Artificial intelligence and relationship lending

Leonardo Gambacorta, Fabiana Sabatini and Stefano Schiaffi*

Abstract

We study the interaction between banks' adoption of artificial intelligence (AI) in credit scoring and relationship lending. Using a unique dataset on Italian banks' investments in AI for the purpose of integrating their credit scoring techniques, matched with credit register data from one year before and one year after the outbreak of the Covid-19 crisis, we find that AI investments help banks mitigate the typical countercyclical effects of relationship lending on firms' credit supply, as well as on their investment and employment decisions.

Keywords: artificial intelligence; machine learning; credit supply; relationship lending.

JEL codes: G01, G21, E50.

* Leonardo Gambacorta (leonardo.gambacorta@bis.org) is at the Bank for International Settlements and affiliated with CEPR, Fabiana Sabatini (fabiana.sabatini@bancaditalia.it) and Stefano Schiaffi (stefano.schiaffi@bancaditalia.it) are at the Bank of Italy, Economic Outlook and Monetary Policy Directorate. We would like to thank Andreas Barth, Tania Babina, Nicola Branzoli, Margherita Bottero, Giuseppe Ferrero, Giacomo Gaggero, Itay Goldstein, Simone Lenzu, Stefano Neri, Matthew Plosser, Edoardo Rainone, Ilaria Supino, Koji Takahashi, Andrea Tiseno for useful comments and suggestions, as well as participants to the AI in Finance Conference, Columbia Business School, 10-11 June 2024, to the 2024 Annual Conference of the International Association of Applied Econometrics, Thessaloniki 25-27 June 2024, to the 2024 annual meeting of the Central Bank Research Association (CEBRA), Frankfurt am Main, 28-30 September 2024 and to the 6th conference on "New Frontiers in Banking and Capital Markets", Rome, 3 December 2024. The views expressed here are those of the authors only, and not necessarily those of the Bank of Italy or the Bank for International Settlements.

1. Introduction

The global financial crisis and advances in technology have brought about significant changes to the banking system (Beck et al., 2016; Carletti et al., 2020). Following the financial crisis of 2007–2009, the banking sector has experienced a compression of interest rate margins with a negative impact on the sector's profitability (Scott et al., 2017). In this context, many banks have gradually reduced traditional brick-and-mortar branches and invested in data gathering and processing, leveraging the use of artificial intelligence (AI).

In this paper, we investigate whether relationship-based lending and new technology-driven financial intermediation complement or substitute each other, both in normal times and during the Covid-19 crisis. We focus on those banks that report using artificial intelligence techniques to support the evaluation of their borrowers' creditworthiness (henceforth: AI banks) in order to reduce asymmetric information problems between lenders and borrowers – both for screening and monitoring.[1] AI technology, with its enhanced analysis of hard, verifiable and codifiable data, can coexist with more traditional ways of reducing asymmetric information between banks and firms, such as the acquisition of soft information through close relationships between intermediaries and clients.

To conduct our study, we use a unique dataset that tracks Italian banks' technology adoption over the recent years, as well as the specific technologies utilized and their specific applications (Regional Bank Lending Survey, RBLS) and match it with loan-level data on volumes and interest rates on loans to non-financial corporations in Italy obtained from the proprietary AnaCredit dataset. In particular, the 2021 wave of the RBLS contains information on Italian banks' investment in AI with the purpose of integrating their evaluation of borrowers' creditworthiness and the year in which they started these investments. This allows us to be very specific and consider AI adoption for credit scoring in each bank. Our definition of AI banks differs, therefore, from previous proxies of technology adoption used in the literature, which typically consider the overall level of IT adoption by banks without distinguishing the specific technology or its intended purpose.

1 AI can be applied to credit scoring both in the screening and in the monitoring process (Albareto et al., 2016). Banks screen borrowers (whether prospective or existing) when granting new loans, and they monitor the capability of repaying a loan afterwards. However, in this study, we are not able to disentangle new loans from existing ones, thus, we prefer to be agnostic as to whether the screening or the monitoring processes are those that are more affected by AI.

We conduct our analysis in two steps. First, we examine how the interaction between (i) AI used for credit scoring and (ii) relationship lending affects firms' loan volumes and interest rates, distinguishing between term loans and credit lines. We follow Khwaja and Mian (2008) in using time-varying firm and bank fixed effects to account for observable and unobservable factors affecting firms' demand and banks' supply. This approach allows us to estimate the combined effect of technology and relationship length on lending volumes and interest rates. Second, we examine the impact of these factors on firms' investment and employment decisions.

Our results show that, on average, the length of relationships is associated with a protection of borrowers during the turmoil by increasing credit supply and reducing lending rates, in line with previous literature (see Sette and Gobbi, 2015; Bolton et al., 2016; Banerjee et al., 2021). Moreover, for a given duration of the lending relationship with a certain firm, the application of AI techniques for screening and monitoring capabilities mitigates the rent extraction of relationship lending in normal times, on the one hand, and does not exert further protection on quantities and interest rates for borrowers with longer relationships during the crisis, on the other. In other words, the effects of relationship lending on credit volumes and prices, which are detrimental in normal times but beneficial during crises, are smoothed by the use of AI techniques for credit scoring. Thus, while lending from non-AI banks to relationship firms is countercyclical, AI lending to relationship firms does not appear to be influenced by general macroeconomic shocks, instead being more reactive to firm-specific conditions. These findings are consistent with a recent strand of literature that analyses the cyclical characteristics of credit provided by large technological companies (so-called big techs) and finds that big tech credit does not respond to changes in collateral values (asset prices) and in GDP at the provincial level, while it responds strongly to changes in firm-specific conditions, such as transaction volumes and profits (Frost et al., 2019; Gambacorta et al., 2019).

Looking at firms' employment and investment decisions, we find that during the crisis firms with a longer average relationship with their creditors received more credit and, all else equal, increased investment and employment, as in Jiménez et al. (2022). However, the adoption of AI by the main lender is associated with a dampening of these effects during the crisis, although the magnitude appears to be limited.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature, with a focus on the effects of relationship lending and of technological innovations on lending supply. Section 3 describes our data. In Section 4, we provide evidence on how the use of AI in evaluating the creditworthiness of borrowers and relationship-based lending impact credit conditions for non-financial corporations. Section 5 analyses how these factors affect firms' investment and employment decisions. The last section offers the main conclusions.

2. Literature review

Previous studies have examined how investments in digital financial intermediation impact on banks' productivity (Chowdhury, 2003; Casolaro and Gobbi, 2004; Martin-Oliver and Salas-Fumas, 2007; Koetter and Noth, 2013) and profitability (Beccalli, 2007; Hernando and Nieto, 2007; Scott et al., 2017). Additionally, other papers have focused on the entry of big techs into the provision of financial services (Frost et al, 2019). These papers have evaluated the enhancement that the use of machine learning techniques on big data technology offers for credit scoring and analyzed the main differences between big tech and traditional bank lending in terms of defaults, use of collateral and financial inclusion (Di Maggio and Yao, 2021; Gambacorta et al., 2022; Bech et al, 2023). Unlike this strand of literature, our paper investigates if and how the adoption of AI technologies by banks to mitigate the problem of adverse selection may induce them to use soft information in different ways from those commonly documented in the literature.

Our paper also contributes to the literature on the effects of technological advances on bank credit allocation. Our work is close to Branzoli et al. (2022), who also focus on how information technology adoption by banks affected corporate lending in the months following the Covid-19 outbreak in Italy: their main result is that banks with a higher intensity of AI adoption increased their corporate credit more than others during the pandemic. Unlike Branzoli et al. (2022), we focus on the specific use of AI for credit scoring and consider how AI banks behave with respect to non-AI banks in Covid times controlling for their different use of soft information. Our datasets differ along two main dimensions: i) our definition of AI is more specific and pertains to technological investments (machine learning and big data) with a borrower screening purpose; ii) our data are consolidated, as technological investments in AI are typically performed at the group level and shared with all banks within the same group.

Our paper is also related to the literature on the effects of digitalization on banks' behaviour. Core and De Marco (2021) show 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) suggest that the use of digital technologies for remote work or virtual communication improved the supply of small business loans originated under the US Small Business Administration Paycheck Protection Program (SBA PPP). Ahnert et al. (2022) suggest that technology can improve banks' ability to verify the value of collateral. Pierri and Timmer (2022) find that higher pre-crisis IT adoption resulted in fewer non-performing loans and more lending during the global financial crisis. Other studies link technology adoption to enhanced credit risk management (Baesens et al., 2015; Albanesi and Vamossy, 2019; Berg et al., 2020). Our paper contributes to this strand of literature by analyzing the effect of AI on relationship lending, without relying on proxies but by observing directly banks' technological investments in AI and the length of the bank-firm relationship.

We also contribute to the traditional lending relationship literature. Petersen and Rajan (1994), Angelini et al. (1998) and Harhoff and Korting (1998) show that longer relationships improve firms' access to credit. Berger and Udell (2002), Brick and Palia (2007) and Bharath et al. (2011) find that borrowers with longer relationships pay lower interest rates and face lower collateral requirements. Degryse and Ongena (2005) and Agarwal and Hauswald (2010) indicate that borrowers' transportation costs (geographical distance) are negatively correlated with the level of interest rates. Cenni et al. (2015) show that the number of banking relationships the firm maintains is negatively associated with (overall) credit availability. Bartoli et al. (2013) and Cucculelli et al. (2017) provide evidence that the use of soft information under relationship lending technologies decreases the probability of firms experiencing credit restrictions. Our paper links this literature with the effects of AI on credit scoring and how these effects could alter the bank-firm relationship.

A few papers have tested the impact of relationship lending on credit availability during the last global financial crisis. Sette and Gobbi (2015) and Bolton et al. (2016) find that relationship lenders offer more support than transactional lenders during a crisis: banks located closer to their borrowers, involved in longer relationships, and holding a larger share of the credit obtained by a single borrower granted more loans than other banks in the crisis period. Similar results are provided by Beck et al. (2018), who show that relationship lending alleviates firms' credit constraints during a downturn, especially for small and opaque firms. Analyzing the effects of relationship lending on firms' investment and employment choices, Banerjee et al. (2021) find that following Lehman's default and the European sovereign debt crisis, banks offered more favorable continuation lending terms to firms with which they had stronger relationships, which in turn enabled firms to maintain higher levels of investment and employment. In our paper, we contribute to this literature by studying whether the adoption of AI for integrating the evaluation of borrowers' creditworthiness by banks supplements or substitutes relationship lending, both in the aftermath of the Covid-19 crisis and during the crisis itself.

3. Data and descriptive statistics

3.1 Constructing the dataset

We use a unique dataset that combines five different sources: (i) data on bank loans and interest rates to non-financial corporations in Italy from the ECB's AnaCredit dataset; (ii) information from the Italian Credit Register (CR) on existing lender-borrower relationships (since 2008); (iii) information on Italian banks' balance-sheets from the Bank of Italy's supervisory banking statistics; (iv) data on banks' technological innovation in screening from the Bank of Italy's Regional Bank Lending Survey (RBLS) conducted in 2022; (v) information on firm-level balance-sheets and income statements from the Cerved database.

We construct our dataset by following four main steps.

First, we collect quarterly data on credit volumes and interest rates from the section of AnaCredit that covers credit relationships between banks and firms operating in Italy. These data include loan level information for each individual credit relationship above 25,000 euros. We focus on the period from 2019:Q1 to 2020:Q4 and distinguish between loans with a structural purpose ("term loans") and loans with a liquidity purpose (from now on we call these loans for simplicity "credit lines").[2]

Second, we calculate the duration of each bank-firm relationship for the period under study by merging information from the Italian CR on each relationship existing in the period 2008:Q1-2018:Q4 with the AnaCredit dataset. This allows us to construct a measure of the duration of the bank-firm relationship in quarters.

Third, we merge the dataset with the annual information on firms' balance-sheet from the Cerved dataset for 2018, 2019 and 2020.

Fourth, we collect and merge quarterly information from the Bank of Italy's supervisory banking statistics for the period 2018:Q4 - 2020:Q4 on banks' individual

[2] We consider granted credit lines rather than drawn credit lines because they better represent loan supply shifts.

balance-sheet variables such as capital (Tier 1 capital ratio), size (total assets), profitability (ROA), liquidity ratio, and interbank funding ratio. Information on banks' adoption of AI for credit scoring techniques is provided by the RBLS conducted in 2022 on a sample of Italian banks representing around 85% of lending to Italian firms. This survey reports the initial date on which each bank started using technologies for improving the evaluation of borrowers' creditworthiness.

The information on the use of technological innovation by Italian banks in the provision of credit is obtained directly from the 2022 RBLS survey, without the need for proxies or making any assumptions. A specific section of the survey asks whether the respondent bank is involved in IT projects, broadly defined as new technologies applied to financial services in the areas of payment services, asset management or lending. We focus on banks that use artificial intelligence on big data to improve their evaluation of borrowers' creditworthiness. Specifically, these are the banks that answered (i) "yes" to the question "Have you initiated or planned any projects or investments in fintech over the next three years?"; (ii) "Integration of the evaluation of borrowers' creditworthiness" to the question "For what purposes have you initiated or planned investments in fintech?" and (iii) "Big data and artificial intelligence" to the question: "For which technologies have projects been initiated or do you plan to initiate them?").[3]

Crucially, intermediaries are asked to specify the year of first adoption of the technologies (T). We use this information to classify a bank as an "AI bank" in year t if $T<=t$. Since our measure of AI adoption is at the bank level, we assume that these technologies will affect (albeit in different ways) all its loans, both those to firms with a longer relationship with the bank and those to firms with a shorter relationship. We further assume that once a bank initially adopts AI in year T, it keeps using it in all subsequent years. According to our dataset, in December 2019 AI banks accounted for a total lending volume of €455 billion, compared to €750 billion for non-AI banks. These include (i) banks that did not invest in AI, and (ii) banks that invested in AI but without the purpose of integrating evaluations on borrowers' creditworthiness. The number of AI banks changes over time in our sample: at the beginning of 2019, out of a total of 124 banks, 9 were AI type. During the sample period, 5 banks became AI. At the end of the sample, the number

[3] The data do not distinguish banks that use AI for credit scoring of non-financial corporations from those that use it for credit scoring of households. According to evidence drawn from an additional question in the RBLS 2022 survey, banks that use AI for credit scoring do so for the scoring of both NFCs and households. This is consistent with a recent survey of the use of AI techniques for credit scoring shows that they are generally applied to a wide class of loans (mortgages, retail exposures, corporate loans; Alonso and Carbó, 2020).

of AI banks was 14, while the total number of banks was reduced to 117 due to some closures.

As for our measure of relationship lending, we follow Banerjee et al. (2021) and proxy the quantity of information accumulated by the bank on a specific firm as the log duration of the lending relationship between the two (measured in quarters). This is one of the most commonly used measures of banking relationship intensity (Degryse et al., 2009). Indeed, longer relationships are associated with greater soft information accumulation by the lender about the borrower. Longer relationships can also signal a long-term implicit contract between the bank and the borrower in which the bank provides liquidity insurance (Elsas and Krahnen, 1998). The choice of log-transforming the original duration is motivated by the assumption that the marginal information coming from the relationship decreases over time.

To sum up, our measure of AI adoption is at the bank level, while our measure of relationship lending is at the bank-firm level. With a slight simplification, we can thus say that for each bank-firm couple in quarter *t* we have one of four cases:

i) No information from AI, much soft information from a long relationship;

ii) No information from AI, little soft information from a short relationship;

iii) Information from AI, much soft information from a long relationship;

iv) Information from AI, little soft information from a short relationship.

We assume that banks that invested in AI for credit scoring use it: therefore, AI banks can only have lending relationships of type iii) and iv), while banks that did not invest in AI can only have lending relationships of type i) and ii).

As for firms, in order to include both firm-time and bank-time fixed effects, we select only corporates that had relations with at least two banks. Excluding firms that had only one bank as a lender resulted in a reduction of 2,412,422 out of 6,466,377 observations. As a final step, we winsorize the data at 1% and 99%. Our final dataset includes 124 banks, 170,645 firms, and a total of 590,521 credit relationships, of which 288,614 refer to 2019 and 301,907 to 2020. The final dataset comprises 4,053,955 quarterly observations in total.

3.2 Stylized facts and descriptive statistics

We investigate the combined role of AI applied to credit scoring and lending relationship during the period 2019:Q1-2020:Q4. This horizon covers the aftermath and the subsequent period of the Covid-19 pandemic, during which a dramatic increase in credit growth was observed, mainly as a result of firms' liquidity needs (see Figure 1). The increase in credit was mainly driven by term loans (represented by a dashed line), the type of credit that was most demanded by firms during the pandemic phases, in particular because of the possibility of obtaining government guarantees on it. In contrast, the use of credit lines (represented by a dotted line) fell sharply during the pandemic. The total credit is represented by a continuous line.

Figure 1 visually identifies a sudden exogenous shock to the Italian economy. The Covid-19 shock provides an ideal setting for an econometric analysis for several reasons. First, the global impact of the pandemic and the resulting closure of productive and social activities were unexpected at the beginning of 2020. Therefore, neither banks nor firms could have adjusted their lending policies or credit demand before the event. Another advantage of studying this shock is its systemic nature, which affected almost the entire productive system, and not just a subsample of firms (i.e., the weakest firms).

Figure 2 shows that AI banks and non-AI banks have slightly different degrees of relationship-based lending. At the end of 2018, AI banks have a shorter median lending relationship (10 quarters) than non-AI banks (13 quarters). However, a significant proportion of loans extended by both AI and non-AI banks are issued to borrowers with a long relationship with the credit intermediary (25 per cent of loans have a relationship length of 30 quarters or more for both types of banks).

These two types of banks may have different business models, so it is useful to investigate which bank characteristics are correlated with the adoption of AI for credit scoring. To do this, we estimate the following logit model

$$Pr(AI_{it} = 1 |\, X_{bt}) = \frac{e^{\beta_0+\beta_1\times X_{bt}}}{1+e^{\beta_0+\beta_1\times X_{bt}}} + \varepsilon_{it}$$

where the dependent variable is the probability that a bank uses AI for credit scoring (dummy AI is equal to one), while the variables X_{bt} are bank-specific characteristics, i.e. the tier 1 capital ratio, the size of the bank, the interbank ratio, and the liquidity ratio. Among these characteristics, we also include $\overline{dur}$, the credit weighted average at the bank level of the duration at the bank-firm-time level. The results are reported in Table 1. The probability for a bank to use AI for credit scoring increases with its size. Specifically, moving from the median to the 75th percentile of the size distribution is associated with a 0.16 increase in the log of total assets, corresponding to an increase in the relative probability of being an AI-bank equal of about 35%. Estimating the model focusing on banks that were already of the AI type before the Covid crisis (column 2) does not change the results.

Table 2 reports the names and descriptions of all variables used in the regression analysis, using three different panels: (a) variables at the bank-firm level; (b) variables at the bank level; (c) variables at the firm level. Tables 3-5 report summary statistics for the variables of interest and controls used in the regressions.

Table 3 shows descriptive statistics at the bank-firm level. The growth of total credit is expressed on a 3-month horizon and in percentages. Both the median and the average lending growth over the study period are equal to -1.8%. Credit growth to non-financial corporations had been negative for some years before the outbreak of the Covid-19 pandemic, due in part to the creditless recovery of the Italian economy after the sovereign crisis (Bank of Italy, 2019).

The average cost of credit of loans over the whole sample is 3.0%. This cost reduced significantly during the pandemic. The average and median interest rates on total credit dropped during 2020 to 2.72% and 2.04%, from 3.23% and 2.53%. respectively, reflecting again the dynamic of the cost of credit on term loans. By contrast, the cost of credit lines slightly increased.

We measure the duration of the bank-firm relationship since 2008 (i.e., 10 years before the period under study). The median of the bank-firm relationship is equal to 35 quarters, corresponding to roughly 9 years, and the distribution is negatively skewed, with the average relationship duration equal to 28.5 quarters or slightly more than 7 years. Following Banerjee et al. (2021) we measure the relationship duration in logs because, as well documented by the literature, the marginal accumulation of information about the borrower is likely to decline over time. The additional characteristics at the bank-firm level (see Table 2, panel a) are the share of credit obtained by firm j from bank i over the total bank credit granted to firm j, the log of the credit granted, the residual maturity of the credit standing for each relation (computed as the weighted average of the residual maturity for every loan by the amount of the loan) and the total guarantees over total loans ratio.

Table 4 reports descriptive statistics on bank balance sheet variables: Tier 1 ratio, liquidity ratio, bank profitability (ROA), the interbank funding ratio, and the log of bank assets (size).

Table 5 reports the summary statistics for the variables at the firm level that are used to estimate the real effects of technological innovation and relationship lending. This set of variables includes firms' employment and investment as dependent variables and, as regressors, the following: the log of firm total assets, and indicators on profitability and efficiency, leverage and risk (z-score). The credit dynamic at the firm level is measured by credit flows over total assets of the previous year. Employment is measured as the incidence of labor costs over total lagged assets, a proxy widely used in the literature.[4]

We measure firms' exposure to AI banks with a variable that equals the main lender's share of lending to a given firm if that lender is an AI type and zero otherwise. We measure firms' exposure to banks with longer duration as the share of the credit obtained by the firm's main bank if the relationship duration with that bank is above the sample median and zero otherwise. The average exposure to AI banks is 25%, while the average exposure to banks with longer relationships is 43%.

4. The impact of AI and relationship lending on the credit supply to firms

Investigating the combined effects of using AI for credit scoring and lending relationships during the Covid-19 period poses important identification issues. First, the social distancing measures adopted by the Italian government to contain the spread of the virus led to a strong increase in the demand of funds from firms, that urgently needed emergency liquidity. To disentangle supply effects from demand confounders, we use the approach pioneered by Khwaja and Mian (2008) and add firm-time fixed effects that control for time-varying heterogeneity at the firm level, including for the demand of funds. Including firm-time fixed effects reduces the sample to firms having relationships with at least two banks.[5]

4 Labor cost growth is used as a proxy measure of employment because it brings some advantages (see Gopinath et al. (2017) and Banerjee et al. (2021)). Labor cost is the total wage bill from firm balance sheets, so it combines both the headcount of workers and wages. While this choice is mainly related to better data availability, in several respects it may be preferable to using the number of employees because it can better capture changes in part-time work, overtime and differences in the human capital of employees.

5 Non-random matching may impair this empirical strategy as demand shocks may not be homogeneous within the same pool of lenders and, similarly, supply shocks may not be homogenous within the same pool of borrowers. We therefore control whether firms' characteristics differ between AI and non-AI samples of borrowers, and this is not the case. A dynamic sorting test provides no strong evidence of matching between firms and AI banks (see Appendix).

Second, AI adoption is correlated with banks' characteristics. As shown in the previous section, bigger or more profitable banks may be better able to sustain the high fixed costs required by AI investments. Moreover, it may also be the case that the choice of investing in technologies, the choice of having longer or shorter relationships, and overall lending policies are all correlated with a bank's business model, which is not observed (Beck et al., 2016; Pierri and Timmer, 2022). In order to control for all the time variant heterogeneity at the bank level, we include bank-time fixed effects.

The equation we estimate is the following:

$$\begin{aligned} Y_{ijt} = {} & \beta_1 \log\left(relationship\ duration\right)_{ijt-1} \\ & + \beta_2 \log\left(relationship\ duration\right)_{ijt-1} \times AI_{it-1} \\ & + \beta_3 \log\left(relationship\ duration\right)_{ijt-1} \times D(2020) \\ & + \beta_4 \log\left(relationship\ duration\right)_{ijt-1} \times AI_{it-1} \times D(2020) \\ & + \gamma Z_{ijt-1} + \alpha_{it} + \delta_{jt} + \varepsilon_{ijt} \end{aligned} \tag{1}$$

where the dependent variable Y_{ijt} is either the quarterly change in the log amount or the interest rates on (i) term loans and (ii) credit lines from bank *i* to firm *j* at time *t*. The $\log\left(relationship\ duration\right)_{ijt-1}$ is the natural logarithm of the duration of the relationship between bank *i* and firm *j* at time *t*-1, AI_{it-1} is a dummy variable equal to 1 whether the bank *i*, at time *t*-1, is using AI methods for evaluating the creditworthiness of its borrowers, and zero otherwise; $D(2020)$ is a time dummy equal to 1 for 2020, and 0 otherwise. X_{it-1} is a vector containing bank-specific characteristics such as the Tier 1 ratio, ROA, the liquidity ratio, the log of total assets and the interbank funding ratio. Z_{ijt-1} is a vector of firm-bank controls including: the *share* of credit (the proportion of the total credit obtained by the firm *j* from bank *i*), *log(loan)* (the log of the total amount of credit granted), *res_mat* (the average of residual maturity on bank-firm positions weighted by the value of credit for each position) and *gar_tot* (total private and public guarantees over total credit). α_{it} and δ_{jt} are bank-time and firm-time fixed effects, respectively.

Since we include bank-time fixed effects, neither AI_{it-1}nor $AI_{it-1} \times D(2020)$ can be identified in this model. For comparison, we will include these terms in models that exclude bank-time fixed effects. The presence of firm-time fixed effects makes the presence of $D(post\ 2020)$ collinear.

Table 6 presents the results for the quantities of loans. Columns 1 and 2 focus on the growth rate of term loans. During the pandemic, these loans represented the majority of new loans, as many public guarantees were available as collateral for this type of credit. Column 1 does not include bank-time fixed effects, while column 2 reports the results for the complete equation (1). In column 1, the coefficient on AI is positive and statistically significant, suggesting a positive impact on the supply of new bank credit, as log(duration)=0 indicates newly formed relationships. The coefficient of the interaction between AI and D(2020) is positive but not significant, indicating that the lending behavior of AI banks during the pandemic crisis was similar to that in normal times.

The coefficient on the relationship duration, which is negative in normal times, turns positive during the pandemic crisis, implying that relationship lending is associated with less credit in normal times but a protection of borrowers during the crisis period. This result is in line with the literature (Bolton et al., 2016; Banerjee et al., 2021).

We now turn to our main variables of interest, which are the interaction terms between relationship duration and AI. In both columns 1 and 2, the coefficient on the interaction is positive and significant at the 1% level for the pre-crisis period, indicating that for the same duration of a relationship, the growth of credit obtained by a firm from an AI bank is higher than that obtained by a non-AI bank. Specifically, given a firm with a relationship of the same length with both an innovative bank and a non-innovative bank, the growth of credit obtained from the AI bank will be at least 1.2% higher than that obtained by the non-AI bank. In other words, in normal times AI banks mitigate the borrower's capture associated with longer relationships. However, the interaction of the AI dummy and relationship length with D(2020) is negative; since the sum of this coefficient and that on the interaction of the AI dummy and relationship length is not statistically different from zero, the loan volumes of AI banks after the pandemic do not differ from those of non-AI banks for a given relationship length.

In columns 3 and 4 we report results for credit lines. This type of credit had a limited role during the crisis, mostly because of the possibility to post government guarantees on term loans. The coefficient on AI is negative and statistically significant, possibly reflecting a substitution effect with term loans: the latter are characterized by higher information asymmetries, which AI may have helped assuage. The coefficients on relationship lending are in line with columns 1 and 2. Focusing on the interaction terms between relationship duration and AI, $\log(relationship\ duration)_{ijt-1} \times AI_{it-1}$ and $\log(relationship\ duration)_{ijt-1} \times AI_{it-1} \times D(2020)$, they are both not statistically significant although their signs are consistent with those of columns 1-2.

Table 7 presents the results for the cost of credit and follows a similar structure to Table 6. The first two columns display the estimates for interest rates on term loans obtained by firm *j* from bank *i*. For the relationship duration variable, the results are in line with the literature (see Bolton et al.,2016; Sette and Gobbi, 2015; Banerjee et al., 2021): during normal times, a longer duration is associated with a higher cost of credit (rent extraction effect), while during the pandemic crisis the cost of credit reduces with the length of the relationship. This means that borrowers pay a higher premium in normal times but benefit from a reduction in interest rates and a larger provision of credit during crisis times. The negative interaction between AI and relationship lending suggests that, prior to the pandemic crisis, AI banks mitigated the rent extraction of relationship lending by charging lower interest rates for a given relationship length. At the same time, since the sum of this coefficient and that on the interaction during the Covid period is not statistically different from zero, we find evidence that AI banks do not further shield their borrowers by lowering interest rates during the pandemic period

The last two columns report results for credit lines. Relationship length impacts the cost of credit significantly during normal times, with longer relationships resulting, also in this case, in higher costs. The reduction effect of relationship lending on interest rates during the crisis is not in place, but this could reflect the more limited use of credit lines during the pandemic crisis. The interaction term between AI and relationship lending is instead positive, in line with the effect we find for term loans, but significant only during the crisis.

The results reported in Tables 6 and 7 are robust controlling for some potential identification problems of equation (1), such as sorting (endogenous matching between banks and firms), AI banks' specialisation in specific sectors differently affected by the pandemic, or different attitudes of AI banks in issuing public guarantee loans (see Appendix).

The economic and statistical significance of the results are summarized in Table 8. First, using the coefficients in columns 2 of Tables 6 and 7, for term loans, we perform tests on the statistical significance of the overall impact of relationship duration on credit volumes and prices for AI and non-AI banks, both in normal and in crisis times (respectively, first and second row in the table). Second, we report the test on the statistical significance for the difference between crisis and normal times. For the sake of completeness, we also report the test on the statistical significance for the difference between AI and non-AI banks. The table shows that banks that adopt AI technologies do not change significantly their lending stance in the two periods, both in terms of volume and in terms of lending rates: indeed, in columns 1 and 3 of Table 8, the coefficients in normal time are not statistically different from those in crisis time. In contrast, for non-AI banks the differences in the coefficients in columns 2 and 4 are statistically different from zero. These intermediaries tend to increase loan quantities by 1.36% and reduce interest rates by 9 basis points in crisis time. These results suggest that these credit intermediaries behave in a countercyclical way, extracting rents from borrowers and limiting credit in normal times, while providing higher lending volumes at cheaper prices in crisis times. As a result, while credit conditions offered by AI banks are better than those offered by non-AI banks in normal times, both in terms of volumes and prices, they are not statistically different between the two types of banks during the pandemic period.

This finding is consistent with non-AI banks behaving akin to traditional relationship banks (Gobbi and Sette, 2015; Bolton et al.,2016; Banerjee et al., 2021). On the other hand, the lending supply of AI banks is less influenced by changes in general macroeconomic conditions. This is consistent with Gambacorta et al. (2019), who find that big tech credit does not respond to changes in collateral values (asset prices) and in GDP at the province level, while it responds strongly to changes in firm-specific conditions, such as transaction volumes and profits.[6]

5. The real effects of AI and relationship lending

Our paper makes an additional contribution by identifying the interaction effects of AI for screening purposes and relationship lending on firms' real activity, in terms of investments and employment. Following Banerjee et al. (2021), we estimate the following firm-level regression:

$$\Delta Z_{jt} = \beta_1 \overline{dur}_{j,2018} \times D_t(2020) + \beta_2 \overline{AI}_{j,2018} \times D_t(2020)$$

$$+ \beta_3 \ \overline{dur}_{j,2018} \times \overline{AI}_{j,2018} \times D_t(2020) + \beta_4 X_{jt-1} + \alpha_j + \gamma_t + \varepsilon_{jt} \qquad (2)$$

[6] The characteristics of our quarterly dataset and the firm-specific characteristics reported at the annual level do not allow for a proper test on the differential reactivity of loan quantities and prices to immediate changes in firm-level business conditions, distinguishing between AI and non-AI banks. However, a simple sample split shows that AI banks react significantly more to changes in EBITDA, a measure of a firm's operating performance, than non-AI banks (see Figure A1 in the Appendix).

where $\overline{dur}_{j,2018}$ measures the length of the relationship with the firm's main lender, weighted by the main lender's credit share of the firm's total loans; $\overline{AI}_{j,2018}$ is equal to the share of the main lender if this is an AI bank and zero otherwise. As in Banerjee et al. (2021), $\overline{dur}_{j,2018}$ and $\overline{AI}_{j,2018}$ are time-invariant, and in our case are measured at the end of 2018. This approach helps to address endogeneity concerns related to the formation and breaking of relationships during the study period, especially during the pandemic phase, at the cost that only interactions with the dummy crisis can be estimated. $D_t(2020)$ is a dummy equal to 1 for quarters in 2020, and zero otherwise. The vector X_{jt-1} includes several firm-level controls: (i) ROA, (ii) firm leverage, (iii) the log of firm assets, (iv) the ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) over interest expenses, and the (v) z-score of the firm. The equation also includes firm fixed effects (α_j) and time fixed effects (γ_t).

Table 9 presents the effects of the relationship length, AI and their interaction on firms' credit flows, investment and employment during the crisis. Credit is expressed as the log of total term loans; employment is measured as labor costs over total lagged assets; investment is fixed investment over total lagged assets. Column 1 reports the results for the log of term loans. The positive and significant coefficient on the interaction between $\overline{dur}_{j,2018}$ and $D_t(post\ 2020)$ indicates that firms with a longer average relationship benefited from an increase in bank credit during the pandemic crisis. An increase in the credit-weighted duration of the relationship by one interquartile range (0.95) brings about a 5%increase in the stock of term loans. This effect is dampened for firms whose main lender is an AI bank, as evidenced by the negative and significant coefficient on the interaction between $\overline{dur}_{j,2018}$, $\overline{AI}_{j,2018}$ and $D_t(post\ 2020)$: firms whose main lender is an AI-bank and have a credit share of 50% (the interquartile range of $\overline{AI}_{j,2018}$) will see the effect of relationship length on credit shrink to 2%. The interaction of $\overline{AI_{j,2018}}$ and $D_t(post\ 2020)$ is not significant, coherently with our previous results.

Columns 2 and 3 present the results for investment and employment, respectively. The coefficient on the interaction between relationship duration and $D_t(post\ 2020)$ is positive and significant in both columns, indicating that firms with longer relationships increased both their investments and employment. During the crisis, a one interquartile-range increase in the credit-weighted relationship duration corresponds to an increase in the share of investments equal to 24 percentage points (against an average investment share of 55 percentage points of total assets) and an increase in employment costs to total assets of about 2 percentage points (against an average of 23 percentage points of total assets). This effect is marginally dampened for firms whose main lender is an AI bank: increasing firms' exposure to AI by one interquartile range (50 percentage points) reduces the impact of relationship lending on investment to 22 percentage points and on labor costs to 1.8 percentage points. Overall, Table 9 suggests that AI dampened not only the smoothing effects of relationship lending on the supply of credit, but it also had similar, although somewhat more limited, effects on firms' investment and employment decisions.

6. Conclusions

This paper examines the interplay between relationship-based lending and AI-enhanced financial intermediation. We find that AI banks mitigate the "rent extraction" problem, which is typical of longer lending relationships in normal times, but they do not improve lending conditions comparable to those of non-AI banks during the Covid-19 crisis. While lending from non-AI banks to relationship firms is countercyclical, AI lending to relationship firms does not appear to be influenced by general macroeconomic shocks but rather responds to firm-specific conditions.

Looking ahead, the increasing use of AI for credit scoring by banks may make aggregate credit supply policies less dependent on general macroeconomic conditions; moreover, they could become less influenced by the "collateral channel" and more responsive to firm-specific conditions such as transaction volumes and profitability, with important and policy-relevant implications for the conduct of monetary policy and financial stability.

References

Agarwal, S. and R. Hauswald, 2010. Distance and Private Information in Lending, *The Review of Financial Studies*, 23(7), 2757–2788.

Ahnert, T., S. Doerr, N. Pierri and Y. Timmer, 2022. Does IT help? Information Technology in Banking and Entrepreneurship, *BIS Working Papers*, 998.

Angelini, P., R. Di Salvo and G. Ferri, 1998. Availability and cost of credit for small business: customer relationships and credit cooperatives. *Journal of Banking and Finance* 22, 925–954.

Albanesi, S. and D. F. Vamossy, 2019. Predicting consumer default: A deep learning approach. *NBER Working Paper*, 26165.

Baesens, B., S. Lessmann, H.-V. Seow and L. C. Thomas, 2015. Benchmarking state-of-the art classification algorithms for credit scoring: An update of research. *European Journal of Operational Research*, 247 (1), 124–136.

Banerjee, R. N., L. Gambacorta and E. Sette, 2021. The real effects of relationship lending, *Journal of Financial Intermediation*, Elsevier, 48(C).

Bank of Italy, 2019. Annual report for 2018, 31 May 2019.

Bartoli, F., G. Ferri, P. Murro and Z. Rotondi, 2013. SME financing and the choice of lending technology in Italy: complementarity or substitutability? *Journal of Banking and Finance*, 65.

Beck, T., T. Chen, C. Lin and F. Song, 2016. Financial Innovation: The Bright and the Dark Sides. *Journal of Banking & Finance,* 72.

Beck, T., H. Degryse, R. De Haas and N. van Horen, 2018. When arm's length is too far: Relationship banking over the credit cycle, *Journal of Financial Economics*, 127(1), 174-196,

Beccalli, E., 2007. Does it investment improve bank performance? Evidence from Europe. *Journal of Banking & Finance*, 31 (7), 2205-2230.

Berg, T., V. Burg, A. Gombovic, and M. Puri, 2020. On the rise of fintechs - Credit scoring using digital footprints. *Review of Financial Studies*, 33 (7), 2845–2897.

Berger A. and G.F. Udell, 2002. Small business credit availability and relationship lending: the importance of bank organisational structure, 12(477), F32-F53.

Bharath, S., S. Dahiya, A. Saunders and A. Srinivasan, 2011. Lending relationships and loan contract terms. *Review of Financial Studies,* 24, 1141–1203.

Bolton, P., X. Freixas, L. Gambacorta and P.E. Mistrulli, 2016. Relationship and transaction lending in a crisis. *Review of Financial Studies*, 29(10), 2643-2676.

Bonaccorsi di Patti E., F. Calabresi, B. De Varti, F. Federico, M. Affinito, M. Antolini, F. Lorizzo, S. Marchetti, I. Masiani, M. Moscatelli, F. Privitera and G. Rinna, 2022. Intelligenza artificiale nel credit scoring. Analisi di alcune esperienze nel sistema finanziario italiano. *Occasional Papers,* 721, Bank of Italy.

Branzoli, N., E. Rainone and I. Suino, 2023, The Role of Banks' Technology Adoption in Credit Markets during the Pandemic, *Journal of Financial Stability, forthcoming.*

Brick, I., and D. Palia, 2007, Evidence of jointness in the terms of relationship lending. *Journal of Financial Intermediaries,* 16, 452–476.

Carletti, E., S. Claessens, A. Fatas and X. Vives, 2020. The Bank Business Model in the post-Covid-19 World, *The Future of Banking 2, CEPR Press.*

Casolaro, L. and Gobbi, G., 2004. Information technology and productivity changes in the Italian banking industry. Bank of Italy working papers, 489.

Cenni,S., S. Monferrà, V. Salotti, M. Sangiorgi, and G. Torluccio, Credit rationing and relationship lending. Does firm size matter?, 2015. *Journal of Banking and Finance*, 53, 249-265.

Chowdhury, A., 2003. Information technology and productivity payoff in the banking industry: Evidence from the emerging markets. *Journal of International Development*, 15 (6), 693–708.

Core, F. and F. De Marco, 2021. Public guarantees for small businesses in italy during covid-19. *C.E.P.R. Discussion Papers*, 15799.

Cucculelli, M. and V. Peruzzi, Bank screening technologies and the founder effect: Evidence from European lending relationships, 2017. *Finance Research Letters*, 20, 229-237.

Degryse, H., and S. Ongena, 2005. Distance, lending relationships, and competition. *Journal of Finance*. 60, 231–266.

Degryse, H., M. Kim and S. Ongena, 2009. Microeconometrics of Banking. Oxford

University Press

Di Maggio, M. and V. Yao, 2023. Fintech borrowers: Lax-screening or cream-skimming? 8. *The Review of Financial Studies,* 34, 4565–4618.

Elsas, R. and J. Krahnen, 1998. Is relationship lending special? Evidence from credit-file data in Germany, *Journal of Banking & Finance*, 22(10-11), 1283-1316.

Frost, J., L. Gambacorta, Y. Huang, H. S. Shin and P. Zbinden, 2019. BigTech and the changing structure of financial intermediation, *Economic Policy*, 34(100), 761-799.

Gambacorta, L., Y. Huang, Z. Li, H. Qiu and S. Chen, 2023. Data vs collateral, *Review of Finance*, 27(2), 369–398.

Gopinath, G., S. Kalemli-Ozcan, I. Karabarbounis, L., and C. Villegas-Sanchez, 2017. "Capital allocation and productivity in south Europe", *The Quarterly Journal of Economics*, 132(4) 1915-1967.

Harhoff, D. and T. Karting, 1998. Lending relationships in Germany: Empirical evidence from survey data, *Journal of Banking & Finance*, 22(10-11).

Hernando, I. and M. J. Nieto, 2007. Is the internet delivery channel changing banks' performance? The case of Spanish banks. *Journal of Banking & Finance*, 31 (4), 1083–1099.

Martin-Oliver, A. and V. Salas-Fumas ,2007. The output and profit contribution of information technology and advertising investments in banks. *Journal of Financial Intermediation*, 17 (2), 229–255.

Khwaja, A. I. and A. Mian. 2008. Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market. *American Economic Review,* 98 (4), 1413-42.

Koetter, M. and F. Noth, 2013. IT use, productivity, and market power in banking. *Journal of Financial Stability*, 9 (4), 695–704.

Kwan, A., C. Lin, V. Pursianen and M. Tai, 2021. Stress testing banks' digital capabilities: Evidence from the covid-19 pandemic. *SSRN working papers*, 3694288.

Petersen, M., Rajan, R., 1994. The benefits of lending relationships: evidence from small business data. *Journal of Finance* 49, 3–37.

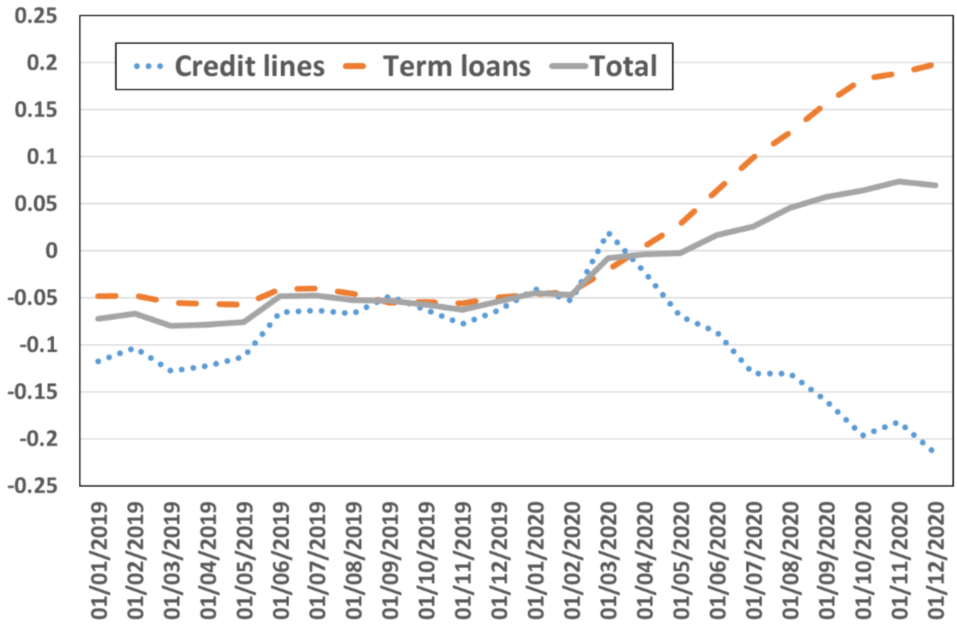
Pierri, N. and Y. Timmer, 2022. The importance of technology in banking during a crisis," *Journal of Monetary Economics*, 128(C), 88-104.

Scott, S., J. Van Reenen and M. Zachariadis, 2017. The Long-Term Effect of Digital Innovation on Bank Performance: An Empirical Study of Swift Adoption in Financial Services (March 20, 2017). *Research Policy*, 46(5).

Sette, E and G. Gobbi, 2015. Relationship Lending During a Financial Crisis, *Journal of the European Economic Association*, 13(3), 453–481.

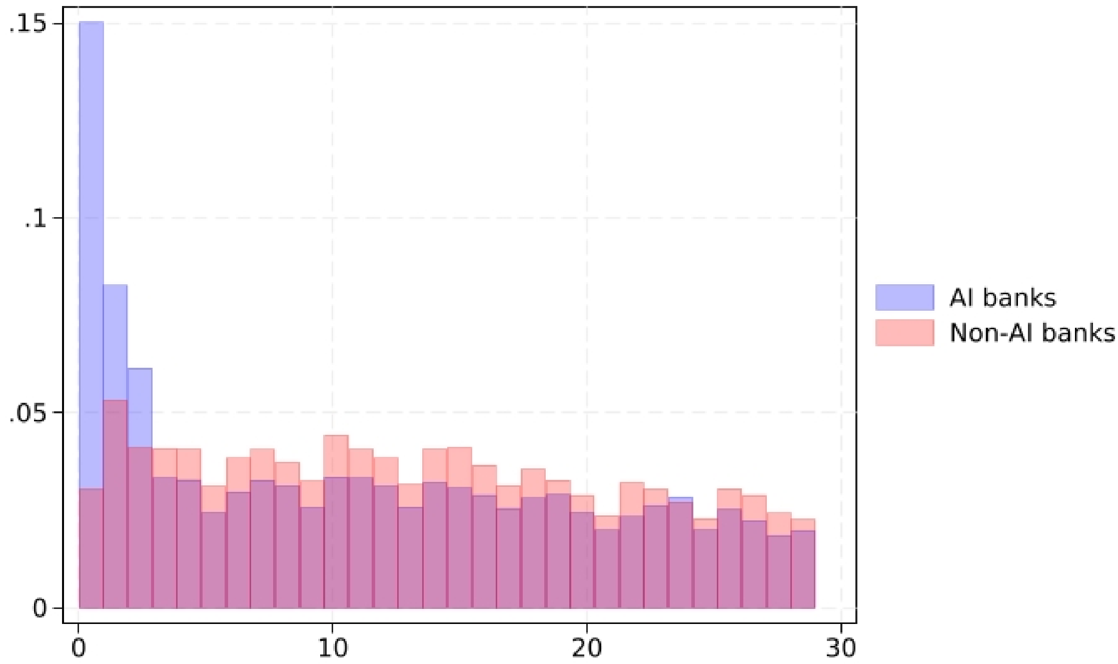
Figures and tables

Figure 1: Lending growth to non-financial corporations in Italy



Source: ECB. Elaborations on AnaCredit data. Notes: 12-month percentage changes. Data are not adjusted for the effects of securitization. This figure includes drawn credit lines and loans with original maturity up to one year (dotted line). Term loans (dashed line) are proxied by loans with original maturity greater than one year.

Figure 2: Distribution of relationship length for AI and non-AI banks (1)



Source: ECB. Elaborations on AnaCredit and Italian credit registry data. Notes: (1) The chart shows the distribution of relationship length (in quarters) for AI and non-AI banks in the sample in December 2018. The chart shows lengths below 30 quarters, i.e. within the time span of our sample.

Table 1: Adoption of AI for credit scoring and bank characteristics

Variables	(1) AI	(2) AI pre Covid
Capital ratio	0.1053	0.2237
	(2.948)	(3.000)
Liquidity ratio	1.9925	1.9506
	(2.177)	(2.335)
ROA	0.5066	0.0899
	(0.475)	(0.541)
Interbank funding ratio	-1.3867	-1.5532
	(1.430)	(1.478)
Size	0.7748***	0.8042***
	(0.187)	(0.194)
Duration	-0.3299	-0.6207
	(0.391)	(0.583)
Constant	-8.4024***	-7.9181***
	(1.756)	(1.878)
Observations	356	239

Notes: The table shows the result of the estimation of a logit model at the bank level where the dependent variable is the probability that the bank is innovative. Robust standard errors are clustered at the bank level. (1) The dependent variable is a dummy equal to 1 if the bank becomes AI throughout the sample. (2) The dependent variable is a dummy equal to 1 if the bank is already AI before the Covid crisis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2: Variables used in regressions and descriptions

Panel a - Variables at the firm-bank level

Variables	**Description**
Δlog (Term loans)	Growth of term loans on the 3-month horizon.
Δlog (Credit lines)	Growth of credit lines on the 3-month horizon.
Interest rates on total credit	Level of interest rates on the stock of total credit.
Interest rates on term loans	Level of interest rates on the stock of term loans.
Interest rates on credit lines	Level of interest rates on the stock of credit lines.
Relationship duration	Duration of the bank-firm relation since 2008 (in quarters).
Log (credit granted)	Log of the amount of credit granted.
Share of credit	Share of bank-firm credit over total credit obtained by the firm.
Residual maturity	Average of residual maturity on bank-firm positions, weighted by credit of each position.
Collateral to loan	Total private and public guarantees over total credit.

Panel b - Variables at the bank level

Variables	**Description**
AI	Dummy variable equal to one if the bank uses fintech techniques for credit scoring.
Tier 1 ratio	Tier 1 capital over risk-weighted assets.
Liquidity ratio	Total of cash and government securities net of repo positions to total assets.
ROA	Return on assets.
Interbank funding ratio	Monetary Financial Institutions (except central bank) deposits and repos over total assets.
Bank size	Log of total assets.

Panel c - Variables at the firm level

Variables	Description
Log of term loans	Log of the stock of term loans at time t-1.
Employment costs	Total labour costs at time t as a percentage of firm's total assets at time t-1.
Investments	Investments in time t as a percentage of firm's total assets at time t-1.
Credit weighted log relationship duration	Credit share of the main lender if its relationship duration with the firm is above the sample median; zero otherwise.
Credit weighted AI	Credit share of main lender if the lender is an AI bank; zero otherwise.
ROA	Return on assets.
Leverage	Total debt to total assets.
EBITDA/interest expenses	Earnings before interest, taxes, depreciation and amortization over financial expenses.
Firm size	Log of total assets.
Z score	Probability of default of the firm, ranging from 1 (lowest risk) to 9 (highest risk).

Table 3: Descriptive statistics: bank-firm relationship level.

	Δlog (Total credit)(1)	Δlog (Term loans) (1)	Δlog (Credit lines) (1)	Interest rates on total credit	Interest rates on term loans	Interest rates on credit lines	Relationship duration (in quarters)	Log (relationship duration)	Log (credit granted)	Share of credit to total bank credit(1)	Residual maturity	Collateral to loan(1)
Mean	-1.8	0.1	-9.5	3.0	2.1	5.8	28.5	3.2	12.1	30.4	2.8	13.5
Median	-1.8	-2.3	0.0	2.3	1.8	4.9	35.0	3.6	12.1	23.5	1.6	1.0
p25	-14.4	-12.1	-29.0	1.2	1.0	2.5	19.0	2.9	11.0	9.8	1.0	0.0
p75	3.9	0.0	18.1	4.0	2.9	7.9	39.0	3.7	13.1	46.1	3.9	1.0
std	68.0	58.9	105.3	2.6	1.5	4.5	11.3	0.6	1.5	24.9	2.7	28.4
N	590,521	491,907	250325	630,062	544,132	295,444	645,167	645,167	732,705	732,705	732,705	732,705

Notes: (1) Expressed in percentages.

Table 4: Descriptive statistics: bank balance-sheet variables.

	Tier1 ratio (1)	Liquidity ratio(1)	ROA(1)	Interbank funding ratio (1)	Log of total assets
Mean	21.95	11.68	-0.17	23.58	11.38
Median	17.68	9.92	-0.04	18.88	12.11
p25	13.97	7.91	-0.32	16.98	10.76
p75	26.37	13.08	0.04	28.05	12.27
std	12.36	6.33	0.34	11.82	1.28
N	391,115	732,705	732,705	732,705	732,705

Notes: (1) Expressed in percentages.

Table 5: Descriptive statistics: firm balance-sheet variables.

	Log of term loans	Employment costs over total lagged assets	Investment over total lagged assets	Credit weighted log relationship duration	Credit weighted AI(1)	Return on assets(1)	Leverage (Debt/total assets) (1)	EBITDA/ interest expenses(1)	Log of total assets	Z score
Mean	11.65	0.23	0.55	0.43	0.25	3.65	31.19	16.93	5.25	4.52
Median	11.50	0.17	0.00	0.37	0.00	3.36	19.10	6.69	5.29	4.00
p25	10.31	0.06	0.00	0.00	0.00	0.72	0.00	1.67	3.83	3.00
p75	12.84	0.33	0.19	0.95	0.50	7.73	61.47	20.50	6.69	6.00
std	1.64	0.23	1.39	0.42	0.39	8.82	33.58	29.78	1.97	1.86
N	607,277	557,006	557,006	702,020	702,020	569,486	568,783	503,623	558,725	569,022

Notes: (1) Expressed in percentages.

Table 6
Effects of AI and lending relationship on quantity of credit

	(1)	(2)	(3)	(4)
Dependent variables:	Term loans	Term loans	Credit lines	Credit lines
Log(Rel. duration)	-1.969***	-1.465***	-0.575	-0.753
× AI× D(2020)	(0.467)	(0.388)	(1.108)	(1.148)
Log(Rel. duration)	1.459***	1.200***	0.239	0.355
× AI	(0.335)	(0.291)	(0.668)	(0.643)
Log(Rel. duration)	2.039***	1.365***	1.238**	1.411**
× D(2020)	(0.347)	(0.277)	(0.612)	(0.620)
Log(Rel. duration)	-0.760***	-0.450**	-1.229***	-1.345***
	(0.194)	(0.183)	(0.311)	(0.313)
AI×D(2020)	5.449		-13.783	
	(7.084)		(14.757)	
AI	1.848**		-5.333**	
	(0.788)		(2.019)	
Observations	957,756	957,750	505,053	505,034
R-squared	0.413	0.417	0.469	0.471
Bank controls	yes	no	yes	no
Bank-firm controls	yes	yes	yes	yes
Bank FE	yes	no	yes	no
Bank*quarter FE	no	yes	no	yes
Firm*quarter FE	yes	yes	yes	yes

Notes: the table shows OLS estimates of regressions for quarter changes in credit by banks operating in Italy to firms in the period 2019:Q1-2020:Q4. Columns 1 and 2 report results for term loans, columns 3 and 4 report results for credit lines. Variables of interest are: Log(Rel. duration): log of duration of relationship (in quarters); AI: a dummy equal to one if the bank uses artificial intelligence on big data to evaluate the creditworthiness of borrowers, zero otherwise; D(2020): a time dummy equal to one if the quarter is equal or subsequent to 2020:Q1. AI and its interaction term with D(2020) are absorbed by bank-time fixed effects in columns 2 and 4. Control variables at the bank-firm levels are: log(credit): log of the size of credit; Share of credit: the share of credit obtained by firm *j* from bank i over the total of bank credit obtained by firm j; Residual maturity: average of residual maturity on bank-firm positions, weighted by credit of each position; Collateral to loan: total private and public guarantees over total credit. Control variables at the bank level for columns 1 and 3 are: Tier 1 ratio: Tier 1 capital over total risk weighted assets; Liquidity ratio: total of cash and government securities net of repo positions to total assets; ROA: Return on assets; Interbank funding ratio: Monetary Financial Institutions (except central bank) deposits and repos over total assets; Size: Log of total assets. All controls are lagged of one period to mitigate endogeneity issues. Double- and triple- interactions of controls and AI, D(2020) are included in every regression but not reported. Robust standard errors in parentheses (clustered at the bank and firm level). The symbols *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

Table 7
Effects of lending relationship on interest rates.

	(1)	(2)	(3)	(4)
Dependent variables:	Term loans	Term loans	Credit lines	Credit lines
Log(Rel. duration)×	0.047*	0.047*	0.126**	0.108*
AI× D(2020)	(0.028)	(0.028)	(0.054)	(0.058)
Log(Rel. duration)×	-0.067***	-0.065***	0.106	0.107
AI	(0.021)	(0.021)	(0.068)	(0.068)
Log(Rel. duration)×	-0.095***	-0.088***	-0.015	-0.019
D(2020)	(0.018)	(0.018)	(0.046)	(0.048)
Log(Rel. duration)	0.161***	0.156***	0.506***	0.509***
	(0.014)	(0.014)	(0.056)	(0.055)
AI × D(2020)	0.118		0.256	
	(0.090)		(0.156)	
AI	0.022		-0.041	
	(0.020)		(0.049)	
Observations	957,756	957,750	545,346	545,335
R-squared	0.672	0.675	0.673	0.673
Bank controls	yes	no	yes	no
Bank-firm controls	yes	yes	yes	yes
Bank FE	yes	no	yes	no
Bank*quarter FE	no	yes	no	yes
Firm*quarter FE	yes	yes	yes	yes

Notes: the table shows OLS estimates of regressions for levels of interest rates on loans by banks operating in Italy to firms in the period 2019:Q1-2020:Q4. Columns 1 and 2 report results for term loans, columns 3 and 4 report results for credit lines. Variables of interest are: Log(Rel. duration): log of duration of relationship (in quarters); AI: a dummy equal to one if the bank uses artificial intelligence on big data to evaluate the creditworthiness of borrowers, zero otherwise; D(2020): a time dummy equal to one if the quarter is equal or subsequent to 2020:Q1. AI and its interaction with D(2020) are absorbed by bank-time fixed effects in columns 2 and 4. Control variables at the bank-firm levels are: log(credit): log of the size of credit; Share of credit: the share of credit obtained by firm *j* from bank i over the total of bank credit obtained by firm j; Residual maturity: average of residual maturity on bank-firm positions, weighted by credit of each position; Collateral to loan: total private and public guarantees over total credit. Control variables at the bank level for columns 1 and 3 are: Tier 1 ratio: Tier 1 capital over total risk weighted assets; Liquidity ratio: total of cash and government securities net of repo positions to total assets; ROA: Return on assets; Interbank funding ratio: Monetary Financial Institutions (except central bank) deposits and repos over total assets; Size: Log of total assets. All controls are lagged of one period to mitigate endogeneity issues. Double- and triple-interactions of controls and AI, D(2020) are included in every regression. Robust standard errors in parentheses (clustered at the bank and firm level). The symbols *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

Table 8
Effects of lending relationship on credit volumes and interest rates

Dependent variables:	Credit volumes (term loans)			Interest rates on term loans		
	(1) AI banks	(2) non-AI banks	(1) – (2)	(3) AI banks	(4) non-AI banks	(3) – (4)
Normal times (a)	0.75***	-0.45**	1.20***	0.09***	0.16***	-0.07***
	(0.236)	(0.183)	(0.291)	(0.017)	(0.014)	(0.021)
Crisis (b)	0.65***	0.91***	-0.26	0.05**	0.07***	-0.02
	(0.275)	(0.242)	(0.360)	(0.020)	(0.015)	(0.024)
(b) – (a)	-0.10	1.36***		-0.04	-0.09***	
	(0.313)	(0.277)		(0.027)	(0.018)	
Observations		957,750			957,750	
R-squared		0.417			0.675	
Bank controls		no			no	
Bank-firm controls		yes			yes	
Bank FE		no			no	
Bank*quarter FE		yes			yes	

Notes: the table shows the effects of Log (Rel. duration) on the quantity and price of term loan. It uses the coefficients of Log(Rel. duration) in column 2 of the regressions in Tables 6 and 7 to evaluate the effects in normal and in crisis times, distinguishing AI and non-AI banks. The lower panel reports the different effects between crisis and normal times; the third and sixth columns report the difference between AI and non-AI banks. Robust standard errors in parentheses (clustered at the bank and firm level). The symbols *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

Table 9

The real effects of relationship lending and financial innovation at the firm level

Dependent variables:	(1) Credit	(2) Investments	(3) Employment
$\overline{Dur}$ x D(2020)	0.0476***	0.2481***	0.0163***
	(0.007)	(0.018)	(0.001)
$\overline{Dur}$ x $\overline{AI}$ x D(2020)	-0.0277**	-0.0883*	-0.0047*
	(0.014)	(0.048)	(0.003)
$\overline{AI}$ x D(2020)	0.0154	0.0255	-0.0007
	(0.010)	(0.031)	(0.002)
Observations	292,666	296,296	220,642
R-squared	0.927	0.696	0.982
Firm controls	yes	yes	yes
Firm FE	yes	yes	yes
Time FE	yes	yes	yes

Note: the table shows OLS estimates at the firm level for: Credit: log(term loans); Employment: labor costs over total lagged assets; Investment: investment over total lagged assets. Variables of interest are: $\overline{Dur}$: durations of firms' relation with main lender, weighted by the main lender's credit size; $\overline{AI}$: share of credit by the firm's main lender if this lender is AI; D(2020): a time dummy equal to one if the quarter is equal or subsequent to 2020:Q1. Bank control variables (not reported in the table) are: firm's ROA: return on assets; Leverage: total debt to total asset; EBITDA/interests expanses: earnings before interest, taxes, depreciation and amortization over financial expanses; Size; log of size of firm. Z score: probability of default of the firm, ranging from 1 (lowest risk) to 9 (highest risk). All controls are lagged of one period to mitigate endogeneity issues. Robust standard errors in parentheses (clustered at the firm level). The symbols *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

Appendix: Robustness checks for potential issues in the estimation of the effects of AI and relationship lending

The methodology adopted in Table 6 and 7 would be flawed if firms' credit demand were specific to certain banks. For example, this could happen if firms prefer innovative (or non-innovative) banks when seeking credit, or if AI banks and non-AI banks with longer (or shorter) relationships specialized in certain sectors of the economy, such as services, which were more affected by the pandemic.

We do not believe that the first concern is valid because of asymmetric information between banks and firms: non-financial corporations are typically not completely aware of whether a bank uses innovative artificial intelligence techniques to improve its screening capacity. We support this claim by performing a dynamic sorting test of the possible matching between banks and firms (see Table A1). We regress several firm characteristics on a dummy that is equal to 1 if the firm has a relationship with an AI-bank and 0 otherwise. The firm characteristics include ROA, leverage, the log of total assets, EBITDA to interest expenses and credit rating. The only marginally significant driver of the match is firm size, however its statistical significance is low and the magnitude of the effect is very limited. We conclude that the dynamic sorting test does not provide strong evidence of the sorting between AI banks and firms with certain characteristics.

Table A1: Dynamic sorting test

Dependent variables:	(1) ROA	(2) Leverage	(3) EBIDTA to int. expenses	(4) Log of total assets	(5) Credit rating
AI	0.6468	-1.9560	-2.1263	0.0324*	0.0354
	(0.509)	(1.338)	(1.785)	(0.018)	(0.026)
Observations	5,440,806	5,437,036	5,092,583	5,376,939	5,436,618
R-squared	0.000	0.000	0.000	0.025	0.017
Bank FE	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes

Notes: Robust standard errors in parentheses (clustered at the firm level). p<0.01, ** p<0.05, * p<0.1

Regarding the second concern, we investigated whether the use of AI by banks or the average duration of banks' relationship are correlated with their activity in the service sector. This test has been developed in different steps. First, we computed the relative exposure of a bank to the service sector: $exp_{it} = \frac{loans\ to\ services}{total\ loans}$; we then constructed exp_$dummy_{it}$, a dummy variable at the bank level that equals 1 if the exposure of bank i is above the median of the distribution of exp_{it} in 2019, and 0 otherwise. As a second step, we performed a regression in which the dependent variable AI_{it} is regressed on $\exp\_dummy_{it}$. Since the coefficient is not significant, we can rule out the possibility that innovative banks specialize with respect to the service sector. Similarly, we constructed the variable $dur\_bank_{it} = \sum_j share\_bank_{ijt} \times \log(dur)_{ijt}$ where $share_bank_{ijt}$is the share of credit obtained by the firm j out of the total credit granted from bank i, while $\log(dur)_{ijt}$ is the log duration of the relationship between firm j and bank *i* at time t. Thus, dur_bank_{it} is a credit weighted measure of the average duration of bank *i* at time *t*. Again, we regress dur_bank_{it} over $\exp\_dummy_{it}$ and we found a non-significant correlation between the average lending duration of a bank and business in specific sectors of the real economy that have been more exposed to the pandemic shock. Results are available upon request.

Table A2: Public guarantee loans and AI

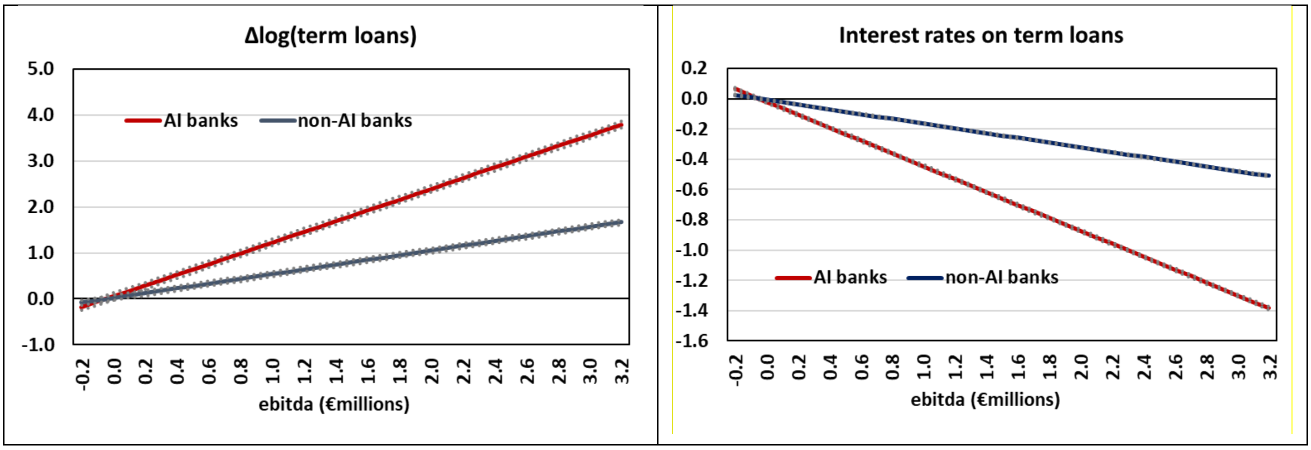
	(1)	(2)
Dependent variables:	Share of public guarantee loans	Share of public guarantee loans
AI	4.84	3.47
	(2.986)	(3.494)
Tier 1		-0.53
		(10.819)
ROA		-42.89
		(266.826)
Liquidity ratio		12.97
		(9.863)
Interbank deposits ratio		-2.22
		(6.818)
Bank size		-0.77
		(0.887)
Size of loan (median)		-2.03
		(1.241)
Share (median)		-0.13***
		(0.044)
Observations	117	117
R-squared	0.029	0.212
Bank fixed effects	yes	yes

Notes: The dependent variable is the incidence of public guarantees over total loans granted during the pandemic Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 All explanatory variables are lagged of one period.

Another potential concern with our methodology is that different types of banks (AI versus non-AI banks) may have had different incentives in granting loans with a public guarantee during the pandemic. We rule out this possibility by running a regression at the bank level where the dependent variable is the incidence of public guarantees over loans granted during the pandemic and the explanatory variables include: the dummy AI, bank controls (capital ratio, liquidity ratio, ROA, interbank funding ratio, size), and bank-measures for loan size (i.e., the median of the size distribution of all loans granted by the bank) and for the share of loans granted by bank *i* on total credit obtained by each borrower (i.e., for each bank, the median of the distribution of its shares with all borrowers). The results are reported in Table A2. The regression is performed at the end of 2020 and all the explanatory variables are lagged. We find that the coefficient on the dummy AI is not significant, indicating that the adoption of artificial intelligence does not correlate with the incentives in granting loans with a public guarantee during the pandemic.

A final test has been conducted to evaluate the differential reactivity of AI and non-AI banks to changes in firm-specific conditions. The characteristics of our quarterly dataset and the firm-specific characteristics reported at the annual level do not permit a proper analysis of the differential reactivity of loan quantities and prices to immediate changes in transaction volumes or profit measures, distinguishing between AI and non-AI banks. However, a simple sample split shows that AI banks react significantly more to changes in EBITDA, a measure of a firm's operating performance, than non-AI banks (see Figure A1). For example, an increase of EBITDA by 1 standard deviation (0.8 million euros), other things being equal, is associated with an increase in the quarterly growth rate of term loans by 1.0% for AI banks and 0.4% for non-AI banks, and a corresponding reduction in the interest rate on term loans by 35 basis points for AI banks and 13 basis points for non-AI banks.

Figure A1: Different reactivity of AI and non-AI banks to changes in EBIDTA



Source: Elaborations on Bank of Italy and Cerved data. Notes: The models include also bank-year fixed effects. The EBITDA focuses on a firm's operating performance by measuring earnings before the impact of financing and accounting decisions. It provides insight into the company's operational profitability. Changes in EBITDA reflect variations in a company's core business performance, such as sales growth, cost management, and overall operational efficiency. Robust standard errors clustered at firm level. Confidence bands at the 95% level.