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Does alternative digital lending affect bank performance? Cross-country and bank-level evidence

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ABSTRACT

This paper examines the effect of alternative digital lending provided by BigTech and FinTech firms on bank performance using cross-country and bank-level data. Using a sample of 67 developed and developing countries, we document a negative relationship between this type of digital lending and banking industry performance. The results are economically meaningful because a one-standard-deviation increase in alternative digital credit implies, on average, an 18.08% and 23.27% decrease in the return on assets (ROA) and net interest margin (NIM) of the banking system, respectively. These effects are larger in countries with less stringent banking regulations and less solid banking sectors, and in developing countries. Using bank-level data from 6205 commercial banks, we also show that the negative effect is observed on ROAs and NIMs at the bank level. Furthermore, we demonstrate that the growth in alternative digital lending negatively affects banking credit, suggesting a substitution effect. The findings remain robust after controlling for endogeneity issues and conducting several robustness tests.

1. Introduction

The most recent wave of the technological revolution in banking has been characterized by the entry of disruptive new financial services providers from outside the incumbent banking system (Beck & Cecchetti et al., 2022). Large technological (BigTech) and financial technology (FinTech) companies have actively entered the finance industry. These competitors are encroaching on banks' traditional business, even though banks are adapting to the digital world (Vives, 2017). Although there are differences between FinTech and BigTech lenders, both types of companies have emerged as providers of digital financial services. From the consumer's perspectives, both types of companies constitute a new alternative (i.e., non-bank) source of lending.

Initially, both types of digital companies were concentrated in the payment segment (Boot, Hoffmann, Laeven, & Ratnovski, 2021; Frost, Gambacorta, Huang, Shin, & Zbinden, 2019; Philippon, 2018). However, in recent years, these firms have also emerged as prominent digital lenders. All credit facilitated by BigTech or FinTech lenders rather than by traditional banks represents a new source of "debt-based alternative finance" (Wardrop, Zhang, Rau, & Gray, 2015). Digital lending by BigTech and FinTech firms has grown significantly in the last few years (Beck, Gambacorta, Huang, Li, & Qiu, 2022; Cornelli et al., 2023; Daud, Ahmad, Khalid, & Azman-Saini, 2022; Kowalewski & Pisany, 2022a; Murinde, Rizopoulos, & Zachariadis, 2022a). From 2013 to 2019, the total volume of loans granted by BigTech and FinTech firms globally reached nearly $2.636 billion. Fig. 1 illustrates the growth of this new type of digital credit, showing that the total volume of BigTech and FinTech credit was over 40 times larger in 2019 than in 2013.[1] As Fig. 1 shows, in 2019, alternative digital credit flows reached $795 billion ($572 bn in BigTech and $223 bn in FinTech credit lending), while in 2013, these flows amounted to only $20.5 billion ($10.6 bn in BigTech and $9.9 bn in FinTech credit lending). Furthermore, the figure shows that BigTech and FinTech lending were over 54 and 25 times larger in 2019 than in 2013, respectively.

Some empirical studies have examined the main drivers of the expansion of alternative digital lending (Cornelli et al., 2023; Frost et al., 2019; Kowalewski & Pisany, 2022a, 2022b), but few have investigated the implications of this expansion for the incumbent banks and the banking industry. Kowalewski and Pisany (2022a, 2022b) find that bank consumer lending decreases as BigTech credit increases. Using data from

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[1] While some banks, mainly those from developed countries, have recently invested in FinTech firms (Bellardini, Del Gaudio, Previtali, & Verdoliva, 2022), the volume of credit provided by digital platforms has grown over time.

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a major Chinese BigTech firm, Hau, Huang, Shan, and Sheng (2021) describe how these large companies use data from firms active on their platforms to build lending relationships. Similarly, Hasan and Li (2021) find evidence of a potential substitution relationship between BigTech lenders and traditional banks, as the presence of BigTech competition significantly mutes the bank lending channel. Cornaggia, Wolfe, and Yoo (2018) observe a 1.2% decrease in the volume of personal loans across commercial banks in markets that had experienced a one-standard-deviation increase in FinTech lending activity. The increase in alternative digital credit constitutes growing competition for the incumbent banking industry and could potentially erode its performance (Beck et al., 2022). This is relevant because lending is the core financial activity undertaken by financial intermediaries.

Although prior studies and 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, there is, to our knowledge, little research examining the effects of the emergence of this type of digital lending on banking sector performance. In particular, prior studies have attempted to examine the impact of FinTech lending on bank performance (Hodula, 2023; Nguyen, Tran, & Ho, 2022; Phan, Narayan, Rahman, & Hutabarat, 2020) relying solely on cross-country analyses or focusing exclusively on one type of alternative digital credit (mainly FinTech lending). This is the first paper, to our knowledge, to address this gap by providing empirical evidence of the effect of BigTech and FinTech credit (alternative digital lending) on bank performance using country- and bank-level data. By using more granular data (at the bank level), we are able to observe effects of the growth of alternative digital lending not just on aggregate banking performance but also on each bank's ROAs and NIMs. Furthermore, this analytical approach allows us to consider the characteristics of individual banks and their ability to withstand the incursion of these new digital lenders.

We also contribute to the literature examining whether the effect of this type of alternative digital credit is homogeneous across banking sectors. Specifically, we explore whether certain distinctive characteristics of the banking industry—banking infrastructure, competition, stability, and regulation—may moderate these effects. This is relevant since, as prior studies have found, the emergence of this type of credit varies across banking systems. As Cornelli et al. (2023) highlight, FinTech credit volumes are greater in countries with less physical banking infrastructure. Murinde et al. (2022a); Murinde, Rizopoulos, and Zachariadis (2022b) suggest that regulation, global infrastructures, and geopolitical frictions shape the competitive environment in the banking industry. In this vein, Havrylchyk, Mariotto, Rahim, and Verdier (2019), Jagtiani and Lemieux (2018), and Zhang, Tan, Hu, Wang, and Wan (2020) also find evidence that FinTech services have primarily emerged in areas underserved by traditional banks. Moreover, previous studies (e.g., Claessens, Zhu, Frost, & Turner, 2018; Frost, 2020; Hodula, 2022) have shown that FinTech and BigTech services are more prevalent in countries with less competitive and sound banking markets.

Finally, we also contribute to the extant literature on banking by showing how the entry of newcomers leveraged via the use of a digital channels (e.g., digital platforms, apps, etc.) to provide alternative credit may erode the performance of the incumbent banking industry. By examining the potential channel through which this effect operates, we are able to investigate whether the loans provided by digital lenders complement or substitute those provided by banks.

Using a sample of 67 developed and developing countries over the 2013–2019 period, we first conduct a cross-country analysis of the effects of BigTech and FinTech lending on banking industry performance. In doing so, as is standard in the banking literature (e.g., Carbó-Valverde, Cuadros-Solas, & Rodríguez-Fernández, 2021; Demirgüç-Kunt & Huizinga, 1999a, 1999b; Lopez, Rose, & Spiegel, 2020), we measure banking industry performance using the ROA ratio and the NIM. We find a negative relationship between alternative digital lending and bank performance. This result is economically significant because a one-standard-deviation increase in digital credit is associated with an 18.08% decrease in ROA and a 23.27% decrease in NIM. Moreover, we find that the impact of alternative digital credit on banking sector performance depends on the characteristics of the banking industry. In countries where the banking sector is well established and sound, has higher market power and largely developed physical infrastructure, and is subject to more stringent regulation, alternative digital credit is likely to have less impact on bank performance. Moreover, we find that the growth of this type of digital lending is negatively correlated with banking credit, which suggests the occurrence of a potential substitution effect from banking to alternative digital credit as these digital lenders have entered the credit markets. We also show that while a negative

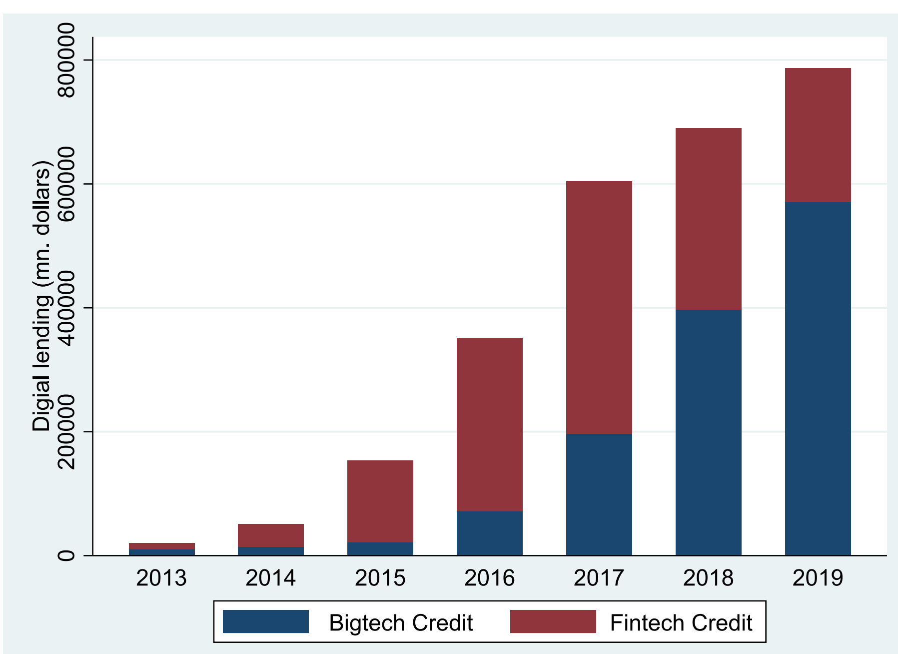

Fig. 1. Evolution of alternative digital lending (BigTech and Fintech Credit).

impact of alternative digital lending on bank performance is observed in developed (high-income) and developing (low-income) countries, the negative effect is smaller (larger) in developed (developing) countries.

These results are confirmed when employing more granular data at the bank level. Using a sample of 6205 commercial banks from the same 67 countries, we investigate the potential effect of alternative digital credit on bank-level performance. Bank returns and intermediation margins are lower for banks operating in countries with a higher volume of alternative digital credit. Moreover, we find that the growth rate of a bank's loan volume is lower if the bank is operating in a country with a higher growth rate in the volume of digital credit.

These findings remain robust after controlling for endogeneity issues. Relatedly, the negative effect of alternative digital credit on bank performance holds after excluding those countries with the largest volumes of alternative digital credit and when conducting separate analyses for FinTech and BigTech credit. Furthermore, the findings hold after including alternative measures of alternative digital lending and bank performance.

The rest of the paper is organized as follows. Section 2 presents the related literature and explains why this type of digital lending may affect bank performance. Section 3 describes the data and the methodology used. Section 4 discusses the main empirical results. Section 5 addresses some endogeneity concerns in the emergence of alternative digital credit. Section 6 presents additional robustness tests. Finally, Section 7 concludes.

2. Related literature: Alternative digital lending and bank performance

The COVID-19 pandemic accelerated the trend of financial digitalization that started some years ago. FinTech start-ups were the first drivers of financial innovation, offering services previously provided only by large financial institutions and delivering greater consumer choice. More recently, the expansion of BigTech into financial services has been observed. Some of the main FinTech start-ups have been acquired by BigTech groups and continue to offer innovative financial services through their platforms (Bains, Sugimoto, & Wilson, 2022).

The digitalization of finance has introduced technologies that challenge the traditional process of intermediation to the extent that they may improve access to finance and introduce new opportunities for investors (Buchak, Matvos, Piskorski, & Seru, 2018). Traditional financial intermediaries such as banks collect funds and make reallocation decisions. They specialize in gathering and processing information (Berger, Miller, Petersen, Rajan, & Stein, 2005; Boot & Thakor, 2000; Diamond, 1984), and due to their screening and monitoring capacities, they have always played a key role in improving investment efficiency.

In this context, technological firms are emerging as new players in financial intermediation. FinTech and BigTech firms employ algorithms to determine credit scores, which are then used to price and distribute loans to small firms and consumers. These algorithms accelerate processes and reduce loan assessment costs (Buchak et al., 2018; Fuster, Plosser, Schnabl, & Vickery, 2019; Jagtiani & Lemieux, 2019). With the generation of new business models based on the use of Big Data, FinTech and BigTech firms have the potential to disrupt established financial intermediaries and banks in particular (Vives, 2017). Banna, Hassan, and Rashid (2021) emphasize that the arrival of FinTech has intensified banks' risk-taking. Additionally, better technology increases the quality of offerings, allowing lenders to gain market share while charging equal or higher rates. Buchak et al. (2018) show that FinTech lenders offer higher interest rates than non-FinTech lenders do. Consumers' willingness to use more expensive FinTech lenders may reflect the convenience of these services.

At the same time, the digitalization of finance has facilitated the matching between firms or projects and investors. Platform-based activities, such as crowdfunding and peer-to-peer lending, use technology to standardize information and provide a means to settle investments, while the individual remains responsible for choosing which project to finance (Bollaert, Lopez-de-Silanes, & Schwienbacher, 2021).

The advantages of FinTech and BigTech platforms in credit provision inevitably affect the traditional banking business and bank–FinTech relationships. The increasing pervasiveness of technology driven by these new firms has placed growing pressure on traditional banks to modernize their core business activities and services (Hornuf, Klus, Lohwasser, & Schwienbacher, 2021).

In this regard, traditional banks are developing their own digital platforms or working with FinTech start-ups. There is evidence that banks with well-defined digital strategies are more likely to establish alliances with FinTech firms. The form of collaboration adopted, however, may depend on what is most beneficial for the particular type of bank. Large banks and banks that focus on certain business segments seem to be more likely to invest in FinTech firms, while small and universal banks may prefer to engage in product-related collaborations (Hornuf et al., 2021). Drasch, Schweizer, and Urbach (2018) show that banks struggle to cooperate with FinTech firms because the relationship between these two parties is complex. The complexity of this relationship would justify the choice of some banks to acquire FinTech firms directly (Carlini, Del Gaudio, Porzio, & Previtali, 2021; Kwon, Molyneux, Pancotto, & Reghezza, 2023). Therefore, it seems unlikely that, in the long run, these new digital lenders could replace banks completely (Murinde et al., 2022a, 2022b). Regardless, these processes and alliances may develop gradually. In the meantime, it is worth analyzing the implications of the expansion of digital credit for the banking system's performance.

Many studies in the banking literature have demonstrated that bank profitability is significantly affected by entity-level characteristics such as size, liquidity, and capitalization (e.g., Berger, 1995; Goddard, Liu, Molyneux, & Wilson, 2013; Goddard, Molyneux, & Wilson, 2004; Lee & Hsieh, 2013; Molyneux & Thornton, 1992; Smirlock, 1985). Furthermore, several authors have found that credit risk has a significant and negative impact on bank profitability (Kutan, Ozsoz, & Rengifo, 2012; Staikouras & Wood, 2011). Goddard et al. (2013) show that scale economies and productive efficiency are positively related to bank profitability. Many studies have also shown that the diversification of business activities increases banks' profitability (Berger, Hasan, & Zhou, 2010; Dietrich & Wanzenried, 2014; Goddard et al., 2004; Goddard et al., 2013). How entities address corporate governance issues may also impact this measure (Aebi, Sabato, & Schmid, 2012; Peni & Vähämaa, 2012). In this regard, Moudud-Ul-huq, Zheng, and Gupta (2018) show that a certain kind of corporate governance increases bank profitability.

Bank performance also seems to be determined by the characteristics of the environment. In this regard, Tregenna (2009) finds that bank concentration increases bank profitability. In the last ten years, research has examined the determinants of performance, analyzing how financial institutions handle external regulation and institutional frameworks (Bitar & Tarazi, 2019; Psillaki & Mamatzakis, 2017), react to monetary policies (Carbó-Valverde et al., 2021; Gambacorta & Shin, 2018), generate intellectual capital (Adesina, 2021; Talavera, Yin, & Zhang, 2018), and engage in shadow banking activities (Tan, 2017).

The development of the FinTech and BigTech sectors in the last decade warrants an examination of how the volume of credit supplied by these firms affects the performance of traditional financial intermediaries. The effect of digital lending on bank performance will depend on whether the products offered by these alternative digital lenders are complementary or substitutionary with respect to those provided by banks. The products would be complementary if digital and traditional lenders could coexist without a significant migration of borrowers and investors to FinTech and BigTech companies. Digital lending is not only provided by technological firms; it can also be provided by financial incumbents through their digital channels (i.e., bank apps or platforms). In this respect, the findings of Balyuk, Berger, and Hackney (2020) suggest that FinTech companies are more efficient at processing hard information. Digital lenders' use of hard information could improve their decisions and reduce potential adverse selection (Freedman & Jin, 2017). Hence, if banks are better able to acquire soft information through long-term lending relationships, they could maintain their competitive advantage in granting loans. In this case, the growing volume of digital credit should not affect bank performance.

Alternative digital lending and banking lending would be substituted if a migration of borrowers and investors from banks to FinTech and BigTech firms occurred. Gopal and Schnabl (2022) document a substitution of bank lending with digital lending after the 2008 financial crisis. Collateral plays an important role in relational loans (Boot & Thakor, 1994). A borrower who lacks collateral or does not constitute a valuable source of soft information for the bank could build a relationship with a traditional bank but face a higher financial cost in doing so. Therefore, such a borrower could be incentivized to raise funds from FinTech and BigTech platforms instead of traditional banks. This would justify the possible migration of borrowers from banks to FinTech and BigTech firms. Furthermore, the opportunity for investors to choose which projects to finance through a platform would justify possible investor migration. In this case, changes in bank performance as a result of the increasing volume of alternative digital credit would be understandable.

The arguments presented above do not allow us to confidently predict the nature of the relationship between alternative digital credit and bank performance. Therefore, how the growth of digital credit affects banking sector performance remains an empirical question, the answer to which may differ depending on the country's level of economic and financial development and the banking regulatory framework. Jagtiani and Lemieux (2018) find that FinTech and BigTech firms have expanded significantly in areas that are underserved by traditional banks. Cornelli et al. (2023) document that FinTech credit is also more prevalent where there are fewer bank branches per capita. On the one hand, it is plausible that in countries with large unbanked or financially excluded populations, digital credit would primarily flow to borrowers who are not being served by banks and, thus, bank performance should not be greatly affected by the growth in digital credit. On the other hand, it is possible that some borrowers in developing countries who were already served by banks may also have migrated to digital platforms. If this were the case, the potential negative impact on banking system performance would be even greater because banks in such economies are not as sound and well-established as those in more financially developed countries. Cornelli et al. (2023) point out that banking regulation may create barriers to the entry of FinTech and BigTech firms, reducing the expansion in this alternative credit in countries with more stringent regulations. Similarly, Claessens et al. (2018) show that FinTech credit volumes are lower in countries with more stringent banking regulations. Therefore, in countries with more stringent regulations, the effect of alternative digital credit on bank performance may be reduced.

3. Data and methodology

3.1. Data and sample description

The sample comprises a panel dataset of 67 countries from 2013 to 2019. According to the United Nations' classification by income level,[2] the sample includes 33 developed countries and 34 developing countries. Because alternative digital credit (provided by FinTech and BigTech firms) has expanded all over the world, our sample is balanced between developed and developing countries. In fact, during the period analyzed, this new type of alternative digital credit experienced significant growth of 37% and 59.6% in developed and developing economies, respectively.

We obtained data on banking system characteristics and macroeconomic indicators from the World Bank Global Financial Development database.[3] We retrieved the volume of alternative digital credit from the Bank for International Settlements (BIS) dataset on alternative lending. This data, which recent studies have also used to examine different aspects of this type of digital finance (e.g., Hodula, 2022; Kowalewski, Pisany, & Ślązak, 2022; Liem, Son, Tin, & Canh, 2022), lists the annual volume of alternative digital lending provided by the main digital non-bank lenders that have emerged since the financial crisis in 2008, namely BigTech and FinTech firms.

In the Appendix, Table A1 lists the countries and their respective volumes of alternative digital credit (in $ million) at the beginning and end of our sample period.[4] In line with Cornelli et al. (2023), Table A1 reflects that China, the US, Japan, Korea, and the UK were the countries with the largest volumes of alternative digital credit in 2019.[5] Nonetheless, Table A1 also shows that this type of credit expanded in most of the sample countries during the sample period. In fact, the total global value of alternative digital lending increased from $18 billion in 2013 to $776.2 billion in 2019. The increase in the relative importance of this alternative financing source could affect the performance of incumbent banks because lending is these banks' core financial activity.

3.2. Empirical modeling

To investigate the potential effect of alternative digital credit on bank performance, our empirical approach relies on a panel regression with country-fixed effects. As is standard in the banking literature (e.g., Carbó-Valverde et al., 2021; Demirgüç-Kunt & Huizinga, 1999a, 1999b; Lopez et al., 2020), we measure banking sector performance using the return on assets (ROA) ratio and the net interest margin (NIM).

$$ROA_{it}(NIM_{it}) = \beta_0 + \beta_1 Digital\ Credit_{it} + \sum_{l=1}^{6} \delta_l Banking\ System_{it-1} + \sum_{h=1}^{3} \delta_h\ Macro_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i and t refer to the country and year, respectively. We regress our proxies for bank performance on the main explanatory variable (digital credit). To provide an accurate measure of alternative digital credit, we compute this variable as the total volume of credit provided by BigTech and FinTech firms as a percentage of GDP. Following previous studies on bank performance (e.g., Batten & Xuun Vinh, 2019; Carbó Valverde & Rodríguez Fernández, 2007; Demirgüç-Kunt & Huizinga, 1999b; Goddard, McKillop, & Wilson, 2008; Molyneux, Reghezza, & Xie, 2019; Molyneux & Thornton, 1992), ***Banking system*** includes a set of bank controls at the country level. In this respect, we control for *size* (measured by bank assets to GDP), *liquidity* (measured by liquid assets to total deposits), *capitalization* (measured by regulatory capital to risk-weighted assets), and *efficiency* (measured by the cost-to-income ratio).

Moreover, because some studies have emphasized that the banking industry's degree of market power and concentration may affect bank performance (e.g., Athanasoglou, Brissimis, & Delis, 2008; Turk Ariss, 2010), we also include bank control variables, namely the *Lerner* index and a measure of *banking concentration.* The *Lerner* index, which has been

[2] Accessible at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519

[3] https://www.worldbank.org/en/publication/gfdr/data/global-financial-development-database

[4] "Initial digital credit" refers to the volume of digital credit in 2013, while "ending digital credit" refers to the volume of digital credit in 2019. If 2013 data are not available for a particular country, we use the earliest year for which information is available. In the same vein, if data are not available for 2019, we use the most recent year for which information is available.

[5] For robustness purposes, in Section 6, we exclude the countries with the largest volume of digital credit.

widely employed in the literature as an indicator of the degree of market power (see e.g. Beck, De Jonghe, & Schepens, 2013; Cruz-García, Fernández de Guevara, & Maudos, 2021; Cubillas & González, 2014; Maudos & Fernández de Guevara, 2004), is defined as the difference between the price (interest rate) and marginal cost expressed as a percentage of the price. The values of the index range from 0 (perfect competition) to 1 (monopoly). *Concentration* is measured as the total assets of the five largest banks as a percentage of total banking assets. In the regressions, all these control variables are lagged by one period to reduce potential endogeneity concerns.

Furthermore, due to the well-known link between business cycle fluctuations and banking sector performance, our regressions include a vector considering macro-level determinants of performance (*macro)*. Following Albertazzi and Gambacorta (2009), we include the annual growth in GDP per capita (*ΔGDPpc*), annual inflation rate (*Inflation*), and the private-credit-to-GDP ratio (*private credit, %GDP*). The variable definitions and data sources are presented in Table A2. The main descriptive statistics are reported in Table 1.

μ_i is a set of country dummy variables used to control for characteristics specific to each country that persist over time. The inclusion of these variables allows us to capture unobserved country-invariant effects. λ_t is a set of year dummy variables that captures country-invariant heterogeneity due to time. $\varepsilon_{i,t}$ is a white-noise error term. Standard errors are clustered at the country level.

In addition to examining the effect of alternative digital credit on bank performance, we also analyze whether and to what extent the characteristics of a country's banking system shape this effect. To do this, we extend the baseline model (eq.1) by including the banking-specific characteristics of each country's banking sector and their respective interactions with the variable accounting for alternative digital lending. The interaction terms (γ_i) would reflect whether the effect of this type of digital lending on bank performance is stronger (or weaker) depending on the soundness and structure of the banking system. Specifically, the extended model is specified as follows:

$$ROA_{it}(NIM_{it}) = \beta_0 + \beta_1 Digital\ Credit_{it} + \gamma_i\ Digital\ Credit_{it} x\ Banking\_Characteristics_{it-1} + \beta_2 Banking\_Characteristics_{it-1} + \sum_{l=1}^{6} \delta_l\ Banking\ System_{it-1} + \sum_{h=1}^{3} \delta_h Macro_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where *Banking_Characteristics*$_{i,t}$ is the vector of variables that captures the banking-specific characteristics of each country related to banking infrastructure, competition, stability, and regulation.

Previous studies have also found evidence that large proportions of unbanked or financially excluded residents explain the emergence of FinTech and BigTech services in a country. Cornelli et al. (2023) highlight that FinTech credit is also more prevalent in countries with fewer bank branches per capita. Havrylchyk et al. (2019), Jagtiani and Lemieux (2018), and Zhang et al. (2020) find that FinTech services have expanded significantly in areas that are especially underserved by traditional banks. To analyze whether the effect of alternative digital lending may differ for bank-based financial systems in which banks are well established as financial intermediaries, we interact our digital credit variable with the banks' assets-to-GDP ratio (*bank-based financial system*). Moreover, to understand whether ease of access to banking services may shape the effect of alternative digital lending on bank performance, we use the number of ATMs per thousand inhabitants (*physical banking infrastructure)*.

Another strand of the literature has examined whether alternative digital lending may act as a substitute for bank credit. Specifically, Hodula (2022) finds that the potential substitution effect of this digital credit differs depending on the banking sector's resilience and soundness. We also consider whether the banking sector's stability may shape the impact of alternative digital lending on bank performance. In doing so, we follow prior studies on bank stability (e.g., Beck et al., 2013; Laeven & Levine, 2009; Schaeck & Cihák, 2014) and consider the *Z*-score (*banking stability*) computed as the ROA plus the capital–asset ratio divided by the standard deviation of asset returns. Because the Z-score is inversely related to the probability of bank insolvency, a higher score indicates that, on average, a banking system is more stable.

Furthermore, prior studies have found that the banking industry's degree of market power drives the arrival and adoption of FinTech and BigTech services (Claessens et al., 2018; Cornelli et al., 2023; Frost, 2020). Thus, we analyze whether the effect of alternative digital lending on bank performance depends on the level of competition in the banking system. In doing so, we consider the Lerner index (*banking market power*) as a proxy for the level of bank market power and thus as an inverse measure of bank competition (Beck et al., 2013; Cubillas & González, 2014; Maudos & Fernández de Guevara, 2004). Higher (lower) values of the Lerner index indicate that, on average, the banking system is less (more) competitive.

Finally, we also consider the possibility that the impact of alternative digital credit may vary depending on the degree of banking regulation. Prior studies have found that less stringent regulation may attract FinTech firms (Claessens et al., 2018; Cornelli et al., 2023; Haddad & Hornuf, 2019). Alternative digital lenders and traditional banks are subject to different regulations, which could affect banking sector performance. The existence of regulation arbitrage may contribute to both the increase in digital credit and the decline in bank performance. In this regard, De Roure, Pelizzon, and Thakor (2022) posit that the substitution effect is contingent on regulatory costs and the presence of adequate capital in the banking system. To measure the stringency of banking regulation, we rely on the IBRN prudential instruments database, which provides a policy-based index that accounts for the macroprudential policies imposed in the banking and financial industries. This index, known as the Macroprudential Index, considers whether countries have implemented 12 policy instruments.[6] These instruments can be grouped into quantitative restrictions on instruments or activities; capital and provisioning requirements for banks; other quantitative restrictions on financial institutions' balance sheets; taxation/levies on activities or balance sheet composition; and other, more institution-oriented measures such as accounting changes, changes to compensation, and concentration limits. The Macroprudential Index is computed based on the Global Macroprudential Policy Instruments (GMPI) database provided by the IMF.[7]

Table A2 presents definitions of all the banking-specific variables and the sources from which they were retrieved. Table 1 also provides the main descriptive statistics. Finally, we include the same bank-level control variables and macro-level determinants of bank performance in our baseline model eq.(1), in addition to country- and year-fixed effects. As before, standard errors are clustered at the country level.

[6] A detailed discussion of the policy instruments used can be found at Cerutti et al. (2016, Cerutti et al., 2017).

[7] An updated version of this dataset is provided at https://www.eugeniocerutti.com/datasets.

Table 1
Descriptive statistics.

	N	mean	sd	min	max	p25	p50	p75
Country-level data								
Digital credit	377	0.11	0.44	0.00	4.38	0.00	0.01	0.04
ROA	377	1.32	1.79	−19.30	6.44	0.77	1.29	1.81
NIM	377	3.93	2.59	0.31	14.27	1.95	3.34	5.49
Size	377	86.20	48.52	0.33	224.86	46.18	74.36	126.43
Capitalization	377	16.48	2.93	10.48	26.97	14.51	16.17	17.98
Liquidity	377	30.17	16.65	6.70	101.32	18.53	25.28	39.53
Cost-to-income	377	55.98	12.79	28.50	144.74	47.52	55.83	63.21
Lerner	377	0.56	0.19	0.17	0.98	0.43	0.56	0.69
Concentration	377	74.88	17.37	31.85	100	62.49	77.22	90.08
Private credit (%GDP)	377	72.08	44.53	10.17	220.1	38.30	60.63	102.55
GDPpc growth	377	2.03	2.42	−6.64	23.99	0.69	1.84	3.27
Inflation	377	3.54	4.32	−3.74	40.28	0.89	2.35	4.82
Mobile phone subscrip.	377	120.39	28.73	56.60	212.63	103.46	121.07	137.19
Bank-level data								
Bank_ROA	27,314	0.78	1.66	−25.57	5.33	0.29	0.53	1.04
Bank_NIM	27,314	2.72	3.62	−19.85	14.42	1.51	2.01	2.87
ΔBank loans	27,314	0.09	0.41	−1.00	34.24	0.00	0.05	0.12
Bank_size	27,314	13.99	1.77	7.12	19.18	12.76	13.95	15.03
Bank_capitalization	27,314	0.10	0.05	0.00	0.66	0.07	0.10	0.12
Bank_cost-to-income	27,314	0.69	0.16	0.26	1.26	0.59	0.69	0.78
Bank_Liquidity	27,314	23.24	16.79	0.03	98.99	10.38	19.12	31.84
Bank_Lerner	27,314	0.55	0.14	0.00	1.00	0.46	0.56	0.64

This table presents the main descriptive statistics (mean; standard deviation; median; minimum, maximum, 25th, and 75th percentiles) of the main variables of interest.

4. Results

Table 2 reports the results for the baseline model of the effect of the emergence of alternative digital credit on bank performance. Columns (1–2) and (3–4) provide the results for ROA and NIM, respectively. For both performance measures, the coefficient of *digital credit* (β_1) is negative and statistically significant. These results suggest that digital credit, as new credit granted by digital firms, leads to relatively lower bank returns and intermediation margins. Thus, this type of digital credit negatively affects the banking industry's performance. Furthermore, these results are economically meaningful because a one-standard-deviation increase in *digital credit* (equal to 0.443, see Table 1) would imply, on average, an 18.08% (0.443 x − 0.408) decrease in ROA and a 23.27% (0.443 x − 0.525) decrease in NIM. These results are consistent with a possible migration of investors and borrowers from banks to digital lenders. Therefore, it seems plausible that the products offered by digital lenders may substitute, at least in part, for those provided by banks. A borrower who lacks collateral could obtain funding from a traditional bank rather than an alternative lender, but at a higher financial cost. This increased cost could incentivize the borrower to raise funds from FinTech and BigTech platforms. Likewise, the possibility for investors to choose which projects to finance through a platform would also justify this migration.

In relation to the control variables, the positive and statistically significant coefficients of *size*, *capitalization*, and *Lerner* in column (2) indicate that a banking system is more profitable if it is large and stable and if the entities operating in it have high market power. The *cost-to-income* variable presents a negative and statistically significant coefficient in column (4). This coefficient reflects that less efficient banking systems have lower intermediation margins. The negative coefficients obtained for *private credit (%GDP)* in column (2) and *concentration* in column (4) were unexpected. Finally, the positive and significant coefficient of *GDP* per capita *growth* in column (2) is consistent with the link between business cycle fluctuations and banking sector performance.

Table 3 reports the results of the regressions that examine whether banking sector characteristics may shape the influence of alternative digital lending on bank performance. Columns (1–5) report the results for ROA, while columns (6–10) present the results for NIM. In all the estimates, the coefficient of the percentage of *digital credit* (β_1) is negative and statistically significant. This result suggests that after accounting for banking sector characteristics (banking infrastructure, competition, stability, and regulation), alternative digital lending also negatively impacts bank performance.

First, the positive and statistically significant coefficient of the interaction of *digital credit x bank-based financial system* (columns 1 and 6) suggests that in countries where banks play a larger role in the economy (i.e., where there is a high ratio of bank assets to GDP), the impact of alternative digital credit on bank performance is relatively smaller. This result suggests that banks in bank-based financial systems are likely to be less affected by the emergence of alternative digital lending compared to banks in market-based financial systems. In countries where banks are well established as financial intermediaries, it is more difficult for alternative digital lenders to erode bank performance. Furthermore, the effect on bank performance (columns 2 and 7) also differs by the degree of stability of the banking industry, which is measured by the *Z-score*. The negative impact of digital lending on bank performance is statistically larger in banking sectors that exhibit high instability. In a sense, this finding confirms the previous result related to bank-based financial systems. If the banking sector is sound (more stable) and well established in the economy, digital credit is likely to have a smaller impact on bank performance.

Column (3) of Table 3 presents the results for the heterogeneous effect of banking market power on ROA. The positive and statistically significant coefficient of the interaction term *digital credit x banking market power* reveals that banking sectors with high market power are likely to be less affected by the emergence of alternative digital credit. In other words, if the banking sector is more able to price its financial services above its marginal costs as alternative digital credit increases, the negative impact on its performance will be reduced. However, as column (8) shows, we do not find evidence of a differential impact of banking market power on NIM.

With respect to physical banking infrastructure, measured by the number of ATMs per thousand inhabitants, columns (4) and (9) show that the coefficient associated with the interaction term *digital credit x physical banking infrastructure* is negative and statistically significant. Thus, in countries where banks have extensive physical infrastructure,

Table 2
Baseline results: Digital credit and bank performance.

Dependent Variable	ROA		NIM	
	(1)	(2)	(3)	(4)
Digital credit	−0.329*	−0.408**	−0.427**	−0.525***
	(0.06)	(0.03)	(0.04)	(0.05)
Size		0.011**		0.003
		(0.11)		(0.47)
Capitalization		0.109*		0.041
		(0.09)		(0.35)
Liquidity		0.022		−0.007
		(0.30)		(0.43)
Cost-to-income		−0.010		−0.010*
		(0.47)		(0.55)
Lerner		2.025*		0.269
		(0.07)		(0.63)
Concentration		−0.014		−0.014*
		(0.25)		(0.06)
Private credit (% GDP)		−0.030*		−0.005
		(0.25)		(0.58)
GDPpc growth		0.068*		0.007
		(0.09)		(0.83)
Inflation		0.007		0.018
		(0.77)		(0.38)
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	Country level	Country level	Country level	Country level
Observations	377	377	377	377
# countries	67	67	67	67
p-value (chi2)	0.03	0.00	0.03	0.04
R-squared	0.01	0.17	0.03	0.19

This table presents the results for the impact of alternative digital credit on banking industry performance. The dependent variable in columns 1 and 2 is ROA, return on assets (i.e., pre-tax profits as a share of total assets). The dependent variable in columns 3 and 4 is net interest revenue (NIM) as a share of average interest-bearing (total earning) assets. *Digital credit* is the total credit volume provided by BigTech and FinTech firms as a share of GDP. The remaining variables are defined in Table A2. Year- and country-fixed effects are included but not reported. *P*-values for the clustered standard errors (at country level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the negative effect of alternative digital credit on bank performance is smaller. This result suggests that the development of the banking sector's physical infrastructure sector influences the effect of alternative digital credit on banking sector performance, as does the population's access to banking services and extent of financial inclusion.

Finally, columns (5) and (10) present the results for the interaction term *digital credit x banking regulatory stringency*. The positive and statistically significant coefficient of this interaction term reveals that banking regulation counteracts the negative effect of alternative digital credit on bank performance. As previous studies have shown (see, among others, Cornelli et al., 2023), banking regulation can inhibit the entry of FinTech and BigTech firms. Consequently, the negative effect of alternative digital credit on bank performance would be lower for banking sectors with more stringent banking regulations.

Overall, our findings indicate that the impact of the emergence of alternative digital credit on banking sector performance depends on the characteristics of the incumbent banking industry. In a sense, all our results are aligned. The negative impact of this type of digital credit on performance is smaller for robust and solid banking sectors. If the banking sector is well established (i.e., banks play an important role as credit providers in the economy), is sound (i.e., banks are largely stable or less likely to default), has high market power (i.e., banks are able to charge relatively high prices compared to their marginal costs), has developed a large physical infrastructure in the country (i.e., the population has easy access to financial services offered by banks), or/and is subject to more stringent regulation (i.e., financial intermediaries face a larger regulatory burden), an increase in alternative digital credit is likely to have a smaller impact on performance.

5. Endogeneity concerns and potential channel

An important concern regarding the impact of alternative digital credit on banking sector performance is that the volume of this type of credit is likely to be driven by certain intrinsic banking sector characteristics. Consequently, the impact of this type of digital credit on banks is potentially endogenous. To address this potential endogeneity, we employ an instrumental variables (IV) methodology. In the first stage, we regress our key explanatory variable (*digital credit*) using the total number of mobile phone subscriptions per 100 inhabitants (*mobile subscriptions*) as our main instrument. The use of this instrument is economically justified based on prior studies of the drivers of BigTech and FinTech credit (e.g., Banna, Mia, Nourani, & Yarovaya, 2022; Haddad & Hornuf, 2019; Hodula, 2023; Kong & Loubere, 2021; Kowalewski, Pisany, & Slazak, 2021; Zhao, Goodell, Dong, Wang, & Abedin, 2022). Because BigTech and FinTech firms offer their financial services through mobile apps or digital platforms, their success depends on internet and mobile service penetration. Haddad and Hornuf (2019) find that the number of mobile phone subscriptions is a relevant driver of the emergence of FinTech firms. Kowalewski et al. (2021) find that the FinTech credit market develops more rapidly in countries with higher mobile phone penetration. Stern, Makinen, and Qian (2017) observe that FinTech lending is greater in regions with more mobile phone subscriptions. Similarly, Kong and Loubere (2021) document that the expansion of affordable mobile coverage fuels the growth of BigTech financial services. In a setting similar to ours, Hodula (2022, 2023) also use mobile phone subscriptions as an instrument of alternative digital credit. We expect a positive association between the number of mobile phone subscriptions and the provision of alternative digital credit.

Furthermore, the instrument's effectiveness (exclusion restrictions) is also justified by the economic literature. While traditional banks also offer online services, Lashitew, van Tulder, and Liasse (2019), the diffusion of mobile technology is not associated with the number of bank accounts held in the population. In this respect, previous studies underline that it is not the diffusion of technology that impacts banks' performance, but its actual adoption (Campbell & Frei, 2010; Hernández-Murillo, Llobet, & Fuentes, 2010; Xue, Hitt, & Chen, 2011, among others). In any case, to verify that the exclusion restriction is satisfied, we also regress our instrument on both bank performance variables. As Table A3 shows, this variable (mobile phone subscriptions) is not statistically significant, suggesting that the number of mobile phone subscriptions does not affect banking sector performance.

Therefore, we regress the *digital credit* variable on the total number of mobile phone subscriptions per 100 inhabitants (*mobile subscriptions*) in each country, controlling for factors at the banking-system and country levels as in the baseline model, eq. (1). Subsequently, we use the predicted value of the *digital credit* variable ($\widehat{Digital\ credit}$) obtained from the first stage as the main explanatory variable for the second-stage regressions that explain bank performance. Column (1) of Table 4 shows that the coefficient of our instrument (*mobile subscriptions*) is positive and statistically significant, indicating that high mobile phone penetration is associated with more digital credit in a country. In the second-stage regressions (columns 2 and 3), we find that the main results of the paper hold after explicitly controlling for potential endogeneity concerns. Table 4 also shows that the instrument used is relevant (i.e., it is neither weak nor under-identified) and valid (i.e., it does not run into over-identifying restrictions).

To further explore the potential drivers of this deterioration in bank performance, we conduct an additional analysis in which we regress the total credit provided by the banking sector as a share of GDP (*banking credit*) on *digital credit*. In doing so, we can determine whether the negative impact of alternative digital credit on banking sector

Table 3
Heterogeneities: Alternative digital credit and bank performance.

Dependent Variable	ROA					NIM				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Digital credit	−1.287***	−4.692**	−0.856**	−0.690***	−1.166***	−1.273***	−3.613**	−0.796*	−1.134***	−1.356***
	(0.00)	(0.03)	(0.04)	(0.00)	(0.00)	(0.00)	(0.02)	(0.06)	(0.00)	(0.00)
Bank-based financial system	0.010**					0.002				
	(0.02)					(0.51)				
Banking stability		2.799**					1.218**			
		(0.03)					(0.04)			
Banking market power			0.877**					1.351		
			(0.04)					(0.37)		
Physical banking infrastructure				−0.002					0.007	
				(0.41)					(0.28)	
Banking regulatory stringency					−0.189*					−0.006
					(0.07)					(0.93)
Digital credit x bank-based financial system	0.006***					0.005**				
	(0.00)					(0.01)				
Digital credit x banking stability		1.404**					1.012**			
		(0.04)					(0.04)			
Digital credit x banking market power			0.982**					0.459		
			(0.04)					(0.46)		
Digital credit x physical banking infrastructure				0.004*					0.007***	
				(0.08)					(0.00)	
Digital credit x banking regulatory stringency					0.096**					0.100***
					(0.00)					(0.00)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Country	Country	Country	Country	Country	Country	Country	Country	Country	Country
Observations	377	377	377	360	377	377	377	377	360	377
# countries	67	67	67	65	67	67	67	67	65	67
p-value (chi2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.15	0.17	0.26	0.16	0.14	0.16	0.11	0.28	0.08	0.16

This table presents the results for the impact of alternative digital credit on banking industry performance. The dependent variable in columns 1 to 5 is (ROA), return on assets (pre-tax profits as a share of total assets). The dependent variable in column 6 to 10 is net interest revenue (NIM) as a share of average interest-bearing (total earning) assets. *Digital credit* is the total credit volume provided by BigTech and FinTech firms as a share of GDP. The remaining variables are defined in Table A2. Year- and country-fixed effects are included but not reported. P-values for the clustered standard errors (at country level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

performance might be driven by a reduction in banking credit. The results are shown in column (4) of Table 4. The coefficient of *digital credit* is negative and statistically significant, suggesting that a substitution effect from banking to alternative digital credit may be occurring as new digital lenders enter the credit markets (Cornaggia et al., 2018; Di Maggio & Yao, 2021; Gopal & Schnabl, 2022; Tang, 2019). The reduction in banking credit could partially explain why the performance of incumbent banks deteriorates as BigTech and FinTech credit volume increases. Therefore, this result suggests that credit may be the mechanism underlying changes in banking sector performance.

6. Bank-level evidence

Through a country-level analysis, we have provided evidence of the negative relationship between alternative digital lending and banking industry performance. That is, the returns and margins of the traditional banking sector seem to have deteriorated due to the increasing volume of credit offered by digital lenders such as FinTech and BigTech companies. In this section, we use a bank-level database to investigate whether the negative effect of alternative digital credit is also observed in ROA and NIM at the bank level. Using aggregate data (at the country level) from the banking sector allows us to demonstrate that the emergence of alternative digital credit affects the aggregate performance of the banking industry. However, country-level data alone may not be enough to support our findings. Using aggregate and bank-level data may present differences, as the difference within-group levels can be large. By using more granular data, we can observe whether alternative digital credit affects each bank's ROA and NIM individually. Furthermore, this analytical approach allows us to consider the characteristics of individual banks and their ability to withstand the incursion of these new digital lenders.

Using a sample of 6205 commercial banks from the same 67 countries from 2013 to 2019, we investigate the potential effect of alternative digital credit on bank-level performance. Our empirical approach relies on a two-way fixed effects estimation:

$$ROA_{jit}\left(NIM_{jit}\right) = \beta_0 + \beta_1 Digital\ Credit_{it} + \sum_{l=1}^{6} \gamma_l\ Bank\ Controls_{jit-1} + \sum_{h=1}^{3} \delta_h\ Macro_{it} + \mu_j + \lambda_t + \varepsilon_{jit} \quad (3)$$

where *j, i,* and *t* refer to the bank, country, and year, respectively. As dependent variables, we use the bank return on assets (ROA) ratio and the bank net interest margin (NIM), respectively. We regress these proxies for bank-level performance on the main explanatory variable (*digital credit*). As in the county-level analysis, we compute this variable as the total volume of credit provided by BigTech and FinTech firms as a percentage of GDP. To be consistent with our baseline estimations (eq. 1), we include the same control variables capturing bank characteristics, but we now measure these control variables at the bank level. Specifically, we consider the natural logarithm of total assets on the bank balance sheet (*Bank_Size*); the capital-to-assets ratio (*Bank_Cap*); the

Table 4
Endogeneity instrumental variables (IV) analysis and potential channel.

	Instrumental Variables Analysis			Potential Channel
	1st Stage	2nd Stage		
Dependent Variable	Digital credit (1)	ROA (2)	NIM (3)	Banking credit (4)
Digital credit		−0.946** (0.03)	−1.594*** (0.00)	−2.839*** (0.00)
Mobile phone subscriptions	0.006** (0.02)			
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	Country level	Country level	Country level	Country level
Observations	377	377	377	377
# countries	67	67	67	67
p-value (chi2)	0.00	0.00	0.00	0.00
R-squared	0.27	0.65	0.08	0.65
Sargan-Hansen (*p*-value)		0.87	0.79	
Kleibergen-Paap weak identification F-test		21.01***	20.97***	
Kleibergen-Paap under-identification F-test		32.97***	32.92***	
Stock and Yogo maximal IV relative bias 10%		16.38	16.38	

This table shows the results for the IV analysis (columns 1 to 3). The dependent variable in column 1 is Digital credit, the total credit volume provided by BigTech and FinTech firms as a share of GDP. The dependent variable in column 2 is ROA, the return on assets (i.e., pre-tax profits as a share of total assets). The dependent variable in column 3 is NIM, the share of average interest-bearing (total earning) assets.In column 4, the total credit provided by the banking sector as a share of GDP (i.e., banking credit) is regressed on alternative digital credit. Year- and country-fixed effects are included but not reported. P-values for the clustered standard errors (at country level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

cost-to-income ratio as an inverse proxy for bank entity efficiency (*Bank_Cost-to-income*); the ratio of liquid assets to total assets, where liquid assets are the sum of cash and balances with central banks, net loans, and advances to banks and Level 1 assets (*Bank_Liquidity*); and the bank market power proxied by the Lerner index (*Bank_Lerner*). This index is defined as the difference between the price (interest rate) and marginal cost expressed as a percentage of the price, considering that the divergence between product price and the marginal cost of production is the essence of monopoly power. We construct the Lerner index at the bank level following the methodology commonly used in the banking literature (Cruz-García et al., 2021; Cubillas & González, 2014). The main descriptive statistics of these bank-level variables are reported in Table 1. We lag all these bank variables by one period to reduce potential endogeneity concerns. We also include a vector of the same controls included in eq. (1) to consider certain macro-level determinants of performance (*concentration, private credit (%GDP), GDPpc growth, and inflation*). μ_j is a set of bank dummy variables used to control for characteristics specific to each bank that persist over time. The inclusion of these variables allows us to capture unobserved bank-invariant effects. λ_t is a set of year dummy variables that captures country-invariant heterogeneity due to time. $\varepsilon_{j,i,t}$ is a white-noise error term. Standard errors are clustered at the bank level.

Table 5 reports the results for the bank-level model of the effect of the emergence of alternative digital credit on bank performance. Columns (1–2) and (3–4) show the results for ROA and NIM, respectively. For both performance measures, the coefficient of digital credit (β1) is negative and statistically significant. These results indicate that bank returns and intermediation margins decrease on average as new digital credit increases. These findings at the bank level support the claim that aggregate banking performance is affected at the country level, as the individual effects of alternative digital lending on each bank's ROA and NIM are significant enough to decrease the profitability of the entire banking sector.

Following an approach similar to that used in the country-level analysis, we also explore the potential drivers of this deterioration in bank performance. In doing so, in column (5) of Table 5, we regress the annual growth of bank loans on the annual growth of alternative digital credit. This approach allows us to examine whether the increase in alternative digital credit affects the dynamics of each bank's loan volume. Column (5) shows that the coefficient of the annual growth of alternative digital credit is negative and statistically significant. This result reflects that the growth rate of loans is lower for banks operating in countries with more growth in the volume of alternative digital credit. As was shown at the country level, this finding suggests a possible substitution effect from banking to alternative digital credit due to a migration of investors and borrowers from banks to digital lenders. These results are consistent with those obtained in the main analysis at the country level.

7. Additional analyses and robustness checks

7.1. *Developed (high-income) versus developing (low-income) countries*

As Table A1 shows, FinTech and BigTech credit has grown significantly in developed and developing countries in recent years. In this context, to provide additional evidence on the heterogeneities that may shape the effect of alternative digit credit on bank performance, we also analyze whether this effect differs across countries depending on the level of income. To do so, we estimate the baseline regressions (eq.1) differentiating between high- and upper-middle-income countries (developed countries) and lower-middle- and low-income countries (developing countries) according to the World Bank's income level classifications.[8] Furthermore, we extend the baseline model (eq.1) by including the interaction between the variable accounting for alternative digital lending and a dummy variable that takes the value of 1 for high and upper-middle (developed) economies and 0 otherwise.

The results in columns (1–4) of Table 6 show that the negative effect of alternative digital credit on ROA and NIM holds for both groups of countries. These results confirm that alternative digital credit has a negative impact on bank performance in both developed and developing countries. However, in columns (5) and (6), the positive and statistically significant coefficient of the interaction term *digital credit x high income* reveals that the negative impact of alternative digital lending on bank

[8] A description of the World Bank's methodology for classifying countries based on income level can be found at https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2021-2022.

Table 5
Bank-level evidence: Digital credit and bank performance.

Dependent Variable	ROA		NIM		Δbank loans
	(1)	(2)	(3)	(4)	(5)
Digital credit	−0.111***	−0.090**	−0.008**	−0.142***	
	(0.00)	(0.01)	(0.05)	(0.00)	
ΔDigital credit					−0.0002**
					(0.01)
Bank_Size		−0.001*		0.0008	−0.416***
		(0.08)		(0.34)	(0.00)
Bank_Cap.		0.0001		0.010	0.140
		(0.99)		(0.55)	(0.87)
Bank_Liquidity		−0.0001		−0.0001***	0.005***
		(0.19)		(0.00)	(0.00)
Bank_Cost-to-income		−0.0006		−0.002**	0.041*
		(0.21)		(0.02)	(0.06)
Bank_Lerner		0.003**		−0.004	−0.054
		(0.03)		(0.32)	(0.67)
Concentration		0.0001		−0.0001**	0.0005
		(0.37)		(0.03)	(0.31)
Private credit (%GDP)		0.0001		−0.0001	−0.004***
		(0.33)		(0.12)	(0.00)
GDPpc growth		0.0001		−0.0001	0.023***
		(0.13)		(0.58)	(0.00)
Inflation		−0.0001		−0.0001	0.015***
		(0.56)		(0.66)	(0.00)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Bank	Bank	Bank	Bank	Bank
Observations	27,314	27,314	27,314	27,314	20,293
# banks	6205	6205	6205	6205	5680
p-value (chi2)	0.00	0.00	0.00	0.00	0.00
R-squared	0.01	0.03	0.03	0.03	0.04

This table presents the results for the impact of alternative digital credit on banks' performance. The dependent variable in columns 1 and 2 is (ROA), return on assets (i.e., pre-tax profits as a share of total assets). The dependent variable in columns 3 and 4 is net interest revenue (NIM) as a share of average interest-bearing (total earning) assets. The dependent variable in column 5 is the annual growth of banks' loans. *Digital credit* is the total credit volume provided by BigTech and FinTech firms as a share of GDP. Δ*Digital credit* is the annual growth of Digital credit. Year- and bank-fixed effects are included but not reported. P-values for the clustered standard errors (at bank level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Developed (high-income) and developing (low-income) countries.

Dependent variable	Developed (high and upper-middle)		Developing (low and lower-middle)		All countries	
	ROA	NIM	ROA	NIM	ROA	NIM
	(1)	(2)	(3)	(4)	(5)	(6)
Digital credit	−0.372*	−0.429**	−0.816***	−1.054**	−1.125***	−1.112***
	(0.09)	(0.04)	(0.00)	(0.08)	(0.00)	(0.00)
Digital credit x high-income					0.818**	0.683**
					(0.02)	(0.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard errors	Country level	Country level	Country level	Country level	Country level	Country level
Observations	285	285	92	92	377	377
# countries	52	52	15	15	67	67
p-value (chi2)	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.11	0.17	0.10	0.08	0.15	0.15

This table shows the results for the impact of alternative digital credit on the banking industry's performance. The dependent variable in columns 1 and 3 is ROA, return on assets (pre-tax profits as a share of total assets). The dependent variable in columns 2 and 4 is the net interest revenue (NIM) as a share of its average interest-bearing (total earning) assets. *Digital credit* is the total credit volume provided by BigTech and FinTech firms as a share of GDP. In columns 1 and 2, the regression is estimated for those countries the World Bank classifies as high- and upper-middle-income countries. In columns 3 and 4, the regression is estimated for those countries the World Bank classifies as lower-middle- and low-income countries. In columns 5 and 6, the regressions are estimated considering whether the level of income of countries shapes the effect of digital credit on bank performance and NIM, respectively. In this latter case, the difference between high- and low-income countries is captured by means of a dummy variable. *High income* takes the value of 1 for high and upper-middle economies and 0 otherwise. The rest of the variables are defined in Table A2. Year- and country-fixed effects are included but not reported. P-values for the clustered standard errors (at the country level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Robustness checks.

Panel A. Robustness checks I

	Alternative Performance Measures		Log [1 + Digital Credit]		Digital Credit per capita		Digital Credit/Banking Credit	
Dependent Variable	**ROE**	**%ΔROA**	**ROA**	**NIM**	**ROA**	**NIM**	**ROA**	**NIM**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Digital credit	−3.729**	−0.188*	−1.166**	−1.405***	−0.003**	−0.003**	−29.373***	−23.464**
	(0.01)	(0.09)	(0.01)	(0.00)	(0.03)	(0.03)	(0.00)	(0.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered std. errors	Country level	Country level	Country level	Country level	Country level	Country level	Country level	Country level
Observations	377	377	377	377	377	377	317	317
# countries	67	67	67	67	67	67	62	62
p-value (chi2)	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.08	0.08	0.16	0.14	0.11	0.06	0.16	0.29

Panel B. Robustness checks II

	Lagged Digital Credit		**Excluding China, US, UK, Japan, and Korea**		**Excluding Countries Without Digital Credit**		**Controlling for FinTech Investments**	
Dependent Variable	**ROA**	**NIM**	**ROA**	**NIM**	**ROA**	**NIM**	**ROA**	**NIM**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Digital credit	−0.376**	−0.335	−1.153***	−1.152***	−0.427**	−0.529***	−0.403**	−0.534***
	(0.03)	(0.03)	(0.00)	(0.00)	(0.04)	(0.00)	(0.03)	(0.00)
# FinTech deals							−0.0001	0.0002
							(0.81)	(0.55)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered std. errors	Country level	Country level	Country level	Country level	Country level	Country level	Country level	Country level
Observations	311	311	342	342	359	359	377	377
# countries	65	65	62	62	62	62	67	67
p-value (chi2)	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.02
R-squared	0.16	0.18	0.16	0.26	0.17	0.26	0.17	0.17

This table presents the results of the robustness analyses for the impact of alternative digital credit on banking sector performance. In columns 1 and 2 of Panel A, the dependent variables are ROE (pre-tax profits as a share of total equity) and %ΔROA, which is the growth rate of ROA. In columns 3 and 4 of Panel A, digital credit is computed as the natural logarithm of 1 plus the total credit volume provided by BigTech and FinTech firms as a share of GDP [ln(1 + Digital Credit)]. In columns 5 and 6 of Panel A, digital credit is computed as the volume of alternative credit per million inhabitants. In columns 7 and 8 of Panel A, digital credit is computed as a share of banking credit. In columns 1 and 2 of Panel B, digital credit is lagged by one year. As indicated in columns 3 and 4 of Panel B, we re-run our baseline eqs. (1) and (2) excluding China, the US, the UK, Japan, and Korea. As indicated in columns 5 and 6 of Panel B, we re-run our baseline eqs. (1) and (2) excluding countries that had no BigTech and FinTech credit throughout the sample period according to Cornelli et al. (2023). In columns 7 and 8 of Panel B, we re-run our baseline eqs. (1) and (2) including the total number of equity investment deals in the FinTech sector as an additional control. Year- and country-fixed effects are included but not reported. *P*-values for the clustered standard errors (at country level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

performance is statistically smaller in developed (high- and upper-middle-income) countries.[9] Because developed countries tend to have more solid and well-established banking systems, these results are in line with those reported in Section 4 when considering the characteristics of the banking system.

7.2. Measurement of bank performance and alternative digital credit

First, we re-run our main regressions using two alternative performance measures: return on equity (ROE) and the growth rate of ROA (*%ΔROA)*. Columns (1) and (2) of Panel A in Table 7 show that the coefficient of *digital credit* remains negative and statistically significant after considering these alternative dependent variables. Second, to ensure that our results are not driven by the overdispersion of *digital credit* in our sample of countries, we re-run our main analysis, taking the natural logarithm of our main explanatory variable, namely log (1 + digital credit). Columns (3) and (4) of Panel A in Table 7 confirm the negative effect of alternative digital credit on bank performance.

We also consider alternative ratios for measuring digital credit. First, instead of scaling the total volume of digital credit by GDP, we scale the volume of alternative credit by population (*digital credit* per capita*)*. This variable is computed as the volume of alternative credit per million inhabitants. Columns (5) and (6) of Panel A in Table 7 show that our results hold using a measure of digital credit that accounts for the population of the country. Second, we consider the ratio of alternative digital credit to banking credit (alternative credit/banking credit). This variable represents the volume of alternative credit for each dollar of credit issued by the banking sector. Columns (7) and (8) of Panel A in Table 7 show that the coefficient of this alternative variable is negative and statistically significant, suggesting that there is a negative relationship between the proportion of credit provided by digital lenders and banking sector performance. This finding aligns with the baseline results.

Finally, we lag our digital credit variable for one period (*lagged digital credit*) because an increase in digital lending may take time to affect bank performance. Columns (1) and (2) of Panel B in Table 7 show that the coefficient of our lagged variable is negative and statistically significant, suggesting that there is a negative relationship between the proportion of credit provided by digital lenders in the previous year and the current performance of the banking sector.

7.3. Subsample analyses

To ensure that our results are not driven by a larger concentration of

[9] We obtain similar results when considering OECD membership as the main criterion for classifying countries as developed or developing.

Table 8
Differentiating between FinTech and BigTech credit.

Dependent variable	ROA	NIM	ROA	NIM
	(1)	(2)	(3)	(4)
FinTech credit	−0.309*	−0.592**		
	(0.09)	(0.01)		
BigTech credit			−0.477**	−0.561**
			(0.02)	(0.01)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Clustered standard errors	Country level	Country level	Country level	Country level
Observations	377	377	377	377
# countries	67	67	67	67
p-value (chi2)	0.00	0.00	0.00	0.04
R-squared	0.18	0.32	0.17	0.20

This table shows the results for the impact of FinTech and BigTech credit on the banking industry's performance. The dependent variable in columns 1 and 3 is ROA, return on assets (pre-tax profits as a share of total assets). The dependent variable in columns 2 and 4 is the net interest revenue (NIM) as a share of its average interest-bearing (total earning) assets. *FinTech credit* is the total credit volume provided by FinTech firms as a share of GDP. *BigTech credit* is the total credit volume provided by FinTech firms as a share of GDP. The rest of the variables are defined in Table A2. Year- and country-fixed effects are included but not reported. P-values for the clustered standard errors (at the country level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

alternative digital credit in a subset of countries, we re-run our regressions excluding the countries with the largest volumes of digital credit provided by FinTech and BigTech firms (see Table 1).[10] The results are presented in Columns (3) and (4) of Panel B in Table 7 and are consistent with the baseline findings. Additionally, we re-run our model excluding those countries for which the BIS dataset provides no evidence of BigTech or FinTech credit throughout the sample period.[11] Columns (4) and (5) of Panel B in Table 7 show that the coefficient of *digital credit* remains negative and statistically significant.

7.4. FinTech investments

Another robustness check we perform accounts for the possibility that the volume of FinTech investments and not the lending activity of FinTech companies in a given country may explain the deterioration in bank performance. We control for this possibility by including in our main regression the total number of equity investment deals in the FinTech sector, which we retrieved from the BIS dataset (Cornelli, Doerr, Franco, & Frost, 2021). Columns (7) and (8) of Panel B in Table 7 show that our results hold after accounting for the funding of FinTech firms. Moreover, this variable is not statistically significant, which suggests that it is specifically the volume of credit provided by these firms that affects bank performance.

7.5. FinTech versus BigTech credit

While the objective of this paper is to examine the effect of the total volume of alternative digital lending on bank performance, FinTech and BigTech lenders may differ in terms of the competition they pose to incumbent banks. Consequently, we also differentiate between FinTech and BigTech credit in our baseline model. As Table 8 shows, the negative effect on bank performance persists in the separate FinTech and BigTech credit regressions.

8. Conclusions

Over the last decade, new digital competitors have actively entered the finance industry. BigTech and FinTech firms have expanded their financial services offerings by providing loans to consumers and businesses. Because these technological companies may be providing credit to customers previously reliant on banks, the growth of this type of digital lending may affect traditional banks' business models and thus banking sector profitability. This paper examined the relationship between BigTech and FinTech lending and banking industry performance in a sample of 67 developed and developing countries. The results show that large volumes of digital credit are associated with poorer performance of incumbent banking industries. Our results also reveal that the influence of FinTech and BigTech lending on bank performance is shaped by the characteristics of the country's banking system. Specifically, the negative effect of alternative digital lending on bank performance is smaller in countries where the banking sector is sound (i.e., banks are largely stable or less likely to default), has a high market power and extensive physical infrastructure, and is subject to more stringent regulation.

Our main findings are confirmed when employing more granular data at the bank level. Using a sample of 6205 commercial banks from the same 67 countries, we show that returns and intermediation margins are lower for banks operating in countries with a higher volume of alternative digital credit. Furthermore, the results indicate that an increase in BigTech and FinTech credit negatively affects traditional credit granted by incumbent banks. The growth rate of each bank's loan volumes is lower if the bank is operating in a country with a higher growth rate in digital credit volumes.

The latter result indicates a potential substitution effect from banking to alternative digital credit as new digital lenders enter the credit market. These results remain robust after controlling for the potential endogeneity of alternative digital credit and conducting additional analyses and various robustness tests. In fact, we find that the negative effect of alternative digital credit is observed in developed (high-income) and developing (low-income) countries, but this effect is stronger in developing countries in which banking systems are less solid and established.

These findings have implications for the incumbent banking industry and policymakers. The negative impact of the arrival of new digital competitors on bank performance suggests that the banking industry may need to adapt its business models to compete in an increasingly digital environment. As Demirgüç-Kunt and Detragiache (1998) highlight, bank profitability is an important predictor of financial crises. In this sense, if bank capital is sufficiently low and it is too costly to issue new capital, a decrease in bank profitability may result in banks reducing lending to meet regulatory capital requirements (Basel III requirements), while FinTech and BigTech firms are not subject to these regulatory requirements. The reduction in bank lending, if not compensated for by the increase in alternative digital credit, could negatively affect economic growth by reducing consumption and investment. Therefore, national and supranational authorities should consider regulating these new participants in the credit markets when designing policies to ensure the financial stability of the entire system.

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Appendix A. Appendix

Table A1
Sample description

Country	Initial Digital Credit ($ mn)	Final Digital Credit ($ mn)	Country	Initial Digital Credit ($ mn)	Final Digital Credit ($ mn)
Argentina	0.80	8.20	Latvia	0.00	0.00
Australia	11.40	51.92	Lebanon	1.66	6.90
Austria	0.43	2.22	Luxembourg	4.04	4.04
Bahrain	0.00	0.00	Malaysia	1.00	534.66
Bangladesh	0.05	0.05	Mexico	0.78	376.41
Belgium	0.54	31.66	Morocco	0.00	0.00
Bolivia	5.06	5.06	Netherlands	48.63	3742.92
Brazil	0.80	1752.46	New Zealand	0.42	190.31
Bulgaria	0.00	0.00	Nigeria	3.31	27.43
Cambodia	4.49	35.53	Norway	3.27	30.00
Canada	8.14	681.17	Pakistan	101.53	151.75
Chile	11.73	483.94	Panama	0.80	1.66
China	4813.91	626,713.60	Paraguay	0.02	37.91
Colombia	130.67	448.26	Peru	0.08	429.93
Costa Rica	9.80	17.82	Philippines	22.19	405.68
Czech Republic	0.02	88.78	Poland	2.11	656.86
Denmark	21.79	297.64	Portugal	0.88	32.39
Ecuador	4.40	10.89	Russia	2234.07	2585.22
Egypt	0.03	0.50	Singapore	5.37	646.67
El Salvador	4.85	3.72	Slovakia	1.33	47.81
Finland	19.32	60.44	Slovenia	0.01	3.32
France	69.26	201.04	South Africa	0.16	28.33
Germany	48.33	205.58	Spain	3.75	736.04
Ghana	2.17	982.44	Sweden	93.09	2.51
Guatemala	3.50	21.93	Switzerland	0.13	2.19
India	3.84	1285.05	Tanzania	1.99	608.47
Indonesia	0.50	4918.04	Thailand	153.13	507.03
Ireland	2.22	2.22	Turkey	0.11	0.17
Israel	0.32	1643.64	UAE	0.50	67.64
Italy	3.32	1048.83	United Kingdom	931.20	11,588.91
Japan	8176.04	27,866.38	United States	3839.02	78,454.77
Kazakhstan	0.00	0.00	Uruguay	0.70	9.03
Kenya	59.28	2052.16	Zambia	1.27	79.49
Korea	0.83	14,673.67	Total	18,021.07	779,176.7

This table provides the initial and final alternative digital credit (total credit volume provided by BigTech and FinTech firms in millions of U.S. dollars) for the 67 developed and developing countries during the sample period. "Initial digital credit" refers to the volume in 2013, while "Final digital credit" refers to the volume in 2019. If 2013 data are not available for a particular country, we use the earliest year with information available. In the same vein, if information is not available for 2019, we use the data on the latest year available.

Table A2
Definition of variables and sources

Variable	Definition	Source
PANEL A: Main variables		
Digital credit	Total credit volume provided by FinTech and BigTech firms as a share of GDP.	BIS
ROA	Return on assets (pre-tax profits as a share of total assets).	Global Financial Development Database (World Bank)
NIM	Net interest revenue as a share of its average interest-bearing (total earning) assets.	
PANEL B: Banking sector variables		
Size	Total assets held by deposit money banks as a share of GDP.	
Liquidity	The ratio of the value of liquid assets (easily converted to cash) to short-term funding plus total deposits.	
Capitalization	The ratio of total regulatory capital to its assets held. Assets are weighted according to their risk.	
Cost-to-income	Operating expenses of a bank as a share of the sum of net-interest revenue and other operating income.	
Concentration	Total assets of the five largest banks as a share of total commercial banking assets.	
Lerner	The difference between the output pricing (interest rate, P_{it}) and marginal (MC_{it}) cost expressed as a percentage of output pricing. This index moves between 0 (pure perfect competition) and 1 (perfect monopoly). $L_{it} = \frac{P_{it} - MC_{it}}{P_{it}}$	Global Financial Development Database (World Bank)
Bank-based financial system	Total banks' assets-to-GDP ratio.	
Banking stability	*Z*-score: computed by the return on assets plus the capital–asset ratio divided by the standard deviation of asset returns.	
Banking market power	Lerner index of the banking industry.	

(*continued on next page*)

Table A2 (*continued*)

Variable	Definition	Source
Physical banking infrastructure	Number of ATMs per thousand inhabitants.	
Banking regulatory stringency	Macroprudential index of policies instruments for the banking sector. This index moves between 0 (no regulation) and 12 (maximum regulation)	IBRN prudential instruments database
PANEL C: Instrumentation variables		
Mobile_Subs	Mobile-cellular subscriptions per 100 inhabitants.	ITU (UN) telecommunication
PANEL D: Macroeconomic control variables		
GDPpc growth	Annual percentage growth rate of GDP per capita.	Global Financial Development Database (World Bank)
Inflation	Annual percentage change of end-of-period consumer price index.	
Private credit, %GDP	Ratio of private credit by deposit money banks and other financial institutions to GDP.	

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

Table A3
Mobile subscriptions and bank performance

Dependent variable	ROA	NIM
	(1)	(2)
Mobile phone subscriptions	−0.005	−0.008
	(0.32)	(0.30)
Controls	Yes	Yes
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Clustered standard errors	Country level	Country level
Observations	377	377
# countries	67	67
p-value (chi2)	0.00	0.00
R-squared	0.19	0.30

This table shows the results for the impact of the diffusion of mobile subscriptions on the banking industry's performance. The dependent variable in column 1 is ROA, return on assets (pre-tax profits as a share of total assets) and, the dependent variable in column 2 is the net interest revenue as a share of its average interest-bearing (total earning) assets. *Mobile phone subscriptions* is the total number of mobile-cellular subscriptions per 100 inhabitants. Year- and country-fixed effects are included but not reported. P-values for the clustered standard errors (at the country level) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

References

Adesina, K. S. (2021). How diversification affects bank performance: The role of human capital. *Economic Modelling, 94*(October 2020), 303–319. https://doi.org/10.1016/j.econmod.2020.10.016

Aebi, V., Sabato, G., & Schmid, M. (2012). Risk management, corporate governance, and bank performance in the financial crisis. *Journal of Banking and Finance, 36*(12), 3213–3226. https://doi.org/10.1016/j.jbankfin.2011.10.020

Albertazzi, U., & Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability, 5*(4), 393–409. https://doi.org/10.1016/j.jfs.2008.10.002

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets Institutions and Money, 18*, 121–136. https://doi.org/10.1016/j.intfin.2006.07.001

Bains, P., Sugimoto, N., & Wilson, C. (2022). BigTech in financial services: Regulatory approaches and architecture. In *International Monetary Fund (issue 002)*.

Balyuk, T., Berger, A. N., & Hackney, J. (2020). What is fueling fintech lending? The role of banking market structure. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3633907

Banna, H., Hassan, M. K., & Rashid, M. (2021). Fintech-based financial inclusion and bank risk-taking: Evidence from OIC countries. *Journal of International Financial Markets, Institutions & Money, 75*(February), Article 101447. https://doi.org/10.1016/j.intfin.2021.101447

Banna, H., Mia, M. A., Nourani, M., & Yarovaya, L. (2022). Fintech-based financial inclusion and risk-taking of microfinance institutions (MFIs): Evidence from sub-Saharan Africa. *Finance Research Letters, 45*(May 2021), Article 102149. https://doi.org/10.1016/j.frl.2021.102149

Batten, J. A., & Xuun Vinh, V. (2019). Determinants of Bank profitability evidence from Vietnam. *Emerging Markets Finance & Trade, 55*, 1417–1428. https://doi.org/10.1080/1540496X.2018.1524326

Beck, T., Cecchetti, S., Grothe, M., Kemp, M., Pelizzon, L., & Sánchez-Serrano, A. (2022). Will video kill the radio star? Digitalisation and the future of banking. In *, 12. ESRB Working Paper* (pp. 1–64).

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation, 22*(2), 218–244. https://doi.org/10.1016/j.jfi.2012.07.001

Beck, T., Gambacorta, L., Huang, Y., Li, Z., & Qiu, H. (2022). Big techs, QR code payments and financial inclusion. In *BIS Working Papers No 1011* (pp. 1–47). May 2022.

Bellardini, L., Del Gaudio, B. L., Previtali, D., & Verdoliva, V. (2022). How do banks invest in fintechs? Evidence from advanced economies. *Journal of International Financial Markets Institutions and Money, 77*(December 2021), Article 101498. https://doi.org/10.1016/j.intfin.2021.101498

Berger, A. N. (1995). The profit-structure relationship in banking–tests of market-power and efficient- structure hypotheses. *Journal of Money, Credit and Banking, 27*(2), 404–431.

Berger, A. N., Hasan, I., & Zhou, M. (2010). The effects of focus versus diversification on bank performance: Evidence from Chinese banks. *Journal of Banking and Finance, 34*(7), 1417–1435. https://doi.org/10.1016/j.jbankfin.2010.01.010

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics, 76*(2), 237–269. https://doi.org/10.1016/j.jfineco.2004.06.003

BIS. (2018). *Implications of fintech developments for banks and bank supervisors (Issue February)*.

Bitar, M., & Tarazi, A. (2019). Creditor rights and bank capital decisions: Conventional vs. Islamic banking. *Journal of Corporate Finance, 55*(February 2018), 69–104. https://doi.org/10.1016/j.jcorpfin.2018.11.007

Bollaert, H., Lopez-de-Silanes, F., & Schwienbacher, A. (2021). Fintech and access to finance. *Journal of Corporate Finance, 68*(March), Article 101941. https://doi.org/10.1016/j.jcorpfin.2021.101941

Boot, A., Hoffmann, P., Laeven, L., & Ratnovski, L. (2021). Fintech: what's old, what's new? *Journal of Financial Stability, 53*. https://doi.org/10.1016/j.jfs.2020.100836

Boot, A., & Thakor, A. V. (1994). Moral Hazard and secured lending in an infinitely repeated credit market game. *International Economic Review, 35*(4), 899–920.

Boot, A. W. A., & Thakor, A. V. (2000). Can relationship banking survive competition? *Journal of Finance, 55*(2), 679–713.

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics, 130*(3), 453–483. https://doi.org/10.1016/j.jfineco.2018.03.011

Campbell, D., & Frei, F. (2010). Cost structure, customer profitability, and retention implications of self-service distribution channels: Evidence from customer behavior in an online Banking Channel. *Management Science, 56*(1), 4–24. https://doi.org/10.1287/mnsc.1090.1066

Carbó Valverde, S., & Rodríguez Fernández, F. (2007). The determinants of bank margins in European banking. *Journal of Banking & Finance, 31*(7), 2043–2063. https://doi.org/10.1016/j.jbankfin.2006.06.017

Carbó-Valverde, S., Cuadros-Solas, P. J., & Rodríguez-Fernández, F. (2021). The effects of negative interest rates: A literature review and additional evidence on the performance of the European banking sector. *European Journal of Finance*. https://doi.org/10.1080/1351847X.2021.1927784

Carlini, F., Del Gaudio, B. L., Porzio, C., & Previtali, D. (2021). Banks, FinTech and stock returns. *Finance Research Letters*, 102252. https://doi.org/10.1016/j.frl.2021.102252. June.

Cerutti, E., Claessens, S., & Laeven, L. (2017). The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability, 28*, 203–224. https://doi.org/10.1016/j.jfs.2015.10.004

Cerutti, E., Correa, R., Fiorentino, E., & Segalla, E. (2016). Changes in Prudential policy instruments. *International Journal of Central Banking, 13*(16/110), 477–503.

Claessens, S., Zhu, F., Frost, J., & Turner, G. (2018). Fintech credit markets around the world: Size, drivers and policy issues. *BIS Quarteley Review*, 29–49. September.

Cornaggia, J., Wolfe, B., & Yoo, W. (2018). *Crowding out banks : Credit substitution by peer-to-peer lending.* Working Paper.

Cornelli, G., Doerr, S., Franco, L., & Frost, J. (2021). Funding for fintechs: Patterns and drivers. *BIS Quarterly Review*, 31–43. September.

Cornelli, G., Frost, J., Gambacorta, L., Rau, P. R., Wardrop, R., & Ziegler, T. (2023). Fintech and big tech credit: Drivers of the growth of digital lending. *Journal of Banking and Finance, 148*, Article 106742. https://doi.org/10.1016/j.jbankfin.2022.106742

Cruz-García, P., Fernández de Guevara, J., & Maudos, J. (2021). Bank competition and multimarket contact intensity. *Journal of International Money and Finance, 113*. https://doi.org/10.1016/j.jimonfin.2020.102338

Cubillas, E., & González, F. (2014). Financial liberalization and bank risk-taking: International evidence. *Journal of Financial Stability, 11*(1), 32–48. https://doi.org/10.1016/j.jfs.2013.11.001

Daud, S. N. M., Ahmad, A. H., Khalid, A., & Azman-Saini, W. N. W. (2022). FinTech and financial stability: Threat or opportunity? *Finance Research Letters, 47*(PB), Article 102667. https://doi.org/10.1016/j.frl.2021.102667

De Roure, C., Pelizzon, L., & Thakor, A. (2022). P2P lenders versus banks: Cream skimming or bottom fishing? *Review of Corporate Finance Studies, 11*(2), 213–262. https://doi.org/10.1093/rcfs/cfab026

Demirgüç-Kunt, A., & Detragiache, E. (1998). Financial liberalization and financial fragility. In *IMF Working Paper, WP/98/83*.

Demirgüç-Kunt, A., & Huizinga, H. (1999a). Determinants of commercial bank interest margins and profitability: Some international evidence. *World Bank Economic Review, 13*(May), 379–408.

Demirgüç-Kunt, A., & Huizinga, H. (1999b). Determinants of commercial bank interest margins and profitability: Some international evidence. *World Bank Economic Review, 13*(2), 379–408. https://doi.org/10.1093/wber/13.2.379

Di Maggio, M., & Yao, V. (2021). Fintech borrowers: Lax screening or cream-skimming? *The Review of Financial Studies, 34*(10), 4565–4618. https://doi.org/10.1093/rfs/hhaa142

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies, 51*(3), 393–414.

Dietrich, A., & Wanzenried, G. (2014). The determinants of commercial banking profitability in low-, middle-, and high-income countries. *The Quarterly Review of Economics and Finance, 54*(3), 337–354. https://doi.org/10.1016/j.qref.2014.03.001

Drasch, B. J., Schweizer, A., & Urbach, N. (2018). Integrating the 'troublemakers' : A taxonomy for cooperation between banks and fintechs. *Journal of Economics and Business, 100*(March), 26–42. https://doi.org/10.1016/j.jeconbus.2018.04.002

Financial Stability Board. (2019). *FinTech and market structure in financial services: Market developments and potential financial stability implications (Issue February)*.

Freedman, S., & Jin, G. Z. (2017). The information value of online social networks: Lessons from peer-to-peer lending. *International Journal of Industrial Organization, 51*, 185–222. https://doi.org/10.1016/j.ijindorg.2016.09.002

Frost, J. (2020). The economic forces driving FinTech adoption across countries. In *BIS Working Papers No 838*. https://doi.org/10.2139/ssrn.3515326

Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., & Zbinden, P. (2019). BigTech and the changing structure of financial intermediation. In *BIS Working Papers, No. 779*. https://doi.org/10.1093/epolic/eiaa003

Fuster, A., Plosser, M., Schnabl, P., & Vickery, J. (2019). The role of Technology in Mortgage Lending. *Review of Financial Studies, 32*(5), 1854–1899. https://doi.org/10.1093/rfs/hhz018

Gambacorta, L., & Shin, H. S. (2018). Why bank capital matters for monetary policy. *Journal of Financial Intermediation, 35*(558), 17–29. https://doi.org/10.1016/j.jfi.2016.09.005

Goddard, J., Liu, H., Molyneux, P., & Wilson, J. O. S. (2013). Do Bank profits converge? *European Financial Management, 19*(2), 345–365. https://doi.org/10.1111/j.1468-036X.2010.00578.x

Goddard, J., McKillop, D., & Wilson, J. O. S. (2008). What drives the performance of cooperative financial institutions? Evidence for US credit unions. *Applied Financial Economics, 18*(11), 879–893. https://doi.org/10.1080/09603100701262818

Goddard, J., Molyneux, P., & Wilson, J. O. S. (2004). The profitability of european banks: A cross-sectional and dynamic panel analysis. *The Manchester School, 72*(3), 363–381. https://doi.org/10.1111/j.1467-9957.2004.00397.x

Gopal, M., & Schnabl, P. (2022). The rise of finance companies and FinTech lenders in small business lending. *The Review of Financial Studies, 35*, 4859–4901. https://doi.org/10.1093/rfs/hhac034

Haddad, C., & Hornuf, L. (2019). The emergence of the global fintech market: Economic and technological determinants. *Small Business Economics, 53*, 81–105.

Hasan, I., & Li, X. (2021). Technology adoption and the Bank Lending Channel of monetary policy transmission. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3928813

Hau, H., Huang, Y., Shan, H., & Sheng, Z. (2021). FinTech credit and entrepreneurial growth. In *Working paper, research P(N°21-47)*.

Havrylchyk, O., Mariotto, C., Rahim, T., & Verdier, M. (2019). What drives the expansion of the peer-to-peer lending? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2841316

Hernández-Murillo, R., Llobet, G., & Fuentes, R. (2010). Strategic online banking adoption. *Journal of Banking and Finance, 34*(7), 1650–1663. https://doi.org/10.1016/j.jbankfin.2010.03.011

Hodula, M. (2022). Does Fintech credit substitute for traditional credit ? Evidence from 78 countries. *Finance Research Letters, 46*(PB), Article 102469. https://doi.org/10.1016/j.frl.2021.102469

Hodula, M. (2023). Interest rates as a finance battleground? The rise of Fintech and big tech credit providers and bank interest margin. *Finance Research Letters*, 103685. https://doi.org/10.1016/j.frl.2023.103685. December 2022b.

Hornuf, L., Klus, M. F., Lohwasser, T. S., & Schwienbacher, A. (2021). How do banks interact with fintech startups? *Small Business Economics, 57*, 1505–1526. https://doi.org/10.1007/s11187-020-00359-3

IMF. (2017). *Fintech and financial Services: Initial Considerations*. https://doi.org/10.1109/PACT.2007.23

Jagtiani, J., & Lemieux, C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks ? *Journal of Economics and Business, 100*(April), 43–54. https://doi.org/10.1016/j.jeconbus.2018.03.001

Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: Evidence from the LendingClub consumer platform. *Financial Management, 48*(4), 1009–1029. https://doi.org/10.1111/fima.12295

Kong, S. T., & Loubere, N. (2021). Digitally down to the countryside: Fintech and rural development in China. *Journal of Development Studies, 57*(10), 1739–1754. https://doi.org/10.1080/00220388.2021.1919631

Kowalewski, O., & Pisany, P. (2022a). Banks' consumer lending reaction to fintech and bigtech credit emergence in the context of soft versus hard credit information processing. *International Review of Financial Analysis, 81*(102116).

Kowalewski, O., & Pisany, P. (2022b). The rise of fintech: A cross-country perspective. *Technovation*, 102642. https://doi.org/10.1016/j.technovation.2022.102642. *October*.

Kowalewski, O., Pisany, P., & Slazak, E. (2021). *What determines cross-country differences in fintech and bigtech credit markets?*. Working Paper, April.

Kowalewski, O., Pisany, P., & Ślązak, E. (2022). Digitalization and data, institutional quality and culture as drivers of technology-based credit providers. *Journal of Economics and Business, 121*(August 2021). https://doi.org/10.1016/j.jeconbus.2022.106069

Kutan, A. M., Ozsoz, E., & Rengifo, E. W. (2012). Cross-sectional determinants of bank performance under deposit dollarization in emerging markets. *Emerging Markets Review, 13*(4), 478–492. https://doi.org/10.1016/j.ememar.2012.07.003

Kwon, K. Y., Molyneux, P., Pancotto, L., & Reghezza, A. (2023). Banks and FinTech Acquisitions. *Journal of Financial Services Research*. https://doi.org/10.1007/s10693-022-00396-x (Issue December 2022). Springer US.

Laeven, L., & Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics, 93*(2), 259–275. https://doi.org/10.1016/j.jfineco.2008.09.003

Lashitew, A. A., van Tulder, R., & Liasse, Y. (2019). Mobile phones for financial inclusion: What explains the diffusion of mobile money innovations? *Research Policy, 48*(5), 1201–1215. https://doi.org/10.1016/j.respol.2018.12.010

Lee, C. C., & Hsieh, M. F. (2013). The impact of bank capital on profitability and risk in Asian banking. *Journal of International Money and Finance, 32*(1), 251–281. https://doi.org/10.1016/j.jimonfin.2012.04.013

Liem, N. T., Son, T. H., Tin, H. H., & Canh, N. T. (2022). Fintech credit, credit information sharing and bank stability: Some international evidence. *Cogent Business and Management, 9*(1). https://doi.org/10.1080/23311975.2022.2112527

Lopez, J. A., Rose, A. K., & Spiegel, M. M. (2020). Why have negative nominal interest rates had such a small effect on Bank performance? Cross country evidence. *European Economic Review, 124*, 01–32. https://doi.org/10.24148/wp2018-07

Maudos, J., & Fernández de Guevara, J. (2004). Factors explaining the interest margin in the banking sectors of the European Union. *Journal of Banking and Finance, 28*(9), 2259–2281. https://doi.org/10.1016/j.jbankfin.2003.09.004

Molyneux, P., Reghezza, A., & Xie, R. (2019). Bank profits and margins in a world of negative rates. *Journal of Banking & Finance, 107*, Article 105613. https://doi.org/10.1002/ir.37019906803

Molyneux, P., & Thornton, J. (1992). The determinants of European Bank profitability: A note. *Journal of Banking & Finance, 3*(6), 57–68.

Moudud-Ul-huq, S., Zheng, C., & Gupta, A. D. (2018). Does bank corporate governance matter for bank performance and risk-taking? New insights of an emerging economy. *Asian Economic and Financial Review, 8*(2), 205–230. https://doi.org/10.18488/journal.aefr.2018.82.205.230

Murinde, V., Rizopoulos, E., & Zachariadis, M. (2022a). The impact of the FinTech revolution on the future of banking: opportunities and risks. *International Review of Financial Analysis*. https://doi.org/10.1016/j.irfa.2022.102103. Forthcomin.

Murinde, V., Rizopoulos, E., & Zachariadis, M. (2022b). The impact of the FinTech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis, 81*(December 2021), Article 102103. https://doi.org/10.1016/j.irfa.2022.102103

Nguyen, L., Tran, S., & Ho, T. (2022). Fintech credit, bank regulations and bank performance: A cross-country analysis. *Asia-Pacific Journal of Business Administration, 14*(4), 445–466. https://doi.org/10.1108/APJBA-05-2021-0196

OECD. (2020). *Digital disruption in banking and its impact on competition*.

Peni, E., & Vähämaa, S. (2012). Did good corporate governance improve Bank performance during the financial crisis? *Journal of Financial Services Research, 41* (1–2), 19–35. https://doi.org/10.1007/s10693-011-0108-9

Phan, D. H. B., Narayan, P. K., Rahman, R. E., & Hutabarat, A. R. (2020). Do financial technology firms influence bank performance? *Pacific-Basin Finance Journal, 62* (November 2018), Article 101210. https://doi.org/10.1016/j.pacfin.2019.101210

Philippon, T. (2018). *The FinTech opportunity. National Bureau of economic research*. Working Paper. March.

Psillaki, M., & Mamatzakis, E. (2017). What drives bank performance in transitions economies? The impact of reforms and regulations. *Research in International Business and Finance, 39*, 578–594. https://doi.org/10.1016/j.ribaf.2016.09.010

Schaeck, K., & Cihák, M. (2014). Competition, efficiency, and stability. *Financial Management*, 215–241.

Smirlock, M. (1985). Evidence on the (non) relationship between concentration and profitability in banking. *Journal of Money, Credit, and Banking, 17*(1), 69–83.

Staikouras, C. K., & Wood, G. E. (2011). The determinants of European Bank profitability. *International Business & Economics Research Journal (IBER), 3*(6), 57–68. https://doi.org/10.19030/iber.v3i6.3699

Stern, C., Makinen, M., & Qian, Z. (2017). FinTechs in China – With a special focus on peer to peer lending. *Journal of Chinese Economic and Foreign Trade Studies, 10*(3), 215–228. https://doi.org/10.1108/JCEFTS-06-2017-0015

Talavera, O., Yin, S., & Zhang, M. (2018). Age diversity, directors' personal values, and bank performance. *International Review of Financial Analysis, 55*(October 2017), 60–79. https://doi.org/10.1016/j.irfa.2017.10.007

Tan, Y. (2017). The impacts of competition and shadow banking on profitability: Evidence from the Chinese banking industry. *North American Journal of Economics and Finance, 42*, 89–106. https://doi.org/10.1016/j.najef.2017.07.007

Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements? *Review of Financial Studies, 32*(5), 1900–1938. https://doi.org/10.1093/rfs/hhy137

Tregenna, F. (2009). The fat years: The structure and profitability of the US banking sector in the pre-crisis period. *Cambridge Journal of Economics, 33*(4 SPEC. ISS), 609–632. https://doi.org/10.1093/cje/bep025

Turk Ariss, R. (2010). On the implications of market power in banking: Evidence from developing countries. *Journal of Banking and Finance, 34*(4), 765–775. https://doi.org/10.1016/j.jbankfin.2009.09.004

Vives, X. (2017). The impact of FinTech on the banking industry. *European Economy, 2*, 97–105.

Wardrop, R., Zhang, B., Rau, R., & Gray, M. (2015). Moving mainstream. In *The European Alternative Finance Benchmarking Report* (Issue February).

Xue, M., Hitt, L. M., & Chen, P. (2011). Determinants and outcomes of internet banking adoption. *Management Science, 57*(2), 291–307.

Zhang, X., Tan, Y., Hu, Z., Wang, C., & Wan, G. (2020). The trickle-down effect of Fintech development: From the perspective of urbanization. *China & World Economy, 28*(1), 23–40. https://doi.org/10.1111/cwe.12310

Zhao, Y., Goodell, J. W., Dong, Q., Wang, Y., & Abedin, M. Z. (2022). Overcoming spatial stratification of fintech inclusion: Inferences from across Chinese provinces to guide policy makers. *International Review of Financial Analysis, 84*(October), Article 102411. https://doi.org/10.1016/j.irfa.2022.102411