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ADBI Working Paper Series

THE PARADOX OF PROGRESS: TECHNOLOGICAL ADVANCEMENTS IN BANKING AND THE DUAL IMPACT ON SME BANK BORROWING

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Abstract

This study delves into the impact of technological bank innovations on small and medium-sized enterprise (SME) borrowing across the European Union. By analyzing a comprehensive dataset of 179,921 SME-bank lending relationships from 2009 to 2019, we explore the mechanisms through which technological advancements in banking reshape traditional lending practices. Our empirical analysis documents that banks' technological innovations have a more substantial impact on SMEs' long-term credit growth than on their short-term growth, indicating the usefulness of these technologies in providing data that not only reduce information asymmetry but also enhance long-term decision channels. Specifically, blockchain and automation play a crucial role in expanding bank credit to SMEs. However, we also identify a paradoxical dual effect: while technological advancements facilitate credit access, they simultaneously increase the cost of borrowing for SMEs. This finding highlights a complex interplay where technological progress in banking presents both opportunities and challenges, especially for more opaque firms seeking financing.

Our study contributes to the understanding of the nuanced role of innovation in banking, offering insights into the dualistic nature of the impact of technology on SME financing.

Keywords: SME financing, bank technology, innovation, collateral, cost of intermediation

JEL Classification: G21, O16, O33, G23, G32

Contents

1.	INTRO	DUCTION	.1
2.	DATA	AND METHODOLOGY	.4
	2.1 2.2	Sample Description Methodology	.4 .7
3.	EMPIR	RICAL RESULTS1	1
	3.1 3.2	Banks' Digitalization and SME Borrowing	1
	3.3	The Role of Different Types of Bank Technology in SME Borrowing1	5
4.	THE C	HANNELS OF THE TECHNOLOGICAL EFFECTS ON SME BORROWING.1	8
	4.1 4.2	Reduction in Information Frictions and Reliance on Collateral1 Credit Access and Cost of Intermediation	8 20
5.	ROBU	STNESS CHECKS2	21
	5.1 5.2	Endogeneity Concerns and Instrumental Variable Regression (IV)2 Identification Strategy	21 25
6.	CONC	LUSIONS2	29
REFE	RENCE	S	30

1. INTRODUCTION

In the face of rapid technological evolution, the banking industry has been at the forefront of embracing change. From the convenience of electronic payments to the insightful world of big data analytics and the intelligence of AI solutions and blockchain, banks have harnessed these innovative technologies to revolutionize their decision-making processes. These recent advancements in technology can introduce new lending paradigms that could extend novel opportunities to traditionally underserved customers, like SMEs.

Small and medium-sized enterprises (SMEs) play a vital role in promoting sustainable economic growth worldwide via fostering innovation and competition, and creating employment. In Europe, SMEs account for 99% of the enterprise population and for more than half of its GDP and employment.¹ Despite their well-acknowledged importance for the economy, SMEs receive a disproportionately small share of credit from financial institutions, and such a trend persists across both developed and developing countries (Beck and Demirgüç-Kunt 2006; ECB SAFE Survey 2020; World Bank 2018, 2023). These financing constraints are rooted in the inherent information opacity of SMEs, which exacerbates the asymmetry between lenders and borrowers and leads to credit rationing, as proven by Stiglitz and Weiss (1981). Additionally, the lack of valuable collateral and unproportionally high costs of bank financing for SMEs exclude the latter from bank financing even further (Beck and Demirgüç-Kunt 2006; De Blick, Paeleman, and Laveren 2023; Harrison et al. 2022; Yaldiz Hanedar, Broccardo, and Bazzana 2014).

In this research, we investigate whether the most recent technological innovations adopted by banks can resolve the existing challenges faced by SMEs when they seek bank financing, and which technological advancements can contribute to SMEs' improvement in accessing bank credit.

Using the Amadeus firm-level panel dataset, our sample includes 179,921 SMEs across the EU, from 2009 to 2019, paired with data from 54 major European banks. We focus on SMEs with existing bank relationships to discern the additive value of technology in providing data to banks. We then merge bank data with information on technological solutions implemented by each bank affiliated with an SME. More importantly, for each bank, we can identify a technological innovation that a bank has implemented as well as the year of its implementation. Thus, by aggregating all the technological innovations implemented by a bank between 2009 and 2019, we can evaluate the level of the bank's technological innovation and track its progression over time. We retrieve technological data from the Crunchbase and CBInsights databases and supplement this information by web-mining processes allowing us to identify banks' announcements on bank technological product acquisition and/or development as well as its nature.

Additionally, we also use alternative measures for bank technological development, such as: (i) the number of filed applications by a bank; (ii) the number of patents granted by a bank; and (iii) the number of deals a bank has been involved with as a venture capitalist (VC). We retrieve this information at a bank-year level from GlobalData. However, a certain caution to these measures must be granted as they are available only for 3,500 public companies, with the banking sector being highly underrepresented. We use these alternative measures of bank technological innovativeness to test the robustness of our results.

¹ https://ec.europa.eu/growth/smes_en.

Our methodology involves two-way fixed-effect regression models, including interaction effects, difference-in-difference (DID) estimations, and two-stage instrumental variable (2SLS IV) techniques to address potential endogeneity between the adoption of bank technology and SME borrowing. We show that the Second Payment Services Directive (PSD2) adopted by the European Commission at the end of 2015 has caused an exogenous shock, significantly speeding up the digitization of the entire financial sector in Europe afterwards. The occurrence of this shock has extended the access to different technologies for banks and provided a solid foundation for our DID estimations.

In contrast to existing literature that examines FinTech and BigTech firms' role in catering to underserved customers, our study offers a unique perspective on the role of technological innovation at banks in accessing credit for opaque borrowers. While there are some academic studies documenting how FinTech and BigTech companies extend financial services to overlooked or underserved customers (for example, Balyuk (2022); Beaumont et al. (2021); Berger et al. (2021); Cornelli et al. (2023); Gambacorta et al. (2019); Gopal and Schnabl (2022); Jagtiani et al. (2021); Jagtiani and Lemieux (2018, 2019);, Ouyang (2022); Palladino (2021)), little is known about how recent banking technological innovations are changing the lending framework toward opaque customers. Though the role of bank digitalization in supplying superior credit has been recently evidenced, mainly during the pandemic crisis (see, for example, Branzoli et al. (2021; Ferri et al. (2019); Kwan et al. (2021); or more generally D'Andrea and Limodio (2023)), these studies are mainly silent concerning the role of technology in supplying credit to underserved customers. To the best of our knowledge, the only study that attempts to look at this question is that of Sedunov (2017), who uses US bank data for the period between 2001 and 2008 - long before the real FinTech development area began. Similarly, Sheng (2021) examines the role of FinTech institutions in providing bank credit to SMEs in the People's Republic of China (PRC); however, the author uses macro data rather than bank-level data. With our study, we close the gaps in the existing literature by utilizing the most recent technological solutions adopted by individual banks to assess their role in improving access to bank credit for underserved customers.

Our study reveals that the recent adoption of technological innovations by banks has enabled SMEs to overcome certain barriers and get better access to bank credit. However, we also found that a certain level of technological development at banks is necessary to effectively address the challenges associated with the information opacity of SMEs. Importantly, we observe a more pronounced impact of bank technology on increased SMEs' long-term borrowing compared to short-term borrowing. This suggests that technological innovation not only mitigates asymmetric information problems but also enhances information efficiency, affecting other channels of bank credit decision-making. This underscores the multifaceted role of different technological innovations in assisting banks with credit decisions for opaque companies.

Additionally, our analysis enriches the literature by examining the role of specific types of technological innovations in banks' credit decision-making for SMEs. We explore the complexity and innovativeness of technological development at banks, including the adoption of electronic payments, online lending, personal finance solutions, data analytics, regulatory technology, blockchain, and automation. Subsequently, we test how these technologies address the unique challenges faced by opaque borrowers. The uniqueness and complexity of our dataset significantly distinguish us from previous academic studies that examine the impact of the general level of bank digitalization, mostly measured by bank IT spending (Branzoli, Rainone, and Supino 2021; D'Andrea and Limodio 2023; Kwan et al., 2020; Martinez Peria et al. 2022; Pierri and Timmer

2022) or by access to the internet (D'Andrea and Limodio 2023). The gradualness of our data allows us to investigate the contribution of each technological solution to address the problems of SMEs and their access to bank credit.

Our research underscores the pivotal role of blockchain technology in mitigating the difficulties encountered by SMEs in obtaining bank credit. In particular, our regression analysis reveals that blockchain technology significantly broadens the spectrum of credit options available to SMEs. Through its ability to collect and process large sets of data, it allows banks to reduce the asymmetric information problem in an efficient way, improving access to bank credit for opaque firms. Moreover, we also find that data analytics and automation also appear to be highly statistically significant in improving SMEs' access to credit. Consequently, our regressions reveal that access to data and efficiency in collecting and processing them seem to be the most important factors in extending credit to opaque customers.

Moreover, our study offers novel and comprehensive insights into various channels through which technological innovation in banks can lead to increased SME borrowing. We focus on how such technology influences the easing of collateral requirements and the cost of intermediated bank credit. While a few studies, such as those by Buchak et al. (2018), Jagtiani and Lemieux (2018), and Beaumont et al. (2021), compare the cost of credit offered by FinTech companies to that of banks, the precise impact of technological advancement on the cost of bank intermediation remains underexplored. These aspects have been primarily discussed in FinTech and BigTech literature, often without definitive conclusions, but are less widely covered in banking literature. Similarly, the current literature has not addressed how bank technology affects the role of collateral in opaque companies accessing bank credit. Although Holmstrom and Tirole (1997) and Gambacorta et al. (2023) argue that greater access to hard data could ease bank requirements for collateral, the existing literature has not empirically verified the link between firm collateral and bank credit. Our data create a great testing ground to test this relationship.

Our regression results document that banks with more innovative technology require less valuable collateral from SMEs than less digitalized banks. In other words, SMEs associated with technologically advanced banks can access credit with lower collateral requirements than those associated with less digitalized banks. This finding seems to suggest that transactional data may also improve the screening processes at banks. At the same time, our regression results challenge the presumption that technologically advanced banks tend to charge SMEs higher interest rates. Our study may indicate that the technology might not perfectly replace the relational soft data that banks accumulate over time, and the ease of the collateral forces banks to charge a higher risk premium.

In our study, we rigorously address various potential biases and endogeneity concerns across various specifications, measures of bank technological development, and the nature of SME-bank relationships. Firstly, we employ OLS regression with an interaction term as well as DID to test the potential issues related to the assumptions of DID. Secondly, we utilize TWFE DID staggered with timing as well as a single treatment period to test the robustness of our DID results. Thirdly, to address potential endogeneity related to banks' individual features and their technological development, we employ two-stage instrumental variable (2SLS IV) regression using country-level variation related to the adoption of PSD2 as an exogenous instrument for banks' technological development. However, to enhance the technological advancement of banks, we conduct additional regressions to address the identification problem. These regressions involve examining the relationship between individual SMEs and banks,

such as firm digital intensity or industry type, which could potentially introduce bias into our estimated results. All our robustness analyses highlight the crucial role of bank technological innovation in shaping SMEs' access to credit.

Our paper is structured as follows. The next section discusses the data and methodology, while Sections 3 and 4 present the results, which are further tested for their robustness in Section 5. Section 6 offers conclusions and policymaking implications.

2. DATA AND METHODOLOGY

2.1 Sample Description

To investigate our research questions, we assemble a variety of data, such as SME data, bank-level data, including information on each bank-implemented technological solution, and macroeconomic country-level data.

Our data collection process starts with the construction of the SME panel sample. For this, 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 of the firms' bank affiliation information. To identify SMEs, we follow the European Commission's definition of SMEs - which is also used by Eurostat - as having fewer than 250 persons employed and an annual turnover of up to EUR50 million or a total balance sheet of no more than EUR43 million. The Amadeus database is also a primary source of information allowing us to link SMEs with their affiliated 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, i.e., Austria, Croatia, Denmark, Estonia, France, Germany, Greece, Hungary, Ireland, Latvia, Poland, Portugal, Slovenia, Spain, and the UK. Table 1 gives an overview of the sample structure by the year and by the number of banks affiliated with a firm. It also provides the features of SMEs used in our analysis.

Table 1: Sample Structure

This table presents a sample structure based on the 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				

continued on next page

Panel B. Sample structure by the number of banks affiliated with a firm							
Banks Affiliated with a Firm	Observations	% of Observations					
1	717,759	71.5					
2	202,319	20.2					
3	63,290	6.3					
4	16,677	1.7					
5	3,363	0.3					
All observations	1,003,408	100.0					

 Table 1 continued

We notice that though the sample covers the 2009–2019 period, it is slightly more concentrated between 2013 and 2018. Interestingly, we also find that most SMEs in the sample 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 technological development on SMEs' access to credit and its cost, we had to collect information on financial technology implemented by each affiliated bank in each sample year. To this end, we use the information retrieved from the Crunchbase and CBInsights databases, which we additionally supplement with web-mining techniques on banks' announcements of technological purchases or developments. 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 technological innovation is very wide and includes the latest technological solutions implemented by banks, such as: automation software (AUTOMATIZATION). blockchain technology (BLOCKCHAIN), data analytics (ANALYTICS), lending solutions (ONLINE LENDING), electronic payments (ELECTRONIC PAYMENTS), personal finance (PERSONAL FIN), and regulatory technology (REG TECH). We also construct a measure of a bank's overall technological innovativeness, calculated as the sum of the seven above-mentioned variables (BANK.INNOV). Figure 1 documents the implementation of technology at banks over the analyzed sample period.



Figure 1: The Number of Bank FinTech Solutions Across Time

In Figure 1, we see a notable upward trend in the number of digital solutions adopted by banks. The highest spike in the increase can be seen after 2015, which coincides with the adoption of PSD2 by the European Commission at the end of that year. The new regulatory framework has led to a substantial increase in the number of payment technological startups and the entry of several major payment players, including Google Pay (Babina et al. 2024). However, it has also spurred the adoption of technologies at banks such as payment systems, data analytics, or blockchain (Polasik et al. 2020; Preziuso, Koefer, and Ehrenhard 2023).

Nevertheless, the plot underscores the pronounced heterogeneity in the European banking sector's technological development. While the median number of implemented solutions peaked at three in 2018, there was a compelling divergence in innovation between banks after 2012. This divergence indicates varying paces of digital adoption among different banking institutions. Interestingly, in 2013, half of the banks had still did not integrated any technological solutions, highlighting resistance or possible barriers to digital transformation. Conversely, a few banks reached the 2018 median as early as 2013, underscoring their pioneer status in digital innovation. Figure 2 presents information on the types of bank technological innovation.



Figure 2: Percentage Usage of Individual Technological Solutions by Banks

Figure 2 shows significant variation in the types of solutions adopted by different banks. More specifically, 83% of banks use electronic payments, the most widely adopted innovation. Data analytics and blockchain follow at 57% and 62%, respectively. Online lending solutions are the least popular. These trends are in line with Lerner et al. (2023), who found that payment solutions, cybersecurity, and communication technologies such as chatbots are the most patented areas. Retail, commercial, and investment banking technologies have fewer patents.

2.2 Methodology

To assess how a bank's technological progress affects small and medium-sized enterprises' (SMEs) ability to obtain credit, we utilize a robust statistical method known as a two-way fixed effect (TWFE) difference-in-difference (DID) regression. This method compares changes over time between SMEs that borrow from banks with advanced technology (our treatment group) and those that borrow from less technologically equipped banks (our control group). For our findings to be reliable, the DID method requires two key conditions to be met: firstly, the "parallel trend" assumption, which means that without the banks' technological development, both groups of SMEs would have followed similar credit trends; and secondly, the "no anticipation of shock" condition, which implies that affected banks, and thus SMEs, would not change their behavior without the technological shock.

In our model setting we assume that PSD2 regulation presents an ideal natural experiment that might change the situation of SMEs by offering great opportunities for banks to access alternative data and innovate as a result of an exogenous environment (FinTech entries, the emergence of new technologies offered by third parties, or just accessing more data through open banking opportunities).² Though the decision of a bank to utilize these opportunities could have been endogenous to its financial and operational features (which we discuss further in the Robustness section), the PSD2 has expedited the digitalization of multiple banks. Subsequently, we compare how SME borrowing changed before and after the implementation of the PSD2, depending on whether an opaque company has a relationship with a more technologically innovative or traditional bank.

2.2.1 Linear Regression

We initially perform a regression analysis to investigate the relationship between bank technological innovation (referred to as BANK INNOV) and the expansion of SME credit. Our model integrates an interaction term (BANK.INNOV*YEAR2016 DUMMY) to discern shifts in SMEs' credit accessibility pre- and post-implementation of the PSD2 in 2015, a pivotal factor that has been recognized as a catalyst for the technological development of the financial sector (Babina et al. 2024; Polasik et al. 2020; Preziuso. Koefer, and Ehrenhard, 2023). While we are aware that some potential endogeneity problems are not addressed in this modeling, unlike the DID approach, the OLS regression does not require the identification of treatment and control groups or evaluation of their relationship (parallel trend assumption), which, in many finance studies, has raised doubts and led to biases in academic studies in the past (Baker et al. 2022). However, analyzing trends in SME credit growth before the technological shock using OLS allows for an initial test to determine whether the assumption of similar trends across groups holds. If the trends are found to be parallel, this strengthens the case for using DID methodology to isolate the impact of technological shocks on SME credit growth, Furthermore, Roth, Bilinski, and Poe (2023) demonstrate that the OLS estimator produces consistent and asymptotically valid coefficients similar to the DID method, provided that the assumptions for DID are satisfied. Consequently, it might also be viewed as a robustness verification of our DID analysis. Accordingly, our OLS linear model takes the following form:

² For more information on how the open banking directive has affected the technological development in the financial sector, please see Babina et al. (2024).

$$DEP_{i,t} = f \begin{pmatrix} FIRM_{i,t-1} \\ MAIN. BANK_{j,t-1} \\ COUNTRY_{c,t} \\ BANK. INNOV_{j,t-1} \\ firm fixed effects \\ year fixed effects \end{pmatrix}.$$
(1)

In our linear regression model, we include the firm- and time-fixed effects to capture the heterogeneity between firms in terms of their demand on bank credit, while also controlling for other bank, firm, and macro control variables that change over time. The choice of the fixed-effect model is also justified by the Hausman test, which suggests that the random-effects model is likely to return inconsistent estimates in our setting.

BANK.INNOV_{j,t-1} denotes a level of bank technological innovation measured by the number of solutions implemented in bank j at time t-1. We also investigate the role of individual technologies in SMEs' borrowing possibilities. To this end, we distinguish AUTOMATIZATION, BLOCKCHAIN, ANALYTICS, ONLINE_LENDING, ELECTRONIC_PAYMENT, PERSONAL_FIN, and REG_TECH. We denote one if a bank has adopted a specific solution at time t-1, and zero otherwise. This approach allows us to gain insights into the specific mechanisms through which bank technological innovation affects credit provision to SMEs. We posit that automation, for example, enables banks to manage and process big data efficiently, as evidenced by Ghosh, Vallee, and Zeng (2021) and Ouyang (2022). Additionally, blockchain or payment transactional data enhance the accessibility of alternative data and real-time transactions, which may reduce information asymmetries and improve the credit scoring process and borrower screening (Chiu and Koeppl 2019; Yang, Abedin, and Hajek 2023; Zheng et al. 2022).

To estimate the effect of a bank technological innovation on a firm's access to debt $(DEP_{i,t})$, we construct three proxies for each SME at time *t*, namely: (i) growth of SME total bank debt measured as a sum of short-term and long-term bank debt (DEBT.GR_{it}); (ii) growth of SME short-term bank debt (ST.DEBT.GR_{it}); and (iii) growth of SME long-term bank debt (LT.DEBT.GR_{it}).

We also test the effect of bank technological innovation on SMEs' cost of credit. To this end, we use the interest cost paid by the SME at time *t* to bank *j* on its borrowing, defined as the *total sum of interest paid by the SME on its average bank debt* (INT.COST).

FIRM_{i,t-1} includes a 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 demand on credit. To this end, we use: |(i) a profitability ratio (PROFIT) defined as earnings before interest and taxes (EBIT)to sales ratio; and (ii) 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 hencecollateralizable asset, accessible in an SME. Moreover, we also use (iii) the level ofequity to the firm total asset (EQUITY); (iv) the firm's asset turnover (ASSET.TURN)defined as a ratio of sales to total assets; and (v) a firm's size (FIRM.SIZE) measuredas the natural logarithm of a firm's turnover in constant prices. As an alternativemeasure of firm opaqueness, we also use the firm's age (LN.FIRM.AGE). Additionally, to control for individual bank features that might determine bank credit supply to SMEs we include the set of explanatory variables as suggested by the academic literature (Holmstrom and Tirole 1997; Adrian and Shin 2011) (MAIN. $BANK_{j,t-1}$). Subsequently, we use such variables as: (i) *bank size* (BANK.SIZE); (ii) *loans to asset ratio* (BANK.LOANS); (iii) *bank equity ratio* (BANK.EQUITY); and (iv) *bank deposit growth* (BANK.DEPO.GR).

We also include macroeconomic variables to control for the potential shocks to bank credit supply and firm demand for credit. The set of country variables includes *GDP* growth rate (GDP.GROWTH), unemployment rate (UNEMPL), and a country's level of economic development measured by its *GDP* per capita (GDP.PC) at purchasing power parity (PPP).

2.2.2 Difference-in-Difference Approach

To reveal differences in borrowing activity among SMEs, potentially influenced by the technological development of banks, we utilize the TWFE DID (firm and time fixed-effect regression model). This approach is valuable not only for examining the impact of varying levels of technological development across banks on SME borrowing but also for addressing potential endogeneity concerns associated with preexisting relationships between banks and SMEs.

We identify the control and treatment group based on the level of technological development of banks. In our methodology, banks and affiliated SMEs are assigned to either the treated sample or the control group based on the number of adopted technological solutions. Banks that have adopted at least five technological solutions in a given year, which reflects the 95th centile of distribution of adopted technological solutions data, are referred to as "high digital adopters" (HIGH.DIGITAL) and enter the treated sample in a year when this threshold has been achieved (i.e., a form of staggered DID with different treatment periods). Since Baker, Larcker, and Wang (2022) and Roth, Bilinski, and Poe (2023) document that TWFE-staggered DID with variant treatment periods may lead to biased estimators, we also propose an alternative definition of the treatment group, which consists of banks that have implemented any technological solution since the treatment year, while its technological development is measured by the maximum number of adopted solutions observed over the entire sample period between 2016 and 2019 (MAX.DIGITAL). This stricter criterion enhances our analysis, with one treatment period (2016) and a consistent control group allowing us to draw a more rigorous comparison between treated banks and those perpetually untreated, thereby putting the parallel trend assumption to a more stringent test (Roth, Bilinski, and Poe 2023). Consequently, the coefficients for the interaction term (HIGH.DIGITAL*TREATMENT YEARS; MAX.DIGITAL*TREATMENT YEARS) serve as our key variable of interest, informing us about a change in SME bank borrowing, as a result of a higher level of bank technological advancement. The post-treatment period refers to the years between 2016 and 2019, which are denoted as TREATMENT YEARS.

$$DEP_{i,t} = f \begin{pmatrix} FIRM_{i,t-1} \\ MAIN. BANK_{j,t-1} \\ HIGH. DIGITAL_{j,t} \\ COUNTRY_{c,t} \\ HIGH(MAX). DIGITAL_{j,t} * TREATMENT_YEARS \\ firm fixed effects \\ year fixed effects \end{pmatrix}$$

(2)

All control variables used in the regressions remain the same as described in Section 2.2.1. Table 2 summarizes the definitions of all variables constructed for our study, while Table 3 presents descriptive statistics.

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 varial	bles
PROFIT	Ratio of EBIT to sales
COLLATERAL	Ratio of fixed assets to total assets
LOW.COLLATERAL	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 four years
DIGITAL.FIRM\	Binary variable taking one for firms classified as operating in a more digitalized sector
HIGH.CAPITAL	Binary variable taking one for firms classified as operating in a highly capital-intensive sector
C. Country-level variable	28
PRI.CREDIT	Domestic credit to private sector provided 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
D. Fundamentals of the	firm main bank*
BANK.SIZE	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*
AUTOMATIZATON	Binary variable identifying situations in which a firm's main bank used technological solutions classified as <i>Automation software</i> in a given year
BLOCKCHAIN	Binary variable identifying situations in which a firm's main bank used technological solutions classified as <i>Blockchain</i> in a given year
ANALYTICS	Binary variable identifying situations in which a firm's main bank used technological solutions classified as <i>Data analytics</i> in a given year
ONLINE_LENDING	Binary variable identifying situations in which a firm's main bank used technological Solutions for lending in a given year
ELECTRONIC_ 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
REG_TECH	Binary variable identifying situations in which a firm's main bank used technological solutions classified as <i>Regulatory technology</i> in a given year
BANK.INNOV	The index of overall innovativeness of a bank, i.e., the sum of AUT.SOFT, BLOCKCHAIN, ANALYTICS, ROBO_ADV, ONLINE_LENDING, ELECTRONIC_PAYMENTS, PERSON.FIN, and REG_TECH
HIGH.DIGITAL	Banks that have adopted more than four technological solutions
MAX.DIGITAL	Banks with the highest number of their technological solutions over the total sample period
YEAR2016_DUMMY	Binary variable taking one for years starting in 2016 onward, and zero for previous years
INSTRUMENT_PSD2	Interaction between UK adoption of the PSD2 and post-treatment years (2016–2019) equal to one; zero for all other countries

Table 2: Variable Definitions

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

Table 3: Descriptive Statistics

This table presents descriptive statistics for the sample.

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
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
DIGITAL.FIRM	1,731,608	173,161	0.030	0.171	0.000	0.000	0.000	0.000	1.000
HIGH.CAPITAL	1,731,608	173,161	0.014	0.117	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
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 a b	ank								
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
BANK.INNOV	1,003,408	179,921	1.294	1.770	0.000	0.000	0.000	2.000	7.000
HIGH.DIGITAL	1,731,608	173,161	0.138	0.345	0.000	0.000	0.000	0.000	1.000
MAX.DIGITAL	1,643,512	164,351	2.750	2.096	0.000	1.000	3.000	4.000	7.000

3. EMPIRICAL RESULTS

3.1 Banks' Digitalization and SME Borrowing

We start our analysis by investigating the general impact of bank technological advancement on SME borrowing over time. Table 4 presents the regression results on whether, and if so how, bank technological innovation (BANK.INNOV) is correlated with different types of credit growth at SMEs. More specifically, we examine the role of technology in overall credit growth, as well as long-term and short-term growth, presented in Specifications (1)–(3), respectively.

As discussed in the previous section, the PSD2 has fostered innovation and technological advancements through the entry of new firms offering innovative financial products and services, thereby increasing the technological development of many other financial institutions, including banks. To see whether we could also notice a change in SME borrowing before and after a potential shift in bank technological innovation,

we interact the BANK.INNOV variable with the year dummies equal to one for the years after the adoption of PSD2 (2016–2019) and zero otherwise (YEAR2016_DUMMY). The results are presented in Specifications (4)–(6). All results from this section are presented in Table 4.

Table 4: The Role of Bank Technological Innovations in SMEs' Credit Growth

The table presents the regression results for firm- and year-fixed-effect panel models of bank technological innovation on SMEs' credit growth. DEBT.GR represents the growth of SMEs' combined short-term and long-term bank debt at time t, divided by the previous year's total assets (inflation-adjusted). LT.DEBT.GR indicates the growth of SMEs' long-term credit at time t, while ST.DEBT.GR denotes the growth of the SMEs' short-term credit. BANK.INNOV is a measure of a bank's technological innovation, defined as the sum of all technological solutions adopted by bank *i* at time *t*. YEAR2016_DUMMY takes one for the period after PSD2 adoption (years 2016–2019). In the interest of brevity, we do not present coefficients for the year dummy variables. Standard errors, clustered at the firm level, are shown in parentheses. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR
L. BANK.INNOV	0.00109***	0.000984***	0.000240**	0.00119***	0.000921***	0.000824***
	(0.000166)	(0.000137)	(0.000101)	(0.000281)	(0.000232)	(0.000163)
YEAR2016_DUMMY*				0.000530**	0.000462**	-1.91e-06
BANK.INNOV				(0.000221)	(0.000185)	(0.000122)
L.FIX_A	-0.0573***	-0.0634***	0.00627***	-0.0572***	-0.0633***	0.00631***
	(0.00171)	(0.00145)	(0.000856)	(0.00171)	(0.00145)	(0.000856)
L.EBIT_S	-0.00573***	-0.00643***	0.000909	-0.00579***	-0.00648***	0.000870
	(0.00120)	(0.00104)	(0.000639)	(0.00120)	(0.00104)	(0.000639)
L.EQUITY	0.135***	0.0909***	0.0393***	0.135***	0.0910***	0.0395***
	(0.00144)	(0.00119)	(0.000747)	(0.00144)	(0.00119)	(0.000747)
L.TAT	0.0140***	0.00819***	0.00508***	0.0140***	0.00818***	0.00507***
	(0.000283)	(0.000213)	(0.000151)	(0.000283)	(0.000213)	(0.000151)
L.LN_SALES	-0.0100***	-0.00628***	-0.00282***	-0.0100***	-0.00627***	-0.00281***
	(0.000461)	(0.000375)	(0.000252)	(0.000461)	(0.000375)	(0.000252)
L.LN_FIRM_AGE	-0.0135***	-0.00906***	-0.00456***	-0.0132***	-0.00884***	-0.00437***
	(0.000958)	(0.000757)	(0.000516)	(0.000960)	(0.000759)	(0.000517)
PRICREDIT	0.0165***	0.0234***	0.00394***	0.0187***	0.0252***	0.00522***
	(0.00218)	(0.00179)	(0.00119)	(0.00219)	(0.00180)	(0.00121)
GDPGROWTH	0.331***	0.286***	0.215***	0.358***	0.307***	0.232***
	(0.0150)	(0.0120)	(0.00939)	(0.0155)	(0.0125)	(0.00978)
GDPPCPPP	-0.000544*	-0.000439*	-0.00167***	-0.000470	-0.000414*	-0.00158***
	(0.000324)	(0.000251)	(0.000189)	(0.000322)	(0.000250)	(0.000188)
UNEMPL	-0.223***	-0.194***	-0.177***	-0.226***	-0.198***	-0.177***
	(0.0172)	(0.0137)	(0.00944)	(0.0172)	(0.0136)	(0.00949)
L.BANK_LN_ASSETS	-0.00122	-0.00176*	-0.00554***	-0.00235*	-0.00258***	-0.00635***
	(0.00120)	(0.000990)	(0.000698)	(0.00121)	(0.00100)	(0.000708)
L.BANK_LOANS	-0.00919**	-0.00696*	-0.0140***	-0.0147***	-0.0109***	-0.0175***
	(0.00436)	(0.00377)	(0.00246)	(0.00445)	(0.00386)	(0.00254)
L.BANK_EQUITY	-0.0299**	-0.000445	-0.0289***	-0.0269**	0.00141	-0.0273***
	(0.0129)	(0.0107)	(0.00790)	(0.0130)	(0.0107)	(0.00796)
L.BANK_DEPO_GR	0.00253*	0.00277**	0.00285***	0.00286**	0.00283**	0.00344***
	(0.00137)	(0.00112)	(0.000880)	(0.00135)	(0.00110)	(0.000866)
	0.0335*	0.0384***	0.142***	0.0452**	0.0481***	0.149***
Constant	(0.0175)	(0.0148)	(0.00953)	(0.0176)	(0.0149)	(0.00961)
Observations	1,003,408	1,034,658	1,011,309	1,003,408	1,034,658	1,011,309
R-squared	0.043	0.036	0.041	0.043	0.036	0.041
Number of FIRM_ID	179,921	183,557	180,751	179,921	183,557	180,751
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Our findings offer interesting insights into SME borrowing and bank technological advancement. Primarily, we see that bank technological advancement is positively correlated with all forms of SME credit growth. More specifically, we find that SMEs affiliated with more technologically advanced banks experience higher credit growth. This gives us a first insight into the role of bank technological innovation in extending access for SMEs to bank credit. Interestingly, we find that the impact of bank technological innovation appears to be more pronounced on long-term than on shortterm credit. The SMEs affiliated with a bank that has one additional solution experience a 0.09% higher credit growth in long-term credit, whereas the effect on short-term credit growth is only 0.024%. This result is economically valid as the mean for the credit growth at SMEs for the whole sample is negative. The result means that SMEs could offset the negative market trend associated with more technologically advanced banks. These findings are particularly promising as they suggest that technological solutions not only reduce the asymmetric information problems to facilitate SME short-term credit but probably also improve other channels affecting banks' long-term lending decisions.

The regression results on interaction presented in Specifications (4)–(6) offer additional insight into our analysis. They document that the effect of bank technological innovation on SME borrowing did not occur homogeneously over time. The regression results seem to suggest that when bank technological innovation has sped up, we can see higher credit growth at SMEs. This conclusion is supported by the positive and statistically significant coefficients of interaction variables between BANK.INNOV and YEAR2016_DUMMY. At the same time, we notice that BANK.INNOV variables remain highly statistically significant with a positive coefficient across all specifications. This finding is in line with other academic findings on the role of payment data in banks' lending decisions (Ghosh, Vallee, and Zeng 2021; Ouyang 2022). Our results document that the periods of these technological developments coincided with higher SME credit growth, potentially suggesting that these solutions could support banks in their lending decisions by increasing the efficiency in collecting and processing information.

3.2 Banks' Technology and SMEs' Borrowing: A Difference-in-Difference Approach

In this section we compare SME borrowing before and after the introduction of the PSD2. Subsequently, we also group banks affiliated with SMEs based on the level of their technological innovation depending on the number of adopted solutions to be able to compare the SME borrowing affiliated with highly digitized and less digitalized banks as described in the Methodology section. Table 5 presents the regression results for DID estimations.

Our results present interesting insights. First, we note that the results from the DID render the same conclusions as from the linear regression. This could suggest that endogeneity related to the bank-SME relationship might not be present. More specifically, we see that SMEs associated with more technologically advanced banks have experienced much higher credit growth, both short-term and long-term, than those associated with less innovative banks. This finding has significant implications, suggesting that banks that have followed the technological revolution since the PSD2 have probably improved their access to different data and their processing. This finding is consistent with Angelini, Tollo, and Roli (2008), Bazarbash (2019), Fuster et al. (2019), Jagtiani and Lemieux (2019), Khandani et al. (2010)documenting the

importance of big data, data sharing, AI, and other automated procedures in improving banks' credit scoring processes.

Table 5: The Role of Bank Technological Innovations in SMEs' Credit Growth

The table presents the DID estimations for the firm- and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' credit growth. The treatment period commenced in 2016 and continued onwards. Treated banks are those that adopted more than four technological solutions in a given year (HIGH.DIGITAL) or banks that have adopted any technological solution since 2016, while the maximum number is taken between 2016 and 2019 as a measure of bank technological development (MAX.DIGITAL). DEBT.GR represents the growth of an SME's combined short-term and long-term bank debt at time *t*, divided by the previous year's total assets (inflation-adjusted). LT.DEBT.GR indicates the growth of an SME's long-term credit at time *t*, while ST.DEBT.GR denotes the growth of the SME's short-term credit. For the sake of 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR
YEAR2016_DUMMY*	0.00341***	0.00273***	0.00118***			
HIGH.DIGITAL	(0.000578)	(0.000455)	(0.000364)			
YEAR2016_DUMMY*				0.00108***	0.000918***	0.000468***
MAX.DIGITAL				(0.000137)	(0.000115)	(8.06e-05)
L.FIX_A	-0.0573***	-0.0634***	0.00626***	-0.0572***	-0.0633***	0.00629***
	(0.00171)	(0.00145)	(0.000856)	(0.00171)	(0.00145)	(0.000856)
L.EBIT_S	-0.00570***	-0.00641***	0.000914	-0.00573***	-0.00644***	0.000900
	(0.00120)	(0.00104)	(0.000639)	(0.00120)	(0.00104)	(0.000639)
L.EQUITY	0.135***	0.0908***	0.0393***	0.135***	0.0909***	0.0394***
	(0.00144)	(0.00118)	(0.000747)	(0.00144)	(0.00119)	(0.000747)
L.TAT	0.0140***	0.00819***	0.00508***	0.0140***	0.00818***	0.00508***
	(0.000283)	(0.000213)	(0.000151)	(0.000283)	(0.000213)	(0.000151)
L.LN_SALES	-0.0100***	-0.00629***	-0.00282***	-0.0101***	-0.00631***	-0.00283***
	(0.000461)	(0.000375)	(0.000252)	(0.000461)	(0.000375)	(0.000252)
L.LN_FIRM_AGE	-0.0135***	-0.00909***	-0.00455***	-0.0133***	-0.00893***	-0.00444***
	(0.000957)	(0.000757)	(0.000516)	(0.000959)	(0.000758)	(0.000517)
PRICREDIT	0.0153***	0.0224***	0.00358***	0.0180***	0.0247***	0.00470***
	(0.00219)	(0.00180)	(0.00119)	(0.00220)	(0.00180)	(0.00121)
GDPGROWTH	0.325***	0.280***	0.215***	0.339***	0.293***	0.222***
	(0.0149)	(0.0120)	(0.00927)	(0.0151)	(0.0122)	(0.00940)
GDPPCPPP	-0.000716**	-0.000600**	-0.00169***	-0.000763**	-0.000645***	-0.00170***
	(0.000320)	(0.000247)	(0.000187)	(0.000319)	(0.000246)	(0.000186)
UNEMPL	-0.235***	-0.205***	-0.179***	-0.227***	-0.199***	-0.175***
	(0.0170)	(0.0135)	(0.00931)	(0.0170)	(0.0135)	(0.00941)
L.BANK_LN_ASSETS	-0.000302	-0.000963	-0.00532***	-0.00180	-0.00220**	-0.00597***
	(0.00119)	(0.000991)	(0.000692)	(0.00120)	(0.000995)	(0.000707)
L.BANK_LOANS	-0.00649	-0.00450	-0.0136***	-0.0143***	-0.0110***	-0.0171***
	(0.00431)	(0.00373)	(0.00243)	(0.00449)	(0.00390)	(0.00257)
L.BANK_EQUITY	-0.0317**	-0.00205	-0.0286***	-0.0298**	-0.000674	-0.0273***
	(0.0129)	(0.0107)	(0.00790)	(0.0129)	(0.0107)	(0.00789)
L.BANK_DEPO_GR	0.00140	0.00167	0.00272***	0.00153	0.00179	0.00286***
	(0.00135)	(0.00110)	(0.000864)	(0.00134)	(0.00110)	(0.000860)
Constant	0.0305*	0.0361**	0.141***	0.0499***	0.0522***	0.149***
	(0.0175)	(0.0149)	(0.00954)	(0.0176)	(0.0148)	(0.00965)
Observations	1,003,408	1,034,658	1,011,309	1,003,408	1,034,658	1,011,309
R-squared	0.043	0.036	0.041	0.043	0.036	0.041
Number of FIRM_ID	179,921	183,557	180,751	179,921	183,557	180,751
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Similarly, as in the previous regressions, we also find that bank technological development renders a different effect on short-term versus long-term credit growth at SMEs. We notice that technology impacts long-term SME credit more significantly than short-term SME credit. Similarly, as in the linear regression, this could suggest that technology is efficient in reducing the information asymmetry by improving data collection and processing. This could be highly beneficial, especially for the short-term nature of credit. However, for long-term credit our finding might suggest that bank technologies also improve other decision channels (such as, for example, credit scoring models or screening procedures). These advantages are particularly significant for banks when making long-term rather than short-term credit decisions.

Interestingly, while the statistical effects remain constant across different definitions of bank treatment group (HIGH.DIGITAL and MAX.DIGITAL), we observe some heterogeneity in terms of economic effects. As anticipated, the economic influence of bank technological development on SME credit growth is less prominent when we categorize banks into a treatment group, defined as those with any adopted solution after 2015, while the technological progress of these banks is gauged as the maximum number of solutions adopted between 2016 and 2019 (Specifications (4)-(6)). This definition introduces additional heterogeneity across banks, as banks with one solution as well as those with seven solutions enter the treatment group, rendering different effects on SMEs' credit growth. At the same time, HIGH.DIGITAL variable includes highly technologically advanced banks. Interestingly, the regression results indicate that our effects apply to both short-term and long-term SME credit, though the effect on long-term SME borrowing is again more pronounced. These results unambiguously tend to suggest that SMEs affiliated with more technologically advanced banks experience higher credit growth than those affiliated with less innovative banks. At the same time, this highlights the transformative potential of bank technological solutions in reshaping the landscape of SME borrowing.

As regards other control variables, we find that most coefficients are strongly statistically significant and exhibit the expected signs. For example, unsurprisingly we observe that higher bank debt growth is reported by younger (LN.FIRM.AGE) and smaller (FIRM.SIZE) companies with the capacity to increase the role of debt in their financing structure. However, firms with a high asset turnover (ASSET.TURN) or limited share of fixed assets in total assets (FIXED.ASSETS) are more likely to be on the point of reaching their production capacity limits and, as a result, may be more inclined to raise them through investments financed with additional debt. Interestingly, we also observe that more profitable firms (PROFIT) are less likely to incur more debt, which is in line with pecking order theory: Firms first finance their investment out of retained earnings, which is the cheapest and most readily available alternative, then out of debt, and lastly by issuing equity, seen as the most expensive option for firms.

3.3 The Role of Different Types of Bank Technology in SME Borrowing

The impact of bank technological innovativeness on firm borrowing seems to be a multifaceted issue. So far, our results have documented that the level of bank technological advancement might improve an SME's situation with regard to bank credit due to improved access to technologies supporting banks with the data collection and processing, thereby affecting the credit scoring models and screening procedures. Yet, the exact role played by different individual technological innovations in shaping a bank's credit decisions on SMEs' credit growth remains unclear. To investigate this, we next evaluate the impact of banks' technological solutions on SMEs' short-term and

long-term borrowing. This allows us to assess the value of each solution for SMEs' borrowing. Table 6 presents the results of our regression analyses. Panel A considers the effects on long-term borrowing while Panel B of Table 7 focuses on short-term borrowing. In addition to a bank technological solution type, we include the general level of a bank's technological innovation as a separate control variable in all specifications. We also report the results by including all solutions in the same regression model (Specification (8) of Panels A and B).

Table 6 (PANEL A): The Role of Individual Technological Innovations in SMEs' Credit Growth

The table presents the regression results for firm- and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' credit growth. LT.DEBT.GR indicates the growth of SMEs' long-term credit at time t. BANK.INNOV is a measure of a bank's technological innovation, defined as the total number of all technological solutions adopted by bank i at time t. For brevity reasons, 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), or 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	LT.DEBT.GR	LT.DEBT.GR	LT.DEBT.GR	LT.DEBT.GR	LT.DEBT.GR	LT.DEBT.GR	LT.DEBT.GR	LT.DEBT.GR
L. ELECTRONIC.	-0.00219***							-0.000
PAYMENTS	(0.000691)							(0.000677)
L. ONLINE.LENDING		-0.00309***						-0.00179**
		(0.000735)						(0.000897)
L. PERSONAL_FIN			0.000702					-0.000635
			(0.000690)					(0.000858)
L. ANALYTICS				-0.000165				0.00175**
				(0.000728)				(0.000738)
L. REG_TECH					-0.000231			0.00108
					(0.000746)			(0.000813)
L. BLOCKCHAIN						0.00309***		0.00457***
						(0.000629)		(0.000648)
L. AUTOMATIZATION							0.000738	0.00213***
							(0.000641)	(0.000663)
L.BANK.INNOV	0.00144***	0.00146***	0.000919***	0.00100***	0.00102***	0.000491***	0.000901***	
	(0.000195)	(0.000180)	(0.000151)	(0.000159)	(0.000191)	(0.000166)	(0.000156)	
Constant	0.0416***	0.0349**	0.0379**	0.0383***	0.0383***	0.0321**	0.0402***	0.0339**
	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0148)	(0.0150)	(0.0150)	(0.0152)
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
R-squared	0.036	0.036	0.036	0.036	0.036	0.036	0.036	183,557
Number of FIRM_ID	183,557	183,557	183,557	183,557	183,557	183,557	183,557	0.036
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6 (PANEL B): The Role of Individual Technological Innovations in SMEs' Credit Growth

The table presents the regression results for firm– and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' short-term credit growth. ST.DEBT.GR denotes the growth of the SMEs' short-term credit. BANK.INNOV is a measure of a bank's technological innovation, defined as the total number of all technological solutions adopted by bank i at time t. In the interest of 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), or 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	ST.DEBT.GR	ST.DEBT.GR	ST.DEBT.GR	ST.DEBT.GR	ST.DEBT.GR	ST.DEBT.GR	ST.DEBT.GR	ST.DEBT.GR
L. ELECTRONIC.	-0.00493***							-0.00400***
PAYMENTS	(0.000503)							(0.000495)
L. ONLINE.LENDING		-0.00139**						0.00107
		(0.000555)						(0.000728)
L. PERSONAL_FIN			0.000702					0.000712
			(0.000690)					(0.000629)
L. ANALYTICS				0.000928*				0.00253***
				(0.000542)				(0.000558)
L. REG_TECH					0.000732			-0.000577
					(0.000711)			(0.000818)
L. BLOCKCHAIN						0.00209***		0.00334***
						(0.000456)		(0.000497)
L. AUTOMATIZATION							0.00167***	0.00131**
							(0.000474)	(0.000520)
L.BANK.INNOV	0.00126***	0.000456***	0.000919***	0.000145	0.000115	-9.26e-05	5.16e-05	
	(0.000141)	(0.000143)	(0.000151)	(0.000123)	(0.000165)	(0.000119)	(0.000110)	
Constant	0.150***	0.141***	0.0379**	0.143***	0.142***	0.138***	0.146***	0.146***
	(0.00960)	(0.00955)	(0.0149)	(0.00953)	(0.00953)	(0.00959)	(0.00971)	(0.00978)
Observations	1,011,309	1,011,309	1,034,658	1,011,309	1,011,309	1,011,309	1,011,309	1,011,309
R-squared	0.041	0.041	0.036	0.041	0.041	0.041	0.041	180,751
Number of FIRM_ID	180,751	180,751	183,557	180,751	180,751	180,751	180,751	0.041
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The regression results provide compelling evidence. We observe that blockchain technology stands out as a predominant force, demonstrating the most significant economic impact among the technologies evaluated. Its capacity to provide a wide range of real-time data seems to be especially advantageous in reducing asymmetric information and improving credit scoring models, as supported by recent literature (Yang, Abedin, and Hajek 2023; Zheng et al. 2022). We also find that automation solutions play an important role in SMEs accessing long-term financing. This might suggest that the efficiency of information collection and processing is extremely important (Garg et al. 2021). Not surprisingly, our regression results document that blockchain has the greatest effect on the improved access of SMEs to long-term credit. Interestingly, our findings reveal that online lending solutions are negatively associated with long-term credit growth, suggesting that banks may still prioritize a mix of soft and hard information over purely data-driven insights for long-term loan decisions. However, at the same time, we note that the BANK.INNOV variable measuring the general level of bank technological innovation seems to be highly statistically and economically significant, suggesting that the general level of bank technological development, i.e., a mix of different technologies adopted by banks, is important while

considering the long-term nature of SME borrowing. These results confirm the complex nature of bank long-term decisions requiring different technologies supporting banks' credit decisions.

In contrast, our findings related to short-term SME borrowing (Panel B) illuminate the significance of specific technological applications such as automation, data analytics, and blockchain technology. Interestingly, the aggregate level of a bank's technological advancement seems to be less important. This can be attributed to the nature of short-term loans, which are characterized by smaller sums and shorter durations, requiring less exhaustive data and a simplified risk evaluation process. For such financial products, banks leverage automated technologies to reduce information asymmetry and expedite credit issuance efficiently. Interestingly, advanced payment solutions negatively impact short-term funding at SMEs, potentially due to a crowding-out effect. Meanwhile, well-developed electronic payment systems at banks seem to improve clients' liquidity management, reducing their short-term borrowing needs, in line with findings from Carbó-Valverde, Cuadros-Solas, and Rodríguez-Fernández (2020).

4. THE CHANNELS OF THE TECHNOLOGICAL EFFECTS ON SME BORROWING

4.1 Reduction in Information Frictions and Reliance on Collateral

So far, our results suggest that bank technological advancements provide banks with a wide spectrum of different data, which significantly seems to mitigate the asymmetric information problems, reducing credit risk for banks. Furthermore, access to a large set of real-time data could allow banks to switch to advanced credit scoring models, thus reducing banks' demand for collateral.³ Therefore, technological innovation could lead to relaxed collateral requirements for SMEs, which remains one of the major barriers to loan access identified in the literature (Beck and Demirgüç-Kunt 2006; Chan and Thakor 1987; Yaldiz Hanedar, Broccardo, and Bazzana 2014; Niinimäki 2018).

In this section, we examine the impact of bank technology on collateral requirements by interacting a bank's level of technological innovation (BANK.INNOV) and the value of an SME's collateral (COLLATERAL). A statistically significant coefficient of the interaction term (COLLATERAL*BANK.INNOV) would indicate a moderating effect of bank technology on the reliance of collateral for SME borrowing (Specification (1)). Furthermore, we consider SMEs with lower-value collateral (LOW.COLLATERAL) – those whose fixed asset to total asset ratio is below the median – and introduce it into the model as another interaction term (LOW.COLLATERAL*BANK.INNOV). The regression results are presented in Table 7.

³ This is in line with the BASEL III requirements. According to these, banks that use advanced credit scoring models may ease the requirements for collateral without imposing additional capital (BIS 2017).

Table 7: The Role of Collateral in Accessing Bank Credit for SMEs

The table presents the regression results for firm- and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' credit growth. DEBT.GR represents the growth of an SME's combined short-term and long-term bank debt at time t, divided by the previous year's total assets (inflation-adjusted). LT.DEBT.GR indicates the growth of an SME's long-term credit at time t, while ST.DEBT.GR denotes the growth of the SME's short-term credit. BANK.INNOV is a measure of a bank's technological innovation, defined as the total number of technological solutions adopted by bank i at time t. COLLATERAL refers to the value of a firm's fixed assets as a proportion of its total assets at time t. LOW.COLLATERAL is a binary variable that takes a value of one if the firm's fixed asset value is below the sample median, and zero if it is above the median. The interaction term (COLLATERAL*BANK.INNOV or LOW.COLLATERAL*BANK.INNOV) includes a one-period lagged collateral and a measure of bank technological innovation (BANK.INNOV) at time t. For the sake of 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), or 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Variables	DEBT.GR	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR
COLLATERAL*BANK.INNOV	0.00606***			
	(0.000406)			
LOW.COLLATERAL*BANK.INNOV		0.00177***	0.00198***	-3.80e-06
		(0.000171)	(0.000136)	(0.000105)
L.LOW.COLLATERAL		-0.0263***	-0.0267***	0.000304
		(0.000635)	(0.000524)	(0.000345)
BANK.INNOV	-5.04e-05	0.000868***	0.000432***	0.000823***
	(0.000205)	(0.000197)	(0.000166)	(0.000117)
L.COLLATERAL	-0.0615***	-0.0772***	-0.0833***	0.00656***
	(0.00177)	(0.00192)	(0.00163)	(0.000949)
Observations	1,003,165	1,003,408	1,034,658	1,011,309
R-squared	0.043	0.046	0.041	0.041
Number of FIRM_ID	179,904	179,921	183,557	180,751
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

The findings reveal that the importance of a bank's technological innovativeness is neutralized when a firm has adequate collateral (Specification 1). The interaction term (COLLATERAL*BANK.INNOV) emerges as positive and significant, suggesting that technology complements firm collateral in facilitating funding access for SMEs. However, the negative coefficient of collateral alone hints at a potential reduction in the impact of collateral on borrowing when bank technology is considered, particularly in the context of more technologically advanced banks.

Interestingly, we also observe a positive coefficient for the interaction of low-value collateral and bank technological innovation (LOW.COLLATERAL*BANK.INNOV) (Specification 2), suggesting that firms with less collateral benefit from higher credit growth when aligned with technologically adept banks. The bank's technological innovativeness variable itself is positively correlated with firm borrowing, while a low collateral value remains a significant negative factor. This implies that technological innovation may help firms with limited collateral obtain external funding by counterbalancing the negative effects of low collateral value.

Distinct differences are noted when segregating the effects of short-term and long-term SME borrowing. The positive impacts of bank technological advancement on collateral requirements are particularly pronounced for long-term credit, resonating with academic findings that emphasize the critical role of collateral in securing long-term financing (Schmalz, Sraer, and Thesmar 2017). These results underscore the potential for bank technology to aid opaque firms in obtaining long-term funding, an essential component of sustainable business growth.

4.2 Credit Access and Cost of Intermediation

The potential of technology to enhance information collection and processing efficiency is significant, which in turn might influence the cost of intermediation – a notable barrier for SMEs seeking external funding in Europe. Thus, understanding the effect of a bank's technological advancement on credit costs could provide vital insights. This section presents regression results reflecting the impact of bank technological innovation on intermediated bank credit to SMEs. Table 8 presents the regression results. Specifications (1)-(2) utilize standard linear models with interaction variables, while Specifications (3)-(4) apply a DID approach.

Table 8: The Impact of Bank Technological Innovations on the Cost of Credit for SMEs

The table presents the regression results for firm- and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' cost of credit. INT.COST represents the sum of all interest payments made by an SME at time t on its average value of short-term and long-term bank debt, adjusted for inflation. Specifications (1) and (2) detail the regressions on the interaction between bank technological innovativeness (BANK.INNOV) and year dummies for periods after 2015. Specifications (3) and (4) present the results of difference-in-difference regressions, where the treatment effect began in 2016 and continues onwards. Here, treated banks are identified as those that adopted more than four technological solutions in a given year (HIGH.DIGITAL) after 2015. Alternatively, digitalized banks are defined as those adopting any technological solution after 2015, with the level of digitalization measured by the maximum number of solutions adopted throughout the total sample period (MAX.DIGITAL). In the interest of 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), or 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Variables	INT.COST	INT.COST	INT.COST	INT.COST
YEAR2016_DUMMY*BANK.INNOV		0.00150**		
		(0.000657)		
BANK.INNOV	0.000441	-0.00185**		
	(0.000468)	(0.000851)		
YEAR2016_DUMMY*HIGH.DIGITAL			0.00342**	
			(0.00156)	
YEAR2016_DUMMY*MAX.DIGITAL				0.000834**
				(0.000406)
Observations	634,770	634,770	634,770	634,770
R-squared	0.012	0.012	0.012	0.012
Number of FIRM_ID	129,387	129,387	129,387	129,387
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

The regression outcomes from Specification (1) suggest that the broad adoption of technological solutions by banks does not uniformly affect the cost of intermediation. as evidenced by the statistically insignificant coefficient of the lagged BANK.INNOV variable. This initially surprising result may be explained by the nuanced effects that distinct technological solutions exert on SME borrowing costs. For instance, banks that rely solely on hard data, such as online lending platforms, might impose a risk premium, reflecting the limitations of technology in capturing the full spectrum of borrower information, as suggested by our previous results. The one possible explanation might be that that banks might charge higher rates for credit when decisions are based exclusively on hard data. In contrast, Specification (2) shows a negative and significant effect of bank technological advancement, with an interaction term indicating higher costs post-2015, correlated with increased bank digitization following the PSD2. DID estimations in Specifications (3) and (4) reconfirm these findings, suggesting an economically significant rise in SME credit costs from 0.01 (Specification (2)) to 0.3 percentage points (Specification (3)), assuming other factors remain constant. These regression results seem to suggest a shift in banks' risk assessment postures. With more relaxed borrowing conditions, banks could be incentivizing higher risk premiums. This would be in line with the hypothesis that hard information stemming from technology does not fully replace the role of the relationship between borrower and lender, and the consequent importance of soft information in bank credit decision-making. This is in line with the findings of Sheng (2021).

5. ROBUSTNESS CHECKS

5.1 Endogeneity Concerns and Instrumental Variable Regression (IV)

The primary challenge in establishing a causal relationship between the technological innovativeness of banks and SME borrowing lies in the issue of endogeneity. This issue arises from the fact that a bank's choice of technology and its lending strategy could be determined simultaneously as part of its operations. In other words, the decisions regarding the adoption of certain technologies and the formulation of lending strategies are not independent of each other but might be interrelated components of SME borrowing.

We have attempted to control for this endogeneity by incorporating a broad range of solutions into our bank technological measure in BANK_INNOV. These solutions target various aspects of bank operations, making it difficult to attribute them specifically to a particular business model of a bank or the type of clients the bank targets.

Nevertheless, to formally test whether or not our results are biased toward any specific business model, we conducted robustness checks by running the instrumental variable regression (IV). This approach requires identifying the variable that is highly correlated with our bank technological innovation measure while it should not be related to any other individual features of banks. We start our regression by estimating the Tobit model, introducing censoring on the left-hand side at (0) and on the right-hand side at the maximum for every technological solution analyzed in our paper. Given bank technology solution distributions, this approach works well for running the first step of the IV models (in line with Woodridge's (2010) control function approach). In this regression, we test whether a bank's IT spendings (IT.INVESTMENT_TA) can explain

the adoption of a bank technological solution.⁴ The regression results suggest that the lagged value of bank investment in IT is always highly significant across all technological solutions used by banks with varying signs between positive and negative, suggesting a hierarchical order effect in prioritizing the introduction of specific technology solutions in the shorter term. However, the effect switches to positive in subsequent lags, such as the second and third. Nonetheless, using more lags results in a loss of observations. As a result, we take the predicted values from Tobit regressions as instruments for our IV regressions. Table 9 presents the regression results for short-term and long-term SME credit growth and the cost of intermediation.

Table 9: Robustness: 2SLS Instrumental Variable Regression

This panel presents the results of the second-stage regressions of the instrumental variable of bank technological innovation on SMEs' credit growth. We instrumentalize BANK.INNOV with yearly IT spendings of a firm's main bank divided by the bank's total assets. For brevity reasons, 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), or bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Robust standard errors are shown in parentheses. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR	INT.COST
BANK.INNOV _{t-1}	0.00742***	0.00984***	0.00442***	-0.000951
	(0.00224)	(0.00213)	(0.00147)	(0.00358)
Observations	712,380	740,726	716,827	527,096
Kleibergen-Paap rk LM (underidentification test)	2,205	1,599	2,065	3,593
Kleibergen-Paap rk LM, p-value	0	0	0	0
Kleibergen-Paap rk Wald F (weak identification test)	1,976	1,443	1,858	3,112
Cragg-Donald Wald F (weak identification test)	2,353	1,807	2,186	4,089

Interestingly, the regression results support our baseline findings. We find that bank technological innovation positively affects SME credit growth. Again, we find that this effect is higher for long-term than for short-term credit, supporting our notion that technology supports banks in their credit decisions, providing them with access to the data in an efficient manner, while at the same time improving the credit scoring processes. However, interestingly, as in the standard linear regression models, we do not find that technology changes the cost of credit. This might be due to the offsetting effects of different technologies on the cost of intermediation.

After conducting various tests, the results indicate that the instrumental variable used in our estimations is both relevant and strong. The Kleibergen-Paap rk LM statistic yielded p-values of 0 for all tests, rejecting the null hypothesis of underidentification. Additionally, both the Kleibergen-Paap rk Wald F statistic and Cragg-Donald Wald F statistic exceed conventional critical values, indicating that there are no concerns regarding weak identification in our model.

⁴ As these results are not important from an interpretation point of view, for reasons of brevity, we do not report these results here. They are, however, available upon request.

Additionally, we also adopt a second approach to address the endogeneity problem from a different perspective. Our study aims to confirm that the PSD2 regulation has been a significant driver of technological upgrades in banks. A key challenge in proving this is ensuring that the technological changes we observe at banks are truly due to the PSD2, and not because of some observed or unobserved features of individual banks. Even though the introduction of the PSD2 was a shock that banks did not control, it might not have affected all banks in the same way. Some banks might have been more ready or willing to change because of their own characteristics.

To tackle this, we also use two-stage instrumental variable regression (2SLS IV). This method helps us to separate the direct impact of the PSD2 from other factors. We look at how the PSD2 was implemented in different countries and use these differences as a tool in our analysis. According to Babina et al. (2024), the way countries adopted the PSD2 was completely independent of the banks themselves. This gives us a good tool for studying the effects of the PSD2.

Our study zeroes in on Europe, where the UK pioneered the adoption of the PSD2 in 2016, ahead of other European countries that implemented it in 2018 and 2019. This variation in adoption offers us a natural experiment to investigate how early or late adoption of the PSD2 influenced the technological progress of banks in our study period. In our analysis, we assign a value of "1" to UK banks that embraced the PSD2 at the outset, and "0" to banks in countries that followed later. This distinction serves as a foundation to explore whether the variation in the development of the PSD2 across countries after 2016 is a reliable indicator of technological advancement in banks, and to understand its subsequent impact on SME lending practices to SMEs. We present the regression results in Table 10 for both the short and long term.

Our results document that cross-country variations in the adoption of the PSD2 significantly influence banks' technological development, as evidenced by the number of solutions adopted by these banks. This finding holds strong statistical significance at the 1% level, underscoring the impact of government policies on open banking. Importantly, we also observe that this instrumental variable has a statistically significant effect on SME credit growth. Notably, this effect is positive for both short-term and long-term credit growth, providing compelling evidence that bank technological development enhances credit opportunities for SMEs.

The tests indicate that the instrumental variables used in the 2SLS regression are statistically valid and strong. The null hypothesis that the model is underidentified as indicated by the underidentification test (Anderson canon. corr. LM statistic) is rejected. This shows that the instruments are correlated with the endogenous explanatory variables. The Cragg-Donald Wald F statistic is well above the threshold values, implying that the instruments are not weak; they are considered strong, providing reliable identification in the 2SLS regression. The Sargan statistic is 0.000, proving that the equation is exactly identified. Overall, all tests suggest that the 2SLS estimates can be considered reliable.

Table 10: Robustness: 2SLS Instrumental Variable Regression

This panel presents the results of the first-and second-stage regressions of the instrumental variable with firm and time fixed effects of bank technological innovation on SMEs' credit growth. LT.DEBT.GR indicates the growth of an SME's long-term credit at time t, while ST.DEBT.GR denotes the growth of the SME's short-term credit. We instrumentalize BANK.INNOV with INSTRUMENT PSD2, which is an interaction between a dummy taking one for the UK as a country with the earliest adoption of the PSD2 and treatment years (after 2016), and zero for all other countries. For the sake of 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), or bank-level control variables (BANK.SIZE, BANK.LOANS, BANK.EQUITY, and BANK.DEPO.GR), the constant term, and year dummy variables. Robust standard errors are shown in parentheses. First-stage and second-stage refer to the 2SLS IV regression results for the first- and second-stage estimations, respectively. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	First-stage	Second-stage	First-stage	Second-stage
	(2)	(1)	(4)	(3)
	BANK.INNOV	SH.DEBT.GR	BANK.INNOV	LT.DEBT.GR
BANK.INNOV		0.000218		0.00482*
		(0.15)		(2.38)
INSTRUMENT_PSD2	0.711***		0.692***	
	(68.37)		(67.57)	
L.FIX_A	-0.0482***	0.00623***	-0.0495***	-0.0634***
	(-5.93)	(7.85)	(-6.20)	(-57.71)
L.EBIT_S	0.0624***	0.000895	0.0605***	-0.00675***
	(9.24)	(1.35)	(9.12)	(-7.37)
L.EQUITY	-0.190***	0.0394***	-0.199***	0.0917***
	(-26.65)	(53.01)	(-28.48)	(88.70)
L.TAT	0.00819***	0.00507***	0.00878***	0.00812***
	(6.52)	(41.36)	(7.18)	(48.29)
L.LN_SALES	-0.0220***	-0.00280***	-0.0201***	-0.00614***
	(-9.54)	(-12.43)	(-8.89)	(-19.69)
L.LN_FIRM_AGE	-0.315***	-0.00442***	-0.294***	-0.00716***
	(-66.01)	(-6.69)	(-63.34)	(-8.02)
GDPGROWTH	-19.16***	0.209***	-19.28***	0.326***
	(-226.32)	(6.87)	(-231.49)	(7.52)
GDPPCPPP	-0.308***	-0.00143**	-0.296***	0.00211***
	(-172.44)	(-3.07)	(-174.56)	(3.30)
UNEMPL	-14.08***	-0.160***	-13.30***	-0.0467
	(–169.18)	(-8.16)	(-168.94)	(-1.76)
L.BANK_LN_ASSETS	1.496***	-0.00611**	1.455***	-0.0102***
	(208.42)	(-2.87)	(207.13)	(-3.45)
L.BANK_LOANS	5.196***	-0.0145	4.937***	-0.0285**
	(195.87)	(-1.79)	(189.81)	(-2.60)
L.BANK_EQUITY	-3.341***	-0.0315***	-2.460***	-0.00767
	(-44.57)	(-3.66)	(-34.36)	(-0.70)
L.BANK_DEPO_GR	-1.335***	0.00302	-1.313***	0.00944**
	(–154.87)	(1.39)	(-154.96)	(3.12)
Observations	994,908	994,908	1,018,422	1,018,422
R-squared		0.0455		0.0355
Time FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Short-Term Credit Growth Regression:

The Anderson canonical correlation LM statistic (p-value) is 0.000.

Long-Term Credit Growth Regression:

is 0.000

The Anderson canonical correlation LM statistic (p-value) The Cragg-Donald Wald F statistic is 4,565.532.

The Cragg-Donald Wald F statistic is 4,674.407.

The Sargan statistic for overidentification is 0.00.

The Sargan statistic for overidentification = 0.000.

5.2 Identification Strategy

In this section, we aim to delve into the potential identification issues that may emerge from the relationship between SMEs and banks, and how these issues could impact the accessibility of credit for SMEs. It will also address the endogeneity of bank technological development and SME borrowing.

Our primary objective is to ascertain whether the observed increase in SME credit growth, attributed to bank digitalization, is genuinely a consequence of technological advancements within the banking sector. We want to eliminate the possibility that this growth is merely a result of any SME and/or bank features that have motivated them to invest in technological development. Firstly, we want to ensure that any SME technological development is not responsible for the better conditions for these SMEs within a digitalization shock in the financial sector. Secondly, we also want to test and eliminate the situation where more digitalized firms are more likely to be linked with more digitalized banks "a priori" and the financial digitalization shock has only enhanced this relationship. This could also address the situation that some banks are more likely to invest in technology to spur the relationship with specific SMEs (for example, more digitally advanced SMEs).

To address these kinds of challenges we perform a few robustness checks. Firstly, to prove that more digitalized companies did not receive more credit after a bank's technological development or had not already received it beforehand, we start by segmenting companies based on their digitalization level, informed by their respective NACE codes.⁵ Firms in sectors such as computer programming, consultancy, data processing, web portal operations, and online retail are classified as more digitalized. This classification allows us to examine the identification problem that these companies received more credit after the technological revolution in banking, which happened after the introduction of the PSD2. It could be because of these firms' individual features, which have made them prone them to such a situation.

Secondly, we also analyze whether more digitalized firms are more likely to be associated with more digitalized banks. This could also address the identification issue related to the fact that some banks could have been more motivated to invest in technological development due to their strong relationship with SMEs.

Our methodology includes a DID regression analysis where we interact a digital firm indicator with the post-2015 period (DIGITAL.FIRM*YEAR2016_DUMMY) to evaluate whether digital firms have exhibited enhanced credit growth during the period of intensified bank digitalization, starting in 2016. In our specification we also control for bank technological development using BANK.INNOV to isolate the effect of the banks' digitalization on the expansion of SME credit. The outcomes of this regression, presented in Table 11, will provide insights into whether the credit growth of digital firms has exceeded the credit growth of nondigital firms during the banks' digitalization period. Again, we look at three types of credit growth variables presented in Specifications (1)–(3).

⁵ NACE ("Nomenclature statistique des activités économiques dans la Communauté Européenne") codes are a European industry standard classification system. They are used to categorize business activities and economic data in the European Union (EU). The system is similar to the North American Industry Classification System (NAICS) in the United States and Canada, and the Standard Industrial Classification (SIC) system previously used in the UK.

Table 11: Robustness: The role of SMEs' Digitalization in the Access to Bank Credit

The table presents the regression results for firm- and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' credit growth. DEBT.GR represents the growth of an SME's combined short-term and long-term bank debt at time t, divided by the previous year's total assets (inflation-adjusted). LT.DEBT.GR indicates the growth of an SME's long-term credit at time t, while ST.DEBT.GR denotes the growth of the SME's short-term credit. BANK.INNOV is defined as the number of technological solutions adopted by bank i at time t. DIGITAL.FIRM denotes all firms operating in the digital sector, classified according to NACE codes. This category includes codes such as Computer programming activities (NACE: 6201); Computer consultancy activities (NACE: 6202); Computer facilities management activities (NACE: 6203); Other information technology and computer service activities (NACE: 6209); Data processing, hosting, and related activities (NACE: 6311); Web portals (NACE: 6312); Publishing of computer games (NACE: 5821); Other software publishing (NACE: 5829); and Retail sale via mail order houses or via the internet (NACE: 4791). All regressions include firm, bank, and country control variables as specified in the Methodology section. For the sake of 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), or 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Variables	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR
YEAR2016_DUMMY*DIGITAL.FIRM	0.000238	-0.00212*	0.00142
	(0.00161)	(0.00127)	(0.000900)
L.BANK.INNOV	0.00109***	0.000982***	0.000242**
	(0.000166)	(0.000138)	(0.000101)
Observations	1,003,408	1,034,658	1,011,309
R-squared	0.043	0.036	0.041
Number of FIRM_ID	179,921	183,557	180,751
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Our regression findings emphasize the pivotal role of banks' technological advancements in enhancing SMEs' access to credit. Interestingly, the lack of statistical significance in the interaction term (DIGITAL.FIRM*YEAR2016_DUMMY) suggests that simply being more digitally oriented firm does not correlate with increased credit growth post-2015. Instead, it is the banks' technological innovativeness that emerges as a significant driver of credit access for SMEs. Moreover, our regression results confirm the notion from previous analyses that the impact of banks' technological innovations is particularly significant in the realm of long-term financing for firms, rather than in short-term credit scenarios.

Moreover, we also address the potential identification issue related to the fact that more digitalized firms could have been more inclined towards specific banks that increased the bank credit access during the bank digitalization period. Alternatively, this might also test the endogeneity issue related to the fact that banks more likely to be inclined towards such firms might have been more motivated to invest in technological development. To this end, we control for the degree of bank technological advancement using the interaction between bank HIGH.DIGITAL*YEAR2016_DUMMY and DIGITAL.FIRM. This approach sheds light on whether the credit growth observed for digitally advanced firms at more digitalized banks after 2016 is distinct from other firms. The statistical significance of the HIGH.DIGITAL variable, regardless of the

interaction, would indicate that banks' move towards digitalization has an inherent value in facilitating SME credit growth that is separate from any preexisting relationships. This distinction is critical, as our HIGH.DIGITAL definition specifically includes banks that have undergone digitalization since 2015. The methodology, therefore, allows us to account for historical SME borrowing patterns before 2016, and observe the evolution of credit relationships following the digitalization shift. The results presented in Table 12 capture these dynamics and provide insights into the influence of bank technological advancement on SME financing.

Table 12: Robustness: The Role of SMEs' Digitalization in the Access to Bank Credit

The table presents the regression results for firm- and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' credit growth. DEBT.GR represents the growth of an SME's combined short-term and long-term bank debt at time t, divided by the previous year's total assets (inflation-adjusted). LT.DEBT.GR indicates the growth of an SME's long-term credit at time t, while ST.DEBT.GR denotes the growth of the SME's short-term credit. BANK.INNOV is defined as the number of technological solutions adopted by bank i at time t. DIGITAL.FIRM refers to all firms operating in the digital sector, classified according to NACE codes. This category includes Computer programming activities (NACE: 6201); Computer consultancy activities (NACE: 6202); Computer facilities management activities (NACE: 6203); Other information technology and computer service activities (NACE: 6209); Data processing, hosting, and related activities (NACE: 6311); Web portals (NACE: 6312); Publishing of computer games (NACE: 5821); Other software publishing (NACE: 5829); and Retail sale via mail order houses or via the internet (NACE: 4791). HIGH.DIGITAL denotes highly digitalized banks, defined as those exceeding four technological solutions adopted. For the sake of 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), or 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Variables	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR
YEAR2016_DUMMY*HIGH.DIGITAL	0.00341***	0.00284***	0.00110***
	(0.000582)	(0.000459)	(0.000365)
YEAR2016_DUMMY*HIGH.DIGITAL*DIGITAL.FIRM	0.000217	-0.00400	0.00309
	(0.00360)	(0.00249)	(0.00260)
Observations	1,003,408	1,034,658	1,011,309
R-squared	0.043	0.036	0.041
Number of FIRM_ID	179,921	183,557	180,751
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

The econometric analysis yields no evidence to support the hypothesis that firms with a pronounced digital presence secured more credit in the aftermath of 2015, coinciding with an era of intensified bank digitalization. Additionally, the empirical data do not affirm the predilection for digitally advanced firms to establish credit relationships with similarly digitalized banking institutions. Contrarily, the variable HIGH.DIGITAL, which is indicative of a bank's technological advancement, exhibits a statistically significant and positive association with the growth in SME credit. This robust correlation underscores that the digitalization of banks serves as a more critical determinant in augmenting SMEs' access to external financing than the digital attributes of the SMEs themselves.

Lastly, we employ a reverse approach using a randomized sample method, where we create a sample comprising companies from the least digitalized industries. We hypothesize that these companies are likely to be from capital-intensive industries. We classify them based on their NACE codes,⁶ assigning a dummy variable of one to companies assigned to these codes (HIGH.CAPITAL). If a bank's technological development favours more digitalized companies than companies operating in less digital environment, we could see a statistically significant effect of the interaction term between dummies identifying more capital-intensive companies (HIGH.CAPITAL) and more digitalized banks (HIGH.DIGITAL) with a negative sign after 2016. Table 13 presents the regression results on interaction and HIGH.DIGITAL as a separate control variable.

Table 13: Robustness: Randomized Control Sample Using Capital-Intensive Firms

The table presents the regression results for firm- and year-fixed-effect panel models examining the impact of bank technological innovation on SMEs' credit growth. DEBT.GR represents the growth of an SME's combined short-term and long-term bank debt at time t divided by the previous year's total assets (inflation-adjusted). LT.DEBT.GR indicates the growth of an SME's long-term credit at time t, while ST.DEBT.GR denotes the growth of the SME's short-term credit, BANK INNOV is defined as the number of technological solutions adopted by bank i at time t. HIGH.CAPITAL denotes all firms operating in the nondigital sector, classified according to NACE codes. This category includes codes such as: Construction of residential and nonresidential buildings (NACE: 4120); Freight transport by road (NACE: 4941); Restaurants and mobile food service activities (5610). HIGH.DIGITAL denotes highly digitalized banks, defined as those exceeding four technological solutions adopted. For reasons of 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), or 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Variables	DEBT.GR	LT.DEBT.GR	ST.DEBT.GR
YEAR2016_DUMMY*HIGH.DIGITAL*HIGH.CAPITAL	0.00295	0.00231	0.000641
	(0.00194)	(0.00159)	(0.00102)
HIGH.DIGITAL	0.00317***	0.00254***	0.00113***
	(0.000594)	(0.000464)	(0.000380)
Observations	1,003,408	1,034,658	1,011,309
R-squared	0.043	0.036	0.041
Number of FIRM_ID	179,921	183,557	180,751
Time FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

The regression results present interesting findings. We notice that the interaction term of HIGH.CAPITAL and HIGH.DIGITAL is statistically insignificant. This finding suggests that less digitalized firms do not seem to experience lower credit growth than any other firms when they are associated with more digitized banks. At the same time, we can see that the HIGH.DIGITAL variable is highly statistically significant, indicating a positive sign. The regression results support our previous finding that this is a bank technological development that extends access to funding for SMEs and not any

⁶ These industries and respective NACE codes are: 4120 – construction of residential and nonresidential buildings; 4941 – freight transport by road; 5610 – restaurants and mobile food service activities.

individual features of the companies or banks. More specifically, we also note that bank technological development supports long-term credit growth in particular, and to a lesser extent short-term SME borrowing.

6. CONCLUSIONS

The recent digitalization of financial services has raised a lot of public and academic debate on the role of bank technology in addressing financing constraints faced by SMEs. For years this specific group of companies has been underfunded by traditional banks due to their information opaqueness. The recent adoption of technological innovations by banks has brought some hope of increasing data access and its efficient processing, which should lead to better credit availability for these companies.

This study investigates the impact of bank technological innovations on borrowing by SMEs and the way they transform traditional lending frameworks of banks. The research utilizes a comprehensive dataset encompassing 179,921 SME-bank lending relationships across the European Union from 2009 to 2019.

Our results emphasize that bank technological innovations have a more substantial impact on long-term borrowing by SMEs than on short-term borrowing, indicating the usefulness of these technologies in providing data that not only reduce information asymmetry but also enhance long-term decision channels, such as banks' credit scoring processes. Moreover, our regression results highlight the pivotal role of blockchain technology and automation as technologies that enhance the efficiency of data collection and processing, thereby mitigating the difficulties encountered by SMEs in obtaining bank credit.

The study also highlights a dual effect of technology on SME borrowing. While it eases collateral constraints, it paradoxically raises the cost of credit for SMEs. This is especially observable since the introduction of the European PSD2, which caused a significant upsurge in bank digitization. The results indicate that relaxing the requirements for SMEs to access bank credit may challenge banks to increase the risk premium due to a potentially looser relationship or a relaxed attitude toward the collateral.

Our investigation into the impact of bank technological innovation on SME borrowing suggests targeted policy interventions. To improve the situation of SMEs in their bank credit access, regulators should incentivize the adoption of specific technological solutions. Moreover, they must also ensure that such innovations do not disproportionately raise the cost of credit for SMEs. Supporting competitive pricing, especially for the most opaque firms, and maintaining the benefits of relationship banking amidst digitalization seem to be key. Oversight of banks' pricing strategies is essential to prevent the undue transfer of technology investment costs to SME borrowers. Ultimately, policies should aim to balance technological advancement with equitable credit access, reinforcing the foundation for sustainable economic growth driven by robust SME financing.

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