2008). Moreover, empirical evidence shows that many incumbent institutions acknowledge the superiority of fintech start-ups and have incorporated these start-ups and/or their products and services into their own business models (Hornuf et al., 2020). For these financial institutions, the emergence of fintech start-ups results in a beneficial partnership rather than a threat (PwC, 2016). For example, the verification of customers' identity through account or video verification supports the customer onboarding process, without cannibalizing existing business from incumbents.

Historically, some scholars have claimed that the opposite is true and that IT could bring enormous challenges to commercial banks (Holland et al., 1997), because IT, globalization, and deregulation allow for new market entrants, disintermediation, innovation, and customer changes on a massive scale. Accordingly, fintech start-ups would take over several key functions of traditional financial institutions (Li et al., 2017). New market entrants benefit from their lack of legacy infrastructure and low levels of organizational complexity, which allows them to be more agile, innovate faster, and be more radical in their approach to innovation (Brandl and Hornuf, 2020). In other words, fintech start-ups are likely to absorb the inefficient operation of traditional financial institutions' existing business. This substitution effect is also in line with disruptive theory (Christensen, 2013), which claims that new entrants effectively compete with traditional players by providing accessible and cost-effective goods and services to customers. As a result, start-ups eventually replace incumbents. Fintech have already sparked such a disruptive evolution when offering financial products and services to customers in novel and more cost-efficient ways (Ferrari, 2016). The efficiency increase due to fintechs results, for example, from disintermediation that significantly lowers transaction costs for consumers (KMPG, 2016; PwC, 2016). Blockchain technology is one of the most prominent inventions that can accomplish such efficiency increases (Wood and Buchanen, 2015; Peters and Panayi, 2016), for example, by making the clearing and settlement of securities and many other services of the financial sector more cost-effective.

Moreover, fintechs have developed applications to improve efficiency in financial services across a range of other services, including mobile and instant payment services, automated asset management, and digital information and data management (Villeroy de Galhau, 2016). These innovations take advantage of traditional financial institutions because many incumbents still rely on an outdated IT infrastructure (Laven and Bruggink, 2016; Brandl and Hornuf, 2020) and have difficulties in adopting new financial products and services or in the same quality as fintechs. Furthermore, traditional financial institutions are often less likely to adopt new technologies quickly because of restrictions stemming from the regulatory environment that applies to fully regulated institutions (Hannan and McDowell, 1984).

It might also be argued that fintechs have no effect on banks performance, because fintechs attract customers who traditional financial institutions do not serve. One of the most prominent examples is the implementation of mobile payment and banking services in Kenya (Jack and Suri, 2014; Suri and Jack, 2016). Moreover, Jagtiani and Lemieux (2018) find that consumer-lending activities on the platform LendingClub have penetrated areas that may be underserved by traditional banks, mostly in highly concentrated markets and areas that have had fewer bank branches. For example, risky start-up firms and consumers who lack credit history often do not obtain access to credit, especially if the desired loan amounts are small and associated with high transaction costs (Demos, 2016; Hayashi, 2016). Fintech start-up often use novel, sometimes algorithm-driven technology to assess borrowers' creditworthiness at lower costs, which has been an advantage over traditional banks that operate physical branches and employ human loan officers (Hayashi, 2016).

Finally, existing financial institutions can acquire fintech start-ups perceived as "too" innovative and cost-effective. In this way, incumbent institutions gain access to new technology and can adapt it to their own specific needs. For example, Capital One, one of the largest banks in the U.S. in total assets and market capitalization, acquired the fintech start-up Level Money in 2015. Level Money was a San Francisco–based digital banking technology firm that provided customers with a simple overview of their finances. With more than 800,000 downloads, the Level Money app connects to 250 U.S. financial institutions (Li et al., 2017). After its acquisition, Level Money became part of Capital One's Digital Innovation Team, which enables the bank to strengthen its capabilities in digital banking technologies (High, 2016).

With the acquisition of fintech start-ups, financial institutions might not only obtain new retail customers but also extend their existing business through fintech corporate clients. Some of the more traditional financial institutions have realized the potential that stems from the emergence of fintech start-ups and have specialized in what is called "banking as a service" (BaaS) or "banking as a platform" (BaaP). In the BaaS business models, financial institutions operate a licensed and regulated banking back end and offer BaaS middleware to fintech start-ups that cannot or do not want to incur the costs of being fully regulated themselves. In other cases, financial institutions might offer regulatory advice or technology to fintechs that have not yet acquired the respective knowledge or find doing so not cost-efficient. In either case, the division of value creation between fintechs and banks might ultimately benefit both. Overall, we therefore conjecture that financial institutions will not go down without a fight or without any attempt to improve their business models after the emergence of fintech start-ups. We therefore hypothesize the following:

H1. Fintech start-up formations are positively related to traditional financial institutions' performance.

Extensive theoretical and empirical research has investigated the determinants of the default risk of financial institutions, because financial stability is of utmost importance for the economy and financial supervisory authorities. Finance scholars have examined the default risk of financial institutions mostly from two perspectives. The first stream of literature focuses on financial institutions' characteristics, including their size (Saunders et al., 1990; Laeven and Levine, 2009; Afonso et al., 2014), liquidity (Diamond and Dybvig, 2000; Diamond and Rajan, 2012), diversification of funding activities (Demirgüç-Kunt and Huizinga, 2009), bank capital as a share of risk-weighted credit exposures (Furlong and Keely, 1989), and corporate governance (Agoraki et al., 2010; Chen et al., 2017). The second stream of literature focuses on the determinants of risk-taking that results from external sources, such the degree of bank competition (Boyd and De Nicolò, 2005; Beck et al., 2006; Beck et al., 2013), monetary policy (Borio and Zhu, 2012; Chen et al., 2017), deposit insurance schemes (Demirgüç-Kunt and Detragiache, 2002; Angkinand and Wihlborg, 2010), external regulation (Barth et al., 2004; Klomp and De Haan, 2012) such as creditor and minority shareholder protection (La Porta et al., 2000; Houston et al., 2010), and political institutions (Chen et al., 2015; Ashraf, 2017; Wang and Sui, 2019).

In this study, we investigate the default risk of financial institutions following the emergence of fintech start-ups. Fintechs' impact on the default risk of financial institutions is not clear per se. Several factors could lead to an increase in the default risk in the financial industry. Fintech start-ups often provide similar financial products and services to those of incumbents (Dorfleitner et al., 2017; Yao et al., 2018; Kommel et al., 2019), and in some cases, their business models are inherently linked to traditional financial institutions. For example, in many jurisdictions commercial loans can only be extended by institutions that possess a banking license. Marketplace lending platforms, for example, often do not possess a banking license, and a bank in the background ultimately extends the loan between the borrower and the lenders (Cumming and Hornuf, 2020). Thus, banks are often an integral part of fintech business models. However, start-ups generally fail more often than established firms (Evans, 1987; Dunne et al., 1989; Cressy, 2006), which could increase the risk of firms that collaborate with them.

Buchak et al. (2018) provide empirical evidence in the U.S. that the shadow bank market share in residential mortgage origination almost doubled from 2007 to 2015. The increase in shadow banks came with a dramatic growth in online fintech lenders, technological advantages, and regulatory differences among U.S. counties. In other cases, banks and fintechs cooperate closely to benefit both parties (Romānova and Kudinska, 2016, Hornuf et al., 2020). As a result of these interconnections, the risks resulting from fintech formations could spill over to individual financial institutions (European Banking Authority, 2017; He et al., 2017). Moreover, banks themselves are actively involved and participate in the development of fintech technology (Acar and Çıtak, 2019), which might result in increasing legal and technical risks, such as data security risk,[1] data privacy risk, and transaction risk, which could increase financial institutions default risk (IBM Corporation, 2020; Yadron et al., 2014).

Conversely, fintechs could also lower the default risk of financial institutions. The digitalization of lending activities likely lowers transaction costs and improves the efficiency of the loan origination and maintenance processes (BIS, 2017). This could reduce the costs of capital for borrowers and improve the risk-adjusted returns for fintechs and traditional financial institutions. Moreover,

[1] An example is the massive data breach at JP Morgan (https://www.theguardian.com/business/2014/oct/02/jp-morgan-76m-households-affected-data-breach).

because fintech start-ups employ modern technology and use big data, at least theoretically, they can better address information asymmetries (Lin et al., 2013; Ge et al., 2017; Xu and Chau, 2018). Ecosystems that promote the sharing of data can further enable the development of novel products and services. The European Banking Authority (2019) expects a positive effect of application programming interfaces, which allow for a more direct exchange of data, leading to increased competitive pressure and improved customer experiences. We therefore hypothesize the following:

H2a. Fintech start-up formations decrease financial institutions' default risk.

Traditional financial institutions invest in fintech start-ups, which allows them to better access their knowledge (Lee and Shin, 2018, Hornuf et al., 2020). As fintechs grow larger and become more integrated and interconnected with the financial sector, they may also affect systemic risk. A prominent example is the German payment acquirer Wirecard, which in 2020 collapsed and subsequently filed for default because of a series of fraudulent accounting activities and inflated profits. Although Wirecard had been part of the Prime Standard, the market segment of the Frankfurt Stock Exchange with the highest transparency standards, it was itself considered a fintech company. Wirecard not only collaborated with other fintech start-ups, such as Holvi, Lendico, Number 26 (now N26), Rate Pay, and Zencap,[2] but also engaged in alliances with large financial conglomerates such as the insurance company Allianz (Reuters, 2020). To offer lending services, Wirecard operated the subsidiary Wirecard Bank, which had a banking license and was fully regulated and monitored by the Federal Financial Supervisory Authority (*Bundesanstalt für Finanzdienstleistungsaufsicht* [BaFin]). Wirecard was not classified as a financial holding company, and only the subsidiary had been classified as a financial company by BaFin, which

[2] See http://ir.wirecard.de/download/companies/wirecard/Presentations/WDIInvestorPresentationQ22015_01.pdf.

implied that the holding company's activities were supervised only loosely, and accounting fraud remained undetected (Navaretti et al., 2020).

Although bank–fintech collaborations have been rapidly growing in many economies, related supervision has developed only slowly, as the Wirecard case evidences. After the collapse of Wirecard, the German legislator proposed a draft law to strengthen financial market integrity (*Finanzmarktintegritätsstärkungsgesetz*), targeting a wide range of financial market regulations. While the Wirecard accounting scandal did not affect the German or European financial system as such, it raised questions about how financial subsidiaries of tech companies can seamlessly continue operating after a holding company files for default and how business partners can seamlessly switch their operations to another institution. Without doubt, as fintechs become more mature and interconnected, concerns about market risk and systematic risk rise. However, it should be noted that the collapse of Wirecard did not result in a financial turmoil comparable to the collapse of Lehman Brothers in 2008.

Moreover, having access to alternative financial products such as marketplace or mobile loans, which, to a lesser degree, are correlated with other loans and institutions, can reduce systemic risk in the financial industry (BIS, 2017). A greater share of fintech credit through marketplace loans or mobile loans could thus mitigate problems of too-big-to-fail or too-systemic-to-fail institutions. Marketplace lending platforms operated by fintechs have minimal direct financial exposure to each other, a systemic benefit that might disappear if fintechs become more interconnected over time (BIS, 2017). Furthermore, the use of biometric information and other enhanced data security measures that fintechs implemented early on are considered to have improved data security, potentially lowering the risk of cyber-attacks. Finally, systemic risk could also be reduced through enhanced market transparency, which could result from the more extensive use of cloud computing and decentralization (European Banking Authority, 2017). We therefore hypothesize the following:

H2b. The exposure of traditional financial institutions to systemic risk is negatively related to fintech start-up formations.

3. Data and method

3.1. Dependent variables

To investigate whether fintech start-up formations affect incumbent institutions' performance and default risk, we consider eight dependent variables. For most of these variables, we need daily stock returns as a basis. For U.S. financial institutions, we obtained daily stock returns from the Center for Research in Security Prices (CRSP) US Stock Database, and for all other countries, we used the Compustat World Database. Because fintechs might affect not only the business models of banks but also those of other financial institutions, we extract 8,092 financial institutions[3] from 87 countries with Standard Industrial Classification codes starting with 60 to 67 during the period 2005–2018 (for an overview, see Table A1 in the Appendix). For each listed financial institution, we collect adjusted prices or adjustment factors, the number of shares outstanding, the location of the headquarters, and calculated annual returns.[4] With adjusted prices and number of shares outstanding, we can compute market valuation.

[3] Because of data limitations with our explanatory variables and given that we use a lag of one year, our sample reduces to the period 2006–2018, covering only 6,406 financial institutions.
[4] For the Compustat World Database, we compute returns by considering adjustment factors according to the guidelines from Compustat manuals.

We use returns and market valuation of financial institutions to compute value-weighted market return indices of the financial sector of each country. Because we need yearly financial institution–level variables to assess the impact of fintech formation on financial institutions' performance, we collapsed all daily firm data to yearly data. To test hypothesis 1, and in line with Phan et al. (2020), we calculate the net interest margin, return on assets (ROA), return on equity (ROE), and Tobin's Q as measures of financial institutions' performance. Tobin's Q traditionally measures the sum of the market value of equity and the book value of liabilities divided by the book value of total assets. We compute financial institutions' performance also with a market measure. We chose to analyze annual stock returns because stock prices better reflect current information about and expectations of firms' future profitability and growth (Anilowski et al., 2007).

To test hypothesis 2a, we use accounting and market measures of risk in our analysis. The first measure of financial institution default risk is the Z-score of each financial institution, which equals the ROA plus the capital-asset ratio divided by the standard deviation of the ROA. The Z-score thus measures the number of standard deviations below the mean by which profits would have to fall to deplete the financial institution's equity capital completely (Boyd et al., 2006). The measure has a long tradition in the finance literature (Roy, 1952) and is still used in empirical research to capture a financial institution's distance from default (Laeven and Levine, 2009; Pathan, 2009; Houston et al., 2010, Jin et al., 2013; Bhagat et al., 2015). A higher Z-score value indicates a lower default risk and greater stability of the respective financial institution. Because the Z-score is often highly skewed, we follow Laeven and Levine (2009) and use the natural logarithm of the Z-score in our estimations. Our second measure of financial institution default risk is the volatility of stock returns, which has been widely used in prior research (Pathan, 2009; Sun and Liu, 2014; Brown et al., 2015). It captures the market's perception of the risk inherent in banks' assets, liabilities, and off-balance-sheet positions (Pathan, 2009).

To test hypothesis 2b, we consider the marginal expected shortfall, which captures a financial institutions' exposure to systemic risk. It measures the average of individual stock returns on a subset of sample days that correspond with the 5% worst days of the equally weighted market index.

3.2. Explanatory variables

The data source for our explanatory variable of interest is the CrunchBase database, which contains detailed information on fintech start-up formations and their financing. The database is assembled by more than 200,000 company contributors, 2,000 venture partners, and millions of web data points[5] and has recently been used in scholarly articles (Cumming et al., 2016; Bernstein et al., 2017; Haddad and Hornuf, 2019). We retrieved the data for our analysis on July 9, 2019. Because CrunchBase might collect some of the information with a time lag, the observation period in our sample ends on December 31, 2018. Overall, we identified 12,549 fintech start-ups from 87 countries for our relevant sample period.

To account for financial institution and cross-country heterogeneity, we consider several variables frequently used as controls in the bank performance literature (Agoraki et al., 2011; Tabak et al., 2012; Phan et al., 2020). Following Pathan and Faff (2013), Shaban and James (2018), Dietrich and Wanzenried (2014) and Berger et al. (2017), we control for total assets as a measure of average firm size, the capital ratio, the cost income ratio, the interest income margin, and the book-to-market ratio. All variables came from the CRSP and Compustat databases. To address country-

[5] See https://about.crunchbase.com.

time-specific heterogeneity, we consider several macroeconomic indicators. We control for gross domestic product (GDP), because it might influence bank performance through the business cycle. When the economy faces a recession or an economic crisis, the quality of borrowers deteriorates, which in turn worsens banks' loan portfolio and affects their performance. On the loan demand side, borrowers are less willing to invest in long-term projects in times of crisis and often cut spending. Not surprisingly, the empirical literature shows that economic growth also stimulates the financial system (Athanasoglou et al., 2008; Albertazzi and Gambacorta, 2009). We also account for inflation as a measure of financial institutions' performance, because research shows a positive relationship between inflation and profits (Kasman et al., 2010; Trujillo-Ponce, 2013). However, if inflation is anticipated and financial institutions fail to adjust their interest rate, costs can increase faster than profits, which negatively affects bank performance. Therefore, the effect of inflation on bank performance is ambiguous.

To control for the extent to which countries' political decisions affect bank performance, we include the variable *size of government*, which combines five components: government consumption, transfers and subsidies, government enterprises and investment, top marginal tax rate, and state ownership of assets. The variable ranges from 0 to 10, with higher values indicating that countries rely more on personal choice and markets rather than government budgets and political decision-making. To control for differences in the efficiency of legal protection and enforcement of laws across economies, we consider the variable *legal protection* curated by the Fraser Institute database. It entails several legal system components, including rule of law, security of property rights, an independent and unbiased judiciary, and impartial and effective enforcement of the law. These components are indicators of how effectively the protective functions of the legal system are performed. The variable ranges from 0 to 10, with higher values indicating better government efficiency in terms of legal protection.

Finally, we control for the impact of the concentration of banks on bank performance. Empirical research still shows ambiguous results for this variable. In the European context, Delis and Tsionas (2009) find that firms with market power tend to operate inefficiently, because managers enjoy monopoly profits. Maudos and De Guevara (2007) find no evidence of a significant relationship between firm concentration and performance. The measure came from the World Bank database and reflects the sum of market share in terms of total assets of the three largest banks. Table A2 in the Appendix provides definitions of all variables and their sources.

3.3. Model specifications

Our empirical approach is motivated by recent research estimating determinants of bank performance (Köster and Pelster, 2017; Shaban and James, 2018; Phan et al., 2020). To test our hypotheses, we use a two-step generalized method of moments (GMM) system dynamic panel estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). This approach allows us to treat the explanatory variables as endogenous using their past values as instruments (Wintoki et al., 2012). First differences help eliminate time-invariant unobserved heterogeneity and, thus, omitted variable bias. Regarding the lagged explanatory variables of the dependent variable, determining the correct number of lags is important to sufficiently capture the past. We argue that older lags are more likely to be exogenous with respect to the residuals of the present and therefore should be valid instruments. We follow Wintoki et al. (2012) and include two lags to capture the persistence of performance of financial institutions. Our baseline regression model is

$$PER_{i,t} = \alpha + \beta_1\, FINTECH_{c,t-1} + \beta_2 PER_{i,t-1} + \beta_3 PER_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t},$$

where *PER* represents one of five different dependent variables: net interest margin, ROA, ROE, Tobin's Q, and annual stock return. Analogously, we estimate a two-step GMM system dynamic panel model to test hypotheses 2a and 2b:

$$RISK_{i,t} = \alpha + \beta_1\, FINTECH_{c,t-1} + \beta_2 RISK_{i,t-1} + \beta_3 RISK_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t},$$

where *RISK* represents one of three different dependent variables: Z-score, stock return volatility, and marginal expected shortfall. We use year dummies in all models to account for business cycle effects. In addition, we use heteroskedasticity-robust standard errors clustered at the financial institution level.

4. Results

4.1. Benchmark model

Table 1 reports the baseline regression.[6] Columns represent the five dependent variables measuring performance: net interest margin, ROA, ROE, Tobin's Q, and annual stock return. We find that sector-specific and macro-level variables have an economically meaningful and statistically significant impact on financial institutions' performance. The control variables that are significant performance predictors in three models are lagged *cost income ratio* and *market-to-book ratio*.

[6] Table A3 reports summary statistics and Table A4 a correlaction matrix.

Inflation and *bank concentration* are statistically significant in two of the five models, while the *interest income margin* is significant in one model.

--- Table 1 About Here ---

4.2. Lag effect of fintech start-up formations on bank performance and risk-taking

In Table 2, we examine whether fintech formations positively affect the performance of financial institutions. In four of the five models, the coefficient of fintech is statistically different from zero. The number of fintech start-up formations in a country positively predicts *net interest margin*, *ROA*, *ROE*, and *annual stock returns* of traditional financial institutions. The coefficients imply that 10 extra fintech firms entering the market in a given year increase financial institutions' *net interest margin* by 1.7%, ROA by 34.6%, ROE by 8.1%, and annual stock returns by 78.9% of the mean value. This is in line with Hypothesis 1 that fintech start-up formations are positively related to traditional financial institutions' performance. For Indonesia, Phan et al. (2020) find that net interest margin changes by 5.3%, ROA by 93.2%, and ROE by 27.3% for 10 extra fintech start-ups entering the market.

--- Table 2 About Here ---

Next, we test whether the effect of fintech start-up formations on financial institutions' performance differs for large and small institutions. Recent research suggests that financial characteristics of institutions are important predictors of their performance (Dietrich and Wanzenried, 2011; Köster and Pelster, 2017; Talavera et al., 2018). We treat the market value of a financial institutions as a proxy to differentiate large, universal financial institutions from small, specialized financial institutions. On the one hand, we expect large financial institution to adapt their business models at a slower rate than small financial institution, which presumably have already specialized in business models such as BaaP and BaaS. On the other hand, large financial institutions often have deeper pockets and can more forcefully pursue change through acquisitions and in-house experimentation. Our results show a positive and significant association between the formation of fintech start-ups and large financial institutions' performance. The results in Table 3 show that for financial institutions with above-median market value, fintech start-up formations have a positive and robust effect on three of the five measures for financial institutions' performance—ROA, ROE, and annual stock return. For financial institutions with below-median market value, we do not observe any significant association between fintech formations and financial institutions' performance. Large financial institutions might benefit from alliances with fintechs, for example, through product-related corporations or partial acquisitions of fintechs, which help them gain specialized knowledge and improve their performance (Hornuf et al., 2020). This result does not necessary imply that small financial institutions are reluctant to change. Indeed, these institutions might already possess a more modern IT infrastructure and thus benefit only at the margin from fintech start-ups.

--- Table 3 About Here ---

Recent research posits a non-linear relationship between fintech formations and the behaviors of financial institutions over time (Wang et al., 2021). The relationship is explained by the initial threat that fintech start-ups posed to traditional financial institutions, especially during and shortly after the 2007–2008 financial crisis, which later sparked more cooperative business relations. We suspect that fintechs put more pressure on incumbent institutions during the first wave of their formations, while later this pressure relaxed as traditional financial institutions acquired fintechs and adapted their business models. Acquisitions and alliances, however, may not unfold their full value, if incumbent institutions simply eliminate an unpopular competitor from the market. A recent event study shows that at least in the short run, the market perceives announcements of bank–fintech alliances negatively (Hornuf et al., 2020). In a next step, we therefore divide our sample into two subsamples and test whether the development of fintech start-ups has a differential impact on financial institutions' performance for the periods 2005–2011 and 2012–2018.

The results in Table 4 show that fintechs positively affect bank performance during the 2005–2011 period for ROA and ROE. During the 2012–2018 period, however, the impact of fintech start-up formations on financial institutions' performance is only positive and significant at conventional levels for Tobin's Q. For net interest margin, ROA, and ROE, we still find a positive, but only weakly significant, association between fintech start-up formations and financial institutions' performance. Thus, the pressure resulting from fintech start-ups following the financial crisis appears to have vanished over time potentially as a result of more cooperative business models, though the positive association between performance and fintech formations has not entirely disappeared in recent years.

--- Table 4 About Here ---

In Table 5, we test whether fintech start-up formations predict the default risk of financial institutions. The columns report estimates for our dependent variables of interest—Z-score, stock return volatility, and marginal expected shortfall.

Fintech start-up formations have a negative and statistically weak significant effect on the accounting measure Z-score. If this result stems from a lack of statistical power, it would indicate that fintech start-ups are associated with a higher probability of default of financial institutions. However, the results we obtain for the Z-score are weakly significant and thus should be interpreted with caution. First, the Z-score computation is based on accounting data, which are only as good as the underlying accounting and auditing framework. The case of Wirecard constitutes a recent example that accounting measures might not reflect the actual situation of a financial institution. Second, if financial institutions are able to smooth out the reported data, the Z-score provides an overly positive assessment of the financial institution's stability.

Using a market measure for our dependent variable, we find that the development of the fintech sector has decreased financial institutions' stock return volatility. This is in line with Hypothesis 2a that fintech start-up formations decrease financial institutions' default risk.

Finally, the stock return volatility assesses each financial institution separately, neglecting that a default of one financial institution may cause losses to other financial institutions in the system. During the 2007–2008 financial crises, it became evident that many financial institutions were interconnected and market contagion occurred as a domino effect. Using the marginal expected shortfall as our dependent variable, we capture the effect of fintech formations on financial institutions' exposure to systemic risk. We find that the development of fintech start-ups decreases incumbents' exposure to systemic risk, which is in line with Hypothesis 2b. Not only does the spread of fintechs result in more competition and better performance of traditional financial institutions, but it also increasingly diversifies the use and execution of financial services over different market players. In this sense, the rise of fintechs might, to some degree, counteract the too-systemic-to-fail problem.

--- Table 5 About Here ---

To test the robustness of our results, we calculate the number of fintechs founded per year and country and divide them by the total number of start-ups founded during that year in the respective economy as an alternative measure of fintech start-up formations. The data for start-up formations came from the Crunchbase database. As Table 6 reports, the results are similar to previous findings that fintech formations positively predict bank performance. With regard to default risk, we also find that fintech start-up formations negatively affect financial institutions' default risk, as indicated by the decrease in stock return volatility.

--- Table 6 About Here ---

5. Discussion and conclusion

The article investigates whether fintech start-up formations affect financial institution' performance and default risk. We evidence that fintech start-up formations improve financial institutions' performance in terms of accounting and market measures. These findings are in line with previous research (Vives, 2019) that posits that banks rethink and reshape their business model when confronted with competitive pressure. One potential way for financial institutions to improve performance when confronted with fintechs is by cooperating with and integrating the new players in their organization (Hornuf et al., 2020). Moreover, we use the marginal expected shortfall as a measure of systemic risk and find that financial institutions' exposure to systemic risk decreases when more fintech start-ups enter the market. This finding sheds light on how financial institutions can benefit from technology spillovers when confronted with novel technological solutions developed by fintechs (Blalock and Gertler, 2008; Newman et al., 2015).

Technological improvements and new business models improve the efficiency of risk management and consequently reduce default risk. For example, the Industrial and Commercial Bank of China intercepted approximately 900,000 risky transactions by employing digital technology in 2018, which significantly reduced its credit risk (Cheng and Qu, 2020). Moreover, blockchain technology and cloud computing cater to decentralized, real-time transactions, which could improve financial institutions' risk management and reduce their contribution to systemic risk.

Our analysis has some clear limitations. While we find evidence that fintech start-ups have a positive effect on financial institutions' performance, the same might not hold for large technology companies such as Alibaba, Alphabet (Google), Amazon.com, Apple, Facebook, Microsoft, and Tencent, all of which have begun to implement financial services and offer them to their customers. These companies not only are interconnected with large parts of the real economy but are themselves systemically relevant as well. For example, Amazon operates its own payment service (Amazon Pay), lending business (Amazon Lending), and cloud computing business (Amazon Web Services). Although these services are operated by formally independent companies, no one can foresee how a default of one will affect the others. Thus, fintech services offered by large technology companies might negatively affect financial institutions' performance, not least because of their sheer size and market power, and could also negatively affect systemic risk.

When comparing the 2005–2011 and 2012–2018 periods, we find that the pressure from fintech start-ups on financial institutions' performance has somewhat vanished, though the positive association has not yet entirely disappeared. Future research might thus investigate whether this association has completely disappeared by now and the impact of large technology companies on financial institutions' performance and default risk. Moreover, whereas we investigate the overall effect of fintech start-up formations on the performance and default risk of incumbent financial institutions, information systems and finance scholars might disentangle in more detail the channels through which fintechs influence the performance and default risk of incumbents. Such research should most likely be based on case studies and/or experimental interventions on individual branches of financial institutions.

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Table 1. Determinants of financial institution performance.

	(1)	(2)	(3)	(4)	(5)
	NIM	ROA	ROE	Tobin 's Q	RETURNS
$Performance_{t-1}$	0.417***	-0.011	0.045	0.234**	-4.546**
	(5.10)	(-0.14)	(0.68)	(2.40)	(-2.31)
$Performance_{t-2}$	0.087**	-0.106	-0.104†	0.042†	-0.270**
	(2.44)	(-1.55)	(-1.81)	(1.81)	(-2.20)
Size	-0.360	8.272***	11.04***	0.019	-0.202**
	(-1.07)	(3.05)	(3.14)	(0.25)	(-2.52)
Capital ratio	-0.029**	0.255**	0.287	0.006†	-0.015†
	(-2.07)	(2.33)	(1.64)	(1.76)	(-1.92)
Cost income ratio	-0.009	-0.146**	-0.342***	-0.001	-0.024***
	(-1.44)	(-2.25)	(-4.01)	(-0.82)	(-2.58)
Interest income margin	0.036**	0.107	0.057	-0.0003	0.006
	(2.01)	(1.05)	(0.35)	(-0.13)	(0.50)
Market-to-book ratio	0.220	10.23***	11.47***	0.357***	0.514
	(1.28)	(3.58)	(4.17)	(5.49)	(1.54)
GDP growth	0.034	-0.069	0.782	0.001	0.200†
	(0.83)	(-0.19)	(1.29)	(0.10)	(1.69)
Inflation	0.045	0.679**	0.538	-0.016	0.219†
	(1.54)	(2.30)	(1.15)	(-1.17)	(1.89)
Size of government	-1.356**	14.35***	9.433	0.152	0.459
	(-2.13)	(3.65)	(1.61)	(1.31)	(1.52)
Legal protection	-1.242***	2.977	-1.245	0.023	0.701**
	(-3.17)	(1.14)	(-0.28)	(0.31)	(2.15)
Bank concentration	0.021†	0.100	0.321†	0.002	-0.014
	(1.84)	(0.99)	(1.92)	(0.90)	(-0.63)
Constant	24.23**	-291.4***	-282.0***	-1.833	-0.989
	(2.51)	(-3.74)	(-2.85)	(-0.76)	(-0.26)
Observations	42,442	40,102	40,260	38,639	39,986
Financial institutions	6,406	6,151	6,155	6,043	6,126
Year fixed effects	Included	Included	Included	Included	Included
AR(2)	0.148	0.594	0.467	0.571	0.197
Hansen	0.213	0.449	0.126	0.489	0.458

Notes: This table reports regression results from the bank performance determinants model. The model has the following form:

$$PER_{i,t} = \alpha + \beta_1 PER_{i,t-1} + \beta_2 PER_{i,t-2} + \beta_3 SIZE_{i,t} + \beta_4 CAP_{i,t} + \beta_5 CTI_{i,t} + \beta_6 IIS_{i,t} + \beta_7 MTB_{i,t} + \beta_8 DGP_{c,t} + \beta_9 INF_{c,t} + \beta_{10} POL_{c,t} + \beta_{11} LEGAL_{c,t} + \beta_{12} CONC_{c,t} + \varepsilon_{ic,t}.$$

In this regression, performance respectively represents one of the five different dependent variables: net interest margin (NIM), ROA, ROE, Tobin's Q, and RETURNS. The descriptions of the control variables are noted in Table A2 of the Appendix. The estimation method is the two-step GMM system dynamic panel estimator. Year dummies are included in the model to account for heterogeneity across time. p-values are computed by the heteroskedasticity-robust standard errors clustered for bank level. The Arellano–Bond test for serial correlation is based on the null hypothesis of the second-order autocorrelation in the first differenced residuals. The p-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, †, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2. Lag effect of fintech firm formations on financial institution performance.

	(1)	(2)	(3)	(4)	(5)
	NIM	ROA	ROE	Tobin 's Q	RETURNS
$FINTECH_{t-1} \times 10^{-2}$	0.505**	4.810***	4.063***	-0.009	0.789***
	(1.99)	(2.68)	(3.88)	(-0.68)	(4.18)
$Performance_{t-1}$	0.339***	-0.155	0.037	0.341***	-0.528***
	(2.92)	(-1.39)	(0.59)	(3.71)	(-2.70)
$Performance_{t-2}$	0.089**	-0.137**	-0.100†	0.037	-0.538***
	(2.07)	(-1.97)	(-1.83)	(1.53)	(-4.09)
Size	0.510	8.696	12.23***	-0.041	0.605***
	(0.82)	(1.59)	(3.06)	(-0.59)	(4.69)
Capital ratio	-0.009	0.575***	0.375†	0.002	0.048***
	(-0.54)	(3.23)	(1.91)	(0.71)	(3.27)
Cost income ratio	-0.015†	-0.202***	-0.341***	-0.001	-0.010**
	(-1.83)	(-3.18)	(-4.10)	(-1.32)	(-2.38)
Interest income margin	0.073***	-0.047	0.080	-0.003	-0.025**
	(2.88)	(-0.38)	(0.48)	(-1.42)	(-2.04)
Market-to-book ratio	0.291	8.881***	12.40***	0.299***	0.842***
	(1.09)	(2.58)	(4.08)	(5.22)	(3.97)
GDP growth	0.042	-0.067	0.410	0.004	0.056
	(0.80)	(-0.15)	(0.73)	(0.36)	(1.52)
Inflation	0.097**	0.275	0.273	-0.026**	0.014
	(2.57)	(0.59)	(0.58)	(-2.09)	(0.39)
Size of government	0.038	12.34†	7.829†	-0.007	0.999***
	(0.05)	(1.81)	(1.84)	(-0.11)	(2.88)
Legal protection	-0.454†	-1.735	-5.402**	-0.103**	0.313†
	(-1.65)	(-0.72)	(-2.23)	(-2.42)	(1.70)
Bank concentration	0.013	0.241**	0.401***	0.004***	0.010†
	(0.94)	(2.04)	(2.90)	(2.58)	(1.68)
Constant	-8.483	-271.5†	-275.9***	-23.06***	1.402
	(-0.58)	(-1.90)	(-3.05)	(-4.25)	(0.97)
Observations	42,442	40,102	40,260	38,639	39,986
Financial institutions	6,406	6,151	6,155	6,043	6,126
Year fixed effects	Included	Included	Included	Included	Included
AR(2)	0.11	0.90	0.51	0.09	0.41
Hansen	0.47	0.59	0.21	0.1	0.12

Notes: This table reports regression results from the bank performance determinants model augmented with the FINTECH variable. The regression model has the following form:

$$PER_{i,t} = \alpha + \beta_1 FINTECH_{c,t-1} + \beta_2 PER_{i,t-1} + \beta_3 PER_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t}.$$

In this regression, performance respectively represents one of the five different dependent variables: net interest margin (NIM), ROA, ROE, Tobin's Q, and RETURNS. The descriptions of the control variables are noted in Table A2 of the Appendix. The estimation method is the two-step GMM system dynamic panel estimator. Year dummies are included in the model to account for heterogeneity across time. p-values are computed by the heteroskedasticity-robust standard errors clustered for bank level. The Arellano–Bond test for serial correlation is based on the null hypothesis of the second-order autocorrelation in the first differenced residuals. The p-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, †, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Lag effect of fintech firm formations on financial institution performance sorted by financial institution market value.

	NIM	ROA	ROE	Tobin's Q	RETURNS
High market value					
$FINTECH_{t-1} \times 10^{-2}$	0.007	1.186**	2.215**	0.585	0.208†
	(0.05)	(2.34)	(2.42)	(1.62)	(1.80)
Constant	-8.565	-60.96**	-60.88	-18.28	-4.258
	(-1.01)	(-2.17)	(-1.44)	(-1.46)	(-1.00)
AR(2)	0.166	0.667	0.175	0.403	0.527
Hansen	0.201	0.191	0.147	0.320	0.185
Low market value					
$FINTECH_{t-1} \times 10^{-2}$	-0.149	-0.400	0.790	-0.107	1.105
	(-0.04)	(-0.50)	(0.51)	(-0.27)	(0.30)
Constant	9.909	12.21	-172.6	10.44†	-15.92
	(0.13)	(0.23)	(-1.62)	(1.81)	(-0.31)
AR(2)	0.803	0.868	0.869	0.645	0.731
Hansen	0.718	0.574	0.601	0.688	0.90

Notes: The table reports regression results of the lagged effect of FINTECH firms on financial institutions' performance for samples sorted by financial institutions' market value. High market value contains the top-half financial institutions with the highest market value, while low market value includes the bottom-half financial institutions with the lowest market value. These categorizations are based on the median market values. The regression model takes the following form:

$$PER_{i,t} = \alpha + \beta_1 FINTECH_{c,t-1} + \beta_2 PER_{i,t-1} + \beta_3 PER_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t}.$$

In this regression, performance respectively represents one of the five different dependent variables: net interest margin (NIM), ROA, ROE, Tobin's Q, and RETURNS. The descriptions of the control variables are provided in Table A2 of the Appendix. The estimation method is the two-step GMM system dynamic panel estimator. Year dummies are included in the model to account for heterogeneity across time. p-values are computed by the heteroskedasticity-robust standard errors clustered for bank level. The Arellano–Bond test for serial correlation is based on the null hypothesis of the second-order autocorrelation in the first differenced residuals. The p-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, †, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Lag effect of fintech firms on financial institution performance sorted by year.

	NIM	ROA	ROE	Tobin's Q	RETURNS
2005-2011					
$FINTECH_{t-1} \times 10^{-2}$	-2.809	1.281**	5.174***	0.098	-0.002
	(-0.72)	(2.18)	(3.29)	(0.56)	(-0.08)
Constant	35.43	-28.38	-229.0**	14.92***	-1.705
	(0.43)	(-0.53)	(-2.33)	(3.52)	(-0.49)
AR(2)	0.756	0.90	0.0904	0.465	0.561
Hansen	0.752	0.284	0.236	0.558	0.281
2012-2018					
$FINTECH_{t-1} \times 10^{-2}$	0.0537†	2.799†	7.153†	0.409**	-0.0819
	(1.90)	(1.68)	(1.76)	(1.97)	(-0.80)
Constant	-2.650	-32.02†	-15.67	3.373	0.686
	(-0.79)	(-1.68)	(-0.32)	(0.13)	(0.23)
AR(2)	0.345	0.0985	0.831	0.175	0.500
Hansen	0.138	0.400	0.193	0.390	0.142

Notes: The table reports regression results of the lag effect of FINTECH firms on bank performance for panels divided into two subsamples by year. The regression model takes the following form:

$$PER_{i,t} = \alpha + \beta_1 FINTECH_{c,t-1} + \beta_2 PER_{i,t-1} + \beta_3 PER_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t}.$$

In this regression, performance respectively represents one of the five different dependent variables: net interest margin (NIM), ROA, ROE, Tobin's Q, and RETURNS. The descriptions of the control variables are noted in Table A2 of the Appendix. The estimation method is the two-step GMM system dynamic panel estimator. Year dummies are included in the model to account for heterogeneity across time. p-values are computed by the heteroskedasticity-robust standard errors clustered for bank level. The Arellano–Bond test for serial correlation is based on the null hypothesis of the second-order autocorrelation in the first differenced residuals. The p-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, †, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Lag effect of fintech firms on bank risk-taking.

	(1)	(2)	(3)
	Ln Z-score	Volatility	Marginal expected shortfall
$FINTECH_{t-1} \times 10^{-2}$	-0.088†	-0.434***	0.260**
	(-1.69)	(-2.84)	(2.13)
$RISK_{t-1}$	0.916***	-0.278***	-1.259
	(9.19)	(-4.25)	(-0.83)
$RISK_{t-2}$	0.024	-0.133	0.884
	(0.34)	(-0.62)	(0.54)
Size	-0.015	0.308	0.845
	(-1.13)	(0.33)	(1.46)
Capital ratio	-0.0007	-0.057	-0.015
	(-0.66)	(-1.07)	(-0.62)
Cost income ratio	-0.001†	0.002	-0.014***
	(-1.82)	(0.24)	(-2.80)
Interest income margin	-0.0006	-0.028	0.043**
	(-0.54)	(-0.83)	(2.03)
Market-to-book ratio	-0.006	0.117	-0.176
	(-0.18)	(0.29)	(-0.81)
GDP growth	-0.024**	-0.060	0.136**
	(-2.16)	(-0.95)	(2.07)
Inflation	-0.013	0.015	0.021
	(-1.00)	(0.17)	(0.16)
Size of government	-0.025	-0.580	0.313
	(-0.83)	(-0.90)	(1.41)
Legal protection	0.043	0.946***	-0.523
	(0.62)	(2.98)	(-0.57)
Bank concentration	-0.004	0.005	-0.038†
	(-1.54)	(0.32)	(-1.68)
Constant	0.939	-1.831	-14.01**
	(1.51)	(-0.10)	(-2.03)
Observations	38,693	40,419	40,731
Financial institutions	6,062	6,134	6,188
Year fixed effects	Included	Included	Included
AR(2)	0.112	0.904	0.427
Hansen	0.602	0.689	0.469

Notes: This table reports regression results of bank risk-taking model augmented with the FINTECH variable. The regression model has the following form:

$$RISK_{i,t} = \alpha + \beta_1 FINTECH_{c,t-1} + \beta_2 RISK_{i,t-1} + \beta_3 RISK_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t}.$$

In this regression, RISK respectively represents one of the three different dependent variables: Ln Z-score, volatility, and marginal expected shortfall. The descriptions of the control variables are noted in Table A2 of the Appendix. The estimation method is the two-step GMM system dynamic panel estimator. Year dummies are included in the model to account for heterogeneity across time. p-values are computed by the heteroskedasticity-robust standard errors clustered for bank level. The Arellano–Bond test for serial correlation is based on the null hypothesis of the second-order autocorrelation in the first differenced residuals. The p-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, †, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Robustness check. Alternative measure of fintech formation consists on the ratio of the number of fintech founded in a year and country divided by the total number of start-ups founded in a year and country.

I-Lag effect of Fintech firms on bank performance

	(1)	(2)	(3)	(4)	(5)
	NIM	ROA	ROE	Tobin's Q	RETURNS
$FINTECH_{t-1}$	0.027†	0.198**	0.296†	-0.018	0.067†
	(1.73)	(2.02)	(1.80)	(-1.08)	(1.76)
Constant	3.040	-98.17***	-136.5***	4.181***	-0.386
	(1.37)	(-6.55)	(-5.29)	(3.23)	(-0.36)
AR(2)	0.221	0.493	0.193	0.120	0.380
Hansen	0.778	0.142	0.123	0.424	0.316

Notes: This table reports regression results from the bank performance determinants model augmented with the FINTECH variable. The regression model has the following forms: $PER_{i,t} = \alpha + \beta_1 \, FINTECH_{c,t-1} + \beta_2 PER_{i,t-1} + \beta_3 PER_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t}$.

In this regression, performance respectively represents one of the five different dependent variables: net interest margin (NIM), ROA, ROE, Tobin's Q, and RETURNS. The descriptions of the control variables are noted in Table A2 of the Appendix. The estimation method is the two-step GMM system dynamic panel estimator. Year dummies are included in the model to account for heterogeneity across time. p-values are computed by the heteroskedasticity-robust standard errors clustered for bank level. The Arellano–Bond test for serial correlation is based on the null hypothesis of the second-order autocorrelation in the first differenced residuals. The p-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, †, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

II-Lag effect of Fintech firms on bank risk-taking

	(1)	(2)	(3)
	Ln Z-score	Volatility	Marginal expected shortfall
$FINTECH_{t-1}$	0.006	-0.019**	-0.120
	(0.86)	(-2.38)	(-0.32)
Constant	0.699	21.87**	-51.24
	(1.09)	(2.41)	(-0.34)
AR(2)	0.266	0.313	0.741
Hansen	0.311	0.176	0.882

This table reports regression results of the bank risk-taking model augmented with the FINTECH variable. The regression model has the following forms:
$RISK_{i,t} = \alpha + \beta_1 FINTECH_{c,t-1} + \beta_2 RISK_{i,t-1} + \beta_3 RISK_{i,t-2} + \beta_4 SIZE_{i,t} + \beta_5 CAP_{i,t} + \beta_6 CTI_{i,t} + \beta_7 IIS_{i,t} + \beta_8 MTB_{i,t} + \beta_9 DGP_{c,t} + \beta_{10} INF_{c,t} + \beta_{11} POL_{c,t} + \beta_{12} LEGAL_{c,t} + \beta_{13} CONC_{c,t} + \varepsilon_{ic,t}$.

In this regression, RISK respectively represents one of the three different dependent variables: Ln Z-score, volatility, and marginal expected shortfall. The descriptions of the control variables are noted in Table A2 of the Appendix. The estimation method is the two-step GMM system dynamic panel estimator. Year dummies are included in the model to account for heterogeneity across time. p-values are computed by the heteroskedasticity-robust standard errors clustered for bank level. The Arellano–Bond test for serial correlation is based on the null hypothesis of the second-order autocorrelation in the first differenced residuals. The p-value associated with the Hansen test for determining the validity of the overidentifying restrictions is reported. Finally, †, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Appendix

Table A1.
List of countries in the dataset (ranking according to number of fintech start-ups)

World ranking	Country	# Banks	# Fintech started	World ranking	Country	# Banks	# Fintech started	World ranking	Country	# Banks	# Fintech started
1	United States	993	6319	33	Norway	67	40	65	Bulgaria	37	0
2	United Kingdom	803	1601	34	Luxembourg	28	35	66	Cyprus	34	0
3	India	696	541	35	Colombia	19	34	67	Mauritius	28	0
4	Germany	243	321	36	Vietnam	93	31	68	Tunisia	28	0
5	Singapore	129	302	37	Thailand	198	26	69	Qatar	24	0
6	France	128	292	38	Egypt, Arab Rep.	68	24	70	Morocco	23	0
7	Australia	370	289	39	Ghana	11	23	71	Bahrain	22	0
8	Brazil	98	195	40	Portugal	8	22	72	Cayman Islands	21	0
9	Spain	81	173	41	Ukraine	17	18	73	Kenya	20	0
10	Switzerland	104	169	42	Malta	13	18	74	Croatia	17	0
11	Netherlands	48	166	43	Latvia	2	18	75	Zimbabwe	12	0
12	Israel	157	156	44	Peru	28	17	76	Cote d'Ivoire	9	0
13	Hong Kong SAR, China	291	150	45	Hungary	13	17	77	Lebanon	7	0
14	Sweden	102	149	46	Bermuda	26	16	78	Serbia	7	0
15	Ireland	16	124	47	China	437	11	79	Lithuania	6	0
16	Mexico	54	119	48	Uganda	4	11	80	Malawi	6	0
17	Italy	80	115	49	Pakistan	109	10	81	Trinidad and Tobago	6	0
18	Russian Federation	40	104	50	Greece	42	10	82	Czech Republic	5	0
19	South Africa	127	102	51	Iceland	11	10	83	Barbados	1	0
20	Denmark	75	83	52	Slovenia	10	9	84	Belize	1	0
21	Japan	380	71	53	Slovak Republic	6	7	85	Georgia	1	0
22	Belgium	54	64	54	Ecuador	4	4	86	Panama	1	0
23	United Arab Emirates	79	63	55	Zambia	7	3				
24	Nigeria	61	63	56	Namibia	5	2				
25	Poland	176	59	57	Indonesia	168	0				
26	Finland	30	58	58	Korea, Rep.	115	0				
27	Argentina	17	51	59	Jordan	111	0				
28	Estonia	4	51	60	Bangladesh	98	0				
29	Malaysia	161	48	61	Sri Lanka	86	0				
30	Turkey	114	47	62	Philippines	84	0				
31	New Zealand	33	44	63	Saudi Arabia	63	0				
32	Austria	26	44	64	Chile	55	0				

Table A2
List of variables

Variable name	Definition
Dependent variables	
Annual stock return	Annual stock return derived from daily returns using the ascol STATA command. Source: CRSP/Compustat database and own calculation.
Net interest margin	The net interest margin is the ratio of the net interest income to total assets. Source: CRSP/Compustat databases and own calculation.
ROA	The ROA is the ratio of net income to total assets. Source: CRSP/Compustat database and own calculation.
ROE	The ROE is the ratio of net income to total equity. Source: CRSP/Compustat database and own calculation.
Tobin's Q	The sum of the market value of equity plus the book value of liabilities divided by the book value of total assets. Source: CRSP/Compustat database and own calculation.
Z-score	Computed as (ROA + CAR)/STD(ROA), where ROA is earnings before taxes and loan loss provisions divided by assets, CAR represents the capital asset ratio, and STD(ROA) is the standard deviation of ROA over the period studied. Source: CRSP/Compustat database and own calculation.
Volatility	Volatility is the standard deviation of daily stock returns over one year. Source: CRSP/Compustat database and own calculation.
Marginal expected shortfall (MES)	The marginal expected shortfall is the marginal contribution of firm j to the expected shortfall of the financial system. Formally, marginal expected shortfall for firm j is the expected value of the stock return $\tilde{R}_j$ conditional on the market portfolio return $\tilde{R}_M$ being at or below the sample q-percent quantile. Source: CRSP/Compustat database and own calculation.
Explanatory variables	
FINTECH	The number of fintech start-ups founded by year and country. Source: Crunchbase and own calculation
Size	The natural logarithm of total assets in millions of USD. Source: CRSP/Compustat database and own calculation.
Capital ratio	The capital ratio is calculated as the firm's equity over its total assets. Source: CRSP/Compustat database and own calculation.

Cost income ratio	The cost income ratio is total expenses over total generated revenues. Source: CRSP/Compustat database and own calculation.
Interest income margin	The interest income margin is the total interest income over total income. Source: CRSP/Compustat database and own calculation.
Market-to-book ratio	The market-to-book ratio is the market capitalization over the book value. Source CRSP/Compustat database and own calculation.
GDP growth	Country-level annual GDP growth rate. Source: World development indicators database.
Inflation	Country-level annual inflation rate. Source: World development indicators database.
Size of government	Includes five political system measure components: government consumption, transfers and subsidies, government enterprises and investment, top marginal tax rate, and state ownership of assets. The variable ranges from 0 to 10, with higher ratings indicating that country relies more on personal choice and markets rather than government budgets and political decision-making. Source: The Fraser institute database.
Legal protection	Includes nine legal system measure components: rule of law, security of property rights, an independent and unbiased judiciary, and impartial and effective enforcement of the law. The nine components in this area are indicators of how effectively the protective functions of government are performed. The variable ranges from 0 to 10, with higher ratings indicating better government efficiency in terms of legal protection. Source: The Fraser institute database.
Bank concentration	Raw data are from Bankscope. (Sum(data2025) for three largest banks in Bankscope) / (Sum(data2025) for all banks in Bankscope). Only reported if number of banks in Bankscope is 3 or more. Calculated from underlying bank-by-bank unconsolidated data from Bankscope. Source: World development indicators database.

Table A3
Summary statistics.

Variable	Mean	Std. Dev.	Median	Minimum	Maximum
Dependent variables					
Net interest margin	2.84	3.60	1.74	0.00	23.86
ROA	1.32	9.85	1.29	-84.55	31.92
ROE	4.98	21.07	6.89	-185.34	96.49
Annual stock return	0.10	0.49	0.04	-0.99	27.72
Tobin's Q	0.65	1.12	0.35	0.00	13.39
Ln Z-score	2.63	1.14	2.67	-6.47	8.47
Volatility	4.26	207.13	2.15	0.00	47069.74
Marginal expected shortfall	-1.12	1.62	-0.82	-113.22	19.05
Explanatory variables					
FINTECH	67.26	142.27	10.00	0.00	703.00
Size	18.29	4.64	19.10	4.71	26.87
Capital ratio	42.74	32.66	36.23	-30.17	99.83
Cost income ratio	81.52	88.03	78.50	-319.05	1203.72
Interest income margin	37.19	40.56	14.11	-60.60	148.63
Market-to-book ratio	1.52	2.14	0.97	-0.63	27.51
GDP growth	3.55	3.20	2.94	-17.67	26.17
Inflation	3.49	3.46	2.49	-4.86	48.70
Legal protection	6.49	1.44	6.51	2.33	9.14
Size of government	6.72	1.13	6.80	4.09	8.95
Bank concentration	54.53	18.17	52.74	20.85	100.00

Table A4 Correlation matrix.

	NIM	ROA	ROE	RET	Tobin's Q	Ln Z-score	VOL
Net interest margin (NIM)	1.000						
ROA	0.003	1.000					
ROE	0.069	0.707	1.000				
Annual stock return (RET)	0.020	0.184	0.200	1.000			
Tobin's Q	-0.085	-0.030	-0.027	0.019	1.000		
Ln Z-score	0.078	0.245	0.354	0.064	-0.058	1.000	
Volatility (VOL)	-0.002	-0.007	-0.015	0.001	0.005	-0.007	1.000
Marginal expected shortfall (MES)	0.020	0.149	0.145	0.130	-0.067	0.161	-0.008
FINTECH	0.013	-0.024	-0.006	-0.007	-0.114	0.191	-0.003
Size	0.023	0.085	0.086	0.048	-0.062	-0.104	-0.005
Capital ratio	-0.222	-0.103	-0.066	0.004	0.351	-0.057	0.002
Cost income ratio (CTI)	-0.027	-0.198	-0.171	-0.051	0.010	-0.106	0.002
Interest income margin (IIS)	0.632	-0.022	0.050	-0.027	-0.222	0.264	-0.009
Market-to-book ratio	0.005	-0.035	0.006	0.036	0.678	-0.092	0.003
GDP growth	0.078	0.091	0.109	0.060	0.078	0.070	-0.001
Inflation	0.290	0.018	0.028	-0.059	0.029	-0.006	-0.001
Legal protection (LEGAL)	-0.282	-0.045	-0.063	-0.044	0.019	-0.087	-0.002
Size of government	0.150	-0.002	0.003	0.001	0.002	0.089	0.001
Bank concentration (CONC)	-0.127	-0.007	-0.023	-0.010	0.037	-0.174	0.001

	MES	FINTECH	Size	Capital ratio	CTI	IIS	Market-to-book ratio
Marginal expected shortfall (MES)	1.000						
FINTECH	0.025	1.000					
Size	0.084	-0.745	1.000				
Capital ratio	0.028	-0.239	-0.019	1.000			
Cost income ratio (CTI)	-0.102	-0.030	-0.034	-0.116	1.000		
Interest income margin (IIS)	0.050	0.350	-0.218	-0.472	0.091	1.000	
Market-to-book ratio	-0.064	-0.052	-0.040	-0.036	0.046	-0.062	1.000
GDP growth	-0.035	-0.184	0.062	0.057	0.009	-0.037	0.097
Inflation	-0.102	-0.175	-0.009	0.062	0.028	0.091	0.044
Legal protection (LEGAL)	0.018	0.223	-0.066	0.049	-0.055	-0.108	-0.033
Size of government	-0.065	0.143	-0.294	0.078	0.012	0.141	-0.010
Bank concentration (CONC)	0.031	-0.370	0.389	0.096	-0.020	-0.244	-0.017

	GDP growth	Inflation	LEGAL	Size of government	CONC
GDP growth	1.000				
Inflation	0.302	1.000			
Legal protection (LEGAL)	-0.385	-0.517	1.000		
Size of government	0.106	0.296	-0.172	1.000	
Bank concentration (CONC)	-0.162	-0.212	0.315	-0.331	1.000