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Working Paper

The effect of bank monitoring on loan repayment

Staff Report, No. 923

Provided in Cooperation with:

Federal Reserve Bank of New York

Suggested Citation: Branzoli, Nicola; Fringuellotti, Fulvia (2020) : The effect of bank monitoring on loan repayment, Staff Report, No. 923, Federal Reserve Bank of New York, New York, NY

This Version is available at:

<https://hdl.handle.net/10419/241116>

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Federal Reserve Bank of New York
Staff Reports

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Nicola Branzoli
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Staff Report No. 923
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JEL classification: G21, G32, H25, H32

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 that the effect is stronger for the types of loans that benefit most from bank oversight, such as term loans.

Key words: bank monitoring, nonperforming loan, tax policy

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Branzoli: Bank of Italy (email: nicola.branzoli@bancaditalia.it). A significant part of the analysis was conducted during Fulvia Fringuellotti's visiting periods at the Bank of Italy, whose kind hospitality is gratefully acknowledged. The authors thank Viral Acharya, Ida Wolden Bache, Christoph Basten, Emilia Bonaccorsi di Patti, Alessandro Borin, Margherita Bottero, Elena Carletti, Nicola Cetorelli, Francesco Columba, Ricardo Correa, Swati Dhingra, Alberto Felettigh, Xavier Ferixas, Carola Frydman, Sigurd Galaasen, Emilia Garcia-Appendini, Mariassunta Giannetti, Delis Grombe, Giovanni Guazzarotti, Michel Habib, Torbjørn Hægeland, Frédéric Holm-Hadulla, Li He, Anna Kovner, Theresa Kuchler, Thomas Lambert, Seung Lee, Juan-Miguel Londono-Yarce, Mancy Luo, Yueran Ma, Sai Ma, Kaveh Majlesi, Kevin Meyer, Camelia Minoiu, Per Östberg, Steven Ongena, Nicola Pavanini, Anna Pavlova, Christoph Perignon, Diane Pierret, Tomasz Piskorski, Matthew Plosser, Jeffrey Pontiff, Manju Puri, Ricardo Reis, Giacomo Ricotti, Lucia Rizzica, Jean-Charles Rochet, John Rogers, Kasper Roszbach, João Santos, Anatoli Seguravelez, Enrico Sette, Joel Shapiro, Federico Maria Signoretti, Roberto Steri, Philip Strahan, Daniel Streitz, Marta Szymanowska, Leif Anders Thorsrud, Mathijs van Dijkm, Guillaume Vuilleme, Alexander F. Wagner, and Wolf Wagner for very helpful comments and suggestions. They also thank participants at the Banking Research Network Workshop at Bank of Italy; seminar participants at the Bank of Italy, the Federal Reserve Bank of New York, the Federal Reserve Board, Norges Bank, Rotterdam School of Management, University of Lausanne, and University of Zurich. Fulvia Fringuellotti was affiliated with the University of Zurich and the Swiss Finance Institute at the time this paper was written. The views expressed in this paper are those of the authors and do not necessarily represent the position of the Bank of Italy, the Federal Reserve Bank of New York, or the Federal Reserve System.

To view the authors' disclosure statements, visit
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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, to collect information on the ability of a borrower to meet the repayment schedule, to analyze the financial reports of a business or to set up regular talks with the managers of a firm. Second, a bank is likely to increase its monitoring intensity when the repayment prospects of a loan get worse, 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 loan-level information on business loans from the Italian Credit Register. This measure is based on the requests for information to the Credit Register made by banks on their existing borrowers. A request provides information on the amount of each loan granted by other banks to a firm, as well as on the objective conditions of deterioration of any of the individual exposures. We interpret a request for information as evidence that the bank decides to take a closer look at one of its borrowers. Hence, we use the number of requests for information occurring in a given quarter as our proxy for bank monitoring.¹ We acknowledge that a bank can monitor its borrowers also in other ways, for example by talking to the firm’s managers or analyzing the borrower’s financial reports. Our proxy is not intended to quantify all these activities, but rather to capture an observable evidence of the effort exerted by banks in carrying out the various tasks that are useful to monitor their borrowers. With this caveat in mind, we analyze the appropriateness of our proxy for bank monitoring. As expected, we find that banks monitor more intensively opaque borrowers (e.g. small firms with a shorter credit relationship with the bank), riskier borrowers (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 bank monitoring. Our approach builds on a theoretical model that we develop to describe the effects of a corporate income tax on bank incentives to monitor borrowers. 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

¹To ensure that we capture exclusively a monitoring activity, we consider only requests for information that are not associated with an extension of new credit to an existing borrower nor related to exceptional circumstances (such as in the aftermath of a bank M&A).

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 to shareholders. In fact, the model predicts that bank monitoring increases when the corporate tax rate decreases. We therefore rely on this prediction to outline the identification strategy of our empirical study.

We address our research question by exploiting exogenous variation in bank monitoring driven by the Italy Regional Production Tax (“Imposta Regionale Attività Produttiva”, IRAP) rate applied to banks. This tax rate is set at the regional level and varies both across regions and over time. 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. 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 borrower’s condition that may affect the ability to meet the contractual obligations. 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.

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 the IRAP tax rate. Consistently with our theoretical prediction, we find that an increase in the tax rate implies a decrease in bank monitoring. 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, that corresponds to a 1 percentage point decrease in the tax rate, reduces the probability that the credit exposure becomes nonperforming by 3.9 percentage points two quarters ahead. This result is big in economic terms if we take into account that the probability of a delinquency is roughly 11% in our sample.²

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. 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 loan, bank and regional factors. Our results suggest that a 1 percentage point decrease in the tax rate leads to a reduction in the probability of a delinquency by 4.9 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.

²This figure refers to the sample including only firms having multiple bank relationships that we use in our main regression analysis.

In our baseline 2SLS model and reduced form model we estimate the effect 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 an “autoliquidating loan”, i.e. a loan backed by receivables. 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 further 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 autoliquidating loans, consistently with the idea that bank monitoring is more effective in disciplining borrowers in the case of term loans (Acharya et al., forthcoming). This finding allows us also to rule out a potential concern, namely that the actual driver of the positive effect on loan repayment identified in the baseline models is loan renegotiation of credit lines rather than bank monitoring.³

Importantly, 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.⁴ In fact, our theoretical model suggests that banks transfer, to some extent, their tax burden to borrowers by adjusting the lending rate. Consider the case of a firm that borrows from two banks located in two regions with a different tax rate. Then, 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 survive to the inclusion of 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 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 in distress. We find that bank monitoring reduces the likelihood of a delinquency even for *in-bonis* 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.

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 loan level. Our approach to gauge bank monitoring is in the same vein of Gustafson et al. (2020), but we use bank requests for information on lending exposures rather than on financial statements. 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. We show empirical evidence that bank monitoring

³Differently from other types of loan, the contractual terms of a credit line can be renegotiated in an easy way, even before a loan payment is past-due. 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.

⁴Ideally, we would like to estimate our models including the interest rates charged on the various types of loan 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.

is valuable, as it improves in a substantial way the borrower’s 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). Our findings suggest that lenders that extend credit without monitoring their borrowers may experience higher default rates, posing relevant concerns for financial stability.

This work also contributes to the strand of literature investigating the relation between bank stability 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, weakens 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, 2017; Dell’Ariccia et al., 2017; Jiménez et al., 2017). Typically, the relation between bank stability and risk taking has been analysed by focusing on variation in the capital ratio (Allen et al., 2011; Mehran and Thakor, 2011; Dell’Ariccia et al., 2014; Bhat and Desai, 2017; Jiménez et al., 2017) or in the level of the policy rate (Jiménez et al., 2014; Dell’Ariccia et al., 2017). We contribute to this literature by documenting, both theoretically and empirically, that higher bank stability, 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 on risk.

Finally, this work also complements the literature on the effects of taxation on bank risk-taking. Exploiting the same variation in the IRAP tax rates used in this work and performing an analysis at the bank-level, Gambacorta et al. (2017) show that an increase in the corporate tax rate leads to a riskier composition of the asset side of bank’s balance sheet. The model developed in this paper provides a theoretical explanation for their result. Moreover, looking at a diverse set of tax interventions, Schepens (2016), Devereux et al. (2015), Carletti et al. (2020), and Célérier et al. (2019) 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.

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 “Banca d’Italia” (Bank of Italy). This data includes quarterly loan-level information on virtually all business loans extended to limited companies in Italy from 2005 to 2016. 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). Since we aim at investigating bank monitoring, we limit our data only to outstanding credit relationships whose length is longer than one quarter. To address our research question, we need to collect information on borrower’s characteristics. We are able to retrieve such information only for firms included in the CERVED database. This database contains information on balance sheet and income statements of all limited companies operating in Italy. In addition, our identification strategy exploits borrowers having multiple credit relationships, which are typically represented by firms. For these reasons, we focus our attention on business loans to limited companies. Also, for identification purposes, we limit our dataset only to loans granted by small banks operating at the regional level. The reason for that will be clarified in the next subsections where

we illustrate the identification strategy.

Our dataset combines loan-level data from the Italian CR with data on (i) firms 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).

The variables of major interest in our study are those capturing bank monitoring and loan repayment. To build our proxy for bank monitoring we exploit data on requests for information made by banks to the CR on their existing borrowers. Each month banks can submit requests to get information on the total exposure of the banking system to a specific borrower. These requests have different motivations. Our variable for bank monitoring, *Monitor*, is constructed as the total number of requests for information made by a bank on an existing borrower in a given quarter. To build this variable we aggregate all requests for information without making any distinction regarding the stated reason. Our proxy for bank monitoring and the rationale behind it will be discussed in detail in the next subsection.

We consider four different variables for loan repayment: *Past-due dummy*, a dummy variable equal to one if the bank’s credit exposure to a firm is past-due by 90 days or more, and zero otherwise; *UTP dummy*, a dummy equal to one if the bank’s credit exposure to a firm is defined as “unlikely-to-pay”, UTP, meaning that the bank envisages the possibility that the loan(s) extended will not be repaid in full; *Bad dummy*, a dummy equal to one if the bank’s credit exposure to a firm is defined as “bad”, meaning that the bank considers the loan(s) extended as impaired; *NPL dummy*, a dummy equal to one if the bank’s credit exposure to a firm falls into one of the previous categories (nonperforming loan(s), NPL), and zero otherwise. While the latter variable indicates if a credit exposure is in general nonperforming, the first three variables capture a condition of distress which is progressively more severe.

It is worth specifying that bank’s lending exposure to a firm at a given point in time may include different types of credit, such as a term loan, a credit line or an “autoliquidating loan” (backed by receivables). Thus, we complement the variables for loan repayment with a set of indicators on whether a specific type of loan within a bank-firm credit relationship is in distress (*NPL term loan dummy*, *NPL credit line dummy*, and *NPL auto loan dummy*). These consist in a dummy equal to one if a term loan, a credit line, or an autoliquidating loan, respectively, is classified as past-due by 90 days or more, or unlikely-to-pay.⁵

Table 1 provides a detailed description of all the other variables considered in our study.

2.2 Measuring bank monitoring

The most relevant data extracted from the CR concerns the requests for information that banks make on their existing borrowers. Each month, banks can submit these requests in order to get information on the total current credit exposure to a specific borrower by all banks in Italy. In particular, the bank can retrieve information on the amount of each loan granted by other banks to the borrower, as well as on the objective conditions of deterioration of each individual exposure.⁶ This information is provided essentially for free, as the cost of one request amounts to few euro cents. In a given month, a

⁵These variables do not capture if a specific type of loan is defined as bad. This is due to the fact that our dataset does not allow to identify if a term loan, a credit line, or an autoliquidating loan falls into this category of severe distress.

⁶Objective 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.

bank can submit more than one request for information, each one corresponding to a specific stated reason. The reason for a request is classified as “historical information”, “in-depth information”, “credit limit” and “co-signing”.

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 current month. 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 loans granted to a specific firm by other lenders. This is justified by the fact that data in the CR can be subject to amendments. Indeed, the regulatory guidelines of the CR define in detail how banks should correct erroneous information provided and specify penalties to non-compliers, suggesting that amendments are not uncommon. For this reason, the bank may want to act prudently and make 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 the borrowers of one of the two banks involved, and/or to create a new pool of information.⁷

In the former case, the bank requests information from the CR because it has an interest in assessing the condition of the lending exposures of the banking system 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 the 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 cleansing process.

Our original loan-level dataset includes roughly 5.4 million observations on 283,706 credit relationships having a duration greater than one quarter, and involving 225,669 firms and 458 banks. 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 (14,507 observations).⁸ 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 monitoring activity.⁹ Finally, we drop all observations in which we observe an increase in credit

⁷A 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. Nevertheless, this strictly depends on the internal technical infrastructure of the bank and, hence, we do not consider it as a major motivation.

⁸A break corresponds to a lack of information on a specific bank-firm 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 bank-firm relationship will show up again in the CR.

⁹To this end, we use a visual inspection aimed at detecting any atypical clustering in requests for information. We identify 243 observations with anomalies in the average number of requests per client made by a bank in a given quarter. These relate to two banks. We drop all the observations pertaining to the pair bank-quarter in which these anomalies occur. Also, we discard all the requests for information

extended to an existing borrower (792,563 observations). This allows us to eliminate requests for information that are associated with an increase in lending.¹⁰ 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 detect an increase in lending, irrespective of whether a request for information is made or not. In this way, we are able to compare the repayment performance of a given borrower on different loans outstanding with monitoring banks versus non-monitoring banks, once having controlled for a relevant set of factors.

This stringent cleansing process yields a panel of 4,551,985 observations, corresponding to 280,619 lending relationships over the period 2005-2016. We observe at least one request for information in 4,116 observations, roughly 0.1% of our sample, corresponding to an average of 9 requests per bank. We use the total number of requests for information made by a bank in one quarter to build our novel monitoring variable, that captures in a direct way the effort exerted by a bank in checking the ability of its borrowers to comply with the contractual obligations.

Our proxy is not intended to quantify the whole intensity of bank monitoring, but rather to capture an observable evidence of a broader phenomenon, similarly to the tip of an iceberg. As already pointed out, if the bank wants to verify the condition of total lending to the firm, it can limit itself to consult the automatic flow of information received from the CR. More importantly, the 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. Therefore, 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 of the bank. As such, our proxy of bank monitoring resembles the two measures of Gustafson et al. (2020), which consist in the frequency of bank’s requests for information on firm’s financial reports and field exams of the borrower 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 loan-level relates also to other measures identified in the literature. These include the frequency at which the bank reviews the internally generated probability of default of the borrower (Plosser and Santos, 2016), the collateral value, the loan spread, the credit rating and the loan limit (Cerqueiro et al., 2016). Our proxy for bank monitoring and those of Gustafson et al. (2020) allow to capture the effort exerted by the bank in monitoring its borrowers in a more direct way. In what follows we show that the dynamics of our variable are consistent with a bank monitoring interpretation.

made by a bank that has taken part to a M&A during the year of the merger (186 observations).

¹⁰A 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.

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 five from 2005 to 2009, with a sharp acceleration between the third quarter of 2008 and the third quarter of 2009. Consistently with plot (a), the highest value is achieved exactly in 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 a first 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 and the fourth quarter correspond to the highest number of requests for 10 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.¹¹

[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 7.1% of cases. Also, once we move

¹¹Most 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 as 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 repay its loans in this period.

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 13.2% 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.¹² 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 in the quarter on a set of loan and firm variables capturing the conditions of the borrowing firm. We include macro variables and fixed effects as to control for potential confounding factors. In particular, our set of fixed effects contains bank-quarter fixed effects to control for any observable and unobservable, time varying and time invariant condition of the bank. This ensures that we can focus on the relation between firm factors and bank monitoring.

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. 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. 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 term loans with respect to other types of credit, in line with the evidence that, in our sample, borrowers are less likely to be insolvent on term loans vis á vis credit lines.¹³ 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 banks monitor more large and well capitalized 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

¹²The 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 or equal to €250.

¹³In our original loan-level 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.

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* loses 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 stronger the higher the firm’s 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. Intuitively, once we control for 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, once having controlled for 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’s 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 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 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 was intended to estimate the effect of unsecured deposits, the negative and significant coefficient is likely to capture a size effect as well.¹⁴

¹⁴If 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). However, this results seems to suggest that *Nonretail deposit ratio bank* rather captures the size of the bank. In fact, a bigger bank is likely to have a higher fraction of nonretail deposits.

Most of the coefficients of the other factors are in line with expectations, except for *Capital ratio bank*, but are not significant. 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. This findings, as well as the results of the previous specifications, 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, overall, our findings provide support to our methodological approach in measuring bank monitoring.

[Insert Table 2 here]

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 as well, exposing to the threat of reverse causality. Also, unobservable conditions of the borrowing firm can potentially affect its ability to meet the contractual obligations, 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 two main pillars: first, we exploit taxation as a source of exogenous variation in bank monitoring; second, we use firm-time fixed effects to control for time varying and time invariant, observable and unobservable conditions of the firm.

Taxation is likely to affect bank incentives to monitor borrowers through different channels. We focus on the corporate tax rate and we 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 regional variation in the IRAP tax rate to retrieve exogenous variation in bank monitoring.¹⁵ In this way, we are able to investigate the causal effect of bank monitoring on loan repayment.

As for possible confounding factors, we focus our analysis on business loans to limited companies exactly because we have extensive information on these firms that we can use to control for the borrower’s conditions.¹⁶ Nevertheless, even controlling for observable firm’s characteristics, there could still be unobservable factors driving the repayment performance of a loan. For this reason, we saturate our main regressions including

¹⁵We borrow this identification strategy from Bond et al. (2016) and Gambacorta et al. (2017), who exploit small banks and regional variation in the IRAP tax rate to analyze the effects of taxation on bank capital structure.

¹⁶This information would be missing for households.

firm-time fixed effects. This is made possible by the fact that almost 10% of firms in our sample have multiple credit relationships. As a result, we estimate the causal effect of bank monitoring on loan repayment by comparing the repayment performance of different loans granted by different banks to the same firm at a certain point in time. This means that the identification stems from different tax rates applied to banks operating in different regions and lending to the same firm.

Hereinafter, we discuss our first pillar more in detail and we describe the empirical methodology adopted.

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.¹⁷

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. (2017). 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:¹⁸

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

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

¹⁷In 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.

¹⁸There is no agency conflict between bank managers and shareholders as their interests are assumed to be perfectly aligned.

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:

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

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

The proof is provided in the Appendix. This result is in line with a classical “skin in the game” argument, in what it 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.¹⁹

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 1998.²⁰ 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),²¹ 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

¹⁹These results are available upon request.

²⁰The 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.

²¹Article 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.

total funding of the National Health Service (MEF, 2012).²² 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.

Table 3 reports the regional IRAP tax rates applied to banks during our sample period.²³ We detect 59 changes in the local IRAP tax rates occurred between 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. Since revenues from the IRAP tax are mainly used to finance national health care expenditures, the IRAP tax rates are reasonably orthogonal to firm’s conditions affecting the likelihood that the loan is repaid, as well as to bank monitoring incentives. This guarantees the exogeneity of the IRAP tax rates, meaning that our identification strategy is appropriate and sound. One concern, though, could be that local macroeconomic conditions jointly affect firm’s loan repayment, bank monitoring and local IRAP tax rates. For example, during an economic downturn firms might be unable to meet their credit obligations, requiring banks to monitor more intensively; 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 in our estimation models. More importantly, in Section 3.2.1 we conduct an exercise to verify whether local IRAP tax rates depend (at least linearly) on regional macro conditions and aggregate bank factors. We find no evidence of such dependence, corroborating our identification strategy. A further concern could be that there is a correlation between the IRAP tax rate applied to banks and the IRAP tax rate applied to firms, with the latter being able to affect significantly the firm’s ability to repay. In our sample we observe that only 35 of changes in the IRAP tax applied to banks are concomitant with changes in the IRAP tax rate applied to limited companies, meaning that a substantial fraction of the variation concerns only banks and is not affecting firms. More importantly, our methodology focuses on variation within firm-time, as we include firm-time fixed effects in our econometric specifications. This feature is crucial to control for any relevant condition of the firm affecting its likelihood to repay, including the tax burden.

[Insert Table 3 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. 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

²²This 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.

²³Despite our dataset covers the time period 2007-2016, we report the tax rates also for 2006, as in our econometric analysis we use the lagged value of the IRAP tax rate.

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. (2017). 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.²⁴ 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 composition of their balance sheet,²⁵ they experience similar levels of profitability to those of big banks (Bond et al., 2016; Gambacorta et al., 2017). 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.

2.3.4 Empirical methodology

Our empirical strategy includes two main estimation models. The first consists in a 2SLS regression in which we use the IRAP tax rate as instrument for our proxy for bank monitoring. This exercise allows to assess which is the impact of an increase in bank requests for information, driven by a change in taxation, on the repayment performance of a loan.

By construction, our proxy for bank monitoring may underestimate the total monitoring effort exerted by a bank. The theoretical model presented in Section 2.3.1 suggests that the corporate tax rate affects bank incentives to monitor borrowers on the whole. Hence, to circumvent this issue, we exploit variation in the IRAP tax rates as a way to capture changes in the overall monitoring activity of banks. Specifically, we estimate a second reduced form model in which we quantify how an increase in total bank monitoring driven by taxation affects loan repayment.

2.4 Regression dataset

2.4.1 Descriptive statistics

As explained above, our full sample is a panel of 4,551,985 observations that encompasses 280,619 credit relationships involving 223,703 firms and 458 banks. In this panel credit relationships are the cross-sectional unit and years 2005-2016 are the time unit. To build the final dataset used in our main regressions, we merge the loan-level data from the Italian CR with data on bank conditions, local taxation and macroeconomic factors retrieved from different sources. Due to a lack of availability for some variables over specific time periods, we lose a substantial amount of observations.²⁶ Additionally, we discard not only credit relationships having a duration of one quarter, but also those having a duration of two and three quarters. This is necessary because, in most specifications, we include our measure of bank monitoring lagged of two quarters. Hence, we need to ensure that we take into account only the requests for information made with respect to existing borrowers having an established credit relationship with the bank.

²⁴Bond et al. (2016) and Gambacorta et al. (2017) 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.

²⁵For 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.

²⁶For example, data on bank balance sheet are available starting only in 2006.

For the same reason, we also drop all observations in which we observe a break in the credit relationship in the current quarter or in the previous two. More importantly, in the main regressions of our econometric analysis we rely on firm-time fixed effects to control for any observable and unobservable, time varying and time invariant condition of the firm. The reduced sample including only firms that have multiple credit relationships is a panel of 556,284 observations. This encompasses 53,744 credit relationships involving 23,379 firms and 440 banks over the time period 2007-2016.²⁷ Table 4 reports summary statistics of the variables used in our regression analysis for both the full sample and the reduced sample.

2.4.2 Variation exploited

The main results of our econometric study are obtained using the reduced sample pertaining to firms having multiple credit relationships. The inclusion of firm-time fixed effects in our specifications is an essential ingredient of our methodology. In fact, investigating the causal effect of bank monitoring on loan repayment requires to control of any condition of the firm that may influence the likelihood that the firm repays its loan. As noted above, when we include this set of fixed effects we work on a dataset that is roughly one eighth of the original full sample, as we are focusing on firms having multiple credit relationships. More importantly, our identification strategy based on exogenous changes in the IRAP tax rates builds on a specific kind of variation that we need to discuss in detail. In particular, our identification comes chiefly from firms having multiple credit relationships with banks operating in different regions and, hence, subject to different tax rates. To draw any implication for the external validity of our results we need to understand how representative these banks and these firms are.

Figure 3 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 including only firms having multiple credit relationships. More importantly, despite the number of firms is reduced by a factor of nine in the reduced sample, the distribution of firms and banks across regions is virtually unchanged. This is important evidence suggests that the reduced sample is sufficiently representative. This claim is corroborated also from the statistics reported in Table 4. In fact, all variables show similar values in both samples.

The next step is to assess precisely which is the main source of variation that we exploit. First, we observe that 9% of firms included in the reduced sample (2162 firms) borrow, at least in one quarter, from two or more banks operating in different regions. In addition, 13% of firms (3134 firms) borrow, at least in one quarter, from one or more banks located in a different region from their own. We also detect 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 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 find that 62% of observations in which the region of the firm differs from that of the bank are associated to banks that operate only in one region. In these cases, it is certainly the firm which moves in order to borrow from a bank located in a different region. So, it is likely that these firms operate close to the border between two regions.

²⁷The reduced sample corresponds to the sample used in the regressions of Table 7. In the following tables there is a deviation from the number of 556,284 observations depending on the set of variable included in the econometric specifications.

For this reason, in our specifications we control for macroeconomic factors of both the firm's region and the bank's region.

[Insert Figure 3 here]

As a last step, we check if firms included in our sample are representative 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. To assess if our sample of firms is sufficiently representative, we compare the statistics of Table 4 with those of the SMEs CERVED Report of 2014. Clearly, our sample covers a period of 10 years characterized by varying macroeconomic conditions, while the Report refers only to the year 2014. However, this comparison is still useful to understand if the order of magnitude of our variables is consistent with what observed on the national scale. We find that the mean value of the credit score is very close to what described in the SMEs CERVED Report of 2014, but firms in our sample exhibit lower profitability and a lower level of capitalization.

[Insert Table 4 here]

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 4 shows the percentage of nonperforming loans in each quarter against the average number of requests for information submitted by banks one quarter and two quarters before, respectively. Despite the high dispersion, these two plots document that bank requests for information are negatively related to nonperforming loans, suggesting that bank monitoring may have a positive effect on loan repayment.

[Insert Figure 4 here]

This finding is confirmed once we analyze more granular data at the loan level. The first four columns of Table 5 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 the first specification, we include a wide set of controls spanning loan, firm, bank and macroeconomic factors. Specifically, *Loan amount*, *Length relation*, *Term loan dummy*, *Credit line dummy*, *Auto 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 macroeconomic 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.²⁸ All

²⁸The 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.

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.

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 year-quarter and bank 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 4.

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 autoliquidating 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.²⁹

As a next step, we investigate what could be the channels through which bank monitoring is associated with improved loan repayment. Models (5)-(6) analyze the relation between *Monitor* and *ROA firm*, *Capital ratio firm* and *Credit score firm*, respectively. First, we find that bank monitoring is positively related to future firm's capitalization and profitability. This suggests that bank monitoring may not be limited to a mere costly state verification (Townsend, 1979), but may encompass also other activities that are beneficial to the firm. 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. However, these conjectures can be corroborated only through a causal analysis, 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.

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 loses its significance.³⁰ Despite the extensive amount of controls and the fact that we include our measure of bank monitoring lagged of one quarter 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. If banks monitor more intensely loans that are more likely to become overdue, then the coefficient of *Monitor* can be biased upward. In the next subsection we discuss how we deal with this issue and we present the main results of our empirical

²⁹For 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.

³⁰For the sake of brevity, we do not report additional specifications for each type of distress. The results, though, confirm what observed in regression (8). Concerning specifications (5)-(7), we cannot run similar regressions including firm-time fixed effects, as the dependent variable is invariant within the fixed effect.

analysis.

[Insert Table 5 here]

3.2 Main results

To identify the causal relation between bank monitoring and loan delinquency we rely on our identification strategy, exploiting exogenous variation in the regional IRAP tax rates. We first show some necessary exogeneity checks to corroborate our methodological approach. Afterward, we present the main regression analysis.

3.2.1 Exogeneity checks

As a preliminary check, we verify if the IRAP tax rate is indeed exogenous to bank monitoring and loan repayment. Table 6 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 same variables used insofar for the bank's 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, $\Delta IRAP\ health$. 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 rate. Although these results cannot rule out other kinds of dependence than the linear one, they provide evidence that supports 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 whole Italian economy. 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 6 here]

3.2.2 Bank monitoring and loan repayment: A 2SLS approach

We can 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:

$$\text{Monitor}_{i,b,r,t-2} = \alpha + \beta \text{IRAP}_{r,t-6} + \boldsymbol{\gamma}' \mathbf{X}_{i,b,r,t-n} + \mu_{i,t} + \mu_b + \mu_r + \varepsilon_{i,b,r,t-2} \quad (4)$$

2nd Stage:

$$\text{NPL dummy}_{i,b,r,t} = \alpha + \beta \widehat{\text{Monitor}}_{i,b,r,t-2} + \boldsymbol{\gamma}' \mathbf{X}_{i,b,r,t-n} + \mu_{i,t} + \mu_b + \mu_r + \varepsilon_{i,b,r,t} \quad (5)$$

where $\text{Monitor}_{i,b,r,t-2}$ is the number of requests for information made by bank b operating in region r on firm i at time $t - 2$; $\text{NPL dummy}_{i,b,r,t}$ denotes a dummy variable equal

to one if the credit exposure of bank b to firm i is in distress at time t , and zero otherwise; $IRAP_{r,t-6}$ is the tax rate applied to the bank, that we use as instrument for bank monitoring (so called “excluded instrument”). \mathbf{X} stands for a vector of controls, encompassing characteristics of the credit exposure (*Loan amount, Length relation, Term loan dummy, Credit line dummy, Auto loan dummy, Share guarantee, Share exposure 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 loan delinquency. $\mu_{i,t}$, μ_b and μ_r denote firm-quarter, bank and bank’s region fixed effects, respectively. $\widehat{Monitor}_{i,b,r,t-2}$ is the linear projection of $Monitor_{i,b,r,t-2}$ onto all the exogenous variables, namely the excluded instrument and controls. $IRAP$ 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. (2017). Also, all the control variables are lagged to ensure that they are predetermined with respect to the dependent variable in each stage. $t - n$ 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 two quarters ahead. We consider a lag of two quarters because this represents the horizon in which we identify the strongest effect, as evinced in Table 8.³¹

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 healthcare expenditures at the regional level), as well as the evidence that the $IRAP$ tax rate is uncorrelated with local macroeconomic conditions and aggregate bank factors at the regional level (Table 6) suggest that $IRAP$ is undeniably exogenous to bank monitoring and loan repayment. 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 to different $IRAP$ tax rates. Also, this 2SLS model is run on a sample of credit relationships having a length greater than three quarters, in which we have dropped all observations associated with an increase in lending to an existing borrower in the current quarter and/or in the previous two. This ensures that we are investigating in a proper way the effect of bank monitoring on loan repayment. In fact, suppose that in quarter $t - 2$ 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 cleansing process allows us to get 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.

Table 7 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 monitor-

³¹In Table 8 we report the results of our 2SLS model for different horizons, from one to eight quarters ahead.

ing. 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 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 our sample is 0.001 and the standard deviation is 0.029 (panel B of Table 4).³² 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 (4.00) 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 (18.06) 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 (4.92) is relatively low, especially 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; Cornelissen et al., 2016).³³ Specifically, we find that an increase in the number of requests for information, that corresponds to a 1 percentage point decrease in the IRAP tax rate, entails a decrease by 3.9 percentage points in the probability that the lending exposure end 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% in our reduced sample (Table 4). Moreover, an increase in the IRAP tax rate of 1% is a rather realistic event. In fact, in our sample period, we observe five times an absolute change in the regional IRAP tax rate that is greater or equal to 1 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

³²This 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.

³³Our 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.

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 lower *Loan amount*, lower *Share exposure* and better macroeconomic conditions in terms of GDP 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 autoliquidating 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 conjecture, namely that the bank is not willing to exert monitoring effort when a loan is in a hopeless condition.

[Insert Table 7 here]

We have already pointed out that we focus 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 8 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 its maximum two quarters ahead. Afterward, it slowly decreases until it disappears completely eight quarters ahead. 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 8 here]

3.2.3 IRAP tax rate as a proxy for total bank monitoring

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 limited fraction of the actual intensity of bank monitoring. Relying on our theoretical model exposed in Section 2.3.1, we conjecture that variation in the IRAP tax rate affects 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 run the following reduced form regression:

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

where \mathbf{X} denotes the same vectors of loan, bank, and macro regional variables of the 2SLS model. 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 in which we detect an increase in lending in the current quarter or in any of the previous quarters belonging to the year that follows that of the tax rate.³⁴

Table 9 displays the results of this exercise. Looking at the first specification, we find that a decrease of 1 percentage point in the IRAP tax rate implies an increase of 4.9 percentage points in the likelihood of loan distress. The magnitude of this effect is close but somewhat higher than that of the 2SLS model (3.9 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 9. The evidence that the magnitude of the effect of bank monitoring on loan repayment is similar and slightly 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 strongly 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 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 7 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 9 here]

3.3 Different types of credit

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

³⁴In 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.

This exercise allows us also to address a second concern. Differently from a term loan or an autoliquidating loan, the contractual terms of a credit line can be renegotiated by the parties in a straightforward way, even if loan payments are still not in arrears. While loan renegotiation may involve any loan type, this is more likely to occur for a credit line. This means that loan renegotiation on credit lines, which trigger banks' requests for information from the CR, may drive our results rather than bank monitoring.

Table 10 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 autoliquidating loans. However, the magnitude of the effect is sensibly stronger for term loans. In particular, an increase in the number of requests for information, that corresponds to a 1 percentage point decrease in the IRAP tax rate, entails a decrease by 4.8 percentage points in the probability that a term loan becomes nonperforming two quarters ahead, compared to only 3.8 percentage points and 4 percentage points for credit lines and autoliquidating loans, respectively. The reduced form model (specifications 7-9) shows similar results, with even a larger gap 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 autoliquidating loans (Acharya et al., forthcoming). Importantly, these results rule out the possibility that the observed positive effect of an increase in bank's requests for information on loan repayment is due to renegotiation of credit lines.

[Insert Table 10 here]

3.4 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. Then, we would expect 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 form 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. 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 very limited sample of banks which prevents us from performing a proper robustness test.³⁵ So, we opt for an alternative approach.

³⁵Table A1 in the Appendix 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 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. This is due to the fact that

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 bank-firm lending relationship in the regression models. Table 11 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 11 here]

In Table 12 we refine this approach looking at each type of credit separately. Specifically, we estimate similar regressions to those of Table 10 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 10. 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 12 here]

3.5 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 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.³⁶ Table 13 reports the results of this robustness test. 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 (7.1%) 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 7 (albeit still economically strong). Specifically, an increase in the number of requests for information, that corresponds to a 1 percentage point decrease in the IRAP tax rate, implies a decrease by 2.8 percentage points in the likelihood that the loan ends up in distress two quarters ahead. Similarly, the coefficient of *IRAP* in the reduced form model is still positive and statistically significant, but the magnitude is 1 percentage point lower than what observed in Table 9.

[Insert Table 13 here]

Despite only 7.1% of requests for information concern a credit exposure that is already in distress, we may wonder if our result is driven to some extent by loan restructuring rather than bank monitoring in the strict sense. In fact, if a loan gets in arrears

in this subsample there is not enough variation to exploit, as no 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.

³⁶We 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 bank can loosen the borrower’s financial constraints by postponing due payments or even providing additional credit (Brunner and Krahn, 2008). Our data cleansing process implies that we already account for the former, 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 loan covenants. 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 14 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 somewhat smaller.

[Insert Table 14 here]

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 15 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 7 and Table 9.

[Insert Table 15 here]

4 Conclusions

This paper investigates the effect of bank monitoring on loan repayment. Using granular loan-level information on business loans extended in Italy, we derive 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. In other words, we estimate the effect of bank monitoring on loan repayment by comparing the repayment performance of a given firm on different loans granted by different banks at the same time. We find that an increase in the number of requests for information, as driven by a 1 percentage point decrease in the IRAP tax rate, reduces the probability of a delinquency by 3.9 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.

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.

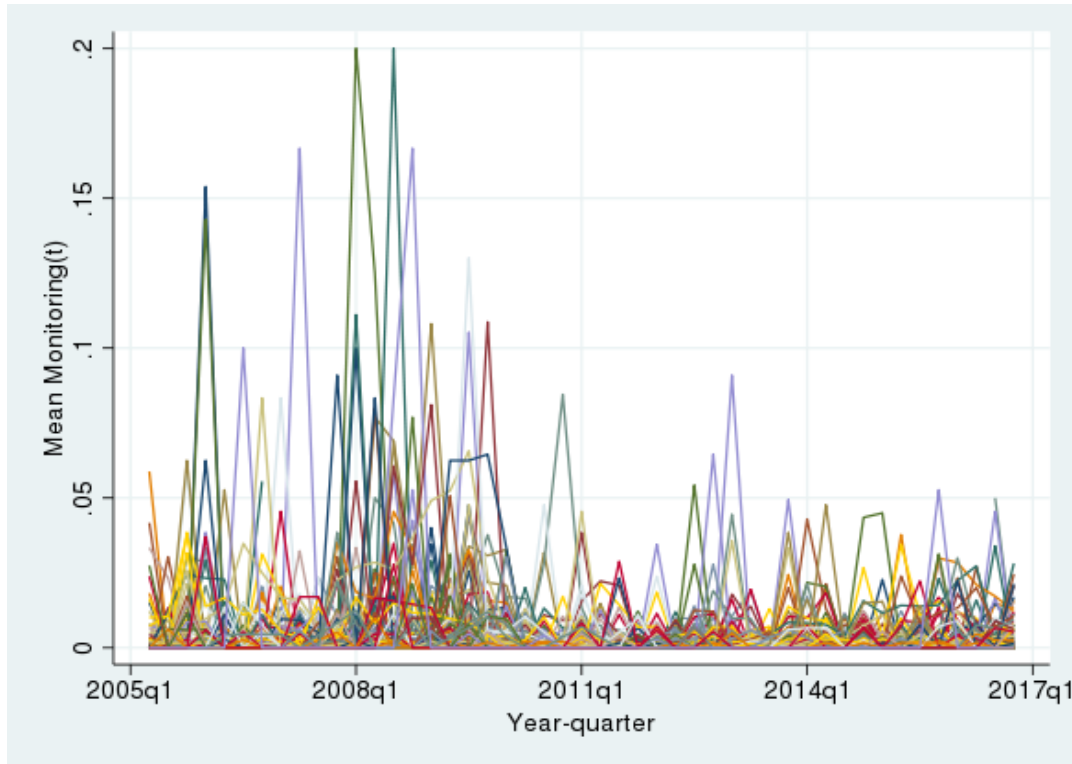
Importantly, our findings are robust to a series of robustness exercises. In particular, we show that the positive effect of bank requests for information on loan repayment is not driven by loan renegotiation or restructuring, neither by the difference in the interest rates charged by banks lending to the same firm, as captured by the difference in the tax rates applied to these banks at loan issuance.

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 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

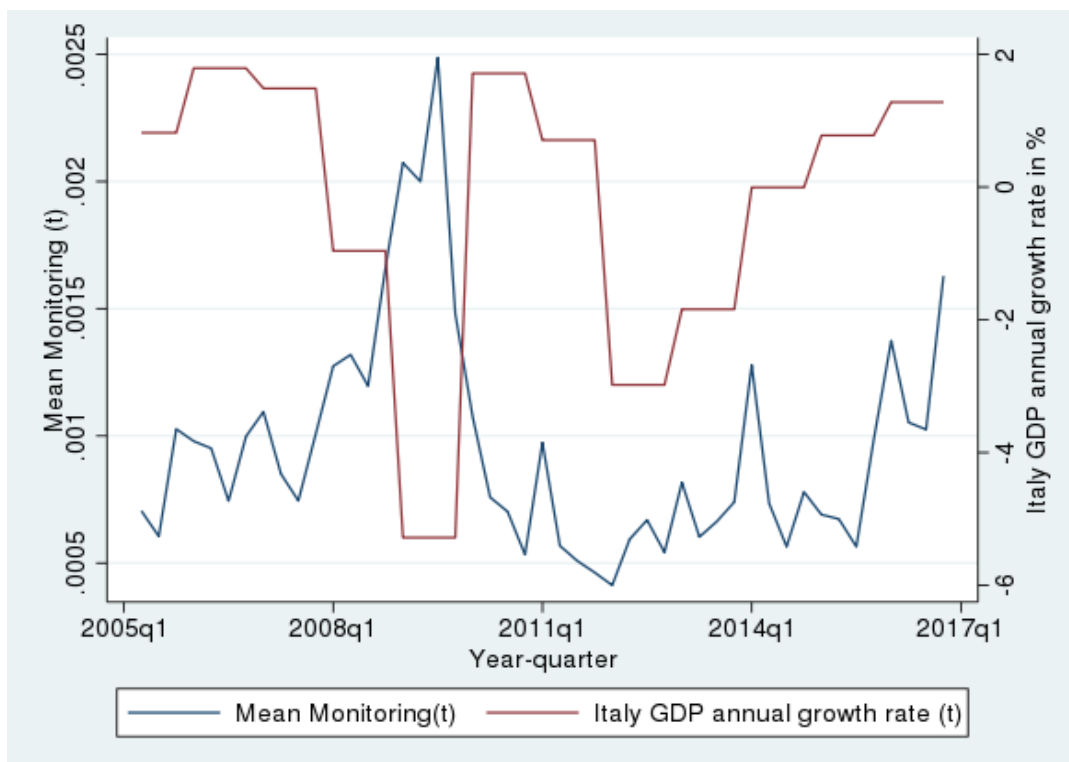


Figure 2: Bank requests for information associated with nonperforming exposures and exposures close to the CR thresholds

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).

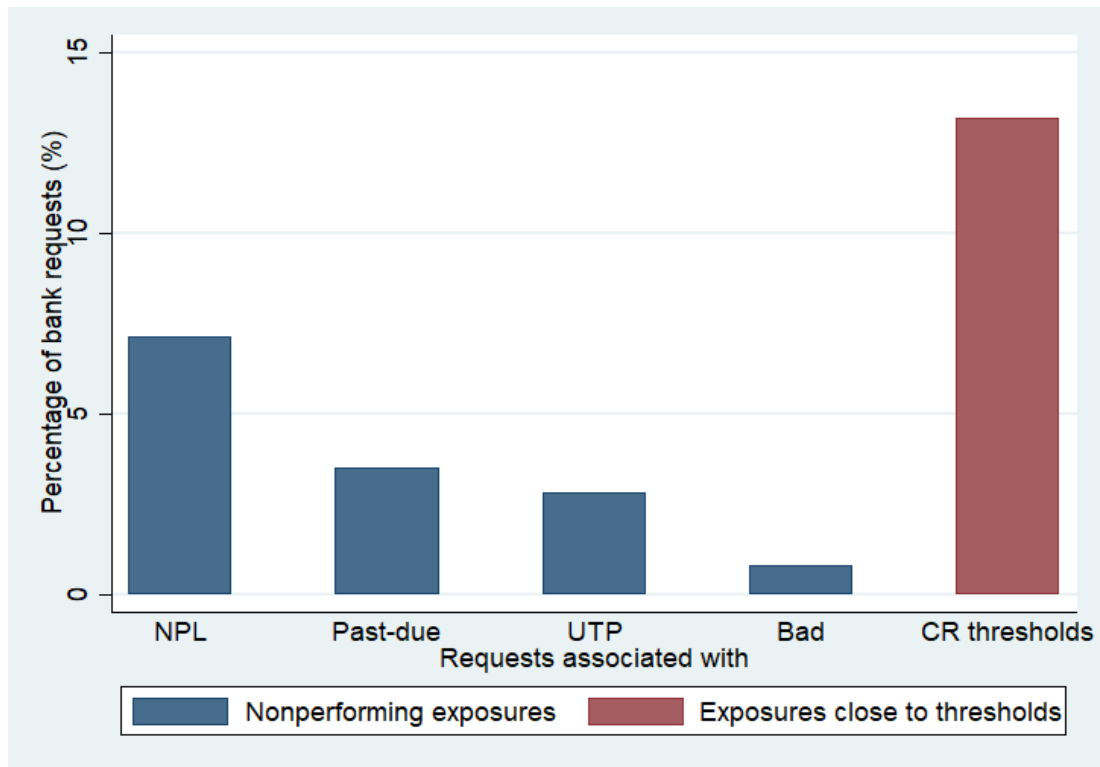


Figure 3: Distribution of firms and banks across Italian regions

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. The full sample includes 4,551,985 observations pertaining to 280,619 credit relationships having a duration greater than one quarter, and involving 223,703 firms and 457 banks over the period 2007-2016. The reduced sample has 556,284 observations and includes 53,744 credit relationships having a duration greater than three quarters, and involving 23,379 firms and 440 banks over the period 2007-2016.

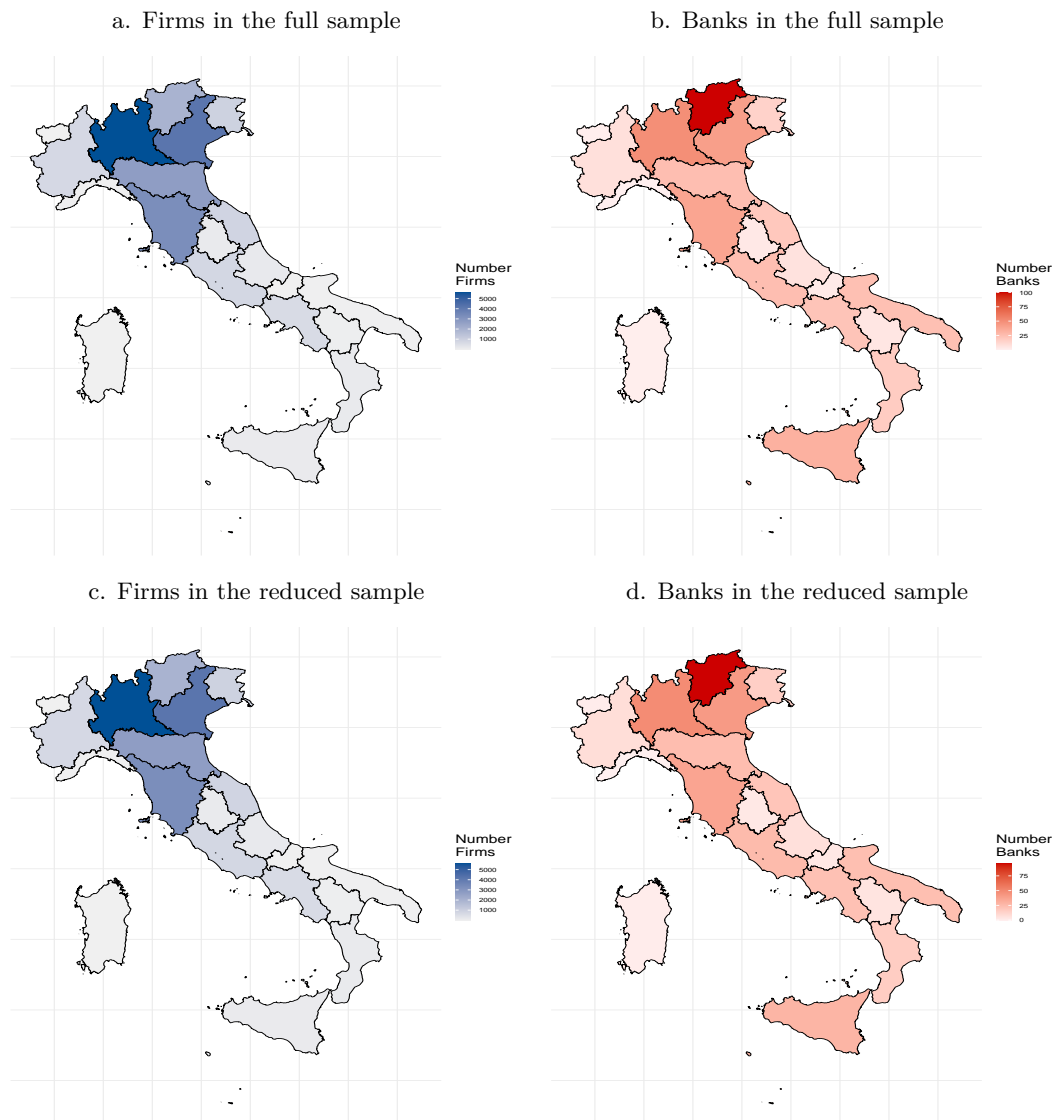
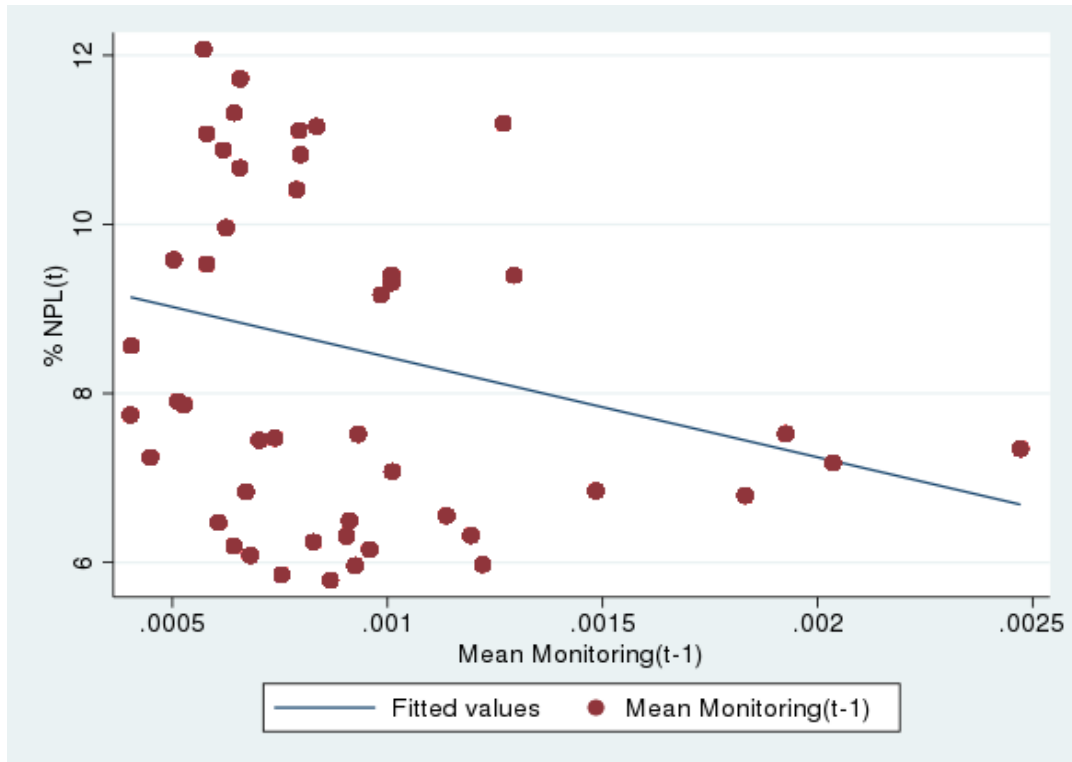


Figure 4: Nonperforming exposures versus bank requests for information

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 (a) and two quarters before (b). The plots refers to our full sample of 4,551,985 observations, covering the time period 2005-2016, from which we have dropped all observations in which we detect an increase in credit in the current quarter and/or in the previous two.

a. NPLs against the average number of requests one quarter before



b. NPLs against the average number of requests two quarters before

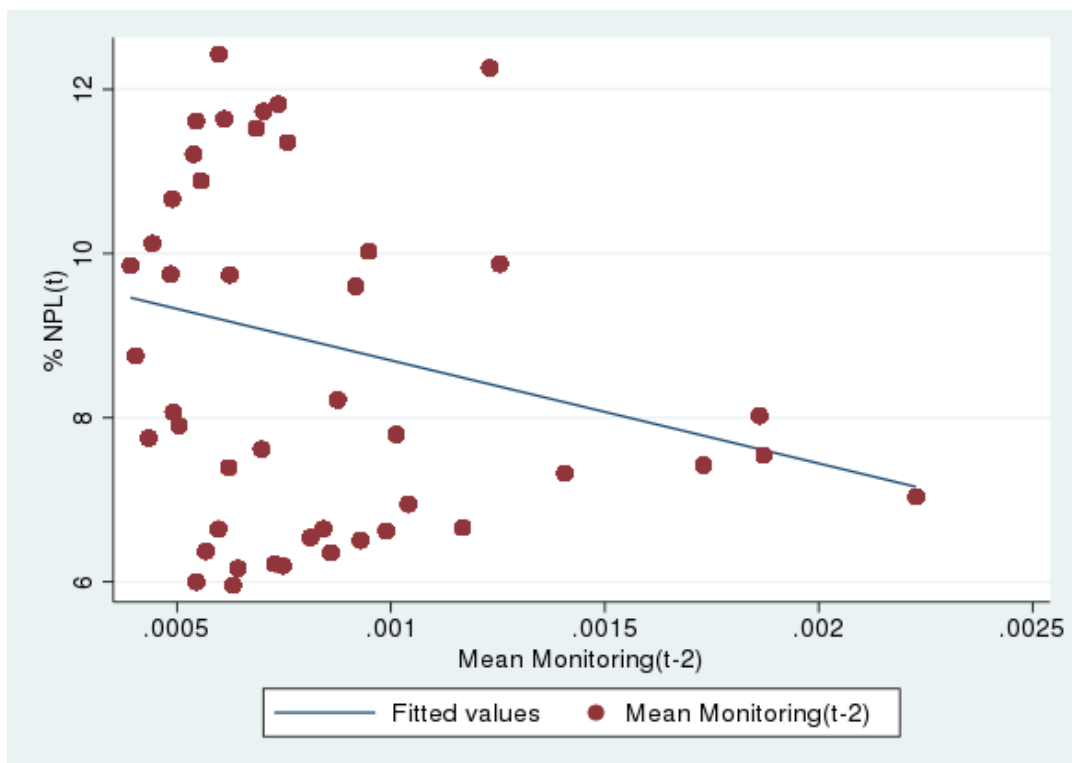


Table 1: Description of variables used in the empirical analysis

Variable name	Description
A. Loan-level variables	
NPL dummy	A dummy variable equal to one if the bank's 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 the bank's 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 the bank's 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 auto loan dummy	A dummy variable equal to one if an autoliquidating 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. To build this variable we aggregate all requests for information without making any distinction with respect to the stated motivation. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Loan amount	Total 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.
Auto loan dummy	A dummy equal to one if the bank's credit exposure to a firm includes an autoliquidating loan. Frequency: quarterly. Source: Credit Register of Bank of Italy.

Continued on next page

Table 1 – *Continued from previous page*

Variable name	Description
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. 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. The exposure is close to the minimum thresholds if (i) the total volume of the credit exposure is close or equal to €75,000 up to 2008 and €30,000 since then, or; (ii) the credit exposure is defined as bad loan and its volume, net of losses, is close or equal to €250. Frequency: quarterly. Source: Credit Register of Bank of Italy.
Average interest rate	Average of the interest rates charged on the various types of credit (term loan, credit line, autoliquidating 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. <i>Credit score firm</i> 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. <i>Industry firm</i> 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.

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Table 1 – *Continued from previous page*

Variable name	Description
D. Regional variables	
IRAP	The regional IRAP tax rate applied to the bank. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
IRAP start loan	The regional IRAP tax rate applied to the bank in the year preceding the start of the bank-firm credit relationship. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
IRAP start term loan	The regional IRAP tax rate 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 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 autoloan	The regional IRAP tax rate applied to the bank in the year preceding the start of the autoliquidating loan. Frequency: yearly. Source: Bank of Italy and Ministry of Economy and Finance.
GDP growth	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: Italian National Institute of Statistics (ISTAT).
Employment	Employment rate of the firm's region, expressed in percentage points. Frequency: yearly. Source: Italian National Institute of Statistics (ISTAT).
Inflation region bank	Inflation rate of the firm's region, expressed in percentage points. Frequency: yearly. Source: Italian National Institute of Statistics (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: Italian National Institute of Statistics (ISTAT).
Employment region bank	Employment rate of the bank's region, expressed in percentage points. Frequency: yearly. Source: Italian National Institute of Statistics (ISTAT).
Inflation region bank	Inflation rate of the bank's region, expressed in percentage points. Frequency: yearly. Source: Italian National Institute of Statistics (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. The independent 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 multicustering 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 .

	Monitored firms			Monitoring banks
	(1) Monitor _t	(2) Monitor _t	(3) Monitor _t	(4) Monitor _t
Loan amount _{t-1}	-0.000 (0.00)	-0.000 (0.00)	-0.000 (0.00)	-0.000 (0.00)
Length relation _{t-1}	-0.010***• (0.00)	-0.013***• (0.00)	-0.018***• (0.00)	-0.010***• (0.00)
Term loan dummy _{t-1}	-0.016***• (0.00)	-0.024***• (0.00)	-0.025***• (0.00)	-0.000 (0.00)
Credit line dummy _{t-1}	-0.000 (0.00)	-0.000 (0.00)	-0.000 (0.00)	0.000 (0.00)
Auto loan dummy _{t-1}	-0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
Share guarantee _{t-1}	-0.000 (0.00)	-0.000 (0.00)	-0.000 (0.00)	0.000 (0.00)
Share exposure _{t-1}	-0.011*• (0.00)	0.000 (0.00)	0.000 (0.00)	-0.000 (0.00)
Close threshold dummy _{t-1}	0.001*** (0.00)	0.001*** (0.00)	0.001*** (0.00)	0.001** (0.00)
Credit score firm _{t-4}	0.007***• (0.00)	0.000 (0.00)	0.000 (0.00)	
Capital ratio firm _{t-4}	0.031***• (0.00)	0.001*** (0.00)	0.001*** (0.00)	
ROA firm _{t-4}	0.000 (0.00)	0.001** (0.00)	0.001** (0.00)	
Size firm _{t-4}	0.010***• (0.00)	-0.049***• (0.00)	-0.001*** (0.00)	
Size firm _{t-4} *Length relation _{t-1}			0.001***• (0.00)	
Capital ratio bank _{t-4}				-0.001 (0.01)
ROA bank _{t-4}				0.020 (0.02)
NPL ratio bank _{t-4}				-0.011 (0.01)
Size bank _{t-4}				-0.002** (0.00)
Liquidity ratio bank _{t-4}				-0.017 (0.02)
Nonretail deposit ratio _{t-4}				-0.004** (0.00)
GDP growth region firm _{t-4}	0.006 (0.00)	0.004 (0.00)	0.004 (0.00)	

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Table 2 – *Continued from previous page*

Employment region firm $_{t-4}$	-0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	
Inflation region firm $_{t-4}$	-0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	
GDP growth region bank $_{t-4}$				-0.030 (0.02)
Employment region bank $_{t-4}$				0.000 (0.00)
Inflation region bank $_{t-4}$				-0.000 (0.00)
Year FE	-	-	-	-
Year-quarter FE	-	-	-	-
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	4180942	4174149	4174149	739202
R ²	0.012	0.114	0.114	0.469
Adjusted R ²	0.008	0.064	0.064	0.008

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
<i>Region</i>											
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: Descriptive statistics

The table reports summary statistics for the variables used in our regression analysis. In panel A, statistics refer to our full sample of 4,551,985 observations. This sample includes 280,619 credit relationships having a duration greater than one quarter, and involving 223,703 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. This panel has 556,284 observations and includes 53,744 credit relationships having a duration greater than three quarters, and involving 23,379 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	4551985	0.082	0.275	0.000	0.000	1.000
Past-due dummy _t	4551985	0.024	0.154	0.000	0.000	1.000
UTP dummy _t	4551985	0.034	0.182	0.000	0.000	1.000
Bad dummy _t	4551985	0.024	0.153	0.000	0.000	1.000
NPL term loan dummy _t	2179907	0.062	0.241	0.000	0.000	1.000
NPL credit line dummy _t	3765861	0.049	0.215	0.000	0.000	1.000
NPL auto loan dummy _t	2325589	0.014	0.118	0.000	0.000	1.000
Monitor _t	4551985	0.001	0.032	0.000	0.000	5.000
Loan amount _t	4551985	311470	700108	0.000	105457	64200000
Length relation _t	4551985	16.704	11.542	2.000	14.000	48.000
Term loan dummy _t	4551985	0.479	0.500	0.000	1.000	1.000
Credit line dummy _t	4551985	0.827	0.827	0.000	1.000	1.000
Auto loan dummy _t	4551985	0.511	0.500	0.000	1.000	1.000
Share guarantee _t	4551985	0.191	4.389	0.000	0.000	334.580
Share exposure _t	4551985	0.470	0.395	0.000	0.352	2.000
Close threshold dummy _t	4551985	0.051	0.220	0.000	0.000	1.000
Average interest rate _t						
Firm-level variables						
Credit score firm _t	4442112	5.212	1.951	1.000	5.000	9.000
Capital ratio firm _t	4498247	0.175	0.272	-1.764	0.134	1.000
ROA firm _t	4530647	-0.017	0.171	-3.023	0.003	0.484
Size firm _t	4551105	7.286	1.467	0.000	7.214	18.060
Bank-level variables						
Capital ratio bank _t	4289848	0.086	0.025	0.023	0.083	0.365
ROA bank _t	4284085	0.002	0.006	-0.202	0.002	0.043
NPL ratio bank _t	4346045	12.548	6.845	2.099	11.371	43.490
Size bank _t	4343292	6.749	0.980	2.378	6.727	9.392
Liquidity ratio bank _t	4289848	0.005	0.003	0.000	0.004	0.044
Nonretail deposit ratio bank _t	4343292	0.173	0.071	0.005	0.166	0.715
Regional variables						
IRAP _t	4551985	0.052	0.005	0.014	0.055	0.057
IRAP start loan	4551985	0.049	0.005	0.014	0.048	0.057
IRAP start term loan	2179907	0.049	0.005	0.014	0.050	0.057
IRAP start credit line	3765861	0.049	0.005	0.014	0.048	0.057
IRAP start auto loan	2325589	0.049	0.005	0.014	0.052	0.057
GDP growth region firm _t	4489971	-0.002	0.025	-0.088	0.006	0.085

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Table 4 – Continued from previous page

Employment region firm _t	4489971	48.177	5.333	30.350	9.860	55.200
Inflation region firm _t	4487358	1.448	1.146	-0.400	1.400	4.400
GDP growth region bank _t	4551985	-0.002	0.025	-0.088	0.006	0.085
Employment region bank _t	4551985	48.299	5.316	30.350	49.900	55.200
Inflation region bank _t	4549336	1.455	1.145	-0.400	1.400	4.400
Panel B: Multiple bank relationships						
Loan-level variables						
NPL dummy _t	556284	0.114	0.317	0.000	0.000	1.000
Past-due dummy _t	556284	0.023	0.150	0.000	0.000	1.000
UTP dummy _t	556284	0.050	0.219	0.000	0.000	1.000
Bad dummy _t	556284	0.040	0.196	0.000	0.000	1.000
NPL term loan dummy _t	556284	0.093	0.290	0.000	0.000	1.000
NPL credit line dummy _t	556284	0.063	0.243	0.000	0.000	1.000
NPL auto loan dummy _t	556284	0.017	0.128	0.000	0.000	1.000
Monitor _{t-2}	556284	0.001	0.029	0.000	0.000	2.000
Loan amount _{t-3}	556284	431176	835174	0.000	162913	55100000
Length relation _{t-3}	556284	17.865	11.039	1.000	16.000	45.000
Term loan dummy _{t-3}	556284	0.459	0.498	0.000	0.000	1.000
Credit line dummy _{t-3}	556284	0.856	0.351	0.000	1.000	1.000
Auto loan dummy _{t-3}	556284	0.596	0.491	0.000	1.000	1.000
Share guarantee _{t-3}	556284	0.142	3.607	0.000	0.000	331.126
Share exposure _{t-3}	556284	0.221	0.238	0.000	0.133	1.000
Close threshold dummy _{t-3}	556284	0.020	0.140	0.000	0.000	1.000
Average interest rate _{t-3}						
Firm-level variables						
Credit score firm _{t-6}	293512	5.444	1.757	1.000	6.000	9.000
Capital ratio firm _{t-6}	291956	0.166	0.194	-0.823	0.126	1.000
ROA firm _{t-6}	295446	-0.009	0.103	-1.427	0.002	0.407
Size firm _{t-6}	296617	8.151	1.403	0.000	8.050	15.665
Bank-level variables						
Capital ratio bank _{t-6}	556284	0.089	0.025	0.024	0.085	0.405
ROA bank _{t-6}	556284	0.003	0.005	-0.051	0.003	0.024
NPL ratio bank _{t-6}	556284	0.099	0.055	0.021	0.083	0.367
Size bank _{t-6}	556284	6.672	0.881	2.420	6.683	9.351
Liquidity ratio bank _{t-6}	556284	0.005	0.003	0.001	0.004	0.044
Nonretail deposit ratio bank _{t-6}	556284	0.168	0.066	0.005	0.161	0.715
Regional variables						
IRAP _{t-6}	556284	0.050	0.006	0.014	0.053	0.057
IRAP start loan	556284	0.048	0.005	0.014	0.048	0.057
IRAP start term loan	238799	0.048	0.006	0.014	0.048	0.057
IRAP start credit line	466882	0.048	0.005	0.014	0.048	0.057
IRAP start auto loan	320182	0.049	0.005	0.014	0.048	0.057
GDP growth region firm _{t-6}	550603	-0.004	0.027	-0.088	0.005	0.085

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Table 4 – *Continued from previous page*

Employment region firm _{<i>t</i>-6}	550603	49.470	4.491	30.350	50.200	55.200
Inflation region firm _{<i>t</i>-6}	550603	1.723	1.088	-0.200	1.600	4.400
GDP growth region bank _{<i>t</i>-6} 0.085	556284	-0.004	0.027	-0.088	1.600	0.005
Employment region bank _{<i>t</i>-6}	556284	49.577	4.514	30.350	50.200	55.200
Inflation region bank _{<i>t</i>-6}	556284	1.730	1.086	-0.200	1.600	4.400

Table 5: 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 (i) loan repayment (specifications (1)-(4) and (7)), and (ii) firm's conditions (specifications (5)-(6)). The dependent variable is displayed at the bottom of each column. The independent 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 10^5 .

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NPL dummy _t	Past-due dummy _t	UTP dummy _t	Bad dummy _t	Capital ratio firm _t	ROA firm _t	Credit score _t	NPL dummy _t
Monitor _{t-1}	-0.010** (0.00)	0.003 (0.00)	-0.005** (0.00)	-0.008*** (0.00)	0.010*** (0.00)	0.008** (0.00)	0.008 (0.02)	0.004 (0.01)
Loan amount _{t-1}	0.001***•• (0.00)	0.000 (0.00)	0.000 (0.00)	0.001***•• (0.00)	-0.001***•• (0.00)	-0.000 (0.00)	0.009***•• (0.00)	0.001***•• (0.00)
Length relation _{t-1}	0.001*** (0.00)	-0.000 (0.00)	0.032***• (0.00)	0.046***• (0.00)	0.012***• (0.00)	-0.005*• (0.00)	-0.001*** (0.00)	0.049***• (0.00)
Term loan dummy _{t-1}	-0.021*** (0.00)	0.010*** (0.00)	0.025*** (0.00)	-0.056*** (0.00)	0.001 (0.00)	-0.002** (0.00)	0.059*** (0.01)	-0.007*** (0.00)
Credit line dummy _{t-1}	-0.017*** (0.00)	0.033*** (0.00)	0.043*** (0.00)	-0.093*** (0.00)	0.025*** (0.00)	0.002* (0.00)	0.009 (0.01)	0.017*** (0.00)
Auto loan dummy _{t-1}	-0.092*** (0.00)	-0.005*** (0.00)	-0.024*** (0.00)	-0.063*** (0.00)	0.036*** (0.00)	0.013*** (0.00)	-0.031*** (0.01)	-0.029*** (0.00)
Share guarantee _{t-1}	0.025***• (0.00)	0.022***• (0.00)	0.000 (0.00)	-0.008*** (0.00)	0.012***• (0.00)	-0.000 (0.00)	-0.000 (0.00)	-0.000 (0.00)
Share exposure _{t-1}	0.017*** (0.00)	-0.001 (0.00)	-0.002 (0.00)	0.020*** (0.00)	0.013*** (0.00)	0.001 (0.00)	-0.119*** (0.01)	0.023*** (0.00)
Close threshold dummy _{t-1}	-0.003 (0.00)	0.002** (0.00)	0.006*** (0.00)	-0.011*** (0.00)	0.010*** (0.00)	-0.001 (0.00)	-0.052*** (0.01)	-0.005 (0.00)
Credit score firm _{t-4}	0.002*** (0.00)	0.001*** (0.00)	0.002*** (0.00)	-0.002*** (0.00)	-0.032*** (0.00)	-0.009*** (0.00)		
Capital ratio firm _{t-4}	-0.255*** (0.01)	0.002 (0.00)	-0.087*** (0.01)	-0.171*** (0.01)		-0.022*** (0.01)	-1.856*** (0.14)	
ROA firm _{t-4}	-0.154*** (0.01)	-0.030*** (0.00)	-0.084*** (0.01)	-0.039*** (0.01)	0.358*** (0.01)		-1.447*** (0.09)	
Size firm _{t-4}	-0.031*** (0.00)	-0.001 (0.00)	-0.014*** (0.00)	-0.016*** (0.00)	0.026*** (0.00)	0.011*** (0.00)	-0.074*** (0.02)	
Capital ratio bank _{t-4}	-0.169* (0.09)	0.098** (0.04)	-0.153** (0.07)	-0.115*** (0.04)	0.150*** (0.04)	0.051 (0.03)	-0.120 (0.33)	0.090 (0.07)
ROA bank _{t-4}	-0.825*** (0.14)	0.134** (0.06)	-0.673*** (0.11)	-0.288*** (0.06)	0.219*** (0.06)	0.186*** (0.05)	-0.138 (0.41)	-0.485*** (0.15)
NPL ratio bank _{t-4}	-0.004 (0.05)	0.001 (0.02)	0.005 (0.04)	-0.008 (0.02)	-0.119*** (0.03)	-0.050*** (0.02)	-0.211 (0.23)	-0.061 (0.08)
Size bank _{t-4}	-0.002 (0.01)	0.005** (0.00)	-0.002 (0.00)	-0.005* (0.00)	-0.001 (0.00)	-0.005** (0.00)	0.030 (0.03)	0.009 (0.01)
Liquidity ratio bank _{t-4}	-0.066 (0.14)	-0.060 (0.10)	-0.048 (0.13)	0.040 (0.09)	0.026 (0.09)	0.013 (0.11)	-2.363 (1.97)	0.064 (0.23)
Nonretail deposit ratio _{t-4}	-0.020 (0.02)	0.012 (0.01)	-0.027* (0.01)	-0.004 (0.01)	-0.006 (0.01)	0.010 (0.01)	-0.243** (0.09)	0.045** (0.02)
GDP growth region firm _{t-4}	0.021 (0.06)	-0.051 (0.03)	0.037 (0.04)	0.033 (0.03)	0.028 (0.03)	0.083** (0.04)	-0.383 (0.29)	
Employment region firm _{t-4}	-0.007** (0.00)	0.001 (0.00)	-0.006*** (0.00)	-0.003** (0.00)	0.001 (0.00)	0.000 (0.00)	0.011 (0.01)	
Inflation region firm _{t-4}	-0.004 (0.01)	-0.002 (0.00)	-0.000 (0.00)	-0.001 (0.00)	0.001 (0.00)	-0.004 (0.00)	-0.003 (0.02)	
GDP growth region bank _{t-4}	-0.020 (0.06)	0.041 (0.04)	-0.028 (0.05)	-0.031 (0.03)	-0.014 (0.03)	-0.060 (0.04)	0.187 (0.33)	-0.187* (0.10)
Employment region bank _{t-4}	0.006* (0.00)	-0.002 (0.00)	0.006*** (0.00)	0.002 (0.00)	-0.000 (0.00)	-0.000 (0.00)	-0.003 (0.01)	-0.001 (0.00)
Inflation region bank _{t-4}	0.004 (0.00)	0.002 (0.00)	0.001 (0.00)	0.002 (0.00)	-0.003 (0.00)	0.003 (0.00)	-0.013 (0.02)	0.006 (0.01)
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Region firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Region bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Industry firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Firm-quarter FE	No	No	No	No	No	No	No	Yes
N	3564475	3564475	3564475	3564475	3560802	3559958	3549357	688071
R ²	0.5291	0.2375	0.4238	0.5800	0.8108	0.4737	0.7905	0.8230
Adjusted R ²	0.5028	0.1949	0.3916	0.5565	0.8002	0.4443	0.7787	0.6692
F-test statistic	70.880***	25.982***	45.853***	38.933***	154.089***	41.270***	32.241***	24.659***
degrees of freedom	(25, 39)	(25, 39)	(25, 39)	(25, 39)	(24, 39)	(24, 39)	(24, 39)	(18, 39)

Table 6: 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. *Basic IRAP* is the basic IRAP tax rate for banks defined at the national level. $\Delta IRAP\ health$ 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 bank* and *ROA region bank* are the aggregate capital ratio and ROA of the banking system at the regional level, respectively. *NPL ratio region bank* is the average ratio of nonperforming loans of banks operating in a specific region. The remaining 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 in the availability 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 multicustering at the year and regional level. Fixed effects are included, "Yes". ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	IRAP _t	IRAP _t	IRAP _t	IRAP _t	IRAP _t	IRAP _t
GDP growth region bank _{t-1}	-0.057 (1.35)	0.040 (1.30)			0.362 (0.83)	0.407 (0.82)
Employment region bank _{t-1}	-0.019 (0.02)	-0.020 (0.02)			0.001 (0.01)	0.000 (0.01)
Inflation region bank _{t-1}	-0.039 (0.02)	-0.036 (0.02)			-0.033 (0.02)	-0.030 (0.02)
Basic IRAP _t	0.978*** (0.10)	0.989*** (0.10)	1.049*** (0.04)	1.066*** (0.03)	1.023*** (0.04)	1.030*** (0.03)
$\Delta IRAP\ health_t$		0.146** (0.07)		0.138** (0.05)		0.098 (0.07)
Capital ratio region bank _{t-1}			3.524 (5.64)	3.894 (5.66)	3.169 (4.40)	3.374 (4.43)
ROA region bank _{t-1}			-1.741 (9.12)	-0.918 (8.75)	-3.419 (7.55)	-3.152 (7.12)
NPL ratio region bank _{t-1}			0.005 (0.01)	0.006 (0.01)	-0.001 (0.01)	0.000 (0.01)
Region bank FE	Yes	Yes	Yes	Yes	Yes	Yes
N	229	229	190	190	187	187
R ²	0.662	0.663	0.728	0.729	0.718	0.718
Adjusted R ²	0.624	0.623	0.692	0.691	0.674	0.672

Table 7: 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. The independent 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 multicustering 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 10^3 , 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}		-9.585*	-4.737	-5.975*	0.916
		(5.31)	(3.89)	(3.43)	(0.90)
IRAP _{t-6}	-0.412**				
	(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}	-0.101***●	-0.000	-0.001	-0.000	0.270***●
	(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)
Auto 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	0.023***	0.011***	0.004	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)	(0.01)	(0.01)	(0.00)
Capital ratio bank _{t-6}	0.019	0.354*	0.282**	0.092	-0.017
	(0.02)	(0.21)	(0.13)	(0.14)	(0.06)
ROA bank _{t-6}	-0.001	-0.359	0.132	-0.293	-0.197**
	(0.02)	(0.33)	(0.17)	(0.21)	(0.09)
NPL ratio bank _{t-6}	-0.005	-0.067	0.030	0.022	-0.118**
	(0.02)	(0.18)	(0.10)	(0.13)	(0.05)
Size bank _{t-6}	-0.001	0.002	-0.004	0.008	-0.002
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)
Liquidity ratio bank _{t-6}	0.008	0.459	0.144	0.175	0.139
	(0.04)	(0.40)	(0.26)	(0.31)	(0.11)
Nonretail deposit ratio bank _{t-6}	-0.004	0.000	-0.012	0.006	0.006
	(0.00)	(0.03)	(0.02)	(0.02)	(0.01)
GDP growth region bank _{t-6}	-0.048	-0.499*	-0.337*	-0.203	0.035
	(0.03)	(0.29)	(0.19)	(0.21)	(0.07)
Employment region bank _{t-6}	0.001*	0.006	0.004	0.004	-0.002
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Inflation region bank _{t-6}	-0.001	0.004	-0.009	0.019*	-0.006
	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)
Firm-quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes	Yes
N	556284	556284	556284	556284	556284
R ²	0.469				

Continued on next page

Table 7 – *Continued from previous page*

Adjusted R ²	0.005				
F-test statistic		10.354***	3.911***	12.538***	8.843***
degrees of freedom		(18, 37)	(18, 37)	(18, 37)	(18, 37)
<i>Underidentification test</i>					
Kleibergen-Paap LM statistic	3.99				
Chi-sq P-val	0.05				
<i>Weak identification test</i>					
Kleibergen-Paap Wald F statistic	4.92				
Cragg-Donald Wald F statistic	18.06				
Stock-Yogo critical value	16.38				
10% maximal IV size					
<i>Anderson-Rubin test</i>					
Anderson-Rubin Wald statistic		6.73***	1.92	6.36**	1.25
Chi-sq P-val		0.01	0.17	0.01	0.26

Table 8: 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. The independent 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 multicustering 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 10², whereas ●● denotes rescaled coefficients that have been multiplied by 10⁸. 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Monitor _{t-1}	NPL dummy _t	Monitor _{t-2}	NPL dummy _t	Monitor _{t-3}	NPL dummy _t	Monitor _{t-4}	NPL dummy _t	Monitor _{t-8}	NPL dummy _t
Monitor _{t-n}		-11.369 (7.68)		-9.585* (5.31)		-7.176* (4.04)		-6.454 (3.93)		-7.065 (6.27)
IRAP _{t-n-4}	-0.317** (0.16)		-0.412** (0.19)		-0.448** (0.21)		-0.475** (0.22)		-0.003 (0.00)	
Loan amount _{t-n-1}	0.000 (0.00)	0.001***● (0.00)	-0.000 (0.00)	0.689***● (0.00)	0.000 (0.00)	0.786***● (0.00)	0.000 (0.00)	0.821***● (0.00)	-0.030*● (0.00)	0.000 (0.00)
Length relation _{t-n-1}	-0.010***● (0.00)	-0.001 (0.00)	-0.101***● (0.00)	-0.000 (0.00)	-0.010***● (0.00)	-0.000 (0.00)	-0.009***● (0.00)	-0.000 (0.00)	-0.009***● (0.00)	-0.000 (0.00)
Term loan dummy _{t-n-1}	-0.000 (0.00)	-0.007*** (0.00)	-0.000 (0.00)	-0.007*** (0.00)	-0.000 (0.00)	-0.008*** (0.00)	-0.000 (0.00)	-0.007*** (0.00)	0.000 (0.00)	-0.003 (0.00)
Credit line dummy _{t-n-1}	0.000 (0.00)	0.014*** (0.00)	0.000 (0.00)	0.011*** (0.00)	0.000 (0.00)	0.010*** (0.00)	-0.000 (0.00)	0.009*** (0.00)	0.000 (0.00)	0.002 (0.00)
Auto loan dummy _{t-n-1}	0.000 (0.00)	-0.021*** (0.00)	0.000 (0.00)	-0.017*** (0.00)	0.000 (0.00)	-0.015*** (0.00)	0.000 (0.00)	-0.013*** (0.00)	-0.000 (0.00)	-0.008* (0.00)
Share guarantee _{t-n-1}	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	-0.000 (0.00)	0.000 (0.00)
Share exposure _{t-n-1}	-0.000 (0.00)	0.020*** (0.00)	-0.000 (0.00)	0.023*** (0.00)	-0.000 (0.00)	0.025*** (0.00)	-0.000 (0.00)	0.024*** (0.00)	0.000 (0.00)	0.024*** (0.00)
Close threshold dummy _{t-n-1}	0.001 (0.00)	0.010 (0.01)	0.001 (0.00)	0.003 (0.01)	0.000 (0.00)	-0.001 (0.01)	0.001 (0.00)	0.003 (0.01)	0.000 (0.00)	-0.001 (0.01)
Capital ratio bank _{t-n-4}	0.012 (0.02)	0.244 (0.20)	0.019 (0.02)	0.354* (0.21)	0.014 (0.02)	0.340** (0.16)	0.034* (0.02)	0.479** (0.20)	0.066 (0.04)	0.749 (0.50)
ROA bank _{t-n-4}	0.002 (0.02)	-0.436 (0.33)	-0.001 (0.02)	-0.359 (0.33)	-0.007 (0.02)	-0.189 (0.27)	0.008 (0.02)	-0.145 (0.25)	0.008 (0.04)	-0.171 (0.38)
NPL ratio bank _{t-n-4}	-0.013 (0.01)	-0.169 (0.21)	-0.005 (0.02)	-0.067 (0.18)	-0.017 (0.02)	-0.188 (0.18)	-0.007 (0.02)	-0.097 (0.15)	-0.047 (0.04)	-0.488 (0.36)
Size bank _{t-n-4}	-0.001* (0.00)	-0.005 (0.01)	-0.001 (0.00)	0.002 (0.01)	-0.001 (0.00)	0.006 (0.01)	-0.000 (0.00)	0.008 (0.01)	0.001 (0.00)	0.029* (0.01)
Liquidity ratio bank _{t-n-4}	-0.023 (0.03)	-0.022 (0.41)	0.008 (0.04)	0.459 (0.40)	0.039 (0.04)	0.422 (0.43)	0.048 (0.05)	0.413 (0.48)	0.082 (0.09)	0.926 (0.79)
Nonretail deposit ratio bank _{t-n-4}	-0.005** (0.00)	-0.020 (0.05)	-0.004 (0.00)	0.000 (0.03)	-0.003 (0.00)	0.014 (0.03)	-0.003 (0.00)	-0.001 (0.03)	-0.000 (0.00)	0.030 (0.04)
GDP growth region bank _{t-n-4}	-0.057** (0.03)	-0.796** (0.39)	-0.048 (0.03)	-0.499* (0.29)	-0.051 (0.04)	-0.388 (0.30)	-0.057 (0.04)	-0.164 (0.35)	-0.082* (0.04)	-0.232 (0.58)
Employment region bank _{t-n-4}	0.001 (0.00)	0.005 (0.01)	0.001* (0.00)	0.006 (0.01)	0.001** (0.00)	0.010 (0.01)	0.001* (0.00)	0.012* (0.01)	0.001 (0.01)	0.006 (0.01)
Inflation region bank _{t-n-4}	-0.001 (0.00)	-0.000 (0.02)	-0.001 (0.00)	0.004 (0.02)	-0.002 (0.00)	-0.005 (0.02)	-0.002 (0.00)	-0.012 (0.02)	-0.001 (0.00)	-0.004 (0.03)
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	677604	677604	556284	556284	461556	461556	389098	389098	204885	204885
R ²	0.470		0.469		0.473		0.472		0.470	
Adjusted R ²	0.009		0.005		0.010		0.006		-0.005	
F-test statistic		9.461***		10.354***		12.042***		11.898***		4.922***
degrees of freedom		(18, 38)		(18, 37)		(18, 36)		(18, 35)		(18, 31)
<i>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 1 p.p. in the tax rate</i>		-3.60%		-3.95%		-3.21%		-3.07%		-0.02%
<i>Underidentification test</i>										
Kleibergen-Paap LM statistic	3.51		3.99		3.71		3.87		2.30	
Chi-sq P-val	0.06		0.05		0.05		0.05		0.13	
<i>Weak identification test</i>										
Kleibergen-Paap Wald F statistic	4.09		4.92		4.58		4.67		2.40	
Cragg-Donald Wald F statistic	11.73		18.06		19.51		19.07		4.97	
Stock-Yogo critical value	16.38		16.38		16.38		16.38		16.38	
<i>Anderson-Rubin test</i>										
Anderson-Rubin Wald statistic		5.95**		6.73***		5.05**		4.59**		2.30
Chi-sq P-val		0.01		0.01		0.02		0.03		0.13

Table 9: 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. The independent 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 multicustering 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 10^6 .

	(1)	(2)	(3)	(4)
	NPL dummy _t	Past-due dummy _t	UTP dummy _t	Bad dummy _t
IRAP _{t-6}	4.914** (1.84)	1.710 (1.65)	3.790*** (1.06)	-0.553 (0.39)
Loan amount _{t-3}	0.008***●● (0.00)	0.000 (0.00)	0.004***●● (0.00)	0.002***●● (0.00)
Length relation _{t-3}	0.001*** (0.00)	-0.008*● (0.00)	0.042***● (0.00)	0.020***● (0.00)
Term loan dummy _{t-3}	-0.007*** (0.00)	-0.001 (0.00)	0.014*** (0.00)	-0.020*** (0.00)
Credit line dummy _{t-3}	0.008*** (0.00)	0.005*** (0.00)	0.034*** (0.00)	-0.031*** (0.00)
Auto loan dummy _{t-3}	-0.017*** (0.00)	-0.008*** (0.00)	-0.002 (0.00)	-0.008*** (0.00)
Share guarantee _{t-3}	0.000 (0.00)	0.000* (0.00)	0.001** (0.00)	-0.001** (0.00)
Share exposure _{t-3}	0.023*** (0.00)	0.011*** (0.00)	0.002 (0.00)	0.010*** (0.00)
Close threshold dummy _{t-3}	-0.003 (0.01)	-0.005 (0.00)	0.001 (0.00)	0.000 (0.00)
Capital ratio bank _{t-6}	0.210** (0.09)	0.208*** (0.06)	-0.010 (0.10)	0.011 (0.06)
ROA bank _{t-6}	-0.328 (0.20)	0.101 (0.11)	-0.202 (0.18)	-0.222** (0.11)
NPL ratio bank _{t-6}	-0.039 (0.11)	0.053 (0.08)	0.066 (0.10)	-0.154** (0.06)
Size bank _{t-6}	0.012* (0.01)	0.001 (0.00)	0.014** (0.01)	-0.004 (0.00)
Liquidity ratio bank _{t-6}	0.533** (0.25)	0.091 (0.22)	0.219 (0.23)	0.221 (0.14)
Nonretail deposit ratio bank _{t-6}	0.050** (0.02)	0.022 (0.01)	0.029 (0.02)	-0.000 (0.01)
GDP growth region bank _{t-6}	-0.058 (0.17)	-0.149 (0.12)	0.119 (0.15)	-0.015 (0.06)
Employment region bank _{t-6}	-0.001 (0.01)	0.001 (0.00)	-0.000 (0.00)	-0.002 (0.00)
Inflation region bank _{t-6}	0.025** (0.01)	-0.001 (0.01)	0.033*** (0.01)	-0.006 (0.01)
Firm-quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes	Yes
N	435367	435367	435367	435367
R ²	0.854	0.554	0.723	0.917
Adjusted R ²	0.725	0.162	0.479	0.844

Table 10: Different types of credit

The table reports panel regression estimates of the 2SLS model of equation 5 and the reduced form model of equation 6 per type of credit (term loan, credit line and autoliquidating loan). The dependent variable is displayed at the bottom of each column. The independent 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 multicustering 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 10^7 . 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		Auto. loan		Term loan	Credit line	Auto. 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}		-3.831*		-8.466		-6.352			
		(1.96)		(5.85)		(3.88)			
IRAP _{t-6}	-1.258**		-0.443*		-0.624*		7.020***	4.410**	3.112**
	(0.61)		(0.25)		(0.34)		(2.47)	(1.67)	(1.29)
Loan amount _{t-3}	0.000	0.000	-0.000	0.000	-0.000	0.000	0.039**●●	0.024**●●	0.074***●●
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Length relation _{t-3}	-0.010***●	0.001**	-0.010***●	-0.001	-0.010***●	-0.000	0.001***	0.036***●	0.036***●
	(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}	0.000	0.005			0.001	0.005	0.005		0.002
	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)		(0.00)
Auto loan dummy _{t-3}	0.001	-0.016***	-0.000	-0.018***			-0.019***	-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	0.009**	0.000	0.006*	0.016*	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	0.004	0.000	0.007	0.001	-0.004	0.019	0.002	-0.013**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
Capital ratio bank _{t-6}	-0.035	-0.051	0.016	0.172	-0.002	-0.047	0.069	0.035	-0.056
	(0.03)	(0.23)	(0.02)	(0.17)	(0.02)	(0.13)	(0.21)	(0.08)	(0.07)
ROA bank _{t-6}	-0.038	-0.734	-0.018	-0.662**	-0.016	-0.246	-0.323	-0.504***	-0.108
	(0.03)	(0.20)	(0.02)	(0.15)	(0.02)	(0.20)	(0.26)	(0.10)	(0.08)
ROA bank _{t-6}	-0.038	-0.734	-0.018	-0.662**	-0.016	-0.246	-0.323	-0.504***	-0.108
	(0.03)	(0.20)	(0.02)	(0.15)	(0.02)	(0.20)	(0.26)	(0.10)	(0.08)
NPL ratio bank _{t-6}	0.003	-0.213	-0.001	0.035	-0.025	-0.249	-0.215	-0.023	-0.140*
	(0.03)	(0.20)	(0.02)	(0.15)	(0.02)	(0.20)	(0.26)	(0.10)	(0.08)
Size bank _{t-6}	-0.002	0.013	-0.001	0.002	-0.000	0.002	0.018	0.008	0.002
	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
Liquidity ratio bank _{t-6}	-0.067	1.050*	-0.042*	-0.292	-0.030	-0.108	1.633**	0.067	0.210
	(0.06)	(0.62)	(0.02)	(0.35)	(0.02)	(0.22)	(0.70)	(0.20)	(0.16)
Nonretail deposit ratio bank _{t-6}	-0.002	0.068	-0.002	0.013	-0.003	0.003	0.080*	0.033	0.025
	(0.00)	(0.04)	(0.00)	(0.03)	(0.00)	(0.03)	(0.05)	(0.02)	(0.02)
GDP growth region bank _{t-6}	-0.151*	-0.147	-0.063	-0.811***	-0.091*	-0.518*	0.761**	-0.303*	0.036
	(0.09)	(0.46)	(0.04)	(0.28)	(0.05)	(0.29)	(0.29)	(0.16)	(0.12)
Employment region bank _{t-6}	0.000	0.002	0.001*	0.012	-0.000	-0.007	0.005	-0.000	-0.006
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Inflation region bank _{t-6}	-0.003	0.019	-0.000	0.004	0.001	0.020	0.034	0.016	0.012
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
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	141646	141646	426771	426771	284519	284519	101664	331624	215762
R ²	0.478		0.479		0.4643		0.7961	0.7615	0.6323
Adjusted R ²	0.018		0.012		-0.0231		0.6158	0.5460	0.2944
F-test statistic		5.975***		5.175***		2.246**	6.578***	5.553***	3.891***
degrees of freedom		(17, 37)		(17, 37)		(17, 37)	(17, 37)	(17, 37)	(17, 37)
<i>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 1 p.p. in the tax rate</i>									
		-4.8%		-3.8%		-4.0%			
<i>Underidentification test</i>									
Kleibergen-Paap LM statistic	3.49		2.86		3.32				
Chi-sq P-val	0.06		0.09		0.07				
<i>Weak identification test</i>									
Kleibergen-Paap Wald F statistic	4.29		3.04		3.43				
Cragg-Donald Wald F statistic	45.50		16.33		20.61				
Stock-Yogo critical value	16.38		16.38		16.38				
<i>Anderson-Rubin test</i>									
Anderson-Rubin Wald statistic		5.42**		7.03***		11.31***			
Chi-sq P-val		0.02		0.01		0.00			

Table 11: 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 equation 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. The independent 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 10^6 . 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 $_{t-2}$		-9.524*	
		(5.26)	
IRAP $_{t-6}$	-0.409**		4.839**
	(0.18)		(1.83)
IRAP start loan	-0.014	0.115	0.464*
	(0.03)	(0.36)	(0.25)
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***	-0.007***
	(0.00)	(0.00)	(0.00)
Credit line dummy $_{t-3}$	0.000	0.011***	0.008***
	(0.00)	(0.00)	(0.00)
Auto 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	0.023***	0.023***
	(0.00)	(0.00)	(0.00)
Close threshold dummy $_{t-3}$	0.001	0.003	-0.003
	(0.00)	(0.01)	(0.01)
Capital ratio bank $_{t-6}$	0.019	0.353*	0.211**
	(0.02)	(0.21)	(0.09)
ROA bank $_{t-6}$	-0.001	-0.358	-0.325
	(0.02)	(0.33)	(0.20)
NPL ratio bank $_{t-6}$	-0.005	-0.066	-0.039
	(0.02)	(0.18)	(0.11)
Size bank $_{t-6}$	-0.001	0.002	0.011
	(0.00)	(0.01)	(0.01)
Liquidity ratio bank $_{t-6}$	0.008	0.459	0.535**
	(0.04)	(0.40)	(0.25)
Nonretail deposit ratio bank $_{t-6}$	-0.004	0.001	0.049**
	(0.00)	(0.03)	(0.02)
GDP growth region bank $_{t-6}$	-0.048	-0.496*	-0.058
	(0.03)	(0.29)	(0.17)
Employment region bank $_{t-6}$	0.001*	0.006	-0.000

Continued on next page

Table 11 – *Continued from previous page*

	(0.00)	(0.01)	(0.01)
Inflation region bank $_{t-6}$	-0.001	0.004	0.025**
	(0.00)	(0.02)	(0.01)
Firm-quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes
N	556284	556284	435367
R ²	0.469		0.8535
Adjusted R ²	0.005		0.7247
F-test statistic		13.156***	15.229***
degrees of freedom		(19, 37)	(19, 37)
<i>Underidentification test</i>			
Kleibergen-Paap LM statistic	4.03		
Chi-sq P-val	0.04		
<i>Weak identification test</i>			
Kleibergen-Paap Wald F statistic	4.96		
Cragg-Donald Wald F statistic	17.77		
Stock-Yogo critical value	16.38		
10% maximal IV size			
<i>Anderson-Rubin test</i>			
Anderson-Rubin Wald statistic		6.53**	
Chi-sq P-val		0.01	

Table 12: 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 equation 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 autoliquidating loan as a control variable. The dependent variable is displayed at the bottom of each column. The independent 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 10^6 . 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		Autoliquidating loan		Term loan	Credit line	Autoliquidating loan
	First stage	Second stage	First stage	Second stage	First stage	Second stage			
	(1)	(2)	(1)	(2)	(1)	(2)	(3)	(3)	(3)
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}		-3.746*		-8.455		-6.404			
		(1.94)		(5.86)		(3.93)			
IRAP _{t-6}	-1.243**		-0.436*		-0.618*		6.841***	4.322**	3.114**
	(0.60)		(0.25)		(0.33)		(2.47)	(1.65)	(1.29)
IRAP start term loan	-0.056	0.404					0.908**		
	(0.05)	(0.45)					(0.43)		
IRAP start credit line			-0.032	0.023				0.587**	
			(0.03)	(0.35)				(0.25)	
IRAP start autoliquidating loan					-0.028	-0.158			-0.011
					(0.04)	(0.34)			(0.21)
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	-0.010***●	-0.000	0.001***	0.040***●	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}	0.000	0.005			0.001	0.005	0.004		0.002
	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)		(0.00)
Auto loan dummy _{t-3}	0.001	-0.016***	-0.000	-0.018***			-0.019***	-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	0.009**	0.000	0.006*	0.016*	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	0.004	0.000	0.007	0.001	-0.004	0.019	0.002	-0.013**
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
Capital ratio bank _{t-6}	-0.035	-0.047	0.016	0.172	-0.002	-0.047	0.075	0.036	-0.056
	(0.03)	(0.23)	(0.02)	(0.17)	(0.02)	(0.14)	(0.21)	(0.08)	(0.07)
ROA bank _{t-6}	-0.038	-0.727	-0.018	-0.662**	-0.016	-0.248	-0.316	-0.499***	-0.108
	(0.05)	(0.45)	(0.03)	(0.32)	(0.03)	(0.26)	(0.45)	(0.17)	(0.13)
NPL ratio bank _{t-6}	0.003	-0.212	-0.001	0.035	-0.025	-0.250	-0.211	-0.024	-0.140*
	(0.03)	(0.20)	(0.02)	(0.15)	(0.02)	(0.26)	(0.20)	(0.10)	(0.08)
Size bank _{t-6}	-0.002	0.013	-0.001	0.002	-0.000	0.002	0.017	0.008	0.002
	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
Liquidity ratio bank _{t-6}	-0.068	1.057*	-0.042*	-0.291	-0.031	-0.111	1.626**	0.067	0.210
	(0.06)	(0.62)	(0.02)	(0.35)	(0.02)	(0.23)	(0.70)	(0.20)	(0.16)
Nonretail deposit ratio bank _{t-6}	-0.002	0.068	-0.002	0.013	-0.003	0.003	0.079*	0.032	0.025
	(0.00)	(0.04)	(0.00)	(0.03)	(0.00)	(0.03)	(0.05)	(0.02)	(0.02)
GDP growth region bank _{t-6}	-0.150*	-0.137	-0.063	-0.810***	-0.091*	-0.523*	0.754**	-0.303*	0.036
	(0.09)	(0.46)	(0.04)	(0.28)	(0.05)	(0.30)	(0.29)	(0.16)	(0.12)
Employment region bank _{t-6}	0.000	0.003	0.001*	0.012	-0.000	-0.007	0.006	-0.000	-0.006
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Inflation region bank _{t-6}	-0.003	0.020	-0.000	0.004	0.001	0.019	0.035*	0.017	0.012
	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)	(0.02)	(0.01)	(0.01)
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	141609	141609	426771	426771	284519	284519	101664	331624	215762
R ²	0.478		0.479		0.4643		0.7962	0.7616	0.6323
Adjusted R ²	0.018		0.012		-0.0231		0.6159	0.5460	0.2944
F-test statistic		5.647***		4.894***		2.231***	6.263***	5.165***	3.717***
degrees of freedom		(18, 37)		(18, 37)		(18, 37)	(18, 37)	(18, 37)	(18, 37)
<i>Underidentification test</i>									
Kleibergen-Paap LM statistic	3.47		2.84		3.33				
Chi-sq P-val	0.06		0.09		0.07				
<i>Weak identification test</i>									
Kleibergen-Paap Wald F statistic	4.24		3.00		3.42				
Cragg-Donald Wald F statistic	44.39		15.84		20.21				
Stock-Yogo critical value	16.38		16.38		16.38				
10% maximal IV size									
<i>Anderson-Rubin test</i>									
Anderson-Rubin Wald statistic		5.02**		6.88***		11.30***			
Chi-sq P-val		0.03		0.01		0.00			

Table 13: 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. The independent 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 10^6 . 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 $_{t-2}$		-6.922*	
		(3.90)	
IRAP $_{t-6}$	-0.411**		3.789***
	(0.19)		(1.35)
NPL dummy $_{t-3}$	-0.000	0.386***	0.396***
	(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)
Auto loan dummy $_{t-3}$	0.000	-0.009***	-0.008***
	(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	-0.001
	(0.00)	(0.01)	(0.00)
Capital ratio bank $_{t-6}$	0.019	0.284*	0.185**
	(0.02)	(0.15)	(0.07)
ROA bank $_{t-6}$	-0.001	-0.202	-0.215
	(0.02)	(0.27)	(0.18)
NPL ratio bank $_{t-6}$	-0.005	0.005	0.013
	(0.02)	(0.14)	(0.08)
Size bank $_{t-6}$	-0.001	0.001	0.008
	(0.00)	(0.01)	(0.01)
Liquidity ratio bank $_{t-6}$	0.008	0.447	0.519**
	(0.04)	(0.32)	(0.24)
Nonretail deposit ratio bank $_{t-6}$	-0.001	-0.003	0.038**
	(0.00)	(0.03)	(0.02)
GDP growth region bank $_{t-6}$	-0.048	-0.362	-0.058
	(0.03)	(0.23)	(0.15)

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Table 13 – *Continued from previous page*

Employment region bank $_{t-6}$	0.001*	0.005	-0.001
	(0.00)	(0.00)	(0.00)
Inflation region bank $_{t-6}$	-0.001	0.008	0.026***
	(0.00)	(0.01)	(0.01)
Firm-quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes
N	556284	556284	435367
R ²	0.469		0.874
Adjusted R ²	0.005		0.762
F-test statistic		134.357***	122.689***
degrees of freedom		(19, 37)	(19, 37)
<i>Underidentification test</i>			
Kleibergen-Paap LM statistic	3.97		
Chi-sq P-val	0.05		
<i>Weak identification test</i>			
Kleibergen-Paap Wald F statistic	4.90		
Cragg-Donald Wald F statistic	17.99		
Stock-Yogo critical value	16.38		
10% maximal IV size			
<i>Anderson-Rubin test</i>			
Anderson-Rubin Wald statistic		5.92**	
Chi-sq P-val		0.01	

Table 14: Loan restructuring

The table reports robustness tests for the 2SLS model of equation 5 and the reduced form model of equation 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. The independent 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 multicustering 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 10^6 . 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 $_{t-2}$		-2.684*	
		(1.38)	
IRAP $_{t-6}$	-0.495**		1.384*
	(0.22)		(0.68)
Loan amount $_{t-3}$	-0.000	0.003***●●	0.004***●●
	(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)
Auto 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	0.010***	0.008***
	(0.00)	(0.00)	(0.00)
Close threshold dummy $_{t-3}$	0.000	-0.001	-0.002
	(0.00)	(0.00)	(0.00)
Capital ratio bank $_{t-6}$	0.022	0.203**	0.191***
	(0.02)	(0.08)	(0.05)
ROA bank $_{t-6}$	-0.011	-0.115	-0.066
	(0.03)	(0.15)	(0.11)
NPL ratio bank $_{t-6}$	-0.002	-0.039	-0.051
	(0.02)	(0.08)	(0.07)
Size bank $_{t-6}$	-0.001	0.003	0.007*
	(0.00)	(0.00)	(0.00)
Liquidity ratio bank $_{t-6}$	-0.014	0.129	0.309*
	(0.04)	(0.17)	(0.17)
Nonretail deposit ratio bank $_{t-6}$	-0.004*	-0.015	0.011
	(0.00)	(0.02)	(0.01)
GDP growth region bank $_{t-6}$	-0.055	-0.285**	-0.219**
	(0.04)	(0.14)	(0.11)
Employment region bank $_{t-6}$	0.001	0.005**	0.001
	(0.00)	(0.00)	(0.00)
Inflation region bank $_{t-6}$	-0.001	0.003	0.012*

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Table 14 – *Continued from previous page*

	(0.00)	(0.01)	(0.01)
Firm-quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Region bank FE	Yes	Yes	Yes
N	490198	490198	379663
R ²	0.467		0.657
Adjusted R ²	-0.003		0.354
F-test statistic		10.346***	11.653***
degrees of freedom		(18, 37)	(18, 37)
<i>Underidentification test</i>			
Kleibergen-Paap LM statistic	4.08		
Chi-sq P-val	0.04		
<i>Weak identification test</i>			
Kleibergen-Paap Wald F statistic	5.02		
Cragg-Donald Wald F statistic	22.19		
Stock-Yogo critical value	16.38		
10% maximal IV size			
<i>Anderson-Rubin test</i>			
Anderson-Rubin Wald statistic		5.85**	
Chi-sq P-val		0.02	

Table 15: Different lags

The table reports robustness tests for the 2SLS model of equation 5 and the reduced form model of equation 6 by including the independent variables with different lags. The dependent variable is displayed at the bottom of each column. The independent 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 multicustering 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 10^6 . 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}		-9.614*			
		(5.32)			
IRAP _{t-6}	-0.412**		4.885**	IRAP _{t-5}	4.894**
	(0.19)		(1.84)		(1.95)
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	-0.009***	-0.007***	Term loan _{t-2}	-0.007***
	(0.00)	(0.00)	(0.00)		(0.00)
Credit line dummy _{t-2}	-0.000	0.011***	0.010***	Credit line _{t-2}	0.010***
	(0.00)	(0.00)	(0.00)		(0.00)
Auto loan dummy _{t-2}	0.000	-0.022***	-0.021***	Auto loan _{t-2}	-0.021***
	(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	0.025***	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	-0.004	Close threshold _{t-2}	-0.004
	(0.00)	(0.01)	(0.01)		(0.01)
Capital ratio bank _{t-6}	0.019	0.356*	0.213**	Capital ratio bank _{t-5}	0.184**
	(0.02)	(0.21)	(0.09)		(0.09)
ROA bank _{t-6}	-0.002	-0.365	-0.325	ROA bank _{t-5}	-0.379*
	(0.02)	(0.33)	(0.20)		(0.19)
NPL ratio bank _{t-6}	-0.005	-0.071	-0.043	NPL ratio bank _{t-5}	-0.022
	(0.02)	(0.18)	(0.11)		(0.11)
Size bank _{t-6}	-0.001	0.002	0.012	Size bank _{t-5}	0.011
	(0.00)	(0.01)	(0.01)		(0.01)
Liquidity ratio bank _{t-6}	0.008	0.453	0.527**	Liquidity ratio bank _{t-5}	0.479**
	(0.04)	(0.40)	(0.25)		(0.23)
Nonretail deposit ratio bank _{t-6}	-0.004	0.000	0.049**	Nonretail deposit ratio bank _{t-5}	0.049**
	(0.00)	(0.03)	(0.02)		(0.02)
GDP growth region bank _{t-6}	-0.048	-0.508*	-0.067	GDP growth region bank _{t-5}	-0.159
	(0.03)	(0.29)	(0.17)		(0.17)
Employment region bank _{t-6}	0.001*	0.006	-0.001	Employment region bank _{t-5}	-0.002
	(0.00)	(0.01)	(0.01)		(0.00)
Inflation region bank _{t-6}	-0.001	0.004	0.026**	Inflation region bank _{t-5}	0.023**
	(0.00)	(0.02)	(0.01)		(0.01)
Firm-quarter FE	Yes	Yes	Yes		Yes
Bank FE	Yes	Yes	Yes		Yes
Region bank FE	Yes	Yes	Yes		Yes
N	557422	557422	436471		440645
R ²	0.469		0.8538		0.8531
Adjusted R ²	0.005		0.7252		0.7240
<i>Underidentification test</i>					
Kleibergen-Paap LM statistic	4.00				
Chi-sq P-val	0.05				
<i>Weak identification test</i>					
Kleibergen-Paap Wald F statistic	4.94				
Cragg-Donald Wald F statistic	18.07				
Stock-Yogo critical value	16.38				
10% maximal IV size					
<i>Anderson-Rubin test</i>					
Anderson-Rubin Wald statistic		6.74***			
Chi-sq P-val		0.01			

Appendix

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:

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

If the borrowers repay their loans, bank shareholders get a net return after tax of $(r_L - r_D (1 - k)) (1 - \tau)$. 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:

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

Taking the first order condition with respect to q yields

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

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 $\mathbb{E}[q|k] = q^*$. Substituting r_D in equation 9, we solve for the optimal monitoring effort:³⁷

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

³⁷The 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.

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

$$\max_k \Pi = \left[\left\{ q^* r_L (1 - \tau) - r (1 - \tau) - k (r\tau + \xi) - \frac{1}{2} c q^{*2} \right\} L(r_L) \right] \quad (11)$$

This yields

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

We then solve for k obtaining

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

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

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

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

$$q^* = \frac{r_L (1 - \tau) (r + \xi)}{c(r\tau + 2\xi + r)} \quad (15)$$

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

$$r_L^* = \sqrt{\frac{2cr(r\tau + 2\xi + r)^2}{(1 - \tau)(3r\xi + r^2 + 2\xi^2 + r^2\tau + r\tau\xi)}} \quad (16)$$

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

$$\frac{\partial r_L^*}{\partial \tau} = \sqrt{\frac{2cr(r^2 + \xi^2)^2 (r + 2\xi + r\tau)^2}{(1 - \tau)^3 (3r\xi + r^2 + 2\xi^2 + r^2\tau + r\tau\xi)^3}} > 0 \quad (17)$$

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

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

Its derivative with respect to the corporate tax rate is

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

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

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

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

Table A1: 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. The independent 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 10^6 . 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	(5)	(6)
	(1)	(2)	(3)	(4)		
	Monitor _{t-2}	NPL dummy _t	Monitor _{t-2}	NPL dummy _t	NPL dummy _t	NPL dummy _t
Monitor _{t-2}		-49.214 (334.88)		-55.756 (397.63)		
IRAP _{t-6}	-0.036 (0.20)		-0.033 (0.20)		0.439 (6.69)	0.404 (6.69)
Loan amount _{t-3}	-0.000 (0.00)	0.000 (0.00)	-0.000 (0.00)	-0.000 (0.00)	0.005*●● (0.00)	0.000 (0.00)
Length relation _{t-3}	-0.013*● (0.00)	-0.006 (0.04)	-0.012*● (0.00)	-0.007 (0.05)	-0.000 (0.00)	-0.000 (0.00)
Term loan dummy _{t-3}	0.000 (0.00)	0.010 (0.10)	0.000 (0.00)	0.007 (0.10)	-0.005 (0.01)	-0.007 (0.01)
Credit line dummy _{t-3}	-0.001 (0.00)	-0.036 (0.23)	-0.001 (0.00)	-0.028 (0.22)	-0.005 (0.01)	-0.001 (0.01)
Auto loan dummy _{t-3}	0.002*** (0.00)	0.089 (0.62)	0.002*** (0.00)	0.097 (0.72)	0.001 (0.01)	-0.001 (0.01)
Share guarantee _{t-3}	-0.000 (0.00)	-0.001 (0.00)	-0.000 (0.00)	-0.001 (0.01)	-0.000 (0.00)	-0.000 (0.00)
Share exposure _{t-3}	-0.000 (0.00)	0.030 (0.07)	-0.000 (0.00)	0.021 (0.12)	0.037*** (0.01)	0.034*** (0.01)
Close threshold dummy _{t-3}	0.000 (0.00)	-0.014 (0.06)	0.000 (0.00)	-0.009 (0.09)	-0.030 (0.02)	-0.029 (0.02)
Average interest rate _{t-3}	0.000 (0.00)	0.012 (0.05)			0.004** (0.00)	
Capital ratio bank _{t-6}	-0.024 (0.03)	-0.825 (8.54)	-0.024 (0.03)	-0.947 (9.96)	0.421** (0.20)	0.435** (0.20)
ROA bank _{t-6}	-0.057 (0.08)	-2.650 (18.73)	-0.057 (0.08)	-3.053 (22.38)	-0.136 (0.55)	-0.134 (0.55)
NPL ratio bank _{t-6}	-0.131 (0.14)	-6.608 (39.88)	-0.131 (0.14)	-7.449 (47.32)	-0.489 (0.41)	-0.493 (0.41)
Size bank _{t-6}	0.000 (0.00)	0.003 (0.14)	0.000 (0.00)	0.008 (0.15)	-0.008 (0.02)	-0.007 (0.02)
Liquidity ratio bank _{t-6}	-0.232* (0.12)	-10.920 (77.96)	-0.231* (0.12)	-12.376 (92.26)	0.197 (0.58)	0.191 (0.58)
Nonretail deposit ratio bank _{t-6}	-0.004 (0.01)	-0.146 (1.37)	-0.004 (0.01)	-0.195 (1.71)	0.066 (0.07)	0.055 (0.08)
GDP growth region bank _{t-6}	-0.015 (0.02)	-0.947 (5.38)	-0.014 (0.02)	-1.000 (6.16)	-0.564 (0.61)	-0.552 (0.61)
Employment region bank _{t-6}	-0.000 (0.00)	-0.017 (0.07)	-0.000 (0.00)	-0.020 (0.08)	-0.003 (0.01)	-0.003 (0.01)
Inflation region bank _{t-6}	-0.001 (0.00)	0.020 (0.22)	-0.001 (0.00)	0.020 (0.24)	0.041 (0.04)	0.043 (0.04)
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	42949	42949
R ²	0.443		0.443		0.813	0.813
Adjusted R ²	-0.069		-0.069		0.641	0.641
F-test statistic		1.932**		1.529	2.967***	3.961***
degrees of freedom		(19, 30)		(18, 30)	(19, 30)	(18, 30)
<i>Underidentification test</i>						
Kleibergen-Paap LM statistic	0.03		0.03			
Chi-sq P-val	0.86		0.87			
<i>Weak identification test</i>						
Kleibergen-Paap Wald F statistic	0.03		0.03			
Cragg-Donald Wald F statistic	0.01		0.01			
Stock-Yogo critical value	16.38		16.38			
10% maximal IV size						
<i>Anderson-Rubin test</i>						
Anderson-Rubin Wald statistic		0.09		0.10		
Chi-sq P-val		0.77		0.76		

References

- Acharya, V., H. Almeida, F. Ippolito, and A. Perez. Credit lines and the liquidity insurance channel. *Journal of Money Credit and Banking* forthcoming.
- Allen, F., E. Carletti, and R. Marquez (2011). Credit market competition and capital regulation. *Review of Financial Studies* 24 (4), 983-1018.
- Andrews, I., J. Stock, and L. Sun (2019). Weak instruments in IV regression: Theory and practice. *Annual Review of Economics* 11, 727-753.
- Angrist, J. D., and J. S. Pischke (2009). Mostly harmless econometrics. Princeton University Press.
- Bank of Italy (2019). Financial Stability Report. Number 1, May 2019.
- Bhat, G., and H. Desai (2020). Bank capital and loan monitoring. *The Accounting Review* forthcoming.
- Bond, S., K. Y. Ham, G. Maffini, A. Nobili, and G. Ricotti (2016). Regulation, tax and capital structure: evidence from administrative data on Italian banks. Bank of Italy Occasional Paper N. 361.
- Brunner, A., and J. P. Krahen (2008). Multiple lenders and corporate distress: Evidence on debt restructuring. *Review of Economic Studies* 75, 415-442.
- Carletti, E., F. De Marco, V. Ioannidou, and E. Sette (2020). Banks as patient lenders: Evidence from a tax reform. Working paper.
- Cerqueiro, G., S. Ongena, and K. Roszbach (2016). Collateralization, bank loan rates, and monitoring. *Journal of Finance* 71 (3), 1295-1321.
- C el erier, C., T. Kick, and S. Ongena (2019). Taxing Bank Leverage: The Effects on Bank Capital Structure, Credit Supply and Risk-Taking. Working paper.
- Cornelissen, T., C. Dustmann, and U. Sh onberg (2016). From LATE to MTE: Alternative methods for the evaluation of policy interventions. *Labour Economics* 41, 47-60.
- Dell’Ariccia, G., L. Laeven, and R. Marquez (2014). Real interest rates, leverage, and bank risk-taking. *Journal of Economic Theory* 149, 65-99.
- Dell’Ariccia, G., L. Laeven, and G. A. Suarez (2017). Bank leverage and monetary policy’s risk-taking channel: Evidence from the United States. *Journal of Finance* 72 (2), 613-654.
- Devereux, M. P., J. Vella, and N. Johannesen (2015). Can taxes tame the banks? Evidence from the European bank levies. Sa id Business School Research Papers.
- Diamond, D.W. (1984). Financial intermediation and delegated monitoring. *Review of Economic Studies* 51 (3), 393-414.
- Diamond, D.W. and R. G. Rajan (2000). A theory of bank capital. *Journal of Finance* 55 (6), 2431-2465.
- Freixas, X., and J. C. Rochet (2008). Microeconomics of banking. Second edition. The MIT Press.
- Gambacorta, L., G. Ricotti, S. Sundaresan, and Z. Wang (2017). The effects of tax on bank liability structure. BIS Working Papers N. 611.
- Gale, D., and M. Hellwig (1985). Incentive-compatible debt contracts: The one-period problem. *Review of Economic Studies* 52, 647-663.

- Gustafson, M. T., Ivanov, I. T., and R. R. Meisenzahl (2020). Bank monitoring: Evidence from syndicated loans. Working paper.
- Jiménez, G., S. Ongena, J. L. Peydró, and J. Saurina (2014). Hazardous time for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica* 82 (2), 463-505.
- Jiménez, G., S. Ongena, J. L. Peydró, and J. Saurina (2017). Macroprudential policy, countercyclical bank capital buffers and credit supply: Evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy* 125 (6), 2126-2177.
- Heckman, J. J., S. Urzuna, and E. Vytlacil (2006). Understanding instrumental variables in models with essential heterogeneity. IZA Discussion Paper No. 2320.
- Holmstrom, B., and J. Tirole (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics* 112 (3), 663-691.
- Keen, M., and R. A. de Mooji (2016). Debt, taxes and banks. *Journal of Money, Credit and Banking* 48 (1), 5-33.
- Krasa, C. M., and A. P. Villamil (1992). Monitoring the monitor: An incentive structure for a financial intermediary. *Journal of Economic Theory* 57, 197-221.
- Mehran, H., and A. Thakor (2011). Bank capital and value in the cross-section. *Review of Financial Studies* 24 (4), 1019-1067.
- MEF (2012). Relazione generale sulla situazione economica del paese 2012.
- Plosser, M. C., and J. A. C. Santos (2016). Bank monitoring. Working paper.
- Schepens, G. (2016). Taxes and bank capital structure. *Journal of Financial Economics* 120, 585-600.
- Staiger, D., and J. Stock (1997). Instrumental variables regression with weak instruments. *Econometrica* 65, 557-586.
- Stock and Yogo (2005). Identification and inference for econometric models: Essays in honor of Thomas Rothenberg. Chapter *Testing for Weak Instruments in Linear IV Regression*, Cambridge University Press, 80-108.
- Townsend, R. (1979). Optimal contracts and competitive markets with costly state verification. *Journal of Economic Theory* 21 (20), 265-293.
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.