Bank financial innovation and SMEs lending: do we experience a transformation in a bank-SME relationship?*

Aneta Hryckiewicz[1]
Kozminski University

Julia Korosteleva[2]
University College London

Lukasz Kozlowski[3]
Kozminski University

Malwina Rzepka[4]
Kozminski University

Ruomeng Wang[5]
University College London

Abstract

While sparked by financial technology firms, the digitalisation trend has also impacted a banking sector, providing greater incentives for traditional banks to become more financially inclusive. The advancements in financial technology development might create new financing opportunities for Small and Medium-sized enterprises (SMEs), which have typically been underserved by the traditional banks. In our paper we raise a question whether the technological advances have increased the interest of banks toward the SMEs lending. Using a sample of 179,921 SMEs, merged with the data from 54 largest European banks over the period of 2008-2019 at a firm level, we analyze the impact of bank digitalisation on the SMEs access to credit and its cost. Our results indicate that bank digitalisation has positively affected SMEs' access to bank credit, though the effect is stronger for short-term lending rather than long-term one. However, our evidence also suggests that bank digitalisation increases the cost of credit to SMEs, though the effect is non-linear. Finally, we also show that the impact of financial innovation at banks manifest via different channels, and it is also conditional on credit market characteristics.

Keywords: bank digitalisation, SMEs lending; loan maturity; cost of borrowing.

* The Project has been funded by the Polish National Science Centre under the decision: 2019/33/B/HS4/02664.
[1] Corresponding Author, Economic Institute for Empirical Analysis, Kozminski University, Jagiellonska Street 57-59, 03-301Warsaw, Poland
[2] University College London, 16 Taviton Street, Office 426, London, WC1H 0BW, UK
[3] Department of Banking and Insurance, Kozminski University, Jagiellonska Street 57-59, 03-301 Warsaw, Poland
[4] Ph.D. Candidate, Economic Institute for Empirical Analysis, Jagiellonska Street 57-59, 03-301 Warsaw, Poland
[5] University College London, 16 Taviton Street, Office 426, London, WC1H 0BW, UK

1. Introduction

Small and Medium-sized enterprises (SMEs) play a vital role in promoting inclusive and sustainable economic growth worldwide via fostering innovation, competition and creating employment. In Europe, SMEs account for 99% of the enterprise population, and account for more than half of its GDP and employment[6]. Despite their well-acknowledged importance for the economy, SMEs receive a disproportionately small share of credit from financial institutions, and such trend persists across both developed and developing countries (Beck et al., 2014). The availability of lending and cost of finance have been well-documented in the literature as a major constraint on growth opportunities for small and medium-sized enterprises (Beck et al., 2006; Gorodnichenko and Schnitzer, 2010; Bottazzi et al., 2014; Berlingieri et al., 2020).

Extensive previous research show that financing constraints SMEs face are primarily attributed to inherent information opaqueness of SMEs that exacerbate the asymmetry of information between the borrower and lender, increasing loan risk for lenders, thus justifying the rationale for credit rationing (Kirschenmann, 2016). The financial crisis of 2008 and the 2019 global pandemic have further aggravated this problem, disadvantaging SMEs in terms of lending provision and charging them higher risk premiums, with further adverse consequences for their performance (Iyer et al., 2014; Chen, Hanson and Stein, 2017; OECD, 2020). If not for unprecedent scope and scale of government interventions to ensure steady supply of bank loans to SMEs, many financially viable small businesses would have struggled to survive through the 2019 Covid pandemic crisis, given serious liquidity shortages they faced (OECD, 2020).

Recent technological developments in credit scoring models, data collection, processing and sharing, using machine learning and AI algorithms, advanced with the emergence of financial technology firms (Fintechs) and BigTechs companies, have brought new funding opportunities for borrowers, including SMEs, that have historically been neglected by traditional banks. Jagtiani and Lemieux (2018a) show that financial technology helps the customers living in the areas underserved by the traditional banks. Fintech and BigTech lending activity is documented to be higher in locations where banking sector mark-ups are higher; there are fewer bank branches; and banking regulation is stricter (Claessens et

[6] https://ec.europa.eu/growth/smes_en

al., 2018; Cornelli et al., 2020). Fintechs also provide more important role in countries where banks do not have tied contacts with their clients (Berg et al., 2020; Ghosh et al., 2021).

The accelerated trend of provision of digital financial services by FinTechs and BigTechs has also challenged incumbent banks urging them to adopt technological innovations, developed either in-house, or via outsourcing to FinTechs and acquiring algorithms from technological giants (EBRD, 2021). The adoption of new technologies by banks is expected to expand the boundaries of lending provision, making it more inclusive rather than just limited to relationship-based banking (Sheng, 2021).

A growing body of academic research so far seems to focus largely on FinTechs, neglecting the role of the technological development at banks (Thakor, 2020). However, due to lower regulations, if any, Fintechs and BigTechs can profit from digitalisation advancement more than banks can do (Buchak et al., 2018). Thus, the answer to the question whether and how bank technological development eases up financing constraints on SMEs still remains unanswered. Branzoli's et al. (2021) study may be the closest one to focus on the effect of financial digital technology on bank lending, and it shows that more digitally developed banks were able to grant more credits than banks with lower IT spendings (less technologically developed) during the COVID-pandemic period. Furthermore, the focus of recent financial technology studies is mainly placed on the analysis of the Fintech development on the access to credit, and less so on the cost of funding. Therefore, according to our knowledge there is lack of empirical studies documenting how financial technology has changed the cost of intermediation to the SMEs.

Overall, while FinTechs have played an important role in augmenting the provision of finance in the economy due to recent financial technological developments, bank credit is to remain the main external source of funding for SMEs (Berger et al., 2014; Schweitzer and Barkley, 2017), and FinTechs will largely continue playing complementary role to bank lending (Tang, 2019; Beaumont et al., 2021; Sheng, 2021).

Thus, the main question which we raise in our study is whether and how the technological advances have affected the traditional banking sector and its potential interest in the SME lending. More specifically, we are interested in looking into the benefits coming from the technological development at banks, and whether it helps reducing information frictions in a SME loan market to increase the traditional bank financing to smaller firms. We expect two opposite effects. On the one hand, the financial technology should extend the credit availability to the SME by reducing the information frictions (Beaumont et al., 2021; Ghosh et al., 2021; Havrylchyk and Ardekan, 2020; Palladino, 2020). Moreover, more precise algorithms and access to different sources of data as well as real-time monitoring should allow banks to compute the credit risk more precisely, and thus ease the collateral requirement for SMEs (Bazarbash, 2019; Gambacorta et al., 2019). This effect should be especially prevalent for more opaque firms for which the “acquisition” of data is especially relevant. Moreover, the digitalisation should also increase the credit availability as the application process is faster and more convenient as it does not require any bank location. For that reason, it also may be more accessible for SMEs operating in rural or in smaller cities. Finally, the technological application does not require a long-term relationship of a borrower with the loan officer, and thus the decisions may be less dependent on personal relationships (Behr et al., 2020).

On the other hand, due to still many limitations regarding the data sharing and regulatory restrictions on the usage of data in the credit scoring models faced by banks, banks may compensate for the loss of relationship by shortening the credit maturity, demand for additional collateral or increase the cost of credit.

To address our research questions we use Amadeus firm-level panel dataset provided by the Bureau Van Dijk, restricting the sample to SMEs only. We merge this sample with data on financial technologies implemented by each bank affiliated with an SME, collected from different sources over the same time period, and financial information for affiliated banks from Bank Focus data from the Bureau Van Dijk . Our sample covers 179,921 SMEs over the period of 2008-2019, merged with the data on 54 largest European banks at a firm level. For each bank we were able to identify the year and the type of implemented solution. Consequently, to investigate how the bank technology affects the SMEs credit availability as well as its cost we use the fixed-effect regressions controlling for bank-time, and country individual features, clustering the standard errors at the bank-level. We also provide a set of different robustness analyses including the SYS-GMM estimator.

Our empirical results provide important contribution to the academic literature. First, our findings complement the fast-growing literature on the effect of digitalisation on financial inclusion. While most studies concentrate on the role of Fintech lending, we test the role of digitalisation at banks and how it translates into a credit availability to SMEs. We document that financial technology at banks expands the lending to SMEs. However, we also notice that this effect is much stronger on short-term debt than long-term funding. This is in line with the study by Sutherland (2018) who document that data sharing increases the chances for a firm to form a new relationship, however such contracts are shorter and require higher payment frequency. This is because data sharing also increases the probability of switching a lender by a borrower more frequently. Moreover, the long-term nature of loans might be also less affected by the digitalisation due to highly regulated and complex process of approval of such loans at banks requiring a set of various information not necessarily being allowed to replace by alternative data.

Second, our study offers novel and rich evidence on different channels via which the effect of financial innovation at banks translates into SMEs' lending. So far, the traditional literature has highlighted the role of relationship and collateral as solutions for solving the information frictions faced by SMEs in accessing the bank lending (Chan and Thakor, 1987; Berger et al., 2011; Peter and Rajan, 1994; Berger and Udell, 1995). However, the Fintech studies document an increasing role of technology as complementary solution. We test whether the patterns which are observable at Fintechs are also available at banks. Therefore, we empirically verify whether the opaquest companies are more likely to access the credit at more digitalized banks. It could then indicate of potential replacement of "soft" information by the "hard" one as suggested by Sedunov (2017). Interestingly, our regression results cannot replicate the results generated on Fintech lending. In turn, we find a negative impact of bank digitalisation on the opaque firms lending suggesting that banking technology cannot replace the "relationship" at the riskiest companies. However, interestingly, we find that financial technology reduces the need of collateral required by banks at SMEs confirming Holmstrom and Tirole's (1997) proposition that collateral can be substituted for information when information is relatively expensive. Also, recently Gambacorta et al. (2020) prove that financial technology granting access to real-time big data decreases the credit risk, and thus can ease the collateral requirement.

Finally, we also provide first-hand evidence on a research question which remains largely understudied in the contemporary academic literature: how bank digitalisation affects the cost of intermediation for SMEs. The role of technology in reducing the borrowing costs has not been widely evidenced. On the one hand, Fintech studies provide the inconsistent evidence whether financial technology offers cheaper services. On the other hand, Phillipon (2018) proves that US financial sector has not experienced the decrease in intermediation costs despite its digitalisation since the 1960s. We analyze such a link using data on interest payments on almost 180'000 bank customers. In general, we find that technological development at banks translates into higher costs to SMEs. However our regression results indicate that this effect is non-linear. While we find that financial technology disproportionally benefits the opaquest companies leading to the reduction of their cost of borrowing, we find that for the rest of SMEs it is not true. The results might indicate that banks favor the new clients while penalize the older ones for a decrease of relationship. This might be explained by the transactional behavior at banks: the lender does not anticipate the repeated interactions, and thus seeks to increase its return (Boot, 2000; Berger and Udell, 2006).

Our paper is structured as follows. The following section overviews the literature and develops the respective hypotheses. Section Three discusses the data and methodology we adopt to test the hypotheses. Section Four presents the results, and the last Section offers conclusions and draws policy-making implications.

2. Literature Review

Access to finance, as manifested by funds' availability and cost, has been emphasized in a number of studies as a major constraint on small and medium-sized enterprises (Beck et al., 2006). Almost 70% of SMEs do not use external financing from financial institutions, and another 15% are underfinanced (World Bank, 2017). SMEs are particularly financially constrained due to their inherent information opaqueness attributed to the lack of credit history and credible reputation (Huyghebaert and Van de Gucht, 2007). By exacerbating the asymmetry of information between the lender and the borrower and by creating moral hazard on the borrower's side, opaqueness increases loan risk and defines the rationale for bank credit rationing. Lack of collateral and high cost of monitoring small-scale projects for financial institutions further aggravate the problem of accessibility of external funding for SMEs (De la Torre, 2010).

2.1 Role of technology in alleviating SMEs' financing constraints

The advances in financial technology associated with, in particular, big data analytics and artificial intelligence, have brought a big hope for SMEs to improve their access to bank credit.

Digitalisation of financial services can alleviate financial constraints for SMEs in multiple ways. First of all, it reduces information frictions through better data availability and its accuracy, that overall improves risk assessment of borrowers. 'Soft' information such as, for example, social media information about borrowers or information from users' digital footprints (e.g. borrowers' credit card transactions) has been increasingly employed in assessment of applicants' creditworthiness by FinTechs and BigTechs (Yan et al., 2015; Ge et al., 2016; Berg et al, 2020), but also more recently by banks (EBRD, 2021). Angielini et al. (2008), Khandani et al. (2010) apply an artificial neutral network approach for the purpose of the credit risk assessment and document that such models are more precise than human evaluation. Jagtiani and Lemieux (2018b) or Berger et al. (2020) also show that the use of alternative data allows borrowers, previously classified as subprime by traditional criteria, to be re-classified into better loan grades, improving access to credit. Second, financial technology can react quicker to SMEs' financial needs. This is because the financial technology reduces the lenders' incentives to collect soft information by replacing them with the hard data (Liberti and Peterson, 2017). Lopez-Espinosa et al. (2017) document that information frictions are reduced after 25 months of a bank-borrower relationship. In contrast, the replacement of "soft" by "hard" data allows for financial auto- or semi-automated systems processing make the loan decisions within a day or few days (Fuster et. al., 2019; Beaumont et al., 2021). Thirdly, data sharing and access to alterative data sources allow for timely monitoring of a borrower, hereby reducing the monitoring costs for banks, and thus increasing their incentives to grant a loan to the opaque firms (Gambacorta et al., 2019). Finally, the digitalisation may also provide more objective decisions and less influenced by personal officer interest (Behr et al., 2020). This, in turn, may increase the credit availability to many SMEs. Respectively, our first hypothesis is formulated as follows:

H1a. Financial innovations at banks stimulate SMEs' access to debt.

The problem of information frictions with regards to SMEs has been addressed by banks in various ways. Mostly, banks tend to enter a relationship with a borrower to acquire information on its behaviour. In the inception of such relationship, banks engage in credit rationing and tend to provide loans with a shorter maturity (Diamond, 1991; Rajan, 1992). The longer duration of relationship as well as its intensity significantly improves the loan contracting by either increasing the loan maturity and/or availability of more credit (Peter and Rajan, 1994; Berger and Udell, 1995). Thus, the reduction of relationship could be perceived by banks as more risky as not all "soft" information could be easily replaced by the "hard" information (Petersen and Rajan, 1994). Consequently, we should expect that digitalization should have a greater effect on access to short-term credit than long-term. Also, Suthlerland (2018) proves that greater data sharing provides externality in SMEs funding. Borrower propensity to switch a lender increases and banks compensate for a loss of relationship by shortening the loan contract. Given above considerations we hypothesize that financial technology can easily respond to the SMEs liquidity needs by providing necessary hard information on a borrower in a quick manner, however it will affect to a lesser extent the long-term debt where the relationship may still matter. Moreover, the credit assessment on long-term funding is a complex process at banks and banks' credit scoring models are highly regulated which reduces the advantages stemming from technological development. Thus, we state the following hypothesis:

H1b: The impact of bank financial innovations is stronger on short-term than long-term debt growth.

In theory, we should expect bank digitalisation to reduce the cost of intermediation. The financial technology should optimize the operational and regulatory costs at banks and provide greater informational availability resulting in a better risk evaluation. The real-life data processing should reduce the credit risk for banks and thus translate into lower cost of financing. Moreover, the technology should also reduce the fixed costs related to banks' operation. Several academic studies document that financial technology indeed increases bank operational efficiency. Using a sample of Chinese banks,Wang et. Al. (2021) or Lee et al. (2021) show that technological progress occurring at Chinese banks improve banks' efficiency. The authors document that the technology adoption has increased profitability, led to innovations, and improved risk control for commercial banks. However, whether a greater efficiency transforms into a lower cost of intermediation to SMEs is not clear. Philippon (2017) analyzing the US banks over the past 130 years document that though technology solutions improve the efficiency of banks, this improvement does not translate into lower cost of intermediation. This is due to an increasing power of big banks which have dominated the credit market.

Alternatively, a higher distance to the borrower, as a result of the loss of the relationship might create higher risk for banks for which banks want to be compensated (DeYoung et al., 2008; Sutherland, 2018). Di Maggio et al. (2021) documents that lack of relationship with the borrowers observed in automated lending procedures may push borrowers into moral hazard, and thus encourage lenders to increase interest rates (Di Maggio et al, 2021). Consequently, we hypothesize that:

H2: Financial innovation at banks is likely to increase the cost of debt.

2.2 The channels of the effect of technology: reduction in information frictions & reliance on collateral

The information friction is especially a severe problem for the opaquest firms. The lack of reliable information on these firms, lack of collateral, reduced market scrutiny, and high agency problem have caused these businesses have been the most neglected by financial intermediaries (Athreya et al., 2012; Sedunov, 2017; Sanchez, 2018). Thus, higher availability and accuracy of the information, increased number of information channels, and information sharing should especially benefit such companies. In contrast, for more transparent companies or companies with already established transactional data, the value of acquiring additional information might have a lesser importance (Lopez-Espinosa et al., 2017). Additionally, the real-time credit monitoring might also reduce the monitoring costs for banks, and thus favor the most neglected borrowers. This leads us to formulating our next hypothesis:

H3a. Financial innovations at banks are more likely to benefit more opaque businesses.

The recent academic contributions document that the loan pricing to SMEs takes a concave shape. The interest rates charged by banks increase up to the point when the level of asymmetric information becomes non-significant (Lopez-Espinosa et al., 2017). In line with this evidence a greater data availability should reduce the information friction for the opaquest companies for which the acquisition of information is especially relevant. In turn, the digitalisation effect might be weaker for larger firms or companies with existing credit history for which information is not an issue. In fact, those customers may even experience higher intermediation costs, because of price discrimination the lenders can engage in, to compensate for the loss of the relationship. Suthlerland (2018) document that greater information availability translates into a higher probability of switching the lender by such a borrower who continuously searches for better lending deals. Overall, such phenomena points towards benefits of bank digitalisation accruing primarily to new clients, typically start-ups, which with proliferation of digital lending platforms can choose between different offers and can benefit more from competition in financial markets powered by digital technology advancements. Following our considerations, we hypothesize:

H3b. Financial innovations at banks are more likely to reduce cost of debt for more opaque firms.

Collateral requirements are often cited among the top important reasons why SMEs, typically characterised by low capacity for holding collateralizable assets, do not apply for loans (Beck et al., 2006). Similarly, lack of required collateral is also one of the main reasons for applying to a FinTech lending (Beaumont et al., 2021). Collateral has been widely regarded in the banking literature as an efficient solution to the problems of information asymmetry in relation to the quality of borrowers (Chan and Thakor, 1987; Berger et al., 2011). At the same time, the lower information frictions, as for example, thanks to a longer lender-borrower relationship, ease the collateral need (Berger and Udell, 1995). Holmstroen and Tirole (1997) argue that information can substitute for collateral when the collateral is very expensive. Consequently, we expect that the increased use of big data and sophisticated credit scoring algorithms allow for more accurate screening of borrowers, and thus may ease the collateral requirement. The effect should be more visible for companies which so far have been excluded by banks due to lack of information. This leads us to postulating our next hypothesis:

H4. Financial innovations at banks make SMEs less dependent on collateral, i.e., the effect of alleviated access to bank debt from innovative banks is more pronounced for SMEs with relatively low value of tangible assets in total assets.

2.2 Credit market characteristics and the role of bank financial innovations

Some more recent evidence suggests that financial technology plays particularly important role in expanding credit in smaller cities or rural areas; remote locations; or highly concentrated markets with weak economic performance, broadly the areas considered to be commonly underserved by traditional banks (Petersen and Rajan, 2002; Jagtiani and Lemieux, 2018a; Huang et al., 2020). Cornelli et al. (2020) document that Fintech and BigTech lending activity is higher where there are fewer bank branches. There is a stronger dependence on transactional banking relying to a greater extent on 'hard' information in screening borrowers in locations, where accessibility to bank services is limited (Berger and Udell, 2006).

Similarly, it can be argued that the role for financial innovation may be reduced in locations with more developed branch networks, making access to bank services easier and creating a greater scope for relationship banking. The closer the physical proximity of the borrower to the bank branch, the more likely the information asymmetry between the bank and the borrower is to be mitigated by relationship banking (Hollander & Verriest, 2016). Beaumont et al. (2021) and Chava et al. (2021) document that in countries with strong relationship lending mode of financing, the Fintech companies do not possess higher informational advantage than banks which are already well-informed about the pool of borrowers, so there is less scope for financial technology to impact credit supply in locations where there is still a stronger local presence of bank branches.

However, we expect that the effect of bank financial innovations is to be more significant in the environments where a FinTech market is better developed. FinTechs have expanded a credit supply particularly to retail customers and SMEs via alternative digital lending platforms, but they remain playing rather a complementary to banks in provision of external finance to SMEs. Banks are less likely to see FinTechs as a threat in the area of SME and corporate lending (EBRD, 2021). More recent evidence from China also shows some augmenting effect of lending provision in markets with FinTechs presence: they help facilitating bank lending to SMEs, having particularly stronger effect in larger than smaller banks (Sheng, 2021). Larger banks have better capacity in embracing the technology trends, driven by FinTechs, that lead to improvement in transaction lending overall. Based on the above considerations, our next hypothesis can be formulated as follows.

H5a: The role of financial innovations in alleviating the constraints in SMEs' access to bank debt is reduced in environments where the traditional banking model is better developed, and increased, where the FinTech market is more developed.

The existing studies document that in locations with more developed bank branch networks, there is a greater scope for relationship lending between SMEs and banks. This helps mitigating information frictions between SMEs and banks, resulting in a better access to credit, but also lower cost of intermediation where such relationship is based on trust (Lopez-Espinosa et al., 2017).

The literature on geographical dimension of bank lending distinguishes between two types of closeness between a borrower and a bank: 'operational' distance, which is distance between bank branches and borrowers, and 'functional' distance, which is a distance between bank headquarters (HQs) and bank branches (Alessandrini et al., 2009; Presbitero et al., 2014). While 'operational' distance can be mitigated via relationship lending and more effective use of soft information by managers of local bank branches, 'functional' distance relies on transactional lending and the use of 'hard' information in decision-making process that may prevent branches, functionally distanced from HQs, from being the most efficient providers of the soft information-intensive, relationship-based SME lending (Stein, 2002; Zhao, Luintel and Matthews, 2020). However, financial innovation at bank HQs, has a greater scope for incorporating 'soft' information in borrowers' screening, allowing to mitigate the effect of functional distance and therefore to re-enforce the effect of relationship banking in lowering the cost of intermediation for SMEs in environments with better local branch density.

While we might see the complementarity between banks and FinTechs in provision of lending to SMEs, we argue that such complementarity is unlikely to benefit SMEs in reducing the cost of intermediation. Buchak et al. (2018) document that Fintech lenders charge higher interest rates than non-fintech lenders which the authors interpret as customers' willingness to pay more for the more convenient services. With the evidence of FinTechs charging higher interest rates, financial innovations at banks are unlikely to reduce the cost of financial intermediation in the markets where the Fintech credit per capita is higher. Furthermore, with exacerbation of a moral hazard problem, often observed among borrowers served by FinTechs (Di Maggio et al, 2021), higher interest rates may be charged by banks to compensate for risk amplified by such borrowers' behavior. This leads us to formulating our last hypothesis.

H5b. Financial innovations at banks play more important role in decreasing SMEs' debt cost in environments where the traditional banking model is better developed, and increasing the cost of intermediation where the FinTech market is more developed.

3. Data and Methodology

3.1. Sample description

To investigate our research questions, we assemble variety of data such as: SMEs data, bank-level data, including information on each bank implemented financial technology solution, and macroeconomic and institutional country-level data.

Our data collection process starts with the construction of the SME panel sample. In this respect, we use the Amadeus database provided by the Bureau Van Dijk, which is the major source for EU comparable financial and accounting data on firms. The process is comprised of two stages: (i) construction of the key financial indicators and firm-level controls for those firms with unconsolidated accounts, and (ii) gathering the firms' bank affiliation information. To identify SMEs, we follow the European Commission's definition of SMEs–also used by Eurostat–as having fewer than 250 persons employed and an annual turnover of up to EUR 50 million or a total balance sheet of no more than EUR 43 million. Amadeus database is also a primary source of information allowing us to link SMEs with their affiliated banks (in our study, we also call them firms' *main banks*). We thus restrict our database to only those firms for which the information on their bank affiliation was available in the database. In total, we can identify 179,921 firms from 15 countries, that is, Austria, Croatia, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Latvia, Poland, Portugal, Slovenia, Spain, and the UK. Table 1 gives overview of the sample structure by year and by the number of banks affiliated with a firm. It also provides the features of SMEs used in our analysis.

[INSERT TABLE 1 ABOUT HERE]

We notice that though the sample covers the 2008–2019 period, it is slightly more concentrated between 2013 and 2018. Interestingly, we also find that most SMEs in the sample (72%) are affiliated with one *main* bank (72%) or with two *main* banks (20%) only.

The second set of information used in our analysis refers to bank data. Since we are interested in the effect of bank digitalisation on the SMEs access to credit and its cost, we had to collect information on financial technology implemented for each affiliated bank in each sample year. To this extent we use the information retrieved from Crunchbase and CBInsights databases which we additionally supplement with hand-collected data from banks' financial statements and other public announcements. More specifically, for each digital solution implemented at a bank, we collect information on the type and the year of its implementation. Our definition of financial innovation is very wide and includes the most popular solutions implemented by banks such as: automation software (AUT.SOFT), blockchain technology (BLOCKCHAIN), data analytics (ANALYTICS), lending solutions (LENDING), payments (PAYMENTS), personal finance (PERSON.FIN), and regulatory technology (REGULAT). Some of these solutions have been already tested in the academic studies as by Chen et al. (2018).

Additionally, we also construct an index of overall innovativeness of a bank affiliated with a firm, calculated as the sum of the seven abovementioned variables (INNOV.ALL). Importantly, if a firm is affiliated with more than one bank, then each technological variable corresponds to the average across all banks affiliated with the firm. Finally, we also supplement our sample with information about the country-year institutional structure (basing on the data on country in which individual SMEs are located), using World Bank Development Indicators (WDI) and Bank for International Settlement (BIS). Table 2 presents descriptive statistics for each bank variable.

[INSERT TABLE2 ABOUT HERE]

We can notice significant heterogeneity of the sample in terms of the banks' technological innovativeness as the share of observations denoting the use of particular innovations by a bank in a year ranges from 8.9% (PERSON.FIN) to 26.6% (PAYMENTS).

3.2. Methodology

To test our research hypotheses, we employ the panel data and estimate fixed-effects regression models with robust standard errors clustered at a firm level[7]. In such a manner, we are able to control for all time-invariant firm-level characteristics, including country and industry features, which can influence not only a company's demand for credit but also its ability to get it. The choice of the fixed-effects model is also justified by the Hausman test which suggests that the random-effects model is likely to return inconsistent estimates in our setting. Equation (1) presents the general form of the model which we use to verify H1a, H1b, and H2:

[7] In Section 6, we additionally verify the validity of our conclusions while employing alternative econometric estimators to account for the potential endogeneity issues.

$$\mathrm{DEP}_{i,t} = f\begin{pmatrix} \mathrm{FIRM}_{t-1} \\ \mathrm{MAIN.BANK}_{t-1} \\ \mathrm{COUNTRY}_{t} \\ \mathrm{BANK.INNOV}_{t} \\ \text{firm fixed effects} \\ \text{year fixed effects} \end{pmatrix}, \tag{1}$$

To estimate the effect of a bank digitalisation on a firm's access to debt (H1a and H1b) we construct three proxies such as: (i) the growth of total debt, comprised of short-term bank debt and total long-term debt (DEBT.GR), (ii) the growth of short-term bank debt (ST.DEBT.GR), (iii) the growth of total long-term debt (LT.DEBT.GR). Those measures are inflation-adjusted, related to the previous year's total assets. However, to test the effect of a bank digitalisation on the SMEs cost of credit we use the interest cost paid by the SMEs defined as a sum of interests paid by SME on its bank debt (INT.COST).

To test the effect of digitalisation we employ time variable BANK.INNOV which describes technological innovations used by a firm's main bank each year. The variable includes such digital solutions implemented at a bank: AUT.SOFT, BLOCKCHAIN, ANALYTICS, LENDING, PAYMENTS, PERSON.FIN, REGULAT, and INNOV.ALL. In all regression models we include the year dummy variables and firm-fixed effects.

Moreover, in all our estimations we include the set of firm-level variables that control for a firm's demand for debt and its financial features. Our control variables have been documented in the academic literature as important determinants of firm credit growth (Berger and Udell, 2001, Lopez-Espinosa et al., 2017). To this extent we use a profitability ratio (PROFIT) defined as earnings before interest and taxes (EBIT) to sales ratio and a share of a firm's fixed asset to its total asset (FIXED.ASSET). The latter variable allows us to capture the degree of asset tangibility, and hence collateralizable asset accessible in a company. Moreover, we also use the level of equity to firm total asset (EQUITY), firm's asset turnover (ASSET.TURN) defined as a ratio of sales to total assets, and a firm's size (FIRM.SIZE) measured as natural logarithm of the number of years in operation.

As an alternative measure of a firm's opaqueness, we also use the firm's age (LN.FIRM.AGE). Additionally, to control for the bank' individual features which might affect banks' credit activity we include the set of explanatory variables as suggested by the academic literature. Consequently, we use such variables as: bank size (BANK.SIZE), loans to asset ratio (BANK.LOANS), bank equity ratio (BANK.EQUITY), and bank deposit growth (BANK.DEPO.GR).

While addressing H3a, H3b, H4, H5a, and H5b, we create the interaction terms using BANK.INNOV variables and firm-level or country-level regressors. More specifically, in case of H3a and H3b where we test the role technological solutions on solving companies' opaqueness to extend the credit availability and cost of credit, we interact the FIRM.SIZE or YOUNG.FIRM[8] with the BANK.INNOV variable group. In turn, to verify H4 (the DEBT.GR regressions), we interact each BANK.INNOV regressor with LOW.COLLAT[9]. More specifically, we construct two binary variables that identify firms with FIXED.ASSETS below the sample median, implying low asset tangibility (LOW.COLLAT) versus companies with higher value of collateral (for those firms we indicate a variable equaling to 0).

However, the set of country variables include GDP growth rate (GDP.GROWTH), unemployment rate (UNEMPL), a country's level of economic development measured by its GDP per capita (GDP.PC) at purchasing power parity (PPP), a proxy for a country's credit market development, calculated as the value of domestic credit to private sector by banks to a country's GDP (PRI.CREDIT), and two measures describing specifically each country's banking/FinTech market, that is, the number of commercial bank branches per 100,000 adults (BRANCHES), and the FinTech credit per capita in USD (FINTECH.CRED). Consequently, to test H5a (the DEBT.GR regressions) and H5b (the INT.COST regressions), we interact each of the BANK.INNOV variable with regressors describing the number of bank branches per capita (BRANCHES) or FinTech credit per capita (FINTECH.CRED) in a firm's country and year.

Table 3 summarizes definitions of all variables constructed for our study.

[INSERT TABLE3 ABOUT HERE]

[8] To properly reflect the incremental impact of the interaction term, the model should also separately include each variable out of the interacted term. As both LN.FIRM.AGE and YOUNG.FIRM refer to a firm's age (however, in a slightly different manner) we do not employ them together, but in models with the interaction term of BANK.INNOV and YOUNG.FIRM we replace the LN.FIRM.AGE regressor used in Eq.(1) among firm-level controls for the YOUNG.FIRM variable.

[9] Consistently, we substitute LOW.COLLAT for the FIXED.ASSETS variable which is originally used in Eq.(1) as one of the firm-level control variables.

4. Empirical results

4.1. Role of technology in alleviating SMEs' financial constraints

To test whether bank digitalisation offers financial inclusion by extending the credit to the SMEs (H1) we are interested in effect of the relationship between a firm's main bank and its access to debt (DEBT.GR). In addition to the digitalisation effect, we also include the control variables which proxy for the type of financial technology incorporated in a main bank. Each specification includes a different regressor describing financial innovation variable implemented at a firm's main bank in a given year (described collectively as BANK.INNOV). The results are presented in the Table 4.

[INSERT TABLE4 ABOUT HERE]

Our results are robust, strongly supporting the hypothesis that financial technology development and digitalisation process at banks favors so far neglected customers giving them a greater access to the credit. Each of our bank digital regressors is positive and strongly statistically significant proving that financial innovation at banks within each of the identified areas tend to boost a firm's access to bank debt. This would be in line with previous academic studies documenting a positive impact of automated algorithms and alternative data use on information flow within credit processes (Lopez-Espinosa et al., 2017; Fuster et. al., 2019; Beaumont et al., 2021), monitoring of borrowers (Gambacorta et al., 2019), and directly on firms' access to debt (Jagtiani and Lemieux, 2018a; Berger et al., 2019; Gambacorta et al., 2019). Interestingly, our regression results also document that innovations play a positive role in alleviating SMEs' access to bank debt not only when they are directly aimed to support lending (e.g., the LENDING variable), but also when they concern other areas of a bank's cooperation with the clients (e.g., the PAYMENTS or PERSON.FIN variables) or even aimed at regulatory efficiency (REGULAT). Thus, our results seem to document that innovation, in general, fosters bank lending and it is not solely related to any specific innovative lending technology: all kind of bank innovation positively translates into a greater credit availability. Importantly, our outcomes are not only statistically significant but also relevant in economic terms. For example, the coefficient for the ANALYTICS variable in specification 3 suggests that when a firm's main bank has implemented financial innovation within the data analytics area the firm's bank debt growth in relation to its assets is expected to be higher by 0.4 percentage points, that is, by 8.6% of the DEBT.GR variable's interquartile range in the sample.

Regarding other control variables, we find that most coefficients are strongly statistically significant. First, unsurprisingly we observe that higher bank debt growth is reported by younger (LN.FIRM.AGE) and smaller (FIRM.SIZE) companies having capacity to increase the role of debt in their financing structure. As expected, higher equity to assets ratio also facilitates SMEs' bank debt growth, working as a financial leverage. Second, the coefficients for the ASSET.TURN and FIXED.ASSETS variables are positive and negative, respectively. Those outcomes can be explained by the fact that firms with high asset turnover (ASSET.TURN) or limited share of fixed assets in total assets (FIXED.ASSETS) are more likely to be at the edge of reaching their production capacity limits, and as a result, may be more inclined to elevate them through investments financed with additional debt. Third, we observe that more profitable firms (PROFIT) are less likely to incur more debt, which is in line with the Pecking Order theory: firms first finance their investment out of retained earnings which is the cheapest and the most readily available alternative, then out of debt, and lastly, by issuing equity, seen as the most expensive option to the firm.

Fourth, each of our country-level macroeconomic variables in most regressions is statistically significant and the coefficients take expected signs, i.e., we observe an increased growth of SMEs' debt in buoyant economic times characterized by high GDP growth (GDP.GROWTH) and low unemployment (UNEMPL). We also find that SMEs have higher bank debt in countries where the bank credit generally plays more important role in financing the private sector (PRI.CREDIT). In turn, when explaining the negative coefficient for the GDP.PC variable, one should be aware that our dependent variable reflects the growth of primarily bank debt (i.e., growth of short-term bank debt and total long-term debt). There is a lower reliance on bank debt in countries where firms are more likely to finance their needs through equity offerings. These are usually more developed countries characterized by the higher income per capita. Finally, only one out of our four bank-level control variables is statistically significant suggesting that SMEs' are more likely to incur new debt if they cooperate with more risky banks, i.e., having lower equity to assets ratios.

So far, we have proven that bank digitalisation has offered a greater credit availability to SMEs, in total. However, we are also interested what type of credit has been influenced by bank digitalisation. A greater access to short-term debt would allow companies to better manage their liquidity needs, and in many cases avoid bankruptcies. Digitalisation seems to be well-suited for it due to its speed, precision and greater data availability to easily access debt in case of the emergency. However, the question whether financial technology can replace the lender-borrower relationship, so far required by banks in funding firms' long-term investment is not clear. To verify how financial technology affects different types of SMEs funding (H1b) we run the regressions with bank digitalisation variables on short-term versus long-term loans provided by the main bank to the SMEs. Table 5 reports the regression results.

[INSERT TABLE5 ABOUT HERE]

Our regression results document that our hypotheses-testing variables from the BANK.INNOV group are positive and strongly statistically significant, i.e., at the level below 1%. However, we also notice that the effect of bank financial technology is stronger on SME's short-term than long-term debt. The estimated coefficients for the BANK.INNOV group of variables show that the implementation of particular financial innovation at banks can increase the share of short-term bank debt in SME total debt by as much as 1.8 percentage points (specification 7) which accounts for 3.1% of the ST.DEBT variable's interquartile range in the sample. These findings support the literature suggesting that automated procedures at banks and greater data sharing provide companies easy access to quick funding, however digitalisation is less successful in extending the long-term funding. This might support the literature suggesting that greater data availability reduces the relationship lending which banks compensate by shortening the maturity of credit to such companies (Sutherland, 2018).

This finding might also partially confirm that "hard" information is not able to replace all "soft" information being processed by banks (Petersen and Rajan, 1994). The lack of this information increases the risk for banks, which results in offering shorter-term credits. At the same time Sutherland (2018) proves that data sharing reveals more information about SMEs which might disadvantage the companies in getting the loan. This especially concerns more risky borrowers which are more likely to be rejected or being offered short-term credit.

Also, our control variables present interesting picture of SMEs applying for credit at banks. Most of them are statistically significant at the level below 1%. First, we observe that the short-term bank debt is more likely at more risky companies. We find that short-term loans dominate over the total long-term debt at less profitable (PROFIT) and more indebted (EQUITY) firms, having low share of fixed assets in asset structure (FIXED.ASSETS), but higher asset turnover (ASSET.TURN). Second, we also find that the short-term bank debt is more likely at companies operating in countries with less developed banking market (PRI.CREDIT) and during the economic downturns (GDP.GROWTH). Third, the coefficients for our bank-level control variables consistently and unsurprisingly show that it is easier for a firm to get a short-term than long-term bank when its main bank has problems with access to deposit financing (DEPO.GR), less liquid assets (LOANS) and a more risky capital structure (i.e., lower EQUITY). The presence of the short-term debt in a firm's debt structure seems to be also more pronounced if a company applies for a loan at a bigger bank (BANK.SIZE).

In our analysis we are also interested how the bank digitalisation affects the cost of credit to SMEs (H2). We claim that digitalisation leads to a greater bank efficiency, which does not necessarily translate into the lower cost of credit, as banks loose the relationship with their customers which might increase the risk for them (Sutherland, 2018). Consequently, we run the regressions using the cost of debt (INT.COST) as our dependent variable with all other control variables staying the same. The results are presented in Table 6.

[INSERT TABLE6 ABOUT HERE]

Our regressions present interesting findings. In contrast to our outcomes reported in Tables 4 and 5, we find that the impact of our BANK.INNOV regressors is mostly statistically insignificant. We only document a positive and statistically important coefficient for the ANALYTICS variable indicating that a firm may bear higher cost of debt when a bank has implemented such a solution. This seems to confirm the findings by Phillipon (2018) that technological development since 1960s in the banking sector has not reduced the cost of intermediation. This might be because of power of big banks in intermediating the credit. Alternatively, greater data analytics can capture more information about the borrower which can disadvantage borrowers, and thus increase the cost of debt. Di Maggio et al. (2021) documents that lack of relationship with the borrowers observed in automated lending procedures may push borrowers into moral hazard, and thus encourage lenders to increase interest rates (Di Maggio et al, 2021).

Regarding other control variables, we find that higher cost of debt experience companies with higher equity to assets ratio (EQUITY), and this outcome can be explained by the fact that firms with predominant equity financing have usually limited credit history, and as a result are offered higher interest rates when they approach a bank for their first loan. The same explanation can be applied to the positive and statistically significant coefficient for the ASSET.TURN variable. While a high value of this ratio suggests high asset efficiency of a company, it can be also a trait for firms with lower, mostly internally financed assets, that is, of firms with no or limited credit history. Finally, three country-level variables are consistently statistically significant. Namely, the debt for SMEs is more expensive in better developed countries (GDP.PC), in periods of higher unemployment rate (UNEMPL), and in case of increased demand for credit during the economic upturns (GDP.GROWTH).

4.2. The channels of the technological effects: reduction in information frictions and reliance on collateral

In this sub-section we are interested in investigating the channels through which financial technology eliminates the problems with SMEs access to credit and its cost. Consequently, we test the hypotheses related to the information friction reduction (H3a, debt growth) and (H3b, cost reduction), and ease of the collateral need (H4).

In the beginning we are interested in whether financial technology can eliminate the information frictions. We test this by creating the interaction terms of bank innovation variables with SME size (Panel A) and age (Panel B), respectively. If digitalisation is successful in eliminating the information frictions, mostly through better data availability and its greater precision, we should see a higher effect on credit accessibility by the opaquest companies, lower cost of intermediation, and the ease of the collateral requirements. Respectively, Table 7 presents the results on credit access and Table 8 - on the cost of intermediation. For brevity we neither report nor comment the results on the control variables[10], and concentrate on the estimated effects for the variables aimed to test our hypotheses.

[INSERT TABLE 7 ABOUT HERE]

The regression results from Table 7 provide interesting conclusions. In general, they show that innovation extends the credit availability to the SMEs, however the effect is less pronounced for more opaque SMEs, i.e., smaller and younger firms (FIRM.SIZE and LN.FIRM.AGE, respectively). This would further suggest that digitalisation does not seem to reduce the information frictions to such extent as the relationship banking does. Lopez-Espinosa (2017) document that relationship banking especially benefits the opaque companies for which the acquisition of information is more relevant. Interestingly, we cannot confirm

[10] However, those outcomes are in line with the baseline results presented in Tables 4 and 6 and can be obtained from the authors upon request.

such a role of financial technology at banks. One of the reasons might be that digital platforms increase the distance between the borrower and the lender, and the "hard" information is not able to substitute for all "soft" information required by banks (Liberti and Mian, 2009; Agarwal and Hauswald, 2010). Moreover, this effect might be even more pronounced at banks whose credit scoring models are highly regulated, and not all alternative data are allowed to be used by bank. Thus, financial innovations, especially automated credit platforms, seem to reduce bank ability to process soft information, and work to the detriment of access to debt for more opaque firms. Our findings document that relationship-based lending model relying on a direct contact between a borrower and lender seems to be more effective in reduction of information friction to the opaquest companies (Petersen and Rajan, 1994). Thus, we reject our Hypothesis 3a.

We consider the impact of the financial technology on the costs of bank intermediation for more opaque companies (smaller and younger). Our hypothesis H3b stated that the costs may not be significantly influenced by a greater data availability due to a loss of relationship which might especially be determinantal for the opaquest companies. Table 8 present the regression results while using the cost of debt as dependent variable and interaction terms between the innovation variables and size and age of companies. Again, Panel A relates to the size and Panel B to the age of the company interactions.

[INSERT TABLE 8 ABOUT HERE]

While the unconditional impact of financial investments is observed only in the area of data analytics (similar to Table 6), and the interaction terms in Panel A (BANK.INNOV x FIRM.SIZE) are mostly statistically insignificant, we observe interesting effects in case of the constructed interaction variable in Panel B (BANK.INNOV x YOUNG.FIRM). They consistently suggest that younger firms may benefit from financial innovations at banks, i.e., they could get lower interest rate for loans taken at more innovative banks than they would obtain at less digitalized banks. The respective coefficients are statistically significant in seven out of eight specifications and in three cases at levels below 1%. Thus, given the results from Tables 7 and 8 we can draw an interesting conclusion: while financial innovation reduces bank ability to process soft information and work to the detriment of an opaque firm access to debt, if such a firm goes successfully through the credit process anyway, then it takes advantage from the lower cost of debt at a more technologically developed bank, as compared to an identical opaque firm served by a bank that does not use financial innovations. However, it is worth stressing that two out of eight specifications from Panel A (specifications 3 and 5) point at an opposite effect, that is larger firms can anticipate lower cost of debt taken from financially innovative banks. Thus, summing up, we conclude that our findings only modestly support H3b.

We also test how the innovation has affected SMEs limited access to the collateral. In Table 9 we present the regression results testing the role of collateral by including the interaction terms between innovation group variables (BANK.INNOV group) and a binary variable identifying SMEs with lower capability to pledge collateral (i.e. firm's fixed asset in relation to total asset is below the sample median).

[INSERT TABLE 9 ABOUT HERE]

The regression results present interesting picture. The coefficients of interaction variables take a positive and statistically significant values (five out of eight cases are at the level below 1%). At the same time, we can still notice a positive and statistically significant effect of bank innovation variables. These outcomes suggest that firms with low value of collateral are more likely to substantially increase their reliance on debt when a bank seems to be more digitalized. These findings support our Hypothesis 4 suggesting that financial innovations at banks make SMEs less dependent on collateral. Those observations are also in line with the view that greater data availability can substitute the information frictions responsible for the collateral requirement (Holmstroen and Tirole, 1997).

4.4. Credit market characteristics and the role of bank financial innovations

The academic literature has documented that the role of financial technology is very dependent on country's financial and legal structure. Therefore, in this subsection we aim to test how our estimated effects, and specifically the access to credit by SMEs may depend on the environment the SMEs operate. To this extent we include the following country variables into our regressions such as: number of branches per '000 inhabitants, banking sector development and Fintech credit per capita. To test the superior effect of financial technology in specific countries on SMEs access to credit, we interact those variables with our bank innovation variables. Table 10 present the regression results.

[INSERT TABLE 10 ABOUT HERE]

The regression results present interesting conclusions. In Panel A we observe negative and statistically significant coefficients (at levels below 1%) for the interaction terms of our BANK.INNOV variables with the number of branches per capita in a country. Those effects seem to suggest that the effect of financial innovation on access to SMEs credit is lower in countries with more developed banking sectors, or more specifically where bank services are more accessible. Interestingly, in Panel B we also observe that our interaction terms of bank innovation and Fintech are statistically positively significant (at levels below 1%) for seven out of eight. These regression results seem to suggest that Fintech companies supports the technological development at banks. More specifically, our estimations document that in countries which are more technologically developed, thanks to a greater Fintech presence, we observe a greater effect of SMEs access to debt. In total, our regression results allow us to positively support H5a, revealing some complementarity between FinTechs and banks in augmenting lending provision. In contrast, in countries with more developed banking sectors where the relationship-based lending model are dominant, banks are already well-informed about their clients, and thus the role of financial technology in removing SMEs' financial constraints is substantially reduced. Interestingly, the positive coefficients for the interaction terms in Panel B also support other academic evidence that development of Fintechs plays important role in the digital transformation of the banking sector (Sheng, 2021).

We also examine the effect of a country's financial institutional structure and banks digitalisation on SMEs cost of debt. We present these results in Table 11.

[INSERT TABLE 11 ABOUT HERE]

Our regression results seem to prove a moderate role of the market factors in shaping the relationship between bank digitalisation and SMEs' cost of debt. While the effects for the interaction terms reported in both panels show weaker relationships than in the case of the DEBT.GR regressions, we still observe some fragmentary evidence supporting Hypothesis 5b. More specifically, three out of eight specifications from Panel A suggest that in more traditional banking markets financial digitalisation at banks reduces the cost of debt more than in countries with less developed financial markets. However, the regression results in Panel B document that five out of eight interaction terms are statistically significant proving that a reduction of cost of debt is higher in countries where the FinTech market is relatively more developed. These findings are consistent with Di Maggio et al. (2020) who suggest that the presence of

FinTechs generally exacerbates the moral hazard problem among borrowers, which, in turn, leads financially innovative banks to charge higher interest rates on loans.

5. Robustness Checks

To check the validity of our regression results, we conduct three arrays of robustness analyses. First, we address the potential endogeneity issues which might be a result of the relationship between firms' access to debt/cost of debt and banks' financial innovation. Second, we modify the sample composition for our calculations and restrict the estimations to SMEs cooperating with only one bank and not with multiple as in our baseline regressions. Third, we reapproach modelling the phenomena in the relationship between banks' financial innovation and SMEs' debt structure by running separate regression for different debt maturity.

While investigating the relationship between banks' financial innovation and SMEs' access to debt or debt cost, it might be argued that those variables are endogenously determined. First, it cannot be ruled out that both firms' increased access to debt and banks technological development are a reflection of common changes occurring in the market driven, for example, by the development of FinTech companies. In such an environment, the scope of banks digital transformation would not determine the level of firms' access to debt but rather it will be correlated with it. Second, one can also assume that another source of potential endogeneity could be bi-directional causality between bank digitalisation and lending to SMEs, implying that as much the banks' innovativeness may impact firms' access to debt, as increasing demand for lending may lead banks to respond to it via offering innovative solutions.

To address both issues, we re-estimate our baseline regression models explaining firms' access to debt (Table 4) and cost of debt (Table 5) with the GMM-SYS estimation procedure (Blundell and Bond, 1998). In the adjusted setting we do not treat the regressors from the BANK.INVEST group as strictly but only sequentially exogenous, and, as a result, we instrumentalize them with suitably lagged values. While in relation to our fixed-effects models the adjusted setting is deprived of the firm-level fixed effects, the GMM-SYS models employ additional regressors: lagged dependent variables that account for time-persistence of the effects at a firm level, as well as country and industry dummy variables. We report these regression results in Table 12.

[INSERT TABLE 12 ABOUT HERE]

The regression results using the GMM-SYS confirm our previous conclusions. Panel A fully corroborates our previous findings that banks financial innovation stimulates SMEs' access to debt. In five out of eight specifications, the respective coefficients are positive and statistically significant at levels below 1%, in two cases–at the 5% level, and in one case–at the 10% level. Second, Panel B of Table 12 gives even more unambiguous outcomes than the results included in Table 6 for the cost of debt. Specifically, while we could see only weak evidence in favor of H2 in Table 6, the GMM-SYS estimations reported in Panel B of Table 12 strongly support this hypothesis as seven out of eight specifications suggest that financial innovations at banks stimulate increased cost of bank debt for SMEs. Consequently, we can argue that the results presented in Table 12 make us more confident that p-values from our baseline regressions are not deflated by potential endogeneity issues.

Our bank-level controls and hypotheses-testing variables contain values averaged over all entities declared by a firm as their main bank. Thus, the sample potentially includes technical links not only between borrowers and their lenders but also, at least to some extent, between SMEs and banks that do not serve as providers of their capital. Thus, to avoid such artificial links in our investigations, we perform an additional robustness check, in which we restrict our sample to only such SMEs that declared only one entity as their main bank. As a result, our sample size drops by ca. 29%, but we are more certain that the reduced dataset reflects a closer relationship between borrowers and lenders. Consequently, we re-estimate our baseline regressions from Tables 4 and 6 using our new setting. Table 13 contains the respective results.

[INSERT TABLE 13 ABOUT HERE]

The outcomes from Panels A and B match respective results from Tables 4 and 6. Thus, in eight out of eight specifications from Panel A, the variables from the BANK.INNOV group increase SMEs' debt growth. We also find some weak support (specification containing the ANALYTICS variable, Table 13 Panel B), suggesting that financial innovations at banks may have a positive effect on SMEs' cost of debt.

Our baseline regressions from Table 4 present the impact of financial innovations on SMEs' short-term bank debt and total debt growth, and Table 5 touches upon the issue of SMEs' debt structure. However, one may argue that the short- and long-term debt have different determinants and the collective incorporation of those debt types in a single regression model may lead to biased results. Therefore, we re-run our models, separately regressing long-term (LT.DEBT.GR) and short-term (ST.DEBT.GR) credit growth variables. Table 14 shows the respective results.

[INSERT TABLE 14 ABOUT HERE]

It is worth noting that the outcomes are not only in line with the baseline results presented in Table 4, but also all bank innovation variables are statistically significant; that is, eight out of eight specifications from Panel A suggest a positive impact of bank financial innovation on an increased access of SME to long-term debt, while six out of eight specifications from Panel B confirm the existence of an equivalent phenomenon for the short-term bank debt. These findings render the following conclusions. First, the results prove that bank innovation increases credit availability to SMEs. Second, the statistically significant coefficients of innovation variables both on short-term and long-term debt, as suggested in Panel A and B (e.g., for the ANALYTICS variable, we obtain 0.00394 in specification 3 and 0.00349 in specification 11) seem to suggest that the short- and long-term debt grow by similar nominal values (to be more precise, they increase by the same proportion of an SME's assets). Thus, the final positive impact of banks' financial innovation on the share of short-term debt (reported in Table 5) seem to result from the lower share of the short-term bank debt in SMEs' liability structure (Table 3 with descriptive statistics shows that the average value of the ST.DEBT variable equals 0.307). Additionally, the outcomes reported in Table 14 confirm our findings on the diminishing role of collateral in SMEs borrowing resulting from a greater bank technological transformation (as compared to less technologically developed banks).

6. Conclusions

The recent digitalisation of financial services has raised a lot of public and academic debate on the role of technology in the financial inclusion. For years specific groups of borrowers have been neglected by traditional banks due to their information opaqueness location, gender or ethnic origin (Huang et al., 2020; Jagtiani and Lemieux, 2018a). Despite their important role in the economic development process, SMEs have been evidenced as one of the largest groups excluded from the bank financing (Beck et al., 2005). The recent technological development has brought some hope to increase the credit availability to these groups, sparking a lot of interest among academic scholars to investigate the effects of financial technology on credit constraints SMEs face to.

While we observe a growing body of research on FinTechs' impact on lending (for overview of this literature see Boot et. al., 2021), the role of banks' adoption of financial technology remains largely under-researched. While the importance of FinTechs in augmenting financial intermediation is undisputed, they are still largely seen as complementary to banks, and banks are to remain the main source of external financing for SMEs (Schweitzer and Barkley, 2017; Beaumont et al., 2021; Sheng, 2021). Therefore, the question of whether technological development in banking sector helps easing financing constraints for SMEs remains of paramount important for policy makers which see SMEs as a driving force behind economic growth and job creation in Europe.

By addressing this gap, this study tests whether banks' adoption of digital solutions helps easing up financing constraints on SMEs. To the best of our knowledge, this is the first study of the scale and geographic scope, which looks at the effect of technological development at banks on SME funding. In addition to looking at debt availability, we also examine how bank financial technology affects the cost of bank intermediation for SMEs. Furthermore, we extend our analysis to examine the channels of the effect, focusing on information frictions and collateral requirements, and also to shed some light on how the role of bank digitalalisation varies, depending on countries' financial market structures.

To test our research hypotheses, we use the sample of over 179'000 SMEs which we link to main banks which serve these SMEs in 23 European countries. For each our sample bank we have collected information on the digital solution a bank has implemented over the period of 2008-2019. This information is available for us for each year. In line with the existing literature, we distinguish the following innovations: automation software, blockchain technology, data analytics, lending solutions, payments, personal finance, and regulatory technology. We then test how the development of these bank innovations as well as their types translates into a total credit growth, short-term vs. long-term credit growth of SMEs and the total interest paid by SMEs. We also test how these variables are affected by SMEs' characteristics, such as collateralized assets; their size and age, which serve as measures of information opaqueness as well as institutional country structure. We test our hypotheses using the fixed-effect regression model clustering standard errors at the firm level. In addition, we also use the SYS-GMM regression to test the robustness of the results to potential endogeneity bias. We also employ a number of other robustness checks beyond the endogeneity issue.

Our regression results present interesting conclusions. They point toward a link between bank digitalisation and financial inclusion of SMEs. More specifically, we find that bank digitalisation increases SMEs' credit growth, disproportionally benefiting short-term vs.

long-term credit growth. We explain the latter arguing that digitalisation can retrieve different set of information to react for liquidity needs of SMEs, but it cannot fully replace the relationship nature for long-term lending. Our results offer also new evidence on that the relationship between bank innovation and cost of intermediation is non-linear. In general, we find that bank digitalisation increases the borrowing costs to SMEs. However, we also find that the younger firms could benefit from lower borrowing rates at more digitalized banks. On the one hand, these results seem to suggest that banks ration the borrowers by discriminating the old borrowers by charging them higher lending rates, probably due to lost of the relationship, while attracting new borrowers at lower interest rates. On the other hand, this may also be explained by different sets of data the banks may use for their lending decisions on different borrowers. Finally, in terms of credit availability, we find that bank digitalisation especially benefits the markets with lower penetration by traditional banks but higher FinTechs presence, but this pattern reverses when it comes to the cost of intermediation.

Our results provide important academic and policymaking conclusions. Firstly, we find that bank digitalisation facilitates financial inclusion of SMEs, being complementary to FinTech augmenting of lending. Secondly, bank digitalisation has a differential impact of cost of intermediation, increasing the cost of lending on SMEs in general, but lowering it for younger firms. Finally, we also illustrate the reduced role of collateral as another important channel via which financial technology facilitates SMEs lending. Consequently, we show that all kind of policy initiatives regarding the digitalisation of financial services are important to increase the access to finance in the context of Europe, though they are not fully sufficient to impact the cost of financial services which may still provide a hurdle for SMEs on average to access the bank credit. It is also important to emphasize the need to tailor the policy of further digitalisation of financial services to reflect peculiarities of the credit market structure.

Table 1. Sample structure

This table presents sample structure basing on observations employed in regressions from specification 1 in Table 4.

Panel A. Sample structure by year

Year	Countries	Observations	% of observations
2009	10	7,395	0.7
2010	12	30,061	3.0
2011	12	74,473	7.4
2012	12	68,994	6.9
2013	13	103,770	10.3
2014	13	116,038	11.6
2015	13	119,877	11.9
2016	14	129,938	12.9
2017	14	133,456	13.3
2018	14	134,228	13.4
2019	15	85,178	8.5
All years	15	1,003,408	100.0

Panel B. Sample structure by the number of banks affiliated with a firm

Banks affiliated with a firm	Observations	% of observations
1	717759	71.5
2	202319	20.2
3	63290	6.3
4	16677	1.7
5	3363	0.3
All observations	1,003,408	100.0

Table 2. Descriptive statistics

This table presents descriptive statistics for the sample basing on observations employed in regressions from specification 1 in Table 4.

Variable	Observations	Firms	Mean	Std.Dev.	Min.	1st Quart.	2nd Quart.	3rd Quart.	Max.
A. Dependent variables									
DEBT.GR	1,003,408	179,921	-0.004	0.116	-0.547	-0.042	-0.016	0.006	0.856
ST.DEBT	769,199	152,714	0.307	0.372	0.000	0.000	0.114	0.582	1.000
INT.COST	629,578	128,922	0.086	0.274	-0.057	0.007	0.029	0.064	4.003
LT.DEBT.GR	1,001,487	179,830	-0.008	0.098	-0.547	-0.036	-0.016	0.003	0.763
ST.DEBT.GR	1,002,321	179,867	-0.008	0.069	-0.536	-0.024	-0.012	0.003	0.756
B. Other firm-level variables									
PROFIT	1,003,408	179,921	0.026	0.159	-2.000	0.007	0.028	0.070	0.600
FIXED.ASSETS	1,003,408	179,921	0.299	0.259	0.000	0.075	0.231	0.473	1.000
LOW.COLLAT	977,667	176,325	0.499	0.500	0.000	0.000	0.000	1.000	1.000
EQUITY	1,003,408	179,921	0.466	0.264	0.000	0.246	0.450	0.679	1.000
ASSET.TURN	1,003,408	179,921	1.679	1.514	0.000	0.750	1.303	2.102	14.999
FIRM.SIZE	1,003,408	179,921	-0.268	1.688	-10.125	-1.392	-0.229	0.835	3.912
LN.FIRM.AGE	1,003,408	179,921	2.724	0.818	0.000	2.398	2.890	3.219	5.541
YOUNG.FIRM	1,003,408	179,921	0.086	0.280	0.000	0.000	0.000	0.000	1.000
C. Country-level variables									
PRI.CREDIT	1,003,408	179,921	1.081	0.366	0.324	0.937	1.112	1.306	1.921
GDP.GROWTH	1,003,408	179,921	0.017	0.022	-0.143	0.007	0.020	0.029	0.084
GDP.PC	1,003,408	179,921	35.385	5.202	21.024	31.305	35.969	38.906	86.550
UNEMPL	1,003,408	179,921	0.155	0.067	0.031	0.097	0.153	0.214	0.275
BRANCHES	983,408	177,962	52.246	21.305	8.930	35.460	55.110	67.510	99.300
FINTECH.CRED	826,827	147,789	6.853	24.512	0.000	0.080	0.700	3.010	278.530
D. Bank fundamentals									
BANK.SIZE	1,003,408	179,921	12.073	1.502	8.252	10.920	12.301	13.288	14.625
BANK.LOANS	1,003,408	179,921	0.597	0.093	0.131	0.561	0.595	0.655	0.863
BANK.EQUITY	1,003,408	179,921	0.080	0.031	0.011	0.063	0.070	0.081	0.224
BANK.DEPO.GR	1,003,408	179,921	0.055	0.105	-0.424	-0.003	0.034	0.085	1.311
E. Financial innovations at bank									
AUT.SOFT	1,003,408	179,921	0.223	0.375	0.000	0.000	0.000	0.500	1.000
BLOCKCHAIN	1,003,408	179,921	0.153	0.338	0.000	0.000	0.000	0.000	1.000
ANALYTICS	1,003,408	179,921	0.134	0.301	0.000	0.000	0.000	0.000	1.000
LENDING	1,003,408	179,921	0.191	0.348	0.000	0.000	0.000	0.333	1.000
PAYMENTS	1,003,408	179,921	0.266	0.422	0.000	0.000	0.000	0.500	1.000
PERSON.FIN	1,003,408	179,921	0.089	0.260	0.000	0.000	0.000	0.000	1.000
REGULAT	1,003,408	179,921	0.238	0.387	0.000	0.000	0.000	0.500	1.000
INNOV.ALL	1,003,408	179,921	1.294	1.770	0.000	0.000	0.000	2.000	7.000

Table 3. Variable definitions

Variable	Definition
A. Firm-level dependent variables	
DEBT.GR	Growth of short-term bank debt and long-term debt divided by the previous year's total assets (inflation-adjusted)
ST.DEBT	Ratio of short-term bank debt to the sum of short-term bank debt and long-term debt
INT.COST	Interest paid to average short-term bank debt and long-term debt (inflation-adjusted)
LT.DEBT.GR	Growth of long-term debt divided by the previous year's total assets (inflation-adjusted)
ST.DEBT.GR	Growth of short-term bank debt divided by the previous year's total assets (inflation-adjusted)
B. Other firm-level variables	
PROFIT	Ratio of EBIT to sales
FIXED.ASSETS	Ratio of fixed assets to total assets
LOW.COLLAT	Binary variable identifying firms with FIXED.ASSETS below the sample median
EQUITY	Ratio of equity to total assets

ASSET.TURN	Ratio of sales to total assets
FIRM.SIZE	Natural logarithm of turnover in millions of euros (in constant prices)
LN.FIRM.AGE	Natural logarithm of firm age in years
YOUNG.FIRM	Binary variable identifying firms no older than 4 years
C. Country-level variables	
PRI.CREDIT	Domestic credit to private sector by banks to a country's GDP
GDP.GROWTH	GDP growth rate
GDP.PC	GDP per capita (divided by 1000), PPP (constant 2017 USD prices)
UNEMPL	Unemployment rate
BRANCHES	Commercial bank branches (per 100,000 adults)
FINTECH.CRED	Fintech credit per capita (USD)
*D. Fundamentals of the firm main bank**	
BANK.SIZEA	Natural logarithm of assets (in millions) in constant prices
BANK.LOANS	Ratio of net loans to total assets
BANK.EQUITY	Ratio of equity to total assets
BANK.DEPO.GR	Growth rate of customer deposits
*E. Financial innovations at the firm's main bank**	
AUT.SOFT	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Automation software* in a given year
BLOCKCHAIN	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Blockchain* in a given year
ANALYTICS	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Data analytics* in a given year
LENDING	Binary variable identifying situations in which a firm's main bank used technological *Solutions for lending* in a given year
PAYMENTS	Binary variable identifying situations in which a firm's main bank used technological *Solutions for payments* in a given year
PERSON.FIN	Binary variable identifying situations in which a firm's main bank used technological *Solutions for personal finance* in a given year
REGULAT	Binary variable identifying situations in which a firm's main bank used technological solutions classified as *Regulatory technology* in a given year
INNOV.ALL	The index of overall innovativeness of a bank, i.e., the sum of AUT.SOFT, BLOCKCHAIN, ANALYTICS, LENDING, PAYMENTS, PERSON.FIN, AND REGULAT

* If a firm declared more than one main bank the values are averaged over all those bank

Table 4. Financial innovations at banks vs. SMEs' bank debt growth

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for the constant term and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
A. Financial innovations at bank								
$BANK.INNOV_t$	0.00360***	0.00364***	0.00412***	0.00225***	0.00403***	0.00393***	0.00219***	0.00172***
	(0.000639)	(0.000568)	(0.000781)	(0.000760)	(0.000524)	(0.000636)	(0.000694)	(0.000175)
B. Firm-level control variables								
$PROFIT_{t-1}$	-0.00573***	-0.00574***	-0.00570***	-0.00570***	-0.00576***	-0.00573***	-0.00571***	-0.00579***
	(0.00120)	(0.00120)	(0.00120)	(0.00120)	(0.00120)	(0.00120)	(0.00120)	(0.00120)
$FIXED.ASSETS_{t-1}$	-0.0573***	-0.0573***	-0.0573***	-0.0573***	-0.0572***	-0.0573***	-0.0573***	-0.0572***
	(0.00171)	(0.00171)	(0.00171)	(0.00171)	(0.00171)	(0.00171)	(0.00171)	(0.00171)
$EQUITY_{t-1}$	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***
	(0.00144)	(0.00144)	(0.00144)	(0.00144)	(0.00144)	(0.00144)	(0.00144)	(0.00144)
$ASSET.TURN_{t-1}$	0.0140***	0.0140***	0.0140***	0.0140***	0.0140***	0.0140***	0.0140***	0.0140***
	(0.000283)	(0.000283)	(0.000283)	(0.000283)	(0.000283)	(0.000283)	(0.000283)	(0.000283)
$FIRM.SIZE_{t-1}$	-0.0100***	-0.0100***	-0.0100***	-0.0100***	-0.0100***	-0.0100***	-0.0100***	-0.0100***
	(0.000461)	(0.000461)	(0.000461)	(0.000461)	(0.000461)	(0.000461)	(0.000461)	(0.000461)
$LN.FIRM.AGE_{t-1}$	-0.0134***	-0.0135***	-0.0135***	-0.0136***	-0.0134***	-0.0135***	-0.0135***	-0.0132***
	(0.000959)	(0.000957)	(0.000957)	(0.000957)	(0.000958)	(0.000957)	(0.000958)	(0.000960)
C. Country-level control variables								
$PRI.CREDIT_t$	0.0163***	0.0172***	0.0149***	0.0169***	0.0195***	0.0159***	0.0170***	0.0190***
	(0.00218)	(0.00219)	(0.00220)	(0.00220)	(0.00221)	(0.00219)	(0.00219)	(0.00219)
$GDP.GROWTH_t$	0.326***	0.343***	0.313***	0.320***	0.338***	0.331***	0.325***	0.358***
	(0.0150)	(0.0157)	(0.0149)	(0.0149)	(0.0151)	(0.0151)	(0.0152)	(0.0155)
$GDP.PC_t$	-0.000660**	-0.000531	-0.000876***	-0.000902***	-0.000888***	-0.000490	-0.000929***	-0.000521
	(0.000321)	(0.000324)	(0.000319)	(0.000319)	(0.000318)	(0.000326)	(0.000319)	(0.000322)
$UNEMPL_t$	-0.240***	-0.230***	-0.238***	-0.241***	-0.238***	-0.230***	-0.245***	-0.232***
	(0.0169)	(0.0170)	(0.0169)	(0.0169)	(0.0169)	(0.0170)	(0.0170)	(0.0170)
D. Bank-level control variables								
$BANK.SIZE_{t-1}$	-0.00203	-0.000963	-0.000490	-0.000501	-0.000912	-0.00179	-0.000491	-0.00246**
	(0.00124)	(0.00119)	(0.00119)	(0.00119)	(0.00119)	(0.00122)	(0.00119)	(0.00121)
$BANK.LOANS_{t-1}$	-0.00596	-0.0109**	-0.00748*	-0.00717	-0.00704	-0.00672	-0.00852*	-0.0144***
	(0.00431)	(0.00442)	(0.00434)	(0.00437)	(0.00432)	(0.00431)	(0.00445)	(0.00444)
$BANK.EQUITY_{t-1}$	-0.0408***	-0.0296**	-0.0366***	-0.0367***	-0.0294**	-0.0339***	-0.0382***	-0.0303**
	(0.0129)	(0.0130)	(0.0129)	(0.0129)	(0.0129)	(0.0129)	(0.0129)	(0.0129)
$BANK.DEPO.GR_{t-1}$	0.00234*	2.17e-05	0.00102	0.000398	0.00225*	0.00214	0.000305	0.00266**
	(0.00138)	(0.00135)	(0.00135)	(0.00134)	(0.00136)	(0.00136)	(0.00134)	(0.00135)
Observations	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408
Firms	179,921	179,921	179,921	179,921	179,921	179,921	179,921	179,921

Table 5. Financial innovations at banks vs. SMEs' debt structure

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for the constant term and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$ST.DEBT_t$	$ST.DEBT_t$	$ST.DEBT_t$	$ST.DEBT_t$	$ST.DEBT_t$	$ST.DEBT_t$	$ST.DEBT_t$	$ST.DEBT_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
A. Financial innovations at bank								
$BANK.INNOV_t$	0.00357**	0.0161***	0.0114***	0.0143***	0.0143***	0.0129***	0.0181***	0.00654***
	(0.00178)	(0.00167)	(0.00221)	(0.00238)	(0.00146)	(0.00189)	(0.00209)	(0.000536)
B. Firm-level control variables								
$PROFIT_{t-1}$	-0.0262***	-0.0264***	-0.0262***	-0.0262***	-0.0264***	-0.0263***	-0.0263***	-0.0265***
	(0.00287)	(0.00287)	(0.00287)	(0.00287)	(0.00287)	(0.00287)	(0.00287)	(0.00287)
$FIXED.ASSETS_{t-1}$	-0.0759***	-0.0756***	-0.0759***	-0.0759***	-0.0756***	-0.0758***	-0.0757***	-0.0753***
	(0.00410)	(0.00410)	(0.00410)	(0.00410)	(0.00410)	(0.00410)	(0.00410)	(0.00410)
$EQUITY_{t-1}$	0.0233***	0.0237***	0.0234***	0.0234***	0.0238***	0.0235***	0.0235***	0.0242***
	(0.00409)	(0.00409)	(0.00409)	(0.00409)	(0.00409)	(0.00409)	(0.00409)	(0.00409)
$ASSET.TURN_{t-1}$	0.00667***	0.00670***	0.00667***	0.00668***	0.00664***	0.00667***	0.00670***	0.00667***
	(0.000775)	(0.000774)	(0.000774)	(0.000774)	(0.000774)	(0.000775)	(0.000774)	(0.000774)
$FIRM.SIZE_{t-1}$	0.0110***	0.0110***	0.0110***	0.0110***	0.0111***	0.0111***	0.0110***	0.0111***
	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00126)
$LN.FIRM.AGE_{t-1}$	0.0174***	0.0175***	0.0175***	0.0174***	0.0178***	0.0175***	0.0180***	0.0187***
	(0.00286)	(0.00286)	(0.00286)	(0.00286)	(0.00286)	(0.00286)	(0.00286)	(0.00286)
C. Country-level control variables								
$PRI.CREDIT_t$	-0.0748***	-0.0718***	-0.0803***	-0.0701***	-0.0655***	-0.0770***	-0.0703***	-0.0704***
	(0.00883)	(0.00880)	(0.00890)	(0.00883)	(0.00889)	(0.00886)	(0.00880)	(0.00880)
$GDP.GROWTH_t$	-0.347***	-0.240***	-0.374***	-0.335***	-0.284***	-0.310***	-0.300***	-0.218***
	(0.0454)	(0.0463)	(0.0458)	(0.0456)	(0.0462)	(0.0453)	(0.0456)	(0.0460)
$GDP.PC_t$	0.000830	0.00224*	0.000568	0.000439	0.000273	0.00195*	0.000364	0.00189
	(0.00116)	(0.00117)	(0.00116)	(0.00116)	(0.00116)	(0.00118)	(0.00116)	(0.00116)
$UNEMPL_t$	-0.128**	-0.0795	-0.117**	-0.127**	-0.128**	-0.0921	-0.147**	-0.0974*
	(0.0585)	(0.0589)	(0.0586)	(0.0586)	(0.0585)	(0.0592)	(0.0584)	(0.0588)
D. Bank-level control variables								
$BANK.SIZE_{t-1}$	0.0181***	0.00866**	0.00784**	0.00965**	0.00950**	0.00837**	0.00584	0.00864**
	(0.00486)	(0.00397)	(0.00395)	(0.00394)	(0.00394)	(0.00393)	(0.00397)	(0.00394)
$BANK.LOANS_{t-1}$	0.157***	0.0615***	0.0416***	0.0566***	0.0514***	0.0633***	0.0597***	0.0351***
	(0.0148)	(0.0129)	(0.0129)	(0.0128)	(0.0128)	(0.0129)	(0.0129)	(0.0129)
$BANK.EQUITY_{t-1}$	-0.180***	-0.398***	-0.354***	-0.390***	-0.390***	-0.354***	-0.381***	-0.405***
	(0.0507)	(0.0382)	(0.0382)	(0.0381)	(0.0381)	(0.0384)	(0.0382)	(0.0382)
$BANK.DEPO.GR_{t-1}$	-0.00517	-0.0113***	-0.0152***	-0.0118***	-0.0135***	-0.00706**	-0.00759**	-0.0145***
	(0.00354)	(0.00318)	(0.00317)	(0.00319)	(0.00318)	(0.00324)	(0.00331)	(0.00319)
Observations	783,012	783,012	783,012	783,012	783,012	783,012	783,012	783,012
Firms	154,905	154,905	154,905	154,905	154,905	154,905	154,905	154,905

Table 6. Financial innovations at banks vs. SMEs' cost of borrowing

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for the constant term and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
A. Financial innovations at bank								
$BANK.INNOV_t$	-0.00207	-0.000347	0.00526**	-0.00146	-0.000883	-0.000555	-0.00299	-0.000397
	(0.00166)	(0.00157)	(0.00221)	(0.00232)	(0.00139)	(0.00186)	(0.00224)	(0.000511)
B. Firm-level control variables								
$PROFIT_{t-1}$	0.00263	0.00263	0.00265	0.00263	0.00263	0.00263	0.00263	0.00263
	(0.00300)	(0.00300)	(0.00300)	(0.00300)	(0.00300)	(0.00300)	(0.00300)	(0.00300)
$FIXED.ASSETS_{t-1}$	-0.0541***	-0.0541***	-0.0541***	-0.0541***	-0.0541***	-0.0541***	-0.0541***	-0.0541***
	(0.00437)	(0.00437)	(0.00437)	(0.00437)	(0.00437)	(0.00437)	(0.00437)	(0.00437)
$EQUITY_{t-1}$	0.0831***	0.0831***	0.0832***	0.0831***	0.0831***	0.0831***	0.0831***	0.0831***
	(0.00449)	(0.00450)	(0.00449)	(0.00449)	(0.00450)	(0.00449)	(0.00449)	(0.00450)
$ASSET.TURN_{t-1}$	0.0148***	0.0148***	0.0148***	0.0148***	0.0148***	0.0148***	0.0148***	0.0148***
	(0.00105)	(0.00105)	(0.00105)	(0.00105)	(0.00105)	(0.00105)	(0.00105)	(0.00105)
$FIRM.SIZE_{t-1}$	-0.0101***	-0.0101***	-0.0101***	-0.0101***	-0.0101***	-0.0101***	-0.0101***	-0.0101***
	(0.00128)	(0.00128)	(0.00128)	(0.00128)	(0.00128)	(0.00128)	(0.00128)	(0.00128)
$LN.FIRM.AGE_{t-1}$	-0.0210***	-0.0209***	-0.0209***	-0.0209***	-0.0209***	-0.0209***	-0.0209***	-0.0209***
	(0.00325)	(0.00325)	(0.00325)	(0.00325)	(0.00325)	(0.00325)	(0.00325)	(0.00325)
C. Country-level control variables								
$PRI.CREDIT_t$	-0.0161	-0.0167*	-0.0214**	-0.0172*	-0.0167*	-0.0164*	-0.0161	-0.0160
	(0.00983)	(0.00982)	(0.0101)	(0.00977)	(0.00981)	(0.00992)	(0.00985)	(0.00992)
$GDP.GROWTH_t$	0.227***	0.227***	0.212***	0.228***	0.228***	0.228***	0.226***	0.225***
	(0.0453)	(0.0461)	(0.0460)	(0.0454)	(0.0457)	(0.0454)	(0.0453)	(0.0457)
$GDP.PC_t$	0.00471***	0.00471***	0.00460***	0.00479***	0.00478***	0.00469***	0.00476***	0.00469***
	(0.00118)	(0.00119)	(0.00118)	(0.00118)	(0.00118)	(0.00121)	(0.00118)	(0.00119)
$UNEMPL_t$	0.484***	0.479***	0.487***	0.481***	0.479***	0.478***	0.479***	0.477***
	(0.0645)	(0.0650)	(0.0649)	(0.0645)	(0.0646)	(0.0655)	(0.0647)	(0.0652)
D. Bank-level control variables								
$BANK.SIZE_{t-1}$	-0.00348	-0.00456	-0.00483	-0.00456	-0.00454	-0.00439	-0.00424	-0.00409
	(0.00370)	(0.00377)	(0.00375)	(0.00375)	(0.00375)	(0.00382)	(0.00377)	(0.00389)
$BANK.LOANS_{t-1}$	-0.00904	-0.00845	-0.00868	-0.00768	-0.00967	-0.00892	-0.00496	-0.00815
	(0.0119)	(0.0118)	(0.0119)	(0.0118)	(0.0122)	(0.0120)	(0.0117)	(0.0118)
$BANK.EQUITY_{t-1}$	0.0627*	0.0601	0.0680*	0.0609	0.0573	0.0602	0.0629*	0.0571
	(0.0377)	(0.0376)	(0.0376)	(0.0376)	(0.0382)	(0.0376)	(0.0377)	(0.0377)
$BANK.DEPO.GR_{t-1}$	-0.00240	-0.00125	-0.000853	-0.00124	-0.00165	-0.00155	-0.000976	-0.00171
	(0.00348)	(0.00341)	(0.00349)	(0.00347)	(0.00355)	(0.00360)	(0.00346)	(0.00358)
Observations	634,770	634,770	634,770	634,770	634,770	634,770	634,770	634,770
Firms	129,387	129,387	129,387	129,387	129,387	129,387	129,387	129,387

Table 7. Financial innovations at banks vs. SMEs' bank debt growth: the moderating role of firm size and firm age

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for firm- (PROFIT, FIXED.ASSETS, EQUITY, ASSET.TURN, and LN.FIRM.AGE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Moderating role of firm size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$FIRM.SIZE_{t-1}$	-0.0108***	-0.0103***	-0.0103***	-0.0102***	-0.0102***	-0.0103***	-0.0103***	-0.0102***
	(0.000625)	(0.000470)	(0.000467)	(0.000465)	(0.000472)	(0.000472)	(0.000465)	(0.000471)
$BANK.INNOV_t$	0.00322***	0.00299***	0.00343***	0.00184**	0.00391***	0.00297***	0.00210***	0.00154***
	(0.000646)	(0.000573)	(0.000799)	(0.000763)	(0.000525)	(0.000651)	(0.000696)	(0.000180)
$BANK.INNOV_t$ x $FIRM.SIZE_{t-1}$	0.00130***	0.00143***	0.00178***	0.00106**	0.000703***	0.00179***	0.000461	0.000239***
	(0.000323)	(0.000274)	(0.000481)	(0.000441)	(0.000231)	(0.000344)	(0.000352)	(6.79e-05)
Observations	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408
Firms	179,921	179,921	179,921	179,921	179,921	179,921	179,921	179,921

Panel B. Moderating role of firm age

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$YOUNG.FIRM_{t-1}$	0.00858***	0.00776***	0.00759***	0.00835***	0.00851***	0.00744***	0.00835***	0.00951***
	(0.00100)	(0.000960)	(0.000977)	(0.00101)	(0.000975)	(0.000956)	(0.00105)	(0.00104)
$BANK.INNOV_t$	0.00448***	0.00425***	0.00463***	0.00272***	0.00498***	0.00465***	0.00301***	0.00195***
	(0.000637)	(0.000566)	(0.000780)	(0.000757)	(0.000522)	(0.000633)	(0.000692)	(0.000174)
$BANK.INNOV_t$ x $YOUNG.FIRM_{t-1}$	-0.0137***	-0.0168***	-0.00646*	-0.0102***	-0.0172***	-0.0172***	-0.00579***	-0.00422***
	(0.00287)	(0.00370)	(0.00388)	(0.00312)	(0.00260)	(0.00466)	(0.00218)	(0.000709)
Observations	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408	1,003,408
Firms	179,921	179,921	179,921	179,921	179,921	179,921	179,921	179,921

Table 8. Financial innovations at banks vs. SMEs' bank debt growth: the moderating role of collateral

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for firm- (PROFIT, EQUITY, ASSET.TURN, LN.FIRM.AGE, and FIRM.SIZE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$LOW.COLLAT_{t-1}$	0.0134***	0.0138***	0.0138***	0.0139***	0.0133***	0.0138***	0.0135***	0.0131***
	(0.000614)	(0.000593)	(0.000599)	(0.000615)	(0.000605)	(0.000588)	(0.000626)	(0.000626)
$BANK.INNOV_t$	0.00172**	0.00283***	0.00272***	0.00163*	0.00278***	0.00245***	0.000638	0.00139***
	(0.000824)	(0.000707)	(0.00105)	(0.000953)	(0.000636)	(0.000845)	(0.000900)	(0.000207)
$BANK.INNOV_t$ x $LOW.COLLAT_{t-1}$	0.00351***	0.00198**	0.00320**	0.00101	0.00321***	0.00355***	0.00275***	0.000776***
	(0.000914)	(0.000771)	(0.00127)	(0.00112)	(0.000641)	(0.000980)	(0.00102)	(0.000185)
Observations	977,732	977,732	977,732	977,732	977,732	977,732	977,732	977,732
Firms	176,327	176,327	176,327	176,327	176,327	176,327	176,327	176,327

Table 9. Financial innovations at banks vs. SMEs' cost of debt: the moderating role of firm size and firm age

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for firm- (PROFIT, FIXED.ASSETS, EQUITY, ASSET.TURN, and FIRM.SIZE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Moderating role of firm size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$FIRM.SIZE_{t-1}$	-0.0101***	-0.00994***	-0.00951***	-0.00992***	-0.00955***	-0.0101***	-0.0100***	-0.00966***
	(0.00130)	(0.00130)	(0.00130)	(0.00132)	(0.00132)	(0.00129)	(0.00132)	(0.00134)
$BANK.INNOV_t$	-0.00207	9.60e-06	0.00724***	-0.00107	-0.000458	-0.000460	-0.00279	-0.000163
	(0.00171)	(0.00164)	(0.00220)	(0.00244)	(0.00140)	(0.00197)	(0.00247)	(0.000553)
$BANK.INNOV_t$ x $FIRM.SIZE_{t-1}$	8.80e-06	-0.000645	-0.00420***	-0.000790	-0.00125*	-0.000150	-0.000273	-0.000246
	(0.000910)	(0.000864)	(0.00127)	(0.00133)	(0.000702)	(0.00107)	(0.00120)	(0.000219)
Observations	634,770	634,770	634,770	634,770	634,770	634,770	634,770	634,770
Firms	129,387	129,387	129,387	129,387	129,387	129,387	129,387	129,387

Panel B. Moderating role of firm age

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable:	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$YOUNG.FIRM_{t-1}$	0.0122***	0.0114***	0.0106***	0.0129***	0.0125***	0.0105***	0.0125***	0.0144***
	(0.00328)	(0.00304)	(0.00316)	(0.00335)	(0.00312)	(0.00300)	(0.00333)	(0.00338)
$BANK.INNOV_t$	-0.00131	0.000382	0.00538**	-0.000837	-0.000113	-9.56e-06	-0.00228	-0.000208
	(0.00168)	(0.00158)	(0.00222)	(0.00232)	(0.00140)	(0.00188)	(0.00224)	(0.000511)
$BANK.INNOV_t$ x $YOUNG.FIRM_{t-1}$	-0.0124**	-0.0246***	-0.00502	-0.0168**	-0.0176***	-0.0161**	-0.0155**	-0.00538***
	(0.00601)	(0.00612)	(0.00785)	(0.00708)	(0.00485)	(0.00712)	(0.00708)	(0.00147)
Observations	634,770	634,770	634,770	634,770	634,770	634,770	634,770	634,770
Firms	129,387	129,387	129,387	129,387	129,387	129,387	129,387	129,387

Table 10. Financial innovations at banks vs. SMEs' bank debt growth: the moderating role of a country's banking model and FinTech market

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for firm- (PROFIT, FIXED.ASSETS, EQUITY, ASSET.TURN, LN.FIRM.AGE, and FIRM.SIZE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Moderating role of a the development of the traditional banking model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BRANCHES_{t-1}$	0.000579***	0.000566***	0.000592***	0.000564***	0.000649***	0.000611***	0.000531***	0.000666***
	(6.30e-05)	(6.27e-05)	(6.39e-05)	(6.31e-05)	(6.39e-05)	(6.36e-05)	(6.26e-05)	(6.39e-05)
$BANK.INNOV_t$	0.0212***	0.0292***	0.0188***	0.0171***	0.0108***	0.0281***	0.0119***	0.00604***
	(0.00218)	(0.00301)	(0.00289)	(0.00292)	(0.00171)	(0.00365)	(0.00198)	(0.000552)
$BANK.INNOV_t$ x $BRANCHES_{t-1}$	-0.000354***	-0.000468***	-0.000258***	-0.000258***	-0.000109***	-0.000451***	-0.000202***	-8.21e-05***
	(4.03e-05)	(5.52e-05)	(5.20e-05)	(4.80e-05)	(3.09e-05)	(6.96e-05)	(3.77e-05)	(1.08e-05)
Observations	983,408	983,408	983,408	983,408	983,408	983,408	983,408	983,408
Firms	177,962	177,962	177,962	177,962	177,962	177,962	177,962	177,962

Panel B. Moderating role of the development of the FinTech market

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$FINTECH.CRED_{t-1}$	-5.41e-05***	-2.97e-05**	-5.23e-05***	-5.02e-05***	-5.70e-05***	-3.71e-05***	-7.13e-05***	-7.16e-05***
	(1.38e-05)	(1.40e-05)	(1.40e-05)	(1.38e-05)	(2.18e-05)	(1.38e-05)	(1.43e-05)	(1.52e-05)
$BANK.INNOV_t$	-0.000746	0.00374***	0.00151*	0.000566	0.00308***	0.00344***	0.000511	0.00132***
	(0.000728)	(0.000657)	(0.000871)	(0.000837)	(0.000634)	(0.000739)	(0.000791)	(0.000215)
$BANK.INNOV_t$ x $FINTECH.CRED_{t-1}$	0.000167***	0.000157***	0.000118***	0.000132***	1.20e-05	0.000148***	0.000158***	3.44e-05***
	(1.87e-05)	(2.28e-05)	(3.46e-05)	(2.40e-05)	(1.90e-05)	(2.32e-05)	(2.82e-05)	(4.95e-06)
Observations	826,827	826,827	826,827	826,827	826,827	826,827	826,827	826,827
Firms	147,789	147,789	147,789	147,789	147,789	147,789	147,789	147,789

Table 11. Financial innovations at banks vs. SMEs' cost of debt: the moderating role of a country's banking model and FinTech market

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for firm- (PROFIT, FIXED.ASSETS, EQUITY, ASSET.TURN, LN.FIRM.AGE, and FIRM.SIZE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Moderating role of a the development of the traditional banking model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BRANCHES_{t-1}$	0.000289**	0.000283**	0.000244*	0.000306**	0.000282**	0.000253**	0.000283**	0.000268**
	(0.000123)	(0.000123)	(0.000125)	(0.000125)	(0.000126)	(0.000124)	(0.000123)	(0.000125)
$BANK.INNOV_t$	0.0166***	-0.00286	-0.00770	0.0273***	-0.00837*	-0.0135	0.0110**	0.00189
	(0.00557)	(0.00650)	(0.00829)	(0.00778)	(0.00494)	(0.0101)	(0.00556)	(0.00173)
$BANK.INNOV_t$ x $BRANCHES_{t-1}$	-0.000381***	5.28e-05	0.000250*	-0.000487***	0.000143	0.000237	-0.000277**	-4.55e-05
	(0.000109)	(0.000120)	(0.000142)	(0.000128)	(9.30e-05)	(0.000192)	(0.000108)	(3.31e-05)
Observations	622,263	622,263	622,263	622,263	622,263	622,263	622,263	622,263
Firms	127,814	127,814	127,814	127,814	127,814	127,814	127,814	127,814

Panel B. Moderating role of the development of the FinTech market

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable:	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$FINTECH.CRED_{t-1}$	7.38e-06	1.67e-05	1.90e-05	1.30e-05	6.02e-05	1.47e-05	-2.60e-05	-1.44e-05
	(2.84e-05)	(2.83e-05)	(2.88e-05)	(2.85e-05)	(3.79e-05)	(2.85e-05)	(3.08e-05)	(3.01e-05)
$BANK.INNOV_t$	-0.00316*	-0.000383	0.00658***	-0.00276	-0.00109	-0.00107	-0.00328	-0.000564
	(0.00177)	(0.00172)	(0.00224)	(0.00262)	(0.00153)	(0.00212)	(0.00242)	(0.000586)
$BANK.INNOV_t$ x $FINTECH.CRED_{t-1}$	0.000109***	7.16e-05	0.000105	7.07e-05*	-5.48e-05	8.39e-05*	0.000205***	2.21e-05**
	(3.49e-05)	(4.41e-05)	(8.04e-05)	(3.90e-05)	(3.51e-05)	(4.47e-05)	(5.32e-05)	(9.52e-06)
Observations	607,658	607,658	607,658	607,658	607,658	607,658	607,658	607,658
Firms	125,417	125,417	125,417	125,417	125,417	125,417	125,417	125,417

Table 12. Robustness check: endogeneity test

This table presents the results of the GMM-SYS estimations. For brevity, we do not present coefficients for the lagged dependent variables (the first and the second lag), as well as firm- (PROFIT, FIXED.ASSETS, EQUITY, ASSET.TURN, LN.FIRM.AGE, and FIRM.SIZE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year, country and industry dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Impact on bank debt growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BANK.INNOV_t$	0.00189***	0.00308***	0.00252***	0.00138*	0.00527***	0.00148**	0.00166**	0.00131***
	(0.000697)	(0.000745)	(0.000793)	(0.000753)	(0.000780)	(0.000727)	(0.000694)	(0.000191)
Observations	726,769	726,769	726,769	726,769	726,769	726,769	726,769	726,769
Firms	150,117	150,117	150,117	150,117	150,117	150,117	150,117	150,117
AR(1)	-90.83***	-90.81***	-90.81***	-90.81***	-90.82***	-90.80***	-90.82***	-90.83***
AR(2)	-0.294	-0.279	-0.292	-0.277	-0.372	-0.310	-0.246	-0.322

Panel B. Impact on cost of debt

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable:	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BANK.INNOV_t$	0.00909***	0.00415**	0.00750***	0.0117***	0.00293	0.00568***	0.00764***	0.00219***
	(0.00201)	(0.00209)	(0.00268)	(0.00230)	(0.00200)	(0.00204)	(0.00229)	(0.000558)
Observations	410,634	410,634	410,634	410,634	410,634	410,634	410,634	410,634
Firms	98,160	98,160	98,160	98,160	98,160	98,160	98,160	98,160
AR(1)	-24.21***	-24.18***	-24.18***	-24.20***	-24.22***	-24.16***	-24.19***	-24.23***
AR(2)	1.369	1.466	1.436	1.393	1.387	1.474	1.410	1.337

Table 13. Robustness check: estimations for firms that declared only one main bank

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for firm- (PROFIT, FIXED.ASSETS, EQUITY, ASSET.TURN, LN.FIRM.AGE, and FIRM.SIZE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Impact on bank debt growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$	$DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BANK.INNOV_t$	0.00395***	0.00328***	0.00296***	0.00216***	0.00357***	0.00368***	0.00250***	0.00159***
	(0.000697)	(0.000631)	(0.000837)	(0.000818)	(0.000577)	(0.000700)	(0.000738)	(0.000190)
Observations	631,200	717,759	717,759	717,759	717,759	717,759	717,759	717,759
Firms	122,269	131,253	131,253	131,253	131,253	131,253	131,253	131,253

Panel B. Impact on cost of debt

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable:	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$	$INT.COST_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BANK.INNOV_t$	-0.00126	-0.00172	0.00582**	-0.00149	-0.00162	-0.00106	-0.00242	-0.000530
	(0.00185)	(0.00179)	(0.00242)	(0.00252)	(0.00156)	(0.00211)	(0.00243)	(0.000569)
Observations	402,736	402,736	402,736	402,736	402,736	402,736	402,736	402,736
Firms	85,109	85,109	85,109	85,109	85,109	85,109	85,109	85,109

Table 14. Robustness check: growth rate of debt depending on its maturity

This table presents the results of the estimations for the fixed-effects panel models. For brevity, we do not present coefficients for firm- (PROFIT, FIXED.ASSETS, EQUITY, ASSET.TURN, LN.FIRM.AGE, and FIRM.SIZE), country- (PRI.CREDIT, GDP.GROWTH, GDP.PC, and UNEMPL), and bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Standard errors clustered at the firm-level are shown in parentheses. *, **, *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Impact on long-term debt

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$LT.DEBT.GR_t$	$LT.DEBT.GR_t$	$LT.DEBT.GR_t$	$LT.DEBT.GR_t$	$LT.DEBT.GR_t$	$LT.DEBT.GR_t$	$LT.DEBT.GR_t$	$LT.DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BANK.INNOV_t$	0.00320***	0.00272***	0.00394***	0.00153***	0.00312***	0.00295***	0.00195***	0.00139***
	(0.000531)	(0.000470)	(0.000652)	(0.000593)	(0.000438)	(0.000510)	(0.000562)	(0.000145)
Observations	1,034,658	1,034,658	1,034,658	1,034,658	1,034,658	1,034,658	1,034,658	1,034,658
Firms	183,557	183,557	183,557	183,557	183,557	183,557	183,557	183,557

Panel B. Impact on short-term bank debt

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable:	$ST.DEBT.GR_t$	$ST.DEBT.GR_t$	$ST.DEBT.GR_t$	$ST.DEBT.GR_t$	$ST.DEBT.GR_t$	$ST.DEBT.GR_t$	$ST.DEBT.GR_t$	$ST.DEBT.GR_t$
Regressor used as BANK.INNOV:	$AUT.SOFT_t$	$BLOCKCHAIN_t$	$ANALYTICS_t$	$LENDING_t$	$PAYMENTS_t$	$PERSON.FIN_t$	$REGULAT_t$	$INNOV.ALL_t$
$BANK.INNOV_t$	0.00376***	-0.000300	0.00349***	0.000880*	0.00185***	0.00213***	0.000623	0.000822***
	(0.000403)	(0.000345)	(0.000461)	(0.000471)	(0.000318)	(0.000393)	(0.000416)	(0.000109)
Observations	1,011,309	1,011,309	1,011,309	1,011,309	1,011,309	1,011,309	1,011,309	1,011,309
Firms	180,751	180,751	180,751	180,751	180,751	180,751	180,751	180,751

References:

1. Agarwal, S. and Hauswald, R. (2010). Distance and Private Information in Lending. *Review of Financial Studies*, vol. 23, pp.2757-2788.
2. Alessandrini, P., Presbitero, A. F., and Zazzaro, A. (2009). Banks, distances and firms' financing constraints. *Review of Finance*, vol. 13, pp.261-307.
3. Angelini, E., di Tollo, G. and Roli, A. (2008). A neural network approach for credit risk evaluation. *The Quarterly Review of Economics and Finance*, vol. 48, pp.733-755 .
4. Athreya, K., Tam, X.S. and Young, E.R. (2012). A Quantitative Theory of Information and Unsecured Credit. *American Economic Journal: Macroeconomics*, vol. 4, pp.153-183.
5. Bazarbash, M. (2019). FinTech in Financial Inclusion: Machine Learning Applications in Assessing Credit Risk. *IMF Working Papers*, no. 19.
6. Beaumont, P., Tang, H. and Vansteenberghe, E., (2021). The role of FinTech in small business lending. Working paper, available from https://paulhbeaumont.github.io/pdfs/bvt.pdf [last accessed 20 December 2021].
7. Beccalli, E. (2007). Does IT investment improve bank performance? Evidence from Europe. *Journal of Banking & Finance*, vol. 31, pp.2205-2230.
8. Beck, S., Cusmano, L., Durrani-Jamal, S., Holden, P., Khor, N., Kaousar Nassr, I., Robano, V. and Shinozaki, S. (2014). ADB-OECD Study on Enhancing Financial Accessibility for SMEs Lessons from Recent Crises. Available from https://www.oecd.org/cfe/smes/adb-oecd-study-enhancing-financial-accessibility-smes.pdf [last accessed 20 December 2021].
9. Beck, T., Demirgüç-Kunt, A., Laeven, L. and Maksimovic, V. (2006). The determinants of financing obstacles. *Journal of International Money and Finance*, vol. 25, pp.932-952.
10. Behr, P., Drexler, A., Gropp, R., and Guettler, A. (2020). Financial Incentives and Loan Officer Behavior: Multitasking and Allocation of Effort under an Incomplete Contract. *Journal of Financial and Quantitative Analysis*, vol. 55, pp.1243-1267.
11. Berg, T., Burg, V., Gombović, A., and Puri, M. (2021). On the rise of fintechs: credit scoring using digital footprints. *Review of Financial Studies*, vol. 33, pp.2845-2897.
12. Berger, A.N., Espinosa-Vega, M.A., Frame, W.S. and Miller, N.H. (2011). Why do borrowers pledge collateral? New empirical evidence on the role of asymmetric information. *Journal of Financial Intermediation*, vol. 20, pp.55-70.
13. Berger, A.N., Goulding, W. and Rice, T. (2014). Do small businesses still prefer community banks? *Journal of Banking & Finance*, vol. 44, pp.264-278.

14. Berger, A.N. and Udell, G.F. (1995). Universal Banking and the Future of Small Business Lending. *NYU Working Paper*, No. FIN-95-009.
15. Berger, A.N. and Udell, G.F. (2001). Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure. *The Economic Journal*, 112(477), pp.F32–F53.
16. Berger, A.N. and Udell, G.F. (2006). A more complete conceptual framework for SME finance. *Journal of Banking & Finance*, vol. 30, pp.2945- 2966.
17. Berlingieri, G., Calligaris, S., Criscuolo, C. and Verlhac, R. (2020). Laggard firms, technology diffusion and its structural and policy determinants. *OECD Science, Technology and Industry Policy Papers*, No. 86.
18. Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, vol. 87, pp.115-143.
19. Boot, A., Hoffmann, P., Laeven, L. and Ratnovski, L. (2021). Fintech: what's old, what's new? *Journal of Financial Stability*, vol. 53, pp.100836.
20. Boot, A.W.A. (2000). Relationship Banking: What Do We Know? *Journal of Financial Intermediation*, vol. 9, pp.7-25.
21. Booth, J.R. and Booth, L.C. (2006). Loan Collateral Decisions and Corporate Borrowing Costs. *Journal of Money, Credit, and Banking*, vol. 38, pp.67-90.
22. Bottazzi, G., Secchi A., and Tamagni F. (2014). Financial Constraints and Firm Dynamics. *Small Business Economics*, vol. 42, pp.99-116.
23. Branzoli, N., Rainone, E. and Supino, I. (2021). The Role of Banks' Technology Adoption in Credit Markets during the Pandemic. *SSRN Electronic Journal*. Available at SSRN: https://ssrn.com/abstract=3878254 or http://dx.doi.org/10.2139/ssrn.3878254.
24. Buchak, G., Matvos, G., Piskorski, T. and Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, vol. 130, pp.453-483.
25. Chan, Y.S. and Thakor, A.V. (1987). Collateral and Competitive Equilibria with Moral Hazard and Private Information. *The Journal of Finance*, vol. 42, pp.345-363.
26. Chava, S., Rohan, G., Paradkar, N., and Zhang, Y. (2021). Impact of marketplace lending on consumers' future borrowing capacities and borrowing outcomes. *Journal of Financial Economics*, vol. 142, pp.1186-1208.
27. Chen, B. S., Hanson, S., G., Stein, J. C. (2017), The Decline of Big-Bank Lending to Small Business: Dynamic Impacts on Local Credit and Labor Markets. *NBER Working Paper* No. W23843.

28. Chen, Z., Li, Y., Wu, Y. and Luo, J. (2017). The transition from traditional banking to mobile internet finance: an organizational innovation perspective - a comparative study of Citibank and ICBC. *Financial Innovation,* vol. 3, pp.3-12.
29. Claessens, S., Frost, J., Turner, G. and Zhu, F. (2018). Fintech credit markets around the world: size, drivers and policy issues. *BIS Quarterly Review,* September, pp.29-49.
30. Cornelli, G., Frost, J., Gambacorta, L., Rau, P. R., Wardrop, R., and Ziegler, T. (2020). Fintech and Big Tech Credit: A New Database. *BIS Working Paper* No. 887.
31. De la Torre, A., Martínez Pería, M.S. and Schmukler, S.L. (2010). Bank involvement with SMEs: Beyond relationship lending. *Journal of Banking & Finance*, vol. 34, pp.2280-2293.
32. DeYoung, R., Frame, W.S., Glennon, D., McMillen, D.P. and Nigro, P. (2008). Commercial lending distance and historically underserved areas. *Journal of Economics and Business*, vol. 60, pp.149-164.
33. DeYoung, R., Frame, W.S., Glennon, D. and Nigro, P. (2011). The Information Revolution and Small Business Lending: The Missing Evidence. *Journal of Financial Services Research,* vol. 39, pp.19-33.
34. Di Maggio, M. and Yao, V. (2021). Fintech Borrowers: Lax-Screening or Cream-Skimming? *The Review of Financial Studies*, vol. 34, pp.4565-4618.
35. Diamond, D. W. (1991). Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt. *Journal of Political Economy*, vol. 99, pp.689-721.
36. Ding, J., Huang, J., Li, Y. and Meng, M. (2019). Is there an effective reputation mechanism in peer-to-peer lending? Evidence from China. *Finance Research Letters*, vol. 30, pp.208-215.
37. EBRD, 2021: Transition Report 2021-22. System upgrade: Delivering the Digital Dividend.
38. Fuster, A., Plosser, M., Schnabl, P. and Vickery, J. (2019). The Role of Technology in Mortgage Lending. *The Review of Financial Studies*, vol. 32, pp.1854-1899.
39. Gambacorta, L., Huang, Y., Li, Z., Qiu, H. and Chen, S. (2020). Data vs collateral, *CEPR Discussion Paper* No. DP15262. Available at: https://ssrn.com/abstract=3696342 [last accessed on 22 December 2022]
40. Gambacorta, L., Huang, Y., Qiu, H., and Wang, J. (2019). How do machine learning and nontraditional data affect credit scoring? New evidence from a Chinese fintech firm. *BIS Working Papers* No. 834.
41. Ge, R., Feng, J. and Gu, B. (2016). Borrower's default and self-disclosure of social media information in P2P lending. *Financial Innovation,* vol. 2, pp.2-30.

42. Ge, R., Feng, J., Gu, B. and Zhang, P. (2017). Predicting and deterring default with social media information in peer-to-peer lending. *Journal of Management Information Systems*, vol. 34, pp.401-424.
43. Ghosh, P., Vallee, B. and Zeng, Y. (2021). FinTech Lending and Cashless Payments. *Proceedings of Paris December 2021 Finance Meeting EUROFIDAI - ESSEC*, Available at SSRN: https://ssrn.com/abstract=3766250 or http://dx.doi.org/10.2139/ssrn.3766250.
44. Gorodnichenko, Y. and Schnitzer, M. (2013). Financial constraints and innovation: Why poor countries don't catch up. *Journal of the European Economic association*, vol. 11, pp.1115-1152.
45. Havrylchyk, O. and Mahdavi Ardekani, A. (2020). Real Effects of Lending-Based Crowdfunding Platforms on the SMEs. *SSRN Electronic Journal*. Available at SSRN: https://ssrn.com/abstract=3717170 or http://dx.doi.org/10.2139/ssrn.3717170.
46. Hernández-Cánovas, G. and Martínez-Solano, P. (2010). Relationship lending and SME financing in the continental European bank-based system. *Small Business Economics*, vol. 34, pp.465-482.
47. Hollander, S., and Verriest, A. (2016). Bridging the gap: The design of bank loan contracts and distance. *Journal of Financial Economics*, vol. 119, pp.399-419.
48. Holmstrom, B. and Tirole, J. (1997). Financial Intermediation, Loanable Funds, and The Real Sector. *The Quarterly Journal of Economics*, vol. 112, pp.663-691 .
49. Huang, Y., Zhang, L., Li, Z., Qiu, H., Sun, T., and Wang, X. (2020). Fintech Credit Risk Assessment for SMEs: Evidence from China. *IMF Working Papers*, No. 193.
50. Huyghebaert, N. and Van de Gucht, L.M. (2007). The Determinants of Financial Structure: New Insights from Business Start-ups. *European Financial Management*, vol. 13, pp.101-133.
51. Iyer, R., Peydro, J.-L., Da-Rocha-Lopes, S., and Schoar, A. (2014). Interbank liquidity crunch and the firm credit crunch: evidence from the 2007-2009 crisis, *The Review of Financial Studies*, vol. 27, pp.347-372.
52. Jagtiani, J. and Lemieux, C. (2018a). Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business*, vol. 100, pp.43-54.
53. Jagtiani, J. and Lemieux, C. (2018b). The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform. *Working paper (Federal Reserve Bank of Philadelphia)*.
54. Khandani, A., E., Kim, A.J. and Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, vol. 34, pp.2767-2787.

55. Kirschenmann, K. (2016). Credit rationing in small firm-bank relationships. *Journal of Financial Intermediation*, vol. 26, pp.68-99.
56. Kwan, A., Lin, C., Pursianen, V. and Tai, M. (2021). Stress testing banks' digital capabilities: Evidence from the covid-19 pandemic. *SSRN working papers*, no. 3694288.
57. Liberti, J.M. and Mian, A.R. (2009). Estimating the Effect of Hierarchies on Information Use. *Review of Financial Studies*, vol. 22, pp.4057-4090.
58. Liberti, J.M. and Petersen, M.A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, vol. 8, pp.1-41.
59. López-Espinosa, G., Mayordomo, S. and Moreno, A. (2017). When does relationship lending start to pay? *Journal of Financial Intermediation*, vol. 31, pp.16-29.
60. Lopez-Gracia, J. and Mestre-Barberá, R. (2015). On the relevance of agency conflicts in SME debt maturity structure. *Journal of Small Business Management*, vol. 53, pp.714-734.
61. OECD (2020), The impact of COVID-19 on SME financing: A special edition of the OECD Financing SMEs and Entrepreneurs Scoreboard, *OECD SME and Entrepreneurship Papers*, No. 22.
62. Palladino, L.M. (2020). The impacts of fintech on small business borrowing. *Journal of Small Business & Entrepreneurship*, vol. 33, pp.1-23.
63. Petersen, M.A. and Rajan, R.G. (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. *The Journal of Finance*, vol. 49, pp.3-37.
64. Petersen, M.A. and Rajan, R.G. (2002). Does Distance Still Matter? The Information Revolution in Small Business Lending. *The Journal of Finance*, vol. 57, pp. 2533-2570.
65. Philippon, T. (2015). Has the US Finance Industry Become Less Efficient? On the Theory and Measurement of Financial Intermediation. *American Economic Review*, vol. 105, pp. 190-218.
66. Presbitero, A. F., Udell, G. F., & Zazzaro, A. (2014). The Home Bias and the Credit Crunch: A Regional Perspective. *Journal of Money, Credit and Banking*, vol. 46, pp.53–85.
67. Rajan, R.G. (1992). Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt. *The Journal of Finance*, vol. 47, pp.1367-1400.
68. Reynolds, P., Bosma, N., Autio, E., Hunt, S., De Bono, N., Servais, A., Lopez-Garcia, P., and Chin, N. (2005). Global Entrepreneurship Monitor: data collection design and implementation 1998–2003. *Small Business Economics*, vol. 24, pp.205–231.
69. Salman, A., Bell, S., Conner, G. (2017). What's Happening in the Missing Middle? Lessons from Financing SMEs. *World Bank.*
70. Sanchez, J.M. (2018). The information technology revolution and the unsecured credit market. *Economic Inquiry*, vol. 56, pp.914–930.

71. Schweitzer, M.E., Barkley, B. (2017). Is "fintech" good for small business borrowers? Impacts on firm growth and customer satisfaction. *Federal Reserve Bank of Cleveland Working Paper* No.1.
72. Sedunov, J. (2017). Does bank technology affect small business lending decisions? *Journal of Financial Research,* vol. 40, pp.5–32.
73. Sheng, T. (2021). The effect of fintech on banks' credit provision to SMEs: Evidence from China. *Finance Research Letters* 39, pp.101558.
74. Stein, J.C. (2002). Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. *The Journal of Finance*, vol. 57, pp.1891–1921.
75. Stulz, R.M. (2019). FinTech, BigTech, and the Future of Banks. *Journal of Applied Corporate Finance*, vol. 31, pp.86–97.
76. Sutherland, A. (2018). Does credit reporting lead to a decline in relationship lending? Evidence from information sharing technology. *Journal of Accounting and Economics*, vol. 66, pp.123–141.
77. Tang, H. (2019). Peer-to-Peer Lenders Versus Banks: Substitutes or Complements? *The Review of Financial Studies*, vol. 32, pp.1900–1938.
78. Thakor, A.V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, vol. 41, p.100833.
79. Wang, Y. and Sui, X. (2020). Can Fintech Improve the Efficiency of Commercial banks? —An Analysis Based on Big Data. *Research in International Business and Finance*, vol. 55, pp.101338.
80. Yan, J., Yu, W. and Zhao, J.L. (2015). How signaling and search costs affect information asymmetry in P2P lending: the economics of big data. *Financial Innovation*, vol. 1, pp.1-19
81. Zhao, T., Luintel, K.B. and Matthews, K. (2021). Soft information and the geography of SME bank lending. *Regional Studies*, vol. 55, pp.679-692.

Websites:

https://ec.europa.eu/growth/smes_en