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THE ROLE OF BANKS' TECHNOLOGY ADOPTION IN CREDIT MARKETS DURING THE PANDEMIC

by Nicola Branzoli*, Edoardo Rainone* and Ilaria Supino*

Abstract

This paper shows that greater information technology (IT) adoption by banks was associated with a larger increase in corporate lending in the months following the COVID-19 outbreak in Italy. By examining banks with different levels of IT adoption, we investigate the dynamics of credit and its allocation across firms using a new database with detailed information on banks' IT expenditure and use of innovative technologies, combined with matched bank-firm data on credit growth before and during the pandemic. Using a diff-in-diff approach, we find that banks with a higher share of IT spending increased their credit more than other banks during the pandemic. The increase was concentrated in term loans granted to smaller and financially sounder firms; the effect was stronger in the initial phase of tighter restrictions on firms' activity and individual mobility, and more significant for those in the sectors most affected by the shock. We provide evidence that these results are driven by banks' ability to offer credit entirely online and their use of artificial intelligence for credit risk assessment. Physical proximity between borrowers and lenders was important for the provision of credit during the pandemic, but only when combined with a high level of IT adoption.

JEL Classification: G21, G22, G23, G24.
Keywords: bank credit, information technology, firms, COVID-19 pandemic.
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Contents

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* Bank of Italy, Economic Research and International Relations.

1 Introduction[1]

The COVID-19 pandemic hastened the trend toward digitalisation in the banking sector. Empirical estimates at the global level suggest that between the beginning of 2020 and the second quarter of 2021 total assets of so-called Fintech banks, i.e. banks whose business model heavily relies on digital technologies, grew by roughly twenty-five percent compared to fifteen percent growth at traditional banks (IMF, 2022). This acceleration raises several questions. How did new technologies improve credit intermediation during the pandemic? What technologies were most important? Which borrowers benefited the most from the degree of IT adoption of their banks? The answers to these questions are key to understand the potential impact of technological innovation on credit intermediation and markets in the coming years.

In this paper, we investigate the role of bank digitalisation in driving credit growth to the corporate sector during the pandemic in Italy, the first Western country to be impacted by the pandemic, whose effects Italian banks could neither have known nor anticipated. To this end, we create a new database with detailed information on the characteristics of Italian banks, their IT expenditures and their use of new technologies for the provision of online lending services, credit risk assessment and other purposes. We merge these data with bank-firm level information on credit growth before and during the pandemic and compare the changes in credit to the same firm that borrows from banks with different degrees of IT adoption.

We find that, controlling for firms' observable and unobservable heterogeneity and for a large set of bank characteristics, lenders with higher shares of IT expenditures relative to total operating costs increased credit more than others in the months following the COVID-19 outbreak. The expansion of credit was concentrated in term loans extended to smaller and financially sounder companies; the effect of IT adoption on lending was stronger during the second quarter of the year (when restrictions on firm activity and individual mobility were tighter) and spanned across industries, but was more significant

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for firms in the sectors most affected by the shock.

We then explore some of the mechanisms through which IT may have supported credit growth during the pandemic. First, we assess whether our results are driven by the ability of banks with higher shares of IT spending to offer credit entirely online or by their use of digital technologies for credit risk assessment. Second, we examine the role of bank-firm physical distance and its complementarity with lender's degree of IT adoption. We find that companies with higher credit growth during the pandemic had borrowed from banks with online lending services and from banks using new technologies to assess the quality of their borrowers. Our results also indicate that bank-firm physical proximity was important only when offline and online channels coexisted and complemented each other. To the extent of our knowledge, our paper is the first to document the complementarity between offline and online channels in the credit market.

Our paper is mainly related to the rapidly growing literature on the impact of recent technological innovation on the banking sector (Vives, 2019; Carletti *et al.*, 2020a). Four recent papers are closest to our analysis. Core and De Marco (2021) show that banks' level of digitalization, proxied by clients' ratings of their lender mobile app, influenced the supply of government guaranteed credit during the pandemic in Italy. Kwan *et al.* (2021) provides evidence that bank use of digital technologies for remote or virtual work and online communication improved the supply of small business loans in the US. Silva *et al.* (2021) find that in Brazil bank branches with greater pre-pandemic IT spending were able to supply more loans outside municipalities most hit by the pandemic, thereby mitigatinga potential decline in their market power induced by the pandemic. Using a measure of IT adoption similar to ours, Dadoukis *et al.* (2021) find that high-tech banks experienced milder declines in their price of capital (proxied by their stock price) and higher loan growth after the COVID-19 outbreak. Our results are consistent with these findings and extend these studies in several directions. In particular, our analysis explicitly accounts for specific use-cases of digital technologies such as online lending services and technology-based credit risk assessment. Therefore, we can analyze mechanisms through which bank IT adoption improved credit supply. Furthermore, using borrower-level data, we are able to investigate how these effects vary with firm characteristics, including bank-firm physical distance. Our paper also complements the results in Pierri and Timmer (2022), who highlight that bank intensity of IT adoption led to lower levels of non-performing loans during the great financial crisis; it is also related to recent works on the advantages of using digital technologies for credit risk assessment (Baesens *et al.*, 2015; Albanesi and Vamossy, 2019; Gambacorta *et al.*, 2019; Berg *et al.*, 2020; Frost *et al.*, 2019). Finally, our study also contributes to the literature on the role of physical distance in credit markets (Kroszner and Strahan, 1999; Petersen and Rajan, 2002; Bofondi and Gobbi, 2006; Hertzberg *et al.*, 2010; Nguyen, 2019; Granja *et al.*, 2022), which broadly finds that branch closeness to borrowers facilitates soft information gathering and helps improve loan quality. Our results suggest that bank branches positively affected credit growth only when they also operated an online channel, in a blend of physical and digital presence that turned out to be key in lending during the pandemic.

The remainder of the paper is organized as follows. Section 2 presents the data used for the analysis and describes our measure of IT adoption. Section 3 provides descriptive evidence on lending patterns across clusters of bank technology, followed by a description of the identification strategy in Section 4. The baseline results are reported in Section 5, while Section 6 provides additional evidence to shed light on the potential explanations of our main findings. The final section concludes.

2 Data

We construct a novel dataset of firm-bank relationships by drawing information from six main sources: (a) the Italian Credit Register (CR), which tracks the credit exposure of borrowers from resident financial intermediaries; (b) the Italian Supervisory Reports, which contain balance sheet data for Italian banks; (c) the Company Accounts Data System (CADS), which provides accounting data for the universe of Italian non-financial corporations; (d) the Survey of Industrial and Service Firms (also known as Invind) on the investments of Italian firms; (e) the Regional Bank Lending Survey (RBLS), which supplies information on bank business model choices, including those related to their digitalization strategies; and (f) the GIAVA database managed by the Bank of Italy, which contains the exact location of all banks' branches. This section describes each data source, the summary statistics of our baseline sample and the construction of our key variables.

2.1 Credit data

The CR reports data on borrowers with outstanding debt exposure above 30,000 euros toward credit institutions (banks and other specialized financial intermediaries).[2] For each exposure, we are able to retrieve information on both the granting institution and the individual borrower (e.g. the tax identification number), as well as on specific features of the lending position (including the amount of credit granted and drawn by the type of contract). Loans listed in the CR include those backed by account receivables, fixed-term loans, and overdraft facilities (revolving credit lines).

2.2 Firm characteristics

Credit data is matched to firm accounting data collected by the Cerved group. The CADS proprietary database stores balance sheet and income statement data deposited by firms to the Chambers of Commerce. Self-employed workers and partnerships with unlimited liabilities do not report standardized balance sheet information in Italy and are not covered by the CADS database. The data for firms refer to fiscal year 2019 and include measures of firm size (total assets, number of employees), financial structure (leverage, liquid assets, etc.), sectoral affiliation and geographic location; riskiness is measured with Altman's Z -score.

For a subsample of firms operating in services and manufacturing, accounting data are integrated with information from the Invind. The survey is conducted annually over a sample of approximately 4,000 businesses, which is representative of all private, industrial firms with more than 20 employees; the survey gathers information on firm behavior (management practices, future expectations), production inputs (workforce, investments) and outputs (sales, exports). We restrict our analysis to the 2019 wave that contains one question about the investments in technologies such as big data, artificial intelligence and others; more specifically, firms were required to report the share of investments in advanced digital technologies as a percentage of total investments made in the reporting year.

[2] This threshold is extremely low for loans to corporations and is unlikely to bias our main results.

2.3 Bank characteristics

The supervisory reports collected by the Bank of Italy provide consolidated and unconsolidated balance sheet data on all banks operating in Italy. We obtain the information used to construct the measure of banks' IT adoption described in Section 2.4 from these reports. In our analysis we use unconsolidated data for two reasons. First, borrowers benefit from the quality of digital services provided by their (individual) bank. The banking group is relevant insofar it improves digital services of its subsidiaries. Our IT data take into account this potential effect including information on IT services outsourced to banks within the same group. Second, new technologies may be used by some banks in a group. Given that we have information on the use of new technologies at the individual bank level, pooling this information at the group level could create measurement errors. This approach allows us to exploit variation in the level of IT adoption and other relevant bank characteristics (i.e. the presence of online credit and the use of innovative technologies for credit risk assessment) even within banking groups. Bank data include proxies for profitability, size and funding structure. To isolate the effect of bank digitalization to lending capacity from other relevant channels and pandemic-specific confounders, we control for several bank characteristics. For example, the capital ratio - computed as equity divided by total liabilities - accounts for structural differences between intermediaries and also for potentially different effects of the capital reliefs and dividend restrictions placed on banks at the height of the COVID-19 pandemic. Other changes in bank regulations are taken into account: we control for the massive public loan guarantee schemes introduced by the government in response to the crisis by taking into consideration the extent to which a bank's credit portfolio is backed by state guarantees.

Data on bank branches are sourced from the GIAVA database administered by the Bank of Italy. We geocode the branches of all banks operating in the country between 2019 and 2020. Locations of branches are matched with those of firms. Information on the distribution and financial structure of Italian banks is complemented with the evidence collected through the RBLS, which is conducted on a yearly basis over a large sample of Italian banks representing 90 per cent of the deposits of the entire banking system. In addition to monitoring the main credit supply and demand factors in the Italian market on a regular basis, since 2017 the survey also includes a set of questions that specifically assesses the status of the respondents' digital transformation.

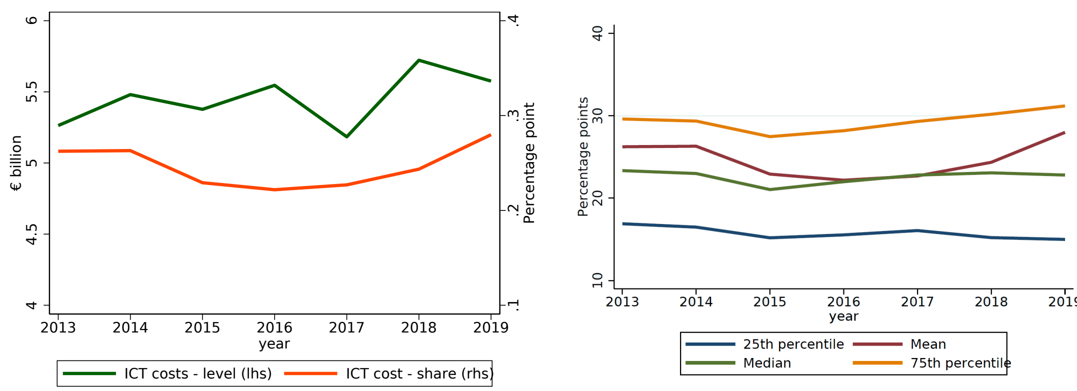
To obtain our baseline sample, we merge credit register data with balance sheet data available for banks and firms. To control for unobservable demand factors, following the identification strategy described below, we restrict the analysis to firms that borrowed from multiple banks. This matching yields a sample of 463 banks, 366,000 non-financial companies and over one and a half million credit relationships spanning the years 2019-2020. A detailed description and summary statistics of the variables used is provided in Table A.1.

2.4 Measuring banks' level of IT adoption

We measure banks' level of IT adoption using costs for the automatic processing of data reported in banks' income statements. These costs include a variety of IT-related expenses, and in particular expense incurred for (i) the purchase of hardware (e.g. personal computers, servers, mainframes) or software; (ii) gross wages paid to IT specialists (e.g. computer support engineers); and (iii) the outsourcing of IT services to external providers. Thus, the richness of our data gives us a comprehensive picture of the technological level of the bank and allows us to compare banks with different IT strategies.[3] To obtain our measure of IT adoption, we normalize these costs by bank's total operating costs. Figure 1 describes the evolution of IT costs since 2013. Italian banks spend around €5.5 billion per year on IT. The ratio of IT costs to total operating costs has increased mildly since 2016, driven by banks on the right-hand of the IT spending distribution. Indeed, as shown in the right panel, the 75^{th} percentile of the distribution of the share of IT costs has grown slightly in the last 5 years while the 25^{th} percentile and the median have remained substantially unchanged. Overall, this evidence suggests that banks' IT costs were relatively stable over time.

[3] Our data contains yearly costs and the amortized share of each investment in IT. Using similar data, Casolaro and Gobbi (2004) and Mocetti *et al.* (2017) construct a measure of bank's IT capital from investment data using the permanent inventory method. Although their data on investment are strictly related to ours on the amortized costs of hardware, software and data sources (the "amortized" share of their investment data is included in our information on costs), our measure also includes IT-related information that are not recorded as investment, such as outsourcing and compensation of IT specialists.

Figure 1 – *IT COSTS FOR ITALIAN BANKS*
- Evolution and share over total operating costs -



NOTES. Yearly data. The left-hand graph shows the evolution of banks' IT and of the share of bank's IT costs over total operating costs for the entire banking sector. The right-hand graph shows the evolution of the 25th percentile, the median and the 75th percentile of the distribution of the share of IT costs in each year.

In principle, IT costs give an indication of how much banks have spent to purchase, maintain and manage the personnel and equipment associated with IT. However, it fails to provide a direct measure of technology adoption given that IT costs may simply reflect the prices paid to secure dedicated staff and resources; for example, a bank may display higher hardware costs because it overpaid for its personal computers and not necessarily because it bought more of them or because they are of better quality.

To assess whether a greater incidence of IT costs is actually related to a higher degree of IT adoption and digitalization, we analyse the relationship between the bank's IT expenditures and its use of digital technologies to innovate the business model. We exploit RBLS data to investigate whether banks with a higher share of IT costs are those with a broader supply of online products and services and more inclined to innovate with new technologies (for example by using big data and artificial intelligence for credit risk assessment, or robotics and cloud services to reduce operating costs).

To validate our cost-based measure of IT adoption, we explore its relationship with a list of indicators based on responses to RLBS (2019 round). The survey contains questions on the scope of online services offered to households (i.e. peer-to-peer payments, consumer credit or wealth management) and firms (including invoice trading and credit lines); banks are also asked to specify if they have any innovative projects under way, which technology underlie them and the purpose (for instance, improving consumer profiling or cross-selling). [4] Results are reported in Table 1.

***Table 1** – IT COSTS, ONLINE BANKING AND R&D PROJECTS*

Online banking		R&D projects using digital technologies			
Service provided:	$\hat{\beta}$	Technology used :	$\hat{\beta}$	Purpose:	$\hat{\beta}$
P2P payments	0.159**	Big Data	0.598**	Consumer services	0.529*
	(0.074)		(0.250)		(0.297)
Mortgages	0.458**	Artificial intelligence	0.685***	Costumer profiling	0.687**
	(0.219)		(0.235)		(0.325)
Consumer credit	0.493***	Biometrics/robotics	0.549***	Cross-selling	0.563**
	(0.112)		(0.239)		(0.307)
Investment services	0.360**	Cloud	0.223	Credit risk assessment	0.538**
	(0.164)		(0.223)		(0.242)
Trade credit	0.020**	API	0.476*	Cost-reduction	0.228*
	(0.090)		(0.276)		(0.301)
Credit lines	0.071	Blockchain	0.481**		
	(0.035)		(0.209)		

NOTES. This table presents estimates from the following regression:

$$Y_b = \alpha + \beta \text{ Share IT costs}_b + \gamma \text{ Bank controls}_b + \epsilon_b$$

where Y_b is a dummy variable equal to 1 if the bank: offers online peer-to-peer payment services, mortgages, consumer credit or investment services to households; trade credit and credit lines to firms; has started an R&D project using new technologies, the specific technology used (i.e. big data, artificial intelligence, biometric/robotics, cloud, application program interfaces, blockchain) and the broad purpose of its projects (i.e. improving consumer information, consumer profiling, cross-selling, credit risk assessment, efficiency/cost reduction). Observation period: 2019. We run a separate regression for each online service, technology or purpose of R&D projects, for a total of 17 regressions (6 online service, 6 technologies and 5 purposes).
All regressions include: bank controls, which are: two dummy for whether the bank is part of a banking group and whether the group or the stand-alone bank is a significant institution under the supervision of the European Central Bank, bank's total assets in log, capital ratio, cost-income ratio, the share of interest income over operating income, the loans to the non-financial sector, the share of sovereign bonds over total assets, the share of deposits of households and non-financial corporations over total liabilities. N. observations: 260. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels.

Controlling for a rich set of bank characteristics (including total assets, funding composition and profitability), we find the share of IT costs to be positively correlated with both the presence of online services and the use of new technologies for innovative projects. The relationship is positive and statistically significant for the services offered online to households. It is also positive for services provided digitally to firms, although not significant for credit lines; this evidence is consistent with the fact that in Italy the supply of banking services through the internet is generally more developed for individuals than for companies (Visco, 2019; Michelangeli and Viviano, 2021). Similarly, we show a strong correlation between our proxy of bank digitalization and the propensity to innovate. The results on R&D projects involving new technologies are positive and quantitatively significant: for example, within the distribution of the IT costs share, a shift from the first to the third quartile (from 17 to 28 percent), is

[4] RBLS questions are presented comprehensively in Table A.2 in the Appendix.

associated to a 5 percentage points increase in the probability of experimenting with big data or artificial intelligence, which is considerable given that about 10 percent of the banks in our sample reported to have adopted these technologies.

All in all, these results suggest that a larger share of IT costs is strongly related to a greater likelihood of offering digital services and engaging in innovative processes.

3 Lending during the pandemic

Italy was one of the first countries in the world to be hit by COVID-19. As the pandemic began to escalate, authorities made increasing efforts to tackle the public health crisis. At the beginning of March 2020 the Italian government enacted drastic rules aimed at fighting the rapid surge in positive cases. Containment measures included travel restrictions, a ban on public gathering and self-isolation. In the initial phase of the crisis, authorities ordered the shutdown of all non-essential businesses; supermarkets, pharmacies, post offices and banking service providers could remain open. Enforced closings and the fear of contagion severely reduced the mobility of the population (Buono and Conteduca, 2020; Pepe *et al.*, 2020; Beria and Lunkar, 2021), with adverse effects on the economy.

Lockdowns and social distancing reframed the way individuals worked, consumed and interacted. In the attempt to adapt to the unfolding situation, firms and individuals were forced to switch to online channels for delivering and buying products, respectively. Restrictions on physical movement resulted in a shift in the demand for e-commerce: between February and November 2020 online retail sales grew by 30 per cent in terms of volumes,[5] and this change spilled over to other sectors. Remote work increased sharply: 14 per cent of private sector employees worked from home in the second quarter of 2020 compared to a far lower share (barely 1 per cent) in the same period of 2019 (Depalo and Giorgi, 2021). Consumers and businesses also changed their financial habits: though not able to visit their local bank branch in person, individuals and entrepreneurs continued to need assistance to deposit checks, pay bills, transfer funds or apply for mortgages and they turned to online services more than ever before.

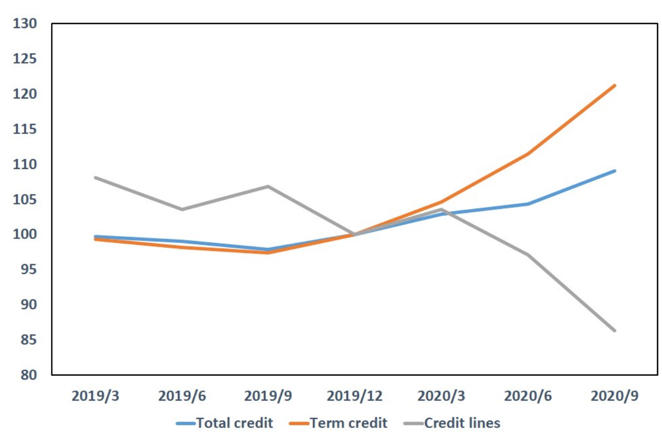
[5] Our calculations are based on data on retail e-commerce from Eurostat available here.

Like all industries, the financial sector has been impacted. Both fiscal and prudential measures have been adopted in order to preserve the stability of the system and to support the flow of credit to the economy (Casanova *et al.*, 2021). Fiscal measures included debt moratoria and public guarantee schemes for bank loans. Under the (legislative and non-legislative) moratoria, eligible borrowers were granted deferment on loan installment payments for a specific time; guarantee programs transferred some or all default risk to the government, thus encouraging banks to provide new lending to firms with urgent liquidity needs. Prudential relief measures were also introduced to free up bank capital and support lending; authorities released the capital buffers in order to strengthen bank balance sheet capacity and also imposed temporary restrictions on dividend payouts.

COVID-19 policy support helped boost lending (Bank of Italy, 2020). Banks processed a larger-than-usual number of credit applications and loans to firms rose significantly during the pandemic (see Figure 2). The increase involved all types of credit in the early months of the crisis, while the upward trend was driven by a surge in term loans during the second and third quarters of 2020.

***Figure 2** – THE EVOLUTION OF CREDIT DURING THE PANDEMIC*

- Type of credit -



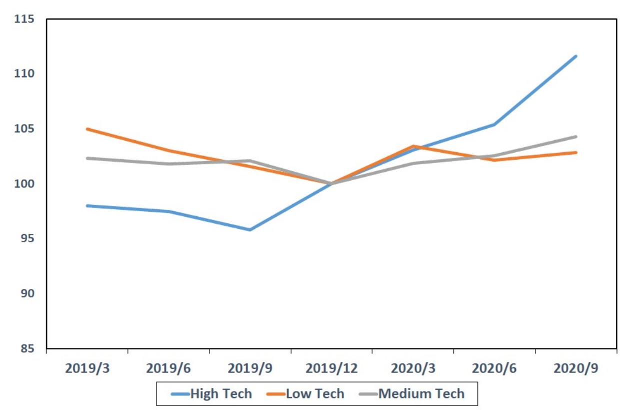
NOTES. Quarterly data. The total amount of each type of credit (total credit, term credit and credit lines) are normalized to 100 based on the amount of outstanding in December 2019.

3.1 Lending patterns and IT adoption

As customers confined to home rapidly turned to digital touchpoints as their primary way of interacting, banks adjusted their business activity by switching in-branch visits to appointment-only, by rerouting financial transactions over the internet and by encouraging virtual interactions.[6] However, Italian banks found themselves facing the pandemic crisis with rather heterogeneous levels of digital maturity. Depending on their digital readiness, intermediaries may have been either well- or under-equipped to handle the challenges arising from the emergency.

In the lending segment, a good level of technology adoption may have helped banks handle the upturn in credit demand. Indeed, ex-ante digital capabilities may have been valuable in processing a larger-than-usual volume of loan applications and in providing a quick response to the market (Kwan *et al.*, 2021). Figure 3 shows the evolution of lending across banks characterized by different levels of technology adoption. While all banks showed an increase in the amount of credit, lending by the more technology-based banks rose at a faster pace: between December 2019 and September 2020 credit drawn by High Tech banks, i.e. banks in the top quartile of the distribution of IT costs' share, increased by 11 percent, twice that of other banks.

Figure 3 *– THE EVOLUTION OF CREDIT DURING THE PANDEMIC*
- Lenders with different levels of IT adoption -



NOTES. All banks in our sample are split into three groups according to their level of IT costs over total operating costs. Given the distribution of the IT costs' share at the end 2019, banks are classified as "Low Tech" if they fall in the bottom quartile, "Medium Tech" if they stand between the second and third quartile and, "High Tech" if they are in the top quartile. The total amount of credit per each bank group is normalized to 100 based on the amount of outstanding credit in December 2019.

[6] See BCG (2021) for a cross-country study.

4 Empirical strategy

Our goal is to understand the effect of banks' IT level on firms' credit during the pandemic crisis. To this end, we use a difference-in-differences approach in which we compare the evolution of credit in firms borrowing from lenders with different levels of IT adoption. More formally, our main specification takes the following form:

$$log\left(\frac{C_{ib,t}}{C_{ib,t-k}}\right) = \alpha + \beta I_{t\in P} Tech_b + \delta X_{ib,t} + \theta_{i,t} + \epsilon_{ib,t}, \tag{4.1}$$

where $log\left(\frac{C_{ib,t}}{C_{ib,t-k}}\right)$ represents the growth of credit drawn by firm i from bank b at time t, measured in percentage points, k is a time lag that we describe below, $I_{t\in P}$ is an indicator function which is equal to one if the period between t and $t-k$ is characterized by the pandemic (P) and zero otherwise, $Tech_b$ is the bank's IT cost ratio, $X_{ib,t}$ is a wide set of bank and/or firm controls (which include $Tech_b$ and the dummy variable $I_{t\in P}$), $\theta_{i,t}$ represent firm-time fixed effects, and $\epsilon_{ib,t}$ is the error component.[7]

We analyze three time periods, i.e. three combinations of t and k. The first period is between March and June (t = June and $k = 1$, given that we have quarterly data), the second is between June and September (t = September and $k = 1$) and the third is between March and September (t = September and $k = 2$). In each case, we compute credit growth at firm-bank level between the beginning and the end of the period and we include in the sample the credit growth in the same period of 2019. For example, when we study the growth of credit between March and September 2020, we include the growth of credit in the same period of 2019. Firm-time fixed effects ($\theta_{i,t}$) guarantee that we are comparing loans to the same firm at the same time, thus controlling for any time-varying observable and unobservable heterogeneity of borrowers (Khwaja and Mian, 2008)[8].

Our parameter of interest is β, which measures the variation in credit growth following the pandemic as a function of the IT level of the bank. A positive β implies that the more technological banks granted more credit during or after the great lockdown.

[7]In our sample, the bank-specific IT measure does not vary over time and is observed before the shock. It follows that any variation along this dimension will be absorbed by bank fixed effects. This is why we rely on a vast set of controls to capture banks' heterogeneity along different dimensions.

[8]This approach, which is standard in the literature (see for example Cingano *et al.*, 2016; Sette and Gobbi, 2015) implies that we study only changes in the intensive margin of credit. The analysis of the extensive margin, i.e. of whether firms switched to lenders with higher levels of IT after the great lockdown, is left for future research.

The matrix $X_{ib,t}$ includes multiple bank characteristics obtained from supervisory reports.[9] In particular, we control for banks size and the characteristics of their portfolios by including the logarithm of total assets, membership in a significant banking group (if any), the share of loans to households and non financial firms over total assets, and the share of sovereign bonds over total assets; we control for banks' funding and risk appetite by including the share of households and firm deposits over total liabilities, the share of bonds over total liabilities, and the capital ratio. We control for bank business model and efficiency by including the interest margin and the cost-income ratio. This allows us to estimate the relationship between banks' IT level and credit controlling for multiple confounding factors stemming from bank characteristics. However, our estimates should be interpreted with some caution because there could still be a selection-bias due to unobservable or omitted bank characteristics, although the inclusion of a large set of bank controls provides strong support to the significance of the estimated relationship.

Part of the analysis below will extend the basic model presented in equation (4.1) to disentangle the role played by specific technologies or applications (e.g. impact of IT on banks internal processes, such as credit risk assessment) after the advent of the pandemic. In particular, we interact our IT measure with dummies capturing online loan facilities offered to firms and the use of new technologies for credit risk assessment.

This setting provides a promising approach to understand how the COVID-19 pandemic has changed the role played by IT in the economy for several reasons. First, our measure of IT adoption was recorded in December 2019, just two months before the outbreak of the pandemic. Second, IT projects require time and investment and costs and cannot be adjusted in few weeks or other short period, as shown by (Silva *et al.*, 2021). Therefore, banks could not have reacted immediately to the pandemic shock to adapt their IT equipment or supply structure rapidly (e.g. the network of branches). The adjustment of the branch networks and technology adoption are sticky processes that the pandemic may change, but not in the short time span we are examining in this paper. All these arguments suggest that the heterogeneity of banks' IT adoption is arguably exogenous to the shock and our measure of

[9] Matrix $X_{ib,t}$ also includes $Tech_b$ and $I_{t \in P}$, i.e. the levels (not interacted) of our variables of interest. Furthermore, in the specifications that do not include firm-time fixed effects, the matrix $X_{ib,t}$ also contains firm variables such as firm size, level of indebtedness and gross operating profits.

banks' technology adoption represents a good proxy for the level of IT with which banks had to face the COVID-19 pandemic.

5 Main results

5.1 Baseline estimates

Table 2 presents our baseline results on the relationship between banks' IT adoption and credit growth during the pandemic crisis. We first show estimated parameters for the entire time span, then we split the sample in two sub-periods. Column (1) reports results controlling for a large set of firm observable characteristics. Columns (2) and (3) sequentially add firm-time fixed effects to address time-varying unobserved heterogeneity and include bank-level controls and a control variable that measures the share of state-guaranteed loans held by each bank in order to account for the surge in loan demand due to public intervention.

Our results indicate that banks with higher IT levels have increased corporate lending significantly more than other banks. The estimated coefficient of IT adoption is positive, stable across different specifications and always significant at the 1 percent level. Our estimates from column (3) imply that a 10 percentage point increase in the IT cost ratio, which is roughly equivalent to the interquartile range of the distribution of the IT cost ratio in 2019, is associated with a 2 percent increase in credit growth over the full period. If compared to other studies (Kwan *et al.*, 2021), the magnitude of the estimated effects is smaller. This could be due to the measurement of banks'IT, the different institutional environment and the type of loans considered.

Comparing results from sub-periods, we note that the relationship is stronger for the first phase (March to June of 2020). This indicates that the role of digitalization in boosting the provision of credit was important particularly when restrictions to firm activity and individual mobility were tighter.

In the appendix we provide several robustness checks and extensions. Table A.4 compares the results of columns (2) and (3) of Table 2 with the restricted set of observations in which the borrower appears in the CADS dataset, as in column (1) of Table 2. The results are stable, the CADS sample presents slightly higher coefficients. Table A.5 reports the results from the same regressions in Table 2, when the sample is not restricted to firms with multiple relationships, and thus not including firm fixed effects. In this case the point estimates are similar to those of Table 2. Finally, we exploit the unique information in the RBLS and investigate the role of the specific technologies listed in the third column of Table 1. Table A.6 provides the results.[10] Our estimates provide strong evidence for the importance of cloud-based technologies and indicate the potential relevance of artificial intelligence and big data. In Section 6, we investigate in more depth the role of technology in online lending services and credit risk assessment.

Table 2 *– BASELINE RESULTS*
- IT and credit growth-

Dependent variable: bank-firm level credit growth				
		(1)	(2)	(3)
Full period				
	$\hat{\beta}$	0.1977*** (0.0158)	0.2002* (0.0874)	0.2125** (0.0712)
	Observations	776,442	1,520,155	1,518,801
	R^2	0.00141	0.41552	0.41600
Phase I				
	$\hat{\beta}$	0.1141*** (0.0129)	0.1303* (0.0598)	0.1468** (0.0496)
	Observations	806,748	1,600,118	1,598,715
	R^2	0.00055	0.40778	0.40812
Phase II				
	$\hat{\beta}$	0.0852*** (0.0125)	0.0862* (0.0369)	0.0926** (0.0317)
	Observations	804,364	1,593,454	1,592,026
	R^2	0.00100	0.40084	0.40141
	Firm controls	Yes	No	No
	Firm-time F.E.	No	Yes	Yes
	Bank controls	No	No	Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. Coefficients of other regressors for the full period are reported in Table A.3 in the appendix. In the full period $t =$ September 2019, September 2020 and $k = 2$. In phase I $t =$ June 2019, June 2020 and $k = 1$. In phase II $t =$ September 2019, September 2020 and $k = 1$.

[10] In particular, we first change model 4.1 substituting $Tech_b$ with a dummy variable equal to one if the bank uses a specific technology. More precisely, we consider dummies capturing whether the bank has a project in production or testing phase involving cloud-based technologies, artificial intelligence, and so on for each technology listed in Table A.2. Secondly, we consider all the dummies in the model, and thirdly we include also our aggregate measure of IT adoption

5.2 Firm Heterogeneity

5.2.1 Industry

We now investigate whether high-tech lenders provided more credit to some corporate borrowers rather than others. Given that Italy adopted sectoral lockdown measures to contain the spread of COVID-19, industry affiliation is a key firm feature to look into. Under the specification from column (3) of Table 2, we explore the heterogeneity of our estimates across firms that perform different economic activities.
Table 3 reports the regression outcomes. The relatioship between IT adoption and credit growth is more significant in the manufacturing and service sector, which are among those characterized by the greatest declines in value added output as a consequence of the pandemic-induced shock (De Socio *et al.*, 2021). Coefficients decrease in significance in the energy and construction sectors and become insignificant for real estate companies.

5.2.2 Size

The intensity of the pandemic varied greatly across firm size classes. Reduction in cash inflows and lack of on-hand liquidity to finance unexpected losses exposed SMEs to profit shortfalls more than other companies (Alekseev *et al.*, 2020; Carletti *et al.*, 2020b). Even in normal times, SMEs navigate difficult conditions in accessing funds and value traditional channels in their relationships with lenders; they show a preference for in-person interactions, which drives them to greater branch and physical banking usage (Nguyen, 2019).
The pandemic might have accelerated the shift away from on-site to digital experiences. Despite lagging behind large firms in digitalization, SMEs might have started valuing the digital content of financial services as the crisis began unfolding. Elements such as convenience and ease of access might have become crucial. To understand whether firm size drove borrowing from digitally advanced banks, we split our sample into four classes.[11]
Table 4 shows that credit from banks with higher IT adoption flowed more to smaller borrowers: bank IT adoption contributed to a greater increase in lending to SMEs compared to large firms (for which

[11]To define firm size categories we use a combination of number of employees and turnover (or total assets).

Table 3 *– IT AND CREDIT GROWTH*

- Heterogeneity by firm sector -

Dependent variable: bank-firm level credit growth			
All			
		$\hat{\beta}$	0.2125** (0.0712)
		Observations	1,518,801
		R^2	0.41600
Most hit sectors			
	Services		
		$\hat{\beta}$	0.2292** (0.0835)
		Observations	476,644
		R^2	0.42487
	Manufacturing		
		$\hat{\beta}$	0.2941** (0.0993)
		Observations	364,444
		R^2	0.36546
Less hit sectors			
	Agriculture		
		$\hat{\beta}$	0.3413** (0.1255)
		Observations	17,676
		R^2	0.39777
	Energy		
		$\hat{\beta}$	0.2869* (0.1434)
		Observations	11,625
		R^2	0.38332
Other sectors			
	Construction		
		$\hat{\beta}$	0.2874* (0.1177)
		Observations	112,955
		R^2	0.43141
	Real estate		
		$\hat{\beta}$	0.1146. (0.0664)
		Observations	53,128
		R^2	0.50489
	Firm controls		No
	Firm-time F.E.		Yes
	Bank controls		Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Coefficients of other regressors are omitted for brevity. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. Observation period t = September 2019, September 2020 and $k = 2$.

the main effect is not significant). In Section 6.1 we take a closer look at aspects related to changes in firm preferences.

Table 4 *– IT AND CREDIT GROWTH*
- Heterogeneity by firm size -

Dependent variable: bank-firm level credit growth		
All		
	$\hat{\beta}$	0.2125** (0.0712)
	Observations	1,518,801
	R^2	0.41600
Micro		
	$\hat{\beta}$	0.3154*** (0.0657)
	Observations	435,649
	R^2	0.50212
Small		
	$\hat{\beta}$	0.3337** (0.1263)
	Observations	386,261
	R^2	0.40309
Medium		
	$\hat{\beta}$	0.2634* (0.1022)
	Observations	160,845
	R^2	0.31152
Large		
	$\hat{\beta}$	0.1039 (0.0920)
	Observations	53,751
	R^2	0.26361
	Firm controls	No
	Firm-time F.E.	Yes
	Bank controls	Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Coefficients of other regressors are omitted for brevity. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. Observation period t = September 2019, September 2020 and $k = 2$.

5.2.3 Riskiness

There is mixed evidence on whether technology helps financial institutions improve credit risk management. While a sizable portion of the empirical evidence in the literature shows that lenders with high digitalization tend to "lax-screen" borrowers, selecting marginal and less creditworthy ones (de Roure *et al.*, 2018; Tang, 2019; Maggio and Yao, 2020), some papers point to the opposite direction challenging the idea that more digitalized lenders cater to riskier clients (Fuster *et al.*, 2018; Jagtiani and Lemieux, 2018).

To examine the variation of our estimates across risk cohorts, we group firms into four classes based on their ex-ante level of riskiness.[12] As can be seen from Table 5, the effect of bank IT adoption on lending increases with firm soundness. Lower values of the coefficients associated with riskier firms suggest that a greater use of technology allowed banks to lend to undertakings which were classified as safer before the outbreak of the pandemic. In Section 6.1 we will discuss further the lending behavior of banks that adopt digital technologies to assess borrowers' creditworthiness.

Table 5 *– IT AND CREDIT GROWTH*
- Heterogeneity by firm risk -

Dependent variable: bank-firm level credit growth		
All		
	$\hat{\beta}$	0.2125** (0.0712)
	Observations	1,518,801
	R^2	0.41600
Risky		
	$\hat{\beta}$	0.1753* (0.0693)
	Observations	183,006
	R^2	0.39548
Vulnerable		
	$\hat{\beta}$	0.1996* (0.0986)
	Observations	397,175
	R^2	0.38684
Solvable		
	$\hat{\beta}$	0.3130*** (0.0885)
	Observations	341,285
	R^2	0.41060
Sound		
	$\hat{\beta}$	0.4352*** (0.1304)
	Observations	104,397
	R^2	0.42527
	Firm controls	No
	Firm-time F.E.	Yes
	Bank controls	Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Coefficients of other regressors are omitted for brevity. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. Observation period t = September 2019, September 2020 and $k = 2$.

[12] Risk classes are defined according to the Cerved Group Credit Score, an indicator which takes discrete values between 1 and 10.

5.2.4 Technology adoption

Another characteristic that could generate heterogeneous responses to the pandemic shock across firms is their degree of technological adoption. On the one hand, assortative matching between highly technological banks and firms may have resulted in high-IT businesses getting more credit when the crisis hit. On the other hand, low tech firms may have been forced to shift their preferences toward digital lenders since health emergency and related restrictions strongly limited physical interactions with financial intermediaries.

To explore how firm innovativeness correlates with bank digitalization, we exploit our unique data on firm investment in IT. Based on the information collected via Invind (see section 2 for a detailed description), we are able to capture the degree of technology adoption for a sub-sample of firms; the survey requires respondents to report the percentage of total investments allocated to advanced technologies in the year. We use this share to classify firms into three groups: low tech firms, with tech-related expenditures below 5 percent of the investments; medium-tech firms when investments in technologies are up to 40 percent; the remaining are flagged as high-tech corporations. Table 6 reports our results. The estimated effects are less significant and decreasing in firms' technological degree. Even if standard errors are much smaller for low tech firms (which are the most numerous in our sample) the coefficient is more than four times higher. The increase in credit from high tech banks (as defined in Figure 3) was 50 per cent higher for low tech firms as compared to high tech firms.[13]. In the next section, we further investigate the possible mechanisms driving this evidence. In particular, we explore the heterogeneity of complementarities between the digital and the physical channels (through branches) in the allocation of credit between firms and across their levels of technology adoption.

To test for differential effects more formally, in Table A.7 in the Appendix we also report the estimates of triple interactions models, where $I_{t \in P} Tech_b$ is interacted with all the different features. The results are very robust across firm types.

[13] Our results confirm that banks' lending policies did not amplify adverse effects during this crisis (Cascarino *et al.*, 2022). We have no evidence that the pandemic accelerated reallocation (Foster *et al.*, 2016) since less innovative firms have not being forced out the credit markets

***Table 6** – IT AND CREDIT GROWTH*
- Heterogeneity by firm technological adoption -

Dependent variable: bank-firm level credit growth		
All		
	$\hat{\beta}$	0.2125** (0.0712)
	Observations	1,518,801
	R^2	0.41600
High tech firm		
	$\hat{\beta}$	0.1085 (0.2170)
	Observations	1,894
	R^2	0.24836
Medium tech firm		
	$\hat{\beta}$	0.3204 (0.3686)
	Observations	3,404
	R^2	0.29739
Low tech firm		
	$\hat{\beta}$	0.4428*** (0.1303)
	Observations	10,943
	R^2	0.27027
	Firm controls	No
	Firm-time F.E.	Yes
	Bank controls	Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Coefficients of other regressors are omitted for brevity. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. Observation period t = September 2019, September 2020 and $k = 2$.

6 Exploring the mechanisms

The preceding section documents robust differences in the evolution of credit during the pandemic across banks with different levels of technology adoption. This evidence is consistent with several theories in finance which deal with the role of digital technologies in banking. In this section we discuss how our results fit into these theoretical frames and we provide additional evidence to distinguish among several potential mechanisms that may determine our main estimates.

Goldfarb and Tucker (2019) point out that digital technologies reduce five types of economic costs (search, replication, transportation, tracking and verification costs) by lowering the price of data storage, computation and transmission. These economic costs map naturally into banking theories and provide a framework to understand the drivers of our results.

On the one hand, search, replication and transportation costs mainly influence the relationship between banks and their clients, or so-called "front-office" activities (Berger, 2003). These costs are mostly related to the industrial organization approach to banking (Degryse *et al.*, 2009): for example, lower search costs tend to increase competition and reduce prices charged by banks to their customers (Zephirin, 1994; Kiser, 2002; Honka *et al.*, 2017); lower transportation and replication costs allow banks to reach more geographically distant clients and to improve the quality of their services.[14] On the other hand, tracking and verification costs are closely related to the selection and the monitoring of clients and risks, suggesting a link with theories of banking intermediation based on asymmetric information issues (Diamond, 1984). In this area, the adoption of digital technologies can improve banks' risk assessment, including credit risk evaluation.

This discussion leads to two potential interpretations of our results. Theories based on the industrial organization approach to banking suggest that the observed higher credit growth for the more technologically banks may be driven by the ability of these banks to provide better digital services to their clients. In particular, during the pandemic firms' managers have realized the importance of having a bank with high quality digital services and directed their demand for credit to these banks. Theories of banking intermediation based on asymmetric information issues suggest that the increase in corporate lending by the more technologically-advanced banks may be driven by their greater ability to select clients and monitor risks using new technologies. For example, during the pandemic, banks that used digital technologies for credit risk assessment could have been able to provide more credit (w.r.t. less technological banks) because they were able to identify sounder borrowers amid heightened uncertainty and increasing potential losses.

We emphasize that these two sets of theories are not mutually exclusive in explaining our findings. Banks are complex organizations with variegated service offerings. While asymmetric information theories are best suited to study credit intermediation (where adverse selection and moral hazard are key issues), industrial organization approaches are specifically useful in the attempt to understand the

[14] More precisely, lower transportation costs increase the set of potential consumers by widening the geography of markets. Lower replication costs imply that banks' can offer their services to more consumers, including those with greater value-added such as investment services provided through robo-advising, with little additional costs.

mechanisms behind services such as deposit taking or payment transactions, which are in turn inextricably tied to credit provision. All in all, both the above mentioned theoretical frameworks can help systematize the evidence we have collected so far.

To identify and disentangle the drivers underlying our main results we first rely on RBLS data. As discussed in detail in Section 2.4, the RBLS allow us to know whether a certain bank offers online credit (either to individuals or firms) or has embarked on R&D projects involving new technologies for credit risk assessment. Exploiting this information we construct two binary variables that capture if the bank channels credit to firms via digital outlets or if it uses new technologies for creditworthiness assessment. We include these two variables in our model and we re-estimate equation 4.1 with the aim of isolating the effects related to the digital content of the banking offer and to the use of technology for client selection and monitoring purposes.

Second, we investigate whether our results change if we add data on bank branches. We define a dummy variable equal to one if the bank has a branch in the same municipality where the firm is located, and we interact it with our measure of technology adoption. This supplementary analysis sheds light on how digital versus physical distribution channels affected the relationship between banks and their clients during the pandemic. For example, a positive coefficient associated to this dummy would suggests that physical distance between the borrower and the lender did play a role in influencing credit allocation as the pandemic progressed throughout 2020, similarly to what Nguyen (2019) has shown in the 2000's.

6.1 Online lending and credit risk assessment

We now use our difference-in-differences approach to compare the evolution of credit at the borrower level using information from RBLS on whether the bank offers online loan facilities to firms and carries on R&D projects that implement new technologies for credit risk assessment.[15] To this end, we augment model (4.1) with two additional dummy variables and their interactions with bank's IT cost ratio. These variables are OC_b, which is equal to one if bank b offers online credit to firms, and CR_b, which is equal

[15]Based on our data, we are not able to calculate the amount of new credit originated via internet nor to know if the bank has assessed the credit risk of a specific borrower using new technologies. Therefore, we use the information in the RBLS survey on the supply of credit lines and trade credit online (see the first panel of Table A.2) as a proxy for the online supply of all credit instruments.

to one if bank b uses digital technologies for credit risk evaluation. More formally, we estimate the following model:

$$log\left(\frac{C_{ib,t}}{C_{ib,t-k}}\right) = \alpha + I_{t\in P}Tech_b(\beta + \beta_{OC}OC_b + \beta_{CR}CR_b) + \delta X_{ib,t} + \theta_{i,t} + \epsilon_{ib,t}. \tag{6.1}$$

$X_{ib,t}$ includes all the covariates described in Section 4 as well as OC_b, CR_b and their interaction with $I_{t\in P}$ and $Tech_b$ (separately).

Our parameters of interest are β_{OC} and β_{CR}, which measure the variation in credit growth following the pandemic shock as a function of the IT level of the bank, the availability of online credit services and the use of technology-based credit risk assessment. Positive β's imply that banks with higher level of IT adoption and supplying credit to firms through the internet or using advanced technologies for borrowers' risk assessment lent more credit during the pandemic.

Table 7 – DIGITAL SERVICES AND CREDIT RISK EVALUATION

Dependent variable: bank-firm level credit growth

Panel A: All firms

	Full period	Phase I	Phase II
$\hat{\beta}$	-0.2060* (0.0797)	-0.0979** (0.0352)	-0.0559 (0.0579)
$\hat{\beta}_{CR}$	0.6480*** (0.1506)	0.4417*** (0.1008)	0.1939* (0.0871)
$\hat{\beta}_{OC}$	1.552*** (0.2123)	1.111*** (0.1849)	0.5971*** (0.1327)
Observations	1,362,703	1,429,632	1,423,975
R^2	0.45254	0.44627	0.43652
Firm controls	No	No	No
Firm-time F.E.	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes

Panel B: Results by firm size for the full period

	Micro	Small	Medium	Large
$\hat{\beta}$	-0.1845** (0.0621)	-0.4825*** (0.0915)	-0.2090 (0.1364)	0.0657 (0.2084)
$\hat{\beta}_{CR}$	0.5733*** (0.1719)	0.7139** (0.2659)	0.4164 (0.2827)	0.0962 (0.3825)
$\hat{\beta}_{OC}$	0.3785** (0.1325)	0.8826*** (0.2063)	0.4821* (0.2185)	0.5811* (0.2869)
Observations	394,639	346,980	142,437	45,806
R^2	0.53757	0.43817	0.34244	0.31099
Firm controls	No	No	No	No
Firm-time F.E.	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes

Panel C: Results by firm risk for the full period

	Sound	Solvable	Vulnerable	Risky
$\hat{\beta}$	-0.2867. (0.1690)	-0.3109** (0.0957)	-0.3716*** (0.0828)	-0.0849 (0.0831)
$\hat{\beta}_{CR}$	0.7312* (0.3662)	0.8187** (0.2893)	0.6014** (0.2164)	0.1661 (0.1925)
$\hat{\beta}_{OC}$	0.6530* (0.2719)	0.5608** (0.1901)	0.7567*** (0.1659)	0.3438* (0.1572)
Observations	92,007	305,782	357,052	162,203
R^2	0.46501	0.44576	0.42260	0.42982
Firm controls	No	No	No	No
Firm-time F.E.	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes

NOTES. OLS estimates of model (6.1). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. In the full period $t =$ September 2019, September 2020 and $k = 2$. In phase I $t =$ June 2019, June 2020 and $k = 1$. In phase II $t =$ September 2019, September 2020 and $k = 1$.

In panel A of Table 7, we estimate equation (6.1) for three time periods as in Section 5: March-June, June-September and March-September.

Our results highlight that both the supply of credit online and the use of digital technologies for credit risk assessment have played a role in determining the evolution of bank credit to firms during the pandemic. Our estimates show that a firm with lending relationships with two banks - one offering credit via digital channels, and one that lends only through its branches - benefited from a greater increase in credit provided by the bank with online lending. This evidence suggests that availing of online loan services influenced firms' demand for credit, even if the two banks had the same level of IT adoption. Similarly, the estimated value of β_{CR} indicates that a firm borrowing from two banks, one of which uses new technologies to assess the risk of prospective borrowers while the other does not, received more credit from the former.

Looking at the full period, our estimates imply that a ten percentage point increase in the IT cost ratio is associated with an increase in credit growth of 15 percent for banks that provide credit online and of 6 percentage points for banks that use technologies for credit risk assessment, compared to a 2 percent increase on average for all banks (see Section 5). We confirm that the estimated effects are larger for the first sub-period, when restrictions to firm activity and individual mobility were severe.

In panel B of Table 7, we present the results by firm size for the entire time span.[16] The evidence provided for the full sample are confirmed, although we observe that OC_b and CR_b are more significant for micro and small firms and no relevant at all for larger companies. These findings are consistent with the interpretation provided above: while large firms typically receive dedicated efforts by the bank's staff and are likely to have secured this individualized contact even during the pandemic, smaller businesses might have found staying in touch with their loan officer harder (Hertzberg *et al.*, 2010) resulting in a stronger use of digital channels. At the same time, exploiting digital technologies for credit risk assessment is likely to improve banks' ability to screen and serve more opaque borrowers, such as small firms (Gambacorta *et al.*, 2019).

Finally, Panel C of Table 7 presents the estimated coefficient for the full period splitting our sample by firm risk category.[17] These results provide two key messages, broadly consistent with our interpretation. First, online credit provision by banks influenced demand for credit by firms across all risk

[16]Results by firm size for the two sub-periods are consistent with the evidence discussed for the entire period.

[17]Firm riskiness, which is based on balance sheet data, is not yet available for the period that followed the onset of the pandemic.

classes. Second, technology played a major role in the evaluation of sounder firms, while it is not significant for riskier firms.

6.2 Geographic proximity

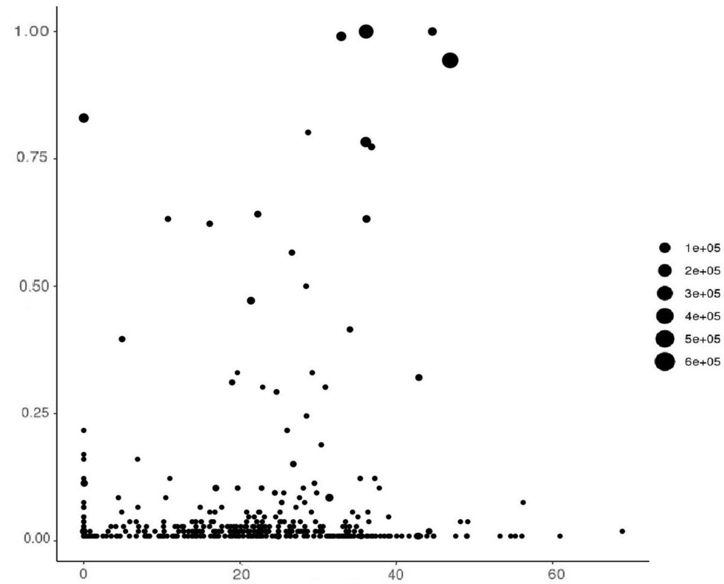
We now study whether distance between banks and firms influenced the effect of technology adoption on credit during the pandemic. Since the work by Kroszner and Strahan (1999) and Petersen and Rajan (2002), several studies have examined whether the diffusion of digital technologies reduces the importance of physical distance in banking. On the one hand, Bofondi and Gobbi (2006), Agarwal and Hauswald (2010) show that the presence of branches in the same area (e.g. province or county) where the borrower is located helps banks collect soft information that is relevant to overcome informational asymmetries and select better clients. On the other hand, branches are shown to be relevant also for the provision of banking services other than credit, such as deposit taking, advisory and investment services (Canhoto, 2004).[18]

In Figure 4 we provide an aggregate picture of the reach of the Italian banking system in terms of physical (through branches) and technological (measured by the IT cost ratio) coverage. On the x-axis we plot our measure of IT adoption, while on the y-axis we report the percentage of provinces in which the bank has at least a branch.[19] The size of the dots represents the asset size of the bank. Interestingly, the figure shows that there are many banks with low physical reach and with very diverse technological levels. Also at comparable technological levels, the dispersion of the physical presence reflects a quite high heterogeneity in banks strategies. In addition, even though big banks tend to have high tech and branch diffusion, overall there is enough variation to study the relative importance of these two dimensions in the credit market during the pandemic.

[18]The fact that the presence of branches helps banks collect soft information on their borrowers (i.e. it is relevant for theories of banking intermediation based on asymmetric information issues) and provide banking services to clients (i.e. it is relevant for the industrial organization approach to banking), implies that geographic proximity does not provide information to disentangle these two sets of theories.

[19]Figure A.1 in the appendix reports the same plot when we consider municipalities instead of provinces.

Figure 4 – PHYSICAL AND DIGITAL REACH



NOTES. x-axis: ICT costs ratio. y-axis: percentage of provinces in which the bank has a branch. Size of dots: total assets in million of euro. All computed in 2020.

To investigate the role of distance in our results, we construct a dummy variable equal to one if the bank has a branch in the same municipality where the firm is located. We estimate the following model,

$$log\left(\frac{C_{ib,t}}{C_{ib,t-k}}\right) = \alpha + \beta I_{t\in P}Tech_b + I_{t\in P}Branch_{ib}(\beta_{Branch} + \beta_{Branch,Tech}Tech_b) + \delta X_{ib,t} + \theta_{i,t} + \epsilon_{ib,t}, \tag{6.2}$$

where matrix $X_{ib,t}$ includes all the covariates described in Section 4 as well as $Branch_{ib}$ and its interaction with $Tech_b$ (without $I_{t\in P}$).

The parameter β_{Branch} captures the role of physical presence on credit growth since the pandemic erupted, while the parameter $\beta_{Branch,Tech}$ measures the variation in credit growth during the same period as a function of both the bank IT level and the presence of a bank branch in the same municipality where the firm is located. A positive estimate of $\beta_{Branch,Tech}$ means that proximity to a physical branch increased the effect of IT on the amount of credit flowing to firm from march 2020 onwards. In Table 8, panel A, we estimate equation (6.1) also for sub-periods.

We find a negative coefficient estimate for the dummy variable that identifies the presence of a bank

Table 8 – IT, BRANCHES AND CREDIT GROWTH

Dependent variable: bank-firm level credit growth

Panel A: All firms

	Full period	Phase I	Phase II
$\hat{\beta}$	0.1228* (0.0614)	0.0754. (0.0450)	0.0592* (0.0281)
$\hat{\beta}_{Branch}$	-0.0643*** (0.0195)	-0.0445** (0.0146)	-0.0347*** (0.0098)
$\hat{\beta}_{Branch,Tech}$	0.2461*** (0.0682)	0.1883*** (0.0505)	0.0982** (0.0340)
Observations	1,518,801	1,598,715	1,592,026
R^2	0.41604	0.40816	0.40142
Firm controls	No	No	No
Firm-time F.E.	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes

Panel B: Results by firm size for the full period

	Micro	Small	Medium	Large
$\hat{\beta}$	0.2108** (0.0690)	0.1575 (0.1042)	-0.0009 (0.0066)	0.0391 (0.0880)
$\hat{\beta}_{Branch}$	-0.0358. (0.0211)	-0.1094*** (0.0310)	-0.3055 (0.2619)	-0.0609 (0.0515)
$\hat{\beta}_{Branch,Tech}$	0.1879* (0.0730)	0.3590** (0.1088)	-0.1338 (0.0998)	0.4127* (0.1733)
Observations	435,649	386,261	160,845	53,751
R^2	0.50215	0.40318	0.31157	0.26376
Firm controls	No	No	No	No
Firm-time F.E.	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes

Panel C: Results by firm tech adoption for the full period

	Low tech firm	Medium tech firm	Large tech firm
$\hat{\beta}$	0.2466 (0.1647)	-0.0665 (0.4501)	0.0586 (0.2579)
$\hat{\beta}_{Branch}$	-0.2600** (0.0980)	-0.0011 (0.2195)	-0.1689 (0.4776)
$\hat{\beta}_{Branch,Tech}$	1.076** (0.3497)	0.7499 (0.7328)	0.2001 (1.511)
Observations	10,943	3,404	1,894
R^2	0.27092	0.29854	0.24878
Firm controls	No	No	No
Firm-time F.E.	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes

NOTES. OLS estimates of model (6.1). Clustered at firm-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. In the full period t = September 2019, September 2020 and $k = 2$. In phase I t = June 2019, June 2020 and $k = 1$. In phase II t = September 2019, September 2020 and $k = 1$.

branch in the same municipality where the firm is located; this demonstrates that credit growth during the pandemic was significantly less for banks that relied only on physical interactions with their borrowers. The difference is quantitatively sizable, given that our estimate for the full period points to a difference of around 6 percentage points between a credit relationship with and without a branch. Our evidence supports the fact that branches alone did not enhance credit origination during the pandemic. Again, the estimated coefficient is larger during the first period of very arduous restrictions.

The coefficient attached to the interaction term (between the branch dummy and the measure of technology adoption) instead is positive and significant in all specifications. Our estimates for the whole period imply that a ten percentage points increase in the IT costs ratio between banks with and without a proximate branch results in a 2.5 percentage points difference in terms of impact, slightly larger than the average effect across all banks. This evidence points to strong complementarity between physical and digital banking during the pandemic.

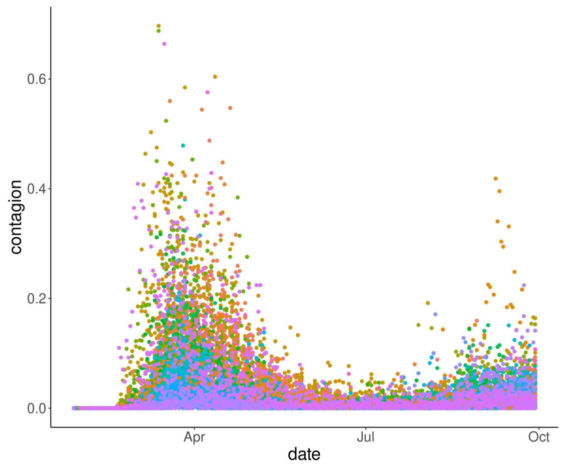
In Panel B we present the results obtained by estimating equation (6.2) for different categories of firms' size. These results confirm the evidence discussed above. Interestingly, large firms, which probably rely less on physical banking, do not drive the results; they do not show the highly significant coefficients that characterize smaller firms.

Panel C reports the results obtained for different categories of firms' tech adoption. These results support the idea that especially low tech firms attached more value to complementarities between the digital and physical channels, which is coherent with a partial change in their preferences during the pandemic crisis: even if they were forced to shift to the more digital lenders, they still rely on a the branch as a value added to the credit relationship.

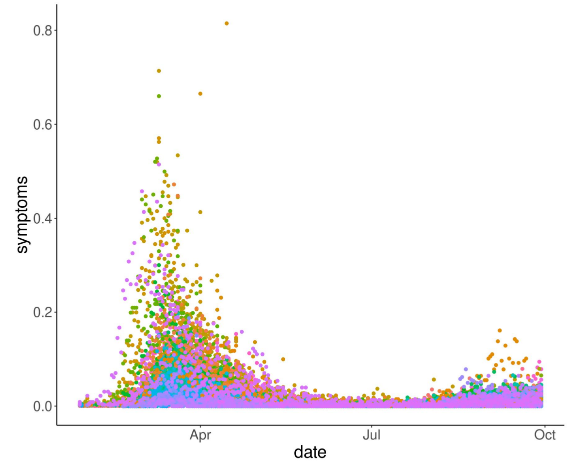
To investigate in more detail the complementarities between digital and physical banking during the pandemic crisis, we exploit the heterogeneity in the pandemic's intensity across Italian provinces. We retrieve data on the intensity of the pandemic from the Italian National Institute of Statistics (ISTAT). In particular, ISTAT publishes official information on the daily number of people hospitalized and those deceased by age category in each Italian province. We aggregate these data at the quarterly-province level and divide them by the number of residents of each province to have proxies for the intensity of the pandemic.

The four panels of Figure 5 report respectively the daily number of recorded cases of contagion, people infected, hospitalizations and deaths for every 1000 inhabitants in each Italian province. Importantly for identification, we can see that some provinces were hit more severely than others with different intensities in the time span considered in our sample.

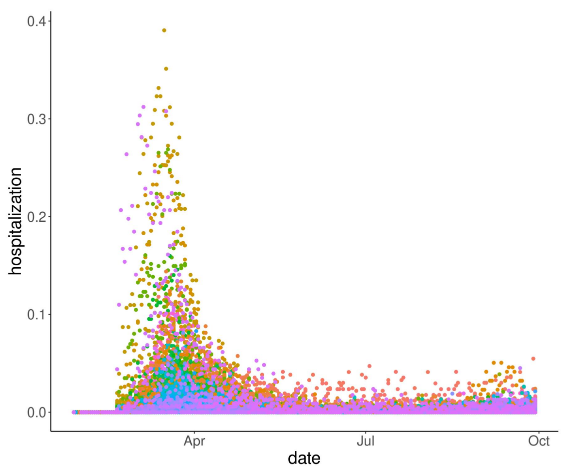
Figure 5 *– THE DIFFERENTIAL EVOLUTION OF THE PANDEMIC CRISIS*
- Heterogeneity across Italian provinces -



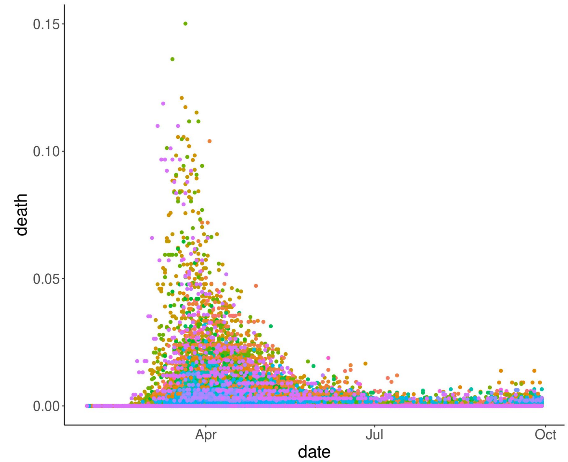
(a) Contagion



(b) Symptoms



(c) Hospitalization



(d) Death

NOTES. x-axis: days in January - September 2020. y-axis: number of events over 1000 inhabitants of the province. Each province is represented in a different color. Data from the Italian National Institute of Statistics (ISTAT)

To test more formally whether the complementarities between the physical and the digital channel were stronger where the pandemic crisis was more intense, we estimate the following model:

$$log\left(\frac{C_{ib,t}}{C_{ib,t-k}}\right) = \alpha + \beta H_{t,p(i)} Tech_b + H_{t,p(i)} Branch_{ib}(\beta_{Branch} + \beta_{Branch,Tech} Tech_b) + \delta X_{ib,t} + \theta_{i,t} + \epsilon_{ib,t}, \tag{6.3}$$

where $H_{t,p(i)}$ measures the intensity of the pandemic crisis at time t in province p, where firm i is located. If it is true that banks relying only on branches were more penalized, while banks using both digital and physical channels granted more credit, we should observe this pattern not only on the extensive (as in Table 8) but also on the intensive margin of the health crisis. Table 9 reports the results when the four indicators used in Figure 5 are used to compute $H_{t,p(i)}$.

***Table 9** – IT, BRANCHES AND CREDIT GROWTH*
- Heterogeneity of the pandemic crisis across Italian provinces -

Dependent variable: bank-firm level credit growth				
Health emergency measure:	Contagion	Symptoms	Hospitalization	Death
$\hat{\beta}$	0.0367*** (0.0094)	0.0630*** (0.0166)	0.1754** (0.0590)	0.6314 (0.5987)
$\hat{\beta}_{Branch}$	-0.0280*** (0.0043)	-0.0345*** (0.0072)	-0.1068*** (0.0274)	-1.307*** (0.2587)
$\hat{\beta}_{Branch,Tech}$	0.1179*** (0.0152)	0.1663*** (0.0252)	0.4759*** (0.0902)	6.006*** (0.8803)
Observations	1,518,801	1,518,801	1,518,801	1,518,801
R^2	0.24582	0.24582	0.24577	0.24578
Firm Controls	No	No	No	No
Firm-time F.E.	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes

NOTES. OLS estimates of model (6.3). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. In the full period $t =$ September 2019, September 2020 and $k = 2$.

We can see that the results on complementarities are largely confirmed using this alternative, and more granular, source of variation. The magnitude of the coefficients increases with the gravity of the health emergency measure considered.

7 Conclusions

In this paper we investigate the role of bank digitalization in corporate credit markets in Italy during the pandemic crisis. We construct a measure of bank digitalization based on IT costs reported in supervisory data and we show its ability to capture the propensity to innovate on several dimensions of the banking services spectrum.

We find that borrowers from more technological banks benefited on average from a larger increase in credit in the months following the pandemic outbreak, especially when restrictions on physical mobility were tighter. Our estimates indicate that a 10 percentage points increase in IT costs (over total costs) is associated with an increase of 2 percentage points in credit growth after the pandemic's onset. The increase, driven by term loans, was most pronounced for smaller and financially sounder companies.

We investigate the potential mechanisms underlying our results, by exploiting detailed information on banks' ongoing innovative projects, availability of digital lending and geolocation for each bank-firm pair. In particular, we study whether the higher credit growth for the more technological banks is driven by the supply of online credit services or by the use of digital technologies for credit risk assessment. We find that both play an important role, but along two different dimensions. Online credit services contributed the most to credit growth in the case of smaller firms, the market segment with the greatest unlocked potential for digitalization. The use of digital technologies for riskiness evaluation also turned out to be an important driver of banks' credit provision during the pandemic.

Indeed, we find that banks relying only on branches showed a significantly lower credit growth. However, borrowers' preferences for branches remained relevant if combined to ever-increasing offer digitalization. Banks that reach customers through both traditional and digital channels showed the highest credit growth after the onset of the pandemic.

These findings provide evidence of the increased relevance of IT adoption in the credit markets during the pandemic and carry several potential implications for both academics and supervisors. First, it will be important to understand better whether the use of digital technologies for banks' internal processes, including credit risk assessment, also affected the quality of credit originated during the pandemic, when new loans reached historically high levels. Second, to determine how the enhanced role of IT may impact banks' production and distribution processes (e.g. amount of outsourcing, branch network) and access to credit, particularly for micro and small firms which may lack adequate digital tools or skills. Finally, it will be important to discern the potential long-lasting effects of IT on consumer preferences, competition and the structure of credit markets.

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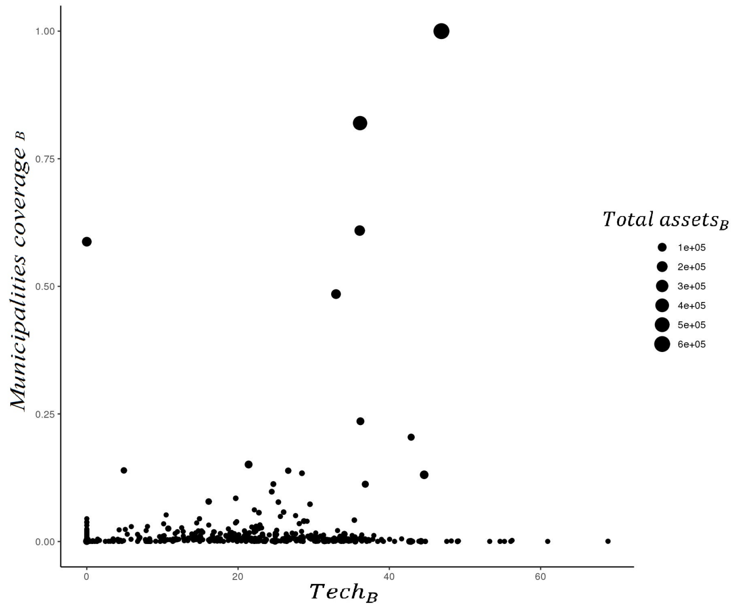
Appendix

Figure A.1 *– PHYSICAL AND DIGITAL REACH*
- Municipalities -



NOTES. x-axis: ICT costs ratio. y-axis: percentage of municipalities in which the bank has a branch. Size of dots: total assets in million of euro. All computed in 2020.

Table A.1 – *VARIABLES DESCRIPTION AND SUMMARY STATISTICS*

Name	Description	N	Mean	St.Dev.	Min	Pctl(25)	Pctl(75)	Max
Credit growth	Logarithm of the ratio between outstanding credit drawn in Q1 and in Q3 at the bank-firm level.	1,520,155	−0.036	0.949	−17.948	−0.189	0.070	16.455
Branch	Dummy variable equal to one if the bank has a branch in the same municipality where the firm is located.	1,996,609	0.636	0.481	0.000	0.000	1.000	1.000
Lending bank								
IT cost ratio	IT costs over total operating costs on yearly basis. IT costs include any expense incurred for (i) the purchase of hardware (e.g. personal computers, servers, mainframes) or software; (ii) gross wages paid to IT specialists (e.g. computer support engineers); (iii) the outsourcing of IT services to external providers.	1,996,609	0.267	0.162	0.000	0.211	0.361	1.000
Tech-based credit risk assessment	Dummy variable equal to one if bank b uses digital technologies for credit risk evaluation. The information in the RBLS survey on the purpose of IT projects (see the last panel of Table A.2) is used in combination with the implementation year, which is set greater or equal to 2019.	1,781,613	0.487	0.500	0.000	0.000	1.000	1.000
Online credit services	Dummy variable equal to one if bank b offers online credit to firms. The information in the RBLS survey on the supply of credit lines and trade credit online (see the first panel of Table A.2) is used as a proxy for the online supply of all credit instruments.	1,781,613	0.283	0.450	0.000	0.000	1.000	1.000
ROE	Return on equity of the bank.	1,994,513	0.005	9.584	−223.879	0.008	0.041	200.469
Cost income ratio	Cost income ratio.	1,994,513	0.692	0.499	−2.509	0.575	0.755	42.434
Fees ratio	Ratio of fee income over total income	1,994,513	0.341	0.176	−14.398	0.320	0.406	3.027
Interest margin ratio	Ratio of interest income over total income	1,994,513	0.498	0.250	−1.799	0.387	0.559	13.889
Loans to non IFM/TA	Share of loans to households and non financial corporations over total assets.	1,996,609	56.156	12.139	0.000	48.367	62.132	95.938
Govt. bonds/TA	Share of government bonds held over total assets.	1,996,609	11.290	9.579	−1.524	4.829	15.843	65.997
Bonds issued/TA	Share of bonds issued by the bank over total liabilities.	1,996,609	13.023	8.679	0.000	5.191	20.643	79.470
Household deposits/TA	Households' deposits over total liabilities.	1,996,609	30.388	13.143	0.000	24.590	36.382	86.278
Deposits SNF/TA	Deposits from non-financial corporations over total liabilities.	1,996,609	11.051	5.208	0.000	9.010	13.847	82.442
log Total assets	Logarithm of total assets.	1,996,609	10.566	2.234	1.331	8.681	12.120	13.313
Significant lender	Dummy variable equal to one if the bank is a significant institution.	1,996,609	0.713	0.453	0.000	0.000	1.000	1.000
Capital ratio	Ratio of common tier 1 capital over total liabilities.	1,996,609	0.116	0.042	−1.579	0.093	0.124	0.690
State guaranteed loans	Share of outstanding loans covered by state guarantees.	1,931,988	0.188	0.253	0.000	0.000	0.422	0.940
Borrowing firm								
Total Assets (TA)	Total assets of the firm expressed in million of euro.	1,399,929	39.557	1,008.596	0.000	1.052	8.651	94,028.137
EBITDA/TA	Earnings Before Interest, Taxes, Depreciation and Amortization over total assets of the firm	1,399,929	0.070	0.895	−652.000	0.031	0.119	15.333
Liquid assets/TA	Liquid assets over total assests.	1,399,929	0.080	0.114	0.000	0.007	0.106	1.000
Leverage	The ratio of financial debt to the sum of financial debt and net equity at book value; values are winsorized at the 99th percentile.	1,058,068	0.568	0.378	0.000	0.330	0.766	2.556
Financial debt	Loans from banks and other intermediaries over total financial debts.	1,022,023	0.580	0.323	0.000	0.318	0.875	1.000
Industry	Industry bins based on six-digit ATECO 2007 classification codes. Categories and frequencies are reported.	agriculture	energy	manufacturing	services	construction	real estate	missing
		22,743	17,31	479,972	650,062	151,521	78,386	596,615
Size	Micro firms: fewer than 10 workers and a turnover (or total assets) not exceeding 2 million; small firms: fewer than 50 workers and a turnover (or total assets) not exceeding 10 million; medium-sized firms: fewer than 250 workers and a turnover (or total assets) not exceeding 50 million (43 million); and large firms are all the remaining firms. Categories and frequencies are reported.	micro	small	medium	large	missing		
		597,058	507,972	215,505	79,524	596,550		
Riskiness	Riskiness classes based on Altman's Z-score. Sound firms: with Z-score between 1 and 2; solvable firms: with Z-score between 3 e 4; vulnerable firms:with Z-score between 5 and 6; Risky firms:with Z-score between 7 and 10. Categories and frequencies are reported.	sound	solvable	vulnerable	risky	missing		
Tech adoption	Firms are grouped into three categories based on their investments in advanced digital technologies (as a percentage of the total investments made in the reporting year). low tech firms: investments in tech below 5 per cent of total investments; medium tech: investments in tech between 5 per cent and 40 per cent of total investments; high tech: investments in tech above 40 per cent	high tech	medium tech	low tech	missing			
		2,573	4,863	15,278	1,973,895			

NOTES. All statistics are computed over firm-bank credit relationships in our sample. Balance sheet variables refer to the end of year statements of 2019.

Table A.2 – RBLS QUESTIONS ON ONLINE SERVICES AND IT USE

Question	Target clientele	Answers
Does the bank offer peer-to-peer payment services online?	Households	Yes/No
Does the bank offer mortgages online?	Households	Yes/No
Does the bank offer consumer credit online?	Households	Yes/No
Does the bank offer investment products (e.g. shares of mutual funds) online?	Households	Yes/No
Does the bank offer credit lines online?	Firms	Yes/No
Does the bank offer trade credit online?	Firms	Yes/No

Question	Answers^{A}
Is the bank currently involved in R&D projects with digital technologies (Yes/No)	
If yes, is it experimenting with **Big Data**?	0; 1; 2; 3; 4.
If yes, is it experimenting with **Artificial Intelligence**?	0; 1; 2; 3; 4.
If yes, is it experimenting with **biometrics or robotics**?	0; 1; 2; 3; 4.
If yes, is it experimenting with **cloud**?	0; 1; 2; 3; 4.
If yes, is it experimenting with **API**?	0; 1; 2; 3; 4.
If yes, is it experimenting with **blockchain**?	0; 1; 2; 3; 4.

Question	Answers^{B}
Indicate the purpose of the R&D projects and the technology used:	
Improving information provided to clients (e.g. summary of expenses)	0; 1; 2; 3; 4; 5; 6; 7.
Client profiling	0; 1; 2; 3; 4; 5; 6; 7.
Cross-selling	0; 1; 2; 3; 4; 5; 6; 7.
Credit risk assessment	0; 1; 2; 3; 4; 5; 6; 7.
Internal efficiency and cost reduction	0; 1; 2; 3; 4; 5; 6; 7.

NOTES. This table presents the survey questions used to analyze the relationship between banks' share of ICT costs and banks' propensity to provide online services, to have R&D projects involving innovative technologies, the purpose of the R&D project and the technology used. ^{A}: 0=No; 1=No, but we plan to start a project within 3 years; 2=Yes, a proof-of-concept study; 3=Yes, the project is at a testing phase; 4=Yes, the project is in production phase. ^{B}: 0=None; 1=Big Data; 2=Artificial Intelligence; 3=Biometric or robotics; 4=Cloud computing or storage; 5=API; 6=Blockchain; 7=Other.

Table A.3 – *BASELINE RESULTS*

	(1)	(2)	(3)	(4)
$\hat{\beta}$	0.1987*** (0.01559)	0.2002*** (0.01465)	0.2125*** (0.01362)	0.2144*** (0.01393)
Firm controls				
Total Assets (TA)	4.525e-09*** (1.343e-09)			
EBITDA/TA	8.287e-05 (0.001123)			
Liquid assets/TA	0.2079*** (0.01252)			
Winsorized leverage	-0.04292*** (0.003295)			
Financial debt	-0.03529*** (0.003925)			
Energy	-0.01843 (0.0143)			
Manufacturing	0.02928** (0.009327)			
Services	0.02553** (0.009284)			
Construction	0.05179*** (0.009834)			
Real estate	0.01272 (0.0109)			
Bank controls				
ROE			0.00023** (8.554e-05)	9.763e-05 (0.0001262)
Cost income ratio			-0.01024** (0.003551)	-0.0006317 (0.003889)
Fees ratio			-0.0459*** (0.004451)	-0.1057*** (0.009547)
Interest margin ratio			-0.009417 (0.007606)	-0.007446 (0.007969)
Loans to non IFM/TA			-0.0002982** (0.0001098)	-0.0001445 (0.0001171)
Govt. Bonds/TA			0.0003275. (0.0001681)	0.000387* (0.0001821)
Bonds issued/TA			0.0004407** (0.0001402)	0.0003495* (0.0001429)
Household Deposits/TA			0.0008198*** (0.0001017)	0.0008909*** (0.0001122)
Deposits SNF/TA			-9.742e-05 (0.0002441)	-0.0001091 (0.000277)
TA			-0.0009883 (0.0009127)	0.001136 (0.001038)
Significant institution			-0.004217 (0.003301)	-0.006805. (0.003636)
Capital ratio			-0.1119*** (0.02223)	-0.1025*** (0.02474)
State gurantee share				0.04953*** (0.006838)
	785,762	1,520,155	1,518,801	1,471,860
	0.0014	0.41552	0.416	0.42535
	Yes	No	No	No
	No	Yes	Yes	Yes
	No	No	Yes	Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Observation period $t =$ September 2019, September 2020 and $k = 2$.

Table A.4 *– SAMPLE COMPOSITION*
- Firms in CADS vs all firms -

		firms in CADS		All firms	
Dependent variable: bank-firm level credit growth					
Credit drawn					
Full period					
	$\hat{\beta}$	0.2481* (0.1153)	0.2485** (0.0858)	0.2002* (0.0874)	0.2125** (0.0712)
	Observations	1,037,478	1,036,506	1,520,155	1,518,801
	R^2	0.40363	0.40424	0.41552	0.41600
Phase I					
	$\hat{\beta}$	0.1500. (0.0776)	0.1642** (0.0611)	0.1303* (0.0598)	0.1468** (0.0496)
	Observations	1,037,478	1,079,689	1,600,118	1,598,715
	R^2	0.40363	0.39535	0.40778	0.40812
Phase II					
	$\hat{\beta}$	0.1112* (0.0467)	0.1107** (0.0365)	0.0862* (0.0369)	0.0926** (0.0317)
	Observations	1,082,032	1,080,997	1,593,454	1,592,026
	R^2	0.38559	0.38627	0.40084	0.40141
	Firm Controls	No	No	No	No
	Firm-time F.E.	Yes	Yes	Yes	Yes
	Bank controls	No	Yes	No	Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. In the full period t = September 2019, September 2020 and $k = 2$. There are slightly more observations than in column (1) of Table 2 because of possible missing data in specific control variables included in column (1) of Table 2.

Table A.5 – *SAMPLE COMPOSITION*
- Firms without multiple relationships -

Dependent variable: bank-firm level credit growth

		(1)	(2)	(3)
Full period				
	$\hat{\beta}$	0.2022*** (0.0142)	0.2002* (0.0874)	0.2125** (0.0712)
	Observations	934,802	2,374,819	2,373,397
	R^2	0.00220	0.57493	0.57528
Phase I				
	$\hat{\beta}$	0.1167*** (0.0117)	0.1303* (0.0598)	0.1468** (0.0496)
	Observations	967,173	2,481,576	2,480,102
	R^2	0.00070	0.56814	0.56841
Phase II				
	$\hat{\beta}$	0.0881*** (0.0112)	0.0862* (0.0369)	0.0926** (0.0317)
	Observations	970,058	2,521,056	2,519,562
	R^2	0.00138	0.55308	0.55351
	Firm controls	Yes	No	No
	Firm-time F.E.	No	Yes	Yes
	Bank controls	No	No	Yes

NOTES. OLS estimates of model (4.1). Clustered at firm-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. In the full period $t =$ September 2019, September 2020 and $k = 2$.

Table A.6 – *ADDITIONAL RESULTS ON SPECIFIC BANK TECHNOLOGIES*

Dependent variable: bank-firm level credit growth									
Big data	0.0604* (0.0279)							-0.0252 (0.0221)	-0.0214 (0.0212)
AI		0.0422* (0.0209)						0.0024 (0.0196)	-0.0082 (0.0206)
Cloud			0.0808*** (0.0239)					0.0005 (0.0216)	0.0016 (0.0210)
Block chain				0.0825** (0.0259)				0.0607*** (0.0175)	0.0590*** (0.0177)
Biometrics & robotics					0.0260 (0.0242)			-0.0287 (0.0232)	-0.0300 (0.0236)
API						0.0331 (0.0251)		0.0214 (0.0208)	0.0249 (0.0192)
Other tech.							0.1327*** (0.0201)	0.1219*** (0.0271)	0.1112*** (0.0257)
$\hat{\beta}$									0.0704 (0.0621)
Observations	1,518,801	1,518,801	1,518,801	1,518,801	1,518,801	1,518,801	1,518,801	1,518,801	0.00204
R^2	0.41614	0.41588	0.41612	0.41615	0.41588	0.41588	0.41655	0.42598	0.42599
Firm controls	No	No	No	No	No	No	No	No	No
Firm-time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

NOTES. Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. All models use the full period $t =$ September 2019, September 2020 and $k = 2$ and use the full set of bank controls and firm-time fixed effects as in column 3 of Table 2.

Table A.7 *– INTERACTIONS WITH FIRMS' TYPES*

- Sector, size, risk and technology -

Dependent variable: bank-firm level credit growth					
Baseline	0.2125** (0.0712)	0.3121* (0.1311)	0.2852*** (0.0575)	0.4392** (0.1340)	0.4731** (0.1511)
Energy		-0.0512 (0.1955)			
Manufacturing		-0.0136 (0.1683)			
Services		-0.0729 (0.1483)			
Construction		-0.0611 (0.1654)			
Real estate		-0.2038 (0.1334)			
Small			0.0599 (0.0968)		
Medium			-0.0061 (0.0891)		
Large			-0.1263 (0.0922)		
Solvable				-0.1194 (0.0859)	
Vulnerable				-0.2435* (0.0947)	
Risky				-0.2710* (0.1110)	
Medium tech firm					-0.2734 (0.3702)
High tech firm					-0.2814 (0.1585)
Observations	1,518,801	1,036,472	1,036,506	1,025,863	16,238
R^2	0.41600	0.40426	0.40426	0.40370	0.27337
Firm controls	No	No	No	No	No
Firm-time F.E.	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes

NOTES. Clustered at firm-time and bank-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. Firm controls are: Total Assets (TA), EBITDA/TA, Liquid assets/TA, Leverage and Financial debt. Bank controls are: ROE, Cost income ratio, Fees ratio, Interest margin ratio, Loans to non IFM/TA, Govt. bonds/TA, Bonds issued/TA, Household deposits/TA, Deposits SNF/TA, log Total assets, Significant lender and Capital ratio. See Table A.1 for a detailed description. In the full period t = September 2019, September 2020 and $k = 2$. The baseline coefficients include the omitted category for each type.

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