Digital disruptors at the gate. Does FinTech lending affect bank market power and stability?

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September, 2023

Abstract:

This paper examines the effect of FinTech lending on the market power and stability of incumbent banks. Using an international sample of 6,309 banks during the period 2013-2019, our results show that the volume of credit provided by FinTech lenders negatively affects bank market power and stability. This negative effect is less relevant in countries with greater protection of creditor rights. We also find that the impact of FinTech lending on bank stability is partially channeled by the effect of FinTech credit on the market power of incumbent banks. Our main results – lower bank market power and stability – are also observed at the country level, after addressing potential endogeneity concerns related to FinTech lending and several robustness checks.

Keywords: FinTech; bank market power; bank stability; legal and institutional environment.

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Acknowledgments:

The authors acknowledge Francisco Rodríguez, Yener Altunbas, Santiago Carbó, Annalisa Ferrando, Silvia Del Prete, Gene Ambrocio, Jorge Ponce, Haikun Zhu, Louis Bertucci, Daniel Broby, Md Sohel Saklain, Víctor González, María Jesús Castrillo Lara, and all the participants at the 2022 FMA Annual Meeting, the 2022 Europe FMA Annual Meeting, the 28th Annual Meeting of the German Finance Association (DGF), the IFABS 2022 Naples Conference, the 28th Annual Meeting of the German Finance Association (DGF), the 2022 Wolpertinger Annual Meeting and XXXI ACEDE Conference. We are grateful for the financial support from the regional government of Madrid – UAM Research Project for Young Researchers (SI3-PJI-2021-00276). Pedro J. Cuadros acknowledges financial support from financial support from the Spanish Ministry of Science and Innovation, Project PID2021-128994NA-I00 and TED2021-132896A-100, the regional government of Andalusia under Grant P18-RT-3571 Project and P12.SEJ.2463. Elena Cubillas acknowledges financial support from the Spanish Ministry of Science and Innovation, Project MCI-20-PID2019-108503RB-I00 and from the regional government of Asturias to the Financial Economic Research Group GECOFIN, AYUD/2021/50878. Nuria Suárez acknowledges financial support from the Spanish Ministry of Economy and Competitiveness, Project PID2020-118064GB-I00, and from the Professorship Excellence Program in accordance with the multi-year agreement signed by the regional government of Madrid and the Universidad Autónoma de Madrid (Line #3).

1. INTRODUCTION

The digital revolution that has been taking place in recent decades has driven the birth of new business models (Stiglitz, 2017). The advent of recent innovations in information technology - data collection and processing - and communication - distribution and connectivity - is having a deep impact on financial intermediation (Carletti et al., 2021; Goldstein et al., 2019). Specifically, the emergence of new technological innovations (i.e. artificial intelligence, big data, machine learning) is expanding the possibilities of accessing financial markets, increasing the diversity in the availability of products, and reducing costs (Financial Stability Board, 2019).

This digital revolution has fostered the arrival of new players in the credit market who, unlike incumbents (traditional banks), are digitally native. While FinTech firms have a key role to play in democratizing credit access and thereby increasing financial inclusion (Maskara et al., 2021), as well as in improving the consumer experience through a faster and more efficient provision of financial services (Allen et al., 2022), their disruptive potential is considered to be a game-changer for the financial services industry (Beck et al., 2022; Vives, 2019). Native digital companies have benefited from the deployment of new technological innovations to develop customer-centric business models (Pousttchi & Dehnert, 2018; Puschmann & Alt, 2016) focused on providing financial services.

At the forefront of this disruption are FinTech lenders, who have proved their ability to provide a growing amount of credit to borrowers all over the world. FinTech lending has gained ground as an alternative to traditional bank-based funding sources over the last few years. Figure 1 shows the evolution of the credit provided by the FinTech sector (in $bn. and as a percentage of GDP). As can be seen, this new type of credit has experienced sizeable growth (by 122.82%) during the period 2013-2019.

<INSERT FIGURE 1>

From the standpoint of traditional financial intermediation, this reality is particularly worthy of attention, insofar as it implies recognizing the need to rethink the more traditional bank business models. The Basel Committee on Banking Supervision (BIS, 2017) recognizes that although the changes taking place are emerging with greater disruptive force it is not the first time that the banking sector has faced a technological revolution. However, an added factor to this new reality is the reduced capacity to establish barriers to entry into the sector, which facilitates the emergence of new competitors in the provision of financial services. As the Financial Stability Board (2019) underlines, new entrants into the financial services space could materially alter the universe of financial services providers and thereby affect financial stability.

Although prior studies (see among others, Allen et al., 2022; Carletti et al., 2021; Vives, 2019), as well as policymakers (BIS, 2018; Financial Stability Board, 2019; IMF, 2017; OECD, 2020), suggest that the entry of new digital competitors is likely to disrupt the banking industry, the question of to what extent the FinTech phenomenon is impacting the incumbent banking industry remains largely unexplored. Thus, the primary objective of this paper is to further explore the impact of FinTech lending on the market power and financial stability of the banking sector.

Among the few studies that have sought to examine the impact of FinTech lenders on banks' stability (Banna et al., 2021; Haddad & Hornuf, 2021; Wang et al., 2021), a broad approach to FinTech competition has been adopted. To proxy for FinTech competitive pressure, these studies have mainly relied on indirect measures such as the number of FinTech firms in a given country or the media attention paid to the FinTech phenomenon. Such an approach might prove to be problematic since the main source of bank instability emerges from their lending activity (Köhler, 2015; Koziol & Lawrenz, 2009). Moreover, as prior studies have shown (Bellardini et al., 2022; Hornuf et al., 2021; Kou et al., 2021), most of these FinTech firms could be collaborating with banks in other segments of activity (i.e. payment services, asset management activities, or financial infrastructure, among others) but competing in the provision of credit. These proxies for the development of FinTech in a given country may not therefore be accurately reflecting the extent to which these FinTech companies are lending to consumers and businesses, and consequently, affecting banks' stability. To circumvent this issue, this study focuses directly on the annual volume of FinTech lending granted in each country. This allows us to observe more clearly the impact that is driven through the core financial activity undertaken by financial intermediaries (lending). Moreover, none of the prior studies considers that the impact of FinTech lending might be mediated by the well-known relationship between market power and bank stability (see among others, Allen & Gale, 2000, 2004; Boyd & Nicoló, 2005; Hellmann et al., 2000) nor shaped by the legal and institutional characteristics that drive the emergence of FinTech firms (see among others, Claessens et al., 2018; Cornelli et al., 2023; Kowalewski & Pisany, 2022)

This paper thus offers a threefold contribution to the literature on FinTech and banking. Firstly, the study provides additional insight into what is the impact that FinTech lending has on the banking industry by empirically examining the market power and stability of incumbent banks. Since institutional quality seems to affect bank market power, financial stability and the emergence of FinTech firms (Beck et al., 2013; Claessens & Laeven, 2004; Cornelli et al., 2023; Cubillas & González, 2014; Kowalewski & Pisany, 2022), this paper also contributes to the literature by exploring whether the strength of the effects associated with FinTech lending may be contingent on the characteristics of the institutional environment. Thirdly, the paper provides an empirical approach that allows us explain how bank market power acts as one of the channels by which FinTech lending affects banks' stability.

The empirical analysis is carried out for an international database composed of 6,309 banks from 70 countries over the period 2013–2019. Our baseline results are consistent with a negative effect of FinTech lending on bank market power and stability. These effects are economically significant.

Indeed, the results show that the magnitude of the economic effect of FinTech lending increased during the period analyzed, with the effect being even greater than other traditional determinants of market power and bank stability (such as profitability, efficiency, the growth of bank loans, and the economic cycle).

Our results also reveal that the influence of FinTech lending on bank market power and stability is shaped by the country's institutional setting. In particular, the negative effect of FinTech lending on bank market power and stability is less relevant in countries that offer greater protection of creditor rights and that have a stronger legal framework applicable to judicial liquidation and reorganization proceedings. Moreover, we provide evidence of a less negative impact of FinTech lending on bank stability in countries with higher levels of institutional quality. We also find evidence concerning the role of market power as a channel underlying the relationship between FinTech lending and bank stability. This relationship is confirmed when a country-level dataset is used and when accounting for potential endogeneity concerns.

These findings raise concerns about the reduction in bank market power as a result of the growing volume of FinTech lending. At the same time, these results also shed some light on the importance of adopting appropriate mechanisms to enhance bank stability in a scenario in which FinTech companies are breaking into the credit activity market as alternative lenders. In turn, the results may not only have implications for policymakers (e.g., by helping to understand what policies might prove more effective for fostering innovation and financial inclusion in the financial system whilst not sacrificing financial stability) but also for traditional banks (e.g., by learning what the costs of failing to keep pace with financial innovation could be) as well as newcomers (e.g., by identifying under what institutional framework they could be more successful in acquiring incumbents' market shares).

The rest of the paper is organized as follows. Section 2 presents the related literature and discusses the potential effects of FinTech lending on bank market power and stability. Section 3 describes the sample, variables, and econometric models. Section 4 discusses the main empirical results. Section 5 examines the role of bank market power as a mechanism through which FinTech lending influences bank stability. Section 6 reports a country-level analysis and addresses potential endogeneity problems. Section 7 presents some additional robustness tests. Finally, Section 8 concludes.

2. RELATED LITERATURE AND HYPOTHESES

Although the FinTech phenomenon is quite recent, prior literature has already explored the factors driving the emergence of new entrants in the banking industry. In this context, Zavolokina et al. (2016) argue that this phenomenon is not triggered by just one factor, but rather is influenced by a combination of economic, technological, and regulatory aspects.

Some prior literature has found that FinTech companies have started to offer services because the cost of financial intermediation has traditionally been relatively high. In this vein, Philippon (2018) found that while banks have benefited more than other industries from improvements in information technologies, these enhancements have not been passed on as lower costs to the end-users of financial services. In line with this, Frost (2020) states that the existence of relatively uncompetitive banking markets may drive the arrival and adoption of FinTech services. Claessens et al. (2018) also find that there is more FinTech credit activity in countries that evidence a less competitive banking sector. Similarly, and using a large panel dataset from 2013 to 2018 made up of 79 countries, Cornelli et al., (2023) show that the intensity of FinTech and BigTech competition is greater in countries where banking sector mark-ups are higher.

Other papers have highlighted that regulation may also play a role. In particular, FinTech credit volumes are greater in countries that have less stringent banking regulations. However, in countries with more prudential regulation and stricter bank licensing regimes, it may be more difficult to start new lending activities (Claessens et al., 2018; Cornelli et al., 2023). Kowalewski et al., (2022) find that the development of FinTech credit services is fostered by the strength of the rule of law and credit institutions, especially in terms of insolvency framework effectiveness, since they may contribute to limiting credit risk and thus making lending more attractive. Similarly, Cornelli et al., (2023) find that FinTech and BigTech credit are more established where it is easier to do business and where investor protection disclosure, as well as the efficiency of the judicial system, are more developed.

Furthermore, the existence of large proportions of the unbanked or financially excluded population is also likely to explain the emergence of new competitors. Jagtiani & Lemieux (2018) and Zhang et al. (2020) find that these firms have largely penetrated rural areas that are especially underserved by traditional banks. Cornelli et al., (2023) document that FinTech credit is also more prevalent where there are fewer bank branches per capita. These findings would help to understand better why countries such as Brazil, China, India, Mexico, or South Africa, where there is a large fraction of underbanked population, exhibit the highest FinTech adoption rates (EY, 2019). In this sense, FinTech firms seem to play a key role in fostering financial inclusion (Demir et al., 2020; Maskara et al., 2021; Yang & Zhang, 2022). Finally, greater distrust in the financial system, and particularly in the traditional banking sector in the wake of the 2008 financial crisis, also seems to have proven key to the emergence of non-bank institutions that are likely to compete with traditional banks (Cojoianu et al., 2020; Kowalewski et al., 2022). Bertsch et al., (2020) find that bank misconduct may have played an economically significant role in facilitating the expansion of FinTech products, services, and instruments

While all the above-mentioned literature has examined the drivers underlying the emergence of FinTech, the question is whether and how these FinTech lenders may disrupt the market power of incumbent banks in the lending markets and their stability. As regards the potential impact on bank competition, and given that the degree of competition in the sector is important in terms of innovation, financial service efficiency, and the quality of financial products (Claessens, 2009), one major aspect to consider concerns potential changes in market power that incumbent banks experience because of FinTech lending activity. According to Agarwal & Zhang (2020), Berg et al., (2022), Boot et al. (2021), Le et al. (2021), or Thakor (2019), FinTech lenders in most countries are allowed to provide credit to borrowers under less stringent regulatory conditions compared to banks. This is ultimately fostering FinTech lender entry into the lending market but not into other segments such as deposits. In a sense, these regulatory differences can to a large extent explain the recent growth of FinTech lender market shares (Buchak et al., 2018) as FinTech lenders and traditional banks could potentially serve the same base of borrowers.

The expansion of FinTech lending has resulted in the emergence of some preliminary evidence vis-à-vis what impact this alternative credit might be having on bank competition. Irani et al. (2021) and Buchak et al. (2018) document that an upward trend in FinTech lending is putting pressure on banks. Using U.S. data, Buchak et al. (2018) show a dramatic growth in FinTech lender market shares in residential mortgage originations. Also using U.S. data, Cornaggia et al. (2018) observe that a one-standard-deviation increase in FinTech lending activity reduces the relative fraction of the bank's personal loan segment by 1.2%. Similarly, Tang (2019) finds evidence for substitution between banks and FinTech lenders. Empirically, Di Maggio & Yao (2021) use a unique dataset of loans originated by FinTech and banks to conclude that FinTech lenders are attracting market share away from banks. The potential negative impact for the incumbents of the arrival of FinTech platforms is evident in the mutual funds industry. You et al., (2022) document that funds distributed through FinTech platforms attract more flows relative to funds only distributed via traditional methods. In this sense, although financial intermediaries have made substantial progress in developing their digital channels, new competitors are increasing the level of contestability in the financial services market, and mainly on the lending activity (Carletti et al., 2021).

As FinTech firms face no significant barriers to entry in the lending industry - coupled with their capacity to acquire bank market share in lending - we could expect banks' market power to be eroded as FinTech lending grows. In line with all these arguments, we state our first hypothesis as follows:

H1: FinTech lending reduces incumbent banks' market power.

Apart from the potential influence on market power, credit-related activity carried out by FinTech companies may also influence bank stability. The novel information technology and innovative methods used by these digital lenders are likely to influence the level of efficiency of financial intermediation. The ability of new entrants to collect and process non-financial data may, at least in part, substitute their lack of access to *soft information* on borrowers (Boot et al., 2021).

Several studies have documented a superior capacity of FinTech lenders to assess borrowers' creditworthiness compared to incumbent lenders (Frost et al., 2019; Fuster et al., 2019; Gambacorta et al., 2019). After comparing the unsecured consumer lending by a Fintech lender and by traditional bank lenders, Hughes et al., (2022) find that bank lenders are less efficient than the FinTech lender. Balyuk et al. (2020) find that FinTech lenders gain market share in markets in which incumbent banks primarily process *hard information*, which is consistent with FinTech lenders being more efficient at processing this type of data. Using loan-level data from a large Indian FinTech lender, Ghosh et al. (2021) find that, compared to traditional banks, FinTech lenders are able to screen borrowers more efficiently, in particular because they are able to screen better borrowers' verifiable payment information. In a similar vein, Beck et al., (2022b) documents that firms' use of innovative payment methods generates vast amount of data that can be used by digital lenders to better assess the risk profile of customers. This capacity of FinTech lenders is also shown by Di Maggio & Yao (2021), who find that the rates set by FinTech lenders are even better predictors of defaults than those charged by traditional institutions, which suggests that FinTech lenders might be better at pricing on the intensive margin.

Based on FinTech lenders' use of superior technology, models based on informational advantages such as those produced by Almazan (2002), Chiesa (1998), and Hauswald & Marquez (2003, 2006), suggest that FinTech lenders might create adverse selection problems for incumbent commercial lenders. Berg et al. (2020) conclude that FinTech lenders, with their superior ability to access and process digital footprints, may threaten the information advantage of financial intermediaries and thereby challenge financial intermediaries' business models. Hence, if FinTech companies are better than traditional banks at evaluating the creditworthiness of potential clients thanks to a more efficient treatment of *hard information*, we may expect them to be more able to discern safe investments more quickly and to be ahead of banks in their financing (Havrylchyk, 2018). Banks would therefore have to settle for financing borrowers who evidence a greater level of uncertainty, which will increase their average level of risk. Empirically, Cornaggia et al. (2018) show that commercial banks are beginning to hold loans with higher default probabilities as a result of FinTech competition. In particular, these authors document that a one-standard-deviation increase in FinTech lending appears to drive a 1.7% increase in quarterly bank loan delinquencies and a 3.9% increase in quarterly charge-off rates. Even in those cases in which FinTech lenders target the subprime population, prior studies have found that FinTech lenders use more data and more complex modeling to identify low-risk profile borrowers from the subprime pool. Dolson & Jagtiani (2021) find that within the subprime pool of consumers, those who are likely to receive personal loan credit offers from FinTech lenders tend to be borrowers with higher income and higher credit balances. Yang & Zhang, (2022) documents that FinTech lenders are not willing to give credit to those low-consumption households categorized as risky borrowers. By using a unique data set from loan applications that directly links FinTech lending to SME borrowers, Eça et al., (2022) find that FinTech lenders cater to high quality, high profitability, and low credit risk firms. Similarly, Chen et al., (2022) find that firms with access to FinTech credit are less likely to go bankrupt or exit the business in the future.

Furthermore, seminal papers in banking literature coincide with the role of competition to explain bank stability (Allen & Gale, 2004; Boot & Thakor, 2000; Matutes & Vives, 2000). From a theoretical point of view, Boot & Thakor (2000) predict that if banks face higher levels of competition from non-banks then they would decide to invest more in increasing the value of their loans. Degryse & Ongena (2007) provide empirical evidence in this regard and conclude that if banks perceive FinTech activity as a serious competitive threat they will invest more in relational loans, which are mostly dependent on acquiring *soft information*. In these types of loans, collateral plays an important role (Boot & Thakor, 1994). A borrower who lacks collateral or, in other words, who fails to provide an interesting source of *soft information* for the bank, may not be able to build a relationship with a traditional bank entity to obtain funding in this way. However, such a borrower is also a potential candidate to raise funds from an individual lender through potential FinTech services. This would justify possible borrower migration from bank to FinTech lending. Agreeing with this, Eça et al., (2022) show that firms use FinTech to obtain long-term unsecured loans and substitute long-term bank debt for FinTech debt. Following this line of argument, the arrival of FinTech as lenders could therefore make banks willing to take more risks in order to reduce borrower migration as much as possible. Moreover, as underlined by seminal papers on bank risk-taking behavior and bank stability (Allen & Gale, 2004; Hellmann et al., 2000; Keeley, 1990; Matutes & Vives, 2000), excessive levels of competition may reduce bank franchise value and induce risk-taking by banks, who will seek additional sources of income.

Consequently, given that FinTech companies could have a superior capacity to assess borrowers' risks and that incumbent banks could be more prone to take greater risks in an effort to retain their customers from newcomers, we state our second hypothesis as follows:

H2: FinTech lending reduces incumbent banks' stability.

The influence of FinTech lending on bank market power and stability might ultimately depend on the specific characteristics of each country in terms of legal and institutional features. Prior studies have shown that institutional and regulatory settings are relevant vis-à-vis explaining the emergence of FinTech firms (Claessens et al., 2018; Cornelli et al., 2023; Kowalewski et al., 2022). Prior literature has also highlighted the relevance of institutional quality and regulatory characteristics in terms of understanding different dimensions of banking activity and the interconnection between the financial sector and the real economy. Previous papers have shown that the legal and institutional environment can influence bank market power (Claessens & Laeven, 2004), shape the impact of crisis episodes on competitive conditions in banking markets (Cubillas & Suárez, 2013) and modulate the relationship between bank competition and financial stability (Beck et al., 2013; Cubillas & González, 2014). Therefore, because the ultimate effects of FinTech lending on bank market power and stability may be heterogeneous and dependent on cross-country differences at the institutional and regulatory level, we state a third hypothesis:

H3: The legal and institutional framework shapes the effect of FinTech lending on incumbent banks' market power and stability.

3. DATA, VARIABLES, AND MODELS

3.1. Data

Empirically, we test these hypotheses using a unique dataset retrieved from several sources. Bank-level information comes from the ORBIS Bank Focus Database (Bureau Van Dijk). FinTech lending information, computed by Cornelli et al., (2023), is available on the website of the Bank for

International Settlements (BIS)[1]. This database provides information on FinTech lending volumes for a sample of 79 countries from 2013 to 2019. Data on the characteristics of the banking industry and macroeconomic indicators are obtained from the Global Financial Development database, available on the World Bank website, and from the International Financial Statistics dataset provided by the International Monetary Fund (IMF). Information on the features of the legal and institutional environment has been collected from the World Bank Governance Indicators Database and from the World Bank Doing Business Database.

Once the lack of data of the main variables of interest has been accounted for, and given that we require bank-level information to be available for at least three consecutive years, the final sample is made up of an unbalanced panel of 6,309 banks in 70 (developed and developing) countries during the 2013–2019 period. This makes a total of 28,695 bank-year observations in our sample. Table 1 reports the list of countries included in our sample.

3.2. Variables

3.2.1. Key variables: FinTech lending, bank market power, and bank stability

We use the amount of credit provided by FinTech firms as the main proxy for the lending activity of the FinTech sector (*FINTECH*). Table 1 shows the list of countries that make up our sample, and each country' volume of FinTech lending (in millions of USD), both at the beginning and at the end of our sample period.[2] In line with Cornelli et al., (2023), as can be seen in Table 1, China, the United States, and the United Kingdom are the countries with the highest volumes of FinTech lending in

[1] In particular, this paper describes extensively the methodology and the sources used to compute the annual volumes of FinTech lending.

[2] In Table 1, we consider 2013 as the initial period. If 2013 data are not available for a particular country, we use the earliest year with information available. In the same vein, we consider 2019 as the last year. If information is not available for 2019, we use the data on the latest year available.

2019.[3] Although, FinTech credit is mainly concentrated in these countries, Table 1 shows how this type of credit has experienced major growth in most countries during the sample period. Together with the evolution of FinTech lending shown in Figure 1, this evidences the increase in the relative importance of this source of financing as an alternative to traditional bank-based funding. Said increase involves new competitors and could have potential effects on both the level of market power and the stability of incumbent banks.

<INSERT TABLE 1>

The Lerner index (*LERNER*) measures the level of bank market power, i.e., it is an inverse proxy for bank competition. The Lerner index has been widely used in the banking sector as an indicator of the degree of market power (see, for instance, Beck et al., 2013; Cruz-García et al., 2021; Cubillas & González, 2014; Maudos & Fernández de Guevara, 2004). This index defines the difference between the price (interest rate) and marginal cost expressed as a percentage of the price, taking into account that divergence between product price and marginal cost of production is the essence of monopoly power.[4] It takes the value 0 in the case of perfect competition, and 1 under perfect monopoly. As shown in Table 3, the mean value of the Lerner index for the whole sample period analyzed is 0.55 and its standard deviation is 0.14.

We use the Z-score as a proxy for bank stability (*ZSCORE*). Previous papers have traditionally used this variable (see Beck et al., 2013; Laeven & Levine, 2009; Schaeck & Cihák, 2014, among others) and it is computed by the return on assets plus the capital asset ratio divided by the standard deviation of asset returns. A 3-year moving window is used to estimate standard deviations for each bank in each year. A higher Z-score indicates that a bank is more stable because it is inversely related to the

[3] For robustness, we run our baseline regressions excluding China, the United Kingdom, and the United States from the sample. The results obtained are reported in Section 7.

[4] Appendix A describes in detail the construction of the Lerner index.

probability of bank insolvency. Given that the Z-score is highly skewed, we use the natural logarithm of the Z-score, which is normally distributed. Table 3 shows that the *ZSCORE* variable is distributed with a mean value of 4.39 and a standard deviation of 1.20 in our international sample of banks.

3.2.2. Control variables

Following previous papers on bank market power (Anginer et al., 2014; Cubillas & González, 2014; Laeven & Levine, 2009; Maudos & Fernández de Guevara, 2004) and on bank stability (Beck et al., 2013; Behr et al., 2010; Laeven et al., 2016), we include a set of both bank- and country-level controls in all the estimates. As regards bank-level control variables, we consider the natural logarithm of total assets in the bank balance sheet as the proxy for bank size (*Size*). We also include the total capital-to-assets ratio (*Capital*) and the share of interest income in total assets (*Traditional*) as proxies for bank soundness and bank business activity, respectively. Moreover, we consider the cost-to-income ratio as an inverse proxy of bank entity efficiency (*Cost-to-Income*), annual growth rate in total profits (*∆Profits*), and annual growth rate in the volume of granted loans (*∆Loans*).

In order to control for the possible influence of the economic cycle on bank market power and stability, we include the annual growth rate of GDP per capita (*∆GDPpc*) and the annual percentage change in consumer price index (*Inflation*). Furthermore, we consider the ratio of private credit by deposit money banks to GDP (*FinDev*) in order to consider each country's financial development.

Detailed definition on all the variables and the sources from where they were retrieved can be found in Table 2. Their main descriptive statistics are also reported in Table 3[5].

<INSERT TABLES 2 AND 3>

3.3. Econometric modeling

[5] All variables are winsorized at the 1st and 99th percentile levels to reduce the influence of outliers.

Our empirical approach relies on a linear regression with panel data estimators. We regress our proxies for bank market power and bank stability on the main explanatory variable: the volume of credit provided by FinTech lenders. Apart from explicitly controlling for traditional bank- and country-level variables explaining both the degree of bank market power and stability, in all the estimates we use bank fixed-effects estimator to capture the effects of potential unobserved heterogeneity:

$$LERNER_{it} = \beta_0 + \beta_1 FINTECH_{jt} + \sum_{l=1}^{6} \gamma_l \ BANK_{it-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad [1]$$

$$ZSCORE_{it} = \beta_0 + \beta_1 FINTECH_{jt} + \sum_{l=1}^{6} \gamma_l \ BANK_{it-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad [2]$$

where *i*, *j*, *t* refer to the bank, country, and year, respectively. The dependent variable in eq.(1) is the Lerner index (*LERNER*), negatively related to bank competition. The proxy for bank stability, the bank Z-score (*ZSCORE*) is the dependent variable in eq.(2). *FINTECH* is the main explanatory variable and captures the annual credit volumes provided by FinTech firms (Cornelli et al., 2023).

In both regressions, the vector (*BANK*) includes the abovementioned bank-level control variables which enter the regressions lagged by one period in order to reduce potential endogeneity concerns. Following previous literature (Beck et al., 2013; Cubillas & González, 2014; Goetz, 2018, among others), the Lerner index is also a control included in eq.(2). Additionally, the vector (*COUNTRY*) includes the country-level controls.

μ_i is a set of bank dummy variables to control for characteristics that are specific to each bank, provided these are persistent over time. These specific controls allow us to capture any unobserved bank-invariant effects that are specific to each bank and that are not directly included in the regressions. λ_t is a set of year dummy variables to capture any unobserved bank-invariant time effects not included in the regression. $\varepsilon_{i,t}$ is a white-noise error term. Moreover, in order to account for possible correlations of the dependent variable (*LERNER, ZSCORE*), standard errors are clustered at the bank-level.

Another question of interest is whether certain characteristics of the institutional environment may shape the influence of FinTech lending on bank market power and bank stability. To this end, the baseline models [eq.1 and eq.2] are extended to include a set of variables reflecting the legal and institutional environment of each country and their respective interactions with the variable accounting for FinTech lending. These extended models [eq.3 and eq.4] are thus specified as follows:

$$LERNER_{it} = \beta_0 + \beta_1 FINTECH_{jt} + \beta_2 LEGAL_{jt-1} + \beta_3 FINTECH_{jt} * LEGAL_{jt-1} + \sum_{l=1}^{6} \gamma_l \ BANK_{it-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad [3]$$

$$ZSCORE_{it} = \beta_0 + \beta_1 FINTECH_{jt} + \beta_2 LEGAL_{jt-1} + \beta_3 FINTECH_{jt} * LEGAL_{jt-1} + \sum_{l=1}^{6} \gamma_l \ BANK_{it-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad [4]$$

where $LEGAL_{j,t}$ is the vector of variables that capture the quality of the legal and institutional environment. Inclusion of these variables allows us to rule out the possibility that effects attributed to the credit provided by FinTech companies are not caused by alternative country characteristics related to legal and institutional quality. Specifically, we consider four different variables that proxy for the level of legal and institutional quality in each country. First, we consider the regulatory quality (*Regulatory Quality*) and the rule of law indicator (*Rule of Law*). Both variables are retrieved from the World Bank Worldwide Governance Indicators Database. *Regulatory Quality* is an indicator that captures perceptions of government ability to formulate and implement sound policies and regulations that allow and promote private sector development. In a similar vein, *Rule of Law* captures perceptions of the extent to which agents have confidence in and abide by the rules of society and, particularly, the quality of contract enforcement, property rights, the police, the courts, as well as the likelihood of crime and violence. Higher values of both variables are associated with better regulatory quality and rule of law.

Second, we consider the legal rights index developed by the World Bank (Doing Business Database) to measure a borrower country's overall creditor rights (*Creditor Rights*). The strength of the legal rights index measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders. Higher values of this variable indicate better protection of creditor rights. Additionally, we consider the *Resolving Insolvency* variable, as an indicator of the bankruptcy regime. As stated by the Doing Business Group, "*data for the resolving insolvency indicators are derived from questionnaire responses by local insolvency practitioners and verified through a study of laws and regulations as well as public information on insolvency systems. The ranking of economies on the ease of resolving insolvency is determined by sorting* *their scores for resolving insolvency. These scores are the simple average of the scores for the recovery rate and the strength of insolvency framework index*".[6]

4. RESULTS

4.1. FinTech lending, bank market power, and bank stability

In this section, we present the results for our baseline models, explaining how the provision of credit by FinTech companies affects bank market power and bank stability. The results are presented in Table 4. In column (1) of Panel A, the dependent variable is the *LERNER* variable. The results for the *ZSCORE* are reported in Panel B, column (3).

As can be seen in column (1) of Table 4, we find that *FINTECH* lending has a negative and significant effect on market power (*LERNER*). In line with our first hypothesis (*H1)*, this finding indicates that, on average, as the volume of FinTech lending increases, bank market power decreases. This result suggests that the emergence of FinTech companies as suppliers of alternative credit implies an increased level of competition in the lending market. Hence, although incumbent banks may have put substantial efforts into developing their digital channels, the arrival of these new competitors in the credit market seems to be increasing the level of contestability in the financial services market, thereby reducing bank market power.

As regards the control variables, *Size* presents a positive and statistically significant coefficient in column (1), indicating that the larger the bank the greater its market power. Moreover, banks with a higher annual growth in terms of loans, with more diversified sources of income and that are highly efficient would enjoy greater market power. As for country-level variables, *ΔGDPpc* shows a positive

[6] https://www.doingbusiness.org/en/methodology/resolving-insolvency

coefficient, indicating that higher growth rates of GDP per capita positively affect bank market power. *Inflation* and *FinDev* show no statistically significant coefficients.

<INSERT TABLE 4>

The negative and statistically significant coefficients of the *FINTECH* variable obtained in column (3) reveal that the development of FinTech lending negatively influences incumbent banks' stability, thereby confirming our second hypothesis (*H2*). To some extent, these results could be related to a more risk-aggressive response by banks to the arrival of new competitors in the lending market. The emergence of FinTech as credit providers may foster banks' incentives to reduce as much as possible the negative consequences of potential borrower migration to the FinTech sector, thereby affecting their level of stability. In line with Ghosh et al. (2021) and Di Maggio & Yao (2021), this suggest that if FinTech lenders are more efficient at dealing with *hard information*, they are also supposed to be able to discern safe investments more quickly. Hence, they would be ahead of banks in the provision of funding. Given this argument, banks would have to settle for financing less solvent borrowers, which will reduce their average level of stability.

We also obtain a positive and significant coefficient of the measure of bank market power (*LERNER*), indicating that more market power (less competition) positively affects individual bank stability. This is in line with the conclusions drawn by the so-called *competition-fragility view*, suggesting that more bank competition reduces banks' charter value and, therefore, their incentives to behave prudently (Cubillas & González, 2014; Hellmann et al., 2000; Keeley, 1990; among others).

As regards the control variables, *Size* presents a positive and statistically significant coefficient. Moreover, bank stability is positively affected by bank capital (*Capital*). The negative and statistically significant coefficients obtained for the variables *ΔGDPpc* and *FinDev* suggest that growing phases of the economic cycle and high levels of financial development in a country reduce bank stability. This is also consistent with the main reason for the existence of the Basel III counter-cyclical capital buffer.

4.2. Economic impact

The estimated parameters of these baseline regressions only reflect the sign of the influence of FinTech lending on bank market power and stability, thereby providing an insight into whether the influence is statistically significant vis-à-vis explaining differences and the marginal effect of each explanatory variable on bank market power and stability. Quantifying the magnitude of these variables' influence (i.e., economic impact) is therefore of interest, taking the sample variation and the evolution of each variable into account.

Firstly, columns (2) and (4) of Table 4 show the economic impact on bank market power and bank stability of all the explanatory variables. Specifically, for each explanatory variable, we compute the economic impact associated with moving from a value in the 25th percentile of the distribution of the specific explanatory variable to a value in the 75th percentile for the whole sample period. Column (2) of Table 4 shows that if FinTech lending increases in a given country from a low (25th percentile) to a high volume (75th percentile), bank market power decreases on average by 0.35%. Column (4) shows that this same increase in FinTech lending would reduce banks' stability, on average, by 6.57%. In other words, given two identical banks - except for the volume of FinTech lending granted in the country (Low vs. High) -, we could expect bank stability to be 6.57% lower for the bank operating in the banking system with a high volume (75th percentile) of FinTech lending compared to the bank operating in a banking system with a low (25th percentile) volume of FinTech lending.

Furthermore, while Table 4 shows that FinTech lending has an economic impact on bank market power and bank stability, we also examine whether the magnitude of the economic impact has changed over time. To do so, we conduct the same kind of analysis as in Table 4 (Low vs. High), but separately, at the start – 2013 – and the end of the sample period – 2019. Figure 2 shows that the economic impact has not remained constant over time. Increasing FinTech lending from a low (25^{th} percentile) to a high volume (75^{th} percentile) in 2019 had a greater impact on market power and bank stability than in 2013. Specifically, the effect on market power (bank stability) in 2013 is, on average, 0.05% (0.86%), whereas in 2019 it is 0.74% (14.07%). Furthermore, in 2019 the economic effect of FinTech lending is seen to be more relevant than is derived from bank-level variables such as *Capital, ⊿Profits,* and *⊿Loans*. In the same vein, the economic effects associated with the variables related to the economic cycle (*⊿GDP* and *Inflation*) are lower.

These results thus add evidence of the economic importance of Fintech lending, and confirm the two hypotheses concerning the negative effect that this type of credit has on the market power (H1) and bank stability (H2) of the traditional banking system. Furthermore, the results show that the relevance of Fintech lending increased over the period analyzed. The effect is even more prominent than other traditional determinants of market power and bank stability such as profitability, efficiency, the growth of banks loans, and the macroeconomic situation.

<INSERT FIGURE 2>

4.3. The role of the legal and institutional environment

We now analyze whether certain characteristics of the institutional environment might shape the influence of FinTech lending on bank market power and bank stability. To address this issue, we sequentially add each proxy for these characteristics of the legal and institutional environment and their interactions with FinTech lending.

The results obtained are presented in Table 5. In Panel A, the dependent variable is the Lerner index *(LERNER)*. The results obtained when the dependent variable is the Z-score indicator (*ZSCORE*) are reported in Panel B. In columns (1)-(4) and (5)-(8), we sequentially introduce the variables that seek to capture the characteristics of the institutional environment in each country (*LEGAL*): *Regulatory Quality*, *Rule of Law, Creditor Rights*, and *Resolving Insolvency*.

Results in Panel A indicate that the negative and significant coefficient at conventional levels (β_1<0) of *FINTECH* remains invariant to explain *LERNER*. This would suggest that the global effect on bank market power associated with the credit provided by FinTech companies holds after accounting for the characteristics of the legal and institutional environment. However, the results of the interaction terms suggest that the influence of FinTech lending on bank market power varies across countries, depending on the institutional quality. In particular, we obtain positive coefficients for the interactions between the FinTech lending variable and measures of the institutional environment. However, these are only statistically significant in terms of explaining *LERNER* when the *Creditor Rights* and *Resolving Insolvency* variables are used. This would suggest that the negative effect of FinTech lending on bank market power is less relevant in countries with greater protection of creditor rights and a stronger legal framework that is applicable to judicial liquidation and reorganization proceedings. This result is in line with the notion that banks whose rights as lenders are more protected are also more able to face the rivalry from FinTech companies and to maintain their market power than banks in countries with weaker creditor rights protection. However, *Regulatory Quality* and *Rule of Law* do not seem to exert any significant influence on the impact that FinTech lending has on bank market power.

As can be seen in Panel B, the effect of FinTech lending on bank stability remains negative and statistically significant (β_1<0) when the legal and institutional environment is considered. This result indicates that, after explicitly considering the characteristics of the legal and institutional quality, the global effect on bank stability associated with the credit provided by FinTech companies remains invariant. However, the influence of FinTech lending on bank stability varies across countries and depends on institutional quality (β_3). In particular, the interaction terms between the *FINTECH* variable and each proxy of institutional quality ($FINTECH * LEGAL$) are positive and statistically significant at conventional levels. This implies that the negative effect of FinTech lending on bank stability is counteracted by the level of institutional quality. In particular, the positive coefficients obtained for the interaction terms of FinTech lending with both *Regulatory Quality* and *Rule of Law* indicate that in countries where the overall quality of institutions and legal enforcement is higher, the effect of FinTech on the *ZSCORE* is less negative. According to law and finance literature (La Porta et al., 1998) countries characterized by higher levels of institutional quality suffer from less important problems of information asymmetry. This better informational context would allow banks to target and price their loans more accurately, thereby reducing adverse selection problems (Jappelli & Pagano, 2002). Hence, if the quality of information asymmetry-reduction mechanisms – based on the quality of the institutional environment – is higher, – the - negative effect on bank stability associated with FinTech lending is less relevant. Furthermore, the positive interactive terms with *Creditor Rights* and *Resolving Insolvency* variables are consistent with the fact that, in countries with stronger creditor rights protection, lenders are more likely to take collateral, force repayment, or even gain control of the borrower when in financial trouble. Furthermore, in the event of bankruptcy, stronger protection of creditor rights would lead to higher recovery rates for the creditor. Overall, these arguments could explain why banks from countries with higher levels of creditor rights protection might counteract the negative effect of FinTech lending on bank stability better.

<INSERT TABLE 5>

5. THE IMPACT OF FINTECH LENDING ON BANK STABILITY THROUGH MARKET POWER

Prior literature has already examined the relationship between bank market power and bank stability (Allen & Gale, 2004; Boot & Thakor, 2000; Boyd & Nicoló, 2005; Degryse & Ongena, 2007;

among others) as well as if, and to what extent, different events affecting bank market structure (e.g. implementing financial liberalization measures, entry of foreign competitors or adopting deregulation measures) influence market power and, thereby, bank stability.

There is evidence to suggest that changes in market power that are directly driven by a reorganization of the bank market structure can affect banking stability. One stream of theoretical literature has modeled the link between market structure and bank stability through changes in bank market power (Boyd & Nicoló, 2005; Hellmann et al., 2000; Repullo, 2004). Most previous studies thus propose that market power could be an underlying mechanism explaining changes in bank stability. On the empirical side, Cubillas & González, (2014) find that market power is the main channel through which liberalization affects financial stability in developed countries.

In our context, and as the baseline empirical results suggest, the entry of FinTech lenders has a significant (direct) effect on the degree of banks' market power. Specifically, our baseline results reveal that the arrival of FinTech lending has lowered the market power of banks. In this sense, if FinTech lending reduces banks' market power, we might expect a reduction in market power directly driven by the entry of FinTech lenders to also trigger a negative effect on banking stability. Consequently, together with the direct effect of FinTech lending on bank stability, we also aim to examine whether the reduction in market power resulting from FinTech lending may also have an indirect effect on bank stability.

To do so, our empirical analysis considers that the relevance of FinTech lending may affect banks' market power and that potential changes in the competition level caused by these alternative sources of financing may influence bank stability. This analysis requires a two-stage procedure to control for potential endogeneity in banks' market power and bank stability and for their potential simultaneous dependence on FinTech lending. We thus use instrumental variables in a Two-Stage Least Squares (2SLS) procedure for panel-data models.

We regress our proxy for bank stability on FinTech lending and on our measure of bank market power, controlling for other relevant factors at both bank and country level. The structural equation to be estimated is defined as follows:

$$ZSCORE_{it} = \beta_0 + \beta_1 FINTECH_{jt} + \beta_2 \widehat{LERNER}_{it-1} + \sum_{l=1}^{6} \gamma_l \ BANK_{it-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \mu_i + \lambda_t + \varepsilon_{i,j,t} \quad [5]$$

where *i*, *j*, *t* refers to the bank, country, and year, respectively. $\widehat{LERNER}_{it-1}$ is the instrumented Lerner index obtained in a first-stage regression. In eq.(5), coefficient β_2 would indicate how FinTech lending affects bank stability through market power. A significant β_1 coefficient would indicate that part of the effect of FinTech lending on bank stability is not taking place through bank market power.

In order to be consistent, the first-stage equation (Lerner equation) is the same one as used in the baseline model eq. (1). This 2SLS procedure requires including its own predetermined variables or instruments in the first-stage equation, which should affect the second-stage variable only through their effect on the first-stage endogenous variable. Specifically, we consider the index of financial freedom (*FinFree*) and the degree of concentration (*Concentration*) as instruments for explaining the Lerner index.

Since the index of financial freedom (*FinFree*) reflects, among other aspects, how easy it is to open and operate financial service firms (for both domestic and foreign individuals), it may influence the number of entities operating in the sector and therefore impact the level of competition. Prior literature has found that financial freedom essentially impacts bank stability through market power. The theoretical paper of Hellmann et al., (2000) highlights that there is a connection between liberalization and bank stability driven by changes in bank market power. They argue that financial liberalization increases competition; competition erodes profits; lower profits imply lower franchise values; and lower franchise values curtail the incentives for making good loans, thereby increasing the incentives to take greater risks. Empirically, Demirgüç-Kunt & Detragiache, (1998) find that financial liberalization affects bank stability as it erodes bank monopolistic power through a reduction in banks' franchise values. Beck et al., (2013) show that the relationship between bank competition and bank stability depends on a set of regulatory and institutional features that define the degree of financial liberalization. Using a sample of developing countries undergoing a wave of financial liberalization, Turk Ariss, (2010) documents the overall degree of bank stability change triggered by an increase in the degree of bank market power. In a similar vein, Salas & Saurina, (2003) find that implementing a set of liberalization measures in Spain had a negative impact on bank stability due to an increase in banking competition and the erosion of bank market power. Specifically, these authors find that the effect of changes in bank market power caused by deregulation measures reduces the charter value of banks, thereby increasing their incentive to take risks. All these findings would support using the degree of financial liberalization as an instrument, as it affects bank stability not directly but through market power. Based on these prior findings, we expect a negative coefficient for the *FinFree* variable when it explains bank market power in the first stage.

As regards bank market concentration (*Concentration*), it may translate into a lower level of competition by favoring the adoption of collusive agreements between entities. On the other hand, competition may increase by causing banks that are considered to be inefficient to disappear from the market. Some theoretical arguments and country comparisons suggest that banking market concentration may affect bank stability through market power (Allen & Gale, 2000, 2004). As bank concentration changes, so does bank market power, and this latter change in market power may affect bank stability. Boyd & Nicoló, (2005) show that as concentration is positively associated with market power, there is an indirect relationship between concentration and bank stability channeled by market power. Cubillas & González, (2014) use bank concentration as an instrument when examining the relationship between market power and bank stability and find that banking systems with higher levels of concentration promote a greater degree of individual banks' market power. Hence, these prior studies suggest that bank market concentration has an effect on market power and that this relationship is channeled and leads to an effect on bank stability.

Table 6 provides the result of the 2SLS procedure. The results of the first-stage regressions from which we obtain the predicted *Lerner index* according to eq. [1] (Lerner equation) are reported in column (1). As can be observed, we find a negative and statistically significant coefficient for the *FinFree* variable, indicating that more financial liberalization leads to lower levels of market power. Also consistent with previous literature, we find a positive and statistically significant coefficient for bank concentration, suggesting that in more concentrated banking markets banks have a higher degree of bank market power.[7] The second-stage regressions [eq.5] reported in column (2) show that the coefficient of $\widehat{LERNER}_{it-1}$ (β_2) is positive and statistically significant.[8] This result provides empirical evidence of the indirect effect of FinTech lending on bank stability through bank market power. In particular, this finding suggests that the reduced degree of market power caused by the provision of

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[7] It should be noted that all the bank- and country-level variables explaining Lerner in eq.(1) are also considered in this first-stage regression.

[8] In order to be consistent throughout the paper, in model [5] we employ the lagged value of the predicted Lerner index. As the annual FinTech lending volumes reported by Cornelli et al., (2023) start in 2013, we cannot obtain the predicted Lerner index for 2012. This would explain why in the second-stage regression the number of observations is lower than the baseline regressions.

alternative credit from FinTech firms affects bank stability. This result points to the role of market power as a channel underlying the relationship between FinTech lending and bank stability. Moreover, we also find that the coefficient of $FINTECH_{jt}$ (β_1) is negative and statistically significant, suggesting there is a direct negative effect of FinTech lending on bank stability. In other words, part of the effect of FinTech lending on bank stability is not taking place through bank market power.

This could be justified based on the superior capacity of FinTech firms to assess borrowers' risks and the efforts of incumbent banks to retain their customers from newcomers. This may in turn result in banks financing projects that are exposed to a higher level of risk and uncertainty, thereby affecting their stability levels.

To test the validity of both instruments, we compute the Sargan-Hansen test of overidentifying restrictions (orthogonality conditions). The joint null hypothesis of this test is that the instruments are valid (i.e., uncorrelated with the error term) and that the excluded instruments are correctly excluded from the estimated equation. We also compute the statistic of Kleibergen-Paap rk LM (under-identification test) and the statistic of the Kleibergen-Paap rk Wald F test (weak identification test) in order to determine whether the instruments are under-identified and/or weak. According to the p-value of the Sargan-Hansen test, reported in Panel A of Table 6, the null hypothesis (instruments are valid) cannot be rejected, suggesting that our instruments do not run into overidentifying restrictions. Moreover, the statistics of Kleibergen-Paap rk LM (under-identification test) and the statistic of the Kleibergen-Paap rk Wald F test (weak identification test) are statistically significant, suggesting that our instruments are neither under-identified nor weak.

<INSERT TABLE 6>

6. COUNTRY LEVEL ANALYSIS AND THE ENDOGENEITY OF FINTECH LENDING

6.1. Country-level analysis

In order to provide additional insights into the impact of FinTech lending on bank market power and stability, we also examine this relationship from a country-level perspective. The main aim of conducting this additional empirical exercise is to explore further whether the observed effects caused by the FinTech sector at the bank level – lower bank market power and lower bank stability – are also observed at the country level. In this sense, given that the impact of FinTech lending seems to be economically significant for both bank market power and stability it is interesting to examine whether these results are also found at the country-level. If aggregate market power and stability were affected at the country-level this would suggest that the individual effects of FinTech lending on each bank's Lerner and Z-Score are significant enough to cause the whole banking sector-level to be less stable but more competitive.

In order to do this, and being consistent with the identification and econometric strategy followed at bank-level, we run two regressions on bank market power and stability for the same set of 70 countries considered in the baseline regressions [eq.1 and eq.2]. As country-level dependent variables, we employ the same proxies of bank market power and bank stability defined at country-level (*LERNERBS* and *ZSCOREBS*). In both cases, these variables are calculated using the same procedure followed at bank-level. As in the bank-level regressions, *FINTECH* is the explanatory variable capturing the annual credit volumes provided by FinTech lenders (Cornelli et al., 2023). We also include a set of banking-sector aggregated variables (*BANKING*) and country-level (*COUNTRY*) control variables to control for the same banking-related aspects (*Size, Capital, Traditional, Cost-to-Income*, *ΔProfits, ΔLoans*) – and country dimensions (*ΔGDPpc, Inflation, FinDev*). The size of the banking sector is proxied by the ratio of total bank assets to GDP (*SizeBS*), whereas the level of country-level capital is proxied by the ratio of total bank capital and reserves to total assets (*CapitalBS*). To control for traditional banking revenues, in this case we use the ratio of bank income by non-interest related activities-to-total bank income ratio (*TraditionalBS*), which is an inverse proxy of the level of traditional banking revenues. The level of efficiency of the banking industry is proxied by the cost-to-income ratio (*Cost-to-IncomeBS*). We also control for the annual growth in banking sector profits (*⊿ProfitsBS*) and the annual growth of loans (*⊿LoansBS*). As regards macroeconomic controls, we employ the same set of variables as in the bank-level regressions (*⊿GDPpc* and *Inflation*). All these control variables have been retrieved from the Global Financial Development Database, available on the World Bank website, and the International Financial Statistics Dataset provided by the International Monetary Fund (IMF). Country-level regressions with panel data estimators are defined as follows:

$$LERNERBS_{jt} = \beta_0 + \beta_1 FINTECH_{jt} + \sum_{l=1}^{6} \gamma_l \ BANKING_{jt-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \pi_j + \lambda_t + \varepsilon_{j,t} \quad [6]$$

$$ZSCOREBS_{jt} = \beta_0 + \beta_1 FINTECH_{jt} + \beta_1 LERNERBS_{jt} + \sum_{l=1}^{6} \gamma_l \ BANKING_{jt-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \pi_j + \lambda_t + \varepsilon_{j,t} \quad [7]$$

where *j* refers to the country and *t* to the year. As with the bank-level regressions, our estimations include country-fixed effects (π_j) and time-fixed effects (λ_t).

The main results of equations (6) and (7) are shown in Panel A of Table 7. The negative and statistically significant coefficients ($\beta_1 < 0$) of the *FINTECH* variable obtained in both columns (1) and (2) reveal that FinTech lending negatively influences the level of market power in the banking sector as well as the level of financial stability. These results are in line with the bank-level regressions [eq.1 and eq.2] shown in Table 4. In a similar vein, this result suggests that as banks are losing market power when FinTech lenders enter the credit market, there is an aggregate increase in the level of competition in the commercial banking sector (i.e., a reduction in the Lerner index). Moreover, the arrival of new competitors in the credit market leads to a less stable banking sector.

Overall, the country-level estimations confirm that FinTech lending exerts an impact which stretches beyond individual banks' effects. In those countries where FinTech firms have been very active in providing credit, there seems to be an impact in terms of market power and stability for the whole banking sector.

6.2. The potential endogeneity of FinTech lending

One important concern about the impact of FinTech lending on bank market power and stability is that FinTech lending is likely to be driven by some of the intrinsic characteristics of the banking sector. In other words, the status of the traditional banking sector may also become a determinant for the emergence of non-bank institutions that are likely to compete with traditional banks. Consequently, the impact of FinTech lending on banks could be potentially endogenous.

We therefore apply an instrumental variables (IV) method. In the first stage, we regress the FinTech lending variable (*FINTECH*) based on prior literature addressing the drivers of FinTech. We thus employ the percentage of the rural population (*RURAL*) in each country as our main instrument. The use of this instrument is economically motivated by prior empirical evidence. Several papers have underlined the role of the FinTech phenomenon in enhancing financial inclusion (Cornelli et al., 2023; Demir et al., 2020; Kong & Loubere, 2021; Maskara et al., 2021), with the rural population often being associated with a lower level of financial inclusion (Lenka & Barik, 2018). Hau et al., (2019) and Zhang et al., (2020) document that FinTech firms have been particularly active in providing credit lines to rural areas of China. Gabor & Brooks, (2017) argue that digital financial services are increasing in regions with larger rural areas as a solution to the problem of financial exclusion. This also seems to be happening in developed economies. Jagtiani & Lemieux, (2018) show that FinTech lending in the U.S. has penetrated strongly into rural areas, which are often neglected by traditional banks. This is to be expected, since rural populations benefit more from FinTech services (Maskara et al., 2021; Zhang et al., 2020). These findings on the high penetration of FinTech lending in rural areas would explain why Cornaggia et al., (2018) document that banks in rural U.S. counties are more affected by the emergence of FinTech lending. These empirical findings are also supported by anecdotal evidence. Countries with a large percentage of their population living in rural areas have been more prone to adopt FinTech services, as is the case of India.[9] Consequently, based on the above-mentioned findings, we expect a positive association between the share of the rural population and the provision of FinTech credit. We thus regress FinTech lending on the percentage of the rural population (*RURAL*) in each country, controlling for other relevant factors at both bank- and country-level.

$$FINTECH_{jt} = \beta_0 + \beta_1 RURAL_{jt} + \sum_{l=1}^{6} \gamma_l \ BANK_{jt-1} + \sum_{h=1}^{3} \delta_h \ COUNTRY_{jt} + \pi_j + \lambda_t + \varepsilon_{j,t} \qquad [8]$$

where *j* and *t* refer to the country and year, respectively. Apart from considering the variable *RURAL* as the main instrument in the first-stage regression, we are also required to include all the control variables of our country-level baseline model. Subsequently, we use the predicted value of the

[9] "Rural consumption: How 'sachetisation' by FinTechs can get financial services to bottom of rural stratum". Financial Express. 1st April 2021. Available at: Available at: https://www.financialexpress.com/industry/rural-consumption-how-sachetisation-by-fintechs-can-get-financial-services-to-bottom-of-rural-stratum/2224916

FINTECH variable ($\widehat{FINTECH}_{jt-1}$) obtained from the first stage as the main explanatory variable for the second-stage regressions explaining *LERNERBS* and *ZSCOREBS* as in eq, [6] and eq. [7]. The results are reported in Panel B of Table 7. In column (3), we report the first-stage regression results [eq.8]. As regards the effect of our instrument (*RURAL*), it presents a positive coefficient ($\beta_1 > 0$) as expected, indicating that countries with large rural areas are associated with more FinTech lending.

In addition to selecting our instrument based on economic arguments, we require it to be relevant and valid. All the first-stage F-tests are above the rule of thumb of 10, and the Kleibergen-Paap tests reject the null hypothesis of weak instruments, suggesting that the instrument is valid. In a similar vein, the p-value of the Sargan-Hansen test shows that the null hypothesis (instruments are valid) cannot be rejected. The second-stage results are reported in columns (4) and (5). In these second-stage regressions, we find that the main results for the relationship between FinTech lending , bank market power, and bank stability hold completely. Hence, after explicitly controlling for potential concerns regarding the endogeneity of FinTech lending, our results still support the negative effect of FinTech lending on bank market power and stability.

<INSERT TABLE 7 >

7. ROBUSTNESS

7.1. Alternative measures of market power and bank stability

To ensure that our results are robust, we analyze the impact of FinTech lending using alternative measures of market power and bank stability. Firstly, as an alternative measure of market power, we employ the net interest margin, which is commonly used in banking literature (see among others, Calderon & Schaeck, 2016; Claessens, 2009; González, 2022; Koetter et al., 2012) also as a measure of market power.

As underlined in Appendix A, the standard computation of the Lerner index would require using the number of employees as the denominator of the price of labor. However, doing so would lead us to miss a large number of observations, since the ORBIS Bank Focus does not report the number of employees for many of the banks in our sample. For this reason, and as has been done in other papers (Bikker & Haaf, 2002; Claessens, 2009; Delis, 2012; Fernández De Guevara et al., 2005; Staikouras & Koutsomanoli-Fillipaki, 2006, among others), we used total assets as the denominator to calculate the price of labor in the main regressions. However, for robustness purposes, assuming the drop in the number of observations, we compute the Lerner index using the number of employees. In columns (1) and (2) of Panel A of Table 8, we see how the results are consistent with our prior findings.

Secondly, we also use alternative measures of bank stability. In column (3), we use the Z-score using a five-year moving window. In column (4), following Berger et al., (2020) and Demirgüç-Kunt & Huizinga, (2010), we use the accounting Sharpe ratio, which is defined as the return on equity divided by the standard deviation of the return on equity using a 3-year rolling time window. In column (5), the dependent variable is the standard deviation of the return on assets using a 3-year rolling time window. Finally, in column (6), we use the natural logarithm of the ratio of total impaired loans to total equity[10]. As can be seen from these columns of Panel A (Table 8), we continue to observe a negative relationship between FinTech lending and bank stability.

7.2. Measuring FinTech competition: FinTech investments

While our FinTech variable serves to directly capture FinTech lending activity, we also employ an additional proxy of the relevance of the FinTech phenomenon. We use the natural logarithm of annual total investments in the FinTech sector per capita. This variable, which is retrieved by the BIS (Cornelli

[10] For robustness purposes, we also employ the natural logarithm of the ratio of total impaired loans to total assets as the dependent variable. The results, available upon request, are consistent with the paper's findings.

et al., 2021), allows us to account for the total investments received by the FinTech sector in each country in a given year. This variable would reflect the competitive strength of the FinTech sector. A more solid FinTech sector is able to attract a larger amount of investments. In this sense, a FinTech sector with a lot of available funding would be more eager to grant credit to consumers and businesses. Columns (1) and (2) of Panel B in Table 8 show that our results hold using these alternative variables of FinTech competitive activity.

7.3. Subsample analyses

To ensure that our results are not driven by a set of countries in our sample, we conduct several subsample analyses. Given that the volume of FinTech lending is larger in some countries – as can be seen in Table 1 -, we conduct a subsample analysis excluding those countries with the highest volumes of FinTech lending during our sample period[11]. We thus ensure that our results are not just driven by the impact of FinTech lending on banks located in those countries. Consistent with Table 1, for this analysis we exclude banks located in China, the United Kingdom, and the United States[12]. Even after excluding banks in these countries, the results are consistent with the baseline findings - columns (3) and (4) of Panel B of Table 8. [13] Moreover, we also re-run our models for those countries where banks have a lower presence. In doing so, we re-run our regressions for banks located in countries where the average number of ATMs per 100,000 adults is below the median. The results reported in columns (5) and (6) of Panel B of Table 8 are qualitatively similar to those reported in Table 4.

[11] In unreported regression, we also exclude banks from countries that do not report any FinTech lending activity during the whole period (Bahrain, Cabo Verde, Kazakhstan, and Morocco). The results, available upon request, are qualitatively similar.

[12] The results also hold when only China, the United Kingdom, and the United States are included in the analysis. The results are available upon request.

[13] Since prior studies have shown that FinTech lending has played a relevant in emerging economies, we also aim to ensure that the results are not driven by these countries. In unreported regressions but available upon request, we also re-run our regression for the OECD countries (advanced economies) of our sample. The results reported are consistent when considering only these developed economies.

7.4. Alternative econometric modeling

As an alternative to the bank-fixed effects model, we estimate a random-effects model with country-fixed effects. The results, reported in columns (6) and (7) of Panel C in Table 8, show that our main findings hold after employing a country-fixed effects model.

7.5. Banks' business orientation

While in the main regression we control for the business orientation of banks by including a variable (*Traditional*) that proxies for the business activity of banks, it is important to ensure that the results are not uniquely driven by some types of banks. In doing so, we split the sample into those banks which are less traditionally oriented (with more diversified sources of income) and banks more traditionally oriented (with less diversified sources of income) depending if the bank-year value of *Traditional* is below or above the median value of the sample. Columns (8) to (11) of Panel C show that the main results hold for both types of banks.

<INSERT TABLE 8>

8. CONCLUSIONS

This paper analyzes how the emergence of FinTech companies in recent years and their activity as credit providers has affected the market power of incumbent banks and the level of stability in the more traditional commercial banking sector. We use a bank-level database from 70 countries to examine the impact of FinTech lending on banks in terms of market power and stability during the 2013-2019 period. Using an international dataset allows us to capture differences across countries depending on certain features of the institutional environment. Since the potential changes in the competition level resulting from FinTech lending may also influence bank stability, we also apply a 2SLS procedure to distinguish the direct impact of FinTech lending on bank stability from the effect triggered by changes in the market power of entities. Furthermore, we explore the relationship between FinTech lending, bank market power, and stability from a country-level perspective. This country-level perspective allows us to consider potential endogeneity concerns related to FinTech lending.

Baseline results reveal that, on average, FinTech lending negatively affects bank market power, confirming that the arrival of FinTech companies in the credit market has led to an increase in competition levels. Our empirical findings also indicate that FinTech lending negatively influences bank stability. This finding suggests that the emergence of FinTech as an alternative lender may foster banks' incentives to take more risks in order to reduce potential borrower migration to the FinTech sector as much as possible. Likewise, the higher efficiency of FinTech companies are more efficient in processing borrowers' information may also arise a source of instability for banks. These results are also found to be economically significant. Specifically, the results show that the effect of FinTech lending on bank stability and market power increased during the period analyzed. The economic effect becomes even more prominent than other traditional determinants of market power and bank stability (such as profitability, efficiency, the growth of banks loans, and the macroeconomic situation).

We consider that the effect of FinTech lending on bank market power and stability could ultimately depend on the characteristics of the legal and institutional environment. The negative effect of FinTech lending on both bank market power and on bank stability is less relevant in countries with greater creditor rights protection and a stronger legal framework applicable to judicial liquidation and reorganization proceedings. Moreover, we obtain a less negative impact of FinTech lending on bank stability in countries characterized by higher levels of institutional quality. The results of the 2SLS procedure evidence the role of market power as a channel underlying the relationship between FinTech lending and bank stability, confirming that part of this effect is occurring through bank market power. Our results are consistent at the country-level and after addressing the potential endogeneity of FinTech lending.

In terms of policy implications, this paper sheds some light on the importance of appropriate mechanisms to promote bank stability. This is particularly important in the current scenario where the emergence of FinTech as an alternative credit supplier seems to be intensifying incumbent banks' competition and stability. Our results raise concerns about the reduction in market power experienced by banks because of the growing volume of FinTech lending. Although the arrival of new competitors to the lending market may contribute to financial inclusion, economic performance, and overall economic stability positively, greater regulation of FinTech company activities is needed in order to overcome potential information asymmetry and risk effects derived from their activity. Finally, our paper also points out the relevance of institutional quality and benefits from creditor rights protection as counteracting factors of the negative impact of FinTech lending on the traditional commercial banking sector.

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APPENDIX A: Estimating Lerner index

The Lerner index measures the capacity of a bank to set a price above its marginal cost. Specifically, it defines the difference between price and marginal cost expressed as a percentage of price. It assumes that the divergence between product price and marginal cost of production is the essence of monopoly power, such that the higher the margin, the greater its market power. The Lerner index ranges between 0 and 1, with 0 being the case of perfect competition, and 1 of perfect monopoly.

Algebraically the Lerner index for each bank *I* and year *t* is calculated as follows:

$$L_{it} = \frac{P_{it} - MC_{it}}{P_{it}}$$

[A1]

where P_{it} is the average price of the output of bank *i* in year *t*. It is estimated as the ratio between total income and total assets. The underlying assumption is that the flow of goods and services that banks produce is proportional to their total assets, generating financial and non-financial income. MC_{it} is the marginal cost of bank *i* in year *t*. The traditional approximation of the Lerner index does not consider the credit risk faced by banks. If a bank sets a higher interest rate as a result of the risk it assumes, a greater difference between price and marginal cost does not necessarily imply greater market power but may simply be reflecting the higher cost of risk. Following Maudos and Fernández De Guevara (2004), marginal cost is calculated based on a translog cost function, that we correct for credit risk as in Cruz et al. (2018, 2021)[14]:

[14] Jiménez et al., (2013) construct a risk-corrected Lerner index, using information on the probability of default (PD) from the Central Credit Registry (CCR) of Bank of Spain, to which we do not have access.

$$lnC_{it} = \alpha_0 + \alpha_1 lnTA_{it} + \frac{1}{2}\alpha_k (lnTA_{it})^2 + \sum_{j=1}^{4} \beta_j lnw_{jit} + \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4} \beta_{jk} lnw_{jit} lnw_{kit} + \frac{1}{2}\sum_{j=1}^{4} \gamma_j lnTA_{it} lnw_{jit} + \mu_1 Trend + \frac{1}{2}\mu_2 Trend^2 + \mu_3 Trend\ lnTA_{it} + \sum_{j=1}^{4} \delta_j Trend\ lnw_{jit} + v_i + u_{it} \quad [A2]$$

where *C* is total costs (financial costs, operating costs, and provisions) of bank *i* at time *t*. The cost function differs from the traditional one in that as well as the financial and operational costs, it includes the provisions that a bank makes each year, with this variable being an ex-post proxy of the cost of risk. *TA* is total assets and *w* the price of the different production factors of bank *i* at time *t*. We consider the price of four inputs:

w_1: Price of labor = staff costs / total assets[15]
w_2: Price of lendable funds = financial costs / lendable funds
w_3: Price of capital = operating costs (except staff costs) / fixed assets
w_4: Price of credit risk = provisions / volume of lending[16]

We estimate the costs' function (and hence marginal costs) separately for each country over the sample period. We allow the parameters of the cost function to vary from one country to another to reflect different technologies. To capture the influence of variables specific to each bank, we estimate the function by introducing fixed individual effects (v_i). We capture the influence of technical change in the cost function over time by including Trend. u_{it} is a random disturbance.

[15] The price of this input (labor) could be calculated as staff costs over number of employees (instead of staff costs over total assets). However, the "number of employees" variable is not available in ORBIS Bank Focus for many of the banks in our sample (implying about 16,000 fewer observations). For this reason, we decided to use total assets as the denominator to calculate the price of labor.
[16] Given that risk is included in the dependent variable, it is necessary to include the unit cost of this production input, which we can call "credit risk", as a determinant, approximating it as a ratio between provisions and the volume of lending.

Figure 1. Evolution of FinTech Lending

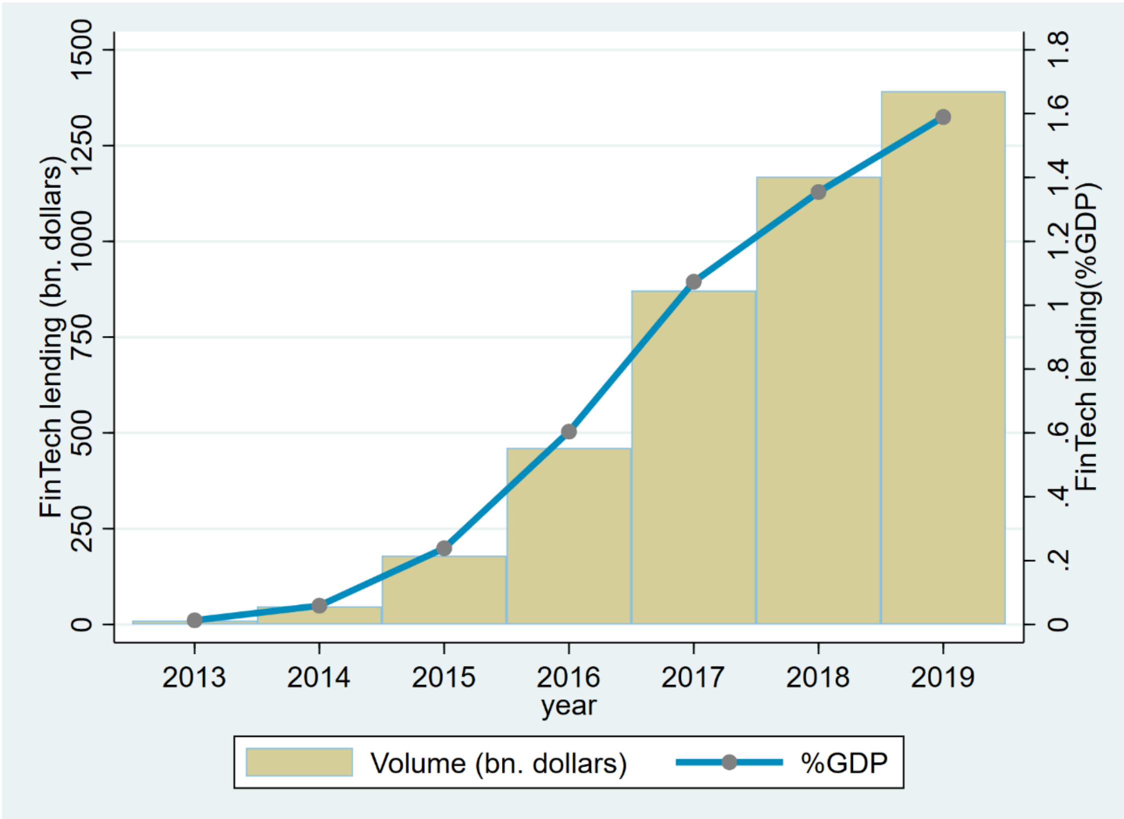

Table 1. Sample description.

This table provides the initial and final FinTech lending in millions of US dollars for the 70 developed and developing countries during the sample period.

Country	Initial FinTech Lending ($ mn)	Final FinTech Lending ($ mn)	Country	Initial FinTech Lending ($ mn)	Final FinTech Lending ($ mn)
Argentina	0.8	313.0	Korea	0.8	2300.2
Australia	11.4	1119.6	Latvia	16.7	538.8
Austria	0.4	25.5	Lebanon	1.7	6.9
Bahrain	0.0	0.0	Luxembourg	4.0	4.0
Bangladesh	0.1	0.1	Malaysia	1.0	191.5
Belgium	0.5	94.2	Mali	1.8	0.8
Bolivia	5.1	3.3	Mexico	0.8	327.7
Brazil	0.8	1460.3	Morocco	0.0	0.0
Bulgaria	1.4	84.8	Netherlands	48.6	3742.9
Cabo Verde	0.0	0.0	New Zealand	0.4	283.0
Cambodia	4.5	11.3	Nigeria	3.3	26.4
Canada	8.1	681.2	Norway	3.3	30.0
Chile	11.7	483.9	Pakistan	0.0	1.6
China	4813.9	110835.9	Panama	0.8	1.7
Colombia	130.7	448.3	Paraguay	0.0	37.9
Costa Rica	9.8	17.8	Philippines	18.4	326.9
Czech Republic	0.0	88.8	Poland	2.1	656.9
Côte d'Ivoire	3.9	0.1	Portugal	0.9	32.4
Dem. Rep. Congo	1.5	4.7	Russia	6.7	273.4
Denmark	21.8	297.6	Singapore	5.4	629.1
Ecuador	4.4	10.9	Slovakia	1.3	47.8
El Salvador	4.9	3.7	Slovenia	0.0	76.2
Finland	19.3	636.0	South Africa	0.2	28.1
France	69.3	1370.7	Spain	3.8	736.0
Germany	48.3	1868.5	Sweden	93.1	241.4
Ghana	2.2	9.8	Switzerland	0.1	125.6
Guatemala	3.5	21.9	Tanzania	2.0	8.5
India	3.8	1115.1	Thailand	0.8	6.8
Indonesia	0.5	3802.5	Turkey	0.1	0.2
Ireland	0.0	40.0	United Arab Em.	0.5	67.6
Israel	0.3	1643.6	United Kingdom	916.8	11476.0
Italy	3.3	1048.8	US	3752.3	70207.7
Japan	78.5	2172.6	Uruguay	0.7	9.0
Kazakhstan	0.0	0.0	Zambia	1.3	1.7
Kenya	9.3	51.2	Zimbabwe	0.7	1.9

Table 2. Definition of variables and sources

This table describes the variables used in the paper and indicates the sources from which the data were retrieved.

Variable	Definition	Source
PANEL A: Main variables		
FINTECH	The natural logarithm of the total credit volume provided by FinTech firms.	BIS
LERNER	The difference between the interest rate and marginal cost expressed as a percentage of price. This index moves between 0 (pure perfect competition) and 1 (perfect monopoly). $$L_{it} = \frac{P_{it} - MC_{it}}{P_{it}}$$	Own calculations using data from BankFocus
ZSCORE	The natural logarithm of (ROA + CAP)/sd(ROA), where ROA is the return on assets, CAP is the capital to asset ratio, and sd(ROA) is an estimate of the standard deviation of the rate of return on assets. To calculate the standard deviation of ROA, we use a three-year moving window. A higher Z-score indicates that the bank is more stable because it is inversely related with the bank's default probability.	BankFocus
PANEL B: Bank-level control variables		
Size	The natural logarithm of total bank assets	BankFocus
Capital	Total bank equity to total bank assets	BankFocus
Traditional	Total interest income to total bank assets. A higher ratio means that the bank is less diversified.	BankFocus
Cost-to-Income	Total operating expenses by total operating income. It represents the efficiency of a bank's operations. A lower ratio means the bank is more efficient.	BankFocus
⊿Profits	Annual growth rate in total profits of the bank.	BankFocus
⊿Loans	Annual growth rate in the volume of bank loans.	BankFocus
PANEL C: Macroeconomic control variables		
⊿GDPpc	Annual percentage growth rate of GDP per capita.	IMF
Inflation	Annual percentage change of end-of-period consumer price index.	IMF
FinDev	Private credit by deposit money banks and other financial institutions to GDP.	Global Financial Development Database (World Bank)
PANEL D: Legal and institutional environment		
Regulatory Quality	It captures perceptions of government ability to formulate and implement sound policies and regulations that permit and promote private sector development.	Governance Indicators Database (World Bank)

Rule of Law	It captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	Governance Indicators Database (World Bank)
Creditor Rights	It is the strength of the legal rights index. It measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders.	Doing Business Database (World Bank)
Resolving Insolvency	It is the simple average of the scores for the recovery rate of insolvency proceedings involving domestic entities, as well as the strength of the legal framework applicable to judicial liquidation and reorganization proceedings.	Doing Business Database (World Bank)
PANEL D: Instrumentation variables		
FinFree	Financial Freedom index of the Heritage Foundation. This index is graded on a scale from 0 (lowest degree of financial freedom) to 100 (highest degree of financial freedom).	Heritage Foundation
Concentration	Assets of the three largest commercial banks as a share of total commercial banking assets.	Global Financial Development Database (World Bank)
Rural	Percentage of the total population living in rural areas.	World Bank
PANEL E: Banking sector variables		
LERNERBS	It is the bank-sector Lerner index.	Global Financial Development Database (World Bank)
ZSCOREBS	Natural logarithm of the bank-sector Z-Score.	
SizeBS	Total assets held by deposit money banks as a share of GDP.	
CapitalBS	Ratio of bank capital and reserves to total assets. Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions, and valuation adjustments.	
TraditionalBS	A bank's income generated by non-interest related activities as a percentage of total income (net-interest income plus non-interest income) in the banking sector. It is an inverse proxy of the level of traditional banking revenues.	
Cost-to-IncomeBS	Operating expenses of a bank as a share of the sum of net-interest revenue and other operating income.	
ΔProfitsBS	Annual growth of banking-sector profits.	
ΔLoansBS	Annual growth of banking-sector volume of loans.	

Table 3. Descriptive statistics.

This table shows the main descriptive statistics (mean, standard deviation, median, 25th, 50th, 75th, 1st, and 99th percentiles) of the main variables of interest. Panel A. provides the descriptive statistics for the bank-level dataset. (Section 5 and 6). Panel B. provides the descriptive statistics for the bank-level dataset (Section 8). *FINTECH* is the natural logarithm of the annual amount of FinTech lending in each country (mill. US dollars). *LERNER* is the Lerner index for each bank. *ZSCORE* is the bank-level indicator of stability. *Size* is the natural logarithm of total assets of each bank. *Capital* is the total capital-to-assets ratio. *Traditional* is the interest income over total assets. *Cost-to-Income* is the cost-to-income ratio. *⊿Profits* and *⊿Loans* are the growth in bank profits and bank loans, respectively. *⊿GDPpc* is the growth of GDP per capita. *Inflation* is the inflation rate. *FinDev* is the ratio of private credit by deposit money banks over GDP. *Regulatory Quality* is the indicator that proxies for the regulatory quality in each country. *Rule of Law* measures the level of efficiency of legal enforcement. *Creditor Rights* is the indicator of the extent to which creditor rights are protected. *Resolving Insolvency* is the indicator for the protection of creditor rights in bankruptcy. *FinFree* is the indicator of financial freedom. *Concentration* is the three-bank assets concentration ratio. *LERNERBS* is the bank-sector Lerner index. *ZSCOREBS* is the natural logarithm of the bank-sector Z-Score. *SizeBS* is the ratio of total assets held by deposit money banks to GDP. *CapitalBS* is the ratio of bank-sector capital and reserves to total bank-sector assets. *TraditionalBS* is the bank-sector's income generated by non-interest related activities as a percentage of total bank-sector income. *Cost-to-IncomeBS* is the bank-sector cost-to-income ratio. *⊿ProfitsBS* and *⊿LoansBS* are the annual growth of bank-sector profits and loans, respectively. *Rural* is the percentage of the total population living in rural areas.

	Obs.	Mean	St. Dev.	25%	Median	75%	1%	99%
Panel A. Bank-level dataset								
FINTECH	28,695	5.19	3.02	2.86	5.33	6.78	0.00	11.16
LERNER	28,695	0.55	0.14	0.46	0.56	0.64	0.14	0.87
ZSCORE	28,695	4.39	1.20	3.69	4.46	5.16	0.98	7.13
Size	28,695	13.99	1.77	12.76	13.95	15.03	10.29	19.13
Capital	28,695	0.10	0.05	0.07	0.10	0.12	0.02	0.36
Traditional	28,695	0.03	0.03	0.02	0.02	0.03	0.01	0.15
Cost-to-Income	28,695	0.69	0.16	0.59	0.69	0.78	0.27	1.22
⊿Profits	28,695	0.05	1.90	-0.18	0.01	0.24	-7.51	6.71
⊿Loans	28,695	0.08	0.22	0.00	0.05	0.12	-0.31	0.96
⊿GDPpc	28,695	1.34	1.45	0.64	1.36	1.84	-2.97	6.26
Inflation	28,695	1.70	2.80	0.51	1.26	1.91	-0.87	15.53
FinDev	28,695	84.66	33.68	58.56	79.30	100.75	15.38	194.10
Regulatory Quality	28,695	1.20	0.67	0.95	1.40	1.72	-0.83	1.91
Rule of Law	28,695	1.23	0.78	0.99	1.60	1.79	-0.82	2.02
Creditor Rights	28,695	49.98	22.62	33.33	50	58.33	16.66	91.66
Resolving Insolvency	28,695	80.68	13.91	71.87	81.25	93.75	25	93.75
FinFree	28,695	65.20	12.51	60.00	70.00	70.00	30.00	90.00
Concentration	28,695	61.21	22.90	36.17	62.77	84.84	24.09	94.41
Panel B. Country-level dataset								
LERNERBS	449	0.55	0.19	0.42	0.54	0.69	0.17	0.97
ZSCOREBS	449	2.67	0.63	2.28	2.70	3.12	0.86	3.91
SizeBS	449	86.80	48.04	48.19	77.98	125.69	15.18	209.39
CapitalBS	449	9.51	3.08	7.10	8.92	11.56	4.94	18.1
TraditionalBS	449	35.65	13.27	26.09	33.59	44.52	11.18	76.27
Cost-to-IncomeBS	449	56.86	12.97	12.97	57.70	64.92	29.96	88.67
⊿ProfitsBS	449	-0.05	1.65	-0.14	-0.01	0.14	-4.40	3.62
⊿LoansBS	449	0.01	0.07	-0.02	0.00	0.03	-0.20	0.21
Rural	449	24.90	12.03	18.14	22.74	30.15	8.30	65.97

Table 4: FinTech lending, bank market power and stability.

This table shows the results for the relationship between FinTech lending, bank stability and bank market power. The dependent variable in column (1) of Panel A is the Lerner index. In Panel B, column (3) the dependent variable is the Z-score. Columns (2) and (4) show the economic impact of each determinant associated with moving from a value in the 25th percentile of the distribution of that variable (Low FinTech lending) to a value in the 75th percentile (High FinTech lending). The economic impact is calculated for the whole sample period and taking as reference the estimated coefficients presented in column (1) for the Lerner Index and column (3) for the ZSCORE. *FINTECH* is the natural logarithm of the annual amount of credit provided by the FinTech sector. *Size* is the natural logarithm of total assets of each bank. *Capital* is the total capital-to-assets ratio. *Traditional* is the interest income over total assets. *Cost-to-Income* is the cost-to-income ratio. *ΔProfits* and *ΔLoans* are the growth in bank profits and bank loans, respectively. *ΔGDPpc* is the growth of GDP per capita. *Inflation* is the inflation rate. *FinDev* is the ratio private credit by deposit money banks over GDP. In all the estimates, bank and year fixed effects are included (not reported). T-statistics for the clustered standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	**PANEL A: LERNER**		**PANEL B: Z-SCORE**	
	Eq. (1)		Eq. (2)	
	(1)	(2) Ec. impact (%ΔLERNER)	(3)	(4) Ec. impact (%ΔZ-SCORE)
FINTECH	-0.0016** (-1.96)	-0.35%	-0.0309*** (-3.00)	-6.57%
LERNER			0.253* (1.84)	4.44%
Size	0.0143*** (3.45)	3.24%	0.116*** (3.02)	26.31%
Capital	0.0967 (1.49)	0.45%	0.929*** (3.56)	4.34%
Traditional	-0.346*** (-3.02)	-0.58%	-1.365 (-1.35)	-2.27%
Cost-to-Income	-0.0239** (-2.03)	-0.46%	-0.0324 (-0.66)	-0.62%
ΔProfits	0.0001 (0.92)	0.01%	0.0047 (1.64)	0.20%
ΔLoans	0.0010*** (3.14)	0.01%	-0.0021 (-0.90)	-0.02%
ΔGDPpc	0.0014** (2.23)	0.17%	-0.0344*** (-4.41)	-4.13%
Inflation	0.0005 (1.12)	0.08%	-0.0026 (-0.51)	-0.37%
FinDev	-0.0002 (-1.52)	-1.10%	-0.0055** (-2.53)	-23.25%
Time Fixed Effects	Yes		Yes	
Bank Fixed Effects	Yes		Yes	
Observations	28,695		28,695	
Number of banks	6,309		6,309	
Clustered Standard Errors	Bank-level		Bank-level	
F-Test (p-value)	0.0000		0.0000	

Figure 2. Economic impact of each determinant of LERNER and Z-SCORE (2013 *vs* 2019).

Figure 2 shows the economic impact on *LERNER* (Fig.2.A) and *Z-SCORE* (Fig.2.B) associated with moving from a value in the 25th percentile of the distribution of that variable (Low FinTech lending) to a value in the 75th percentile (High FinTech lending) for: a) the beginning (2013) and b) the end (2019) of the sample period. Economic impact is calculated by taking the estimated coefficients presented in Table 4 as a reference. The results for 2019 are presented in bold.

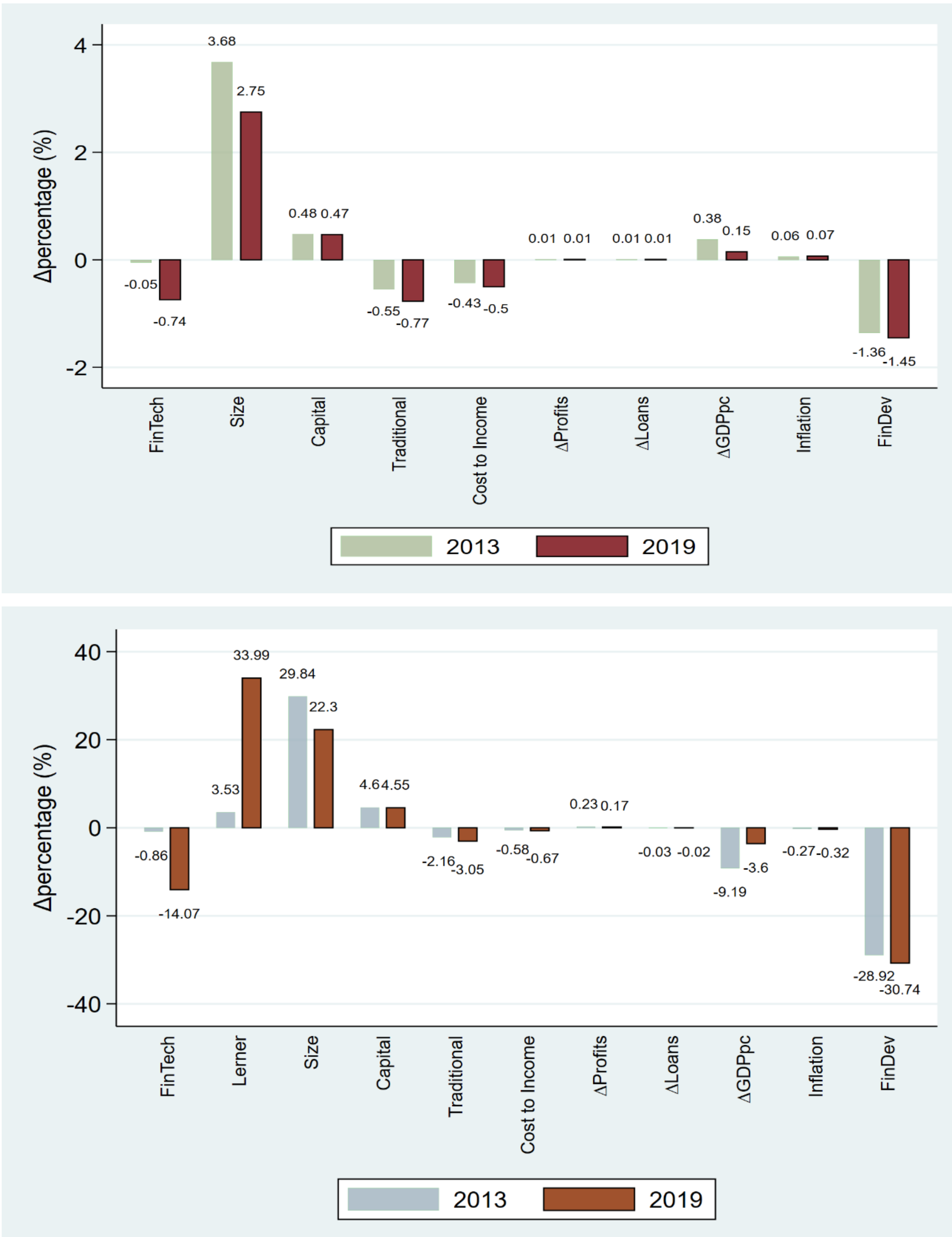

Table 5: The role of the legal and institutional environment.

This table shows the results for the role of the characteristics of the relationship between FinTech lending, bank market power, and bank stability. The dependent variable in Panel A is the Lerner index. In Panel B, the dependent variable is the Z-score. *FINTECH* is the natural logarithm of the annual amount of credit provided by the FinTech sector. *Regulatory Quality* is the indicator that proxies for the regulatory quality in each country. *Rule of Law* measures the level of efficiency of legal enforcement. *Creditor Rights* is the indicator of the extent to which creditor rights are protected. *Resolving Insolvency* is the indicator for the protection of creditor rights in bankruptcy. In all the estimates, bank- and country-level controls and bank- and year-fixed effects are included (not reported). T-statistics for the clustered standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

Dependent variable:	**PANEL A: LERNER**				**PANEL B: Z-SCORE**			
	Eq. (3)				Eq. (4)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FINTECH	-0.0021**	-0.0017**	-0.0023***	-0.0075**	-0.0373***	-0.0426***	-0.0730***	-0.102***
	(-2.47)	(-2.04)	(-3.16)	(-2.56)	(-3.31)	(-3.95)	(-5.09)	(-2.86)
LERNER					0.240*	0.235*	0.273**	0.252*
					(1.74)	(1.72)	(1.99)	(1.81)
*FINTECH * Regulatory Quality*	0.001				0.0225***			
	(1.43)				(2.96)			
*FINTECH * Rule of Law*		0.0003				0.0346***		
		(0.59)				(5.28)		
*FINTECH * Creditor Rights*			2.50e-05*				0.001***	
			(1.93)				(4.17)	
*FINTECH * Resolving Insolvency*				7.72e-05**				0.001**
				(2.08)				(2.52)
Regulatory Quality	-0.004				0.215**			
	(-0.61)				(2.50)			
Rule of Law		-0.009				0.154		
		(-1.17)				(1.55)		
Creditor Rights			-0.0002***				0.002	
			(-3.13)				(1.49)	
Resolving Insolvency				0.0001				-0.0186***
				(0.57)				(-4.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,695	28,695	28,695	28,695	28,695	28,695	28,695	28,695
Number of banks	6,309	6,309	6,309	6,309	6,309	6,309	6,309	6,309
Clustered Standard Errors	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level
F-Test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 6: Market power as a mechanism

This table shows the results for the 2SLS estimator testing the role of bank market power as the mechanism through which FinTech lending affects bank stability. Column (1) shows the first-stage results for the Lerner index indicator. Column (2) shows the results for the second stage explaining the Z-Score indicator. *FinFree* is the indicator of financial freedom. *Concentration* is the three-bank assets concentration ratio. *FINTECH* is the natural logarithm of the annual amount of credit provided by the FinTech sector. In all the estimates bank- and country-level controls and bank- and year-fixed effects are included (not reported). T-statistics for the clustered standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	1st Stage LERNER	2nd Stage Z-SCORE
	(1)	(2)
FinFree	-0.00204***	
	(-11.02)	
Concentration	0.00016***	
	(2.60)	
FINTECH	-0.0040***	-0.0382***
	(-4.11)	(-3.30)
$\widehat{LERNER}$		0.0133***
		(5.94)
Controls	Yes	Yes
Time Fixed Effects	Yes	Yes
Bank Fixed Effects	Yes	Yes
Observations	28,695	23,502
Number of banks	6,309	6,008
Clustered Standard Errors	Bank-level	Bank-level
Sargan-Hansen (p-value)		0.43
Kleibergen-Paap weak identification F-Test		85.85***
Kleibergen-Paap underidentification F-Test		142.13***

Table 7: Country-level evidence and endogeneity concerns.

This table shows the results for country-level evidence of the relationship between FinTech lending, bank market power, and bank stability (Panel A) as well as for endogeneity concerns (Panel B). *LERNERBS* is the Lerner index of the banking sector in each country. *ZSCOREBS* is the Z-Score indicator of each banking sector. *FINTECH* is the natural logarithm of the annual amount of credit provided by the FinTech sector. *FinFree* is the indicator of financial freedom. *Concentration* is the three-bank assets concentration ratio. In all the estimates, bank- and country-level controls and bank and year fixed effects are included (not reported). T-statistics for the clustered standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	PANEL A: COUNTRY-LEVEL EVIDENCE		**PANEL B: ENDOGENEITY**		
	Eq. (6)	Eq. (7)	Eq.(8)		
Dependent variable	LERNERBS	ZSCOREBS	1st-Stage FINTECH	2nd Stage LERNERBS	2nd Stage ZSCOREBS
	(1)	(2)	(3)	(4)	(5)
FINTECH	-0.0071**	-0.0140*			
	(-2.07)	(-1.77)			
$\widehat{FINTECH}$				-0.0193*	-0.0661*
				(-1.79)	(-1.68)
LERNERBS		0.301**			0.294*
		(2.27)			(1.72)
SizeBS	-0.0001	0.0021**	0.0118***	-4.67e-05	0.0025***
	(-0.49)	(2.51)	(2.92)	(-0.14)	(2.99)
CapitalBS	0.0061	0.0301***	0.0892	0.0074*	0.0355***
	(1.44)	(3.22)	(1.02)	(1.92)	(3.31)
TraditionalBS	-0.0007*	-0.0009	0.0024	-0.0007*	-0.0009
	(-1.71)	(-0.84)	(0.25)	(-1.71)	(-0.64)
Cost-to-IncomeBS	-0.0005	7.44e-05	0.0047	-0.0004	0.0003
	(-0.99)	(0.07)	(0.77)	(-0.96)	(0.24)
ΔProfitsBS	0.0002	0.0021	0.0108***	0.0004	0.0026
	(1.32)	(1.52)	(2.92)	(0.68)	(1.18)
ΔLoansBS	0.0392	-0.0658	0.126	0.0476	-0.0294
	(0.88)	(-0.52)	(0.12)	(0.95)	(-0.28)
ΔGDPpc	0.0045*	0.0124**	0.0226	0.0049**	0.0143**
	(1.83)	(2.45)	(0.46)	(2.43)	(2.41)
Inflation	-0.0006	0.0009	-0.0114	-0.0006	0.0009
	(-0.62)	(0.23)	(-0.40)	(-0.41)	(0.24)
FinDev	0.0005	-0.0054***	-0.0172*	0.0003	-0.0061***
	(0.50)	(-3.59)	(-1.74)	(0.55)	(-3.45)
Rural			0.514***		
			(2.90)		
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	449	449	449	449	449
Clustered Standard Errors	Country-level	Country-level	Country-level	Country-level	Country-level
F-Test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000
Sargan-Hansen (p-value)				0.30	0.17
Kleibergen-Paap weak identification F-Test				31.17***	31.42***
Kleibergen-Paap underidentification F-Test				32.44***	32.82***

Table 8: Robustness checks

This table shows the results for the robustness checks. In Panel A, alternative measures of market power and bank stability are used. In column (1), the dependent variable is the net interest margin (difference between interest income and interest expenses relative to the amount of total assets). In column (2), the dependent variable is the Lerner index, calculated using the number of employees as the denominator to calculate the price of labor. In column (3), the dependent variable is the natural logarithm of the Z-score using a five-year moving window. In column (4), the dependent variable is the Sharpe ratio defined as the return on equity divided by the standard deviation of the return on equity using a 3-year rolling time window. In column (5), the dependent variable is the standard deviation of the return on assets using a 3-year rolling time window. In column (6), the dependent variable is the natural logarithm of the ratio of total impaired loans to total equity. In Panel B, other robustness checks are conducted. In columns (1) and (2), *FINTECH* is the natural logarithm of annual total investments in the FinTech sector per capita. In columns (3) and (4), the baseline equations are re-run excluding the U.S., China, and the UK. In columns (5) and (6), the baseline equations are re-run for those banks located on countries with a lower presence of banks (ATMs per 100,000 adults is below the median value). In columns (6) and (7) of Panel C, an alternative random-effects estimator controlling for country and year dummies is used. In Columns (8) to (11), banks are split depending on the business orientation according to their share of total interest income to total assets. T-statistics for the clustered standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

PANEL A. ALTERNATIVE MARKET POWER AND BANK STABILITY MEASURES

	Alternative dependent variables					
Dependent variable:	Net interest margin (1)	Alternative Lerner (2)	Z-score [5yrs] (3)	Sharpe Ratio (4)	Sd (ROA) (5)	Impaired loans/Equity (6)
FINTECH	-0.0004**	-0.0015*	-0.0499***	-0.0443***	0.0003***	0.0453***
	(-2.42)	(-1.82)	(-5.26)	(-4.25)	(3.27)	(5.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std. Errors	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level
Observations	28,695	19,514	24,776	26,937	28,695	22,365
Number of banks	6,309	4,326	6,014	6,053	6,309	5,103
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00

PANEL B. ALTERNATIVE FINTECH VARIABLE, SUBSAMPLE ANALYSES AND COUNTRY FIXED EFFECTS

	Alternative FinTech variable: FinTech investments		Excluding the U.S., China and United Kingdom		Subsample: Countries with a lower presence of banks	
Dependent variable:	Lerner (1)	Zscore (2)	Lerner (3)	Zscore (4)	Lerner (5)	Zscore (6)
FINTECH	-0.0010*	-0.0166**	-0.0036***	-0.0399**	-0.0057***	-0.0388***
	(-1.66)	(-2.22)	(-4.11)	(-3.64)	(-4.51)	(-2.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Country	Country
Clustered Std. Errors	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level
Observations	28,070	28,070	24,035	24,035	10,649	10,649
Number of banks	6,120	6,120	5,530	5,530	3,199	3,199
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00

PANEL C. COUNTRY FIXED EFFECTS AND BANKS' BUSINESS ORIENTATION

			Banks' Business Orientation			
	Alternative econometric modelling: Country FE		Less traditionally oriented (more diversified sources of income)		More traditionally oriented (less diversified sources of income)	
Dependent variable:	Lerner (6)	Z-score (7)	Lerner (8)	Z-score (9)	Lerner (10)	Z-score (11)
FINTECH	-0.0013*	-0.0247**	-0.0045**	-0.0331**	-0.0008*	-0.0283**
	(-1.65)	(-2.50)	(-2.28)	(-2.09)	(-1.79)	(-2.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Country	Country	Yes	Yes	Country	Country
Clustered Std. Errors	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level	Bank-level
Observations	28,695	28,695	14,348	14,347	14,348	14,347
Number of banks	6,309	6,309	3,860	4,401	3,860	4,401
F-Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00