The role of banks' technology adoption in credit markets during the pandemic

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Abstract

This paper shows that higher information technology (IT) adoption by banks led to a larger increase in corporate lending in the months following the Covid-19 outbreak in Italy. Examining banks with heterogeneous degrees of IT adoption, we investigate the dynamics of credit and its allocation across firms using a new database with detailed information on bank IT expenditures and propensity to innovate matched with bank-firm level data on credit growth before and during the pandemic. Using a difference-in-differences identification strategy, we find that banks with higher intensity of IT adoption increased their credit more than others during the pandemic. The increase was concentrated in term loans extended to smaller and financially sounder companies; the effect was stronger in the initial phase of tighter restrictions to firm activity and individual mobility, and more significant for undertakings active in the sectors most affected by the shock. We provide evidence that these results are driven by both bank's ability to offer credit entirely on-line and bank's use of digital technologies for creditworthiness assessment. We find that physical proximity between borrowers and lenders remained important for credit provision during the pandemic, but only when combined with high level of IT adoption.

JEL Classification: G21, G22, G23, G24.

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1 Introduction

The surge in the use of Internet and other rapidly advancing technologies (such as artificial intelligence or cloud computing) are opening doors to disruptive innovation in banking. Improvements in information technology (IT) tools and facilities are reshaping the way financial services are supplied and demanded. While new tech players enter the market and leverage their novel operating and business models to gain ground in traditional banking activities (including lending and payment services), incumbents embrace digital transformation to stay ahead of the competition.

In the Italian financial landscape, technology adoption is happening swiftly but its development across banks still displays heterogeneous patterns (Bank of Italy, 2019). Large intermediaries are fully committed to digitalization, but also smaller banks are making significant advancements to stay abreast of technology trends. In their attempt to keep up with fast-paced innovation, all banks face a number of challenges related, for example, to legacy systems, investments in employees' know-how and technological skills and changes in the organizational structure.

The Covid-19 pandemic has presented banks with an opportunity to assess their digital prowess. The risk of infection and adherence to social distancing measures forced financial institutions to rethink their workforce strategy and to revisit a distribution model that could no longer fit customer needs. The pandemic-induced crisis provides an ideal setting for assessing at which stage banks are on the digital maturity scale and which effects such positioning has on lending behavior.

Several support measures (including a broad programme of public loan guarantees) have been adopted to maintain the ability of banks to provide funds to the real economy (IMF, 2020). Such interventions resulted in a sizeable expansion in credit (Cascarino *et al.*, 2021; Socio *et al.*, 2021), which has been generalized across intermediaries and firms. As lending grew due to the public policies put in place, banks had to deal with a significant increase in the demand for business financing and may have increasingly relied on their technological capabilities to process applications, administer and originate loans.

In this paper we explore the role of bank digitalization in driving credit growth to the corporate sector during the pandemic. Examining banks with heterogeneous degrees of IT adoption, we investigate the dynamics of credit and its allocation across firms. To this end, we introduce a new database with detailed information on bank IT expenditures and propensity to innovate. We merge these data with bank-firm level information on credit growth from the Italian Credit Register before and during the pandemic. We follow the identification strategy proposed by Khwaja and Mian (2008), comparing the change in credit to the same firm that borrows from banks with different levels of IT expenditures.

We find that higher intensity of IT adoption by banks led to a larger increase in credit growth in the months following the Covid-19 outbreak in Italy. The increase was concentrated on 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 to firm activity and individual mobility were tighter) and spanned across industries, but was more significant for undertakings in the sectors most affected by the shock. All in all, these results provide causal evidence that banks with higher level of IT adoption originated a larger share of new corporate lending following the economic impact of the health crisis and authorities' measures to support the flow of credit to the real economy.

There are several possible explanations for these findings. First, we investigate whether the higher credit growth associated to more technologically-advanced banks was driven by their ability to offer credit entirely online or by their use of digital technologies for creditworthiness assessment. Second, we examine the role of geographical nearness to the lending bank(s) in influencing firm preference toward a specific type of distribution channel (physical versus digital). We find that companies experiencing higher credit growth during the pandemic were those that borrowed from banks with online lending services and those clients of banks with technology-based credit risk assessment. Physical proximity to the lender turned out to be still important, but only when offline and online channels coexist and complement each other.

Our analysis contributes to a strand of research on the effects of technology on banking outcomes. Prior studies have investigated the relationship between IT investments, bank value (Anderson *et al.*, 2006), profitability (Beccalli, 2007; Hernando and Nieto, 2007; Scott *et al.*, 2017) and productivity (Chowdhury, 2003; Casolaro and Gobbi, 2004; Martin-Oliver and Salas-Fumas, 2007; Koetter and Noth, 2013). From a broader perspective, Vives (2019) and Carletti *et al.* (2020a) examine the ongoing and potential impact of technological advancements on bank business models at large.

This paper also relates to the rapidly growing literature on the consequences of FinTech for credit allocation. Existing research has focused on two core issues: understanding the drivers that underlies access to credit intermediated by technology-enabled lenders (Claessens *et al.*, 2018; Haddad and Hornuf, 2018; Cornelli *et al.*, 2020; Barkley and Schweitzer, 2021) and assessing the benefits stemming from the use of digital technologies in the process of borrower screening (Fuster *et al.*, 2018; Tang, 2019; Maggio and Yao, forthcoming). However, all these empirical studies have looked outside the traditional banking sector, investigating the activity of new players such as crowdfunding platforms or BigTechs.

Our analysis departs from the majority of past research by focusing on banks and on their lending activity in both normal and crisis times. Closest to us, Core and De Marco (2021) shows that banks' level of digitalization, proxied by clients' ratings of lenders' 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 originated under the US Small Business Administration Paycheck Protection Program (SBA PPP). Our results are consistent with the findings of these papers, contributing to the growing evidence on the importance of digital technologies for credit provision during the pandemic, and extend these studies in several directions. In particular, our measure of bank IT adoption captures a wider range of innovative features, including online lending services and technology-based credit risk assessment. Therefore we can analyze several mechanisms (related to both the use of Internet for the interaction with clients and the organization of banks' internal processes, such as credit risks assessment) through which bank IT adoption improved the supply of credit. Furthermore, using borrower-level data on the universe of loans extended to firms in Italy, we are able to investigate how these effects vary with firm characteristics. Our paper also complements the results in Pierri and Timmer (2020), who highlight that bank intensity of IT adoption can affect credit quality by showing that it 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 artificial intelligence and other digital technologies for credit risk assessment (Baesens *et al.*, 2015; Albanesi and Vamossy, 2019; Gambacorta *et al.*, 2019; Berg *et al.*, 2020). We provide evidence that the use of new technologies for credit risk evaluation helped increase credit growth during the pandemic.

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), which broadly finds that branch closeness to borrowers eases soft information gathering and helps improve loan quality. Our results suggest that bank branches positively affected credit growth only when they operated alongside an online channel, in a blend of physical and digital presence that turned 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 for our main findings. The final section concludes.

2 Data

We construct a novel dataset of firm-bank relationships by drawing information from five main sources. The Italian Credit Register (CR), maintained by the Bank of Italy, contains individual data on resident borrowers with outstanding debt exposure above 30,000 euros toward credit institutions (banks and other specialized financial intermediaries). 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, or the type of contract). Loans listed in the CR include those backed by account receivables, fixed-term loans, and overdraft facilities (revolving credit lines).

The Company Accounts Data System (CADS), managed by the Cerved group, and the supervisory reports collected by the Bank of Italy provide accounting data for Italian non-financial companies and banks, respectively. The former stores information on firm size, riskiness, financial structure, sectoral affiliation, and geographic location; the latter supplies consolidated and unconsolidated balance-sheet data on all Italian banks and the information used to construct the measure of IT adoption described in section 2.1.[1] 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. Finally, we obtain information on bank digitalization from the Regional Bank Lending Survey (RBLS). RBLS is conducted on a yearly basis over a large sample of Italian banks representing 90 per cent of the deposits of the whole banking system. Since 2017 RBLS includes a set of questions that specifically assesses the status of digital transformation of the respondents.

To control for unobservable demand factors, following the identification strategy described below, we restrict the analysis to firms that borrowed from multiple banks. To obtain our baseline sample, we merge credit register data with balance sheet data available for banks and firms. This matching yields to a sample of 463 banks and 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 all variables used is provided in Table A.1.

2.1 Measuring banks' level of IT adoption

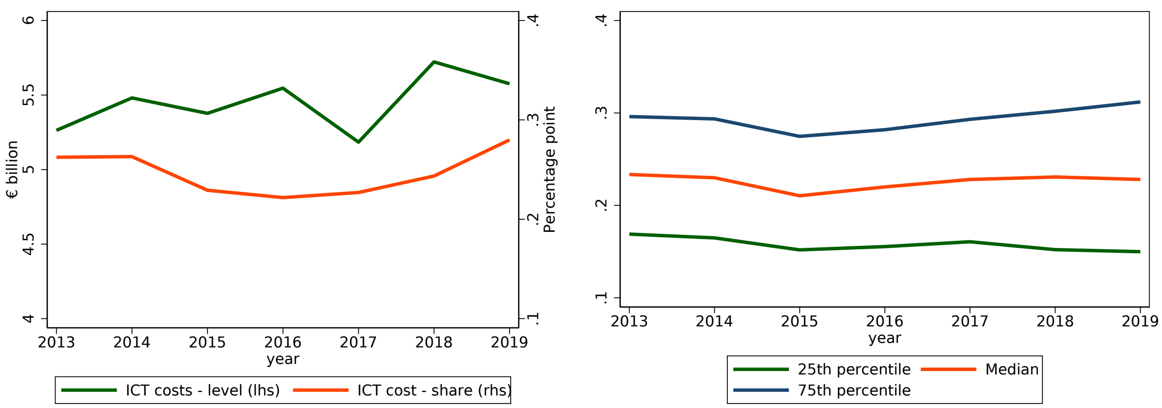
We measure banks' level of IT adoption using costs for the automatic processing of data reported in banks' income statements. These costs include a variety of IT-related expenses, and in particular expense incurred for (i) the purchase of hardware (e.g. personal computers, servers, mainframes) or software; (ii) gross wages paid to IT specialists (e.g. computer support engineers); (iii) the outsourcing of IT services to external providers. The richness of our data thus gives us a comprehensive picture of the technological level of the bank and allows us to compare banks with different IT strategies.[2] To

[1] In our analysis we use unconsolidated data for two reasons. First, borrowers benefit from the quality of digital services provided by their (individual) bank, not by the whole banking group. The latter 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 use of innovative technologies for credit risk assessment) within banking groups.

[2] 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.

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. IT costs to total operating costs began to increase 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 slightly grown 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.

***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 25^{th} percentile, the median and the 75^{th} 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 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 adopotion 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 products and services online and are 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 underline them and which is the purpose (for instance, improving consumer profiling or cross-selling). [3] 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 statis-

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

tically significant for the services offered online to households. It is positive also 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 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 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 report to have adopted these technologies.

All in all, these results suggest that larger shares of IT costs are strongly related to both a higher likelihood of offering digital services and engaging in innovative processes.

3 Lending during the pandemic

Italy has been one of the first countries in the world to be hit by Covid-19. As the pandemic outbreak began to escalate, authorities made increasing efforts to tackle the public health crisis caused by the disease. At the beginning of March 2020 the Italian government enacted drastic rules aimed at fighting the rapid surge in positive cases confirmed across the country. 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 except supermarkets, pharmacies, postal and banking service providers. 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.

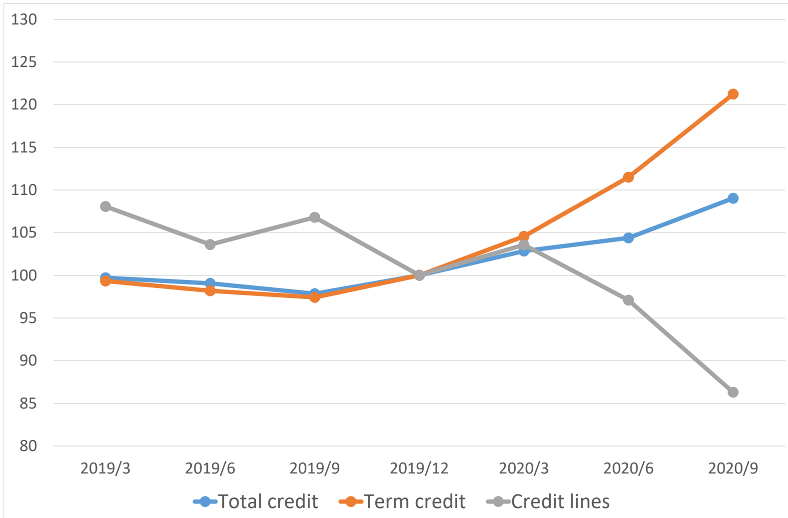
Lockdowns and social distancing reframed the way individuals worked, consumed and interacted. In the attempt to adapt to the unfolding situation, firms and individuals were forced to switch to online channels for delivering and buying products, respectively. Restrictions on physical movement resulted 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[4], and this change spilled over other sectors. Remote work increased sharply: 14 per cent of the 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). Like all industries, the financial sector has been impacted. Banks stayed at the forefront in accommodating clients' requests as they mutate in response to Covid-19 spread. On the consumer segment, while not being able to visit their local bank branch in person, individuals continued to need assistance to deposit checks, pay bills, transfer funds or apply for mortgages. Specularly, non-financial corporations increased their recourse to bank borrowing in order to face urgent liquidity needs, plausibly valuing more rapid and easy access to credit (and complementary services) provided via Internet.

Lending 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 has been driven by a surge in term loans during the second and third quarters of the 2020.

Banks processed a larger-than-usual number of loan applications, boosted by the introduction of a broad programme of public guarantees (Bank of Italy, 2020).

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

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

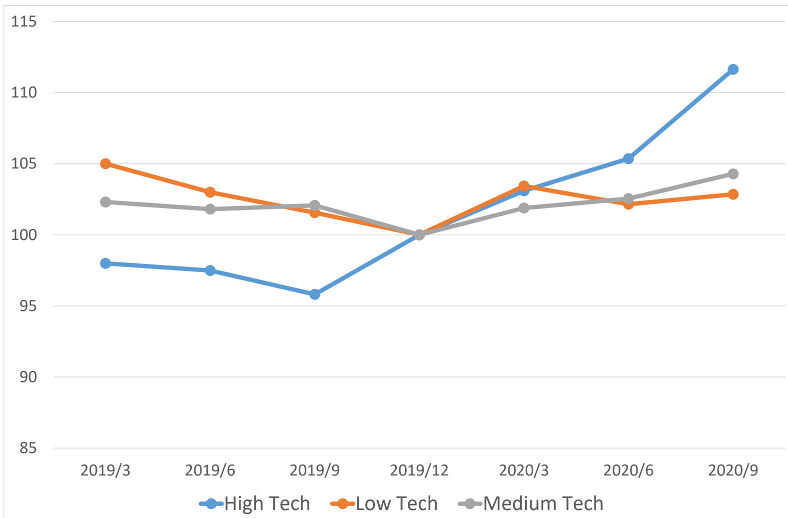
As customers confined at home rapidly turned to digital touchpoints as their primary way of interacting, banks adjusted their business activity by switching in-branch visits to appointment-only, by rerouting financial transactions over the internet and by reinforcing virtual interactions.[5] However, 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 experienced an increase in the amount of credit, lending by more

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

technology-based banks rose at 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 the growth recorded by their peers.

***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.

4 Empirical strategy

Our goal is to understand the causal effect of banks' IT level on firms' credit during the pandemic crisis. To this end, we use a difference-in-differences approach in which the pandemic is the treatment, whose effect on firm credit depended on bank level of IT.[6] The treatment effect is identified using within-firm variation, by comparing changes in credit that the same firm borrowed from banks with different

[6] An equivalent but slightly less intuitive way of thinking about our empirical approach is that the treatment variable is the *combination* of the pandemic and the level of IT of banks. In other words, bank's IT level is akin a measure of treatment intensity, whereby firms borrowing from banks with higher levels of IT have been less impacted by the shock. This interpretation would be consistent with the empirical specification described below in equation (4.1). Given that we do not have randomized or partial population treatments (because the pandemic shock impacted every firm and bank), our estimates cannot be interpreted as pure treatment effects. However, they can inform on the different effect of the shock across banks' IT levels.

levels of IT. The inclusion of firm-time fixed effects, in line with Khwaja and Mian (2008), controls for possible confounding factors related to the *average* change in amount of credit of the firm across different lenders.[7]

More formally, our main specification has 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 $C_{ib,t}$ represents credit drawn by firm i from bank b at time t, 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 firm controls (which include $Tech_b$ and the dummy variable $I_{t \in P}$), $\theta_{i,t}$ represent firm-time fixed effect, $\epsilon_{ib,t}$ is the error component.

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.

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 more technological banks gave more credit during or after the great lockdown.

The matrix $X_{ib,t}$ includes multiple bank characteristics obtained from supervisory reports. 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

[7]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.

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. Finally, we control for bank business model and efficiency by including the interest margin and the cost-income ratio. This allows us to estimate the marginal effect of the IT level during the pandemic controlling for multiple confounding factors stemming from bank characteristics. 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. Finally, $X_{ib,t}$ also includes $Tech_b$ and $I_{t \in P}$, i.e. the levels (not interacted) of our variables of interest.

In this application, including $\theta_{i,t}$ controls for the average change in firm's credit across lenders in period t but it does not rule out the possibility that our results may be driven by bank-specific demand factors, such as changes in firms' preferences for banks with high quality digital services. For example, it is possible that a firm whose credit has increased by 10 percent on average across two lenders decided to increase more his demand from the most technological lender because during the pandemic the firms' managers have realized that having a lender that provides digital services with higher quality might be important in case of a second lockdown (i.e. the net benefits of borrowing from a high-tech bank may have increased because of the shutdown).[8] In this example, we would observe a larger increase in the credit provided by the most technological lender driven by firm's demand, even after controlling for the average change in firm's amount of credit across lenders. For this reason, part of the analysis presented below will extend the basic model presented in equation (4.1) to disentangle the role played by demand factors (e.g. changes in firms' preferences for digital services) and supply factors (e.g. impact of IT on banks internal processes, such as credit risk assessment) after the advent of the pandemic.

This is possible because of two unique ingredients in our analysis. First, the outbreak of the Covid-19 pandemic in Italy represents an ideal setting. The shock was large and unexpected (also by the

[8] We show below that even controlling for firm-time fixed effects, credit growth can vary as a function of demand factors, like preferences over more digital services. Even if we do not formally model substitution across same-borrower credit relationships, which would require significant innovations in the estimation procedure, our evidences highlight some shortcomings of the common assumptions made in the Khwaja and Mian (2008) approach, in which the firm fixed effects are supposed to control for every variation on the demand side. The development of a methodology that allows to estimate substitution effects has a wider scope, we leave it for future research. For the empirical purposes of this paper, our reduced form estimates are reliable as long as we capture the relevant dimension, the IT level of the bank, correctly.

Italian banks), and it caused dramatic changes in the business environment over a few weeks. Italy was the first Western country to be affected by the pandemic and the policy measures during COVID-19 could neither be known to nor anticipated, oppositely to the subsequent spread of the pandemic in other industrialized countries. Banks were key players in supporting the real economy and had to respond promptly but while some processes could adjust rapidly, others could not. The supply of online services requires investments and organizational changes, banks can not adapt in the short term, so the new equilibrium outcome emerges from variation in the preferences over digitalization from the demand side. On the contrary, banks using IT for credit risk assessment can react immediately and differently to the shock, changing the equilibrium from the supply side. Second, an aggregate measure of IT adoption can not help disentangle these two driving forces. Having detailed data on IT projects allows us to accurately capture the relevant heterogeneity across banks in both these two dimensions. We interact our IT measure with dummies capturing online loan facilities offered to firms and the use of new technologies for credit risk assessment.

It is worth noting that the great lockdown and more generally the Covid-19 shock impacted every firm and every bank in our sample (although to different extents), meaning that our treatment is not a "partial population" shock.[9] Our specification studies variations due to pre-treatment heterogeneity across banks, namely the degree of IT adoption. This level of pre-treatment heterogeneity across banks is arguably exogenous with respect to the treatment and provides an interesting setting 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, investment and costs and cannot be built up in few weeks or closely around. Therefore, banks could not have reacted immediately to the shock implied by the pandemic and adapted their IT equipment or supply structure rapidly (e.g. the network of branches). Branches configuration and technology adoption are sticky processes that the pandemic may change, but not in the short time span we are examining here. All these arguments suggest that our measure of banks' technology adoption represents a good proxy for the level of IT with which banks had to face

[9] A large part of empirical research in banking relies on a partial population treatment approach, in which only a portion of the population receive the treatment, and estimate treatment effects assuming that the untreated are not impacted. In this framework instead, the treatment is received by everybody. So instead of estimating an average treatment effect, we focus on the differential effect of a generalized treatment along the IT dimension.

the Covid-19 pandemic.

5 Main results

5.1 Baseline estimates

Table 2 presents our baseline results for the effects of IT adoption on credit growth during the pandemic crisis. We first show estimated effects 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.

We find positive and statistically significant effects of IT adoption across all specifications. The estimated coefficient is stable across different specifications and always significant at 1 percent. Our results suggest that banks with higher IT levels have increased corporate lending significantly more than other banks. The estimated coefficients associated with our measure of IT adoption are larger in magnitude for the first sub-period, the one that goes from March to June of 2020; in other words, our evidence points to the role of digitalization being critical in boosting the provision of credit when restrictions to firm activity and individual mobility were tighter.

Our estimates from column (3) imply that a 10 percentage points increase in the IT costs' ratio, which is roughly equivalent to the interquantile range of the distribution of IT costs' ratio in 2019, is associated with an increase of 2 percent in credit growth over the full period. These results also hold when we control for credit demand and for a set of bank-level characteristics (including size and capitalization). In order to account for the surge in loan demand due to public intervention, we also include a control variable that measures the share of state-guaranteed loans held by each bank. We report the estimated coefficients of our regression model for the full period in the first three columns of Table A.3 in the appendix.[10]

[10]Column (4) of Table A.3 augments column (3) with the bank's share of state loan-guarantee.

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

Dependent variable: bank-firm level credit growth				
		(1)	(2)	(3)
Full period				
	$\hat{\beta}$	0.1987*** (0.01559)	0.2002*** (0.01465)	0.2125*** (0.01362)
	Observations	785,762	1,520,155	1,518,801
	R^2	0.0014	0.41552	0.416
Phase I				
	$\hat{\beta}$	0.1123*** (0.01277)	0.1303*** (0.01371)	0.1468*** (0.01143)
	Observations	816,837	1,600,118	1,598,715
	R^2	0.00057	0.40778	0.40812
Phase II				
	$\hat{\beta}$	0.08664*** (0.01233)	0.08625*** (0.009594)	0.09261*** (0.01027)
	Observations	814,027	1,593,454	1,592,026
	R^2	0.00098	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 level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. 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 $k = 1$.

5.2 Firm Heterogeneity

5.2.1 Industry

We now investigate whether high-tech lenders provide more credit to some corporate borrowers than others. Since Italy has 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. Effects of IT adoption on credit growth are more significant in hardest-hit sectors; that is, manufacturing and services characterized by higher falls in the value added output as a consequence of the pandemic-induced shock (De Socio *et al.*, 2021). Coefficients decrease in significance across other sectors, while we find an insignificant effect for real estate companies.

Table 3 *– IT AND CREDIT GROWTH*
- Heterogeneity by firm sector -

Dependent variable: bank-firm level credit growth			
All			
		$\hat{\beta}$	0.2125*** (0.01362)
		Observations	1,518,801
		R^2	0.416
Most hit sectors			
	Services		
		$\hat{\beta}$	0.2319*** (0.02234)
		Observations	484,549
		R^2	0.42468
	Manufacturing		
		$\hat{\beta}$	0.2971*** (0.0281)
		Observations	368,541
		R^2	0.3651
Less hit sectors			
	Agriculture		
		$\hat{\beta}$	0.3424* (0.1344)
		Observations	17,827
		R^2	0.39464
	Energy		
		$\hat{\beta}$	0.2851* (0.1148)
		Observations	11,697
		R^2	0.38536
Other sectors			
	Construction		
		$\hat{\beta}$	0.2917*** (0.05641)
		Observations	114,865
		R^2	0.4308
	Real estate		
		$\hat{\beta}$	0.1133. (0.06419)
		Observations	53,727
		R^2	0.50002
	Firm controls	No	No
	Firm-time F.E.	Yes	Yes
	Bank controls	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. Coefficients of other regressors are omitted for brevity. Observation period t = September 2019, September 2020 and $k = 2$.

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 perilous conditions in accessing funds and value traditional channels to reach their 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 on 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 the main effect is not significant). In Section 6.1 we take a closer look at aspects related to changes in firm preferences.

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, forthcoming), some papers point to the opposite direction challenging the idea that more digitalized lenders cater for 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 to 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.

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

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

Table 4 *– IT AND CREDIT GROWTH*

- Heterogeneity by firm size -

Dependent variable: bank-firm level credit growth		
All		
	$\hat{\beta}$	0.2125*** (0.01362)
	Observations	1,518,801
	R^2	0.416
Micro		
	$\hat{\beta}$	0.3134*** (0.02837)
	Observations	444,615
	R^2	0.50171
Small		
	$\hat{\beta}$	0.337*** (0.03137)
	Observations	390,605
	R^2	0.4023
Medium		
	$\hat{\beta}$	0.2714*** (0.03997)
	Observations	161,911
	R^2	0.31187
Large		
	$\hat{\beta}$	0.107. (0.06225)
	Observations	54,122
	R^2	0.26242
	Firm controls	No
	Firm-time F.E.	Yes
	Bank controls	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. Coefficients of other regressors are omitted for brevity. 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 - by lowering the cost of data storage, computation and transmission - reduce five types of economic costs, related to search, replication, transportation, tracking and verification. These costs map naturally into banking theories and provide a framework to understand the drivers of our results.

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

Dependent variable: bank-firm level credit growth		
All		
	$\hat{\beta}$	0.2125*** (0.01362)
	Observations	1,518,801
	R^2	0.416
Risky		
	$\hat{\beta}$	0.1909*** (0.03799)
	Observations	179,239
	R^2	0.39809
Vulnerable		
	$\hat{\beta}$	0.2124*** (0.02517)
	Observations	393,765
	R^2	0.3845
Solvable		
	$\hat{\beta}$	0.2944*** (0.0287)
	Observations	338,577
	R^2	0.40708
Sound		
	$\hat{\beta}$	0.4292*** (0.08214)
	Observations	105,557
	R^2	0.42409
	Firm controls	No
	Firm-time F.E.	Yes
	Bank controls	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. Coefficients of other regressors are omitted for brevity. Observation period t = September 2019, September 2020 and $k = 2$.

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, 202; 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.[13] 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 as-

[13]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.

sessment, including credit risk evaluation.

This discussion leads to two potential interpretations for our results. Theories based on the industrial organization approach to banking suggest that the observed higher credit growth for more technological 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 have directed their demand of credit to these banks. Theories of banking intermediation based on asymmetric information issues suggest that the increase in corporate lending for more technological banks may be driven by their higher 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 mechanisms behind services such as deposit taking or payment transactions, which are in turn inextricably tied to credit provision. All in all, both the abovementioned theoretical frameworks can help systematize the evidence we 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 2.1, 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

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. However, we can still 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.[14]

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 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.

[14] 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.

Table 6 – DIGITAL SERVICES AND CREDIT RISK EVALUATION

Dependent variable: bank-firm level credit growth

Panel A: All firms

	Full period	Phase I	Phase II
$\hat{\beta}$	-0.206*** (0.02834)	-0.09794*** (0.02329)	-0.05587* (0.02352)
$\hat{\beta}_{CR}$	0.648*** (0.05099)	0.4417*** (0.04129)	0.1939*** (0.0425)
$\hat{\beta}_{OC}$	1.552*** (0.07548)	1.111*** (0.06198)	0.5971*** (0.06369)
Observations	1,362,703	1,429,632	1,423,975
R^2	0.45254	0.44627	0.43652

Panel B: Results by firm size for the full period

	Micro	Small	Medium	Large
$\hat{\beta}$	-0.1897*** (0.05497)	-0.4683*** (0.06561)	-0.2011 (0.1162)	0.02973 (0.2373)
$\hat{\beta}_{CR}$	0.561*** (0.1053)	0.7053*** (0.1168)	0.4028* (0.1812)	0.11 (0.3332)
$\hat{\beta}_{OC}$	0.4007*** (0.0972)	0.8765*** (0.1131)	0.482** (0.178)	0.6071. (0.322)
Observations	402,693	350,934	143,444	46,135
R^2	0.53717	0.43724	0.34279	0.31053

Panel C: Results by firm risk for the full period

	Sound	Solvable	Vulnerable	Risky
$\hat{\beta}$	-0.2928 (0.1784)	-0.3117*** (0.08022)	-0.3628*** (0.06236)	-0.0598 (0.07244)
$\hat{\beta}_{CR}$	0.7285* (0.3386)	0.8508*** (0.1403)	0.5827*** (0.1114)	0.1049 (0.1298)
$\hat{\beta}_{OC}$	0.6265* (0.3098)	0.5366*** (0.1335)	0.7797*** (0.1054)	0.362** (0.1224)
Observations	93,038	303,589	353,800	162,203
R^2	0.46388	0.44241	0.42027	0.42982

NOTES. OLS estimates of model (6.1). All specifications include firm-time fixed effects and bank controls. Clustered at firm-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. 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 6, 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 that offers credit via digital channels, one that lends only through its branches - benefited from higher increase in credit provided by the bank with an online lending. This evidence suggests that availing online loan services influenced firms' demand for credit, even if the two banks had the same level of IT adoption.[15] 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 points increase in the IT costs 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 6, 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 harder staying in touch with their loan officer (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 6 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 classes. Second, technology played a major role in the evaluation of sounder firms, while it is not significant for riskier firms.

[15] At a first glance, it could seem counterintuitive that heterogeneity on the supply side triggers variation from the demand side. In this special setting, the unexpected pandemic shock left the supply of online services constant but changed the preferences on the demand side. Given that the supply of online services require investments and organizational changes, banks could not adapt in the short term, so the new equilibrium outcome emerges from variation in the demand.

[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 tha followed the onset of the pandemic.

6.2 Geographic proximity

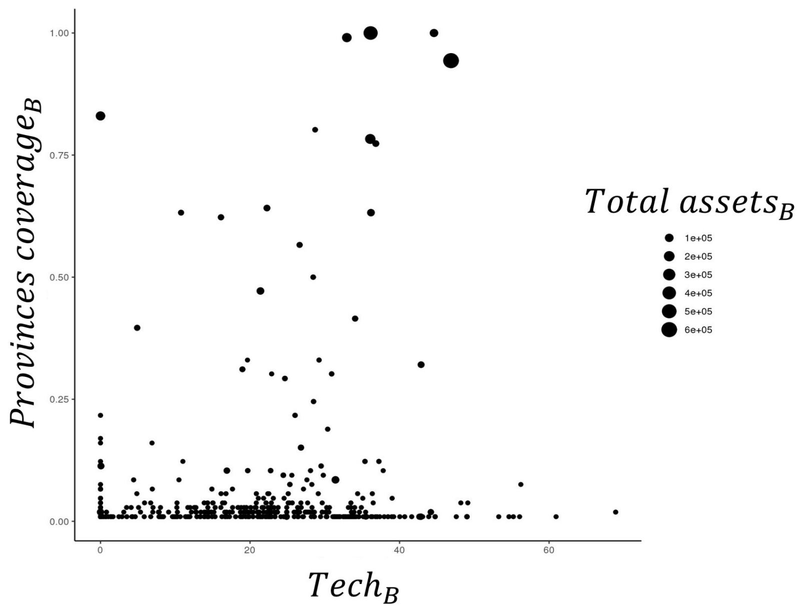
We now study whether distance between banks and firms influenced the effect of technology adoption on credit during the pandemic. Since the work by Kroszner and Strahan (1999) and Petersen and Rajan (2002), several studies have examined whether the diffusion of digital technologies reduces the importance 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 that the Italian banking system has in terms of physical (through branches) and technological (measured by the IT costs 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 width of each dot 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 7, 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 7 *– 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*** (0.01646)	0.07536*** (0.01352)	0.05924*** (0.01361)
$\hat{\beta}_{Branch}$	-0.06431*** (0.008164)	-0.04453*** (0.006732)	-0.03468*** (0.006698)
$\hat{\beta}_{Branch,Tech}$	0.2461*** (0.02814)	0.1883*** (0.02321)	0.0982*** (0.02314)
Observations	1,518,801	1,598,715	1,592,026
R^2	0.41604	0.40816	0.40142

Panel B: Results by firm size for the full period

	Micro	Small	Medium	Large
$\hat{\beta}$	0.2034*** (0.04226)	0.1658*** (0.0432)	0.1948*** (0.04899)	0.04214 (0.08016)
$\hat{\beta}_{Branch}$	-0.03694* (0.01593)	-0.1068*** (0.01796)	-0.0904** (0.02918)	-0.05768 (0.05985)
$\hat{\beta}_{Branch,Tech}$	0.1956*** (0.05829)	0.351*** (0.06489)	0.2415* (0.1004)	0.4071* (0.1982)
Observations	444,615	390,605	161,911	54,122
R^2	0.50173	0.40238	0.31192	0.26257

NOTES. OLS estimates of model (6.1). All specifications include firm-time fixed effects and bank controls. Clustered at firm-time level standard errors are reported in brackets. *, **, *** indicate statistical significance at the 10, 5 and 1 percent levels. 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 smaller 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 heavy restrictions.

The coefficient attached to the interaction term (between the branch dummy and the measure of technology adoption) is instead 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 just discussed above.

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 onset. The increase, driven by term loans, was prominent 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 per each bank-firm pair. In particular, we study whether the higher credit growth for 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 turned out also 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. Indeed, banks that reach customers through both traditional and digital channels showed the highest credit growth after the pandemic.

These findings provide evidence of the increased relevance of IT adoption in retail credit markets during the pandemic and carry several potential implications for both academics and supervisors. First, it will be important to better understand whether the use of digital technologies for banks' internal processes, including credit risk assessment, has also affected the quality of credit originated during the pandemic, when new loans reached historically high levels. Second, the enhanced role of IT may impact on banks' production and distribution process (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 better understand the potential long-lasting effects of IT on consumer preferences, competition and the structure of credit markets.

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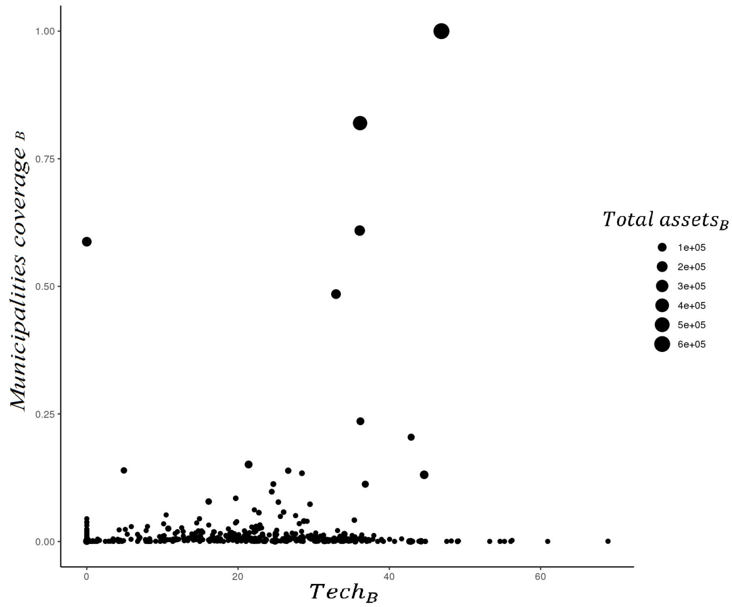
Appendix

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
Interst 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		
		175,226	470,639	498,180	209,309	643,255		

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 TECH R& D PROJECTS*

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 $k = 2$.