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BIRDS OF A FEATHER FLOCK TOGETHER: THE COUPLING OF INNOVATIVE BANKS AND INNOVATIVE FIRMS

by Silvia Del Prete*, Stefano Schiaffi† and Giovanni Soggia‡

Abstract

Financial technology (Fintech) innovation in banking has the potential to improve banks' screening and monitoring abilities, especially for more opaque firms, thereby improving their portfolio and risk allocation. We test the impact of Fintech innovation in borrower monitoring on banks' supply of credit to Italian firms, with a special focus on small innovative businesses. To this end, we use Credit Register data on outstanding loans for Italy at the bank-firm level, combined with information on bank Fintech innovation from the Bank of Italy's Regional Bank Lending Survey, and the classification of innovative young firms under the Italian Start-up Act. We find that banks investing in Fintech-based monitoring technologies provide larger volumes of credit to innovative firms at lower interest rates. Moreover, firms borrowing from these banks seem to benefit from stronger relationships, as they are less likely to exit the credit market. Finally, we find no evidence that Fintech innovation in monitoring increases the likelihood of loans to innovative firms becoming non-performing.

JEL Classification: G01, G21, O33.

Keywords: banking, fintech investments, corporate finance, innovative firms.

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* Banca d'Italia, Bologna Branch, Regional Economic Research Division; email: silvia.delprete@bancaditalia.it.

† Banca d'Italia, Economic Outlook and Monetary Policy Directorate; email:stefano.schiaffi@bancaditalia.it.

‡ Bank of Italy, Cagliari Branch, Regional Economic Research Division; e-mail: giovanni.soggia@bancaditalia.it.

1 Introduction[1]

Theoretical and empirical evidence has shown that innovative companies are typically characterized by limited credit history, lack of collateral, young age and greater incidence of intangible assets like patents; therefore, these firms often suffer from greater external financing constraints compared to other firms because they are generally more difficult to screen and monitor (Magri, 2009).[2]

Against this background, the role of banks' technological innovation in improving innovative firms' credit conditions is *a priori* uncertain. On the one hand, intermediaries that are able to use innovative screening and monitoring technologies may gather alternative hard data on these firms or on their owners and use it to complement existing soft information to gauge credit worthiness and improve monitoring, potentially increasing their credit supply to firms compared to other banks (Branzoli et al., 2024). On the other hand, more traditional banks, which base their lending process mainly on soft information, could preserve a substantial information advantage, in particular with respect to innovative companies, given that soft information would be particularly difficult to incorporate into technological screening and monitoring processes (Flögel and Beckamp, 2019).

While the existing literature on relationship lending has focused primarily on the dimensional symmetry in the bank-firm credit relations,[3] in this paper we study another form of

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[2]Magri (2009) suggests that small firms encounter difficulties in collecting external finance due to greater information problems. For small innovative firms, whose activity is more difficult to evaluate, the cost of external finance could be even higher. For these reasons, banks could not be the more adequate intermediaries to finance innovative firms and innovative start-ups, requiring more focused financing sources, as private equity, business angels, etc.

[3]See, among the others, Boot (2000); Agarwal and Hauswald (2007); Alessandrini et al. (2009); Stein (2002); Liberti and Mian (2009) In this field of the literature a clear dimensional symmetry in bank-firm relationships emerges, due to the fact that smaller, less complex and local banks enjoy a comparative information advantage relative to the larger ones in financing small and opaque firms. Local and smaller banks are better placed, being geographically closer, to collect and manage soft information on more opaque, and therefore harder to screen, customers, as in the case of innovative firms and innovative start-ups.

less explored symmetry in bank-firm credit relationships, namely the *symmetry based on innovation*. Indeed, the aim of the paper is to investigate empirically the "special link" in credit relations between innovative banks and innovative firms. Thus, we test the existence of an "affinity" between banks that invested more in financial innovation technology – especially with the purpose of improving their screening and monitoring processes – and innovative firms, defined according to the 2012 Italian Start-up Act. Specifically, we evaluate whether Fintech banks provide more credit on the extensive and intensive margins to innovative companies with respect to other intermediaries, and whether they offer better credit conditions to innovative activities relative to those faced by firms operating in traditional sectors. To the best of our knowledge, this is the first study investigating the matching between innovative banks and innovative firms.

To this end, we build a unique dataset using bank-firm credit relations from the Italian Central Credit Register (CCR), and we complement these data with the level of technological innovation of Italian banks, drawing information from the Italian Regional Bank Lending Survey (RBLS), which is conducted yearly on a representative sample of Italian intermediaries. In accordance with the 2012 Start-up Act, we define innovative firms as those classified as "innovative start-ups" and/or "small and medium innovative companies" by the Italian Ministry of Enterprises and Made in Italy (Ministero delle Imprese e del Made in Italy, MIMIT).[4] Finally, we add other bank-level characteristics, stemming from the Bank of Italy's Supervisory Reports. In our econometric set-up, we exploit multi-lending relationships, which are typical of the Italian banking system, and firm-year fixed effects (Khwaja and Mian, 2008), in order to isolate the impact of banks' technological investments from demand characteristics by comparing loans granted by Fintech and non-Fintech banks to the same firm and then averaging out the effect across firms.

The empirical analysis yields several important results. Firstly, banks that invested in Fintech projects with the purpose of improving the evaluation of borrowers' creditworthiness

[4] According to the MIMIT principles (in previous years labelled as Ministry of Economic Development, i.e. MISE), these firms have to satisfy the following criteria: i) be operational for less than five years; ii) be headquartered in Italy; iii) have an annual turnover lower than 5 million euros; iv) not be the result of a branch split or merger from a previous company; v) present a mission statement explicitly related to innovation; vi) be a limited company and not publicly listed; and vii) should not have distributed profits. Furthermore, firms need to fulfil at least one of the following three criteria: a) they should have at least 15 percent of R&D expenditure ratio; b) 1/3 of employees should be PhD students or graduates or researchers and/or 2/3 should hold a Master's degree; c) be the holder, depository or licensee of a patent, or owner/author of registered software. For more details, see section 3.2.

– henceforth “Monitoring banks” – provide more credit on the intensive margin and, generally, at lower interest rates to innovative firms. Secondly, the probability of an interruption of the bank-firm relationship shrinks for all firms borrowing from Monitoring banks. Finally, we find no evidence of greater risk-taking by Monitoring banks compared to other banks. On the intensive margin, our results suggest that Monitoring banks are able to reduce the information asymmetry between innovative firms and financial intermediaries more than other banks, leading to a greater supply of credit and to lower interest rates, without increasing credit risk. However, on the extensive margin Monitoring banks do not seem to have an edge compared to other banks. This result is likely due to innovative firms’ access to public guarantees on their loans, which limited the screening impact of Fintech investments for these firms, against the backdrop of a still relevant role of soft information in banks’ decision to originate a new credit relationship in a context of limited hard information.

Our results shed light on the channels through which technological innovation can affect the supply of credit. According to the literature, we can expect that a bank that has invested in technological innovation may be more inclined to finance innovative companies for several reasons, depending on the specific technology and its purpose. Firstly, related to the *“screening and monitoring channel”*, technological innovation and modern data analysis techniques can make it possible to process (hard and soft) information more efficiently and improve bank evaluation processes, which is particularly useful for the youngest and the most financially opaque companies, as well as for those that have intangible patents, or relatively scarce collateral to pledge. It seems reasonable to expect that those banks investing more in Fintech projects – aimed in particular to implement innovative lending technologies or to use more efficiently the information in customers’ screening – will be better equipped to evaluate and finance more innovative or younger companies (Dapp, 2015; Jagtiani and Lemieux, 2017; Philippon, 2016), which, in turn, have less opportunities to offer collateral to guarantee their loans. Second, related to the *“channel of portfolio optimization-diversification”*, banks with higher Fintech investments in sophisticated asset management and monitoring systems can refine the risk diversification process of their loan portfolio, improving overall asset management and allowing to increase the bank’s exposure to more innovative, riskier companies or sectors, with higher potential yield. Finally, linked to the *“efficiency-profitability channel”*, Fintech investments are often aimed at making processes more efficient, leading to an increasing bank profitability, stemming from higher revenues or cost savings. This can free up resources in terms of capital to invest further in new loans, even towards riskier projects-sectors by younger firms, as suggested by recent studies (Martynova et al., 2020). All in all, our results confirm the importance of the screening and monitoring channel in influencing the supply of credit to all firms and especially to the more innovative ones.

The rest of the paper is organized as follows. Section 2 reviews the empirical literature on relationship lending and financial innovation channels in the banking activity, highlighting testable hypotheses. Section 3 describes data used in the empirical exercise, as well as the definitions and the descriptive evidence for both innovative banks and innovative firms we rely on. Section 4 presents the econometric set-up, while Section 5 reports our main findings. Finally, Section 6 concludes the paper and states some policy implications.

2 A literature review

A vast theoretical and empirical literature has proved that the financing of younger and innovative firms could suffer major asymmetric information problems, generating financial constraints. Financing frictions that matter for innovative (new patents and new projects) and younger firms is the crucial concern to address, based on the dilemma of soft *versus* hard information in evaluating customers' creditworthiness and monitoring default status over time.

It is worth noting that innovative young firms have no history, and cannot rely on soft information, needing collateral (hard-information) to signal their credit quality and obtaining finance (Adelino et al., 2019; Corradin and Popov, 2015; Schmalz et al., 2017). More in general, collateral may be a solution to adverse selection, in particular for more opaque and risky firms, especially the youngest ones, as suggested by Jimenez et al. (2006).[5] Related to this point, Adelino et al. (2019) focus on lending to small and medium enterprises (SMEs) and highlight the effectiveness of a "collateral-lending channel" at work in high-developing areas and industries, showing that small firms in areas with greater increases in house prices experienced stronger growth in employment than large firms in the same areas and industries. To identify the role of the "collateral-lending channel" separately from aggregate changes in demand, they show that this effect is more pronounced in industries that need little start-up capital and in which housing collateral is more important. With the same vein, Corradin and Popov (2015) find that housing wealth helps alleviate credit constraints for potential

[5] By the use of collateral, more financially opaque borrowers (as start-ups or innovative firms) can signal the quality of their projects to be financed, and overcome financial constraints due to asymmetric information.

entrepreneurs, by enabling homeowners to extract equity from their property and invest it in their business.

Innovation adds to the framework of small, newly established businesses, a further step of complexity. In general, innovation entails risky projects and is therefore stifled by asymmetric information. Traditional transaction banks have little knowledge to judge whether the innovation is good or bad; this is why innovation relies mainly on relationship lending and qualitative-perspective information (Hombert and Matray, 2016). In this sense, innovation is similar to the financing of small firms, which are riskier than larger ones. Innovative small firms and start-ups are more risky, owing in part to their small size and young age. Moreover, the asymmetric information problem is also emphasized as innovative firms frequently prefer to maintain secrecy about what they are doing to prevent other rivals from using their ideas (Magri, 2009).

Banks are different in their lending technologies, both in screening and monitoring loans and borrowers (Stein, 2002). Lending by banks with higher innovation technology (IT) adoption could be less affected by the problem of asymmetries in processing and passing on qualitative (soft) information along complex and hierarchical banks. In other terms, IT banks could make it easier to process all kinds of information, making internal organization more flat and reducing distance in gathering and processing proprietary soft information (Core and De Marco, 2024).[6] At the same time, we might expect that banks with fewer technological resources for evaluating the economic risk of loans would have a greater incentive to use collateral as a substitute for such evaluation (Manove and Padilla, 1999; Manove et al., 2001). Thus, there may be differences in lending practices across financial intermediaries due to their specialization (Carey et al., 1996), their ownership structure (Saunders et al., 1990; Gorton and Rosen, 1995; Prilmeier, 2017), and innovation too. Banking innovation could thus reduce asymmetric information, hardening soft information, even though this is difficult to demonstrate and measure empirically[7]; anyway, it can decrease screening and monitoring costs, with gains in efficiency along the lending process (Benfratello et al., 2008), benefiting bank borrowers with increasing finance and lower interest rates charged on loans.

[6] Core and De Marco (2024) investigate whether banks' information technology (IT) can substitute for local branch presence in the provision of small business credit. Using loan-level data and the institutional features of the Italian public guarantee scheme during COVID-19, they find that IT partially mitigates the impact of local branch presence, as banks with better IT lend more in areas where they have no bank branches, especially to first-time borrowers.

[7] In the empirical literature very few papers have elaborate a proxy for soft information and measure its effect on credit to firms (see Agarwal and Hauswald, 2007).

Therefore, banks that invest more in Fintech projects could be more apt to screen and lend to innovative and younger borrowers, ultimately supporting real effects of firm innovation. Our main results will support this scope: having better tools and technologies to evaluate companies increase credit and reduce costs, especially for innovative companies and only for banks that aim to implement Fintech investment with the specific purpose to improve the assessment of creditworthiness.

Ahnert et al. (2022) suggest that IT also helps in the evaluation of hard information, by improving US banks' ability to verify the value of collateral; in their theoretical model, banks' cost of verifying the value of collateral is lower for IT banks relative to traditional intermediaries.[8] Overall, innovative banks can help alleviate financial constraints, by making it easier to process hard information and to borrow against collateral, therefore increasing credit for innovative young firms.[9] We find evidence that only technologies more related to the monitoring activity help achieve this goal, rather than the ones involved in the collateral evaluation and the screening process.

Banks can invest in Fintech for other reasons. Firstly, banks can use Fintech to reduce costs and gain in efficiency. Some evidence for the Chinese banking industry shows that, when considering the influence of Fintech development, Fintech innovations not only improve the cost efficiency of banks, but also enhance the technology used by financial intermediaries. This double beneficial effect is more significant in the case of market support service innovations (Lee et al., 2021). Furthermore, improving digital and Fintech investments could also enhance revenues diversification, boosting bank profitability (Singh et al., 2021; Arnaudo et al., 2022). Our results, as well as the descriptive evidence from the RBLS, suggest that efficiency – rather than expanding lending opportunities – might be the driver of (broadly speaking) Fintech investments, with an increased credit supply observed only in the sample of intermediaries that invest in monitoring technologies.

Based on the channels highlighted above, we expect non-IT banks, relying more on

[8] Empirically, they show that: i) job creation by young firms is stronger in US counties that are more exposed to IT-intensive banks; ii) an increase in local house prices boosts start-ups employment by more in counties with higher exposure to banks' IT, and even more so in industries in which start-ups depend more on home equity financing; iii) small business lending by banks with higher IT adoption is more sensitive to changes in local house prices; iv) banks with higher degree of IT adoption are more likely to request collateral for their lending.

[9] We can also expect that – collateral being equal – if IT improves banks' ability to evaluate project, "good" innovation should get more credit, while "bad" innovation should get less credit, with an overall spillover effect on firm productivity and growth.

collateral, to be more effective in financing firms belonging to traditional sectors. On the contrary, Fintech banks investing in monitoring technologies should be more able to process Big Data or other (soft and hard) information, being, consequently, more prone to finance innovative young firms (Branzoli et al., 2024). Referring to the Italian credit market, where the majority of firms are small and medium enterprises, and rely more on relationship lending, we support the view of a preferable matching between innovative banks and innovative firms, based on a more efficient monitoring process implemented by Fintech banks. This is also consistent with some evidence found for US financial markets (Blickle et al., 2025), according to which especially large banks specialize by concentrating their lending disproportionately in a few industries. This specialization is consistent with banks having industry-specific knowledge, reflected in reduced risk of loan defaults and higher propensity to lend to opaque firms in their preferred industry.

In this paper, we use new data, on banks' Fintech adoption and its purpose, to address the following research questions. Firstly, we look at the intensive margin and study whether Monitoring banks extend more credit (and at a lower cost) to innovative firms, relative to other intermediaries. Secondly, we look at the extensive margin and investigate if: a) they are more likely to originate new loans to innovative businesses relative to other banks; b) whether investing in monitoring technologies makes bank-firm relationships more likely to end, or rather it makes the relationships more stable. Finally, we test whether innovative monitoring technologies lead to greater or less risk-taking.

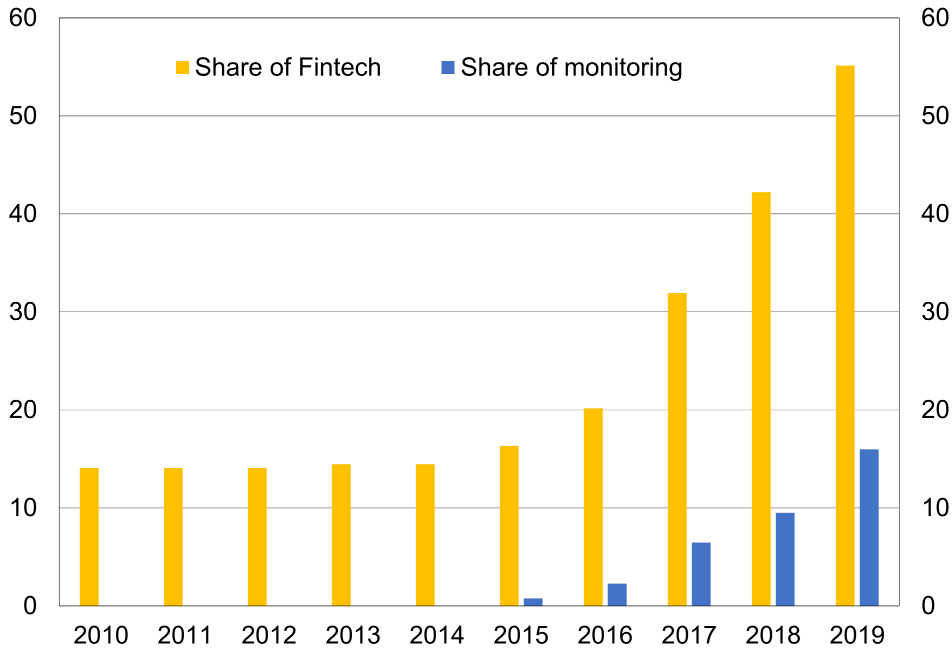
3 Sources, data and descriptive evidence

3.1 Data on banks

For the definition of Fintech banks, we use the Bank of Italy's Regional Bank Lending Survey (henceforth, RBLS). The survey is collected on a sample of Italian banks on a non-consolidated basis and is divided into two parts: in the first one, banks are asked half-yearly to provide information on credit supply and demand, mirroring the structure of ECB's Bank Lending Survey; the second part, conducted only annually, contains specific questions on structural characteristics of financial intermediaries.

We use the 2020 wave of the second section of the questionnaire, which included information on 263 Italian banks (accounting for slightly less than 90 per cent of lending to firms

Figure 1: **Share of Fintech and Monitoring banks** *(percentage values)*



Sources: Authors' elaborations on the Bank of Italy's Regional Bank Lending Survey, Fintech section, 2020 wave.

at the end of 2019). Within the set of structural information provided by the RBLS, we can identify banks that invested in Fintech projects and the year of their first project over the 2010-2019 decade;[10] among the ones that did invest (which afterwards are labelled as "Fintech banks"), we can distinguish those intermediaries that explicitly declared Fintech as a relevant tool to improve their evaluation of borrowers' creditworthiness, thus improving both their screening and their monitoring processes. Typically, banks use evaluation of borrowers' creditworthiness both in their screening and in their monitoring processes; however, as explained in Section 3.3, public guarantee schemes alter the intermediaries' screening procedures, and for our purposes we focus on the monitoring aim of creditworthiness, thus using the label "Monitoring banks" henceforth.[11]

[10]The analysis is conducted using yearly data for the period 2010-2019, thus excluding the Covid crisis and its peculiar credit dynamics (Branzoli et al., 2024).

[11]From the RBLS we know that technologies implemented by Italian banks to improve evaluation and monitoring of firms' creditworthiness are mainly Artificial Intelligence (AI) and Big Data. However, this piece of information is available only in the more recent years of our estimation period. This is why we cannot use the label of AI banks instead of Monitoring banks.

At the beginning of our period of analysis (2010), 37 intermediaries were Fintech banks, none of which were Monitoring banks; at the end of the period (2019), 145 surveyed intermediaries were Fintech banks, 42 of which were Monitoring ones (Figure 1).

Table 1: **Bank characteristics: Fintech and Monitoring investments**

Panel A - Fintech vs. non-Fintech banks

	Non-Fintech banks			Fintech banks			Diff	
Variable	Mean	SD	Obs	Mean	SD	Obs	Diff	Signif
Size	20.262	1.036	99	21.088	1.709	164	-0.826	*
Equity ratio	12.405	2.834	99	12.303	3.695	164	0.101	
ROA	0.105	0.399	99	-0.077	0.655	164	-0.182	*
NPL ratio	4.449	2.382	99	4.398	2.364	164	0.051	
Liquidity ratio	5.929	0.296	99	5.916	0.291	164	0.013	*
Interbank lending	2.791	0.382	99	2.684	0.581	164	0.107	

Panel B - Monitoring vs. non-Monitoring banks

	Non-Monitoring banks			Monitoring banks			Diff	
Variable	Mean	SD	Obs	Mean	SD	Obs	Diff	Signif
Size	20.673	1.439	114	22.035	1.905	50	-1.362	*
Equity ratio	12.141	3.376	114	12.674	4.352	50	-0.534	
ROA	0.130	0.524	114	-0.044	0.878	50	-0.174	
NPL ratio	4.080	2.313	114	5.106	2.813	50	-1.026	*
Liquidity ratio	0.517	0.261	114	0.522	0.351	50	-0.005	
Interbank lending	2.673	0.517	114	2.708	0.712	50	-0.035	

Source: Authors' elaborations on the Bank of Italy's Regional Bank Lending Survey - Fintech section (2020), and Bank of Italy's Supervisory Reports.
* indicates statistically significant differences.

In order to control for bank characteristics, we use data on bank features and performance indicators from the Bank of Italy's Supervisory Reports, which are a regulatory requirement for the intermediaries. Specifically, we use bank size, measured as the natural logarithm of total assets; the return on assets (ROA) as a proxy for profitability; an equity ratio given by the book capital value and reserves over total assets, as a measure of bank capitalization; a liquidity index, measured by the ratio between cash and total assets; the non-performing loans (NPLs) on total assets, as a measure for the portfolio riskiness; and interbank lending on total assets, as an index of liquidity interbank provision.

As shown in Table 1, panel A, Fintech banks are on average larger: this may reflect the fact that there are high sunk costs associated with accessing Fintech technologies, especially for lending purposes, and that small banks are more challenged to make this type of investment. Within the Fintech group, those that invest in monitoring technologies are larger and exhibited a greater fraction of NPLs (Table 1, panel B).

3.2 Data on firms

For the definition of Italian innovative firms, we use the special section of the Business Registry dedicated to innovative young companies, providing information on participants in the "Start-up Act" policy framework.

The "Start-up Act" passed in 2012, defining a set of eligibility criteria to identify innovative firms that may benefit from policy support, in particular posing limits on company size and age, and targeting high-potential ventures. More in details, in order to access the policy framework, each firm had to meet a set of criteria, namely: *i)* the company should be operational for less than five years; *ii)* being headquartered in Italy; *iii)* had an annual turnover lower than 5 million euros; *iv)* not being the result of a branch split or merger from a previous company; *v)* presenting a mission statement explicitly related to innovation; *vi)* being a limited company and not publicly listed; and, *vii)* should not have distributed profits. Furthermore, firms needed to fulfil at least one of the following three criteria: at least 15 percent of R&D expenditure ratio; 1/3 of employees as PhD students or graduates or researchers and-or 2/3 holding a Master's degree; and, being the holder, depository or licensee of a patent, or owner/author of registered software.[12]

Within this policy framework, firms could access a wide range of instruments activated by the "Start-up Act", including policies which cut red tape and facilitate entry into and exit from the market; tax incentives; tailor made labour laws; flexible remuneration schemes; incentives for equity crowd funding; and so on.

Due to this peculiar framework, innovative companies could systematically differ from other firms. In order to investigate such differences, we merge our data with firm balance sheet statements on Italian non-financial companies (Cerved database) to add information on the number of employees, revenues, age, risk classification (share of risky firms), geographical

[12] For an extensive analysis on the Start-up Act, see DeStefano et al. (2018). In our sample, we are not able to distinguish between start-ups and old innovative firms. Since the increasing presence of the latter could influence our evidence, we will try to address this concern in future analysis.

location (share of firms located in the South of Italy), and sector (share of manufacturing firms). We perform balancing tests to assess differences across groups.

The descriptive evidence, reported in Table 2, shows that innovative firms are smaller (both in terms of number of employees and revenues), younger, and less likely to be classified as risky relative to the other non-innovative companies (although they are more frequently classified as vulnerable firms, i.e. with an intermediate level of riskiness). They are also less concentrated in Southern regions and are more likely to operate in the manufacturing sector. These differences underscore the importance of controlling for firm characteristics and support our identification strategy, which isolates within-firm variation across banks.

Table 2: **Balancing Test of Firm Characteristics: Innovative Firms vs. Other Firms**

	Other Firms			Innovative Firms			Diff	
Variable	Mean	SD	Obs	Mean	SD	Obs	Diff	Signif
Employees	11.6	186.4	1,053,735	4.0	7.6	3,121	7.6	*
Revenues (1) (2)	2,415.2	9,407.4	788,631	297.7	847.2	4,777	2,117.5	*
Age (1)	13.1	11.0	1,036,176	2.8	1.5	4,989	10.3	*
Vulnerable	34.5	34.8	763,040	39.1	38.3	4,239	-4.7	*
Risky	28.3	37.1	763,040	25.7	35.3	4,239	2.6	*
South	26.5	44.2	3,152,429	15.7	36.4	5,379	10.8	*
Manufacturing	13.1	33.8	3,152,429	24.2	42.8	5,379	-11.1	*

Source: Authors' elaborations on Cerved database.
(1) The variables are winsorized at the 1 percent and 99 percent cutoff. (2) Revenues are in thousands of euros.
* indicates statistically significant differences.

3.3 Data on firm-bank relationships

Data on credit relationships over the period 2009-2019 are drawn from the Italian Central Credit Register (CCR), which contains monthly information on all outstanding credit exposures above 30,000 euros, and NPLs above 250 euros. The CCR includes both granted and drawn credit; we follow the prevalent literature on credit supply (see, for instance, Bofondi et al., 2018), and we focus on the former, as credit commitments are less likely to be influenced by fluctuations in credit demands. We can further divide granted exposure into three credit categories: self-liquidating loans, revocable credit lines, and term loans. The first two types are often considered as short-term lending and mainly aimed at financing working capital, while term loans have longer maturity and are usually associated with investment financing.

From the CCR, we use information on the outstanding amount (in logarithm) of granted loans, both total and by credit types, to investigate how the level of bank lending (and its cost) changes depending on whether each firm in our sample borrows from a Fintech or a non-Fintech bank, trying to capture different bank behaviours toward innovative firms (intensive margin). We also use the frequencies of entries and exits in CCR to study if Fintech investments act as screening (entry) or disciplining (exit) devices (extensive margin). Finally, we use data on NPLs to understand if Fintech investments alter the attitude of intermediaries toward loan portfolio risk (risk-taking channel).

Information on credit prices comes from the Bank of Italy's TAXIA database, which contains quarterly information on the interest rates charged on loans granted by a representative sample of Italian intermediaries (around 200 Italian banks). Such data are used to investigate whether firms borrowing from Fintech banks (particularly innovative one) have an advantage in terms of credit price with respect to the financing by non-Fintech banks.

Out of a total sample of roughly 3,3 million firms over the whole period, 5,381 of them are innovative companies. Innovative firms significantly differ from other firms for a series of relevant characteristics (Table 3): perhaps surprisingly, they borrow more, on average, and they tend to rely more on term loans; furthermore, they pay less for bank financing in terms of interest rates. These results may appear counterintuitive, as we have argued before that young innovative firms tend to be riskier and with less collateral. Indeed, the difficulty of having collateral for innovative companies is at the basis of some public support interventions. In Italy, innovative firms access credit also thanks to the Guarantee Central Fund (GCF), a public scheme that is able to partially limit the opacity problems highlighted previously (Zecchini and Ventura, 2009).[13] Related to this point, it needs to be acknowledged that within the policy framework of the "Start-up Act", innovative firms had a fast-track,

[13] In the Italian case, also with the aim of enhancing firm growth, the GCF has proven to be effective for financing SMEs, although the most recent evidence is less clear on the positive effects, because public guarantees could negatively influence banks' attitude towards risk (Gropp et al., 2014; de Blasio et al., 2018). Finally, public subsidies could also lead to greater raising of venture capital, activating a financial channel which is more adequate to finance innovative activities, through providing certification and early stage liquidity (Berger and Hottenrott, 2021).

simplified, and free access to SME Guarantee Fund, enabling access to credit through guarantees on bank loans up to 2.5 million euros, thus easing collateral requirements and interest rates. This is one of the reasons why, in the econometric setup discussed in the next section, we argue that the best way to answer our research question is by estimating a within-firm model by using firm-time fixed effects.

The share of loans with pledgeable collateral (measured as property or assets) is much larger for other firms, which apparently is in contrast with the possibility to access the GCF: however, the guarantee offered by the GCF is considered as personal – meaning the Fund has to intervene when the borrower defaults – and therefore it is not recorded as collateral in the Central Credit Register. This explains why innovative firms – despite benefiting from GCF support – appear less collateralized in our data.

Being relatively young, the length of the relationships of innovative firms with intermediaries is shorter; the share of companies with an exclusive lender is relatively larger; the average share of lenders on firm's total loans is bigger; and finally, the average number of bank relationships is smaller. All in all, descriptive evidence on bank-firm credit relations suggests that innovative firms rely less on collateral, more on exclusive and close relationships, preserving valuable information, and on higher bank support, in order to finance innovative and intangible firm investments.

Table 3: **Balancing Test of Relationship Characteristics: Innovative Firms vs. Other Firms**

	Other Firms			Innovative Firms			Diff	
Variable	Mean	SD	Obs	Mean	SD	Obs	Diff	Sig
Total loans (000€) (1)	126.179	262.260	3,354,248	183.641	267.797	5,381	-57.462	*
Self-liquidating loans (000€) (1)	15.090	48.870	3,354,248	19.070	46.783	5,381	-3.980	*
Term loans (000€) (1)	84.112	191.975	3,354,248	146.071	233.047	5,381	-61.959	*
Revocable credit lines (000€) (1)	18.411	44.231	3,354,248	13.250	31.133	5,381	5.160	*
Collateralized dummy	0.254	0.366	3,354,248	0.039	0.153	5,381	0.215	*
Relationship length (years)	2.853	1.415	3,354,248	1.750	0.743	5,381	1.103	*
Exclusive lender dummy	0.594	0.491	3,354,248	0.652	0.477	5,381	-0.058	*
Share of bank b on firm's total bank loans (%)	80.920	26.781	2,749,146	84.257	23.895	5,319	-3.337	*
Number of bank relationships	1.616	1.351	3,354,248	1.465	0.943	5,381	0.151	*
Interest rate (%)	4.688	2.346	1,538,344	3.931	2.052	2,738	0.756	*

Source: Authors' elaborations on the Bank of Italy's Regional Bank Lending Survey - Fintech section (2020), Bank of Italy's Supervisory Reports, and Central Credit Register.
(1) The loan variables are winsorized at the 1 percent and 99 percent cutoff.
* indicates statistically significant differences.

4 The empirical set-up

Using our unique dataset, we set out to test the existence of an "affinity" between banks that invested more in financial innovation technology with the purpose of improving their screening and monitoring processes and innovative firms. Specifically, we evaluate whether Fintech banks provide more credit on the extensive and intensive margins to innovative companies with respect to other intermediaries, and whether they offer better credit conditions to innovative activities relative to those faced by firms operating in traditional sectors.

To this end, Chodorow-Reich et al. (2022) provide a theoretical framework to rationalize why banks invest in monitoring technologies to act as financial providers to SMEs. In their model, the firm's payoff is subject to uncertainty, which could be eliminated by investing in a costly monitoring technology. In the equilibrium, monitoring is convenient for intermediate values of the financial needs of the firm, which intuitively must be not too large (and thus too alarming) but not too small (therefore, not alarming enough to justify incurring monitoring costs). From the firm's point of view, borrowing from monitoring banks is preferable when financial needs are more likely and when the terminal uncertainty is higher – both conditions that usually apply to young innovative firms.

The identification strategy exploits the fact that innovative companies are only partially financed by banks that at a certain point in time have invested in Fintech. This heterogeneity in credit relations allows us to rely on multi-lending relationships, as in Khwaja and Mian (2008). To this end, we use a panel model with firm-time fixed effects, which control for time-invariant demand factors related to firms' characteristics. We augment the model with bank fixed effects, in order to control for unobservable time-invariant bank characteristics, to better estimate the effect on the matching in credit relations between innovative banks and innovative companies. The inclusion of bank fixed effects implies that our coefficients are identified over the banks that switch status at a given point in time in our sample. Additionally, we also include time-varying (bank and bank-firm) controls in the model to take into account relevant bank economic features and relationship characteristics.

We estimate the following equation:

$$y_{f,b,t} = \beta_1 D_{b,t}^{Fintech} + \beta_2 D_f^{Inn} \times D_{b,t}^{Fintech} + \theta' BankChar_{b,t} + \phi' BankFirmChar_{f,b,t} + \gamma_{f,t} + \delta_b + \varepsilon_{f,b,t} \tag{4.1}$$

where:

- $y_{f,b,t}$ can be, alternatively, one of the following variables, depending on the empirical question:
  - the log of the outstanding amount of granted loans by bank b to firm f;
  - the interest rate on the outstanding amount of granted loans;
  - a dummy equal to 1 when the lending relationship between bank b and firm f appears for the first time in the CCR, and zero otherwise;
  - a dummy equal to 1 when the lending relationship between bank b and firm f disappears, and drops from the CCR, and zero otherwise;
  - a dummy equal to 1 when the loan from bank b to firm f becomes non-performing, and zero otherwise;
- $D_{b,t}^{Fintech}$ is a dummy equal to 1 in year t for banks that invested in Fintech as a whole; in alternative to $D_{b,t}^{Fintech}$, in most of the regressions we use $D_{b,t}^{Monitoring}$, which takes value 1 only when Fintech investment is geared to a monitoring purpose. Notice that $D_{b,t}^{Monitoring} = 1$ implies $D_{b,t}^{Fintech} = 1$.
- D_f^{Inn} is a dummy equal to 1 for innovative firms, defined according to the classification provided by the Italian Ministry of Enterprises and Made in Italy;
- $BankChar_{b,t}$ and $BankFirmChar_{f,b,t}$ are control variables for time-varying bank- and bank-firm-level characteristics discussed in the previous section, among which we always control for the length of the bank-firm relationship, as well as (in some estimates) for the share of credit granted by the main bank.
- $\gamma_{f,t}$ and δ_b are firm-time and bank fixed effects, respectively.

The β_1 coefficient captures the effect of Fintech investments or, alternatively, Monitoring investments on $y_{f,b,t}$ relative to banks that did not make such investments. The β_2 coefficient, if statistically significant and positive (negative), signals that the effect captured by β_1 is stronger (weaker) for loans extended to innovative firms compared to those granted to other firms.

We adopt a panel data model with firm-year and bank fixed effects, following the identification strategy by Khwaja and Mian (2008). This approach allows us to exploit multi-lending relationships and to identify the effect of FinTech adoption within firms, by comparing the behavior of different banks, lending to the same firm in the same year. In this econometric setup, the inclusion of firm-year fixed effects controls for time-varying demand-side heterogeneity, while bank fixed effects absorb time-invariant bank characteristics. Since our identification strategy relies on within-firm variation across banks, conditional on firm-year and bank fixed effects, we do not include in the model firm-bank fixed effects, in order to not eliminate the very variation we would exploit - namely, differences in how multiple banks treat the same firm in the same year.

We also contribute to the empirical literature on the topic, by directly testing the predictions of the model by Chodorow-Reich et al. (2022) in the context of financing young innovative firms.

5 Results

5.1 The effect of Fintech investments on the intensive margin of lending to innovative firms and on the cost of credit

In this section, we investigate potential differences in the intensive margin of the credit supply and on pricing by Fintech or in alternative Monitoring banks to innovative firms compared to other banks. To do so, we interact the dummy identifying innovative banks (Fintech and Monitoring) with a dummy that is equal to one for innovative firms. By employing firm-time fixed effects, the coefficients are estimated conditionally on firms having obtained credit both from a non-Fintech bank and from a Fintech – or a Monitoring – bank at time t.

In the first set of regressions, we focus on Fintech banks. The results of our tests, reported in Tables A1 and A2, in the Appendix A, show that the average firm does not seem to be able to borrow more (or at a lower cost) from Fintech banks with respect to non-Fintech intermediaries, once we control for bank characteristics (time-varying and fixed effects) and bank-firm relationship features (columns (3) and (4)). Furthermore, no differential effect is found on innovative firms.

When we focus on Monitoring banks – i.e. banks that invest in Fintech technologies with the specific aim of improving their creditworthiness assessment in the lending process –, we find that innovative firms are able to borrow more from these banks, with respect to other intermediaries:[14] loans granted by Monitoring banks to innovative firms is around 10 percent larger, on average, than the loan granted by other banks (Table 4). Moreover, innovative companies also benefit from a reduction in the interest rates charged by monitoring intermediaries (by about 28 basis points) relative to traditional banks (Table 5).

Table 4: **Effects of Fintech Adoption for Monitoring on Credit to Firms**

	Dependent variable: ln(Total Loans)			
	(1)	(2)	(3)	(4)
Monitoring bank	0.154***	0.154***	0.001	0.023
	(0.058)	(0.058)	(0.018)	(0.015)
Monitoring bank × innovative firm		0.067**	0.109***	0.078*
		(0.034)	(0.037)	(0.046)
Firm×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
Bank FE	No	No	Yes	Yes
R^2	0.610	0.610	0.719	0.729
Adjusted R^2	0.433	0.433	0.577	0.586
F-stat	7.19	7.38	6.99	42.14
Observations	17,544,077	17,544,077	12,778,462	9,026,701

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Since our coefficients are identified from within-firm variation across banks, conditional on firm-year and bank fixed effects, estimates could suffer by a non-random treatment assignment. To address this concern, we have controlled for the treatment along bank characteristics, which could help explore heterogeneous effects. We have thus implemented interactions between the Monitoring bank dummy and bank-level variables to allow for heterogeneous

[14]Results do not change significantly if we replicate columns (1) to (3) by restricting the sample to be the same as in column (4). We also tried to replicate the regressions on the sample of firms for which the information on interest rates is present, without dramatically affecting our findings. These robustness checks are available upon requests.

Table 5: **Effects of Fintech Adoption for Monitoring on Interest Rates**

	Dependent variable: Average IR on Total Loans			
	(1)	(2)	(3)	(4)
Monitoring bank	0.136	0.136	0.027	-0.057
	(0.087)	(0.087)	(0.102)	(0.073)
Monitoring bank × innovative firm		-0.248***	-0.197**	-0.286**
		(0.080)	(0.087)	(0.138)
Firm×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
Bank FE	No	No	Yes	Yes
R^2	0.606	0.606	0.619	0.659
Adjusted R^2	0.422	0.422	0.439	0.488
F-stat	2.45	8.00	16.34	205.93
Observations	8,205,965	8,205,965	7,969,531	5,231,544

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

treatment effects across banks. As shown in Table A3, these interactions do not materially alter our main evidence. Moreover, these additional findings reinforce our interpretation that Monitoring banks are better equipped to serve innovative firms, even after accounting for heterogeneity in bank characteristics.

We also test whether the results come from the systematic differences between banks that decide to invest in innovative technologies and banks that do not. Tables A4 and A5 in Appendix A show that when we replicate the previous regressions only on the sample of Fintech banks, the coefficients are broadly consistent, leading us to believe our results are not driven by a self-selection of investing in Fintech *per se*, but rather by the decision to invest in a monitoring technology to improve credit assessment, conditional on being a Fintech bank.

While our empirical strategy is not based on a difference-in-differences (DiD) framework, we acknowledge that exploring dynamics around the timing of Fintech monitoring adoption should be informative. To this end, we implement an event-study specification as a robustness check, by restricting the sample to those banks that eventually invest in Fintech (either monitoring technology or other investments), and setting the event time to 0 in the year a bank starts investing. Thus, the treatment is equal to 1 for those banks that eventually invest in monitoring technologies, and the control group is made of either banks that invest later in monitoring technology or other Fintech banks. Results in Figure A1 show no evidence of pre-trends in extending loans to innovative firms, supporting the idea that Monitoring banks increase credit to this kind of firms after the adoption of Fintech monitoring investments. Referring to interest rates, while we observe a slightly declining trend prior to the adoption of such technology, which could signal a potential anticipatory behavior or a gradual implementation of monitoring practices, we find that the pre-trend depends on the dynamic of self-liquidating loans, which represent only a small fraction of total loans. Differentiating for loan type, we find no significant pre-trend for the interest rates on term loans and on credit lines. Overall, the event-study results, even though not central to our identification strategy, provide useful complementary evidence and help better clarify the timing of the effects.

Our findings on credit volumes do not appear to be influenced by a specific credit type (Table A6): the coefficient of the interaction between Monitoring banks and Innovative firms is similar across credit lines, self-liquidating loans and term loans, but never significant, signaling an overall Fintech effect on credit availability without a specific channel of financing.[15]

We acknowledge that loan maturity is an important dimension of credit pricing. To this end we re-estimate our interest rates model by distinguishing several credit types (credit lines, self-liquidating loans and term loans) that are characterized by different maturity and risk profiles. Conversely to the outstanding credit granted, the results on lower interest rates faced by innovative firms financed by Monitoring banks are significant for both term loans and credit lines (Table A7), but the effects appear to be larger for the latter, supporting the idea that investing in a monitoring technology has a greater impact on the pricing of the credit type characterized by the highest level of discretion and by less collateral (revocable credit lines).

Furthermore, as depicted in Table 3, approximately two thirds of firms (both innovative and non-innovative) have a single lender; so, the coefficients in our baseline regressions are identified only on one third of bank-firm credit relations. To avoid bias due to sample selection, as a robustness check we consider a different specification that exploits also single-lender firms; in this new setting, we control for possible confounding effects brought by demand shocks by adding fixed effects for all firms belonging to a given 'industry-size-region' group (Degryse et al., 2019).[16] Results are shown in Tables A8 and A9. Estimates coefficients in the loan regression are positive, significant and similar in magnitude to our preferred baseline findings, supporting our main hypothesis that Monitoring banks lend more to innovative firms. Results in the interest rates regression are still negative, but not statistically significant, suggesting more caution on the differential effects on loan pricing to innovative firms.

Finally, to test whether Fintech monitoring banks are simply better at lending to firms that intrinsically have similar characteristics to innovative firms – namely, riskier, smaller or younger firms – rather than specifically to innovative ones, we conducted additional heterogeneity analyses, interacting the Monitoring bank dummy with indicators for small, risky and young firms, respectively. The results are reported in Table A10. Columns (1), (2) and (3) show that Monitoring banks lend significantly less to small, to risky and to young firms. This suggests that the positive effect we observe is not driven by a general preference for

[15]Gambacorta et al. (2024) find that, during the pandemic, Italian banks using AI for credit scoring supplied more credit at lower prices, especially in the form of term loans.

[16]Operatively, we include firm characteristics from the Cerved database, and we use "industry*size*region*year" FEs in addition to firm and bank FEs. Firm size is defined as 4 brackets, based on the number of employees; alternative definitions, for instance based on revenues, yield similar evidence.

businesses with similar characteristics than innovative companies. Analogously, columns (4) and (5) show that the effects on interest rates are not driven by innovative firms also being small and risky, while we find a negative and slightly significant effect on the interaction with the dummy young. Taken together, these placebo tests reinforce our interpretation that the observed effects are not driven by general preferences for small, risky, or young firms. Rather, they reflect a specific and economically meaningful interaction between Fintech monitoring banks and innovative firm characteristics.[17]

5.2 The effect of Fintech investments on the extensive margin of the credit supply

In addition to the effect of monitoring Fintech investments on the intensive margin, we also explore their impact on the extensive margin of credit towards innovative firms. Due to their greater opaqueness and risk (Magri, 2009), these firms may indeed find it more difficult than other companies to initiate a lending relationship. In order to answer this question, we estimate a linear probability model specified as in equation 4.1, where the dependent variable is equal to 1 when a new lending relationship is recorded in the CCR between bank b and firm f, distinguishing innovative intermediaries and business.

According to our main results in Table 6,[18] adopting monitoring technologies does not seem to make Fintech banks more prone to entail new credit relations, either with the average firm or with innovative firms. We do not detect any effects on the probability of obtaining new loans, apart from a weak evidence on term loans with respect to the average firm. No differential effect is found for innovative companies.[19]

In order to investigate whether investing in monitoring technologies results in more stable relationships or in more frequent interruptions, we estimate another linear probability model where the dependent variable is equal to 1 when a lending relationship ceases to exist. There is evidence that the average firm benefits from a reduced probability of exiting the credit

[17] In unreported regressions, we further interacted the Monitoring bank dummy with a composite indicator for firms that are simultaneously small, risky, and young. The results – available upon request – are consistent with the above findings: the interaction is negative and significant in the loan volume regression, and positive and significant in the interest rate regression.

[18] Notice that there are no bank-firm controls in this regression, as new loans are usually issued to firms that do not have prior history in the Credit Register.

[19] Similar findings hold when we consider the broader definition of Fintech banks. Results are available upon requests.

Table 6: **Effects of Fintech for Monitoring on the Probability of Having a New Loan**

	I(new loan)	I(new loan)	I(new loan)	I(new term loan)	I(new credit line)
	(1)	(2)	(3)	(4)	(5)
Monitoring bank	0.003	0.003	0.018	0.021*	0.008
	(0.019)	(0.019)	(0.019)	(0.012)	(0.016)
Monitoring bank × innovative firm		-0.025	-0.005	0.004	-0.011
		(0.022)	(0.017)	(0.013)	(0.014)
Firm×year FE	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes	Yes
R^2	0.405	0.405	0.467	0.412	0.433
Adjusted R^2	0.127	0.127	0.191	0.107	0.139
F-stat	0.02	0.89	9.81	13.31	13.55
Observations	24,829,810	24,829,810	16,453,763	16,453,763	16,453,763

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

market when they borrow from Fintech banks that invested in monitoring technologies (Table 7).[20] We also find some differential positive effects on innovative firms when we focus on term loans, consistently with our previous descriptive evidence, suggesting closer and more stable bank-firm credit relations among Fintech monitoring banks and innovative firms.

Table 7: **Effects of Fintech for Monitoring on the Probability of Exiting the Credit Market**

	I(last loan)	I(last loan)	I(last loan)	I(last term loan)	I(last credit line)
	(1)	(2)	(3)	(4)	(5)
Monitoring bank	-0.060***	-0.060***	-0.059***	-0.035***	-0.044***
	(0.011)	(0.011)	(0.013)	(0.009)	(0.009)
Monitoring bank × innovative firm		0.003	0.000	-0.018*	0.008
		(0.007)	(0.009)	(0.010)	(0.009)
Firm×year FE	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes	Yes
R^2	0.420	0.420	0.515	0.426	0.487
Adjusted R^2	0.150	0.150	0.264	0.128	0.221
F-stat	32.40	16.27	7.66	8.41	7.42
Observations	24,829,810	24,829,810	16,453,763	16,453,763	16,453,763

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 The risk-taking channel of Fintech investments

In this section we examine whether investing in monitoring technologies impacts the probability that their loans become non-performing over time, especially when financing innovative

[20] In this case we could also control for relationship-specific variables: in unreported regressions, we check that these results hold without noticeable changes when we add bank-firm controls to the model.

firms. To this end we estimate equation 4.1 by using as dependent variable a dummy equal to 0 if the loans is performing and equal to 1 if the credit passes through a status of non-performing loan (NPL): either (i) past due/unlikely to pay or (ii) bad loan, the latter being the most severe status.

Table 8 reports our findings. The probability that loans to firms originated by a Monitoring bank become non-performing is unchanged compared to loans originated by other banks. This is the result of a slightly lower chance of a loan becoming past-due or unlikely to pay (-0.4 percentage points) and a marginally greater probability that it becomes a bad loan (0.3 percentage points). Looking at the sub-sample of innovative firms, lending from Monitoring banks appears to be associated with a significantly lower likelihood that credit becomes past-due or unlikely to pay compared to other banks. Estimates indicate that this effect implies a decrease in the probability that loans become non-performing by almost 2 percentage points. This finding is consistent with a comparative advantage that Fintech monitoring banks have in lending to innovative firms (Blickle et al., 2025), due to their increasing knowledge gained in sustaining these more financially opaque companies, which can translate into a reduction of the probability of loan defaults.

Importantly, we include the duration of the relationship between banks and firms among the controls in each equation. This allows us to compare, as far as possible, loans originated by a given bank to a given firm in the same period. A drawback of this model is that it may suffer from censoring bias, since relationships between banks and firms may become non-performing after the end of our sample. To account for this, we also estimate a stratified Cox duration model that regresses the duration of a relationship between a bank and a performing firm on the same explanatory variables of Table 8.[21] According to this model, the length of time before loans become non-performing is not significantly different between Monitoring banks and other banks, both for loans to all firms and for lending to innovative companies. Overall, both the linear probability model in Table 8 and the stratified Cox duration model (see Table A11) do not provide evidence in favour of greater risk-taking by Monitoring banks, in particular for loans to innovative firms.

[21] Duration models, often referred to as survival models or time-to-event models, help solve the censoring problem by appropriately handling situations where the event of interest (such as a loan becoming non-performing) has not occurred for some subjects within the study period. Censoring occurs when the data on some loans is incomplete because they have not yet experienced the event by the end of the observation or study period. In essence, duration models manage the censoring problem by properly handling incomplete information about the event occurrence, allowing for more accurate and robust analyses of time-to-event data.

Table 8: **Effects of Fintech Adoption for Monitoring on the Probability of NPLs**

	NPLs (1)	Other NPLs (2)	Bad Loans (3)
Monitoring bank	-0.001	-0.004**	0.003***
	(0.001)	(0.002)	(0.001)
Monitoring bank × Innovative firm	-0.017***	-0.023***	0.007
	(0.006)	(0.007)	(0.005)
Firm×year FE	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Bank-firm controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R^2	0.837	0.625	0.801
Adjusted R^2	0.752	0.428	0.697
F-stat	54.94	137.53	88.19
Observations	9,939,627	9,939,627	9,939,627

Notes: Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Other NPLs include loans that are considered past due or unlikely to pay.

6 Concluding remarks

Digitalization and Fintech innovation have significantly accelerated in the banking sector in recent years and have the potential to increase bank screening and monitoring abilities, improving bank risk allocation and diversification. This could be particularly true in the case of innovative firms, which are more difficult to screen and monitor having greater intangible assets and less collateral.

Our main findings suggest that Fintech investments in monitoring technologies are associated with increased credit supply to innovative firms, as well as lower interest rates and somewhat more stable lending relationships. Moreover, we find no significant evidence that innovation in monitoring is associated with greater risk-taking, especially towards innovative firms. These results are relevant for the debate on the impact of technological innovation on bank credit provision to firms, confirming the role of Fintech investments as an outward supply shifter, especially to those firms for which asymmetric information concerns could have the largest negative impact on credit conditions.

In the near future, the spread of these Fintech technologies across intermediaries is bound to continue until it reaches a steady-state where adopters include the near universe of banks, thanks to profitability gains for adopters and decreasing investment costs. Thus, their aggregate effects on lending and, in turn, on innovation in production are set to increase over time and the quantitative estimates presented in this paper are likely to be a lower bound of steady-state impacts.

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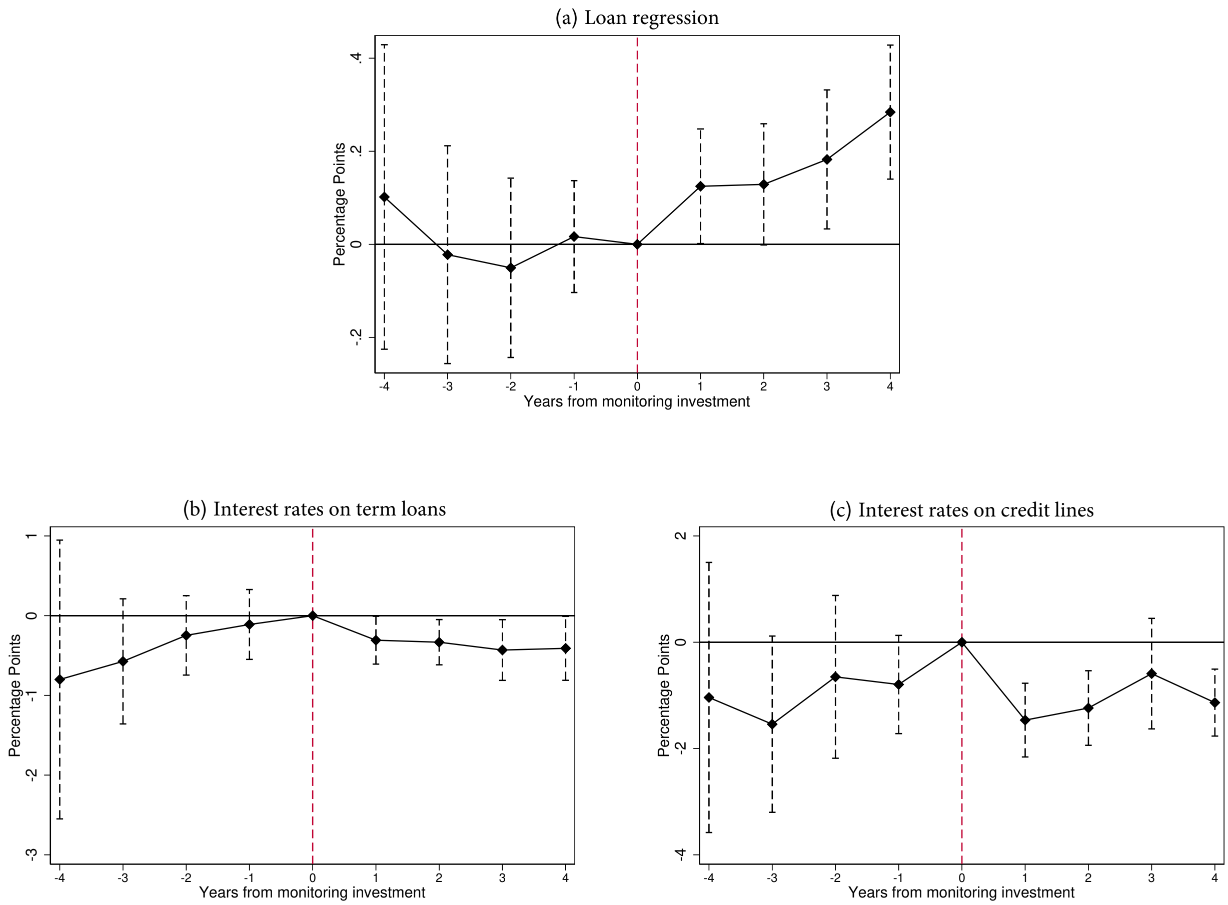
A Additional Figures and Tables

Figure A1: **Pre-trend Analysis on the interaction between monitoring banks and innovative firms**



Note: This figure shows the dynamic effect of Fintech investments in monitoring. Error bars represent 95% confidence intervals. The graph reports the coefficients from the regression:
$Y_{b,f,t} = \alpha_b + \beta_{f,t} + \delta_0 Treated_b + \sum_{\tau=-4}^{+4} \delta_\tau (Treated_b \times D_{\tau=t}) + \sum_{\tau=-4}^{+4} \gamma_\tau D_{\tau=t} + \varepsilon_{b,f,t}$.

Table A1: **Effects of Fintech Adoption on Credit to Firms**

	Dependent variable: ln(Total Loans)			
	(1)	(2)	(3)	(4)
Fintech bank	0.223***	0.223***	-0.001	0.011
	(0.030)	(0.030)	(0.012)	(0.011)
Fintech bank × Innovative firm		-0.008	0.020	0.002
		(0.038)	(0.035)	(0.044)
Firm×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
Bank FE	No	No	Yes	Yes
R^2	0.610	0.610	0.719	0.729
Adjusted R^2	0.434	0.434	0.577	0.586
F-stat	53.60	27.52	6.84	43.83
Observations	17,544,077	17,544,077	12,778,462	9,026,701

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: **Effects of Fintech Adoption on Interest Rates**

	Dependent variable: Average IR on Total Loans			
	(1)	(2)	(3)	(4)
Fintech bank	0.114	0.114	-0.012	-0.016
	(0.074)	(0.074)	(0.078)	(0.064)
Fintech bank × innovative firm		-0.109	-0.086	-0.174
		(0.085)	(0.086)	(0.141)
Firm×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
Bank FE	No	No	Yes	Yes
R^2	0.606	0.606	0.619	0.659
Adjusted R^2	0.422	0.422	0.439	0.488
F-stat	2.40	2.46	18.70	216.34
Observations	8,205,965	8,205,965	7,969,531	5,231,544

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: **Effects of Fintech Adoption for Worthiness Evaluation on Credit to Firms and on Interest Rates Interaction of Bank Controls with Monitoring Bank Dummy**

	(1)	(2)
	ln(Tot. Loans)	IR(Tot. Loans)
Monitoring bank	-0.393	-1.189
	(0.241)	(0.818)
Monitoring bank × innovative firm	0.106***	-0.209**
	(0.038)	(0.091)
Firm × year FE	Yes	Yes
Bank controls	Yes	Yes
Bank controls × Monitoring bank	Yes	Yes
Bank-firm controls	Yes	Yes
Bank FE	Yes	Yes
R^2	0.720	0.619
Adjusted R^2	0.577	0.439
F-Stat	9.45	37.05
Observations	12,778,462	7,969,531

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: **Effects of Fintech Adoption for Worthiness Evaluation on Credit to Firms – Fintech Banks Sample**

	Dependent variable: ln(Total Loans)			
	(1)	(2)	(3)	(4)
Monitoring bank	0.011	0.010	0.007	0.022^{*}
	(0.060)	(0.060)	(0.015)	(0.013)
Monitoring bank × innovative firm		0.150^{***}	0.163^{***}	0.141^{***}
		(0.044)	(0.044)	(0.054)
Firm×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
Bank FE	No	No	Yes	Yes
R^2	0.757	0.757	0.766	0.774
Adjusted R^2	0.609	0.609	0.623	0.633
F-stat	0.03	6.12	8.49	62.77
Observations	5,976,850	5,976,850	5,970,708	4,364,717

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: **Effects of Fintech Adoption for Worthiness Evaluation on Interest Rates – Fintech Banks Sample**

	Dependent variable: Average IR on Total Loans			
	(1)	(2)	(3)	(4)
Monitoring bank	0.088	0.089	0.082	-0.033
	(0.093)	(0.093)	(0.095)	(0.063)
Monitoring bank × innovative firm		-0.383***	-0.330***	-0.387***
		(0.103)	(0.099)	(0.142)
Firm×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
Bank FE	No	No	Yes	Yes
R^2	0.646	0.646	0.653	0.692
Adjusted R^2	0.440	0.440	0.452	0.509
F-stat	0.90	6.92	19.24	294.85
Observations	3,870,435	3,870,435	3,870,435	2,843,231

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: **Effects of Fintech Adoption for Monitoring on Credit to Firms, by Credit Type**

	ln(Self-Liquidating Loans)	ln(Term Loans)	ln(Credit Lines)
	(1)	(2)	(3)
Monitoring bank	0.029**	-0.001	0.032
	(0.014)	(0.025)	(0.025)
Monitoring bank × innovative firm	0.022	0.065	0.003
	(0.063)	(0.049)	(0.100)
Firm×year FE	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Bank-firm controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R^2	0.770	0.679	0.726
Adjusted R^2	0.656	0.489	0.576
F-stat	34.26	20.12	23.43
Observations	4,467,612	4,360,148	6,697,752

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: **Effects of Fintech Adoption for Monitoring on Interest Rates, by Credit Type**

	IR(Self-Liquidating Loans)	IR(Term Loans)	IR(Credit Lines)
	(1)	(2)	(3)
Monitoring bank	0.039	-0.047	-0.062
	(0.060)	(0.058)	(0.120)
Monitoring bank × innovative firm	-0.278*	-0.226**	-0.768***
	(0.145)	(0.090)	(0.232)
Firm×year FE	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Bank-firm controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R^2	0.776	0.626	0.593
Adjusted R^2	0.665	0.405	0.372
F-stat	94.82	96.52	100.41
Observations	2,618,621	2,601,226	3,565,365

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: **Effects of Fintech Adoption for Worthiness Evaluation on Credit to Firms, including Single Bank-Firm Relationships**

	Dependent variable: ln(Total Loans)			
	(1)	(2)	(3)	(4)
Monitoring bank	-0.010	-0.010	-0.009	0.007
	(0.021)	(0.021)	(0.017)	(0.010)
Monitoring bank × innovative firm		0.057**	0.061**	0.105***
		(0.026)	(0.028)	(0.031)
Firm FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Industry×size×region×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
R^2	0.670	0.670	0.733	0.810
Adjusted R^2	0.639	0.639	0.704	0.787
F-stat	0.22	2.38	4.55	1,706.96
Observations	26,837,254	26,837,254	21,081,918	15,509,883

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: **Effects of Fintech Adoption for Worthiness Evaluation on Interest Rates, including Single Bank-Firm Relationships**

	Dependent variable: Average IR on Total Loans			
	(1)	(2)	(3)	(4)
Monitoring bank	-0.024	-0.023	-0.000	-0.054
	(0.096)	(0.096)	(0.107)	(0.080)
Monitoring bank × innovative firm		-0.113	-0.112	-0.131
		(0.076)	(0.077)	(0.118)
Firm FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Industry×size×region×year FE	Yes	Yes	Yes	Yes
Bank controls	No	No	Yes	Yes
Bank-firm controls	No	No	No	Yes
R^2	0.556	0.556	0.558	0.609
Adjusted R^2	0.508	0.508	0.510	0.560
F-stat	0.06	1.36	4.11	238.51
Observations	13,160,524	13,160,524	12,911,297	8,970,352

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: **Placebo Test for Small, Risky, and Young Firms**

	ln(Total Loans) (1)	ln(Total Loans) (2)	ln(Total Loans) (3)	IR(Total Loans) (4)	IR(Total Loans) (5)	IR(Total Loans) (6)
Monitoring bank	0.071***	0.034**	0.029*	-0.003	0.009	0.037
	(0.025)	(0.017)	(0.017)	(0.104)	(0.104)	(0.104)
Monitoring bank × Small firm	-0.137***		0.053			
	(0.045)		(0.056)			
Monitoring bank × Risky firm		-0.084***			0.272*	
		(0.016)			(0.162)	
Monitoring bank × Young firm			-0.068***			-0.147*
			(0.022)			(0.078)
R^2	0.728	0.723	0.712	0.642	0.647	0.640
Adjusted R^2	0.585	0.602	0.581	0.462	0.491	0.474
F-stat	42.81	29.41	28.84	27.56	26.27	11.41
Observations	8,810,524	5,373,504	5,977,360	5,168,665	3,627,623	4,014,510

Notes: Standard errors in parentheses are clustered at the firm and bank level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: **Duration Model**

	Hazard Ratio for a Loan Becoming a NPL
Monitoring bank	0.995
	(0.006)
Monitoring bank × innovative firm	1.197
	(0.156)
Bank size	0.984***
	(0.001)
Equity ratio	1.004***
	(0.001)
ROA	0.890***
	(0.002)
NPL ratio	1.042***
	(0.001)
Liquidity ratio	0.653***
	(0.004)
Interbank lending	0.769***
	(0.001)
Prob > Chi^2	0.000
Observations	4,088,090

Notes: Exponentiated coefficients. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.