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Article

Fintech credit, credit information sharing and bank stability: some international evidence

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BANKING & FINANCE | RESEARCH ARTICLE

Fintech credit, credit information sharing and bank stability: some international evidence

Nguyen Thanh Liem^{1,2}, Tran Hung Son^{1,2*}, Ho Huu Tin^{1,2} and Nguyen Thi Canh^{1,2}

Abstract: This study relies on an aggregate dataset of 73 countries from 2013 to 2018 to investigate the nexus between fintech credit, credit information sharing on bank stability. We document several significant findings. First, our evidence implies that fintech credit tends to improve bank stability. This suggests that as fintech credit grows, it certainly competes with banks, but it also strengthens banks' stability. Second, credit information sharing increases bank stability. Thirdly, it is found that the impact of fintech credit on bank stability may depend on credit information sharing. Specifically, the presence of credit information sharing institutions may facilitate the positive effect of fintech credit on bank stability. This result remains unchanged to the introduction of alternative regression, as well as an alternative dependent variable. Finally, policy implications are discussed based on the findings of the research.

Subjects: Finance; Banking; Credit & Credit Institutions

Keywords: fintech; credit information sharing; bank stability

Subjects: F21; G32; Q55

1. Introduction

Although traditional lenders such as banks and other financial intermediaries remain the primary source of funds for borrowers in most markets, new financial institutions have emerged and gained traction recently, including fintech lending models that have evolved in many economies (Cornelli et al., 2020). The establishment and development of fintech has significantly impacted banking systems (Petrulia et al., 2019). Fintech has now become widespread in many financial areas such as credit, deposit, capital-raising, payment, and investment. Fintech firms have been competing with traditional financial firms, thus impacting performance and risk-taking behaviors and stimulating innovations of the latter (An & Rau, 2019; Cheng & Qu, 2020; Guo & Shen, 2016; Qiao et al., 2018; Phan et al., 2020; R. Wang et al., 2020). At the same time, the growth of fintech credit volume has been impressive recently. From around USD 9.9 billion in 2013, the volume has grown to over USD 298 billion in 2018 (Cornelli et al., 2020), a growth rate of over 97% per annum. Indeed, traditional banks have lost their market share in main markets such as residential mortgages to these new competitors (Buchak et al., 2018). While still small overall, fintech credit is now a global phenomenon, and central banks and public authorities have begun to use information on fintech credit volume to observe economic and financial conditions, to guide monetary policy decisions, and to set macroprudential policies, such as the countercyclical capital buffer (Cornelli et al., 2020).

In spite of the development of fintech credit and its perceived significant function towards the banking system, the influences of fintech credit on the financial systems are little understood (Li

et al., 2017; Phan et al., 2020). Particularly, the evaluation of the impact of fintech credit on bank performance in terms of profitability and risk-related performance is under-researched (R. Wang et al., 2020). Lending is a main traditional activity of banks, so it is essential to see the effect of fintech on banks' core activities. Importantly, we could not find empirical studies on the link between fintech credit and bank stability.

Traditionally, banks perform their financial mediation function of channelling funds from lenders to borrowers to support economic activities. Nevertheless, the financial sector does not always operate efficiently when there are high levels of information asymmetry, inflicting damages to the whole economy. Information sharing bureaus are the tools that could be used to reduce information issues in the credit market, such as moral hazard and adverse selection (see, Triki & Gajigo, 2014). The presence of information sharing mechanisms allows banks to alleviate borrowers' moral hazard and boost borrowers' motivations to pay back debt (Jappelli & Pagano, 2002). Information sharing conducted through the constitution of private bureaus and public registries is an enabler to banking system development (Barth et al., 2009). Previous studies show evidence in support of the view that information sharing lowers moral hazard, adverse selections and risk of over-indebtedness, thus curbing bad debts and enhancing banking soundness (Doblas-Madrid & Minetti, 2013; Guérineau & Léon, 2019; Houston et al., 2010; Padilla & Pagano, 2000; Pagano & Jappelli, 1993; Kusi et al., 2017; Jappelli & Pagano, 2002; Vercammen, 1995; Fosu et al., 2020). Furthermore, Jappelli and Pagano (2002), Doblas-Madrid and Minetti (2013), and Fosu et al. (2020) argue that information sharing bureaus aid in reducing delinquency. Padilla and Pagano (2000) report that information sharing can decrease the default rates of borrowers by curtailing the hold-up issues, in addition to boosting borrower discipline. Guérineau and Léon (2019), Houston et al. (2010), and Kusi et al. (2017) provide similar findings.

This study contributes to the current literature in several ways. First, we examine the link between fintech credit and bank stability, using the volume of credit provided by fintech firms, composed by Cornelli et al. (2020), as a measure of fintech credit. This helps expand considerably the literature examining the competition between fintech lenders and financial intermediaries since previous related studies use more general proxies for fintech (R. Wang et al., 2020; Y. Wang et al., 2021; Phan et al., 2020; Lee, 2015; Cheng & Qu, 2020). As a consequence, the particular influence of fintech lenders on the bank stability cannot be uncovered. Secondly, fintech credit firms use their models and algorithms to extract information from various sources, and the information is considered quite useful in assessing the creditworthiness of customers (Berg et al., 2020; Frost et al., 2019). Meanwhile, traditional banks could be more dependent on the information sharing bureaus to reduce information issues in the credit market. Furthermore, Kowalewski and Pisany (2021) argue that traditional credit data from information sharing bureaus should be considered cautiously, as it has the potential impact on the relationships between banks and fintech credit firms. Therefore, this implies there should be some moderating effect of credit information sharing on the relationship between fintech credit and bank stability, which has not been investigated. This study provides insights into the joint effect of credit information sharing on the relationship between fintech credit and bank stability to void this gap. Through this, we are able to establish whether banks and fintech rivals cooperate or compete and whether this affects the stability of banks. Finally, we provide a range of approaches to ensure the robustness of the research findings and discuss some implications to improve the stability of banks in the context of the co-existence between banks and fintech lenders.

The remaining of our study is structured as follows. Section 2 discusses theories and relevant studies on the activities of fintech and its impact on banking systems. Section 3 outlines research methodology, where we propose testable hypotheses, estimation strategies, empirical models, and variable definitions. Sections 4 and 5 present the estimation results of the models. Section 6 concludes the paper with policy implications and suggestions for future research directions.

2. Theories and relevant empirical studies

2.1. Credit information sharing and bank stability

Adverse selection and moral hazard resulting from information asymmetry negatively affect the banking sector by reducing the efficiency in the provision of credit and causing nonperforming loans (Freixas & Rochet, 1997; Jappelli & Pagano, 2002; Stiglitz & Weiss, 1987). Therefore, information sharing bureaus can be the essential tools to reduce information-related issues in the credit markets (Triki & Gajigo, 2014). Consistently, credit information sharing agencies have been shown to play a vital role in the development of banking systems (Barth et al., 2009).

The previous studies suggest that information sharing might positively affect banking soundness by addressing moral hazard, adverse selection and risk of over-indebtedness (Doblas-Madrid & Minetti, 2013; Guérineau & Léon, 2019). Regarding the first channel, information sharing institutions can lessen borrowers' moral hazard and boost borrowers' incentives to repay the loans because information sharing motivates debtors to behave (Jappelli & Pagano, 2002). According to Pagano and Jappelli (1993), the second channel is that information sharing among banks assists in reducing the risks and the lending interest rate, as well as adverse selection. Finally, information sharing can lower the risk of over-indebtedness, which is the third channel.

Previous studies find that information sharing is conducive to the soundness of the banking sector. Credit information sharing decreases credit risk (Jappelli & Pagano, 2002; Kusi et al., 2017), default rates (Fosu et al., 2020; Houston et al., 2010; Padilla & Pagano, 2000; Vercammen, 1995), and banking system fragility (Guérineau & Léon, 2019). For instance, Jappelli and Pagano (2002) argue that when banks share information about borrowers, credit risk is lower and the level of bank credit is higher. Kusi et al. (2017) render evidence that private and public credit bureaus decrease the credit risk of banks in African countries. Houston et al. (2010) suggest that in markets with information sharing among creditors, bank profitability improves and default rates lower. The findings of Fosu et al. (2020) show that information sharing bureaus lessen default rates in developing countries. Padilla and Pagano (2000) and Vercammen (1995) report that information sharing can curtail the borrower hold-up issues and boost borrower discipline, therefore decreasing the default rate of borrowers. In addition, Guérineau & Léon (2019) provide evidence that credit information sharing bureaus help tackle financial instability for both developed and developing countries. Therefore, our testable hypothesis is as follows:

H1: credit information sharing is positively associated with bank stability.

2.2. Literature review on fintech and bank stability

On the one hand, many studies have praised fintech for its potential to enhance financial services through improving service quality and business structures, rendering transactions more affordable, more secure, and comfier (Begenau et al., 2018; Chen et al., 2019; Chiu & Koeppl, 2019; Fuster et al., 2019; Li et al., 2017; Vasiljeva & Lukanova, 2016; Zhu, 2019). Furthermore, fintech can support commercial banks regarding diversification strategies (Yao & Song, 2021). Li et al. (2017) argue that there exists a positive association between the growth of fintech activities and the stock returns of banks.

Furthermore, it appears that fintech lenders do not aim to substitute financial institutions entirely, as the former's market share is larger in jurisdictions characterized by higher bank credit denial rates and lower consumer credit scores (De Roure et al., 2019). De Roure et al. (2019) also show that P2P lending platforms target at risky and less profitable customers, so they can help improve the stability of banks.

On the other hand, following the consumer hypothesis and the disruptive innovation hypothesis, the development of fintech could negatively affect the banking sector. The former hypothesis

suggests that, by responding to similar consumer demands, fintech-provided services can replace the incumbent services served by existing financial institutions (Aaker & Keller, 1990). According to the “disruptive innovation hypothesis”, market entrants applying innovative technologies to provide more affordable and accessible services are highly competitive in the market (Christensen, 1997).

Some studies have opined that the rise of information technology could mean challenges to commercial banks because banks are slower in adopting new technologies (Brandl & Hornuf, 2017; Laven & Bruggink, 2016). Traditional institutions have lost market share to fintech credit, as the latter is more leniently regulated and enjoys better technological advantages (Buchak et al., 2018). Fintechs process lending applications faster without enhanced credit risks, compared to traditional credit institutions (Fuster et al., 2019). Further, fintech credit also responds more elastically to shocks on the demand side and has a higher ability to refinance (Y. Wang et al., 2021). Regarding payment settlement, fintech allows mobile payments with much lower costs, reducing the long-term and unique advantages of commercial banks (Berger et al., 1999). Moreover, cloud computing can store and handle customer data efficiently, and support payments better (Y. Wang et al., 2021). Phan et al. (2020) investigate fintech in Indonesia and show that fintech negatively impacts bank performance. R. Wang et al. (2020) find evidence that fintech intensifies the risk-taking of Chinese banks. However, the above nexus is heterogeneous depending on different bank characteristics, e.g., efficiency and size. Against these backgrounds, it is clear that in general fintech firms can impose an impact on bank stability in either direction. Researchers have rarely examined the link between a specific activity of fintech—fintech credit—and banking systems. Buchak et al. (2018) is the first and only study to find that fintech activity in residential mortgages filled the declining activity of traditional banks when they encountered more regulatory burdens. Nonetheless, this study did not investigate the impact of fintech lenders on banks’ stability. Therefore, we anticipate that fintech firms cater to unserved customers or those that are of lower quality to the banks. We expect a less negative impact of fintech credit on banks stability. To summarize, our hypothesis, therefore, is as follows:

H2: Fintech credit has an impact on bank stability

Both credit information sharing and fintech can affect bank operations, but there are key differences between traditional banks and fintech credit firms. Fintech credit firms are the platforms that solve problems of asymmetric information through their screening practices by collecting non-traditional data (digital data) such as e-commerce data, payment data and data from social media. Previous studies show that digital data are at least as useful as traditional credit information from information sharing bureaus (Berg et al., 2020; Frost et al., 2019; Gambacorta et al., 2019).

Meanwhile, information sharing bureaus are the tools that could be used by traditional banks to reduce information-related issues in the credit market, such as moral hazard and adverse selection. Huang et al. (2020) show that information provided by fintech firms can effectively substitute credit registry information in risk screening. In contrast, Berg et al. (2020) show that digital data using by fintech lenders complements rather than substitutes for traditional credit from information sharing companies, suggesting that lenders (fintech firms or banks) can make superior lending decisions when using information from both sources (credit bureau and digital data). Kowalewski and Pisany (2021) also suggest that there is a large room for cooperation between fintechs and banks, where fintechs would provide technological solutions for banks. With a more privileged banks’ access to credit data from credit information sharing bureaus, banks should be more prone to leverage on the support of fintech firms to reap the highest benefit possible.

To summarize, the points discussed above suggest there should be some moderating effect of credit information sharing on the relationship between fintech credit and bank stability. We

provide insights into the joint effect of credit information sharing on the relationship between fintech credit and bank stability to void this gap. Through this, we are able to establish whether banks and fintech rivals cooperate or compete and whether this affects the stability of banks. All things considered, our third hypothesis as:

H3: Credit information sharing moderates the relationship between fintech credit and bank stability.

3. Research methodology

3.1. Data collection and processing

We collect data from a number of sources. The aggregate data on fintech credit are provided by Cornelli et al. (2020), covering 73 countries between 2013 to 2018. The aggregate banking system data and macroeconomic variables are obtained from Financial Development & Structure Dataset (FDSD) and World Development Indicator dataset (World Bank, 2019). Our choice of the period under investigation is driven by data availability.

3.2. Empirical models

To verify the impact of fintech credit and credit information upon bank stability, our empirical research model is as follows:

$$\text{Bankstability}_{i,t} = \alpha_0 + \alpha_1.\text{Fintech}_{i,t} + \alpha_2.\text{CIS}_{i,t} + \alpha_3.\text{CIR}_{i,t} + \alpha_4.\text{NPL}_{i,t} + \alpha_5.\text{LIQ}_{i,t} + \alpha_6.\text{GDP}_{i,t} + \alpha_7.\text{INF}_{i,t} + \alpha_8.\text{BSD}_{i,t} + \alpha_9.\text{Concentration}_{i,t} + \alpha_{10}.\text{CCI}_{i,t} + \omega_{i,t} \quad (1)$$

We modify equation (1) by adding an interaction term between fintech and information sharing to examine the joint effect of these two factors on bank stability:

$$\text{Bankstability}_{i,t} = \gamma_0 + \gamma_1.\text{CIS}_{i,t} + \gamma_2.\text{Fintech}_{i,t} \times \text{CIS}_{i,t} + \gamma_3.\text{CIR}_{i,t} + \gamma_4.\text{NPL}_{i,t} + \gamma_5.\text{LIQ}_{i,t} + \gamma_6.\text{GDP}_{i,t} + \gamma_7.\text{INF}_{i,t} + \gamma_8.\text{BSD}_{i,t} + \gamma_9.\text{Concentration}_{i,t} + \gamma_{10}.\text{CCI}_{i,t} + u_{i,t} \quad (2)$$

1

The variables in equations (1) and (2) are defined below. The Z-score is used to assess bank stability, as indicated by the literature (Lepetit et al., 2008; Stiroh & Rumble, 2006). Higher Z-scores indicate more financial stability and lower overall bank risk:

$$\text{Zscore}_{i,t} = \frac{\text{ROA}_{i,t} + \text{EQTA}_{i,t}}{\text{SDROA}_{ip}}$$

Where: ROA is return on total assets. SDROA_{ip} is the standard deviation of return on total assets over the examined period (Köhler, 2015; Stiroh, 2004). EQTA_{it} is calculated as the ratio of equity to total assets.

3.2.1. Independent variables

$\text{Fintech}_{i,t}$ —the ratio of fintech credit to GDP of the country i in year t —is calculated from the dataset obtained from Cornelli et al. (2020). This is a standardized measure to control for the effect of the size of the economy in providing fintech credit.

CIS is the measure of credit information sharing. Following Barth et al. (2009) and Triki and Gajigo (2014) and others, we resort to depth of credit information index and private credit bureaus and public credit registries (CI_index, PCB and PCR, respectively) in order to gauge the level of credit information sharing.

3.2.2. Bank characteristics

CIR (the cost-to-income ratio) is a measurement of bank efficiency. Studies on the influence of bank efficiency on bank stability tend to offer mixed evidence at best. The skimping hypothesis

argues that banks are prone to see a decrease in bank stability (Berger & DeYoung, 1997). On the other hand, the “bad management” hypothesis argues that cost inefficiency is likely to lead to higher levels of bank instability.

LIQ is calculated as the ratio of bank liquid reserves to total assets to measure bank liquidity. Previous studies find that banks with higher liquidity levels are more likely to have better stability (Tran et al., 2020).

3.2.3. External factors

Bank stability is also subject to external macroeconomic factors such as economic growth, inflation, banking system development, banking system concentration, and corruption discussed further below.

GDP is the annual real GDP growth rate. This variable is included to control for the economic cycle effect. Previous literature shows that economic growth is positively related to bank stability (Baselga-Pascual et al., 2015; Köhler, 2015).

Inflation (INF) is the inflation rate. Inflation is believed to influence bank stability (Baselga-Pascual et al., 2015; Köhler, 2015). Prior literature shows that inflation is negatively related to bank stability (Baselga-Pascual et al., 2015; Köhler, 2015).

BSD (banking system development) measures financial development (Demirgüç-Kunt & Huizinga, 2000). This is calculated as the ratio of bank credit to GDP. The influence of financial development on bank stability tends to offer mixed evidence. Espenlaub et al. (2012) and Williams and Nguyen (2005) show that financial development can reduce bank risk, on the contrary, Vithessonthi (2014) highlighted the positive effect of financial development on bank risk.

Concentration (the ratio of assets of the five largest banks to total assets of commercial banks) is included to account for industry concentration. Banks with high market power can engage in riskier activities, according to the concentration—fragility hypothesis (Boyd & de Nicoló, 2005).

CCI (control of corruption index), is added to control for corruption effect. CCI has a value that runs from −2.5 to 2.5. Higher values of CCI denote less corruption.). Several empirical studies suggest that corruption imposes a negative impact on bank stability (Bougatef, 2015; Tran et al., 2020).

As for the estimation strategy, in line with Claessens et al. (2018), Rau (2020), and Cornelli et al. (2020), we use the pooled ordinary least squares (OLS) and further control for heteroskedasticity.

To ascertain the robustness of research findings, we further examine the impact of fintech credit and credit information sharing on bank stability by constructing a model where the period of proxies of bank stability is one period behind that of independent variables. In line with previous research (Kowalewski & Pisany, 2021), this approach is an effort to address the potential endogeneity that comes from the two-way relationship between the explained and explanatory variables. Finally, we use an alternative dependent variable proxy (non-performing loan ratio) to ensure the robustness of the findings. This is also an effort to address the concern raised in Lapteacru (2016): Zscore is not a perfect proxy for bank stability/risk due to unrealistic assumption of returns on assets.

4. Results and discussions

4.1. Data description

Table 1 describes the variables in the model. For the dependent variable, the mean of Zscore is 3.64. For the whole sample, the ratio of fintech credit to GDP is about 0.04% on average. This

Table 1. Descriptive statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---------------|-----|--------|-----------|--------|---------|
| Zscore | 431 | 3.643 | 1.000 | -2.719 | 6.206 |
| Fintech | 438 | 0.040 | 0.199 | 0.000 | 2.892 |
| CI_index | 438 | 6.251 | 2.262 | 0.000 | 8.000 |
| PCB | 438 | 46.518 | 39.295 | 0.000 | 100.000 |
| PCR | 438 | 17.737 | 28.921 | 0.000 | 100.000 |
| CIR | 365 | 55.830 | 11.683 | 27.835 | 94.851 |
| LIQ | 281 | 17.437 | 11.258 | 0.558 | 63.766 |
| GDP | 426 | 3.350 | 2.513 | -3.868 | 25.121 |
| INF | 426 | 3.524 | 3.811 | 0.008 | 27.283 |
| BSD | 425 | 67.506 | 44.632 | 10.180 | 223.391 |
| Concentration | 351 | 74.489 | 15.959 | 33.794 | 100.000 |
| CCI | 432 | 0.327 | 1.074 | -1.451 | 2.405 |

Source: Calculation from the dataset

implies a modest size compared to a much larger scale of credit provided by traditional financial lenders.

Table 2 gives the pair-wise correlation coefficients of the variables. Fintech credit and credit information sharing have positive associations with Zscore. Also, the low coefficients between pairs of variables suggesting that the problem of multicollinearity is not a concern for the sample. Nevertheless, these correlations do not constitute a valid basis for the statistical inferences; as a consequence, we continue by estimating models to empirically examine the hypotheses.

4.2. Empirical results and discussion

4.2.1. Fintech credit, credit information sharing and bank stability

Table 3 provides empirical results on the impact of fintech credit and credit information sharing on bank stability. We find that fintech credit has a positive impact on Z-score. Thanks to the ability to deploy technology to exploit big data and tackle information asymmetry it can now reach unserved populations better or those that have little chance of being catered by banks due to poor credit history. Therefore, if the banking system cannot absorb these low-quality borrowers (e.g., who lack collateral), fintech credit or other types of shadow banks, represented by P2P lending, can be a substitute (Buchak et al., 2018), and this may spur financial inclusion. Despite the fact that fintech credit would take some market share away from banks, it will not be able to completely replace bank lending in the near future (Thakor, 2020). Firstly, as documented in Thakor (2020), p. 2P lenders are more likely to benefit from more risky borrowers and those unserved by banks. Therefore, they could take away some market share and profits but not all. Also, if the risky borrowers have been approached by fintech lenders, banks could become safer. In the long term, banks would respond to fintech lenders by building their own online lending platforms either by creating their own platforms or partnering with these fintech firms. So, overall, fintech development mitigates risk more than reduce bank return (Thakor, 2020). Furthermore, from the borrowers' perspectives, when fierce competition between banks and others in lending business happens, loans are cheaper for borrowers, which results in lowering borrowing costs and reducing the borrowers' incentive to engage in risk-shifting. Therefore, default risk could be reduced and the financial stability would be improved (Thakor, 2020).

Our results are not in line with the finding of R. Wang et al. (2020) which shows a positive linkage between fintech development and bank risk-taking in China. This inconsistency may be because R. Wang et al. (2020) measure the fintech development by using news headline searching and

Table 2. Correlation matrix between variables

| Variable | Zscore | Fintech | CI_index | PCB | PCR | CIR | LIQ | GDP | INF | BSD | Concentration | CCI |
|---------------|--------|---------|----------|--------|--------|--------|--------|--------|--------|-------|---------------|-------|
| Zscore | 1.000 | | | | | | | | | | | |
| Fintech | 0.081 | 1.000 | | | | | | | | | | |
| CI_index | 0.249 | 0.101 | 1.000 | | | | | | | | | |
| PCB | 0.158 | -0.067 | 0.471 | 1.000 | | | | | | | | |
| PCR | -0.052 | 0.240 | 0.158 | -0.171 | 1.000 | | | | | | | |
| CIR | 0.035 | -0.161 | 0.090 | 0.148 | 0.002 | 1.000 | | | | | | |
| LIQ | 0.062 | -0.094 | -0.121 | -0.320 | 0.216 | 0.081 | 1.000 | | | | | |
| GDP | -0.039 | 0.122 | -0.125 | -0.232 | -0.065 | -0.246 | 0.124 | 1.000 | | | | |
| INF | -0.180 | -0.072 | -0.267 | -0.306 | -0.074 | -0.035 | 0.258 | 0.095 | 1.000 | | | |
| BSD | 0.166 | 0.184 | 0.217 | 0.263 | 0.074 | -0.023 | -0.445 | -0.172 | -0.469 | 1.000 | | |
| Concentration | -0.047 | -0.100 | 0.034 | 0.198 | 0.018 | 0.110 | -0.110 | -0.271 | -0.179 | 0.205 | 1.000 | |
| CCI | 0.146 | 0.013 | 0.244 | 0.395 | 0.009 | 0.151 | -0.319 | -0.255 | -0.460 | 0.619 | 0.489 | 1.000 |

Source: Calculated from the dataset

Table 3. Fintech credit, credit information sharing and bank stability

| | (1) Zscore | | (2) Zscore | | (3) Zscore | |
|--------------------|-----------------------------|-----|-----------------------------|-----|-----------------------------|-----|
| Fintech | 9.112 | *** | 9.057 | *** | 10.076 | *** |
| | (1.796) | | (1.769) | | (1.845) | |
| CI_index | 0.062 | *** | | | | |
| | (0.019) | | | | | |
| PCB | | | 0.005 | *** | | |
| | | | (0.001) | | | |
| PCR | | | | | 0.002 | |
| | | | | | (0.002) | |
| CIR | 0.000 | | −0.001 | | 0.003 | |
| | (0.006) | | (0.006) | | (0.006) | |
| LIQ | 0.015 | *** | 0.015 | ** | 0.012 | *** |
| | (0.004) | | (0.004) | | (0.004) | |
| GDP | −0.049 | ** | −0.034 | | −0.054 | ** |
| | (0.023) | | (0.023) | | (0.023) | |
| INF | −0.067 | *** | −0.057 | *** | −0.066 | *** |
| | (0.013) | | (0.013) | | (0.013) | |
| BSD | 0.003 | | 0.002 | | 0.003 | |
| | (0.002) | | (0.002) | | (0.002) | |
| Concentration | −0.008 | ** | −0.007 | * | −0.007 | * |
| | (0.004) | | (0.004) | | (0.004) | |
| CCI | −0.072 | | −0.095 | | −0.081 | |
| | (0.093) | | (0.095) | | (0.095) | |
| Constant | 3.906 | *** | 4.039 | *** | 4.082 | *** |
| | (0.602) | | (0.597) | | (0.603) | |
| No of observations | 207 | | 207 | | 207 | |
| R2 | 0.277 | | 0.291 | | 0.250 | |

Notes: *, **, and *** show 10%, 5%, and 1% level of significance. Figures in parentheses are robust standard errors.

factor analysis (so what they built represents general fintech firms), whilst our study uses a proxy of fintech credit to GDP, inherited from Cornelli et al. (2020), which relates more directly to the activities of fintech lenders. This is also a significant extension to the current literature in the field of the competition between fintech firms and banks.

When credit information sharing is proxied by the depth of credit information index, we find that credit information sharing increases bank stability. This result is in line with the findings from Fosu et al. (2020); Guérineau & Léon (2019); Kusi et al. (2017). Column (2) in Table 3 provides evidence on the impact of credit information sharing on bank stability through private credit bureaus and public credit registries (PCB and PCR). The result shows that credit information sharing (through private credit bureaus—PCB) is positive and significant influence on bank stability, this result is in line with the findings from Fosu et al. (2020) and Kusi et al. (2017). Whereas, credit information sharing (through public credit registries—PCR) is positive and insignificantly related to bank stability. These results suggest that PCB may play a more significant role compared to PCR. Peria

Table 4. The joint effect of fintech credit and credit information sharing on bank stability

| | (1) Zscore | | (2) Zscore | | (3) Zscore | |
|-----------------------|-----------------------------|-----|-----------------------------|-----|-----------------------------|-----|
| CI_index | 0.056 | *** | | | | |
| | (0. 018) | | | | | |
| PCB | | | 0. 004 | *** | | |
| | | | (0.001) | | | |
| PCR | | | | | 0. 002 | |
| | | | | | (0.002) | |
| Fintech x CI_index | 1.241 | *** | | | | |
| | (0. 214) | | | | | |
| Fintech x PCB | | | 0.093 | *** | | |
| | | | (0.017) | | | |
| | | | | | −0.086 | |
| Fintech x PCR | | | | | (0.144) | |
| CIR | 0. 000 | | −0.000 | | 0.003 | |
| | (0.006) | | (0. 006) | | (0.007) | |
| LIQ | 0. 015 | *** | 0. 014 | *** | 0.009 | ** |
| | (0.004) | | (0. 004) | | (0.004) | |
| GDP | −0. 049 | ** | −0. 030 | | −0.062 | ** |
| | (0. 023) | | (0. 024) | | (0.025) | |
| INF | −0.066 | *** | −0. 057 | *** | −0.077 | *** |
| | (0.013) | | (0.013) | | (0.014) | |
| BSD | 0.003 | | 0. 001 | | 0.000 | |
| | (0.002) | | (0.002) | | (0.002) | |
| Concen tration | −0.007 | * | −0. 006 | | −0.011 | ** |
| | (0.004) | | (0.004) | | (0.018) | |
| CCI | −0.081 | | −0. 074 | | 0.053 | |
| | (0.079) | | (0.092) | | (0.098) | |
| Constant | 3.900 | *** | 4.058 | *** | 4.732 | ** |
| | (0.598) | | (0.600) | | (0.654) | |
| No of Observations | 207 | | 207 | | 207 | |
| R2 | 0.286 | | 0.285 | | 0.163 | |

Notes: *, **, and *** show 10%, 5%, and 1% level of significance. Figures in parentheses are robust standard errors

and Singh (2014) also suggest that credit bureau reforms are more efficient in providing the necessary credit information to the market, compared to credit registry reforms.

For bank characteristics, the cost-to-income ratio (CIR) is not significant with bank stability. LIQ has a positive coefficient on Zscore, indicating that higher liquidity assets increase banking system stability.

For macroeconomic factors, GDP and INF are found to exert negative impacts on bank stability. Stronger rates of economic growth and inflation, in contrast, are found to lower Zscore of the banking system, which disagrees with the ‘cyclical nature of bank risk’ view. These findings are in

Table 5. The individual effect of fintech credit and credit information sharing on bank stability (endogeneity control)

| | (1) Zscore | | (2) Zscore | | (3) Zscore | |
|--------------------|-------------------|-----|-------------------|-----|-------------------|-----|
| Fintech | 8.777 (1.852) | *** | 8.621 (1.791) | *** | 9.752 (1.891) | *** |
| CI_index | 0.062 (0.018) | *** | | | | |
| PCB | | | 0.005 (0.001) | *** | | |
| PCR | | | | | 0.002 (0.002) | |
| CIR | 0.000 (0.007) | | −0.001 (0.006) | | 0.003 (0.006) | |
| LIQ | 0.014 (0.004) | *** | 0.014 (0.004) | *** | 0.011 (0.004) | ** |
| GDP | −0.043 (0.023) | * | −0.026 (0.022) | | −0.047 (0.022) | ** |
| INF | −0.067 (0.012) | *** | −0.057 (0.012) | *** | −0.066 (0.013) | *** |
| BSD | 0.002 (0.002) | | 0.001 (0.002) | | 0.003 (0.002) | |
| Concentration | −0.007 (0.004) | * | −0.006 (0.003) | | −0.006 (0.004) | |
| CCI | −0.044 (0.092) | | −0.069 (0.094) | | −0.053 (0.095) | |
| Constant | 3.813 (0.606) | *** | 3.943 (0.603) | *** | 3.997 (0.608) | *** |
| No of observations | 208 | | 208 | | 208 | |
| R2 | 0.278 | | 0.303 | | 0.251 | |

Notes: *, **, and *** show 10%, 5%, and 1% level of significance. Figures in parentheses are robust standard errors.

line with R. Wang et al. (2020) and the literature that the instability accumulated during economic expansions leads to lower bank stability during recessions (Jiménez et al., 2006).

Industry concentration (Concentration) has a negative impact on bank stability. This agrees with the concentration–fragility hypothesis, which claims that banks with high market power can engage in riskier activities (Boyd & de Nicoló, 2005).

4.2.2. Interaction between fintech credit and credit information sharing on bank stability

Next, we investigate the joint impact of fintech credit and credit information sharing on bank stability by examining the interaction term between these two factors.

Table 4 reports the estimation results of equation (2). Overall, the effects of the control variables are significant and consistent with the estimation results of equation (1). Consistent with Table 3, Table 4 reports that the depth of credit information index and that credit information sharing

Table 6. Interaction effect fintech credit and credit information sharing on bank stability (endogeneity control)

| | (1) Zscore | | (2) Zscore | | (3) Zscore | |
|-----------------------|-----------------------|-----|-----------------------|-----|-----------------------|-----|
| CI_index | 0.056 | *** | | | | |
| | (0.018) | | | | | |
| PCB | | | 0.005 | *** | | |
| | | | (0.001) | | | |
| PCR | | | | | 0.002 | |
| | | | | | (0.002) | |
| Fintech x CI_index | 1.204 | *** | | | | |
| | (0.220) | | | | | |
| Fintech x PCB | | | 0.088 | *** | | |
| | | | (0.018) | | | |
| | | | | | −0.097 | |
| Fintech x PCR | | | | | (0.147) | |
| CIR | 0.000 | | −0.001 | | 0.003 | |
| | (0.007) | | (0.006) | | (0.007) | |
| LIQ | 0.014 | *** | 0.013 | *** | 0.008 | * |
| | (0.004) | | (0.004) | | (0.004) | |
| GDP | −0.043 | * | −0.021 | | −0.055 | ** |
| | (0.022) | | (0.023) | | (0.024) | |
| INF | −0.067 | *** | −0.057 | *** | −0.078 | *** |
| | (0.012) | | (0.012) | | (0.014) | |
| BSD | 0.003 | | 0.001 | | 0.001 | |
| | (0.002) | | (0.002) | | (0.002) | |
| Concentration | −0.0076 | | −0.005 | | −0.009 | ** |
| | (0.004) | | (0.004) | | (0.005) | |
| CCI | −0.054 | | −0.050 | | 0.077 | |
| | (0.092) | | (0.091) | | (0.097) | |
| Constant | 3.804 | *** | 3.962 | *** | 4.628 | ** |
| | (0.602) | | (0.605) | | (0.655) | |
| No of Observations | 208 | | 208 | | 208 | |
| R2 | 0.287 | | 0.297 | | 0.170 | |

Notes: *, **, and *** show 10%, 5%, and 1% level of significance. Figures in parentheses are robust standard errors

(through private credit bureaus—PCB) are positively related to Zscore, implying that credit information sharing tends to enhance bank stability.

Regarding the interaction between fintech credit and credit information sharing (through the depth of credit information index and private credit bureaus), we find that the interaction terms are significantly related to bank stability. This result suggests that the presence of credit information sharing institutions could enhance the positive effect of fintech credit on bank stability.

Table 7. Robustness test using the non-performing loans (NPL)

| | (1) NPL | | (2) NPL | | (3) NPL | |
|--------------------|------------|-----|------------|-----|------------|-----|
| Fintech | -14.489 | *** | -13.211 | *** | -19.974 | *** |
| | (4.746) | | (3.895) | | (4.499) | |
| CI_index | -0.326 | *** | | | | |
| | (0.074) | | | | | |
| PCB | | | -0.034 | *** | | |
| | | | (0.006) | | | |
| PCR | | | | | -0.018 | |
| | | | | | (0.014) | |
| CIR | -0.065 | *** | -0.052 | *** | -0.081 | *** |
| | (0.016) | | (0.013) | | (0.015) | |
| LIQ | -0.036 | ** | -0.038 | ** | -0.018 | |
| | (0.017) | | (0.016) | | (0.019) | |
| GDP | -0.196 | | -0.304 | ** | -0.186 | |
| | (0.135) | | (0.137) | | (0.127) | |
| INF | 0.355 | *** | 0.297 | *** | 0.352 | *** |
| | (0.089) | | (0.090) | | (0.092) | |
| BSD | -0.033 | *** | -0.028 | *** | -0.035 | *** |
| | (0.004) | | (0.004) | | (0.005) | |
| Concentration | -0.026 | ** | -0.031 | *** | -0.032 | *** |
| | (0.010) | | (0.010) | | (0.012) | |
| CCI | 0.252 | | 0.402 | | 0.329 | |
| | (0.261) | | (0.249) | | (0.259) | |
| Constant | 13.974 | *** | 13.475 | *** | 13.413 | *** |
| | (2.057) | | (1.978) | | (2.102) | |
| No of observations | 206 | | 206 | | 206 | |
| R2 | 0.425 | | 0.470 | | 0.402 | |

Notes: *, **, and *** show 10%, 5%, and 1% level of significance. Figures in parentheses are robust standard errors

5. Robustness checks

To ascertain the robustness of research findings, we further examine the impact of fintech credit and credit information sharing on bank stability by: (1) constructing a model where the period of proxies of bank stability is one period behind that of independent variables, as an effort to address the potential endogeneity that comes from the two-way relationship between the explained and explanatory variables (Tables 5 and 6); (2) using the non-performing loans in place of the Zscore as a bank stability variable (see, Davis et al., 2020; Tables 7 and 8).

The results from our first robustness check are in line with those reported earlier, as shown in Tables 5 and 6. Fintech credit has a positive impact on Zscore. The positive coefficient of the interaction term supports the argument that the presence of efficient credit information sharing institutions could enhance the positive effect of fintech credit on bank soundness. Finally, the coefficients of all other control variables are consistent with those estimated earlier.

Table 8. Effect of the interaction between fintech credit and credit information sharing on non-performing loans (NPL)

| | (1) NPL | | (2) NPL | | (3) NPL | |
|-----------------------|-------------------|-----|-------------------|-----|-------------------|-----|
| CI_index | −0.319 (0.075) | *** | | | | |
| PCB | | | −0.033 (0.006) | *** | | |
| PCR | | | | | −0.017 (0.016) | |
| Fintech x CI_index | −1.665 (0.596) | *** | | | | |
| Fintech x PCB | | | −0.121 (0.033) | *** | | |
| Fintech x PCR | | | | | 0.007 (0.629) | |
| CIR | −0.065 (0.016) | *** | −0.052 (0.013) | *** | −0.081 (0.015) | *** |
| LIQ | −0.035 (0.017) | ** | −0.036 (0.016) | ** | −0.013 (0.019) | |
| GDP | −0.195 (0.135) | | −0.309 (0.138) | ** | −0.171 (0.129) | |
| INF | 0.356 (0.088) | *** | 0.298 (0.090) | *** | 0.373 (0.095) | *** |
| BSD | −0.033 (0.004) | *** | −0.027 (0.004) | *** | −0.031 (0.005) | *** |
| Concentration | −0.026 (0.010) | ** | −0.031 (0.010) | *** | −0.024 (0.012) | * |
| CCI | 0.235 (0.262) | | 0.358 (0.250) | | 0.062 (0.263) | |
| Constant | 13.852 (2.051) | *** | 13.378 (1.986) | *** | 12.125 (2.114) | *** |
| No of Observations | 206 | | 206 | | 206 | |
| R2 | 0.423 | | 0.469 | | 0.387 | |

Notes: *, **, and *** show 10%, 5%, and 1% level of significance. Figures in parentheses are robust standard errors

In terms of the dependent variable constructed by taking non-performing loans (Tables 7 and 8), we find that fintech credit is negatively related to non-performing loans, suggesting that fintech credit enhance bank stability. The interaction between fintech credit and credit information sharing (through the depth of credit information index and private credit bureaus) is negatively and significantly related to non-performing loans, suggesting the presence of efficient credit information sharing institutions could enhance the positive effect of fintech credit on bank soundness. Meanwhile, all other control variables are similar to the prior setting.

In general, using alternative regression and controlling for another independent proxy does not change the main results of the paper.

6. Conclusion

Using the aggregate dataset of 73 countries from 2013 to 2018, this study is to investigate whether fintech credit exerts an impact on bank stability. We document some significant findings. First, there is a positive link between fintech credit and bank stability. These results suggest that as fintech grows, it competes with banks, but it also benefits banks in terms of stability. Second, we argue that the effect of fintech credit on bank stability may depend on credit information sharing. We find fintech credit would impose a more positive influence on bank stability with the presence of efficient credit information sharing institutions. These results are robust to regression models with alternative dependent variables.

Regardless of the rise of fintech credit and its perceived effect on the banking system, the effects of fintech credit on the financial system are not well understood (Li et al., 2017; Phan et al., 2020). Particularly, the assessments of the links between fintech credit on bank stability are scarce. We also provide insights into the joint effect of credit information sharing and fintech credit on bank stability. Therefore, this research would provide a much more comprehensive and generalizable result on the influence of fintech credit on the banking system.

From our findings, it is clear that the impact of fintech credit on bank stability is moderated by credit information sharing. This finding implies that banks could leverage on the technological solutions from fintechs to extract more data from different sources. As pointed out in previous studies, the combination of data from digital footprints and credit information sharing bureaus could improve significantly the ability to predict defaults. As a result, in the presence of fintech lenders, credit information sharing entities are still playing a favourable role in enhancing bank stability, and they should not be ignored. To extend this research, other studies may verify the impact of big-tech credit and other forms of fintech firms on bank stability when the relevant data are more available. This will help to comprehend whether different types of fintech firms affect bank stability differently. Also, it would be safer to test the relationship using some other proxies for bank stability, even though we have used two proxies in this study, due to the shortcomings of any single proxy of bank stability.

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Note

1. Equation 2 does not include fintech variable because of multicollinearity problem, which is evident through our Variance Inflation Factor test (not tabulated here).

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