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Abstract

Monitoring is one of the main activities explaining the existence of banks, yet empirical evidence about its effect on loan outcomes is scant. Using granular loan-level information from the Italian Credit Register, we build a novel measure of bank monitoring based on banks' requests for information on their existing borrowers and we investigate the effect of bank monitoring on loan repayment. We perform a causal analysis exploiting changes in the regional corporate tax rate as a source of exogenous variation in bank monitoring. Our identification strategy is supported by a theoretical model predicting that a decrease in the tax rate improves bank incentives to monitor borrowers by increasing returns from lending. We find that bank monitoring reduces the probability of a delinquency in a substantial way and the effect is stronger for the type of loans that benefit the most from bank oversight such as term loans.

Key words: bank monitoring, nonperforming loan, tax policy

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1 Introduction

Bank monitoring consists in all supervising activities aimed at verifying and improving the likelihood that a borrower complies with its loan obligations. From a conceptual perspective, bank monitoring can take the form of "ex ante moral hazard prevention" or "ex post costly state verification". The former consists in a series of actions aimed at reducing the borrower's incentive to select a bad investment (Holmstrom and Tirole, 1997; Mehran and Thakor, 2011). The latter refers to an auditing technology that allows a lender to enforce loan repayment (Townsend, 1979; Diamond, 1984; Gale and Hellwig, 1985; Krasa and Villamil, 1992). Since the early banking literature, monitoring has been identified as a major factor explaining the existence of banks (Diamond, 1984), yet the effect of bank monitoring on loan repayment is rather unexplored.

From an empirical perspective, assessing the causal effect of bank monitoring on loan outcomes is challenging. First, bank monitoring is difficult to measure, as it encompasses a range of activities that are usually unobservable. These include collecting information on borrowers' ability to meet the repayment schedule, analyzing financial reports of a business, looking at credit line usage and checking account activity, or setting up regular talks with the managers of a firm (Norden and Weber, 2010; Gustafson et al., 2021). Second, a bank is likely to increase its monitoring intensity when the repayment prospects of a loan worsen, implying that causality can go in either direction.

In this paper we investigate the causal effect of bank monitoring on loan repayment using a novel measure for bank monitoring and exploiting changes in the corporate tax rate as a source of exogenous variation in bank incentives to monitor.

We build our new measure of bank monitoring using quarterly borrower-bank level requests for information on business loans made by Italian banks to the national Credit Register. The information shared in credit bureaus is crucial for banks to properly evaluate the risk profile of their borrowers (Hertzberg et al., 2011; Liberman et al., 2021). For the specific case of the Italian Credit Register, a single request provides information on the amount of loans granted and guarantees issued by other banks to a firm, as well as on the objective conditions of deterioration of each individual exposure. While banks receive monthly updates on their current borrowers from the Credit Register, ad hoc requests allow banks to obtain borrowers' credit history. To ensure that we capture exclusively a monitoring activity, we consider only requests for information made by banks on their existing borrowers that are not associated with the extension of new credit and are not related to exceptional circumstances, such as in the aftermath of a bank M&A.[1] The number of requests for information submitted by a bank on each existing borrower in a given quarter is our proxy for bank monitoring. As argued above, it is important to stress that banks monitor borrowers in many ways, for example by analyzing a firm's financial reports, conducting site visits, talking with a firm's managers and requesting third-party valuations. Our proxy is not intended to quantify all these activities, but rather to provide an observable measure that captures when banks step up their effort in carrying out the various tasks that are useful to monitor borrowers. In other words, we interpret a requests for information as evidence that the bank has decided to take a closer look at one of its borrowers. With this caveat in mind, we analyze the appropriateness of our proxy for bank monitoring, finding that requests for information are more likely to occur when borrowers are more opaque (e.g. small firms with a short credit relationship with the bank), riskier (those with lower credit rating) and in periods of economic downturns, when the risk of credit deterioration increases.

A preliminary analysis shows that the number of requests for information is negatively related to the future probability of a delinquency, suggesting that bank monitoring may have a positive effect on loan repayment. However, this evidence is not enough to establish causation. To investigate the causal effect of bank monitoring on loan repayment, we use taxation as a source of exogenous variation in banks' incentive to monitor borrowers. Our approach builds on a theoretical model describing the effects of a corporate income tax on bank monitoring. In this model, a representative bank determines the optimal monitoring effort, capital ratio and lending rate by maximizing its expected profits. An increase in the corporate tax rate implies a decrease in net profits after tax and a reduction in the capital ratio, which are only partially counteracted by an increase in the lending rate. Overall, this means that an increase in the corporate tax rate results in lower profits. Intuitively, monitoring incentives are stronger the higher is the fraction of profits that goes to shareholders. In fact, the model predicts that bank monitoring increases when the corporate tax rate decreases.

To apply our identification strategy, we exploit exogenous variation in bank monitoring driven by the Italy Regional Production Tax (Imposta Regionale Attività Produttive, IRAP) rate applied to banks. This tax rate is set at the regional level and varies both across regions and over time. Revenues from the IRAP tax are essentially used to finance the health care system which is administered at the regional level. Not surprisingly, we find that the regional tax rates are uncorrelated to local macro conditions and bank factors, whilst they are positively associated with the basic national tax rate and the event of a regional health care

[1] We are interested in bank monitoring in its strict sense. By restricting our sample to existing borrowers, we overlook bank screening of new clients making a loan application.

deficit.[2] To ensure a one-to-one mapping between banks and the tax rate, we limit our analysis to small banks operating at the regional level, which represent the financial intermediaries mostly affected by changes in this local tax.[3] An advantage of this approach is that we conduct our analysis on a rather homogeneous set of banks for which the IRAP tax rate represents a relevant difference. From an external validity viewpoint, we show that firms borrowing from this subset of banks share very similar attributes to the entire universe of Italian companies.

While the IRAP tax rate applied to banks is partially correlated with the tax rate applied to non-financial firms (which, in turn, may affect firms' loan repayment), we are able to exploit a feature of our data which ensures that our instrument satisfies the exclusion restriction. In particular, a major advantage of our dataset is that it includes a sizable number of firms having multiple credit relationships. This means that we can rely on time-varying firm fixed effects to control for any observable and unobservable, time-varying and time-invariant, borrower's characteristic that may affect its access to finance, credit conditions and ability to meet the contractual obligations. This allows to isolate the effect of bank monitoring on loan repayment from the influence of any relevant firm condition, including its tax burden (as driven by the corporate tax rate). Thus, we focus our attention on firms having multiple credit relationships with small banks which operate at the regional level and are subject to the same or different tax rates. This implies that we estimate the effect of bank monitoring on loan repayment by comparing the repayment performance of a given borrower on different loans granted by different banks at the same time. To see the essence of our empirical strategy more clearly, let us consider a simple example of a firm that borrows contemporaneously from two banks. Bank 1 is located in region A and it is subject to a tax rate of $X_A\%$, whereas bank 2 is located in region B and it is subject to a tax rate $X_B\%$, with $X_A\% > X_B\%$. Keeping all relevant firm conditions equal (via firm-time fixed effects), and once having accounted for loan and bank characteristics, we expect bank 2 to monitor more intensively than bank 1. We, thus, test if the firm is more likely repay the loan(s) granted by bank 2 compared to the loan(s) granted by bank 1.

As a first step, we consider a 2SLS model in which we estimate the effect of bank monitoring on the likelihood that a credit exposure is nonperforming from one to eight quarters ahead. To this end, bank monitoring is instrumented with

[2]Each region is allowed to set its local IRAP tax rate, increasing or decreasing the national basic rate within a certain range. In the event of a health care deficit, the regional IRAP tax rate is automatically increased by law.

[3]Italian banks pay the IRAP tax in proportion to the amount of deposits held in each region. Therefore, large banks, which operate in many regions, are less affected by changes in the tax rate of a single region compared to local banks.

the IRAP tax rate. Consistently with our theoretical prediction, we find that an increase in the tax rate implies a decrease in bank monitoring. In particular, a half percentage point decrease in the tax rate (equivalent to almost one standard deviation) implies an increase in the number of requests for information that corresponds to twice its average in the sample. More importantly, we find that monitoring has a positive and statistically significant effect on loan repayment from two to three quarters after a bank's request for information, with the strongest effect over a two quarter horizon. The economic magnitude is substantial: an increase in the number of requests for information associated to a decrease in the tax rate by half a percentage point (approximately, one standard deviation), reduces the probability that the credit exposure becomes nonperforming by 2 percentage points two quarters ahead. This result is significant in economic terms if we take into account that the unconditional probability of a delinquency is roughly 11% in our sample.[4]

The main limitation of our proxy for bank monitoring is that it captures only a fraction of the entire monitoring activity exerted by a bank. In fact, a bank can monitor its borrower also in other ways, for example by checking the company's financial reports, by visiting the firm on site, and even by providing advisory services. In addition, an active request for information made by a bank to assess the current conditions of loans extended by other banks to the firm may capture only monitoring activities related to particularly negative prospects of the firm, which require a closer inspection. Because variation in the tax rate is likely to affect bank incentives with respect to any potential monitoring approach, we are able to extend our analysis investigating the effect of the overall intensity of bank monitoring on loan repayment.

To this end, we estimate a reduced form model in which we directly use the tax rate to capture the entire monitoring activity of the bank and we control for a wide set of loan, bank and regional factors. Our results suggest that a half percentage point decrease in the tax rate (equivalent to almost one standard deviation) leads to a reduction in the probability of a delinquency by 2.7 percentage points. The magnitude of this effect is close and somewhat higher than what detected in the 2SLS model. Despite the two models are not directly comparable, as they are estimated using a slightly different sample, this finding suggests that the requests for information are highly correlated with other forms of bank monitoring. This means that our novel variable is able to capture to a large extent the overall effect of bank monitoring on loan repayment.

In our baseline 2SLS model and reduced form model we estimate the effect

[4] This figure refers to the sample including only firms having multiple bank relationships with small banks that we use in our main regression analysis.

of bank monitoring on loan repayment considering the whole credit exposure of a bank to a firm at a given point in time. Each exposure may include different types of credit, such as a term loan, a credit line and/or a loan backed by accounts receivable (henceforth abridged "accounts receivable loan"). In principle, bank monitoring should be more effective in fostering loan repayment in the case of term loans. In fact, medium to long-term investments, which are typically funded via term loans, represent the business activities that benefit the most from bank oversight. Thus, to test this hypothesis, we examine the heterogeneity of our findings across different loan types separately. We find that the positive effect of bank monitoring on loan repayment is stronger for term loans vis à vis credit lines and accounts receivable loans, consistently with the idea that bank monitoring is more effective in disciplining borrowers in the case of term loans (Acharya et al., 2021). This finding allows us also to rule out a potential concern, namely that the actual driver of the positive effect on loan repayment observed in the baseline model is loan renegotiation of credit lines rather than bank monitoring.[5]

Our main findings are confirmed even when we account for the different interest rates charged by banks lending to the same firm, as captured by the tax rate applied to these banks at the start of the lending relationship.[6] In fact, our theoretical model suggests that banks transfer, to some extent, their tax burden to borrowers by adjusting the lending rate. Consider, for example, the case of a firm that borrows from two banks located in two regions with a different tax rate. We would expect that, ceteris paribus, the bank subject to the higher tax rate charges a higher interest rate than the bank subject to the lower tax rate. To address this issue, we extend the 2SLS model and the reduced form model by including the tax rate applied to the bank at the start of the credit relationship in the set of controls. We also perform a similar exercise considering each type of loan separately. In both cases, the positive effect of bank monitoring on loan repayment remains virtually unchanged if compared to the baseline models.

We complement our empirical study with three additional robustness tests. First, we show that our main results hold true when we include the lagged dependent variable in the set of explanatory variables to account for a certain persistence in the repayment condition of a loan. Second, to further investigate if our results

[5]Differently from other types of loan, the contractual terms of a credit line can be renegotiated in an easy way, even before a loan becomes overdue. A request for renegotiation initiated by the borrower may induce the bank to make a request for information from the Credit Register. While loan renegotiation may occur on any type of loan, this is more likely in the case of credit lines.

[6]Ideally, we would like to estimate our models including the interest rate charged on the various types of loans among the control variables. Unfortunately, we have information on interest rates only for a very restricted sample of banks, which prevents us from conducting this analysis in a reliable way.

are driven by loan restructuring rather than bank monitoring, we estimate the 2SLS model and the reduced form model on a subsample where we discard all credit exposures that are already overdue. We find that bank monitoring reduces the likelihood of a delinquency even for performing credit relationships taken alone. Finally, we show that our findings are robust to various specifications considering different lags for the independent variables of the baseline models.

As a last exercise, we investigate the economic channels behind the observed negative effect of the tax rate on bank monitoring and the positive impact of bank monitoring on loan repayment, respectively. We show that a decrease in the tax rate implies an increase in the number of bank employees. In addition, we document a positive relation between bank monitoring and both firm's capitalization and profitability.

Our paper relates to the literature studying the role of banks as delegated monitors (Diamond, 1984; Krasa and Villamil, 1992; Holmstrom and Tirole, 1997). We contribute to this literature in various ways. First, we provide a novel and direct proxy for bank monitoring at the firm-bank credit relationship level. Our approach to gauge bank monitoring is in the same vein as Gustafson et al. (2021), who use two metrics to directly capture the monitoring effort of banks in syndicated loans: the frequency of banks' requests for information on the borrower's financial statements and an indicator on whether the firm is subject to field exams initiated or conducted by the lender. Our proxy for bank monitoring can be considered as a complement to those of Gustafson et al. (2021), as it consists in banks' requests for information from the Credit Register on the firm's borrowing conditions. As in Gustafson et al. (2021), we find that banks monitor intensively when the value of information is higher (e.g., opaque firms) and when borrowers become more risky. However, while Gustafson et al. (2021) document a positive relationship between bank monitoring and the share of the loan retained by the lead arranger in a syndicate, we find a negative correlation between bank monitoring and the amount lent to the firm as a fraction of the firm's total borrowing from the banking system. A major difference between our setup and that of Gustafson et al. (2021), is that we look at how the monitoring effort varies depending on the role of a bank vis-à-vis other banks lending to the same firm, rather than the role of a bank versus other non-bank lenders (which typically lack the monitoring technology of banks). Beside this distinctive feature, our finding speaks directly to the literature on multiple credit relationships (Carletti, 2004; Carletti et al., 2007; Guiso and Minetti, 2010), providing empirical support to the theoretical prediction that multiple-bank lending may improve bank incentives to monitor (Carletti et al., 2007).[7]

[7] Carletti et al. (2007) argue that multiple-bank lending implies higher bank monitoring to

More importantly, and to the best of our knowledge, we are the first to investigate the causal effect of bank monitoring on the likelihood of loan repayment using a direct loan-level measure for bank monitoring. Gustafson et al. (2021) show that bank monitoring is positively related to loan renegotiation and covenant violation waivers, which may help firms to meet their contractual obligations, but they do not provide any direct evidence on the relation between monitoring and loan repayment. We argue that the main contribution of our paper is to provide an empirical framework that allows to identify and quantify how bank monitoring fosters loan repayment, hereby filling an existing gap in the literature. The crucial feature of this setup is that it exploits variation in bank monitoring that depends solely on conditions of the lender, and not on characteristics of the borrower. We show empirical evidence that bank monitoring is valuable, as it improves in a substantial way borrowers' repayment performance. Our results provide useful insights for regulators and policy makers, especially in light of the topical debate on the "originate-to-distribute" model (Brunnermeier, 2009). In general. our findings suggest that lenders that extend credit without monitoring their borrowers may experience higher default rates, posing concerns for financial stability.

This paper also contributes to the strand of literature investigating the relation between bank shareholder value and risk-taking. This literature highlights that an increase in the survival probability of the bank (and, hence, in the likelihood of retaining rents from lending) due to a higher capitalization, or, more generally, an increase in expected profits to bank shareholders, weaken bank incentives to take on risk (Allen et al., 2011; Mehran and Thakor, 2011; Dell'Ariccia et al., 2014; Jiménez et al., 2014; Bhat and Desai, 2020; Dell'Ariccia et al. 2017; Jiménez et al., 2017). Typically, the relation between bank shareholder value and risk taking has been analysed by focusing on variation in the capital ratio (Allen et al., 2011; Mehran and Thakor, 2011; Bhat and Desai, 2020; Jiménez et al., 2017) or in the policy rate (Dell'Ariccia et al., 2014; Jiménez et al., 2014; Dell'Ariccia et al., 2017). Exploiting the same variation in the IRAP tax rates used in this work and performing an analysis at the bank-level, Gambacorta et al. (2021) show that a decline in the tax rate improves bank capitalization. We move one step further and contribute to this literature by documenting, both theoretically and empirically, that higher bank shareholder value, as driven by a decrease in the corporate tax rate, results in higher monitoring incentives. Our result is consistent with the existing literature, and, specifically, with the idea that bank shareholders expecting higher profits have more "skin in the game" and are less inclined to take

the extent that it enables the firm to diversify its investment projects. Indeed, diversification of firm investments reduces the volatility of returns from lending, making monitoring more valuable to banks.

on risk.

Our study is also closely related to the work of Schiantarelli et al. (2020), which uses loan-level data from the Italian Credit Register to analyze the relationship between bank stability and loan repayment. Focusing on firms that have multiple credit relationships at the same point in time, the authors show that firms are more likely to miss the repayment schedule of loans extended by weak banks. The interpretation of this result is that firms selectively delay payments to banks that are in a condition of distress. Our paper provides a complementary explanation for this phenomenon. Banks with a weak balance sheet have lower incentives to monitor than healthy banks due to their lower shareholder value.[8] Thus, if weak banks monitor less intensely than healthy banks, borrowers are more likely to delay payments to the former than the latter.[9]

Finally, this work also complements the literature on the effects of taxation on bank risk-taking. Looking at a diverse set of tax interventions, Schepens (2016), Devereux et al. (2019), Carletti et al. (2021), and Célérier et al. (2020) document that taxation is able to shape the riskiness of bank assets in a significant way. We contribute to this literature showing that taxation substantially affects also bank incentives to monitor borrowers, which is an important dimension of bank risk-taking in lending.

The remainder of the paper is organized as follows. Section 2 describes the dataset and the identification strategy. Section 3 presents the results of the empirical analysis. Section 4 concludes.

2 Data and identification strategy

2.1 Data

This paper uses data from the Credit Register (CR) of the Bank of Italy. This data includes quarterly information at the borrower-bank level on virtually all business loans extended to firms in Italy from 2005 to 2016.[10] Specifically, a bank must report to the CR all credit exposures that exceed €30,000 (this threshold used to be €75,000 up to 2008). Each credit exposure may include different types

[8]The lower survival probability of weak banks compared to healthy banks implies lower expected profits to shareholders. This, in turn, makes monitoring less valuable.

[9]Our identification strategy implicitly assumes that a firm is equally likely to repay each of its lenders. Since in our econometric analysis we always control for an extensive set of loan, bank and regional conditions, to invalidate this assumption it should be the case that borrowers understand that banks subject to a higher IRAP tax rate have lower shareholder value than banks subject to a lower IRAP tax rate, all other things equal. We argue that this is very unlikely.

[10]While the raw data from the CR has a monthly frequency, we transformed it into quarterly data to reduce the computational burden of our empirical analysis.

of loans extended to a firm, such as a term loan, a credit line or a loan backed by accounts receivable ("accounts receivable loan"). Our dataset includes a wide set of information on the firm-bank credit relationship: the committed amount and utilized amount of the entire credit exposure and of each loan category; the aggregate value of collateral or personal guarantees; the number and type of requests for information to the CR made by the bank on the firm; the total credit exposure of the banking system to the firm; for a limited subset of banks, the nominal interest rate applied on each loan type. Nonperforming exposures are classified in three categories with an increasing degree of distress: "past-due" exposures, if payments are overdue for 90 days or more; "unlikely-to-pay" exposures, if the bank envisages the possibility that the loan(s) extended will not be repaid in full; "bad" exposures, if the bank considers the loan(s) extended as impaired.

Since we aim at investigating bank monitoring, and not bank screening, we limit our data only to outstanding credit exposures having a duration greater than one quarter. In addition, we focus our attention on business loans to limited companies. The reason is that we need to collect information on borrower's characteristics. Limited companies represent the only category of firms for which we can retrieve detailed information on balance sheet and income statement items. Lastly, as we will explain in Section **??**, we limit our sample to small banks operating at the regional level, the reason being a need of a one-to-one mapping with the regional IRAP tax rate. Our original loan-level dataset includes 5,357,692 observations on 283,706 credit relationships involving 225,669 firms and 458 banks. This dataset is merged with annual data on (i) firm characteristics from CERVED database, (ii) bank conditions from the Credit Bureau managed by the Bank of Italy, (iii) local taxation from the Bank of Italy and the Ministry of Economy and Finance, and (iv) macroeconomic factors from the Italian National Institute of Statistics ("Istituto Nazionale Statistica", ISTAT). Due to a lack of availability for some variables over specific time periods, we lose a certain amount of observations.[11] Table 1 provides a detailed description of all the variables used in our study.

[Insert Table 1 here]

2.2 Measuring bank monitoring

Being able to quantify bank monitoring is a key prerequisite for our investigation. To build our proxy for bank monitoring, we exploit data on requests for information from the CR made by banks on their existing borrowers. Each month banks can submit these requests to get information on the overall credit exposure of the

[11] For example, data on bank balance sheet are available starting only in 2006.

banking system to a specific borrower. In particular, banks can retrieve information on the amount of credit granted by other banks to a given borrower, as well as on the objective conditions of deterioration of each individual exposure.[12] This information is provided essentially for free, as the cost of one request amounts to few euro cents. In a given month, a bank can submit more than one request for information, each one corresponding to a stated reason. The reason for a request is classified as "historical information", "in-depth information", "credit limit" and "co-signing". Since this coarse categorization does not allow to identify the motivation behind a request in a clear way, we construct a unique variable for bank monitoring by aggregating up different requests for information without making any distinction regarding the stated reason. Thus, our proxy for bank monitoring, *Monitor*, consists in the total number of requests for information from the CR made by a bank in a given quarter on an existing borrower.

We have to specify that each bank in Italy automatically receives, on a monthly basis, exactly the same qualitative information that can be requested from the CR. There is a difference, though, in terms of quantity of available information that can be obtained. The automatic updated information received from the CR provides a snapshot of the situation at the present time. An actively submitted request to the CR, instead, allows a bank to retrieve also historical information, up to 36 months backward.

It is likely that banks store the automatic flow of information received from the CR in a proprietary database. This raises the question of why banks request information on their existing borrowers in the first place. There are two main motivations for that. First, the bank wants to obtain the most reliable information on current and past records of credit granted to a specific firm by other lenders. This is justified by the fact that data in the CR can be subject to amendments. The regulatory guidelines of the CR define in detail how banks should correct erroneous information reported to the CR and specify penalties to non-compliers, suggesting that amendments are not uncommon. For this reason, the bank may want to act prudently and submit a request to the CR to ensure that it has reliable and updated information on its client. Second, in extraordinary circumstances, the bank may need to verify or rebuild its database containing information on existing borrowers. For example, after a banking M&A the resulting entity may want to check the existing information on borrowers of one of the two banks involved, and/or to create a new pool of information.[13]

[12]Objective conditions of deterioration occur, for example, when a loan is overdue. Any discretionary assessment of the bank on the likelihood of repayment are not taken into account.

[13]A third explanation consists in anecdotal evidence suggesting that a request to the CR might be less time consuming than consulting the automatic information received from the CR. However, this strictly depends on the internal technical infrastructure of the bank and, hence,

In the former case, the bank requests information from the CR because it has an interest in assessing the condition of loans extended by other banks to a specific borrower. This, in turn, can be justified by two reasons: the borrower has applied for a new loan, or simply the bank wants to monitor the creditworthiness of its client. This means that only a fraction of requests for information from the CR are actually associated with monitoring purposes in the strict sense. To build our proxy for bank monitoring we use exactly this subset of requests, which is identified thanks to a rigorous cleaning process.

In our original dataset, we observe a positive number of requests for information in 11,971 observations, roughly 0.2% of our sample. As a first step, we drop all observations in which a credit relationship is restored after a break (14,904 observations).[14] This ensures that we consider exclusively outstanding loans with a duration greater than one quarter. Second, we discard all observations in which requests for information are driven by exceptional conditions of the bank that have nothing to do with regular monitoring activity.[15] Finally, we drop all observations in which we observe an increase in the committed amount of credit extended to an existing borrower in the current quarter or in the next one (792,206 observations). This allows us to eliminate requests for information that are associated with an increase in lending.[16] As we will explain in more detail in Section 3, this also ensures that we can properly investigate the causal effect of bank monitoring on loan repayment. In fact, additional credit extended to a firm is likely to influence its ability to meet the repayment schedule in the future, especially in the short run. For this reason, we need to make sure that we discard all observations in which

we do not consider it as a major motivation.

[14] A break corresponds to a lack of information on a specific firm-bank relationship in the CR for a certain number of quarters. For instance, it could be the case that the firm gets a first loan from the bank. Once the firm pays it off completely, the loan expires and the credit relationship is not reported anymore in the CR. After a certain period of time the firm may apply for a new loan. If this second loan is approved, the firm-bank relationship will show up again in the CR.

[15] To this end, we use a visual inspection aimed at detecting any atypical clustering in requests for information. We identify 243 observations related to five banks with anomalies in the average number of requests per client made by the bank in a given quarter. We drop all the observations pertaining to the pair bank-quarter in which these anomalies occur. Also, we discard all the requests for information made by a bank that has taken part to a M&A, either as the acquirer or the acquired, during the year in which the merger was finalized (627 observations).

[16] A request for information not associated with an increase in lending may still be an indication of a rejected application rather than monitoring activity. As a consequence, using this subset of requests as a proxy for bank monitoring may lead us to underestimate the effect of bank monitoring on the likelihood of loan repayment. In fact, if these requests for information are exclusively an indication of a loan rejection, we should not find any effect of bank's requests on loan repayment. As we will extensively show in Section 3, we actually find a positive effect. Although we cannot exclude that some of the requests for information are due only to a rejected loan application, our findings limit the concern about a possible underestimation. Additionally, in our main specifications we include firm-time fixed effects, which are aimed to capture any observable and unobservable, time varying and time invariant condition of the borrowing firm, including its demand for credit.

we detect an increase in lending, irrespective of whether a request for information is made or not.

This stringent cleansing process yields a panel of 4,551,817 observations, corresponding to 280,613 lending relationships over the period 2005-2016. We observe at least one request for information in 3,943 observations, roughly 0.1% of our sample. Each request for information signals that the bank is taking a closer look at the borrower. Thus, we argue that our variable for bank monitoring (i.e., the number of requests for information made by the bank on a given firm in the quarter) captures the effort exerted by the bank in checking the ability of the firm to comply with the contractual obligations. As mentioned earlier, if a bank wants to verify the conditions of other loans extended by other banks to the firm, it can limit itself to consult the automatic flow of information received from the CR. More importantly, a bank can monitor its borrower in different ways, for example by checking the company's financial report, by visiting the firm on site, and by providing advisory services, such as funding management and business planning. It is reasonable to think that these activities are to some extent correlated. For example the bank may use the information on total indebtedness to provide the firm with advises on its financial structure. Our proxy is not intended to quantify the monitoring intensity of all these activities, but rather to capture an observable evidence of a broader phenomenon, similarly to observing the tip of an iceberg. What really matters to us is the dynamics of this variable in the cross section and over time, which builds on the idea that the higher the number of requests for information, the stronger is the interest of the bank in assessing the creditworthiness of the borrower, and hence the stronger is the monitoring intensity. As such, our proxy of bank monitoring resembles the two measures of Gustafson et al. (2021), which consist in the frequency of bank's requests for information on firm's financial reports and an indicator on whether field exams of the borrower are initiated by the lender. The main difference is that we use, instead, bank's requests for information on outstanding loans of the firm with the banking system. Our approach to gauge bank monitoring at the lending relationship level relates also to other measures identified in the literature. These include the frequency at which the bank reviews some key features of the credit exposure, such as the collateral value, the loan spread, the loan limit, the credit rating, and the default probability of the borrower (Cerqueiro et al., 2016; Plosser and Santos, 2016), as well as an internal assessment of the effort exerted by loan officers in performing their monitoring activities (Tellez, 2020). In what follows we show that the dynamics of our variable are consistent with a bank monitoring interpretation.

2.2.1 Appropriateness of our measure

To check the appropriateness of our proxy for bank monitoring we start with a visual inspection. Plot (a) of Figure 1 shows that the average number of requests per borrower made by a bank in a given quarter differs across banks, but exhibits a common pattern. Overall, the number of requests for information increases in the first part of the sample up to the recent financial crisis and reaches its peaks in 2008 and 2009. Afterward, it decreases sensibly and stays at a low level until 2012, then it rises somewhat and remains quite stable up to the end of 2016. Looking at higher level of aggregation (plot (b) of Figure 1), we see that the average number of requests per client increases by a factor of three from 2005 to 2009, with a sharp acceleration between the third quarter of 2008 and the beginning of 2009. Consistently with plot (a), the highest values are achieved between the first and the third quarter of 2009 during the great recession. Immediately after, the average number of requests per client decreases, but only for a short period. In fact, as in the case of the great recession, requests for information rise again during the second phase of recession following the sovereign debt crisis in 2012-2014. In general, this plot shows that the number of requests for information are negatively correlated with Italy GDP annual growth. Overall, this provides evidence in favor of our interpretation of requests for information as a proxy for bank monitoring. In fact, it is reasonable to think that banks are more keen on monitoring their borrowers during a period of economic downturn, as borrowers are more likely to miss their repayment schedule. The only exception is the last increase in the number of requests for information in 2015-2016, which is not associated with a negative GDP growth. This presumably is due to the very high ratio of nonperforming loans to gross loans experienced in Italy, which achieved historical heights exactly in 2015 (Bank of Italy, 2019). A second important piece of evidence stemming from the figure is that the average number of requests per client exhibits a certain seasonality, with a higher concentration in the first and in the fourth quarter for most years. In particular, the first or the fourth quarter correspond to the highest number of requests for 11 out of 12 years considered in our sample. This is consistent with the idea that banks may want to control the conditions of their borrowers around the balance sheet date, which is the most relevant period of the year for a company.[17]

[17]Most limited companies in Italy set the balance sheet date on December 31 and approve the annual report by the end of the following April. It is reasonable to think that the bank concentrates its monitoring activity towards the balance sheet date and the approval of the annual report to assess the lending exposure to its clients. In addition, the bank can retrieve the most meaningful and significant information about the company at this time of the year. In fact, at the balance sheet date the firm has a more clear picture of its revenues and expenditures. As a consequence, it is more likely that the firm takes a decision, either voluntary or forced, to

[Insert Figure 1 here]

2.2.2 Monitored firms and monitoring banks

So far we have shown evidence that validates the use of requests for information as a reliable measure of bank monitoring. The next step is to investigate which borrowers are more likely to be monitored and which banks are more likely to monitor. This analysis provides us with further evidence to corroborate the interpretation of our variable as a proxy for bank monitoring.

A first reason why a bank may want to monitor a firm lies in a concern about the ability of the firm to meet its loan obligations. This may occur either before or after a full-blown of payment arrears. Figure 2 shows that bank requests for information are related to a nonperforming exposure only in 6.8% of cases. Also, once we move from past-due exposures to higher degrees of distress, namely unlikely-to-pay and bad exposures, the percentage of requests for information decreases steadily. Overall, this means that banks primarily exert monitoring with the intention of preventing firms from missing their repayment schedule. Once a loan is in arrears, the marginal benefit of monitoring decreases with the severity of the distress.

A lack of information about the firm could be a second driver of bank monitoring. Figure 2 shows that roughly 13.3% of observations with a positive number of requests is related to credit exposures that are close to the minimum thresholds to be reported in the CR.[18] Banks are likely to hold limited information about these loans, as the credit exposure might have become eligible to enter the CR only in recent times. Therefore, this finding suggests that a bank has monitoring incentives if it lacks of knowledge about the conditions of the firm.

[Insert Figure 2 here]

We now look more closely at the individual features that make a firm more likely to be monitored and a bank more likely to monitor. To this end we perform an econometric exercise which is intended to highlight relevant correlations. In the first specification of Table 2 we investigate the role of firm characteristics. Specifically, we regress the number of requests for information made by a bank on a given borrower in the quarter on a set of loan and firm variables capturing the conditions of the borrowing firm. We include macro variables, quarter fixed effects,

repay its loans in this period.

[18] The Italian CR requires banks to provide information on credit exposures when specific conditions are met. To define whether an exposure is close to the minimum threshold, we consider the most relevant requirements: (i) the total volume of the credit exposure is greater or equal to €75,000 up to 2008 and €30,000 since then, or; (ii) the credit exposure is defined as bad and its volume, net of losses, is greater of equal to €250.

firm industry fixed effects and firm region fixed effects to control for potential confounding factors. In addition, since we focus on the relation between firm factors and bank monitoring, we saturate our specification with bank-quarter fixed effects to control for any observable and unobservable, time varying and time invariant condition of the bank.

We find a negative and statistically significant coefficient for *Share exposure*, meaning that the higher the amount lent to a firm with respect to the firm's total borrowing from the banking system, the lower the intensity of bank monitoring.[19] Postulating that the main lender of a firm has access to a greater amount of information, we argue that this variable captures the level of knowledge that the bank has about the firm compared to other lenders. If the bank lacks of a full picture of the borrower's debt position, it is likely to retrieve such information from other lenders exploiting the information sharing role of the CR.[20] But the negative coefficient for *Share exposure* tells us something more. In fact, this result is in line with the idea that multiple-bank lending improves banks' monitoring incentives as the financing of independent investment projects reduces the volatility of returns from their loan portfolio, making monitoring more valuable (Carletti et al., 2007).[21]

A more standard measure of bank's knowledge about the firm is *Length relation*, whose coefficient is negative and highly significant as well. This means that the intensity of bank monitoring is stronger the lower the duration of the lending relationship. If we look at the three different credit types, we observe a significant coefficient only for *Term loan dummy.* The negative sign suggests that banks monitor less if the firm-bank credit exposure includes a term loan compared to other types of credit exposures, in line with the evidence that, in our sample, borrowers are less likely to be insolvent on term loans vis á vis credit lines.[22] We also find a positive and significant coefficient for *Close threshold dummy*, meaning that bank monitoring is higher for credit exposures that are close to the minimum thresholds to be reported in the CR. In addition, the positive and statistically significant coefficient of *Credit score firm* shows that firms with a lower credit quality are more likely to be monitored. Interestingly, it seems that, once having accounted for firm credit quality, banks monitor more large and well capitalized

[19]The median value of *Share exposure* in our sample is 0.352 (panel A of Table 6), suggesting that the median borrower allocates less than half of its total borrowing to small regional banks.

[20]Even in case a bank is the only lender of a firm, it may still be useful to consult the CR as the firm may establish new credit relationships at any point in time.

[21]As we will discuss in Section 2.3.1, bank monitoring becomes more valuable the higher the expected profits to shareholders.

[22]In our original dataset, 29% of observations where a credit exposure is classified as past-due are associated with a past-due term loan, compared to 53% of observations associated with a past-due credit line.

firms.

The regression in the second column of Table 2 improves the preceding by including firm fixed effects to control for any unobservable time invariant condition of the firm. In this way we limit possible concerns of omitted variable bias. The coefficients of *Length relation*, *Term loan dummy*, and *Close threshold dummy* are virtually unchanged and, if anything, slightly stronger. The coefficient of *Credit score firm* looses its significance. This is hardly surprising, as this variable captures the creditworthiness of the firm, which is likely to be stable over time. This means that *Credit score firm* might be partially subsumed by firm fixed effects. In contrast to the previous specification, the coefficient of *Size firm* is negative and highly significant. This suggests that the intensity of bank monitoring is positively associated to firm opacity. Interestingly, we find that *ROA firm* and *Capital ratio firm* are positively correlated with bank monitoring. This somewhat counterintuitive result is fully in line with the theoretical model on bank monitoring presented in Section 2.3.1. Conditionally on the creditworthiness of the borrower, banks have higher incentives to monitor firms with higher ROA and capital ratios, as they can extract higher expected profits from lending to firms in good standing. Indeed, firms with high profitability and capitalization are, unconditionally, less likely to be in financial distress and, hence, more likely to repay. As long as these firms guarantee higher expected profits from lending, banks are more willing to exert a little effort to ensure the repayment of these borrowers rather than to devote a great effort to foster the repayment of firms with low profitability and capitalization. Interestingly, none of the macro variables is statistically significant. Overall, it seems that that, conditionally on firm characteristics and bank characteristics, macro conditions do not play a relevant role.

In the third specification we extend our analysis investigating whether the length of the credit relationship influences the magnitude of the effect of firm opacity. To this end, we include the interaction of *Length relation* with *Size firm* among regressors. As before, we find that a longer credit relationship is associated with lower bank monitoring. The coefficient of *Size firm* remains negative, whereas the coefficient of its interaction with *Length relation* is positive and statistically significant. This result reveals that bank monitoring is stronger for firms that are more opaque, but the effect weakens with the duration of the credit relationship. Indeed, banks achieve a deeper knowledge of their borrowers the longer the credit relationship.

We now turn to bank characteristics affecting the incentives to monitor borrowers. In the fourth specification we estimate a model that is symmetrical to those described so far. Specifically, we regress the number of requests for information made by a bank on a given firm in the quarter on our set of bank variables, including various controls and fixed effects. To make sure that we control for any observable and unobservable, time varying and time invariant characteristic of the firm, we include firm-quarter fixed effects in the specification. This means that we focus on firms having multiple credit relationships with local banks and we compare the number of requests for information across banks lending to the same firm.

Length relation, *Close threshold dummy*, *Size bank*, and *Nonretail deposit ratio bank* are the only variables that turn out to be statistically significant. The coefficients of *Length relation* and *Close threshold dummy* confirm that banks having a better knowledge of their credit exposure and, more generally, of their borrowers are less likely to monitor. Also, the negative and significant coefficient of *Size bank* suggests that large banks are less likely to monitor. As for *Nonretail deposit ratio bank*, although this variable is intended to estimate the effect of unsecured deposits, the negative and significant coefficient is likely to capture a size effect as well.[23]

Most of the coefficients of the other factors are in line with expectations, except for *Capital ratio bank*, but are not statistically significant.[24] Overall, our findings suggest that firm factors play a prominent role than bank factors in driving bank monitoring.

This econometric exercise allowed us to identify in a straightforward way firm and bank characteristics that are correlated with the intensity of bank monitoring. All our results are consistent with a monitoring interpretation of our novel variable based on requests for information from the CR. We conclude that these findings provide support to our methodological approach in capturing bank monitoring.

[Insert Table 2 here]

[23]If a high value of *Nonretail deposit ratio bank* implies a low fraction of secured deposits, we would expect that the higher *Nonretail deposit ratio bank* the higher bank incentives to monitor borrowers. The reason behind lies in the market discipline exerted by unsecured depositors, as suggested by Diamond and Rajan (2000). At the same time, though, larger banks are likely to have a higher fraction of nonretail deposits. Thus, the nonretail deposit ratio may be highly correlated with bank size.

[24]For example, the positive coefficient of *ROA bank* and the negative coefficient of *NPL ratio bank* are consistent with the theoretical predictions presented in Section 2.3.1. A high profitability implies a low bank's probability of default, whilst the opposite applies to the ratio of nonperforming loans. A low default probability, in turn, entails high expected profits to shareholders stemming from lending. Thus, our model suggests that bank stability improves bank incentives to monitor borrowers, one having controlled for borrowers characteristics. The sign of *ROA bank* and *NPL ratio bank* are exactly in line with this intuition. Additionally, the negative coefficient of *Liquidity ratio bank* is in line with the idea that banks holding a high amount of liquid assets are able to take on more risk, as they can easily absorb potential losses. Finally, the negative coefficient of *GDP growth region bank* is consistent with the evidence of Figure 2, namely banks have higher monitoring incentives during periods of economic downturn. Nevertheless, as already pointed out, these coefficients are not statistically different from zero.

2.3 Identification strategy

Which is the effect of bank monitoring on loan repayment? Assessing this causal relation is challenging. The repayment performance of a firm is likely to influence bank monitoring, exposing to the threat of reverse causality. Also, unobservable conditions of the borrowing firm can potentially affect both its ability to meet the contractual obligations and bank incentives to monitor, making it difficult to identify the effect of bank monitoring in a precise way.

To address our research question, we rely on a robust identification strategy that builds on three main pillars. First, we use our proxy for bank monitoring as an observable signal of the monitoring activities conducted by a bank on a given borrower.

Second, we exploit taxation as a source of exogenous variation in bank monitoring. Taxation is likely to affect bank incentives to monitor through different channels. We focus on the corporate tax rate and develop a simple theoretical model to highlight the different mechanisms at play. Our model indicates that an increase in the corporate tax rate entails a decrease in bank monitoring and vice-versa. Then, relying on this prediction, we focus on small banks and we use changes in the Italy Regional Production Tax (IRAP) rate applied to banks as an instrument for bank monitoring. We borrow this identification strategy from Bond et al. (2016) and Gambacorta et al. (2021), who analyze the effects of taxation on bank capital structure. In the next three subsections, we present our theoretical model and discuss in detail why the variation generated by the IRAP tax rate applied to banks is exogenous.

Third, we focus on variation within firm-time, meaning that we saturate our regressions with firm-time fixed effects to control for any time varying and time invariant, observable and unobservable condition of the firm. This is made possible by the fact that about 10% of firms in our sample have multiple credit relationships with small banks in the same quarter. This crucial ingredient of our methodology ensures that we neutralize any role played by firm conditions in making the bank more or less motivated to monitor and the borrower more or less likely to repay. In essence, we estimate the causal effect of bank monitoring on loan repayment by comparing the repayment performance on different loans granted by different banks to the same firm at each point in time. In this setup, identification comes from the different tax rates applied to banks operating in different regions and lending to the same firm. For example, let us consider a firm that borrows from two banks located in two regions characterized by a different tax rate. Suppose that the tax rate applied to bank 1 is higher than the tax rate applied to bank 2. Then, our prior is that bank 2 monitors the borrower more intensely than bank

1 and this, in turn, should foster the repayment of the loan granted by bank 2 vis-à-vis the loan granted by bank 1.

Hereinafter, we discuss our second pillar more in detail by presenting the theoretical model and explaining why the variation generated by the IRAP tax rate applied to banks is exogenous.

2.3.1 A model of taxation and bank monitoring

We develop a simple model of bank monitoring, extending the one of Dell'Ariccia et al. (2014) by introducing a corporate income tax applied to bank profits. Specifically, we consider a representative bank funded only by equity, with fraction k, and deposits, with fraction $1-k$, which operates in a perfectly competitive environment. The bank uses its sources of financing exclusively to grant an arbitrary amount of indistinguishable loans, $L(r_L)$, where r_L denotes the lending rate. The bank faces a downward sloping demand curve, $L'(r_L) \leq 0$. A corporate income tax is applied on revenues from lending, with τ being the tax rate.

Since loans are risky, the bank needs to monitor its borrowers in order to prevent a potential default. The bank possesses a monitoring technology that allows to exert a monitoring effort q, which also represents the probability of loan repayment. Clearly, monitoring does not come for free and entails a certain cost for the bank, $\frac{1}{2}cq^2$, per unit of lending.[25]

There is no deposit insurance, and both shareholders and depositors are assumed to be risk-neutral. As such, they require a return that compensates their opportunity cost. The rate of return crucially depends on the probability of loan repayment and equals $r_E = \frac{r+\xi}{q}$ for shareholders and $r_D = \frac{r}{\mathbb{E}[q|k]}$ for depositors, with r being the risk-free interest rate and ξ a positive equity premium.

We further introduce a friction affecting bank capital structure. We assume that the interests paid on deposits are tax deductible, in line with Gambacorta et al. (2021). This distortion implies that equity is a less convenient source of funding than deposits.

The bank determines the optimal lending rate, r_L^*, the optimal capital structure, k^*, and the optimal monitoring effort, q^*, as to maximize the expected profits:[26]

[25]In our empirical setup we use bank requests for information from the CR as a proxy for bank monitoring. We have highlighted that each request costs only few euro cents. Nevertheless, this does not mean that monitoring is costless. In fact, bank monitoring involves a wide spectrum of activities that go beyond the assessment of the information owned by the CR. These include checking the firm's financial report, performing field exams, visiting the firm on site, providing advisory services etc. All these activities require substantial pecuniary and non-pecuniary costs for the bank.

[26]There is no agency conflict between bank managers and shareholders as their interests are assumed to be perfectly aligned.

$$\underbrace{\max}_{r_L,k,q,0<q\leq 1} \quad \Pi = \left\{ q\left[\left(r_L - r_D\left(1-k\right)\right)\left(1-\tau\right) - r_E k\right] - \frac{1}{2}cq^2 \right\} L\left(r_L\right) \tag{1}$$

Note that in the maximand the cost of bank monitoring does not reduce taxable income. This is consistent with a view of bank monitoring as a non-pecuniary effort exerted by loan officers in assessing and improving the likelihood of loan repayment. However, it is reasonable to think that bank monitoring involves also monetary costs, for example in terms of remuneration of loan officers. As we will discuss in the next section, our empirical setup exploits the IRAP tax applied to banks, whose tax base includes both profits and wages. This implies that the pecuniary costs supported by Italian banks for monitoring purposes do not reduce, but rather increase the IRAP taxable income. Thus, the way we model the costs of bank monitoring is consistent also with the framework of our empirical analysis.

Solving the model provides us with relevant insights. An increase in the corporate tax rate entails three main effects: (i) net profits decrease because of higher tax expenditures; (ii) the capital ratio drops as equity funding becomes less attractive; (iii) the lending rate increases as a result of a shift of tax burden from the bank to its borrowers. The first two effects entail a decrease in bank monitoring, which is only partially counteracted by the latter effect. Hence, overall an increase in the corporate tax rate leads to a decrease in bank monitoring, as stated in Proposition 1.

Proposition 1. Equilibrium bank monitoring decreases with the corporate tax rate, $\frac{\partial q^*}{\partial \tau}$.

Indeed, the resulting optimal level of monitoring effort and its derivative with respect to the corporate tax rate are:

$$q^* = \sqrt{\frac{2r\left(r+\xi\right)^2\left(1-\tau\right)}{c\left(3r\xi + r^2 + 2\xi^2 + r^2\tau + r\tau\xi\right)}} \tag{2}$$

$$\frac{\partial q^*}{\partial \tau} = -2\left(r+2\xi\right)\left(r+\xi\right)\sqrt{\frac{r^3}{c\left(1-\tau\right)\left(3r\xi + r^2 + 2\xi^2 + r^2\tau + r\tau\xi\right)^3}} < 0 \tag{3}$$

The proof is provided in **??**. This result is in line with a classical "skin in the game" argument, in what is suggests that lower rents from lending reduce bank incentives to ensure loan repayment by monitoring its borrowers. Since an increase in the tax rate worsens bank stability, our result is consistent with the literature that points to a negative relation between bank stability and risk-taking (Allen et al., 2011; Mehran and Thakor, 2011; Dell'Ariccia et al., 2014).

Further extensions of our model suggest that, when the capital structure is exogenous, the effect of taxation on bank monitoring is stronger for lowly capitalized banks. Moreover, if deposits are fully insured, bank monitoring incentives are completely insensitive to the corporate tax rate.[27] While the model provides several testable predictions, in our empirical analysis we focus on the overall impact of changes in the corporate tax rate on bank monitoring. We also marginally discuss the effect of changes in the tax rate on lending rates.

2.3.2 IRAP

IRAP is a flat tax on the value added generated by firms and public administrations that was introduced in Italy in 1998.[28] Until 2001 the IRAP tax rate was the same across Italian regions. Since 2002 each region is allowed to set its local IRAP tax rate, increasing or decreasing the national basic rate by maximum one percentage point until 2008 and 0.92 percentage points since then. The IRAP tax rate applied to banks usually differs from that applied to other firms. Typically, the former is larger and has been subject to a higher variation over time than the latter. Revenues from the IRAP tax are mainly used to finance the National Health Service ("Servizio Sanitario Nazionale", SSN),[29] which is organized under the Ministry of Health and administered at the regional level. For instance, in 2012 revenues from the IRAP tax represented about 30% of the total funding of the National Health Service (MEF, 2012).[30] While in normal times regions are free to modify the local IRAP tax rate within the range limit, if a health care deficit occurs the regional IRAP tax rate is automatically increased ex lege. In our sample period, this happened five times, specifically in Abruzzo in 2006, Campania in 2006 and 2010, Calabria in 2010, Lazio in 2010, and Molise in 2010. Since revenues from the IRAP tax are mainly used to finance national health care expenditures, the IRAP tax rate is reasonably orthogonal to monitoring motives of banks.

Table 3 reports the regional IRAP tax rates applied to banks during our sample period.[31] We detect 59 changes in the local IRAP tax rates occurred between

[27] These results are available upon request.

[28] The difference between the IRAP tax and a standard corporate income tax lies in the tax base. For example, for the specific case of the IRAP tax applied to banks, the tax base includes not only profits but also wages.

[29] Article 38 of the Legislative Decree No. 446 of 15 December 1997 states that 90% of revenues from the IRAP tax, net of the quota allocated to the State, are used to finance national health care expenditures.

[30] This corresponds to roughly €38 billions. Such substantial amount is due to the fact that the Italian National Health Service, which provides healthcare to all citizens and residents in Italy, is funded totally by tax revenues.

[31] Despite our dataset covers the time period 2007-2016, we report the tax rates also for 2006,

2006 and 2016, 35 increases and 24 decreases. This guarantees that we are able to exploit a significant variation in the IRAP tax rate both across regions and over time. It is worth mentioning that the IRAP tax rate applied to firms is to a large extent correlated with the IRAP tax rate applied to banks.[32] However, this does not represent a concern for our identification strategy as we focus on variation within firm-time. In fact, including firm-time fixed effects in our econometric specifications is crucial to control for any relevant condition of the firm affecting the likelihood to repay, including its tax burden. This ensure that the exclusion restriction of our instrument is fulfilled.

[Insert Table 3 here]

A more relevant threat to our identification is the possibility that the IRAP tax rate is influenced by regional macroeconomic factors or local aggregate conditions of the banking system that may affect, in turn, banks' incentives to monitor. For example, during an economic downturn banks may experience credit losses that reduce their capital ratios. According to our model, this implies a lower skin in the game and, hence, lower incentives to monitor. At the same time, local governments may increase the IRAP tax rates in response to a reduction in other sources of funding of the National Health Service. To limit this concern, we always control for relevant macroeconomic conditions of the bank's region in our estimation models. More importantly, we conduct an exercise to verify whether local IRAP tax rates depend (at least linearly) on regional macro conditions and aggregate bank factors.

Table 4 reports the results of different specifications in which we regress the IRAP tax rate on a set of local macroeconomic conditions and bank variables. The former encompasses the GDP growth rate, the inflation rate and the employment rate of the region, whereas the latter include the aggregate capital ratio, *Capital ratio region bank*, and ROA, *ROA region bank*, of the banking system at the regional level, as well as the average ratio of nonperforming loans of banks operating in a specific region, *NPL ratio region bank*. We also include among the independent variables the basic IRAP tax rate defined at the national level and a dummy variable equal to one if an increase in the IRAP tax rate occurs in response to a regional health deficit, Δ*IRAP health*. We find that the IRAP tax rate depends exclusively on the current basic IRAP tax rate at the national level and on the event of a regional health deficit. Neither macro factors nor aggregate conditions of the banking system at the regional level correlate with the IRAP tax

as in our econometric analysis we use the lagged value of the IRAP tax rate.

[32] In our sample we observe that 35 changes in the IRAP tax rate applied to limited companies are concomitant with changes in the IRAP tax applied to banks.

rate. Although these results cannot rule out other kinds of dependence than the linear one, they provide evidence that corroborates our identification strategy. As a last remark, we point out that the national basic tax rate is likely to depend on aggregate macroeconomic conditions of Italy. In our main regression models we always include firm-time fixed effects, which means that we actually control for the situation of the Italian economy as a whole. In other words, our identification crucially depends on variation in the IRAP tax rate across regions, which is exogenous as it is driven by differences in healthcare expenditures.

[Insert Table 4 here]

2.3.3 Local banks

Banks that operate in different regions determine the IRAP tax base as a weighted average of the local tax bases calculated in proportion to the amount of deposits held in each region. For this reason, we cannot exploit the local IRAP tax rates as a source of exogenous variation in the monitoring intensity of big banks operating on a national scale. However, this is possible for small banks that operate at the local level, for which we have a one-to-one mapping with the IRAP tax rate. In fact, local banks are typically subject to special regulatory restrictions, implying that they cannot belong to a banking group and must operate in a very limited geographic area. As such, these banks are mostly active in one region. This means that changes in the IRAP tax rate affect the whole tax base, which is why we focus the attention on such local banks. Moreover, up to 2011 local banks were almost exclusively subject to the IRAP tax. As such, the IRAP tax rate exerts a relevant influence on their behavior. Unlike non-financial firms, banks can deduct interest expenses from the IRAP tax base. This implies that changes in the IRAP tax rate have an impact on the capital structure of local banks, as documented by Bond et al. (2016) and Gambacorta et al. (2021). In our context this is likely to play a role in affecting bank monitoring incentives, as suggested by our theoretical model.

To assign each bank to one region we look at the region in which the bank has most of its branches.[33] This approach is sound, as 99% of local banks in our sample has a number of branches in the first region of major activity at least 1.5 times as large as the number of branches in the second region.

Although local banks are subject to a special regulation, which influences the

[33] Bond et al. (2016) and Gambacorta et al. (2021) look, instead, at where the bank is headquartered. Although the outcome is likely to be almost identical, we consider our approach more reliable as the IRAP tax base is determined in proportion to the amount of deposits held in each region.

composition of their balance sheet,[34] they experience similar levels of profitability to those of big banks (Bond et al., 2016; Gambacorta et al., 2021). In light of that, there is no reason to believe that local banks' monitoring incentives respond in a different way from those of big banks to changed economic conditions. If anything, focusing on small regional banks ensures that we conduct our analysis on a rather homogeneous set of banks for which differences in the IRAP tax rate represent an important driver behind different monitoring motives. As we will show in Section 3, firms borrowing from this subset of banks are very similar across different traits to the universe of Italian limited liability companies, ruling out potential concerns on the external validity of our analysis.

3 Results

3.1 Preliminary analysis on bank monitoring and loan repayment

We begin with a graphical inspection of the relation between bank monitoring and loan repayment. Figure 3 shows the percentage of nonperforming loans in each quarter against the average number of requests for information submitted by banks one quarter before. The plot is generated from a dataset obtained according to a similar cleaning process to that described in Section 2.2. In particular, we start from the original sample of 5,357,692 observations, covering the time period 2005-2016, and we drop: (i) observations pertaining to credit relationships with a duration lower than three quarters; (ii) observations in which a credit relationship is restored after a break in the current quarter or in the previous one; (iii) observations pertaining to banks experiencing extraordinary circumstances which impact, or may impact, their number of requests for information from the CR in the current quarter or the previous one; (iv) observations where we detect an increase in the committed amount of credit extended to an existing borrower in the current quarter or in the previous one. This is necessary to ensure that we investigate the relation between bank monitoring and loan repayment considering only existing credit exposures at the time when monitoring is observed and excluding potential confounding factors, as described in Section 2.2. Despite the high dispersion, Figure 3 documents that bank requests for information are negativity related to nonperforming loans, suggesting that bank monitoring may have a positive effect on loan repayment.

[34]For instance, at least 50% of assets of these banks has to be represented either by risk-free assets or loans to shareholders. Also, a high fraction of their profits has to be retained in reserves.

[Insert Figure 3 here]

This finding is confirmed once we examine granular data at the borrower-bank level. The analysis presented in **??** suggests that, conditional on loan characteristics, firm attributes, bank factors and macroeconomic conditions, bank monitoring is associated with a lower probability that a credit exposures becomes nonperforming one quarter ahead.

While this represent a useful preliminary exercise, results cannot be interpreted as causal. In principle, banks have incentives to monitor more closely the credit relationships that are more likely to become overdue. This means that there is an endogeneity problem caused by reverse causality, implying that the coefficient of the lagged monitoring variable may be biased upward. In fact, when we saturate the first specification of Table A1 by adding firm-time fixed effects, the correlation between bank monitoring and the likelihood of a delinquency becomes insignificant. In the next subsection we discuss how we deal with this issue presenting our 2SLS approach.

3.2 Bank monitoring and loan repayment: A 2SLS approach

We now describe the baseline model adopted to investigate the causal link between bank monitoring and loan repayment. Our methodology relies on instrumental variables and consists in estimating the following 2SLS model

1st Stage:

$$\text{Monitor}_{i,b,r,t-h} = \alpha + \beta \text{IRAP}_{r,t-h-4} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,b,r,t-h-n} + \mu_{i,t} + \mu_b + \mu_r + \varepsilon_{i,b,r,t-h} \quad (4)$$

2nd Stage:

$$\text{NPL dummy}_{i,b,r,t} = \alpha + \beta \widehat{\text{Monitor}}_{i,b,r,t-h} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,b,r,t-h-n} + \mu_{i,t} + \mu_b + \mu_r + \varepsilon_{i,b,r,t} \quad (5)$$

where $Monitor_{i,b,r,t-h}$ is the number of requests for information made by bank b operating in region r on firm i at time $t-h$, with h being the selected horizon; $NPL\ dummy_{i,b,r,t}$ denotes a dummy variable equal to one if part or the whole credit exposure of bank b to firm i is in distress at time t, and zero otherwise; $IRAP_{r,t-h-4}$ is the tax rate applied to the bank, that we use as an instrument for bank monitoring (so called "excluded instrument"). $\boldsymbol{X}$ stands for a vector of controls, encompassing characteristics of the credit exposure (*Loan amount*, *Length relation*, *Term loan dummy*, *Credit line dummy*, *A/R loan dummy*, *Share guarantee*, *Share expo-*

sure and *Close threshold dummy*), bank variables (*Capital ratio bank*, *ROA bank*, *NPL ratio bank*, *Size bank*, *Liquidity ratio bank* and *Nonretail deposit ratio bank*), and macro conditions of the bank's region (*GDP growth region bank*, *Employment region bank* and *Inflation region bank*) affecting bank incentives to monitor borrowers as well as the likelihood of a loan delinquency.[35] $\mu_{i,t}$, μ_b and μ_r denote firm-quarter, bank and bank's region fixed effects, respectively. $\widehat{Monitor}_{i,b,r,t-h}$ is the linear projection of $Monitor_{i,b,r,t-h}$ onto all the exogenous variables, namely the excluded instrument and controls. Note that *IRAP* is lagged of four quarters with respect to *Monitor* as this tax is likely to exert its effect on bank monitoring only in the year in which the corresponding IRAP revenue is collected, as highlighted by Gambacorta et al. (2021). Also, all the control variables are lagged to ensure that they are predetermined with respect to the dependent variable in each stage.[36] $t - n$ represents the lag of the regressor expressed in quarters and depends on its frequency. This model allows us to estimate the causal effect of an increase in bank monitoring, as captured by our proxy, on the likelihood of loan repayment h quarters ahead.

This 2SLS model is perfectly identified, as we have a single instrument, *IRAP*, for a unique endogenous variable, *Monitor*. To ensure that the IV estimator is unbiased we need to assess if our instrumental variable satisfies the necessary requirements in terms of relevance and exclusion restriction. Economic considerations (i.e. revenues from IRAP are mainly used to finance health care expenditures at the regional level), the evidence that the IRAP tax rate is uncorrelated with local macroeconomic conditions and aggregate bank factors at the regional level (Table 4), as well as the fact that we include firm-time fixed effects in our specification, suggest that *IRAP* is undeniably exogenous to bank monitoring and loan repayment in this setup. As for the relevance requirement, we rely on standard econometric tests to assess if our instrument is strong enough.

One additional thing to highlight about our model is that, since we include firm-time fixed effects, identification is mainly provided by loans to the same firm granted by two or more banks operating in different regions and, hence, subject

[35] The recognition of a credit exposure as past-due is rather mechanical and occurs each time a loan is past-due by 90 days or more. Banks have, instead, greater flexibility in classifying a credit exposure as unlikely-to-pay or bad, as this depends on a subjective assessment.

[36] This is necessary given the idiosyncrasy between the frequency of the loan level information (quarterly) and that of the bank and macro conditions (annual). As a conservative approach, we also lag the loan controls with respect to our proxy for bank monitoring. That is because *Monitor* is calculated as the sum of requests for information made by the bank on a given borrower in the quarter. If, for example, these requests are concentrated in the first month of the quarter due to specific conditions of the credit exposure which change towards the end of the quarter, we run into the risk that our loan controls are not predetermined. In Section 3.6 we present a robustness exercise where loan controls are defined as contemporaneous to our bank monitoring variable.

to different IRAP tax rates. Note that, although our identification strategy relies crucially on the cross-sectional differences in the regional tax rates applied to banks exposed to the same firm, we decided to include bank and bank's region fixed effects in our baseline specification to control for any time invariant condition of the lender, and of its region, that may influence bank monitoring incentives.

Also, this 2SLS model is estimated on a dataset obtained according to a similar cleaning process to that described in Section 2.2. In particular, we start from the original sample of 5,357,692 observations, covering the time period 2005-2016, and we drop: (i) observations pertaining to credit relationships with a duration lower than $h+2$ quarters; (ii) observations in which a credit relationship is restored after a break in the current quarter or in the previous h quarters; (iii) observations pertaining to banks experiencing extraordinary circumstances which impact, or may impact, their number of requests for information from the CR in the current quarter or the previous h quarters; (iv) observations where we detect an increase in the committed amount of credit extended to an existing borrower in the current quarter or in the previous h quarters. This ensures that we are investigating in a proper way the effect of bank monitoring on loan repayment, considering only existing credit exposures at the time in which monitoring is observed and excluding potential confounding factors. Suppose, for example, that in quarter $t-h$ the bank makes a request for information that is associated with new credit granted to an existing borrower. It is likely that the new loan affects the firm's ability to meet its repayment schedule at quarter t. Our cleaning process gets rid of such observations. In this way, we are able to compare the repayment performance of a given borrower to monitoring versus non-monitoring banks, without worrying about the effect of an increase in lending.

3.2.1 A six-month horizon

We start by presenting the results of the 2SLS model investigating the effect of bank monitoring on loan repayment two quarters ahead, as this the horizon in which we identify the strongest effect, as evinced in Table 7.[37]

Table 5 reports the result of this 2SLS regression analysis. The first stage (column 1) highlights that the coefficient of the IRAP tax rate is negative and statistically significant. Consistently with Proposition 1 of our model presented in Section 2.3.1, this finding reveals that an increase in the IRAP tax rate implies a decrease in bank monitoring. This result is particularly striking if one thinks that the tax rate has only a second order effect on bank monitoring, as highlighted in our model. The magnitude of the effect, though, is rather limited in absolute

[37] As we will show in the next subsection, Table 7 reports the results of our 2SLS model for different horizons, from one to eight quarters ahead.

terms. One percentage point decrease in the IRAP tax rate leads to an increase of 0.004 in the number of requests for information made by the bank. But this is not surprising as the average number of requests for information detected in the sample where this regression is estimated is 0.001 and the standard deviation is 0.028 (panel B of Table 6).[38] Thus, the negative effect of the tax rate on bank monitoring is actually substantial in relative terms. In fact, a one percentage point decrease in the IRAP tax rate implies an increase in the number of requests for information that corresponds to four times its average in the sample.

To assess whether *IRAP* fulfills the relevance requirement, we perform some standard underidentification and weak identification tests. The Kleibergen-Paap rk LM statistic (4.15) leads us to reject the null hypothesis that the model is underidentified at 95% level. This means that our instrument, *IRAP*, is sufficiently correlated with the endogenous regressor, *Monitor*. Also, the Cragg-Donald Wald F-statistic (20.06) and the Stock and Yogo (2005) critical value for a 5% level test that the maximum size of the Wald test is no more than 10% (16.38) suggest that our instrumental variable is strong enough. Nevertheless, both the Cragg-Donald Wald F-statistic and the critical value are meaningful under the assumption of i.i.d. errors. This condition is likely not to hold, which is the reason why we cluster standard errors to draw reliable inference. Thus, we better focus on the Kleibergen-Paap Wald F-statistic, which is cluster-robust. Despite we do not have a specific critical value for this statistic, its value (5.22) is relatively low if confronted with the rule of thumb of 10 suggested by Staiger and Stock (1997). In light of that, we should be careful in concluding that our instrument satisfies, to an acceptable degree, the relevance requirement. For this reason, as suggested by Andrews et al. (2019), we report the results of the Anderson-Rubin test, which allows to derive weak-identification-robust inference.

As for the other covariates, we get similar results to those of Table 2, although only *Length relation* and *Employment region bank* are statistically significant. Specifically, bank monitoring decreases with the duration of the credit relationship. This is in line with the idea that banks monitor less the firms that they know better. Also, a higher employment rate in the bank's region is associated with higher bank monitoring.

Looking at the results of the second stage regressions (columns (2)-(7)), we detect a strong negative effect of bank monitoring on the likelihood that the credit exposure becomes nonperforming two quarters ahead. We interpret the results keeping in mind that our estimates represent essentially a weighted average of local average treatments effects (Heckman et al., 2006; Angrist and Pischke, 2009;

[38] This is exactly why we argue in Section 2.2 that our variable of bank monitoring captures only a limited fraction of the overall monitoring activity conducted by the bank.

Cornelissen et al., 2016).[39] Specifically, we find that an increase in the number of requests for information, that corresponds to half a percentage point decrease in the IRAP tax rate (equivalent to almost one standard deviation),[40] entails a decrease by 2 percentage points in the probability that the lending exposure ends up in distress two quarters ahead. This effect is heavily statistically and economically significant, especially in light of the fact that the probability of a credit exposure being nonperforming is 11.4% in our reduced sample (panel B of Table 6). Moreover, an increase in the IRAP tax rate of 0.5 percentage points is a rather realistic event. In fact, in our sample period, we observe twenty-four times an absolute change in the regional IRAP tax rate that is greater or equal to half a percentage point (Table 3). As mentioned earlier, we perform the Anderson-Rubin test to derive weak-identification-robust inference. This test is similar to a standard t-test, as it allows to assess if the coefficient of the endogenous regressor is statistically different from zero, but is robust to the use of a weak instrument. The Anderson-Rubin Wald statistic confirms that the effect of bank monitoring on loan repayment is statistically significant and the extent of the significance is even higher than that of a standard t-test (1% versus 10%). Looking at the control variables, we see that a lower *Loan amount* and *Share exposure* are associated with a higher probability of loan repayment. Moreover, a credit exposure is less likely to become nonperforming if it includes in a term loan or an accounts receivable loan, whereas the opposite holds if it includes a credit line.

When considering increasing levels of loan distress, we note that the magnitude of the effect strengthens from past-due to unlikely-to-pay exposures, whereas it actually reverts for bad exposures. This finding, as well as the evidence that the coefficient of *Monitor* is significant only in the fourth specification, suggest that the positive impact of bank monitoring on loan repayment is mainly driven by the ability of the bank to prevent a loan from becoming unlikely-to-pay. Additionally, once a credit exposure is in a hopeless condition of distress, bank monitoring seems not to be helpful anymore to foster loan repayment. There could be two different explanations for the latter result. First, when a credit exposure is severely distressed the bank does not have incentives to monitor anymore. Alternatively, the bank still monitors the firm but monitoring is not effective. Looking at Figure 2, we observed that the number of requests for information decreases substantially from past-due to bad exposures. This evidence provides support to our first con-

[39]Our endogenous variable is a count variable. Thus, it can be considered a treatment effect with different levels of treatment (Angrist and Pischke, 2009). As a consequence, we need to interpret our result taking into account a reasonable change in the instrumental variable.

[40]The value of one standard deviation is calculated based on the empirical distribution of the IRAP tax rate in the restricted sample where this regression is estimated, as reported in panel B Table 6.

jecture, namely that the bank is not willing to exert monitoring effort when a loan is in a hopeless condition.

[Insert Table 5 here]

Note that this 2SLS model is estimated on a sample of 556,227 observations, encompassing 53,738 credit relationships, 23,376 firms and 440 banks over the time period 2007-2016. This dataset is roughly eight times smaller than the full sample of 4,551,817 observations where we perform the analysis on our proxy for bank monitoring presented in Section 2.2. This substantial shrinkage of observations is justified by the fact that the 2SLS model is estimated on the reduced sample of firms having multiple credit relationships with small banks at the same point in time. In fact, the inclusion of firm-time fixed effects in our specifications is an essential ingredient of our identification strategy. Summary statistics of the subsample where this model is estimated are reported in panel B of Table 6.

[Insert Table 6 here]

A natural question is whether credit exposures, firms and banks pertaining to the reduced sample differ along some dimensions to credit exposures, firms and banks in the original sample. If that is the case, our 2SLS model might be subject to a selection bias. To address this concern we perform a comparative analysis of the reduced sample with the full sample. Table 6 reports summary statistics of the variables used in our empirical analysis for both the full sample (panel A) and the reduced sample (panel B). All variables exhibit very similar values in the two datasets. Figure 4 shows the distribution of firms and banks across regions in the full sample and the reduced sample. Looking at the full sample, we note that firms and banks are distributed throughout the whole country, but the majority is located in the center-north regions. This remains true even in the sample of firms with multiple credit relationships with small banks. More importantly, despite the number of firms is reduced by a factor of ten in the reduced sample, the distribution of firms and banks across regions is virtually unchanged. Overall, this evidence evidence suggests that the reduced sample is sufficiently representative.

[Insert Figure 4 here]

This claim is confirmed even when we check if firms covered in the reduced sample are representative enough of the whole universe of firms in Italy. Looking at the number of employees and the size of the asset side, we observe that most of these firms fall under the definition of small and medium-sized enterprises (SMEs). This is not surprising, as we focus on firms borrowing from local banks operating at the regional level. Moreover, according to the SMEs CERVED Report 2014, SMEs represent about 96% of the total number of firms operating in Italy. We, then, compare the statistics of Panel A and Panel B of Table 6 with those of Table A2 in **??**, which are calculated over the entire universe of limited companies operating in Italy during our sample period (2005-2016). We find that the average credit score, capital ratio, profitability ratio and size of firms both in our full sample and restricted sample are very close to those of the entire universe of Italian firms.

As a last exercise, we look more closely at the main source of variation that we exploit. First, we observe that 9% of firms included in the reduced sample (2,162 firms) borrow, at least in one quarter, from two or more banks operating in different regions. In addition, 13% of firms (3,134 firms) borrow, at least in one quarter, from one or more banks located in a different region from their own. We also find that 11% of banks (49 banks) in the sample lend, at least in one quarter, to firms located in a different region from their own. A natural question arises: is it that firms move to borrow from banks located in a different region, or rather is it that banks establish branches outside of their region and lend to firms located in other regions? We cannot answer precisely to this question as we do not have information about the branch of the bank where the credit relationship takes place. However, we can provide some useful numbers. Specifically, we observe that 62% of observations in which the region of the firm differs from that of the bank are associated to banks that have branches only in one region. Therefore, it is likely that a substantial portion of the variation that we exploit in our identification comes from firms located close to the border between two regions.

3.2.2 Different horizons

So far we have been focusing on the effect of bank monitoring on loan repayment two quarters ahead, as this is the horizon in which we identify the strongest effect. Table 7 reports the estimates of various specifications of our 2SLS model for different horizons. The results show that the positive effect of bank monitoring on loan repayment is statistically significant only two quarters and three quarters ahead. Differently, if we rely on the Anderson-Rubin test to draw weak-identification-robust inference, we find that the effect of bank monitoring on loan repayment is significant for any horizon except for eight quarters ahead. Ignoring for a second the statistical significance and focusing exclusively on the sign and magnitude of the effect, we observe that the effect is already noticeable over the horizon of one quarter, it increases reaching is maximum two quarters ahead. Afterward, it slowly declines. This finding is consistent with the idea that a request for information may lead the bank to take specific actions to improve the likelihood that the firm repays its loan. For these actions to be effective it takes time and it seems that they deploy their effects mainly six months after the request takes place.

[Insert Table 7 here]

3.3 IRAP tax rate as a proxy for total bank monitoring: A reduced form model

So far we have developed the empirical analysis using our measure for bank monitoring based on the requests for information made by banks on their existing borrowers. We have extensively discussed the limits of this measure, which is likely to grasp only a fraction of the actual intensity of bank monitoring. In addition, as mentioned earlier, a bank does not necessarily need to submit an active request for information to assess the current conditions of loans extended by other banks to the firm. In other words, we cannot rule out that our proxy for bank monitoring captures monitoring activities related to particularly negative prospects of the firm, which require a closer oversight. Relying on the theoretical model exposed in Section 2.3.1, we conjecture that variation in the IRAP tax rate affects incentives of any kind of bank monitoring activity. Thus, in order to capture the whole effect of bank monitoring on loan repayment, we directly mimic a change in total bank monitoring using the IRAP tax rate. Specifically, we estimate the following reduced form model:

$$\text{NPL dummy}_{i,b,r,t} = \alpha + \beta \text{IRAP}_{r,t-h-4} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,b,r,t-h-n} + \mu_{i,t} + \mu_b + \mu_r + \varepsilon_{i,b,r,t} \quad (6)$$

where $\boldsymbol{X}$ denotes the same vectors of loan, bank, and macro regional variables of the 2SLS model. We estimate the model on a similar sample to that of the 2SLS, with one major difference. To make sure that we are capturing only the effect of bank monitoring on loan repayment, as driven by the IRAP tax rate, we drop all observations where we detect an increase in the committed amount of credit extended to an existing borrower in the current quarter or in the previous quarters belonging to the year that follows that of the tax rate.[41]

Table 8 displays the results of the reduced form regression estimating the effect of bank monitoring on loan repayment two quarters ahead. Looking at the first specification, we find that a decrease in the IRAP tax rate by half a percentage point (almost one standard deviation) implies an increase of 2.7 percentage

[41] In fact, our model in Section 2.3.1, suggests that a decrease in the corporate tax rate implies a decrease in the lending rate. This, in turn, can cause an increase in credit demand from existing borrowers.

points in the likelihood of loan distress. The magnitude of this effect is close but somewhat higher than that of the 2SLS model (2 percentage points). It is worth mentioning that the two models are run on different samples. However, the similarity in the magnitude of the effect provides us with an important insight on the relevance of our proxy for bank monitoring. If the requests for information were only partially correlated with other monitoring activities, the coefficient of the IRAP tax rate in this regression should have been sensibly higher than what observed in Table 5. The evidence that the magnitude of the effect of bank monitoring on loan repayment is similar, although a bit stronger to what detected in the 2SLS model, suggests that the requests for information are actually highly correlated with other forms of bank monitoring. In other words, the data is telling us that the bank's choice to monitor a borrower is to a large extent dichotomous. Either the bank does not monitor at all, or it carries out different kinds of monitoring activities when it decides to monitor. In fact, it is reasonable to think that, if a bank is concerned about the ability of a firm to meet its repayment schedule, it will control the condition of the other outstanding loans of the firm, check the financial reports, make visits on site and provide advisory services, all at the same time. As a consequence, despite our variable of bank monitoring captures only a fraction of the whole intensity of bank monitoring, it is able to grasp to a large extent the effect of total bank monitoring on loan repayment.

When looking at the subsequent specifications, we observe that the pattern of the coefficients of *IRAP* resembles that of *Monitor* observed in Table 5 but with opposite signs. Also in this case, the positive effect of bank monitoring on loan repayment is mainly driven by the ability of the bank to prevent a given exposure from becoming unlikely-to-pay.

[Insert Table 8 here]

3.4 Different types of credit

The benefit from monitoring in disciplining borrowers depends to a large extent on the type of loan granted by the bank to the firm. In particular, the positive effect of bank monitoring on firm's pledgeable income should be stronger for term loans (Acharya et al., 2021). In our baseline model we estimate the effect of bank monitoring on loan repayment controlling for the different types of credit that characterize a firm-bank-firm lending relationship. In this section we extend our analysis re-estimating our 2SLS and reduced for models for each loan category.

This exercise allows us also to address a second concern. Let us ignore for a second accounts receivable loans, which typically have a very short maturity that makes renegotiation very unlikely. When we compare term loans and credit lines, the contractual terms of the latter can be renegotiated by the parties in a much easier way than those of the former, even if loan payments are still not in arrears. In particular, we argue that it is simpler for a bank to evaluate the risk profile of a credit line compared to that of a term loan. The reason is twofold: first, differently from term loans, credit lines are usually unsecured, meaning that a renegotiation does not require the bank to reassess the value of the asset(s) pledged as collateral; second, the contractual agreement of a credit line typically allows the bank to unilaterally change the credit terms of the loan as well as to withdraw from the contract on short notice. Thus, while loan renegotiation may involve any loan type, this is more likely to occur for a credit line. This means that loan renegotiation of credit lines, which triggers banks' requests for information from the CR, may drive our results rather than bank monitoring (at least, as long as renegotiation improves the credit terms for the borrower).

Table 9 reports the estimates of various specifications of the 2SLS model and the reduced form model where we consider each type of credit separately. For example, in the case of term loans, our setup allows to gauge the effect of bank monitoring on loan repayment by comparing the repayment performance on different term loans extended by different banks to the same firm at the same point in time. We focus, first, on the 2SLS model (specifications 1-6). We observe a negative and statistically significant coefficient of *Monitor* only in the specification that looks at term loans. If we rely on the Anderson-Rubin test to derive weak-identification-robust inference, we find a positive and significant effect of bank monitoring on loan repayment also for credit lines and accounts receivable loans. However, the magnitude of the effect is somewhat stronger for term loans. In particular, an increase in the number of requests for information, that corresponds to a half percentage point decrease in the IRAP tax rate (roughly, a decrease of one standard deviation), entails a decrease by 2.4 percentage points in the probability that a term loan becomes nonperforming two quarters ahead, compared to 1.9 percentage points and 2 percentage points for credit lines and accounts receivable loans, respectively. The reduced form model (specifications 7-9) shows similar results, with even a larger gap in terms of magnitude between term loans and the other two loan types. Overall, our findings are consistent with the idea that the benefit from bank monitoring is stronger for term loans vis-à-vis credit lines and accounts receivable loans (Acharya et al., 2021). Importantly, these results rules out the possibility that the observed positive effect of an increase in bank's requests for information on loan repayment is driven by renegotiation of credit lines.

[Insert Table 9 here]

3.5 Tax rate at the start of the lending relationship

The model presented in section 2.3.1 suggests that banks transfer, at least to some extent, an increase in the tax rate to their borrowers by rising the lending rate. Consider the case of a firm that borrows from two banks operating in two regions with a different tax rate. According to this theoretical prediction, it could be the case that the bank located in the region with the higher tax rate charges a higher interest rate, once having accounted for all the relevant loan, firm and bank characteristics. In the first stage of the 2SLS model, we document that a decrease in the tax rate improves the intensity of bank monitoring. Nevertheless, since we use the tax rate as an instrument for bank monitoring, it could be the case that the effects identified in the 2SLS model and the reduced for model are driven by a gap in the interest rates charged by different banks lending to the same firm, which in turn may depend on the difference in the regional tax rates applied to these banks.

An important reminder is that credit is determined in equilibrium by the interaction of demand and supply. As a consequence, if a bank applies a higher interest rate to a firm than other lenders for a similar loan, the firm may decide not to borrow from this bank. In other words, holding everything else equal, interest rates applied by different banks to the same borrower should converge. For a limited subset of banks for which we have information on lending rates and considering only firms with multiple credit relationships with small banks, Table A3 in **??** presents evidence that is in line with this conjecture. Conditional on loan and bank characteristics, there is a positive and statistically significant correlation between the tax rate applied and the interest rate charged by different banks lending to the same firm only for accounts receivable loans; the relation is, instead, positive but insignificant in the case of term loans and credit lines, or when we consider the average interest rate applied to the various lending components of the firm-bank credit exposure. This is not surprising as, once having controlled for loan characteristics, the interest rate charged crucially depends on the credit quality of the firm.[42]

Nevertheless, we still need to perform a robustness test to check if our results are driven by differences in the interest rates charged by banks lending to the same firm as a result of different tax rates applied to these banks. Ideally, we would like to run our regressions controlling for the interest rates charged on the various types of credit. Unfortunately, we have information on interest rates only for a limited subset of banks. In this subsample, there is not enough variation to exploit, as no

[42]In addition, the increasing values of the coefficients of the tax rate when we move from term loans to accounts receivable loans, suggests that banks have higher incentives to transfer an increase in the tax rate on the lending rate for loans with a shorter duration.

firm happens to borrow simultaneously from two or more banks located in different regions and subject to a different tax rate, with at least one bank monitoring and one bank not making any request.[43] So, we opt for an alternative approach.

In principle, the tax rate of the bank's region should affect the interest rate set at the start of the loan when pricing occurs. Table 3 shows that the IRAP tax rates exhibit a substantial variation both across regions and over time. However, we should still check if our findings are robust to the inclusion of a variable capturing the tax rate of the bank's region at the start of the firm-bank credit relationship in the regression models. Table 10 presents the results of this exercise. We find that, even when controlling for the corporate tax rate applied to the bank at the start of the credit relationship, an increase in the number of requests for information has a strong and positive effect on loan repayment. As expected, the coefficient of *IRAP start loan* is positive in the second stage of the 2SLS model and in the reduced form model, crossing the threshold of statistical significance in the latter.

[Insert Table 10 here]

In Table 11, we refine this approach looking at each type of credit separately. Specifically, we estimate similar regressions to those of Table 9 where we include the tax rate of the bank's region at the start of the loan among the control variables. The coefficients of *Monitor* are virtually unchanged compared to those in Table 9. We conclude that our findings are driven by a difference in the intensity of bank monitoring among banks lending to the same firms rather than a difference in the interest rates charged by these banks.

[Insert Table 11 here]

3.6 Robustness tests

It is reasonable to think that the performance condition of a loan is to some extent persistent over time. For example, if a loan is in distress it is likely that we it will still be so in the next quarter. Thus, as a first exercise, we check if our findings are robust to the inclusion of the dependent variable (a dummy equal to one if the credit exposure is nonperforming and zero otherwise) lagged.[44] Table 12 reports

[43] Table A4 in **??** shows various specifications where we estimate the 2SLS model and the reduced form model including the average of the interest rates applied to the various type of loans extended by a bank to a firm among the set of controls. Our reduced sample shrinks by a factor of ten and in this subsample we do not identify a statistically significant effect of bank monitoring on loan repayment, irrespective of whether we control or not for the average interest rate charged. As mentioned above, this is due to the fact that in this subsample there is not enough variation to exploit, as no firm borrows simultaneously from multiple small banks located in different regions and subject to a different tax rate, with at least one bank monitoring and one bank not making any request.

[44] We include this variable lagged of three quarters so that it is predetermined with respect to the dependent variable in both stages of the 2SLS model.

the results of this dynamic model. The first stage of the 2SLS model is virtually unchanged. Interestingly, there is no evidence that banks monitor more intensively exposures that are already in a condition distress. This is hardly surprising though, as we highlighted that only a negligible fraction of requests for information (6.8%) are associated with nonperforming exposures. The estimates of the second stage of the 2SLS model confirm that bank monitoring has a positive and significant effect on loan repayment, but this is somewhat weaker than what detected in Table 5 (albeit still economically strong). Specifically, an increase in the number of requests for information, that corresponds to a half percentage point decrease in the IRAP tax rate, implies a decrease by 1.4 percentage points in the likelihood that the loan ends up in distress two quarters ahead. Similarly, the coefficient of $IRAP$ in the reduced for model is still positive and statistically significant, but the magnitude is roughly 1 percentage point lower than what observed in Table 8.

[Insert Table 12 here]

Despite only 6.8% of requests for information concern a credit exposure that is already in distress, we may wonder if our results are driven to some extent by loan restructuring rather than bank monitoring in the strict sense. In fact, if a loan gets in arrears the bank can loosen the borrower's financial constraints by postponing due payments, decreasing the interest rate or even providing additional credit (Brunner and Krahnen, 2008). Our data cleaning process implies that we already account for the latter, as we dropped all relevant observations in which we detect an increase in lending to an existing borrower. Nevertheless, the bank may still respond to an overdue by modifying the credit terms. Thus, as a robustness test, we further drop all observations pertaining to exposures that are nonperforming at the time in which we observe bank monitoring, i.e. $t-2$. Table 13 reports the results of this exercise. We find that the negative effect of bank monitoring on loan repayment is still there, both in the 2SLS model and in the reduced form model, but the magnitude is smaller.

[Insert Table 13 here]

One may argue that a renegotiation of credit terms may occur even before a loan becomes past-due. Renegotiation usually involves a decline in the loan spread or an increase in the amount of credit extended to a client. Let us focus on the former, as in our analysis we discard observations associated with an increased of committed credit. Given our methodological approach, to invalidate our interpretation of the results of the 2SLS model and to corroborate the hypothesis that our findings are driven by loan renegotiation, it is necessary that a firm, borrowing from two (or more) banks at the same point in time, requests to renegotiate the loan granted by the bank subject to the lower tax rate. The theoretical model presented in Section 2.3.1 suggests that an increase in the tax burden due to a higher tax rate is partially transferred by banks to their borrowers by increasing the lending rate. Thus, we would expect that banks subject to a high tax rate charge higher interest rates or, at least, not lower interest rates than banks subject to a low tax rate. The results presented in Table A3 of **??** on a limited subset of banks for which we have information on the lending rates corroborate our prior. In particular, when we compare the same type of loan granted by different banks to the same firm at a given point in time, the interest rate charged is positively associated with the tax rate applied to the bank, but this correlation is statistically significant only for accounts receivable loans. Thus, our theoretical predictions together with the empirical evidence, lead us to conclude that there is no reason to believe that a firm borrowing from multiple banks has higher incentives to renegotiate the interest rate charged by the lender subject to a higher tax rate vis-à-vis the other banks.

A third concern comes from the lags that we use for our independent variables in our main specifications. As we have already mentioned earlier, the lags of our regressors are defined in such way that each variable is predetermined with respect to the dependent variable in each stage of the 2SLS model. This ensures that our 2SLS regression is not affected by issues of reverse causality. However, it exposes to the risk that the set of controls is not enough effective. In Table 14 we display the results of robustness checks in which we estimate our main models reducing the lag of the independent variables as much as possible. The results are virtually the same if compared to those of Table 5 and Table 8.

[Insert Table 14 here]

3.7 Economic Channels

A natural question to ask ourselves is why a decrease in the IRAP tax rate applied to banks implies higher incentives to monitor borrowers. As we mentioned in Section 2.3, the IRAP tax base includes not only profits but also wages. Thus, a reasonable hypothesis is that a decrease in the tax rate leads to an increase in the workforce of the bank and/or an increase in wages due to the lower costs associated with employees' compensation (Arulampalam et al., 2012; Fuest et al., 2018; Saez et al., 2019). This, in turn, may improve the monitoring effort of the bank, at least as long as a higher number of employees translates into higher monitoring and loan officers' compensation is tied to their performance in monitoring borrowers.

Our dataset includes information on the number of bank's employees, but not on the number of loan officers neither on their compensation. So, we partially test this hypothesis by collapsing the original dataset from the CR including all credit relationships with businesses, irrespective of their length, at the bank-quarter level and by regressing the logarithm of the number of bank employees on the IRAP tax rate applied to the bank.[45] We saturate the model including a set of bank and regional controls, as well as the bank's region fixed effects. In essence, this model investigates the employment behavior of banks operating in a certain region in response to changes in the tax rate. The specification of Panel A of Table 15 reports the results of this exercise. The negative and statistically significant coefficient of the tax rate suggests that, conditional on bank and local macro conditions, a decrease in the IRAP tax rate implies an increase in the number of bank employees. Nevertheless, according to our model, a decline in the tax rate is partially shifted to borrowers by lowering the lending rate. As a result, credit supply may increase and a higher number of bank employees may not necessarily entail a higher monitoring intensity. Tellez (2020) provide evidence of compensation schemes that are tied to loan officers' monitoring effort. Thus, studying how changes in the corporate tax rate affect bank's compensation policies may shed light on how our theoretical prediction (i.e., the positive effect of a decline in the tax rate on bank monitoring) translates into practice. We leave this analysis for future research.

A second, and perhaps, more relevant question is why a more intense bank monitoring leads to a higher likelihood of loan repayment. While we cannot fully answer this question due to a lack of comprehensive information on the monitoring activity conducted by banks, we can, nevertheless, exploit the available data to shed some light on the mechanism behind the observed positive effect of bank monitoring on loan repayment. One approach is to observe what happens to firm conditions after bank monitoring takes place. This approach, though, requires to depart from our identification strategy using firm-time fixed effects, as the dependent variable cannot be invariant within a firm-time pair.

Models (2)-(4) of Panel B of Table 15 analyze the relation between bank monitoring and firm's capitalization, profitability and credit score, respectively. In particular, we regress *ROA firm*, *Capital ratio firm* and *Credit score firm* at the end of the year of quarter t on our proxy for bank monitoring, *Monitor*, lagged of one quarter, control variables capturing firm, bank and macro conditions, and a set of fixed effects. These are dynamic models, as we include the lagged dependent variable among the regressors to account for a certain persistence in the variables of interest. All regressors are lagged according to their frequency, so as to ensure

[45] The original dataset covers all business loans extended by small banks to Italian firms with a duration of one quarter or above.

that each control is predetermined with respect to the dependent variable and, at most, concomitant with our proxy for bank monitoring. Regressions are estimated on a dataset obtained according to a similar cleaning process to that described in Section 2.2.[46]

First, we find that bank monitoring is associated with an increase in firm's capitalization and profitability. This suggests that bank monitoring may not be limited to a mere costly state verification (Townsend, 1979; Diamond, 1984; Gale and Hellwig, 1985; Krasa and Villamil, 1992), but may encompass also other activities that are beneficial to the firm (Holmstrom and Tirole, 1997; Mehran and Thakor, 2011). For example, if the firm is close to breach a loan covenant, the bank may take actions to prevent a covenant violation. We also find a negative coefficient for the credit score, suggesting a positive correlation also with firm's credit quality, but the coefficient is not statistically significant. Overall, these findings reveal that bank monitoring may entail a series of actions that improve the conditions on the firm and, consequently, its repayment performance. Despite the comprehensive set of controls and the fact that we include the dependent variables lagged of one year to limit reverse causality, we should not be tempted to interpret these results from a causal perspective. In fact, in these regressions there is still room for potential endogeneity. Our conjectures can be corroborated only through a causal study, which is hard in our setup as our identification strategy chiefly relies on the use of firm-time fixed effects. We leave this analysis for future research.

[Insert Table 15 here]

An alternative approach to investigate what could be the channels through which bank monitoring is associated with improved loan repayment, is to look at the evolution of the firm-bank credit relationship after a request for information made by the lender. To this end, we focused the attention on the committed and utilized amounts and the value of collateral and personal guarantees. The econometric analysis does not unveil any statistically significant effect on those variables. This means that a request for information is not followed by a significant decrease in the committed amount of credit,[47] a change in loan drawdowns, a

[46] In particular, we start from the original sample of 5,357,692 observations, covering the time period 2005-2016, and we drop: (i) observations pertaining to credit relationships with a duration lower than three quarters; (ii) observations in which a credit relationship is restored after a break in the current quarter or in the previous one; (iii) observations pertaining to banks experiencing extraordinary circumstances which impact, or may impact, their number of requests for information from the CR in the current quarter or the previous one; (iv) observations where we detect an increase in the committed amount of credit extended to an existing borrower in the current quarter or in the previous one.

[47] Recall that we exclude from the analysis credit relationships that experience an increase in the amount of committed credit.

request of additional collateral or a reassessment of the value of collateral.[48]

4 Conclusions

This paper investigates the effect of bank monitoring on loan repayment. Using granular firm-bank level information on business loans extended in Italy, we construct a novel proxy of bank monitoring. This consists in the number of requests for information made by banks on their existing borrowers to the Italian Credit Register.

To derive causal inference, we exploit taxation as a source of exogenous variation in bank monitoring. Our empirical strategy builds on a theoretical model that we develop to describe the effects of a corporate tax on bank monitoring incentives. The model predicts that a decrease in the corporate tax rate is associated with an increase in bank monitoring. This stems from two main channels. An increase in the tax rate reduces bank profits and leads to a higher leverage ratio. These effects are only partially compensated by the pass-through of the tax rate into the lending rate. As a result, an increase in the tax rate implies a decrease in bank expected profits. This, in turn, weakens bank incentives to monitor borrowers. We use this theoretical prediction to pin down our identification strategy.

Specifically, we study the causal effect of bank monitoring on loan repayment by estimating a 2SLS model in which bank monitoring is instrumented with the local tax rate of the Italy Regional Production Tax (IRAP). We saturate this model with firm-time fixed effects, to ensure that we control for any time varying and time invariant, observable and unobservable condition of the firm that may affect the likelihood of loan repayment. We find that an increase in the number of requests for information, as driven by a half percentage point decrease in the IRAP tax rate (equivalent to the standard deviation), reduces the probability of a delinquency by 2 percentage points two quarters ahead.

We acknowledge that our proxy of bank monitoring grasps only a fraction of the overall monitoring activity conducted by the bank. Thus, since the corporate tax rate is likely to influence bank incentives with respect to any form of monitoring, we extend our analysis estimating the effect of total bank monitoring, as driven by the IRAP tax rate, on the repayment performance of the firm. We find that this effect has a similar and somewhat higher magnitude to that exerted by the requests for information alone. We conclude that our proxy for bank monitoring is able to capture to a large extent the overall effect of bank monitoring on loan repayment.

[48] For the sake of brevity, we did not include these results in a table as they do not document any statistically significant effect. However, results are available upon request.

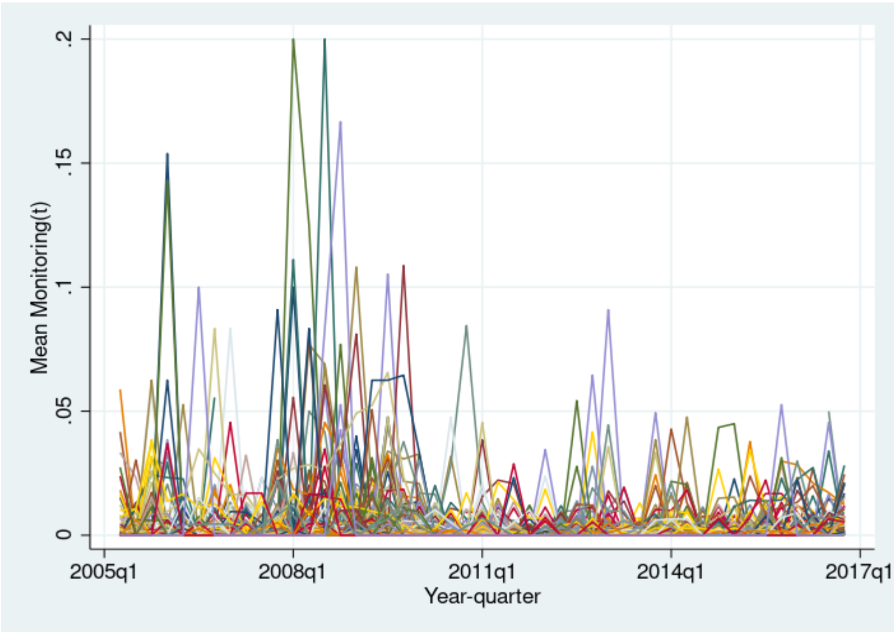
We further extend our analysis looking at different credit types separately. We find that the positive effect of bank monitoring on loan repayment is stronger for term loans compared to credit lines and loans backed by receivables.

Our findings have two key economic implications. First, the real effects of bank monitoring are substantial. Monitoring is valuable for individual banks, as it reduces delinquency rates. Second, taxation affects bank incentives to monitor borrowers in a significant way.

Figure 1: Bank requests for information over time

The figure shows the time series of the average number of requests for information per borrower made by each bank (a), and the average number of requests for information per borrower made all banks in our sample along with the annual percentage growth rate of Italian GDP at market prices (b).

a. Average number of requests for information per borrower by each bank



b. Average number of requests for information per borrower by all banks and Italy GDP annual growth rate

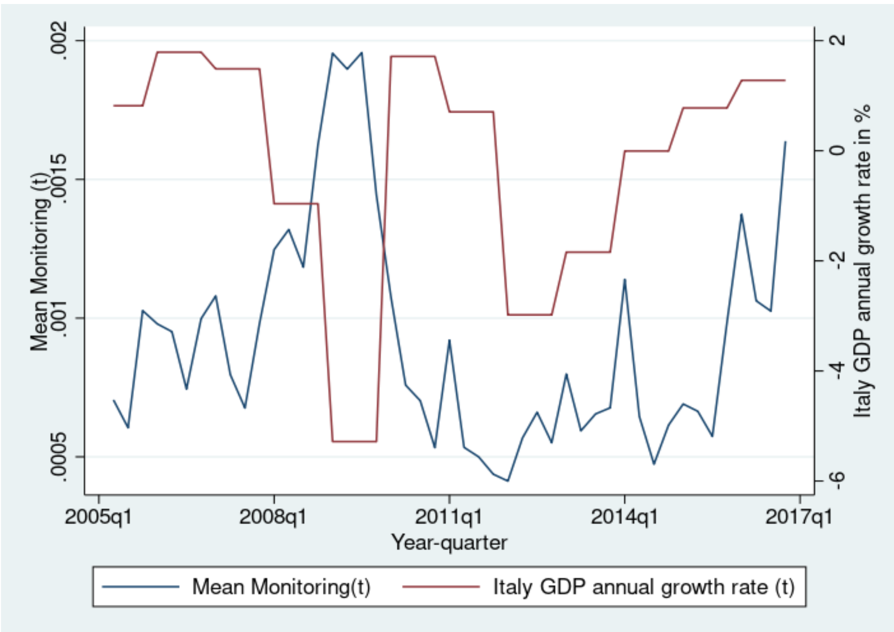


Figure 2: Bank requests for information associated with nonperforming exposures and exposures close to the CR thresholds

The figure shows the percentage of bank requests for information associated with nonperforming exposures and each subcategory (blue bars), and the percentage of bank requests for information associated with credit exposures that are close to the minimum thresholds to be reported in the CR (red bar).

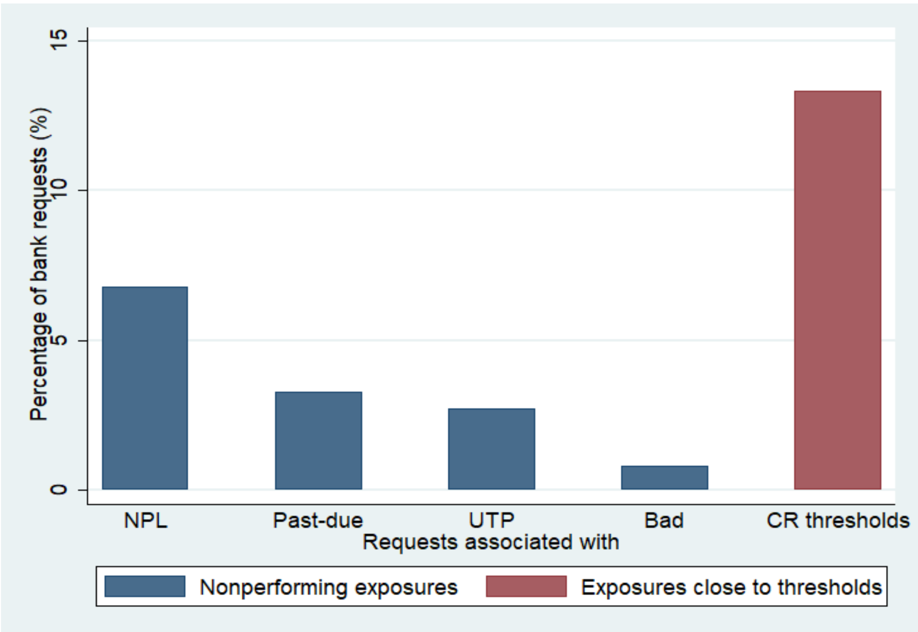


Figure 3: Nonperforming exposures versus bank requests for information

The figure shows the percentage of nonperforming exposures in each quarter against the average number of requests for information per loan submitted by banks one quarter before. Plots are generated from a dataset obtained according to a similar cleaning process to that described in Section 2.2. In particular, we start from the original sample of 5,357,692 observations, covering the time period 2005-2016, and we drop: (i) observations pertaining to credit relationships with a duration lower than three quarters; (ii) observations in which a credit relationship is restored after a break in the current quarter or in the previous one; (iii) observations pertaining to banks experiencing extraordinary circumstances which impact, or may impact, their number of requests for information from the CR in the current quarter or the previous one; (iv) observations where we detect an increase in the committed amount of credit extended to an existing borrower in the current quarter or in the previous one.

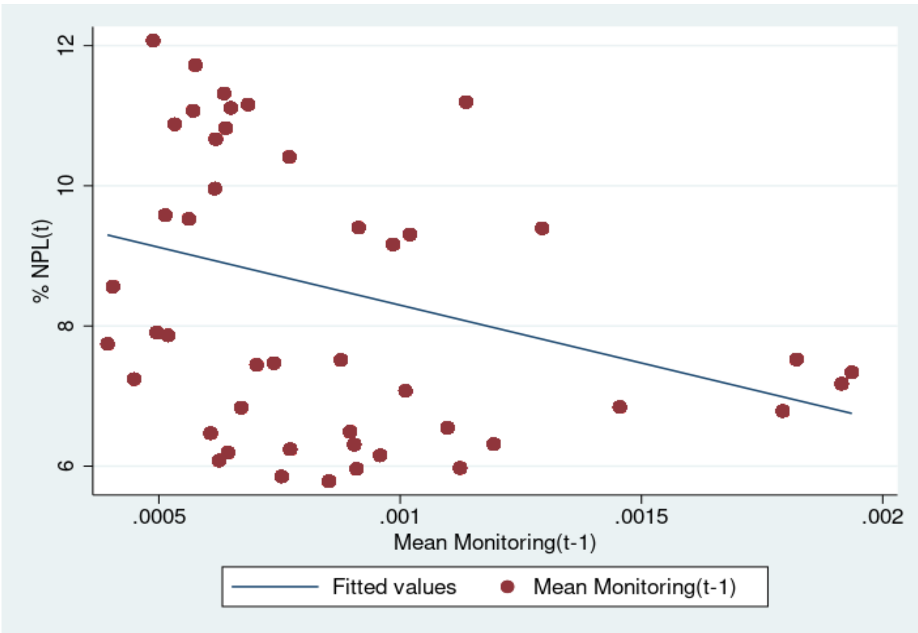
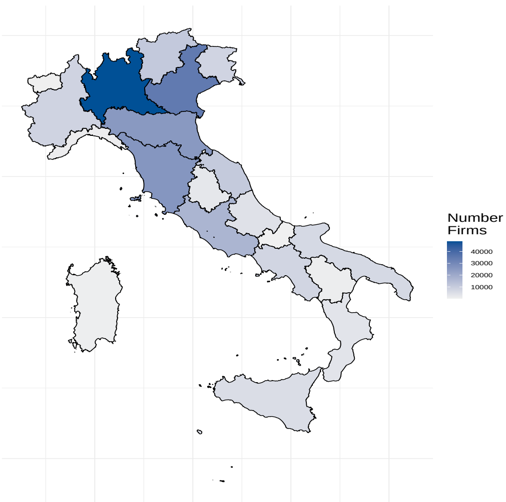


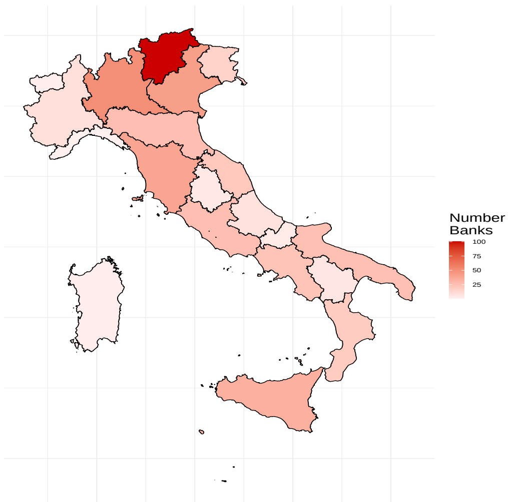
Figure 4: Distribution of firms and banks across Italian regions

The figure shows: the distribution of firms (a) and the distribution of banks (b) across Italian regions in the full sample; the distribution of firms (c) and the distribution of banks (d) across Italian regions in the reduced sample including only firms that have multiple credit relationships with small banks. The full sample includes 4,551,817 observations pertaining to 280,613 credit relationships having a duration greater than one quarter, and involving 225,414 firms and 457 banks over the period 2005-2016. The reduced sample has 556,227 observations and includes 53,738 credit relationships having a duration greater than three quarters, and involving 23,376 firms and 440 banks over the period 2007-2016.

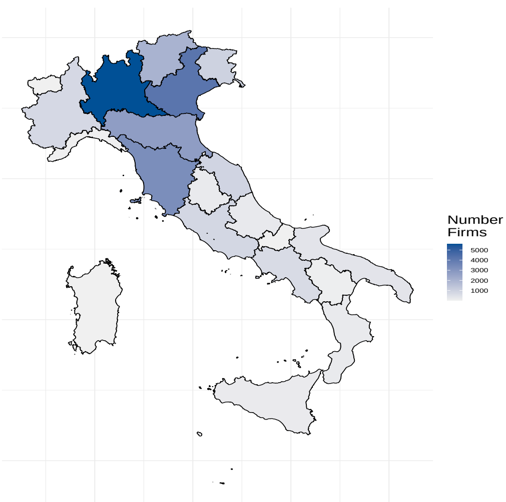
a. Firms in the full sample



b. Banks in the full sample



c. Firms in the reduced sample



d. Banks in the reduced sample

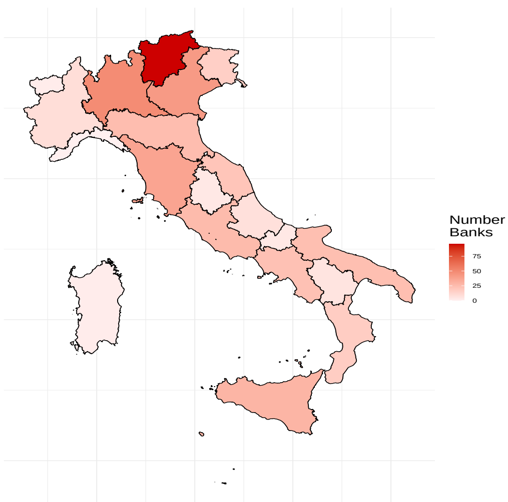


Table 1: Description of variables used in the empirical analysis

Variable name	Description
A. Loan-level variables	
NPL dummy	A dummy variable equal to one if part or the whole credit exposure to a firm is defined either as past-due by 90 days or more, unlikely-to-pay, or bad. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Past-due dummy	A dummy variable equal to one if part or the whole credit exposure to a firm is defined as past-due by 90 days or more. Frequency: quarterly. Source: Credit Register of Bank of Italy.
UTP dummy	A dummy variable equal to one if part or the whole credit exposure to a firm is defined as unlikely-to-pay. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Bad dummy	A dummy variable equal to one if the bank's credit exposure to a firm is defined as bad. Frequency: quarterly. Source: Credit Register of Bank of Italy.
NPL term loan dummy	A dummy variable equal to one if a term loan granted by the bank to a firm is defined either as past-due by 90 days or more, or unlikely-to-pay. Frequency: quarterly. Source: Credit Register of Bank of Italy.
NPL credit line dummy	A dummy variable equal to one if a credit line granted by the bank to a firm is defined either as past-due by 90 days or more, or unlikely-to-pay. Frequency: quarterly. Source: Credit Register of Bank of Italy.
NPL A/R loan dummy	A dummy variable equal to one if an accounts receivable loan granted by the bank to a firm is defined either as past-due by 90 days or more, or unlikely-to-pay. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Monitor	Total number of requests for information made by the bank on an existing borrower in the quarter. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Loan amount	Total utilized amount of the bank's credit exposure to a firm. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Length relation	Duration of the bank-firm credit relationship in quarters. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Term loan dummy	A dummy equal to one if the bank's credit exposure to a firm includes a term loan. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Credit line dummy	A dummy equal to one if the bank's credit exposure to a firm includes a credit line Frequency: quarterly. Source: Credit Register of Bank of Italy.
A/R loan dummy	A dummy equal to one if the bank's credit exposure to a firm includes an accounts receivable loan. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Share guarantee	Fraction of the bank's credit exposure to a firm assisted by a guarantee. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Share exposure	Share of the bank's credit exposure to a firm with respect to the total credit exposure of the banking system to that firm. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Close threshold dummy	A dummy variable equal to one if the bank's credit exposure to a firm is close to the minimum thresholds to be reported in the Credit Register. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Average interest rate	Average of the nominal interest rates charged on the various types of credit (term loan, credit line, accounts receivable loan) extended by the bank to a firm in percentage points. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Interest rate term loan	The nominal interest rate charged on a term loan extended by the bank to a firm in percentage points. Frequency: quarterly. Source: Credit Register of Bank of Italy.

Continued on next page

Table 1 – *Continued from previous page*

Variable name	Description
Interest rate credit line	The nominal interest rate charged on a credit line extended by the bank to a firm in percentage points. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Interest rate A/R loan	The nominal interest rate charged on an accounts receivable loan extended by the bank to a firm in percentage points. Frequency: quarterly. Source: Credit Register of Bank of Italy.
B. Firm-level variables	
Credit score firm	The credit score assigned by CERVED to the firm, which is based on the probability that the credit to the firm becomes bad debt. *Credit score firm* takes 9 progressive values, from 1 to 9. A credit score of 1 corresponds to firms with the highest credit quality, while a credit score of 9 corresponds to firms essentially in default. Frequency: yearly. Source: CERVED.
Capital ratio firm	The equity-to-asset ratio of the firm. Frequency: yearly. Source: CERVED.
ROA firm	Firm profitability, calculated as the ratio of net income to total assets. Frequency: yearly. Source: CERVED.
Size firm	Firm size, computed as the logarithm of total assets. Frequency: yearly. Source: CERVED.
Industry firm	The "ateco" code identifying the industry of the firm. *Industry firm* takes 5 different values, each one corresponding to a specific sector. Frequency: yearly. Source: CERVED.
C. Bank-level variables	
Capital ratio	The equity to asset ratio of the bank. Frequency: yearly. Source: Credit Bureau of Bank of Italy.
ROA	Bank profitability, calculated as the ratio of net income to total assets. Frequency: yearly. Source: Credit Bureau of Bank of Italy.
NPL ratio	The fraction of nonperforming loans to the private sector. Frequency: yearly. Source: Credit Bureau of Bank of Italy.
Size bank	Bank size, computed as the logarithm of total assets. Frequency: yearly. Source: Credit Bureau of Bank of Italy.
Liquidity ratio	The ratio of liquid assets to total assets of the bank. Frequency: yearly. Source: Credit Bureau of Bank of Italy.
Nonretail deposit ratio	The ratio of nonretail deposits to total deposits of the bank. Frequency: yearly. Source: Credit Bureau of Bank of Italy.
Bank Employees	The number of employees of the bank. Frequency: yearly. Source: Credit Bureau of Bank of Italy.
D. Regional variables	
IRAP	The regional IRAP tax rate (in units) applied to the bank. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
IRAP start loan	The regional IRAP tax rate (in units) applied to the bank in the year preceding the start of the bank-firm credit relationship. If there is a break in the credit relationship, this variable corresponds to the regional IRAP tax rate applied to the bank in the year preceding the quarter where the credit relationship is restored. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
IRAP start term loan	The regional IRAP tax rate (in units) applied to the bank in the year preceding the start of the term loan. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
IRAP start credit line	The regional IRAP tax rate (in units) applied to the bank in the year preceding the start of the credit line. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
IRAP start A/R loan	The regional IRAP tax rate (in units) applied to the bank in the year preceding the start of the accounts receivable loan. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
GDP growth region firm	GDP growth of the firm's region, computed as the first difference in the logarithm of GDP. GDP is deflated using CPI with 2010 as the reference year. Frequency: yearly. Source: ISTAT.

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Table 1 – *Continued from previous page*

Variable name	Description
Employment region firm	Employment rate of the firm's region, expressed in percentage points. Frequency: yearly. Source: ISTAT.
Inflation region firm	Inflation rate of the firm's region, expressed in percentage points. Frequency: yearly. Source: ISTAT.
GDP growth region bank	GDP growth of the bank's region, computed as the first difference in the logarithm of GDP. GDP is deflated using CPI with 2010 as the reference year. Frequency: yearly. Source: ISTAT.
Employment region bank	Employment rate of the bank's region, expressed in percentage points. Frequency: yearly. Source: ISTAT.
Inflation region bank	Inflation rate of the bank's region, expressed in percentage points. Frequency: yearly. Source: ISTAT.

Table 2: Monitored firms and monitoring banks

The table reports panel regression estimates of different linear models investigating the relation between bank monitoring and a set of firm and bank variables. The dependent variable is displayed at the bottom of each column. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are either included, "Yes", not included, "No", or spanned by another set of effects, "-". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2.

	Monitored firms			Monitoring banks
	(1)	(2)	(3)	(4)
	Monitor_t	Monitor_t	Monitor_t	Monitor_t
Loan amount$_{t-1}$	-0.000	-0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-1}$	-0.010***•	-0.013***•	-0.017***•	-0.010***•
	(0.00)	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-1}$	-0.017***•	-0.025***•	-0.025***•	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-1}$	-0.000	-0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-1}$	-0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-1}$	-0.000	-0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Share exposure$_{t-1}$	-0.010*•	0.000	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-1}$	0.001***	0.001***	0.001***	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)
Credit score firm$_{t-4}$	0.007***•	0.000	0.000	
	(0.00)	(0.00)	(0.00)	
Capital ratio firm$_{t-4}$	0.032***•	0.001***	0.001***	
	(0.00)	(0.00)	(0.00)	
ROA firm$_{t-4}$	0.000	0.001**	0.001**	
	(0.00)	(0.00)	(0.00)	
Size firm$_{t-4}$	0.009***•	-0.049***•	-0.001***	
	(0.00)	(0.00)	(0.00)	
Size firm$_{t-4}$*Length relation$_{t-1}$			0.001**•	
			(0.00)	
Capital ratio bank$_{t-4}$				-0.002
				(0.01)
ROA bank$_{t-4}$				0.018
				(0.02)
NPL ratio bank$_{t-4}$				-0.016
				(0.01)
Size bank$_{t-4}$				-0.001*
				(0.00)
Liquidity ratio bank$_{t-4}$				-0.008
				(0.02)
Nonretail deposit ratio$_{t-4}$				-0.004*
				(0.00)
GDP growth region firm$_{t-4}$	0.007	0.003	0.003	
	(0.00)	(0.01)	(0.01)	
Employment region firm$_{t-4}$	-0.000	0.000	0.000	
	(0.00)	(0.00)	(0.00)	
Inflation region firm$_{t-4}$	-0.000	0.000	0.000	
	(0.00)	(0.00)	(0.00)	
GDP growth region bank$_{t-4}$				-0.030
				(0.02)

Continued on next page

Table 2 – *Continued from previous page*

Employment region bank$_{t-4}$				0.000
				(0.00)
Inflation region bank$_{t-4}$				-0.000
				(0.00)
Region FE	Yes	Yes	Yes	-
Region bank FE	-	-	-	Yes
Bank FE	-	-	-	Yes
Firm FE	No	Yes	Yes	-
Industry firm FE	Yes	Yes	Yes	-
Firm-quarter FE	No	No	No	Yes
Bank-quarter FE	Yes	Yes	Yes	No
N	4180843	4174046	4174046	739184
R^2	0.011	0.112	0.112	0.468
Adjusted R^2	0.007	0.062	0.062	0.007

Table 3: IRAP tax rates

The table reports the basic national IRAP tax rate and the regional IRAP tax rates applied to banks during 2006-2016.

	IRAP tax rate (%)										
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Basic National IRAP	4.25	4.25	3.90	3.90	3.90	4.65	4.65	4.65	4.65	4.65	4.65
Region											
Abruzzo	5.25	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Basilicata	4.25	4.25	3.90	3.90	3.90	4.65	4.65	4.65	4.65	4.65	4.65
Calabria	4.25	4.25	3.90	4.82	4.97	5.72	5.72	5.72	5.57	5.57	5.57
Campania	5.25	5.25	4.82	4.82	4.97	5.72	5.72	5.72	5.72	5.72	5.72
Emilia-Romagna	4.25	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Friuli-Venezia Giulia	4.25	4.25	3.90	3.90	3.90	4.65	4.65	4.65	4.65	4.65	4.65
Lazio	5.25	5.25	4.82	4.82	4.97	5.57	5.57	5.57	5.57	5.57	5.57
Liguria	5.25	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Lombardia	5.25	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Marche	5.15	5.15	4.73	4.73	4.73	5.48	5.48	5.48	5.48	5.48	5.48
Molise	5.25	5.25	4.82	4.82	4.97	5.72	5.72	5.72	5.72	5.72	5.57
Piemonte	4.25	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Puglia	4.25	4.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Sardegna	4.25	4.25	3.90	3.90	3.90	4.65	4.65	1.4	1.4	5.57	5.57
Sicilia	5.25	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Toscana	4.40	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Trentino-Alto Adige	4.25	4.25	3.44	3.40	3.19	4.65	4.45	4.45	4.65	4.65	4.65
Umbria	4.25	4.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Val D'Aosta	4.25	4.25	3.90	3.90	3.90	4.65	4.65	4.65	4.65	4.65	4.65
Veneto	5.25	5.25	4.82	4.82	4.82	5.57	5.57	5.57	5.57	5.57	5.57
Minimum	4.25	4.25	3.44	3.40	3.19	4.65	4.45	1.40	1.40	4.65	4.65
Mean	4.70	4.85	4.52	4.56	4.58	5.36	5.35	5.19	5.19	5.40	5.39
Maximum	5.25	5.25	4.82	4.82	4.97	5.72	5.72	5.72	5.72	5.72	5.72

Table 4: Exogeneity analysis of the IRAP tax rate

The table reports panel regression estimates of a linear model analyzing the effect of different variables on the IRAP tax rate. Regressions are estimated on a dataset obtained by aggregating our data from the Credit Register at the region-year level. *Basic IRAP* is the basic IRAP tax rate (in units) for banks defined at the national level. Δ*IRAP health* is a dummy equal to one if an increase in the IRAP tax rate occurs in response to a regional health deficit. *Capital ratio region* and *ROA region* are the aggregate capital ratio and ROA of the banking system at the regional level, respectively. *NPL ratio region* is the average ratio of nonperforming loans of banks operating in a specific region. The other variables are described in Table 1. The sample of specifications (1)-(2) covers the time period 2005-2016. The sample of specifications (3)-(6) covers, instead, the time period 2007-2016 because of a lack of data on bank conditions before 2006. The dependent variable is displayed at the bottom of each column. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the region and year level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) IRAP_t	(2) IRAP_t	(3) IRAP_t	(4) IRAP_t	(5) IRAP_t	(6) IRAP_t
GDP growth region_{t-1}	-0.001	0.000			0.006	0.006
	(0.01)	(0.01)			(0.01)	(0.01)
Employment region_{t-1}	-0.000	-0.000			-0.000	-0.000
	(0.00)	(0.00)			(0.00)	(0.00)
Inflation region_{t-1}	-0.000	-0.000			-0.000	-0.000
	(0.00)	(0.00)			(0.00)	(0.00)
Basic IRAP_t	0.992***	0.998***	1.049***	1.065***	1.002***	1.011***
	(0.14)	(0.13)	(0.04)	(0.03)	(0.06)	(0.05)
ΔIRAP health_t		0.001*		0.001**		0.001
		(0.00)		(0.00)		(0.00)
Capital ratio region_{t-1}			0.035	0.039	0.041	0.044
			(0.06)	(0.06)	(0.05)	(0.05)
ROA region_{t-1}			-0.018	-0.010	-0.012	-0.008
			(0.09)	(0.09)	(0.07)	(0.07)
NPL ratio region_{t-1}			0.000	0.000	-0.000	0.000
			(0.00)	(0.00)	(0.00)	(0.00)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
N	230	230	190	190	188	188
R^2	0.669	0.670	0.728	0.729	0.728	0.728
Adjusted R^2	0.632	0.631	0.692	0.691	0.686	0.684

Table 5: 2SLS model

The table reports panel regression estimates of the 2SLS model of equation 5 analyzing the effect of bank monitoring on loan repayment. In this model we have one endogenous variable, *Monitor*, which is instrumented with the IRAP tax rate, *IRAP*. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. ● denotes rescaled coefficients that have been multiplied by 10^3, whereas ●● denotes rescaled coefficients that have been multiplied by 10^6. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test.

	First stage	Second stage			
	(1)	(2)	(3)	(4)	(5)
	Monitor$_{t-2}$	NPL dummy$_t$	Past-due dummy$_t$	UTP dummy$_t$	Bad dummy$_t$
Monitor$_{t-2}$		-9.247*	-4.597	-5.740*	0.884
		(5.05)	(3.74)	(3.25)	(0.87)
IRAP$_{t-6}$	-0.426**				
	(0.19)				
Loan amount$_{t-3}$	-0.000	0.007***●●	0.000	0.004***●●	0.002***●●
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	-0.096***●	-0.000	-0.000	-0.000	0.263***●
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-3}$	-0.000	-0.007***	-0.001	0.010***	-0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-3}$	0.000	0.011***	0.006***	0.030***	-0.025***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-3}$	0.000	-0.017***	-0.007***	-0.003	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-3}$	0.000	0.000	0.000	0.001**	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share exposure$_{t-3}$	-0.000	0.022***	0.011***	0.003	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-3}$	0.001	0.003	-0.001	0.004	-0.001
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Bank controls	Yes	Yes	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes	Yes
N	556227	556227	556227	556227	556227
R^2	0.466				
Adjusted R^2	-0.001				
F-test statistic		10.386***	3.963***	12.684***	8.739***
degrees of freedom		(18, 37)	(18, 37)	(18, 37)	(18, 37)
Underidentification test					
Kleibergen-Paap LM statistic	4.15				
Chi-sq P-val	0.04				
Weak identification test					
Kleibergen-Paap Wald F statistic	5.22				
Cragg-Donald Wald F statistic	20.06				
Stock-Yogo critical value 10% maximal IV size	16.38				
		Anderson-Rubin test			
Anderson-Rubin Wald statistic		6.67***	1.92	6.28**	1.25
Chi-sq P-val		0.01	0.17	0.01	0.26

Table 6: Descriptive statistics

The table reports summary statistics for the variables used in our regression analysis at the firm-bank-quarter level. Variables are described in Table 1. In panel A, statistics refer to our full sample of 4,551,817 observations. This sample includes 280,613 credit relationships having a duration greater than one quarter, and involving 225,414 firms and 457 banks over the period 2005-2016. In panel B, statistics refer to our reduced sample including only firms that have multiple credit relationships with small banks. This panel has 556,227 observations and includes 53,738 credit relationships having a duration greater than three quarters, and involving 23,376 firms and 440 banks over the period 2007-2016.

Panel A: Full sample

Variable Name	Obs.	Mean	Std Dev	Min	Median	Max
Loan-level variables						
NPL dummy$_t$	4551817	0.082	0.275	0.000	0.000	1.000
Past-due dummy$_t$	4551817	0.024	0.154	0.000	0.000	1.000
UTP dummy$_t$	4551817	0.034	0.182	0.000	0.000	1.000
Bad dummy$_t$	4551817	0.024	0.153	0.000	0.000	1.000
NPL term loan dummy$_t$	2179842	0.062	0.241	0.000	0.000	1.000
NPL credit line dummy$_t$	3765716	0.049	0.215	0.000	0.000	1.000
NPL A/R loan dummy$_t$	2325535	0.014	0.118	0.000	0.000	1.000
Monitor$_t$	4551817	0.001	0.031	0.000	0.000	5.000
Loan amount$_t$	4551817	311473	700117	0.000	105458	64200000
Length relation$_t$	4551817	16.705	11.541	2.000	14.000	48.000
Term loan dummy$_t$	4551817	0.479	0.500	0.000	0.000	1.000
Credit line dummy$_t$	4551817	0.827	0.378	0.000	1.000	1.000
A/R loan dummy$_t$	4551817	0.511	0.500	0.000	1.000	1.000
Share guarantee$_t$	4547314	0.191	4.389	0.000	0.000	334.580
Share exposure$_t$	4551817	0.470	0.395	0.000	0.352	1.000
Close threshold dummy$_t$	4551817	0.051	0.220	0.000	0.000	1.000
Interest rate term loan$_t$	518864	4.187	1.657	0.000	3.964	15.907
Interest rate credit line$_t$	775697	7.177	2.683	0.000	6.972	15.185
Interest rate A/R loan$_t$	491692	4.558	1.739	0.000	4.500	13.519
Average interest rate$_t$	255587	5.001	2.137	0.000	4.778	15.907
Firm-level variables						
Credit score firm$_t$	4441952	5.212	1.951	1.000	5.000	9.000
Capital ratio firm$_t$	4498085	0.175	0.272	-1.764	0.134	1.000
ROA firm$_t$	4530482	-0.017	0.171	-3.023	0.003	0.484
Size firm$_t$	4550937	7.286	1.467	0.000	7.214	18.060
Bank-level variables						
Capital ratio bank$_t$	4289681	0.086	0.025	0.023	0.083	0.365
ROA bank$_t$	4283918	0.002	0.006	-0.202	0.002	0.043
NPL ratio bank$_t$	4345877	0.125	0.068	0.021	0.114	0.435
Size bank$_t$	4343124	6.749	0.980	2.378	6.727	9.392
Liquidity ratio bank$_t$	4289681	0.005	0.003	0.000	0.004	0.044
Nonretail deposit ratio bank$_t$	4343124	0.173	0.071	0.005	0.166	0.715
N. Employees$_t$	4342974	186.753	208.805	4.000	125.500	1448.000
Regional variables						
IRAP$_t$	4551817	0.052	0.005	0.014	0.055	0.057
IRAP start loan$_t$	4551817	0.049	0.005	0.014	0.048	0.057
IRAP start term loan$_t$	2179842	0.049	0.005	0.014	0.048	0.057
IRAP start credit line$_t$	3765716	0.049	0.005	0.014	0.048	0.057
IRAP start A/R loan$_t$	2325535	0.049	0.005	0.014	0.052	0.057
GDP growth region firm$_t$	4489804	-0.002	0.025	-0.088	0.006	0.085
Employment region firm$_t$	4489804	48.177	5.333	30.350	49.860	55.200
Inflation region firm$_t$	4487191	1.448	1.146	-0.400	1.400	4.400
GDP growth region bank$_t$	4551817	-0.002	0.025	-0.088	0.006	0.085

Continued on next page

Table 6 – *Continued from previous page*

Employment region bank$_t$	4551817	48.299	5.316	30.350	49.900	55.200
Inflation region bank$_t$	4549168	1.455	1.145	-0.400	1.400	4.400
Panel B: Reduced sample multiple bank relationships						
Loan-level variables						
NPL dummy$_t$	556227	0.114	0.317	0.000	0.000	1.000
Past-due dummy$_t$	556227	0.023	0.150	0.000	0.000	1.000
UTP dummy$_t$	556227	0.050	0.219	0.000	0.000	1.000
Bad dummy$_t$	556227	0.040	0.196	0.000	0.000	1.000
NPL term loan dummy$_t$	238775	0.093	0.290	0.000	0.000	1.000
NPL credit line dummy$_t$	466839	0.063	0.243	0.000	0.000	1.000
NPL A/R loan dummy$_t$	320145	0.017	0.128	0.000	0.000	1.000
Monitor$_{t-2}$	556227	0.001	0.028	0.000	0.000	2.000
Loan amount$_{t-3}$	556227	431193	835180	0.000	162922	55100000
Length relation$_{t-3}$	556227	17.866	11.039	1.000	16.000	45.000
Term loan dummy$_{t-3}$	556227	0.459	0.498	0.000	0.000	1.000
Credit line dummy$_{t-3}$	556227	0.856	0.351	0.000	1.000	1.000
A/R loan dummy$_{t-3}$	556227	0.596	0.491	0.000	1.000	1.000
Share guarantee$_{t-3}$	556227	0.142	3.607	0.000	0.000	331.126
Share exposure$_{t-3}$	556227	0.221	0.238	0.000	0.133	1.000
Close threshold dummy$_{t-3}$	556227	0.020	0.140	0.000	0.000	1.000
Interest rate term loan$_{t-3}$	72004	4.064	1.658	0.000	3.750	15.746
Interest rate credit line$_{t-3}$	121200	6.764	2.573	0.000	6.501	15.181
Interest rate A/R loan$_{t-3}$	87976	4.245	1.673	0.000	4.192	13.500
Average interest rate$_{t-3}$	121026	5.281	1.850	0.000	5.204	15.706
Firm-level variables						
Credit score firm$_{t-6}$	293483	5.444	1.757	1.000	6.000	9.000
Capital ratio firm$_{t-6}$	291931	0.166	0.194	-0.823	0.126	1.000
ROA firm$_{t-6}$	295417	-0.009	0.103	-1.427	0.002	0.407
Size firm$_{t-6}$	296588	8.151	1.403	0.000	8.050	15.665
Bank-level variables						
Capital ratio bank$_{t-6}$	556227	0.089	0.025	0.024	0.085	0.405
ROA bank$_{t-6}$	556227	0.003	0.005	-0.051	0.003	0.024
NPL ratio bank$_{t-6}$	556227	0.099	0.055	0.021	0.083	0.367
Size bank$_{t-6}$	556227	6.672	0.881	2.420	6.683	9.351
Liquidity ratio bank$_{t-6}$	556227	0.005	0.003	0.001	0.004	0.044
Nonretail deposit ratio bank$_{t-6}$	556227	0.168	0.066	0.005	0.161	0.715
N. Employees$_{t-6}$	556227	157.500	133.281	3.000	121.000	1253.000
Regional variables						
IRAP$_{t-6}$	556227	0.050	0.006	0.014	0.053	0.057
IRAP start loan$_t$	556227	0.048	0.005	0.014	0.048	0.057
IRAP start term loan$_t$	238775	0.048	0.006	0.014	0.048	0.057
IRAP start credit line$_t$	466839	0.048	0.005	0.014	0.048	0.057
IRAP start A/R loan$_t$	320145	0.049	0.005	0.014	0.048	0.057
GDP growth region firm$_{t-6}$	550546	-0.004	0.027	-0.088	0.005	0.085
Employment region firm$_{t-6}$	550546	49.471	4.490	30.350	50.200	55.200
Inflation region firm$_{t-6}$	550544	1.723	1.088	-0.200	1.600	4.400
GDP growth region bank$_{t-6}$	556227	-0.004	0.027	-0.088	0.005	0.085
Employment region bank$_{t-6}$	556227	49.577	4.514	30.350	50.200	55.200
Inflation region bank$_{t-6}$	556227	1.730	1.086	-0.200	1.600	4.400

Table 7: 2SLS model with different horizons

The table reports panel regression estimates of the 2SLS model analyzing the effect of bank monitoring on loan repayment for different horizons. In this model we have one endogenous variable, *Monitor*, which is instrumented with the IRAP tax rate, *IRAP*. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-h-4}$, *Size bank*$_{t-h-4}$, *ROA bank*$_{t-h-4}$, *NPL ratio bank*$_{t-h-4}$, *Liquidity ratio bank*$_{t-h-4}$, and *Nonretail deposit ratio bank*$_{t-h-4}$. Region bank controls include *GDP growth region bank*$_{t-h-4}$, *Employment region bank*$_{t-h-4}$, and *Inflation region bank*$_{t-h-4}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the year-quarter and bank level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^8. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test.

	One quarter		Two quarters		Three quarters		Four quarters		Eight quarters	
	First stage	Second stage	First stage	Second stage	First stage	Second stage	First stage	Second stage	First stage	Second stage
	(1) Monitor$_{t-1}$	(2) NPL dummy$_t$	(3) Monitor$_{t-2}$	(4) NPL dummy$_t$	(5) Monitor$_{t-3}$	(6) NPL dummy$_t$	(7) Monitor$_{t-4}$	(8) NPL dummy$_t$	(9) Monitor$_{t-8}$	(10) NPL dummy$_t$
Monitor$_{t-h}$		-11.272		-9.247*		-6.853*		-6.029		-5.601
		(7.61)		(5.05)		(3.79)		(3.61)		(5.06)
IRAP$_{t-h-4}$	-0.320**		-0.426**		-0.464**		-0.498**		-0.364*	
	(0.16)		(0.19)		(0.21)		(0.22)		(0.21)	
Loan amount$_{t-h-1}$	-0.000	0.695***••	-0.000	0.674***••	0.000	0.770***••	0.000	0.821***••	-0.000	0.451***••
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-h-1}$	-0.010***•	-0.001	-0.010***•	-0.000	-0.009***•	-0.000	-0.009***•	0.000	-0.009***•	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-h-1}$	-0.000	-0.007***	-0.000	-0.007***	-0.000	-0.008***	-0.000	-0.007***	0.000	-0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-h-1}$	0.000	0.014***	0.000	0.011***	0.000	0.010***	0.000	0.009***	0.000	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-h-1}$	0.000	-0.021***	0.000	-0.017***	0.000	-0.015***	0.000	-0.012***	-0.000	-0.008*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-h-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share exposure$_{t-h-1}$	-0.000	0.019***	-0.000	0.022***	-0.000	0.024***	-0.000	0.024***	-0.000	0.023***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-h-1}$	0.001*	0.010	0.001	0.003	0.000	-0.001	0.001	0.003	0.000	-0.001
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	677535	677535	556227	556227	461504	461504	389047	389047	204847	204847
R^2	0.467		0.466		0.472		0.471		0.468	
Adjusted R^2	0.005		-0.001		0.008		0.004		-0.008	
F-test statistic		9.616***		10.386***		12.369***		11.706***		5.631***
degrees of freedom		(18. 38)		(18, 37)		(18, 36)		(18, 35)		(18, 31)
Change in the likelihood of loan distress (in p.p.) in response to an increase in the number of requests for information that correspond to a decrease of 0.5 p.p. in the tax rate		-1.8%		-2.0%		-1.6%		-1.5%		-1.0%
Underidentification test										
Kleibergen-Paap LM statistic	3.55		4.15		3.92		4.16		2.87	
Chi-sq P-val	0.06		0.04		0.05		0.04		0.09	
Weak identification test										
Kleibergen-Paap Wald F statistic	4.18		5.22		4.91		5.12		3.08	
Cragg-Donald Wald F statistic	12.34		20.06		21.77		21.86		6.59	
Stock-Yogo critical value 10% maximal IV size	16.38		16.38		16.38		16.38		16.38	
Anderson-Rubin test										
Anderson-Rubin Wald statistic		5.93**		6.67***		4.95**		4.40**		1.84
Chi-sq P-val		0.01		0.01		0.03		0.04		0.17

Table 8: Reduced form model

The table reports panel regression estimates of the reduced form linear model of equation 6 analyzing the effect of bank monitoring, as driven by the IRAP tax rate, on loan repayment. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6.

	(1) NPL dummy$_t$	(2) Past-due dummy$_t$	(3) UTP dummy$_t$	(4) Bad dummy$_t$
IRAP$_{t-6}$	5.414***	2.073	3.852***	-0.481
	(1.86)	(1.73)	(1.02)	(0.39)
Loan amount$_{t-3}$	0.008***••	0.000	0.004***••	0.002***••
	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	0.001***	-0.008*•	0.042***•	0.020***•
	(0.00)	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-3}$	-0.006***	-0.000	0.013***	-0.019***
	(0.00)	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-3}$	0.008***	0.005***	0.033***	-0.030***
	(0.00)	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-3}$	-0.018***	-0.008***	-0.002	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-3}$	0.019*•	0.001**	-0.001**	
	(0.00)	(0.00)	(0.00)	(0.00)
Share exposure$_{t-3}$	0.023***	0.011***	0.003	0.009***
	(0.00)	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-3}$	-0.004	-0.005	0.000	0.000
	(0.01)	(0.00)	(0.00)	(0.00)
Bank controls	Yes	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes
N	454907	454907	454907	454907
R^2	0.851	0.553	0.722	0.915
Adjusted R^2	0.721	0.161	0.479	0.841
F-test statistic	15.343***	6.673***	14.615***	9.935***
degrees of freedom	(18, 37)	(18, 37)	(18, 37)	(18, 37)

Table 9: Different types of credit

The table reports panel regression estimates of the 2SLS model of equation 5 and the reduced form model of e quation 6 per type of credit (term loan, credit line and accounts receivable loan). The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, “Yes”. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^7. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test for the 2SLS model.

	2SLS model						Reduced form model		
	Term loan		Credit line		A/R loan		Term loan	Credit line	A/R loan
	First stage	Second stage	First stage	Second stage	First stage	Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Monitor$_{t-2}$	NPL dummy$_t$	Monitor$_{t-2}$	NPL dummy$_t$	Monitor$_{t-2}$	NPL dummy$_t$	NPL dummy$_t$	NPL dummy$_t$	NPL dummy$_t$
Monitor$_{t-2}$		-3.832*		-8.335		-6.399			
		(1.96)		(5.68)		(3.91)			
IRAP$_{t-6}$	-1.259**		-0.451*		-0.621*		7.946***	4.500***	3.961**
	(0.61)		(0.25)		(0.34)		(2.33)	(1.63)	(1.47)
Loan amount$_{t-3}$	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.039**••	0.025*••	0.074***••
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	-0.009***•	0.001**	-0.010***•	-0.000	-0.009***•	-0.000	0.001***	0.036***•	0.029***•
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-3}$			-0.000	-0.006***	-0.000	-0.002		-0.005***	-0.002
			(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
Credit line dummy$_{t-3}$	0.001	0.005			0.001	0.004	0.004		0.002
	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)		(0.00)
A/R loan dummy$_{t-3}$	0.001	-0.016***	-0.000	-0.018***			-0.018***	-0.015***	
	(0.00)	(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	
Share guarantee$_{t-3}$	0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share exposure$_{t-3}$	0.000	0.021**	-0.000	0.008**	0.000	0.005*	0.014*	0.006**	0.003
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Close threshold dummy$_{t-3}$	-0.000	0.005	0.000	0.007	0.001	-0.004	0.016	0.000	-0.013**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	141636	141636	426737	426737	284488	284488	108376	346617	226761
R^2	0.467		0.479		0.463		0.796	0.761	0.633
Adjusted R^2	-0.002		0.011		-0.026		0.615	0.545	0.296
F-test statistic		6.059***		4.744***		2.259**	8.250***	6.538***	3.925***
degrees of freedom		(17, 37)		(17, 37)		(17, 37)	(17, 37)	(17, 37)	(17, 37)
Change in the likelihood of loan distress (in p.p.) in response to an increase in the number of requests for information that correspond to a decrease of 0.5 p.p. in the tax rate		-2.4%		-1.9%		-2.0%			
Underidentification test									
Kleibergen-Paap LM statistic	3.48		2.95		3.29				
Chi-sq P-val	0.06		0.09		0.07				
Weak identification test									
Kleibergen-Paap Wald F statistic	4.28		3.16		3.29				
Cragg-Donald Wald F statistic	47.01		17.47		21.16				
Stock-Yogo critical value 10% maximal IV size	16.38		16.38		16.38				
Anderson-Rubin test									
Anderson-Rubin Wald statistic		5.43**		7.07***		11.40***			
Chi-sq P-val		0.02		0.01		0.00			

Table 10: Tax rate at the start of the lending relationship

The table reports panel regression estimates of the 2SLS model of equation 5 and the reduced form model of e quation 6 extended by including the IRAP tax rate of the bank's region at the start of the lending relationship as a control variable. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test for the 2SLS model.

	2SLS model		Reduced form model
	First stage	Second stage	
	(1) Monitor$_{t-2}$	(2) NPL dummy$_t$	(3) NPL dummy$_t$
Monitor$_{t-2}$		-9.261*	
		(5.09)	
IRAP$_{t-6}$	-0.419**		5.328***
	(0.18)		(1.85)
IRAP start loan$_t$	-0.030	-0.028	0.510**
	(0.03)	(0.36)	(0.24)
Loan amount$_{t-3}$	-0.000	0.007***••	0.008***••
	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	-0.010***•	-0.000	0.001***
	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-3}$	-0.000	-0.007***	-0.006***
	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-3}$	0.000	0.011***	0.008***
	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-3}$	0.000	-0.017***	-0.018***
	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-3}$	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)
Share exposure$_{t-3}$	-0.000	0.022***	0.023***
	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-3}$	0.001	0.003	-0.004
	(0.00)	(0.01)	(0.01)
Bank controls	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes
N	556227	556227	454907
R^2	0.466		0.851
Adjusted R^2	-0.001		0.721
F-test statistic		12.551***	16.264***
degrees of freedom		(19, 37)	(19, 37)
Underidentification test			
Kleibergen-Paap LM statistic	4.15		
Chi-sq P-val	0.04		
Weak identification test			
Kleibergen-Paap Wald F statistic	5.16		
Cragg-Donald Wald F statistic	19.41		
Stock-Yogo critical value 10% maximal IV size	16.38		
Anderson-Rubin test			
Anderson-Rubin Wald statistic		6.48**	
Chi-sq P-val		0.01	

Table 11: Tax rate at the start of the loan

The table reports panel regression estimates of the 2SLS model of equation 5 and the reduced form model of e quation 6 extended by including the IRAP tax rate of the bank's region at the start of a term loan, a credit line or an accounts receivable loan as a control variable. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. ● denotes rescaled coefficients that have been multiplied by 10^2, whereas ●● denotes rescaled coefficients that have been multiplied by 10^6. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test for the 2SLS model.

	2SLS model						Reduced form model		
	Term loan		Credit line		A/R loan		Term loan	Credit line	A/R loan
	First stage	Second stage	First stage	Second stage	First stage	Second stage			
	(1) Monitort-2	(2) NPL dummy_t	(1) Monitort-2	(2) NPL dummy_t	(1) Monitort-2	(2) NPL dummy_t	(3) NPL dummy_t	(3) NPL dummy_t	(3) NPL dummy_t
Monitor$_{t-2}$		-3.786*		-8.296		-6.458			
		(1.96)		(5.70)		(3.98)			
IRAP$_{t-6}$	-1.240**		-0.443*		-0.613*		7.815***	4.395***	3.949**
	(0.60)		(0.25)		(0.33)		(2.33)	(1.61)	(1.46)
IRAP start term loan$_t$	-0.070	0.213					0.613		
	(0.05)	(0.45)					(0.43)		
IRAP start credit line$_t$			-0.036	0.082				0.619**	
			(0.03)	(0.33)				(0.24)	
IRAP start A/R loan$_t$					-0.038	-0.171			0.070
					(0.04)	(0.31)			(0.20)
Loan amount$_{t-3}$	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.004**●●	0.002**●●	0.007***●●
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	-0.010***●	0.001**	-0.010***●	-0.000	-0.009***●	-0.000	0.001***	0.041***●	0.030***●
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-3}$			-0.000	-0.006***	-0.000	-0.002		-0.005***	-0.002
			(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
Credit line dummy$_{t-3}$	0.001	0.005			0.001	0.004	0.004		0.002
	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)		(0.00)
A/R loan dummy$_{t-3}$	0.001	-0.016***	-0.000	-0.018***			-0.018***	-0.015***	
	(0.00)	(0.00)	(0.00)	(0.00)			(0.01)	(0.00)	
Share guarantee$_{t-3}$	-0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share exposure$_{t-3}$	0.000	0.021**	-0.000	0.008**	0.000	0.005*	0.014*	0.006*	0.003
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Close threshold dummy$_{t-3}$	-0.001	0.005	0.000	0.007	0.001	-0.004	0.016	0.001	-0.013**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	141636	141636	426737	426737	284488	284488	108376	346617	226761
R^2	0.468		0.479		0.463		0.796	0.761	0.633
Adjusted R^2	-0.002		0.011		-0.026		0.615	0.545	0.296
F-test statistic		5.738***		4.523***		2.185**	7.064***	6.064***	3.835***
degrees of freedom		(18, 37)		(18, 37)		(18, 37)	(18, 37)	(18, 37)	(18, 37)
Underidentification test									
Kleibergen-Paap LM statistic	3.44		2.90		3.34				
Chi-sq P-val	0.06		0.09		0.07				
Weak identification test									
Kleibergen-Paap Wald F statistic	4.21		3.09		3.35				
Cragg-Donald Wald F statistic	45.54		16.85		20.59				
Stock-Yogo critical value 10% maximal IV size	16.38		16.38		16.38				
Anderson-Rubin test									
Anderson-Rubin Wald statistic		5.12**		6.87***		11.36***			
Chi-sq P-val		0.02		0.01		0.00			

Table 12: Lagged dependent variable

The table reports robustness tests for the 2SLS model of equation 5 and the reduced form model of equation 6 by including the dependent variable (a dummy equal to one if the credit exposure is nonperforming and zero otherwise) lagged of three quarters among controls. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test for the 2SLS model.

	2SLS model		Reduced form model
	First stage	Second stage	
	(1) Monitor$_{t-2}$	(2) NPL dummy$_t$	(3) NPL dummy$_t$
Monitor$_{t-2}$		-6.671*	
		(3.71)	
IRAP$_{t-6}$	-0.425**		3.990***
	(0.19)		(1.38)
NPL dummy$_{t-3}$	-0.000	0.386***	0.393***
	(0.00)	(0.01)	(0.01)
Loan amount$_{t-3}$	-0.000	0.004***••	0.005***••
	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	-0.010***•	-0.000	0.033***•
	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-3}$	-0.000	-0.004***	-0.003**
	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-3}$	0.000	0.005**	0.003
	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-3}$	0.000	-0.008***	-0.009***
	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-3}$	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)
Share exposure$_{t-3}$	-0.000	0.015***	0.014***
	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-3}$	0.001	0.003	-0.002
	(0.00)	(0.01)	(0.00)
Bank controls	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes
N	556227	556227	454907
R^2	0.466		0.871
Adjusted R^2	-0.001		0.759
F-test statistic		127.925***	123.907***
degrees of freedom		(19, 37)	(19, 37)
Underidentification test			
Kleibergen-Paap LM statistic	4.14		
Chi-sq P-val	0.04		
Weak identification test			
Kleibergen-Paap Wald F statistic	5.20		
Cragg-Donald Wald F statistic	19.98		
Stock-Yogo critical value 10% maximal IV size	16.38		
Anderson-Rubin test			
Anderson-Rubin Wald statistic		5.87**	
Chi-sq P-val		0.02	

Table 13: Loan restructuring

The table reports robustness tests for the 2SLS model of equation 5 and the reduced form model of e quation 6 by excluding observations pertaining to exposures that are nonperforming at time $t-2$. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test for the 2SLS model.

	2SLS model		Reduced form model
	First stage	Second stage	
	(1)	(2)	(3)
	Monitor$_{t-2}$	NPL dummy$_t$	NPL dummy$_t$
Monitor$_{t-2}$		-2.553*	
		(1.29)	
IRAP$_{t-6}$	-0.514**		1.224*
	(0.22)		(0.65)
Loan amount$_{t-3}$	-0.000	0.003***••	0.003***••
	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	-0.010***•	-0.000	0.013***•
	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-3}$	-0.000	-0.002	-0.001
	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-3}$	0.000	0.004**	0.002
	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-3}$	-0.000	-0.007***	-0.006***
	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-3}$	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)
Share exposure$_{t-3}$	-0.000	0.009***	0.008***
	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-3}$	0.000	-0.001	-0.003
	(0.00)	(0.00)	(0.00)
Bank controls	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes
N	490149	490149	397358
R^2	0.463		0.657
Adjusted R^2	-0.009		0.354
F-test statistic		10.787***	12.295***
degrees of freedom		(18, 37)	(18, 37)
Underidentification test			
Kleibergen-Paap LM statistic	4.32		
Chi-sq P-val	0.04		
Weak identification test			
Kleibergen-Paap Wald F statistic	5.42		
Cragg-Donald Wald F statistic	24.96		
Stock-Yogo critical value 10% maximal IV size	16.38		
Anderson-Rubin test			
Anderson-Rubin Wald statistic		5.72**	
Chi-sq P-val		0.02	

Table 14: Different lags

The table reports robustness tests for the 2SLS model of equation 5 and the reduced form model of e quation 6 by including the independent variables with different lags. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*, *Size bank*, *ROA bank*, *NPL ratio bank*, *Liquidity ratio bank*, and *Nonretail deposit ratio bank* at $t-6$ in specifications (1)-(3) and at $t-5$ in specification (4). Region bank controls include *GDP growth region bank*, *Employment region bank*, and *Inflation region bank* at $t-6$ in specifications (1)-(3) and at $t-5$ in specification (4). Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test for the 2SLS model.

	2SLS model		Reduced form model		
	First stage	Second stage			
	(1)	(2)	(3)		(4)
	Monitor$_{t-2}$	NPL dummy$_t$	NPL dummy$_t$		NPL dummy$_t$
Monitor$_{t-2}$		-9.285*			
		(5.06)			
IRAP$_{t-6}$	-0.425**		5.396***	IRAP$_{t-5}$	5.030***
	(0.19)		(1.86)		(1.79)
Loan amount$_{t-2}$	-0.000	0.007***••	0.008***••	Loan amount$_{t-2}$	0.008***••
	(0.00)	(0.00)	(0.00)		(0.00)
Length relation$_{t-2}$	-0.010***•	-0.000	0.001***	Length relation$_{t-2}$	0.001***
	(0.00)	(0.00)	(0.00)		(0.00)
Term loan dummy$_{t-2}$	-0.000	-0.008***	-0.006***	Term loan dummy$_{t-2}$	-0.007***
	(0.00)	(0.00)	(0.00)		(0.00)
Credit line dummy$_{t-2}$	0.000	0.012***	0.010***	Credit line dummy$_{t-2}$	0.010***
	(0.00)	(0.00)	(0.00)		(0.00)
A/R loan dummy$_{t-2}$	0.000	-0.022***	-0.022***	A/R loan dummy$_{t-2}$	-0.022***
	(0.00)	(0.00)	(0.00)		(0.00)
Share guarantee$_{t-2}$	0.000	0.000	-0.000	Share guarantee$_{t-2}$	-0.000
	(0.00)	(0.00)	(0.00)		(0.00)
Share exposure$_{t-2}$	-0.000	0.024***	0.023***	Share exposure$_{t-2}$	0.023***
	(0.00)	(0.00)	(0.00)		(0.00)
Close threshold dummy$_{t-2}$	0.000	-0.002	-0.005	Close threshold$_{t-2}$	-0.006
	(0.00)	(0.01)	(0.01)		(0.01)
Bank controls	Yes	Yes	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes	Yes		Yes
Bank FE	Yes	Yes	Yes		Yes
Region bank FE	Yes	Yes	Yes		Yes
N	557358	557358	456009		534087
R^2	0.466		0.852		0.840
Adjusted R^2	-0.001		0.722		0.700
F-test statistic		9.702***	17.729***		18.532***
degrees of freedom		(18, 37)	(18, 37)		(18, 38)
Underidentification test					
Kleibergen-Paap LM statistic	4.36				
Chi-sq P-val	0.04				
Weak identification test					
Kleibergen-Paap Wald F statistic	5.24				
Cragg-Donald Wald F statistic	20.08				
Stock-Yogo critical value 10% maximal IV size	16.38				
Anderson-Rubin test					
Anderson-Rubin Wald statistic		6.69***			
Chi-sq P-val		0.01			

Table 15: Economic Channels

The table reports panel regression estimates of a set of models investigating (i) the mechanism behind the effect of the IRAP tax rate on bank monitoring (panel A) and (ii) the relation between bank monitoring and firm's conditions (panel B). Model (1) of panel A is estimated on a dataset obtained by collapsing the original data from the Credit Register, including all credit relationships irrespective of their length, at the bank-quarter level. Models (2)-(4) of panel B are estimated on a dataset obtained according to a similar cleaning process to that described in Section 2.2. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-4}$, *Size bank*$_{t-4}$, *ROA bank*$_{t-4}$, *NPL ratio bank*$_{t-4}$, *Liquidity ratio bank*$_{t-4}$, and *Nonretail deposit ratio bank*$_{t-4}$. Region firm and region bank controls include the respecive variables *GDP growth region*$_{t-4}$, *Employment region*$_{t-4}$, and *Inflation region*$_{t-4}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year level in specification (1) and at the bank and year-quarter level in specifications (2)-(4). Fixed effects are either included, "Yes", not included, "No", or spanned by another set of effects, "-". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6.

Panel A		Panel B			
	(1)		(2)	(3)	(4)
	log(N. Employees)$_t$		Capital ratio firm$_t$	ROA firm$_t$	Credit score$_t$
IRAP$_{t-1}$	-4.198*	Monitor$_{t-1}$	0.007***	0.008***	-0.003
	(2.31)		(0.00)	(0.00)	(0.02)
Size bank$_t$	0.875***	Loan amount$_{t-1}$	-0.008***••	-0.000	0.079***••
	(0.01)		(0.00)	(0.00)	(0.00)
Capital ratio bank$_t$	-0.026	Length relation$_{t-1}$	0.012***•	-0.000	-0.001***
	(0.30)		(0.00)	(0.00)	(0.00)
Liquidity ratio bank$_t$	15.880***	Term loan dummy$_{t-1}$	-0.000	-0.001***	0.048***
	(2.28)		(0.00)	(0.00)	(0.00)
ROA bank$_t$	-4.257***	Credit line dummy$_{t-1}$	0.008***	0.002**	0.001
	(0.60)		(0.00)	(0.00)	(0.01)
NPL ratio bank$_t$	-0.832**	A/R loan dummy$_{t-1}$	0.018***	0.013***	-0.037***
	(0.26)		(0.00)	(0.00)	(0.01)
Nonretail deposit ratio bank$_t$	0.033	Share guarantee$_{t-1}$	0.000	-0.000	-0.000
	(0.14)		(0.00)	(0.00)	(0.00)
GDP growth region bank$_t$	0.710	Share exposure$_{t-1}$	0.007***	0.001	-0.115***
	(0.57)		(0.00)	(0.00)	(0.01)
Employment region bank$_t$	0.054***	Close threshold dummy$_{t-1}$	0.003***	-0.001	-0.048***
	(0.01)		(0.00)	(0.00)	(0.01)
Inflation region bank$_t$	0.001	Credit score firm$_{t-4}$	-0.004***	-0.005***	0.232***
	(0.02)		(0.00)	(0.00)	(0.02)
		Capital ratio firm$_{t-4}$	0.627***	-0.048***	-0.928***
			(0.03)	(0.01)	(0.08)
		ROA firm$_{t-4}$	0.164***	0.162***	-0.395***
			(0.01)	(0.01)	(0.07)
		Size firm$_{t-4}$	0.026***	0.005***	-0.098***
			(0.00)	(0.00)	(0.02)
		Bank controls	Yes	Yes	Yes
		Region firm controls	Yes	Yes	Yes
		Region bank controls	Yes	Yes	Yes
		Year-quarter FE	Yes	Yes	Yes
		Region firm FE	Yes	Yes	Yes
Region bank FE	Yes	Region bank FE	Yes	Yes	Yes
		Bank FE	Yes	Yes	Yes
		Firm FE	Yes	Yes	Yes
		Industry firm FE	Yes	Yes	Yes
		Firm-quarter FE	No	No	No
N	4348	N	3549877	3553654	3533530
R^2	0.957	R^2	0.840	0.476	0.798
Adjusted R^2	0.956	Adjusted R^2	0.831	0.447	0.787
F-test statistic	17089.920***	F-test statistic	190.647***	45.289***	84.266***
degrees of freedom	(10, 10)	degrees of freedom	(25, 39)	(25, 39)	(25, 39)

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Appendix

Appendix A Optimal lending rate, optimal capital structure, and optimal monitoring effort

The optimal lending rate, r_L^*, the optimal capital structure, k^*, and the optimal monitoring effort, q^*, are obtained by maximizing the bank's expected profits:

$$\underbrace{\max}_{r_L,k,q,0<q\leq 1} \quad \Pi = \left\{ q\left[\left(r_L - r_D\left(1-k\right)\right)\left(1-\tau\right) - r_E k\right] - \frac{1}{2}cq^2 \right\} L\left(r_L\right) \tag{7}$$

If the borrowers repay their loans, bank shareholders get a net return after tax of $\left(r_L - r_D\left(1-k\right)\right)\left(1-\tau\right)$. Whereas, if the borrowers do not repay, the bank defaults. In this case, bank shareholders receive nothing and depositors are not repaid because of limited liability. The term $r_E k$ represents the opportunity cost for bank shareholders of investing in the bank, adjusted for the probability of loan repayment.

To solve the model, we consider a sequential process. In the first stage, the lending rate is set so that the bank makes zero expected profits, which is the equilibrium condition of a perfectly competitive market. In the second stage, the bank chooses the optimal level of capitalization. Eventually, in the third stage, the bank determines the desired monitoring effort. We solve the model by backward induction, starting from the last stage. The bank's expected profits can be rewritten as:

$$\underbrace{\max}_{r_L,k,q,0<q\leq 1} \quad \Pi = \left\{ q\left[\left(r_L - r_D\left(1-k\right)\right)\left(1-\tau\right)\right] - \left(r+\xi\right)k - \frac{1}{2}cq^2 \right\} L\left(r_L\right) \tag{8}$$

Taking the first order condition with respect to q yields

$$q^* = \frac{\left(r_L - r_D\left(1-k\right)\right)\left(1-\tau\right)}{c}, \quad 0 < q^* \leq 1 \tag{9}$$

Equation 9 shows one channel through which the corporate tax rate affects the desired level of monitoring. Specifically, an increase in the tax rate reduces bank monitoring via its negative impact on the net return from lending. Note that this effect is partially softened by the fact that a rise in the corporate tax rate entails a decrease in the interest burden of deposits as a higher fraction of these interests are tax deductible. Also, note that a higher lending rate and a higher level of capitalization are associated with higher monitoring incentives. Since the lending rate and the level of capitalization are both endogenous in our model, we need to determine how they are affected by the tax rate before identifying the ultimate effect of the corporate tax rate on bank monitoring.

Under the assumption that depositors are risk-neutral, they require a return equal to $r_D = \frac{r}{\mathbb{E}[q|k]}$. The denominator represents depositors' expectations about bank monitoring (and, hence, the survival probability of the bank), as inferred by the level of capitalization. As in Dell'Ariccia et al. (2014), we assume that these expectations are correct in equilibrium, meaning that $\mathbb{E}\left[q\,|k\right] = q^*$. Substituting r_D in equation 9, we solve for the optimal monitoring effort:[49]

$$q^* = \min\left\{\frac{r_L\left(1-\tau\right)+\sqrt{r_L^2\left(1-\tau\right)^2-4rc\left(1-k\right)\left(1-\tau\right)}}{2c}, 1\right\} \tag{10}$$

We can now maximize bank expected profits with respect to the level of capitalization, subject to the equilibrium condition of depositors $r_D = \frac{r}{q^*}$

$$\underbrace{\max}_{k} \Pi = \left[\left\{q^* r_L\left(1-\tau\right) - r\left(1-\tau\right) - k\left(r\tau+\xi\right) - \frac{1}{2}cq^{*2}\right] L\left(r_L\right) \tag{11}$$

This yields

$$\begin{aligned}\frac{\partial \Pi}{\partial k} &= \frac{\partial q^*}{\partial k} r_L\left(1-\tau\right) - r\tau - \xi - \frac{\partial q^*}{\partial k} c q^* = \\ &= \frac{r_L r\left(1-\tau\right)^2}{2\sqrt{r_L^2\left(1-\tau\right)^2-4rc\left(1-k\right)\left(1-\tau\right)}} - r\tau - \xi - \frac{r\left(1-\tau\right)}{2} \stackrel{!}{=} 0\end{aligned} \tag{12}$$

We then solve for k obtaining

$$k^* = 1 - r_L^2\left(1-\tau\right)\frac{\left(\xi+r\right)\left(\xi+r\tau\right)}{rc\left(r\tau+2\xi+r\right)^2} \tag{13}$$

We now derive the optimal lending rate imposing the zero profit condition, stemming from the assumption of a perfect competitive market

$$\left[q^* r_L\left(1-\tau\right) - r\left(1-\tau\right) - k^*\left(r\tau+\xi\right) - \frac{1}{2}cq^{*2}\right] L(r_L) \stackrel{!}{=} 0 \tag{14}$$

To solve equation 14 we have to substitute the expressions for q^* and k^*. First, we replace k^* in the expression for q^* so that

[49] The optimal level of monitoring is obtained by solving a quadratic equation. Formula 10 consists in the root having the highest value. We select this root as, keeping everything else equal, both the bank and the borrowers are better off with higher monitoring.

$$q^{*}=\frac{r_{L}\left(1-\tau\right)\left(r+\xi\right)}{c\left(r\tau+2\xi+r\right)} \tag{15}$$

Then, we substitute the resulting q^* and k^* in equation 14 and we solve for the optimal lending rate

$$r_{L}^{*}=\sqrt{\frac{2cr\left(r\tau+2\xi+r\right)^{2}}{\left(1-\tau\right)\left(3r\xi+r^{2}+2\xi^{2}+r^{2}\tau+r\tau\xi\right)}} \tag{16}$$

From that we can directly obtain the derivative of the desired lending rate with respect to the corporate tax rate

$$\frac{\partial r_{L}^{*}}{\partial\tau}=\sqrt{\frac{2cr\left(r^{2}+\xi^{2}\right)^{2}\left(r+2\xi+r\tau\right)^{2}}{\left(1-\tau\right)^{3}\left(3r\xi+r^{2}+2\xi^{2}+r^{2}\tau+r\tau\xi\right)^{3}}}>0 \tag{17}$$

This derivative is positive, suggesting that, when the corporate tax rate increases, the bank shifts part of the tax burden on its borrowers by rising the lending rate. Then, substituting r_L^* in the expression for k^*, we obtain the optimal level of capitalization

$$k^{*}=\frac{\left(r^{2}+r\xi\right)\left(1-\tau\right)}{3r\xi+r^{2}+2\xi^{2}+r^{2}\tau+r\tau\xi} \tag{18}$$

Its derivative with respect to the corporate tax rate is

$$\frac{\partial k^{*}}{\partial\tau}=-\frac{\left(r^{2}+r\xi\right)\left(4r\xi+2r^{2}+2\xi^{2}\right)}{\left(3r\xi+r^{2}+2\xi^{2}+r^{2}\tau+r\tau\xi\right)^{2}}<0 \tag{19}$$

The negative sign implies that an increase in the corporate tax rate reduces the level of capitalization.

Finally, we can retrieve the optimal monitoring effort by substituting r_L^* in equation 15 and calculate its derivative with respect to the corporate tax rate. This yields

$$q^{*}=\sqrt{\frac{2r\left(r+\xi\right)^{2}\left(1-\tau\right)}{c\left(3r\xi+r^{2}+2\xi^{2}+r^{2}\tau+r\tau\xi\right)}} \tag{20}$$

$$\frac{\partial q^{*}}{\partial\tau}=-2\left(r+2\xi\right)\left(r+\xi\right)\sqrt{\frac{r^{3}}{c\left(1-\tau\right)\left(3r\xi+r^{2}+2\xi^{2}+r^{2}\tau+r\tau\xi\right)^{3}}}<0 \tag{21}$$

Appendix B Non-causal analysis on bank monitoring and loan repayment

In this section we present a non-causal analysis of the relation between bank monitoring and loan repayment. The first four columns of Table A1 report the results of an exercise in which we regress a dummy variable for different types of nonperforming exposures on our variable for bank monitoring lagged of one quarter. In these specifications, we include a wide set of controls spanning loan, firm, bank and macreoconomic factors. Specifically, *Loan amount*, *Length relation*, *Term loan dummy*, *Credit line dummy*, *A/R loan dummy*, *Share guarantee*, *Share exposure*, *Close threshold dummy*, *Size firm*, *ROA firm* and *Credit score firm* capture loan and firm characteristics that may influence the ability and the willingness of the firm to repay its loan. *GDP growth region firm*, *Employment region firm*, *Inflation region firm*, *GDP growth region bank*, *Employment region bank*, and *Inflation region bank* control for macreoconomic conditions of the firm's region and the bank's region that may affect the business environment of the firm and, hence, its repayment performance. Finally, *Capital ratio bank*, *ROA bank*, *NPL ratio bank*, *Size bank*, *Liquidity ratio bank* and *Nonretail deposit ratio bank* capture bank conditions that may influence bank incentives to recognize the credit exposure as nonperforming. All regressors are lagged according to their frequency, so as to ensure that each control is predetermined with respect to the dependent variable and, at most, concomitant with our proxy for bank monitoring. Regressions are estimated on a dataset obtained according to a similar cleaning process to that described in Section 2.2. In particular, we start from the original sample of 5,357,692 observations, covering the time period 2005-2016, and we drop: (i) observations pertaining to credit relationships with a duration lower than three quarters; (ii) observations in which a credit relationship is restored after a break in the current quarter or in the previous one; (iii) observations pertaining to banks experiencing extraordinary circumstances which impact, or may impact, their number of requests for information from the CR in the current quarter or the previous one; (iv) observations where we detect an increase in the committed amount of credit extended to an existing borrower in the current quarter or in the previous one.

The coefficient of *Monitor* suggests that one additional request for information is associated with a decrease of 1 percentage points in the likelihood that the loan becomes nonperforming one quarter ahead. Since we rely on a severe multiclustering at the bank and year-quarter level, the statistical significance of the effect is substantial. When we disaggregate the dependent variable into different dummies capturing an increasing degree of loan delinquency, we find a negative relation for the last two categories, but the correlation is somewhat stronger for bad exposures. Overall, these results are in line with what observed in Figure 3.

If we focus on the other covariates of the first model we see that loan distress is positively associated with the total volume of the credit exposure, the length of the credit relationship, the fraction of the credit exposure assisted by a guarantee and the ratio of loan amount to total firm's borrowing. Differently, a credit exposure is less likely to become non-performing if it includes a term loan or an accounts receivable loan vis-à-vis a credit line. As expected, firms with low profitability, low level of capitalization and bad credit quality, as well as small firms, are more likely to miss the repayment schedule. Also, good macroeconomic conditions in terms of employment rate in the firm's region are correlated with a lower probability that the credit exposure becomes nonperforming. More controversial is the interpretation of the other variables whose coefficient is statistically significant.[50]

The last model extends the first regression replacing firm variables with firm-time fixed effects to control for any observable and unobservable condition of the borrowing firm that may affect its ability to meet the repayment schedule. The coefficient of *Monitor* reverts sign and looses its significance.[51] Despite the extensive set of controls and the fact that we include our measure of bank monitoring lagged of one quarter to limit reverse causality, we cannot interpret these results as causal effects. If banks monitor more intensely loans that are more likely to become overdue, then the coefficient of *Monitor* can be biased upward.

[50]For example, the coefficients of *Capital ratio bank* and *ROA bank* suggest that a nonperforming exposure is positively related with a low level of capitalization and low profitability of the bank. This reveals a certain degree of reverse causality.

[51]For the sake of brevity, we do not report additional specifications for each type of distress. The results, though, confirm what observed in regression (5).

Table A1: Preliminary analysis on bank monitoring and loan repayment

The table reports panel regression estimates of a linear probability model analyzing the relation between bank monitoring and loan repayment. The dependent variable is displayed at the bottom of each column. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the year-quarter and bank level. Fixed effects are either included, "Yes", not included, "No", or spanned by another set of effects, "-". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6.

	(1) NPL dummy$_t$	(2) Past-due dummy$_t$	(3) UTP dummy$_t$	(4) Bad loan dummy$_t$	(5) NPL dummy$_t$
Monitor$_{t-1}$	-0.011**	0.004	-0.007***	-0.008***	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Loan amount$_{t-1}$	0.012***••	0.000	0.002***••	0.009***••	0.008***••
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-1}$	0.001***	-0.000	0.041***•	0.046***•	0.049***•
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Term loan dummy$_{t-1}$	-0.021***	0.010***	0.025***	-0.056***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Credit line dummy$_{t-1}$	-0.017***	0.033***	0.043***	-0.093***	0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
A/R loan dummy$_{t-1}$	-0.092***	-0.005***	-0.024***	-0.063***	-0.029***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share guarantee$_{t-1}$	0.025***•	0.022***•	0.000	-0.008**•	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share exposure$_{t-1}$	0.017***	-0.001	-0.002	0.020***	0.023***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Close threshold dummy$_{t-1}$	-0.003	0.002**	0.006***	-0.011***	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Credit score firm$_{t-4}$	0.002***	0.001***	0.002***	-0.002***	
	(0.00)	(0.00)	(0.00)	(0.00)	
Capital ratio firm$_{t-4}$	-0.255***	0.002	-0.087***	-0.171***	
	(0.01)	(0.00)	(0.01)	(0.01)	
ROA firm$_{t-4}$	-0.154***	-0.030***	-0.084***	-0.039***	
	(0.01)	(0.00)	(0.01)	(0.01)	
Size firm$_{t-4}$	-0.031***	-0.001	-0.014***	-0.016***	
	(0.00)	(0.00)	(0.00)	(0.00)	
Capital ratio bank$_{t-4}$	-0.170*	0.098**	-0.154**	-0.115***	0.089
	(0.09)	(0.04)	(0.07)	(0.04)	(0.07)
ROA bank$_{t-4}$	-0.826***	0.134**	-0.673***	-0.287***	-0.483***
	(0.14)	(0.06)	(0.11)	(0.06)	(0.15)
NPL ratio bank$_{t-4}$	-0.004	0.001	0.005	-0.008	-0.061
	(0.05)	(0.02)	(0.04)	(0.02)	(0.08)
Size bank$_{t-4}$	-0.002	0.005**	-0.002	-0.005*	0.008
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Liquidity ratio bank$_{t-4}$	-0.067	-0.062	-0.048	0.040	0.065
	(0.14)	(0.10)	(0.13)	(0.09)	(0.23)
Nonretail deposit ratio$_{t-4}$	-0.020	0.012	-0.027*	-0.004	0.045**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
GDP growth region firm$_{t-4}$	0.019	-0.051	0.037	0.033	
	(0.06)	(0.03)	(0.04)	(0.03)	
Employment region firm$_{t-4}$	-0.007**	0.001	-0.005***	-0.003**	
	(0.00)	(0.00)	(0.00)	(0.00)	
Inflation region firm$_{t-4}$	-0.004	-0.002	-0.000	-0.001	
	(0.01)	(0.00)	(0.00)	(0.00)	
GDP growth region bank$_{t-4}$	-0.019	0.042	-0.028	-0.031	-0.187*
	(0.06)	(0.04)	(0.05)	(0.03)	(0.10)
Employment region bank$_{t-4}$	0.006*	-0.002	0.006***	0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inflation region bank$_{t-4}$	0.004	0.002	0.001	0.002	0.006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Year-quarter FE	Yes	Yes	Yes	Yes	-
Region firm FE	Yes	Yes	Yes	Yes	-
Region bank FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	-
Industry firm FE	Yes	Yes	Yes	Yes	-
Firm-quarter FE	No	No	No	No	Yes
Two-way clustering	bank, year-quarter	bank, year-quarter	bank, year-quarter	bank, year-quarter	bank, year-quarter
N	3564206	3564206	3564206	3564206	687997
R^2	0.529	0.238	0.424	0.580	0.823
Adjusted R^2	0.503	0.195	0.392	0.557	0.669
F-test statistic	70.708***	25.960***	45.759***	39.079***	24.669***
degrees of freedom	(25, 39)	(25, 39)	(25, 39)	(25, 39)	(18, 39)

Appendix C Characteristics of Italian Firms

In this section we present a table which reports summary statistics of the four variables used to capture firm conditions (i.e., the credit score, the capital ratio, the return-on-assets and the logarithm of total assets) for the entire universe of Italian limited companies covered by the CERVED database over the time period 2005-2016.

Table A2: Descriptive statistics of the entire universe of Italian firms

The table reports summary statistics of the variables used to capture firm conditions for the entire universe of limited companies operating in Italy from 2005 to 2016. Variables are described in Table 1.

Variable Name	Obs.	Mean	Standard Deviation	Minimum	Median	Maximum
Firm-level Variables						
Credit score firm$_t$	9095577	4.939	2.104	1.000	5.000	9.000
Capital ratio firm$_t$	10006816	0.200	0.528	-5.609	0.171	1.000
ROA firm$_t$	10067465	-0.048	0.379	-8.025	0.002	0.832
Size firm$_t$	10107894	6.051	1.888	0.000	6.091	18.254

Appendix D Interest rate charged

In this section we present two tables: the first shows some evidence on the correlation between the interest rate charge by banks on business loans and the IRAP tax rate; the second reports the results of the 2SLS model of equation 5 and the reduced form model of equation 6 extended by including the average of the interest rates charged on the various types of credit extended by the bank to the firm as a control variable.

Table A3: Correlation between the interest rate charged and the IRAP tax rate

The table reports panel regression estimates of a linear model analyzing the relation between the interest rate charged by a bank and the IRAP tax rate. The dependent variable is displayed at the bottom of each column. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and year-quarter level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Average interest rate$_t$	(2) Interest rate term loan$_t$	(3) Interest rate credit line$_t$	(4) Interest rate A/R loan$_t$
IRAP$_{t-4}$	25.900	26.306	42.860	104.358***
	(40.81)	(22.85)	(65.71)	(33.26)
Share guarantee$_t$	0.001	-0.057	-0.001	0.000
	(0.00)	(0.05)	(0.00)	(0.00)
Share exposure$_t$	-0.810***	-0.803***	-0.899***	-0.195***
	(0.11)	(0.13)	(0.15)	(0.06)
Length relation$_t$	0.026***	-0.002	0.038***	0.027***
	(0.00)	(0.00)	(0.01)	(0.00)
Close threshold dummy$_t$	0.259*	0.202	0.563***	0.115
	(0.13)	(0.18)	(0.13)	(0.11)
Term loan dummy$_t$	-0.389***		0.292***	0.002
	(0.05)		(0.04)	(0.03)
Credit line dummy$_t$	1.025***	-0.352***		0.107**
	(0.10)	(0.06)		(0.05)
A/R loan dummy$_t$	-0.426***	0.118*	-0.241***	
	(0.06)	(0.06)	(0.06)	
Size bank$_{t-4}$	0.508**	-0.151	0.380	0.412*
	(0.24)	(0.31)	(0.35)	(0.20)
Capital ratio bank$_{t-4}$	2.673	4.964	-0.100	4.442
	(2.83)	(3.71)	(3.91)	(2.98)
Liquidity ratio bank$_{t-4}$	6.877**	0.789	7.538	6.460**
	(3.05)	(2.99)	(4.63)	(2.43)
ROA bank$_{t-4}$	-5.135	-0.473	-16.711***	-4.788
	(3.83)	(5.30)	(5.31)	(3.32)
NPL ratio bank$_{t-4}$	0.006	8.595*	3.994	-7.692*
	(4.57)	(4.93)	(6.04)	(4.18)
Nonretail deposit ratio bank$_{t-4}$	-1.746*	-1.548*	-2.831*	-1.313
	(0.99)	(0.80)	(1.50)	(0.94)
GDP growth region bank$_{t-4}$	2.383	-5.777*	2.150	6.851**
	(3.05)	(3.11)	(4.38)	(3.14)
Employment region bank$_{t-4}$	-0.098	-0.002	0.152	-0.197**
	(0.08)	(0.12)	(0.13)	(0.09)
Inflation region bank$_{t-4}$	0.305	-0.080	0.102	0.435**
	(0.26)	(0.23)	(0.37)	(0.21)
Firm-quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes
N	75020	29478	74887	54501
R^2	0.816	0.787	0.784	0.849
Adjusted R^2	0.648	0.588	0.586	0.706

Table A4: Interest rate charged

The table reports panel regression estimates of the 2SLS model of equation 5 and the reduced form model of equation 6 extended by including the average of the interest rates charged on the various types of credit extended by the bank to the firm as a control variable. The dependent variable is displayed at the bottom of each column. Bank controls include *Capital ratio bank*$_{t-6}$, *Size bank*$_{t-6}$, *ROA bank*$_{t-6}$, *NPL ratio bank*$_{t-6}$, *Liquidity ratio bank*$_{t-6}$, and *Nonretail deposit ratio bank*$_{t-6}$. Region bank controls include *GDP growth region bank*$_{t-6}$, *Employment region bank*$_{t-6}$, and *Inflation region bank*$_{t-6}$. Variables are described in Table 1. For each independent variable the first row reports the coefficient, the second row reports in parenthesis the robust standard error that is corrected for multiclustering at the bank and level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. • denotes rescaled coefficients that have been multiplied by 10^2, whereas •• denotes rescaled coefficients that have been multiplied by 10^6. At the bottom of the table we report the results of standard underidentification and weak identification tests, as well as of the Anderson-Rubin test for the 2SLS model.

	2SLS model				Reduced form model	
	First stage	Second stage	First stage	Second stage		
	(1) Monitor$_{t-2}$	(2) NPL dummy$_t$	(3) Monitor$_{t-2}$	(4) NPL dummy$_t$	(5) NPL dummy$_t$	(6) NPL dummy$_t$
Monitor$_{t-2}$		-49.214		-55.756		
		(334.88)		(397.63)		
IRAP$_{t-6}$	-0.036		-0.033		2.607	2.582
	(0.20)		(0.20)		(7.29)	(7.27)
Loan amount$_{t-3}$	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Length relation$_{t-3}$	-0.013**•	-0.006	-0.012**•	-0.007	-0.000	0.000
	(0.00)	(0.04)	(0.00)	(0.05)	(0.00)	(0.00)
Term loan dummy$_{t-3}$	0.000	0.010	0.000	0.007	-0.004	-0.006
	(0.00)	(0.10)	(0.00)	(0.10)	(0.01)	(0.01)
Credit line dummy$_{t-3}$	-0.001	-0.036	-0.001	-0.028	-0.007	-0.003
	(0.00)	(0.23)	(0.00)	(0.22)	(0.01)	(0.01)
A/R loan dummy$_{t-3}$	0.002***	0.089	0.002***	0.097	-0.000	-0.002
	(0.00)	(0.62)	(0.00)	(0.72)	(0.01)	(0.01)
Share guarantee$_{t-3}$	-0.000	-0.001	-0.000	-0.001	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Share exposure$_{t-3}$	-0.000	0.030	-0.000	0.021	0.036***	0.033***
	(0.00)	(0.07)	(0.00)	(0.12)	(0.01)	(0.01)
Close threshold dummy$_{t-3}$	0.000	-0.014	0.000	-0.009	-0.030	-0.029
	(0.00)	(0.06)	(0.00)	(0.09)	(0.02)	(0.02)
Average interest rate$_{t-3}$	0.000	0.012			0.004**	
	(0.00)	(0.05)			(0.00)	
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Region bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-quarter FE	Yes	Yes		Yes	Yes	Yes
Bank FE	Yes	Yes		Yes	Yes	Yes
Region bank FE	Yes	Yes		Yes	Yes	Yes
N	55060	55060	55060	55060	45086	45086
R^2	0.443		0.443		0.814	0.814
Adjusted R^2	-0.069		-0.069		0.642	0.642
F-test statistic		1.932*		1.529	380407.59***	-
degrees of freedom		(19, 30)		(18, 30)	(19, 30)	-
Underidentification test						
Kleibergen-Paap LM statistic	0.03		0.03			
Chi-sq P-val	0.86		0.87			
Weak identification test						
Kleibergen-Paap Wald F statistic	0.03		0.03			
Cragg-Donald Wald F statistic	0.01		0.01			
Stock-Yogo critical value 10% maximal IV size	16.38		16.38			
Anderson-Rubin test						
Anderson-Rubin Wald statistic		0.09		0.10		
Chi-sq P-val		0.77		0.76		