THE REAL EFFECTS OF BANK SUPERVISION: EVIDENCE FROM ON-SITE BANK INSPECTIONS[§]

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Abstract. We show that bank supervision reduces distortions in credit markets and generates positive spillovers for the real economy. Exploiting the quasi-random selection of inspected banks in Italy, we show that financial intermediaries are more likely to reclassify loans as non-performing after an audit. Moreover, they change their lending policies as the composition of new lending shifts toward more productive firms. As a result, productive firms invest more in labor and capital, while underperforming firms are more likely to exit the market. Taken together, our results show that bank supervision is an important complement to regulation in improving credit allocation.

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1. Introduction

A weak banking sector can prolong the stagnation of an economy by distorting the allocation of credit.This market failure can arise when banks evergreen loans to otherwise impaired firms to avoid realising losses, which would impact their balance sheets and regulatory capital position (Caballero et al., 2008; Peek and Rosengren, 2005).[1] This issue has regained substantial attention of policymakers following the aftermath of the Great Recession, as it is considered one of the potential explanations for the prolonged low productivity experienced by several European countries (Gopinath et al., 2017; Adalet McGowan et al., 2018). More recently, in the midst of the global pandemic crisis that has forced governments to take actions in the economy, there is fear that these interventions may lead to prolonging the life of many undeserving firms and the "zombification" of many more.[2]

Existing research has shown that policy interventions and bank regulations are insufficient in preventing such distortions in credit allocation and, if anything, make these distortions worse. Acharya et al. (2019b) show that a policy aimed at recapitalizing European banks has not translated into economic growth as credit was allocated to impaired firms who did not undertake real economic activity, such as investment, but instead used these funds to build cash reserves.[3] These distortions in the credit market have negative implications for the real economy, as impaired firms crowd out lending to better performing or new firms (Peek and Rosengren (1995); Caballero et al. (2008); Acharya et al., 2019a; Acharya et al., 2019b; Blattner et al., 2017) and create excessive competition on healthy firms, which as a consequence fail to grow (Acharya et al., 2019a). Simply increasing the regulatory burden is not an effective way to reduce distortions in the credit market.

In this paper, we consider an important complement to bank regulation in reducing this market failure: bank supervision. Empirical evidence studying the causal impact of bank supervision has been limited due to two main difficulties. First, it is hard to confine the domain and the effect of bank supervision. To overcome this issue, we consider a very

[1] Evidence of this issue was first shown in Japan during the 1990s (Tosjitaka et al., 2003; Peek and Rosengren, 2005) and is considered one of the main causes of the Japanese "lost decade" of growth (Caballero et al., 2008.

[2] "What to do about zombie firms" (The Economist, September 26 2020) (`https://www.economist.com/leaders/2020/09/26/what-to-do-about-zombie-firms`); "Why COVID-19 will make killing zombie firms off harder" (The Economist, September 26 2020) (`https://www.economist.com/finance-and-economics/2020/09/26/why-covid-19-will-make-killing-zombie-firms-off-harder`).

[3] Blattner et al. (2017) show that stricter capital requirements increase banks' incentive to distort their lending decisions. Since banks must satisfy a higher regulatory capital ratio, they try to avoid reporting new losses by extending additional credit to support ailing firms.

specific type of bank supervision: on-site bank inspections conducted by the Bank of Italy. These inspections are unexpected, intrusive and consist of thorough audits at the supervised bank's offices.[4] Their main goal is to validate not only the quality of banks' assets, but also their reporting activity to the supervisor.[5] When necessary, the bank inspectors may also force measures upon inspected banks.[6] Second, unless completely randomized, the impact of bank supervision is likely to suffer from an endogeneity problem. Banks that are inspected are more likely to have shown deteriorating conditions that has alarmed the bank supervisor. As a result, it is difficult to infer whether the effect of bank inspections is driven by the supervisory activity or the selection of banks. Our identification strategy exploits the selection process employed by the bank supervisor to define the set of banks that are inspected. Every year, this selection process first identifies a group of eligible banks. Then, it selects a subset of these banks to be inspected in a quasi-random fashion. This selection is based on an unpublished, computer-based algorithm. The algorithm selects and ranks the banks that are inspected. Because the final selection of inspected banks among the group of eligible banks is exogenous to their financial conditions, the selection process allows us to exploit within-bank variation to identify the average effect of the impact of bank inspections.

To estimate the causal effect of bank inspections, we leverage a novel dataset of on-site bank inspections, combining it with a comprehensive administrative dataset from the Bank of Italy on banks, credit, and firms. Specifically, we have detailed information on which banks are audited and the exact timing of the audit for a subset of banks, namely mutual banks (also known as BCC in the Italian context). These banks are particularly important, as they are local and support mostly small and medium enterprises. We merge this information with data on banks' balance sheets from the Supervisory Reports, the universe of loans granted to Italian firms from the Credit Register, data on banks' corporate bodies, information on firms' balance sheets and income statements, and finally with data on employment and local economic activity indicators from the National Institute for Social Security INPS and the

[4] These audits are performed every year. While they are unexpected by the supervised banks, they are part of the standard toolkit available to the bank supervisor.

[5] By law, at the end of each month, banks have to report to the supervisor information about their balance sheets and lending activity. Inspections, among other things, are aimed at assessing whether banks misreport this information to the supervisory authority.

[6] The most common action is forcing banks to reclassify items in their balance sheets such as a loan from performing into non-performing. They can suggest the readjustment of the expected value of the loan by writing-off some of its amount. In case of violations of laws, inspectors can inflict sanctions either of pecuniary nature or that can cause bank administrators to temporarily or permanently lose their fit-and-proper status. In the most serious cases, inspectors can also suggest to take over the control of the bank.

National Institute of Statistics ISTAT.[7] Our main empirical strategy is a dynamic Difference-in-Differences (DiD) model comparing eligible and inspected banks with eligible banks that are not inspected.

We provide three sets of results. First, on-site inspections have a direct effect on the loan classifications of inspected banks. We call this the *informational disclosure effect*. Following an inspection, audited banks increase the stock of loans classified as Non-Performing Loans (NPL) by about 3.6%, 12% of the average share of non-performing loans across all eligible banks.[8] Moreover, inspected banks are more likely to increase loan loss provisions by 3.8%. These effects are limited to the first quarter following the inspection. This short time lag provides evidence that the effect is driven by audits.

Our second set of results sheds light on the implications of inspections for the lending activity of audited banks—the indirect effect of bank inspections. We find that, aggregate lending shrinks by about 2.3% following an inspection. This represent 11% of total lending for the average bank. However, their drop is temporary and reverts to its pre-audit level after seven quarters. Given the supervisory-driven nature of the credit supply shock and the goal of on-site inspections, we test whether there is a *compositional* effect in this credit supply shock. Do inspected banks readjust their portfolio by reducing the credit to inviable firms? This question speaks directly to the role of bank supervision in reducing the problem of zombie lending. To answer this question, we move to a loan-level analysis and employ a model in the spirit of Khwaja and Mian (2008). Specifically, we study the impact of bank inspections on the credit growth for a firm that has lending relationships with both inspected banks and eligible but not inspected banks. Our specification allows us to control for unobserved heterogeneity in credit demand. To study the heterogeneous effect of bank inspections, we construct a new measure of the firm's quality based on the outcomes of the bank audits. We consider a firm to be inviable (i.e. zombie) if its loan is reclassified as an NPL by an inspected bank within a quarter of the inspection. We argue that this measure is better at identifying impaired firms, since it is based on soft information used by inspectors

[7]Specifically, we define the local economy as Italian provinces. These are roughly the size as US counties. In the period considered, there are about 109 provinces.

[8]NPL is a macro-category that includes three types of loans. First, loans that are overdrawn and/or past-due by more than 90 days and above a predefined amount. Second, unlikely-to-pay exposure which are loans for which banks believe debtors are unlikely to meet contractual obligations in full, unless the bank takes action. Third, bad loans are exposures to debtors that are insolvent (or in substantially similar circumstances). https://www.bancaditalia.it/media/views/2017/npl/index.html?com.dotmarketing.htmlpage.language=1. In our paper, we refer to the last category, i.e. bad loans, unless otherwise mentioned.

to judge the economic viability of a firm.[9] First, we find that the aggregate lending cut is driven *exclusively* by impaired firms in the bank's portfolio. On the intensive margin, inspected banks reduce their credit granted to impaired firms by about 66% compared to eligible but not inspected banks. On the extensive margin, they are more likely to cut their credit relationship with zombie firms by 6%. Second, we find evidence of a *reallocation channel*. Credit is reallocated either to healthy firms in the bank's portfolio or to new firms that did not have a credit relationship with the inspected banks. Moreover, loans to new firms granted after the audit are, on average, less risky than loans to new firms before the inspection. Overall, this suggests that inspected banks change their lending policies in response to audits.

We provide evidence on the mechanism causing this change in lending policy. First, we show that inspections drive changes in bank governance. In particular, board members are more likely to leave the board of a bank if it is inspected. Additionally, we show that inspected banks strengthen their internal monitoring efforts by hiring more white-collar workers in the supervision and control units. Second, we document that bank audits lead inspected banks to increase their equity. This potentially reduces moral hazard concerns as banks become important stakeholders in both upside and downside states of the world (Gertner and Scharfstein, 1991).

The main threat to a causal interpretation of these findings is the possibility of selection bias—eligible banks that are actually inspected may be different from eligible banks that are not inspected. We provide a battery of robustness exercises showing that such selection does not drive our results. First, we show that there are no significant differences between the banks that are inspected and other banks that are eligible for inspections. We confirm the anecdotal evidence that the selection rule depends on factors uncorrelated with banks' characteristics. Thus, within the sample of eligible banks, inspections are as good as randomly assigned. Moreover, the absence of pre-trend differences in the outcomes before the inspection supports a causal interpretation. Second, we directly show that the selection rule is not driving the results. Since the computer-based selection rule produces a ranking of eligible banks, we use this information as a sufficient statistic for the selection and show that

[9] We identify about 4% of firms with this method. This is likely to be a lower bound since we do not take into account firms that were already in financial troubles before the inspection. We validate our results by using different measures for firm's quality such as the definition of zombie firm employed by Acharya et al. (2019b) and a measure of total factor productivity at the firm level Wooldridge (2009).

it is not driving the results.[10] Finally, we confirm the baseline results by performing the same analysis employing *only* the set of inspected banks and taking advantage of the difference in the months in which they are inspected. The fact that we find similar magnitudes compared to the baseline model reduces any further concern that selection is an issue in this framework.[11]

Our third and final set of results concerns the spillover effects of bank supervision to the real economy. We first analyze impacts on corporate behaviour. We follow the literature and construct a firm-level measure of exposure to inspected banks based on their share of credit granted by inspected banks (Chodorow-Reich 2013). We find that underperforming firms are more likely to exit the market, leaving room for healthy firms to grow. Healthy firms benefit from greater credit availability. A one standard deviation increase in the exposure to inspected banks is associated to an 11 percentage points increase in the growth of total credit for healthy firms. As a result they invest more in fixed assets by 1.9 percentage points, grow their workforce by about 2 percentage points and increase their sales by about 4.5 percentage points. We then focus on the aggregate effect on the local economy. We construct a similar measure of a province's exposure to bank inspections based on the share of credit granted by inspected banks in that particular province. We find that provinces more exposed to bank inspections experience an increase in entrepreneurship. Specifically, a one standard deviation increase in a province's exposure to bank inspections implies an increase of about 2% in the growth rate of new firms after one year. Aggregate employment suffers in the short term as results of zombie (unproductive) firms exiting the market. We find a negative effect for those provinces more exposed to bank inspections. However, the effect becomes positive after two years. Employment in new firms or in existing firms counterbalance the layoff generated by zombie firms going bankrupt. Finally, we find a positive effect in the aggregate productivity at the province level.[12] This is due to the selection of firms remaining or entering the market which are on average more productive. In some ways bank inspections

[10]The main limitation in our data is that, while we have information on the ranking position of inspected banks, we do not have this information for the eligible but not inspected banks.

[11]We further show robustness along a number of dimensions, including: using the ranking position of audited banks in the inspection plan as a sufficient statistic for the selection rule, and interacting it with the treatment dummy variable; comparing inspected banks ranked in the top quartile with inspected banks ranked in the bottom quartile; applying subsample analysis, including dropping the top-ranked inspected banks; using the ranking position to predict the quality of banks; using propensity score matching based on the probability to be inspected. These exercises provide further evidence that the selection is not an issue in this setting.

[12]Value-Added Productivity per Employee is an indicator that measures the "value-added" per employee and is a measure of the extent to which you are utilizing your employee's strengths.

can overcome the problem of the "unnatural selection" of firms that are staying in the market (Peek and Rosengren, 2005), and this has potential positive effects for the local economy.

Contribution to the Literature: Our paper contributes to several strands of the literature. First, we relate to a body of literature studying the effect of bank supervision on bank performance, risk-taking and lending (Jayaratne and Strahan, 1996; Eisenbach et al., 2016; Hirtle et al., 2017). These papers exploit different sources of variation: changes in the entity of the supervisor (Agarwal et al., 2014; Granja and Leuz, 2019), in the quasi-random assignment of inspectors (Ivanov and Wang, 2019), or the location of the supervisor (Kandrac and Schlusche, 2017); unexpected change in the coverage of the major syndicated loan supervisory program (Ivanov et al., 2017); sharp changes in the frequency of supervisory examinations (Rezende and Wu, 2014) or in the volume of regulatory reporting due to a size threshold rule (Bisetti, 2017). Our paper is closely related to the results found in Agarwal et al. (2014). They take advantage of the mandatory rotation of the federal and state regulators in the on-site supervision of state-chartered banks. While their focus is centered on how institutional design and incentives of different bank supervisors affect the supervisory assessments and banks' corrective actions, our paper focuses more on the *impact* of supervisory assessments in the credit market. We make two contributions to this literature. First, we are among the first to use data on bank audits, which provides detailed information on supervisory activity.[13] Second, by matching this data with granular data at the loan and firm level, we can precisely estimate the implications of the supervisory activity. Unlike other papers that look at the aggregate effect on lending, we move a step further by studying how banks react to supervisory activity and identify the implication for the real economy. We find that there is a compositional effect, with credit pulled back from underperforming firms and reallocated to healthy firms or new firms.

A new strand of the literature on bank supervision developed in the aftermath of the Great Recession studies the impact of bank stress tests on banks' lending activity (Cortés et al., 2020; Acharya et al., 2018; Kok et al., 2019). While there is agreement that banks affected by stress test reduce their credit supply (especially among risky borrowers), Cortés

[13]In a contemporaneous paper Bonfim et al. (2019) use similar data on on-site bank inspections for the largest Portuguese banks and show that bank inspections reduce zombie lending. Their setting is different as they look at one specific special event in which the eight largest banks are inspected, while we look at on-site inspections that are part of the standard procedure employed by the bank supervisor. We confirm their results, i.e. inspections reduce the credit granted to zombie firms. In addition to this, we provide evidence on the spillover effects to the real economy, as well as the potential mechanism driving the change in the lending policies of inspected banks.

et al. (2020) show that the aggregate lending does not fall as non-stressed banks increase their share in those areas more reliant on stress-tested lenders. Our study contributes to this literature by studying the impact of an unexpected audit rather than a supervisory activity that is planned between the supervisor and the supervised bank. This is a critical difference, as we rule out any sort of window-dressing behavior by the supervised bank (Abbassi et al., 2017a).

We also contribute to the literature on zombie lending. Seminal papers show that there is a relation between a weak banking sector and distortions in the credit market (Caballero et al., 2008; Peek and Rosengren, 2005). Existing research has argued that bank shareholders often resist raising new capital (Myers and Majluf, 1984; Admati et al., 2018) and prefer to find other ways to improve their regulatory capital position. One such way is to delay the reporting of losses, even if such loans have negative net present value (NPV). Recent papers establish a causal link between a weak banking sector and distorted credit markets (Acharya et al., 2019b; Blattner et al., 2017; Schivardi et al., 2017; Albertazzi and Marchetti, 2010). While this literature has shown that this problem exists and is related to the distorted incentive of banks to hide losses, it is silent about potential solutions.[14] We show that bank supervision—especially intrusive on-site inspections—affect the lending policies of inspected banks and create an incentive for banks to stop lending to zombie firms.

Finally, our paper is related to the body of research that looks at the real costs of zombie lending. The main takeaway from this literature is that zombie lending has negative spillover effects on performing firms in the same industry (Caballero et al., 2008; Adalet McGowan et al., 2018; Schivardi et al., 2017; Giannetti and Simonov, 2013; Acharya et al., 2019b). We show that bank inspections can mitigate zombie lending and generate positive spillovers for healthy firms. In turn, healthy firms can invest more and stimulate the real economy. Moreover, bank inspections have an impact on firm dynamics. One of the most salient problems with zombie lending is that it prevents new firms from entering a market because they find it harder to obtain financial resources (Adalet McGowan et al., 2018). We find positive spillovers from inspections. First, we show that underperforming firms are more likely to exit the market following a bank inspection; second we document that provinces with more exposure to bank inspections experience an increase in entrepreneurship, aggregate productivity and a positive effect on aggregate employment.

[14] Bruche and Llobet (2014) develops a scheme that supervisors could use to solve this problem. The scheme would induce banks to reveal their bad loans, which can then be dealt with.

The remainder of this paper is organized as follows. Section 2 describes the institutional setting. Section 3 details the data and variables. Section 4 describes the direct effect of bank inspections. Section 5 discusses the indirect effect on lending. Section 6 discusses the validity of our empirical strategy. Section 7 shows the impact of bank inspections on corporate behavior. Section 8 shows the spillover effects to the real economy. Section 9 concludes.

2. Institutional Background

This section provides an overview of the role played by bank supervision.We provide a primer on the different types of supervisory activities, i.e. off-site inspections vs. on-site inspections, and we discuss the latter in the context of the Italian banking system. In particular, we explain the selection process of inspected banks and provide details on why this is an ideal setting to study the impact of bank supervision.

2.1. **A primer on bank supervision.** We provide an overview of supervisory activities, i.e. off-site and on-site inspections, in the Italian context, since some of its institutional features are instrumental to our identification strategy.

Banking supervision can be divided into two main areas: off-site and on-site inspections.[15] The differences between the two are related to: (i) the target of the inspections, and (ii) the way in which supervision is performed. Off-site inspections target all financial intermediaries operating within the national border. Financial intermediaries are required to periodically report information about their balance sheet and income statement to the National Supervisory Authority (NSA, henceforth).[16] This type of supervision does not require a direct interaction between the bank supervisor and the supervised bank. On-site inspections are targeted to a subset of financial intermediaries, which are chosen according to a selection rule.[17] It is worth mentioning that the discipline has changed since the introduction of the Single Supervisory Mechanism (SSM, henceforth) in November 2014. The SSM has transferred some of the supervisory activities from the NSA to the European Central Bank (ECB, henceforth). The ECB is now in charge of the supervision of the Significant Institutions

[15]Note that each country has its own specific rules, structure and organization of bank supervision. However, the two main sub-classes exist in most developed countries (Cihák and Tieman, 2008).
[16]Note that in the paper, we indistinctly refer to bank supervisor as the NSA, or specifically, the Bank of Italy. The Bank of Italy is the institution responsible for the supervision of the banking system in Italy.
[17]We describe in detail the selection process of banks in subsection 2.2.

(SIs, henceforth).[18] SI plan, together with the supervisor, a time to perform an audit. Given the change in the supervisor's entity and in the way off-site inspections are performed, we focus only on the sub-sample of banks that are still under the supervision of the NSA and for which the discipline about on-site inspections has *not* changed, namely mutual banks.

On-site inspections consist of a thorough auditing of selected banks at their office. These audits come as a surprise for supervised banks. Supervised banks know neither that they have been selected for inspections, nor when the inspections will take place.[19] The goal of these inspections is "to check the quality and accuracy of the data submitted by banks during off-site inspections as well as to gain a better understanding of their organization and operations."[20] There are different types of on-site inspections according to the specific target, size and complexity of the financial institution. "Targeted" inspections focus on particular parts of the business, risk areas or governance profiles; "thematic" inspections consider issues of general importance for the entire credit and financial system; "follow-up" inspections, which are carried out to gauge the progress made in implementing corrective measures required by the Bank of Italy or proposed by the intermediaries themselves; or "broad spectrum" inspections which cover the corporate situation overall. In this paper we consider broad spectrum inspections since they evaluate the performance of inspected banks with a particular focus on the implications for their lending activity.

The main information advantage of on-site inspections compared to off-site inspections is the access to an additional set of information on the history of the bank-firm relationship that is not required to be disclosed by the supervised bank during off-site inspections. For instance, inspectors can get information on the firms' credit application, the documents related to the credit approval, information on the collateral backing a credit, and in general, any kind of internal information and documents produced by the bank about the firm, as well as the email and mail exchanges between the bank and the firm. This additional set of information allow the supervisor to evaluate the quality of the reporting of the supervised bank and to better understand whether the bank is assessing the risk of a specific loan in a

[18]Financial institutions are selected to be part of the SI sample if at least one of the following criteria applies: 1) its total assets are above €30 billion; 2) it has obtained public assistance in the past; 3) it is one of the top three banks in the country. With the introduction of the SSM, on-site inspections are no longer unexpected for SIs under the ECB supervision (SSM Supervisory Manual, 2018).

[19]In terms of expectation, this is different from stress tests where supervised banks know exactly when they are assessed. The date is planned together with the bank supervisor (Bernanke et al., 2013) and thus there is some room for window-dressing by the supervised financial institution (Abbassi et al., 2017b).

[20]https://www.bancaditalia.it/compiti/vigilanza/compiti-vigilanza/index.html?com.dotmarketing.htmlpage.language=1

fair way.[21] When needed, an inspector can force inspected banks to take corrective measures. The most common of these is the forced re-evaluation of a loan, which could generate its reclassification from performing to non-performing. Additionally, the inspectors can suggest the readjustment of the expected value of the loan by writing-off some of its amount. In more serious circumstances, the Bank of Italy may also discover potential or actual violations of administrative laws and of secondary regulations, or, in the worst case, of criminal state laws. If criminal violations are found, the Bank of Italy initiates a process, after which the Banking and Supervision and Regulation directorate proposes sanctions that are then administrated by the Board of the Bank of Italy. The sanctions are generally of pecuniary nature and are published on the Bank of Italy website.[22] In the latter case, i.e. actual or potential violations of criminal state laws, the Bank of Italy alerts the competent prosecutors, who have judicial power and may autonomously decide to start an investigation. The Bank of Italy does not have the power to start a prosecution independently.[23]

On-site inspections require a team of inspectors that is proportional to the size and complexity of the bank audited. For mutual banks, which is the set of banks we consider and for which the size is similar, the number of inspectors is five, on average. There are some rules in terms of composition of the team of inspectors. Three inspectors must come from the central office in Rome, and two from the local branches of the Bank of Italy. The latter two inspectors come from the same province where the supervised bank has its offices. The chief of the team cannot be from the local branch. This composition of the team is designed in a way to achieve two goals: having inspectors from the central office reduce any capturing-related problem,[24] while local officers have a deep knowledge of the local economy – soft information – that can be used for supervisory activity. When reviewing the files

[21]For instance, in a recent news report involving a firm that eventually was condemned for fraudulent bankruptcy, the inspection revealed that the bank lending to the firm, *Banco di Sardegna*, was reporting a credit position characterized as "excessive tolerance and lack of transparency" (https://www.sardiniapost.it/cronaca/bancarotta-fraudolenta-le-parole-del-gip-insolvenza-del-gruppo-scanu-dal-2002/. There are plenty of examples where banks misreport the true value of a loan to avoid negative implications to their regulatory capital position.

[22]https://www.bancaditalia.it/compiti/vigilanza/provvedimenti-sanzionatori/index.html?com.dotmarketing.htmlpage.language=102.

[23]This is similar to the USA, where financial crimes are managed by the Financial Crimes Enforcement Network (FinCEN), a bureau of the United States Department of the Treasury that collects and analyzes information about financial transactions in order to combat domestic and international money laundering, terrorist financing, and other financial crimes.

[24]Capturing problem is a serious issue in the banking industry and one of the primary reasons for a convergence toward more regulations and away from discretionary supervisory power in the last decade, especially in the US (Menand, 2017). Moreover, stress tests have been designed in a way to reduce the discretionary power of supervisors and to convey this power into a well-identified rule (Tarullo 2017).

on a particular firm, they can better assess the quality of the reporting given the previous knowledge acquired about that specific firm.

In theory, bank supervisors would prefer to inspect all banks in the banking system. However, given the high amount of resources employed for this activity – both in terms of time and number of people – on-site inspections are limited to a subset of banks each year, within a group of eligible banks. Panel D of Figure A3 shows the average, the maximum and the minimum number of days it takes to complete an audit.[25] A large set of banks are dismissed from the pool of eligible ones and are not considered for inspection in that particular year. Panel A of Figure A3 shows the number of banks eligible for on-site inspections each year, together with those that are not eligible.

2.2. **The selection process.** We discuss the selection process employed by the Bank of Italy to choose audited banks and how it reduces concerns related to selection bias and window-dressing by inspected banks. We argue and show that within a selected group of eligible banks, a quasi-random share is inspected.

Estimation of the causal impact of bank supervision is not trivial; the two main problems are selection and anticipation. Unless completely randomized, supervision activity results from selecting banks that "need an inspection" most. Additionally, unless completely unexpected, banks may anticipate an audit and react before it actually takes place. This would confound the true effect of inspections with the anticipation effect.[26] We exploit the way in which the Bank of Italy selects the banks that are audited each year. This selection process offers us a great setting to overcome the two main issues of anticipation and selection. The anticipation problem is not an issue in our framework, since on-site inspections come at a surprise for inspected banks.[27] Regarding the potential selection bias, we take advantage of a specific mechanism used by the Bank of Italy to select banks that are going to be inspected on-site.

Each year the Bank of Italy defines the list of supervised banks that are inspected in the upcoming year, i.e. an inspection plan (*Piano Ispettivo*). The inspection plan is composed of only banks that are *eligible* to be inspected. The screening employed by the supervisor is

[25]Bank inspections have to be completed within the year and the chief of the inspection team cannot be employed for multiple auditing. This generates logistical constraints in the organization of the inspections.

[26]For instance, in the context of stress test, for which the date is known well in advance, Abbassi et al. (2017b) show that banks adjust their portfolio toward safer investments, and they go back to their original levels after the stress tests are concluded.

[27]Even after the inspection is performed the information does not become public. We empirically confirm the anecdotal evidence that inspections are unexpected by running pre-trend tests and placebo tests.

aimed at discarding banks that passed the standard test used in the pre-inspection phase. We refer to this group as the set of not-eligible banks.[28] Figure 4**A.** shows the distribution of eligible vs. not-eligible banks across years.[29] Eligible banks are rated according to a computer-based selection rule that combines information from off-site supervision, last inspection (vintage), organizational structure of the bank and their geographical macro-area.[30] One of the conditions that has to be satisfied is the geographical representation of each macro-area called *Area Territoriale e Circoscrizionale* (ATC, henceforth). The supervisor has to select eligible banks to be inspected from each ATC in a similar proportion.[31]

The output of the computer-based selection is a *rating of inspected banks* which is then used to rank banks. Ranking banks is a way to define a clear and computer-based rule on which banks are inspected. However, the rating is not a predictor of a bank's quality within the group of eligible banks.[32] Higher rank position according to the rating means greater probability of being inspected. But we show that this is not correlated with bank's performance.

The exact number of banks inspected each year within the ATC-eligible group depends on human resource constraints. Given the fact that audits are performed by inspectors from both the central office in Rome and the local branch near the bank's headquarters, there are constraints in the number of inspections that can be done within a year in a specific macro-area. This implies that some banks are eligible for an inspection, but for reasons related to logistical issues, they are not going to be inspected. This is what we define as

[28]Pre-inspection phase is a standard procedure aimed at assessing bank's resilience and riskiness. It evaluates the sample of credit classified as NPL and a random sample of performing credits together with information on bank's balance sheets. We confirm this in the data. Table A4 shows balance tests for a set of covariates. We find that eligible banks have a higher stock of NPLs, a lower capital ratio and a lower liquidity ratio compared to banks that are not eligible. Figure A7 shows the graphical counterpart of it.

[29]Given that not-eligible banks are quite different from eligible banks, we drop them in all of our analysis. Specifically, when studying the effect of on-site bank inspections we compare only banks among the group of eligible ones. The average number of banks that are eligible each year is about 143 and the number of those that are not-eligible is about 148.

[30]We do not have access to the exact details about the selection rule as it is unpublished and extremely confidential information. However, in our discussions with the supervisors, they argued that the selection rule gives more weight on other factors than the bank's quality, within the group of eligible banks.

[31]An ATC is a macro-area that includes 3 to 5 different regions. There are 5 different macro-areas in Italy, as shown in Figure A1. They roughly represent north-west, north-east, north-center, center, and south.

[32]In other words, the rating is a function of many variables. Most are related to the bank's organizational structure and geographical information and are not correlated with a bank's quality. We show in Section 6.1 that, conditional on the sample of eligible banks, inspections are as good as randomly assigned.

the group of eligible but not inspected banks.[33] The different macro-area-specific groups of eligible banks are then assembled together to define the inspection plan for the next year.

Summing up, we use the fact that the computer-based selection rule is not a predictor of bank's quality as well as that resource constraints drive the decision on the number of inspected banks within each macro-area to argue that, within the group of eligible banks, inspections are as good as randomly assigned.

In finalizing the inspection plan, the supervisory authority can include some additional banks that were not selected among the initial group. These banks that are specifically selected by the supervisor because the authority may have insider information.[34] The final list of inspected banks, as well as the date when the inspections are planned, is confidential information and is not shared with supervised banks and does not become public information even after the inspections are performed.[35]

3. Data and Descriptive Statistics

For our analysis, we leverage a high quality dataset from multiple sources. We use proprietary administrative data from the Bank of Italy as well as data from the Italian National Institute of Statistics (ISTAT, *Istituto Nazionale di Statistica*) and the National Institute for Social Security (INPS, *Istituto Nazionale della Previdenza Sociale*).

3.1. **Information on bank inspections.** To identify the effect of bank inspections we use a novel proprietary dataset from the Bank of Italy containing detailed information about on-site bank inspections performed by the Bank of Italy during the period 2010–2017. We focus on the sample of Italian mutual banks, *Banche Cooperative di Credito* (BCC), because the regulation regarding the supervision of these banks has not changed with the introduction of the SSM,[36] and at the same time, they play a central role in the local economy. In fact, lending represents their main investment activity and they provide funding especially for small and

[33]This group of banks will be used as the control group since these banks are relatively similar to inspected banks (see Figure A6).

[34]For instance, this is the case when there is "soft information" coming from whistle-blowers. In our data, we find that about 7 banks in each inspection plan are picked arbitrarily by the supervisor.

[35]We confirm also in the data that this is the case as there are no pre-trends and the results are robust to additional placebo tests.

[36]At the end of 2014 the European Union adopted the Single Supervisory Mechanism (SSM), which transferred the direct control of the supervisory activity to the ECB for a subset of banks, the Significant Institutions. The SSM has also substantially changed the type of supervision performed to these banks. Our sample contains only banks that have been under the direct supervision of the Bank of Italy for the entire period and for which the introduction of the SSM has not affected the ways in which inspections are performed. Refer to Section 2 for more information.

medium enterprises Dell'Atti and Intonti, 2006. Moreover, they are required by law to lend their resources mostly to the local economy where the headquarter is located.[37]. Figure A2 shows the main characteristics of Italian banks according to their type of ownership. Mutual banks are, in general, smaller in terms of total assets but they have a relatively important stock of NPLs., mainly because their activity is local by definition, with a limited scope for diversification; moreover they are small and tend to lend to small, opaque and risky firms with little or no collateral (Petersen and Rajan, 1995).[38] Given their inability to diversify the risk as well as their legal obligation to invest locally, they are more exposed to shocks affecting the local economy. This is an additional reason why bank supervision is especially critical among this subset of banks.

3.1.1. *Descriptive Analysis.* Figure A3 illustrates the time variation of the inspection activity over the years 2010-2017. Panel A shows the distribution of eligible vs. not-eligible banks over time. On average every year, 148 banks are not eligible and 143 are eligible for a bank inspection. Panel B shows the distribution of three set of banks over time: (i) inspected; (ii) eligible but not inspected; and (iii) not eligible to be inspected.[39] On average, 77 banks are audited every year, and 66 are eligible but not audited. Panel C shows the distribution of inspected banks and eligible but not inspected banks. The number of banks is similar across the years with the exception of 2011 and 2016: in 2011 the European Sovereign crisis put a lot of pressure on banks (Bofondi, Carpinelli, and Sette, 2017; Bottero, Lenzu, and Mezzanotti, 2018), and this resulted in an increase in inspections; while in 2016, it is mostly a consequence of mergers and acquisitions, which were promoted by a banking reform (Coccorese and Ferri, 2019).[40] While the ranking position is produced for the set of eligible

[37]In fact, "at least 95% of their risky investments (i.e. loans) must be invested in the area of competence". http://www.creditocooperativo.it/template/default.asp?i_menuID=35356

[38]Panel A highlights that mutual banks are widespread in Italy. In 2010 (i.e. the first year available in our dataset), they account for more than 50% of overall branches. Panel B shows that they are small and local in their nature. In 2010, they account for just 5.3% of total assets compared to 77% of public banks. Panel C shows that Mutual banks account for about 7.2% of total deposits. Finally, Panel D shows that even if they are small, mutual banks have a relatively large stock of NPLs – about 20.8%. Figure A4 shows the distribution of different technical forms of credits according to a bank's legal form. Mutual banks are mostly involved in the supply of revocable credit lines. This type of credit best approximates a bank's credit supply, since banks can revoke it anytime on short notice.

[39]Note that this last group is composed of mutual banks that are neither inspected nor eligible to be inspected. Section 2 discusses the way in which the three groups are formed.

[40]This is also highlighted in the final year report by the Bank of Italy to the Italian Government. The https://www.bancaditalia.it/pubblicazioni/relazione-gestione/2011/Rel_Parlamento_Governo_2011.pdf, https://www.bancaditalia.it/pubblicazioni/relazione-gestione/2010/Rel_Parlamento_Governo_2010.pdf?language_id=1.

banks, we have this information only for the set of inspected banks. Figure D shows some statistics on the length of inspections. The number of days per inspection is highly volatile, ranging from a minimum of 32 days to a maximum of 142 days. The mean (and median) is 66 days.

Table 2 provides some summary statistics on inspections. In our sample, 384 out of 438 banks are inspected at least once between 2010 and 2017. Among these banks, 53.12% is inspected only once, 41.15% twice and 5.73% three times.[41]

3.2. **Information on bank's balance sheet.** The data from the bank's balance sheet comes from the Supervisory Reports. By law, banks have to provide information on their balance sheet to the Bank of Italy every month.[42] We consider the data at the quarterly level. Variables include total assets, capital and reserves, sovereign bonds, total loans and NPLs. We also have data about a bank's organizational structure, such as the distribution of bank branches at the province level.[43] Panel A of table 1 provides summary statistics on the sample of mutual banks in Italy (both eligible and not-eligible).

3.3. **Information on firms.** We collect detailed information on balance sheets and income statements from the Cerved dataset. This dataset is collected by the CERVED group SpA and contains information on the universe of incorporated businesses (i.e. limited liability companies, LLC). Information is collected yearly and thus the unit of observation is firm-year.[44]. Each firm has a unique identifier (i.e. Social Security Number), which allows us to link balance sheet data to the credit data. We apply standard filters common in the literature using this dataset (Bottero, Lenzu, and Mezzanotti, 2018, Lenzu and Manaresi, 2019, Schivardi, Sette, and Tabellini, 2017). We drop observations of firms operating in the financial and insurance sector and the utilities and government-related industries. Panel C of table 1 provides summary statistics on the sample of firms. The final dataset contains about 652,830 firms that we observe continuously for the entire period.

[41]Figure A5 shows the geographical variation of the bank inspections in a particular year (2010 Inspection). Panel A shows the spatial distribution of eligible and inspected banks, and panel B shows the distribution of eligible but not inspected banks. Darker colors mean more concentration of bank branches belonging to the specific group in a specific province. Specifically the measure of bank branches concentration is constructed in the following way: $share_{t,p} = \frac{\sum_p \#bank\ branches \in \mathfrak{B}^{treated,p}}{\sum_p \#bankbranches_p}$, where $t = \{$inspected, eligible but not inspected$\}$ and p stands for province.

[42]This is what it is defined as off-site inspections. See section 2 for more information.

[43]An Italian province is more or less equivalent to a non-sparsely-populated county in the US.

[44]As highlighted by Lenzu and Manaresi (2019), compared to other popular publicly available datasets (such as Orbis and Amadeus by Bureau van Dijk), CERVED has no selection bias, no issues with merging different vintages, and a substantially richer set of balance sheet, income statement, and registry variables.

3.4. **Information on credit.** We use granular data on lending at the bank-firm-technical form of credit from the Italian Credit Registry. This dataset is collected and maintained by the Bank of Italy and contains detailed information on credit exposure for all borrowers with granted loans above €30,000. Credits are classified into three different technical forms: revocable credit lines, term loans and loans backed by account receivables (LBR). In most of the analysis, we refer to total loan as the sum of the three technical forms. For each, we have information on both granted and drawn credit. Following the literature on credit supply shocks (Khwaja and Mian, 2008; Schivardi, Sette, and Tabellini, 2017; Cingano, Manaresi, and Sette, 2016; Bofondi, Carpinelli, and Sette, 2017 Accornero, Alessandri, Carpinelli, and Sorrentino, 2017), we consider granted loans instead of outstanding loans because the former better captures the decision of banks to supply credit. We also have information about whether a loan becomes non-performing, regardless of the size of the loan. Panel B of table 1 provides summary statistics of the bank-firm credit relationship.

3.5. **Additional Data Sources.** We rely on a variety of complementary data sources.

3.5.1. *TAXIA data.* We use data on loan prices from the TAXIA database: it consists of granular information – at the quarterly frequency – about the loans granted by a representative sample of Italian intermediaries (about 200 Italian banks). For each bank-firm relationship, we have information about the size of the granted loan, the cost and maturity of the loan (i.e. loans with maturity up to one year versus loans with maturities over one year), the repricing date of the loan (i.e. floating-rate versus fixed-rate), and whether or not the loan is subsidized.

3.5.2. *ORSO data.* We obtain information on banks' boards from ORgani SOciali (ORSO) dataset. ORSO contains exhaustive information on the members of the governing bodies of banks and financial intermediaries and their specific appointments over time (e.g. president, executive director, members of the boards of directors, members of supervisory boards, etc.). Panel D of table 1 provides some summary statistics.

3.5.3. *Social Security data.* We use firm-level data from the Italian Social Security INPS. This dataset contains yearly information on the universe of firms with at least one employee active in manufacturing, construction, or market services, as well as their employment level and their legal form. This dataset gives us a detailed picture on firm dynamics and employment. We also use data from the Italian National Institute of Statistics ISTAT (GDP, and other socio-economic indicators at the province level). Panel E of table 1 provides some summary statistics on the variables available at the province level.

4. The direct effect of Banking inspections - Information disclosure effect

The first part of our analysis tests whether bank inspections have a direct impact on a bank's balance sheet. We perform the analysis at the bank level comparing eligible and inspected banks vs. the group of eligible but not-inspected banks. We show that, following an inspection, audited banks are more likely to reveal losses in their balance sheet. Specifically, inspections force inspected banks to reclassify loans into NPLs and to increase loan loss provisions.[45] We call this an *information disclosure effect* as banks are forced to review the information disclosed in their balance sheet. The incentive to misreport losses arises since reported losses reduce the bank's regulatory capital position. Existing research has argued that banks actively avoid raising new capital and try to find other ways to improve their regulatory capital position (Myers and Majluf, 1984; Admati et al., 2018). We show that bank inspections can limit this problem.

4.1. **Empirical Design.** Our goal is to estimate the causal effect of bank inspections, but when addressing this issue there are two identification concerns: selection bias and anticipation. Regarding the former, by comparing the performance of banks that are inspected to that of not inspected banks, we may just pick up the different quality of banks instead of the true effect of the inspections. Our setting provides a good laboratory because we can compare two otherwise similar groups of banks that differ only in whether they are audited (i.e. treated) or not.[46] Thus, in our analysis, we consider that conditional on being eligible, banks are as good as randomly selected for an inspection. Regarding the latter identification concern, i.e. the anticipation effect and the potential window-dressing problem, we confirm the anecdotal evidence that inspections come at surprise. Thus, there is less concern that banks anticipate them and react in advance.

[45]Loan loss provision is an expense set aside as an allowance for uncollected loans and loan payments. This provision is used to cover a number of factors associated with potential loan losses, including bad loans, customer defaults, and renegotiated terms of a loan that incur lower than previously estimated payments.

[46]We confirm the anecdotal evidence that the ranking is a function of several variables of a bank's characteristics and organizational structure, and it is not a predictor of bank quality. See section 6.1 for the tests on this condition.

4.1.1. *Estimating equation.* We estimate both non-parametric and parametric Difference-in-Difference (DiD, henceforth) models. The basic non-parametric DiD specification is the following:

(4.1)

$$y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$$

where b, p, t and m stand for bank, inspection plan, quarter and macro-area. $\left\{\mathbb{1}_{\tau=t} \times Inspected_{bptm}\right\}$ are event time indicator variables interacted with a dummy variable $Inspected$, that takes value 1 if bank b is included in inspection plan p and is inspected at time t. The interaction term takes value 1 if it is quarter τ relative to the quarter in which the bank is inspected and captures the relative effect of banking inspections. These indicator variables are always 0 for banks that are eligible but not inspected. In our experimental design we consider only banks that are included in the inspection plan because they are very different from those not included.[47] $X_{PRE,b,p}$ is a set of pre-specified control variables interacted with quarter dummies. We follow the literature (Schnabl, 2012) and include in $X_{PRE,b,p}$ the following variables: bank size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio.[48] We choose a window of 3 years around the event, with 4 quarters before and 8 quarters after the inspection. In this way we avoid banks that are treated multiple times in the same event.[49] The specification includes bank-inspection plan fixed effects (α_{bp}) and quarter fixed effects (α_t), which absorb fixed differences across banks-inspection plan and across years.[50] The latter is especially critical as the scope and intensity of inspections may have changed over time, due to the European Sovereign Crisis or potential changes in the budget financing inspections. We also include macro-area fixed

[47]We confirm this in different tests. First, we show balance test comparing eligible and not eligible banks. Eligible banks have a significantly higher stock of NPLs, and they have lower capital ratio and liquidity ratio (Figure A7). Second, we perform the same event study as equation 4.1 and show that there is a pre-trend when we compare inspected banks with those that are not eligible (Figure **??**).

[48]We use pre-defined variables as controls to avoid the problem of bad controls (Angrist and Pischke, 2009). Specifically all the variables are computed 4 quarters before the inspection.

[49]Table 2 shows that the average number of days since the last inspection is 1359 with a minimum of 518. As a robustness test, we confirm the baseline results by considering only banks inspected for the first time in the sample. Results are shown in table A2.

[50]Since banks can be included in multiple inspection plans, each bank can enter the sample multiple times as part of different "natural experiments". Thus, the inclusion of inspection plan-quarter-macro-area fixed effects ensures that the outcomes of banks inspected in quarter t and included in inspection plan p are compared to outcomes of banks in the control group in the same quarter t and included in the same inspection plan p.

effects (α_m) which takes into account for differences across different macro-areas.[51] ε_{btpm} are standard errors, two-way clustered at the level of the bank and inspection plan (Petersen, 2009). Our coefficient of interest is β_τ which captures how banks that are inspected alter their business compared to eligible but not inspected banks included in the same inspection plan and operating in the same macro-area, conditional on a set of pre-defined controls $X_{b,PRE}$ and of fixed effects.

We consider also the parametric version of equation 4.1, which allows us to analyze the magnitude of the estimates. We estimate the effect of bank inspections by limiting the period of observation to 4 quarters before and 4 quarters after the inspection, with the following specification:

$$y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post\ Inspection_{bpt} + \gamma X_{b,PRE} + \varepsilon_{btpm} \tag{4.2}$$

where b, p, t and m stand for bank, inspection plan, quarter and macro-area respectively. y_{btpm} is the outcome of interest. $Post\ Inspection_{bpt}$ is a dummy variable taking value 1 for all quarters after the inspection of bank b included in inspection plan p and inspected. It takes value 0 for eligible but not inspected banks. The parameter of interest is β^{ATE}, which measures the change in the outcome variable of the inspected banks compared to the banks that are eligible but not inspected in the same inspection plan-macro area, conditional on a set of pre-defined controls $X_{b,PRE}$ and a set of bank, quarter and inspection plan by macro area fixed effects.

4.1.2. *Identifying Assumption.* The interpretation of β_k in equation 4.1 (or β^{ATE} of equation 4.2) as the causal effect of banking inspections requires two conditions. First, the timing of the bank inspection should be uncorrelated with the bank's economic outcomes, conditional on the set of fixed effects and other control variables. For example, a banking inspection that is preceded by a decrease in a banks' quality and a change in the economic opportunity for firms would violate the identifying assumption.[52] Second, the two set of banks – treated and control – are similar on observables, i.e. there is no selection bias. If banks that are inspected are extremely different from those eligible but not inspected, we may only estimate the effect of these pre-differences instead of the impact of banking inspections. This could potentially be the case if we compare public banks with mutual banks. The former, on average, are bigger and more able to diversify the risk. Also, inspected banks should not

[51] In some specifications, we include macro-area-quarter fixed effects (α_{pt}) to take flexible controls for time trends in specific macro-areas.

[52] We refer to cases in which an economic shock affects economic opportunities and thus the results are driven by the demand side, i.e. firms are not able to repay their loan.

differ in their probability to be inspected compared to eligible but not inspected banks. For instance, if audited banks expect to be inspected, they may react in advance to the audit window-dressing for the supervisor and thus, confounding the effect of bank inspections.

Our experimental design helps us overcome these potential threats: in our setting we compare banks that operate in the same geographical area and are included in the same inspection plan, and thus potentially affected by the same local economic shock. Moreover, we show that the timing of the inspection is uncorrelated to banks' characteristics. That is, the order of the inspections is not a predictor of bank quality (table A9).

To reduce concerns of a potential selection bias, we leverage again our experimental design. First, as described in Section 2, we consider only banks with the same type of ownership, namely mutual banks, that have a very similar business model – they have to comply to the same legal requirements and are exposed to similar challenges.[53] Second, we rely on the selection process that the supervisory authority uses to create the treated and control group. Following this idea, we discard any bank that is not included in the eligible group and the analysis is based only on the comparison of two groups - eligible and inspected vs. eligible but not inspected - which, according to the algorithm used by the Bank of Italy, look similar on observables. Third, we run several balance tests to confirm that: (1) banks eligible to be inspected are different from not-eligible banks, and (2) banks eligible and inspected are not significantly different from banks eligible but not inspected. Fourth, for our research design to be valid, inspected and eligible but not inspected banks should follow parallel trends in the quarters prior to the inspection, which implies that the pre-period β_τ (for $\tau = -4, \ldots, -1$) should not be statistically different from zero. We show that this is the case. Fifth, we show that the results are consistent also by comparing *only* inspected banks included in the same inspection plan that are audited at a different point in time.[54]

4.1.3. ***Results***. The first part of our analysis investigates the impact of banking inspections on a bank's balance sheet. Specifically, we answer the question of whether the supervisor detects and discloses misclassifications in the bank's balance sheet, i.e. the information disclosure effect. We focus on two main dimensions of a bank's balance sheet: the amount of NPLs and loan loss provisions. Figure 2 provides the results. Panel A shows the dynamic

[53]By law, they need to lend at least 95% of their resources in the local economy. This poses a challenge in terms of diversifying their risk.

[54]While this exercise is extremely informative in reducing concerns of a potential selection problem (internal validity of the results), it has some limitations. Since our ultimate goal is to study the spillover effects of bank inspections to a local economy, by limiting the sample to only a subset of banks, i.e. inspected banks, it would be hard to evaluate the overall effect in a local economy (external validity).

effect on the log of outstanding NPLs.[55] We find that bank inspections force banks to reclassify some loans into NPLs. As a result, the levels increase after the first quarter since the inspection is performed. Panel B highlights that the timing coincides with the on-site inspections. The growth rate becomes positive just after the beginning of the inspections and then goes back to zero. Figure 3 shows similar results by looking at other types of NPLs, i.e. unlikely-to-pay (panel A) and past-due exposures B).[56] Banks are also forced to cover for these potential losses by increasing their loan loss provisions for possible losses on bad loans (Figure 4**A.**) and on other NPLs (Figure 4**B.**). Overall, bank inspections force banks to rectify information on their balance sheets by recognizing potential losses.

Table 3 quantifies the effect of on-site bank inspections. Inspected banks' NPL wedge *vis-a-vis* eligible but not inspected banks is about 3.6%. For the average bank in the control group with €NPL = 38.28 million, this implies an increase of about €1.19 million each quarter. In other words, the total effect in the first 4 quarters is about €4.76 million, corresponding to the 12% of the stock of NPLs. The effect is relatively sizeable. Column (2) considers loan loss provision for bad loans and column (3) loan loss provisions for other NPLs.[57] We find statistically significant results for loan loss provision on bad loans but not for other types of NPLs.[58] We confirm the results by performing the same exercise only on the sample of banks that are inspected for the first time (table A2).[59]

Summing up, we find that there is an important information disclosure effect by on-site inspections. This is in line with the idea that inspectors enforce stricter supervision and are able to identify misclassified loans. Banks are forced to reclassify these loans into NPLs and to increase the resources set aside for future loan losses. In the context of the US Granja and

[55]When we consider NPLs, we refer to bad loans unless differently specified. In contrast to other types of NPLs, once a loan is classified as an NPL, it is very unlikely to return to performing.

[56]Unlikely-to-pay and past-due exposures data are not included in the Credit Registry. They come from the Supervisory Reports (SR).

[57]Banks can account for losses on non-performing loans through two different methods. The first consists of the devaluation of the part of the exposure deemed not recoverable. The second is based on the direct "write-off" of the loss component. In general, intermediaries resort to writing-off if the loss is proven by certain and precise elements, while they make use of the devaluation in other cases. For instance, a typical case to write-off a credit is when the borrower is subjected to bankruptcy procedure, or when there are conditions (according to the IFRS/IAS) to write-off, even just for a portion of the credit from the balance sheet.

[58]Note that the information on loan loss provision is reported twice a year and this is the reason of the smaller sample size for column (2) and (3).

[59]As reported in table 2 in our sample we observe about 53% of banks that are inspected only once during the period under consideration, 41.15% are inspected twice and 5.73% are inspected three times.

Leuz (2019) find similar results, showing that stricter supervisors due to the transitioning of a new supervisor force banks to recognize more losses.

5. The indirect effect on Lending

In this section, we study the possible implications for the lending activity of inspected banks. To do so, we run a bank-level analysis comparing inspected banks with the group of eligible but not-inspected banks. We show that lending activity declines in the first few quarters following the inspection.

5.1. **The effect on aggregate lending.** *Ex-ante* it is not clear what could be the overall effect of on-site inspections. On one hand, by forcing supervised banks to reclassify loans into NPLs, bank inspectors generate pressure on the bank's balance sheet, as they are forced to either increase the capital or cut their lending activity. In other words, bank supervision generates a bank capital shock which has negative implications for lending activity.[60] On the other hand, bank inspections may generate a positive effect on lending. By revealing misclassifications and providing guidelines on how to improve the internal management and monitoring, inspectors can reduce moral hazard and agency frictions at the supervised bank. In theory, this could free up resources for lending activity.[61] Thus, what effects prevail is mostly an empirical question.

5.1.1. *Estimating equation.* The empirical models used are the same as equations 4.1 and 4.2. We employ a DiD model, comparing eligible and inspected banks to those eligible but not inspected.

5.1.2. *Results.* Figure 5 shows the effect of the aggregate lending activity for inspected vs. eligible but not inspected banks for the different type of borrowers. Panel 6**A.** considers the overall lending activity, panel 6**B.** focuses only on corporate loans, while panel 6**C.** considers loans to small and medium enterprises (SMEs). We find that lending activity is reduced after the inspection. Considering Table 4 we find that, at impact, total loans drop by about 2.5%, meaning that for the average bank in the control group with total loans of

[60] For instance, Peek and Rosengren (1995) study the direct link between regulatory enforcement actions and the shrinkage of bank loans to sectors likely to be bank dependent. They find that banks involved in regulatory enforcement actions reduce their lending. More generally, there is a large literature showing that bank capital shocks have a negative impact on lending activity (Peek and Rosengren, 2000). The emerging literature on the impact of stress test show that banks more affected by the stress test are more likely to cut their lending (Cortés et al., 2020; Acharya et al., 2018).

[61] This is in line with Granja and Leuz (2019). They find that stricter supervision generates a positive credit supply shock due to the reduction of internal inefficiencies.

€384.19 million there is a drop of about €9.61 million each quarter; thus, the cumulative effect for the first 4 quarters is €38.44 million: roughly 10% of total lending for the average bank in the control group. The results are robust to the inclusions of different sets of fixed effects. Looking at the plots, we do not find substantial differences between banks before the inspections take place, reducing any concern of selection bias. Moreover, the lending activity goes back to baseline levels after around 7 quarters. The drop in the lending activity in the short period can be explained by the increase in the loan loss provision for bad loans as shown in figure 3. Banks have to offset the reduction in profits and the value of their assets due to the increase in potential losses from the existing loans (Accornero, Alessandri, Carpinelli, and Sorrentino, 2017). Thus, a deterioration of a bank's balance sheet due to an increase in NPLs may have broadly the same implications as a decline in capital and this eventually generates a contraction in credit supply (Froot and Stein, 1998; Aiyar et al. 2014). To confirm this idea, we find that bank equity adjusts slowly, as suggested by Figure A15. Thus, banks overcome the need to satisfy the regulatory capital in the short period by cutting the lending activity.

Contrary to a standard bank capital shock due to unforeseen reasons (e.g. failure of Lehman Brothers), this event is induced by supervisory activity. Supervisors can impose corrective measures on banks which may lead to a change in their lending behavior. This is especially important in the context of the Eurozone as it is well documented that banks have been plagued with the problem of zombie lending, especially after the financial crisis (Acharya, Eisert, Eufinger, and Hirsch, 2019b; Adalet McGowan, Andrews, and Millot, 2018; Schivardi, Sette, and Tabellini, 2017) which created negative implications for the real economy (Blattner, Farinha, and Rebelo, 2017; Acharya, Crosignani, Eisert, and Eufinger, 2019a).[62] More generally, Gopinath et al. (2017) document a significant increase in productivity losses from capital misallocation in Southern European countries. They show that the drop in real interest rates following the introduction of the Euro led to a misallocation of capital inflows toward firms that have higher net worth but are not necessarily more productive.

[62] Peek and Rosengren (2005) and Caballero, Hoshi, and Kashyap (2008) show evidence of zombie lending for Japan.

6. Validity of our results

In this part we discuss the main threats to our identification strategy and the ways in which we address these issues. We provide several robustness tests reducing any concern of endogeneity problem.

6.1. **Potential threat to identification.** The main concern with our identification is that results might be driven by a selection bias. That is, inspected banks are different and, in particular, worse than not-inspected banks. To address this issue, we rely on a two-step selection process. As discussed in section 2 the Bank of Italy employs a computer-based selection rule to identify a group of eligible banks based on observable characteristics. Within this group, the system ranks banks to be inspected. In our experiment, we rely on the fact that the latter selection takes into account other components of a bank, not directly correlated with its quality. For instance, one main element is the geographical location of banks; a similar proportion of banks inspected in each macro-area is required.[63] We show that the ranking, which can be considered a sufficient statistic of the selection rule, is neither a predictor of bank's quality, nor does it explain the results we find.

6.2. **Robustness Test.** We perform a battery of robustness tests to confirm the validity of the baseline results. We find no significant differences among the eligible banks (Figures A6 and A7); moreover, we confirm that the ranking neither drives the results (Figures A9 and A11; table A6) nor is correlated with a bank's health (Figure A10). We further rule out any issues of selection bias by performing the same analysis employing *only* the sample of inspected banks (Figure A8). Finally, we run a set of placebo tests to confirm that inspections come at a surprise (Figure A14). Table 5 shows the summary of some robustness tests.[64] Column (1) refers to the log of NPL. Column (2) to the log of credit to firms. Row 1 shows the results of the baseline model as in tables 3 and 4. Row 2 considers a model in which we compare only inspected banks in the top quartile vs. bottom quartile. In other words, the treatment is whether a bank has a high ranking position. We find no evidence that inspections have a significant impact on this group compared to inspected banks in the bottom group. Row 3 employs a specification in which we interact the main regressor with a categorical variable indicating the ranking position of the inspected banks. We create four different quartiles. We find that the dummy *inspection* is the only significant variable in the

[63] We do not exactly know the components of the algorithm, because it is classified information kept by the supervisor. However, from our conversations with inspectors we know that the geographical location of the bank and the last time is inspected are information taken into account by the computer-based selection rule.

[64] For more details and more tests please refer to Appendix A10.

regression. Row 4 tests if the results are driven by inspected banks ranked in the top quartile. We drop this group of banks and find similar results. Row 5 considers only the sample of inspected banks. We take advantage of the different months in which banks included in the same inspection plan are inspected.[65] Row 6 employs a propensity score matching. We match inspected banks with eligible but not inspected banks based on observables and we find similar results.

7. The impact of banking inspections at the firm level

In this section we study the heterogeneous impact of bank inspections to firms. Given the nature of the credit supply shock, i.e. supervisory-driven, we test whether inspections induce banks to change their lending decisions. We introduce a novel method to identify impaired firms based on inspectors' activity. We show that the result on credit contraction established in the previous section is driven by unviable firms only: healthy firms in the inspected banks' portfolio do not suffer from the negative credit supply shock.

This question is extremely important as it is well documented that in the recent years, especially in Europe, there has been a misallocation of credit to underperforming firms (Adalet McGowan et al., 2018) which has generated an aggregate loss in productivity (Gopinath et al., 2017). Granting or extending credit to weak firms keeps them alive and allows banks to prevent reporting new losses that would impair their capital requirements (Caballero et al., 2008; Blattner et al., 2017). In our framework we are able to directly test directly if bank inspections are capable of reducing this problem.

7.1. **Theory: Capital Shock Channel vs. Reallocation Channel.** In this part we discuss the two competing theories behind the potential effect of the credit supply shock, i.e capital shock channel vs. reallocation channel. We construct a new measure on a firm's quality based on supervisory activity. We show that the effects are consistent with the reallocation channel. Inspected banks cut lending to underperforming firms and reallocate it to healthy firms in their portfolio or to new firms.

The experimental setup we employ is quite different from what is used in the vast literature studying the real effect of credit supply shocks. This literature has extensively discussed the effect of these shocks coming from unforeseen "natural experiments" such as the Lehman Brothers collapse (Chodorow-Reich, 2013), the Russian oil crisis (Schnabl, 2012), the Greek bailout (Bottero, Lenzu, and Mezzanotti, 2018), the Japanese banking crisis (Peek and

[65]For this particular specification, we use monthly-level data for the group of banks that are inspected. Figure 1 shows the time variation of inspections within an inspection plan.

Rosengren, 2000, and the Japanese land market collapse (Gan, 2007).[66] The type of shock we study has a different connotation. It is driven by the supervisory activity and it aims to reduce the inefficiencies in the bank's management. Thus, *ex-ante* it is not clear how the supply of credit is affected. On one side, the supervisors, by forcing the reclassification of a large amount of loans, put pressure on banks to either raise capital or reduce their lending.[67] Thus, in this scenario, unless banks are able to raise capital to cover recognized losses during the bank inspections, supervisory activity results in a reduction in the credit supply ("capital shock channel") to all firms in the bank's portfolio (Bernanke et al., 1991; Peek and Rosengren, 1995). On the other, since bank inspections are targeted at cleaning up a bank's balance sheet from specific unprofitable investment, this may induce banks to cut credit lines to underperforming firms. There is evidence showing that banks, especially weak banks, have the tendency to misreport or delay the report of loan losses (Blattner, Farinha, and Rebelo, 2017). Reporting losses would jeopardize their regulatory capital position and therefore they roll over credit to impaired firms just to keep them alive. However, once bank audits force them to truthfully report these losses, banks' incentives to evergreen loans to these firms may disappear. Lending could increase if on-site bank inspections reduce existing agency frictions and/or adverse selection problems that prevented bank managers from lending and adopting better practices unviable before the inspection. Thus, looking from the perspective of the firms, bank inspections may potentially have a double-edged effect: a negative effect on the credit growth of underperforming firms and a positive effect on the credit growth of performing firms, this is what we call a "reallocation channel".[68]

The idea behind the reallocation channel comes directly from the literature on zombie lending.[69]. The main takeaway from this literature is that banks (especially weak banks) have an incentive to keep lending to underperforming firms. In fact banks with a weak balance sheet (i.e. low capital ratio close to the regulatory limit) want to avoid recognizing new losses that may force them to raise new capital. This is especially true for banks whose

[66]The bottom line of these papers is that a credit supply shock derived from a period of unforeseen financial instability may reduce the ability for banks to supply credit with negative implications for the real economy.
[67]A similar question is asked by Granja and Leuz (2019). They study how a change in the strictness of bank supervision affects bank lending and in turn local business activity.
[68]Similarly, Bai et al. (2018) shows how bank deregulation in the US leads to labor and capital reallocation to young and productive firms while Bian (2019) shows that credit reallocation is an important mechanism to boost aggregate productivity in the aircraft sector.
[69]There is a growing literature discussing the role of a weak banking sector and its interaction with "zombie firms" (Peek and Rosengren, 2005; Caballero, Hoshi, and Kashyap, 2008; Schivardi, Sette, and Tabellini, 2017) and the implication for the economy (Acharya, Eisert, Eufinger, and Hirsch, 2019b; Blattner, Farinha, and Rebelo, 2017)

capital ratio is very close to the minimum required by law. Recognizing new losses would force them to raise new capital which is especially costly in periods of financial instability (Hanson, Kashyap, and Stein, 2011). This evergreening of loans has been shown to have negative effects in the credit market with implications on the real economy (Acharya, Eisert, Eufinger, and Hirsch, 2019b, Blattner, Farinha, and Rebelo, 2017). Bank inspections can help break this circle by forcing banks to clean up their balance sheets by reporting true losses. Once losses are reported and banks have internalized their costs, they may have an incentive to permanently remove these loans from their portfolio or at least re-optimize their portfolio toward more productive investments.

7.2. **Estimating equation.** Our framework enables us to test directly if bank inspections contribute to mitigating this problem. Specifically, we study the effect of this "supervisory induced" shock (i.e. on-site bank inspections) on the ability of firms to obtain credit. We therefore move to a firm-bank analysis, tracking the credit relationship over time.

Following the literature, focusing on the sample of firms with multi-lending relationships, we employ an empirical model in which we control for credit demand (Khwaja and Mian, 2008).[70] Moreover, since existing research has shown that banks have an incentive not to report losses that would jeopardize their regulatory capital position, we consider the sample of firms that have only performing credits before the inspection (Bofondi, Carpinelli, and Sette, 2017).[71] This exercise compares the growth of credit for a firm borrowing from a bank exposed to the inspection vs. a bank in the control group (i.e. eligible but not inspected).[72] In this way, we can control for unobserved changes in borrower characteristics.[73] We follow firms one year before and two years after the inspection. We employ the following empirical

[70]Note that multi-lending relationship is common in the Italian banking system. Compared to the United States in which the share of firms with one bank relationship is 56%, in Italy the share of firms with multi-lending relationships is 89% (Detragiache, Garella, and Guiso, 2000; Sette and Gobbi, 2015).

[71]That is, we exclude firms with outstanding NPLs at the beginning of the period and focus only on firms that are in good standing according the the Credit Registry. This analysis speaks directly on the role of bank supervision to force banks to report true losses in their balance sheet as well as to encourage them to change their lending policy.

[72]In robustness checks, we consider the full sample of firms, i.e. we also include firms with only one lending relationship.

[73]As discussed in Section 4.1.3 for our results to be driven by credit demand factors, it must be the case that firms ask for less credit exactly in the same quarter as the bank is inspected − not before because we show there are no pre-trends. While this could be possible, it is very unlikely. Someone may argue that banks are inspected because their poor performance is driven by a local recession. If this is the case, however, we still should see firms demanding less credit even before the inspection. The fact that we do not observe any pre-trend in figure 5 can help rule out this possibility. In table A20 we show that provinces that experience more bank inspections are not preceded by local economic downturn.

model at the firm-bank level:

$$credit\ growth_{ibt} = \beta Post\ Inspected_{bpt} + \alpha_{it} + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp} \tag{7.1}$$

where i, b, p and t stand respectively for firm, bank, inspection plan and quarter. $credit\ growth_{ibt}$ is our outcome variable and it measures the credit growth of firm i borrowing from bank b.[74] $Post\ Inspected_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $X_{b,PRE}$ is a set of pre-determined bank-level controls, the same as the ones included in regressions in Section 4.1.[75] $W_{ib,PRE}$ is a set of pre-determined bank-firm relationship controls. We follow the literature (Khwaja and Mian, 2008) and include: relationship length (number of quarters in which we observe a lending relationship between the firm and the bank); the firm's credit share (i.e. share of the firm's loan balance in the bank's loan portfolio); main lender, a dummy equal to 1 if the bank is the firm's largest lender; and bank share, which refers to the share of the bank in the firm's loan portfolio. ϵ_{ibpt} is the error term. Our coefficient of interest is the β: a positive value would imply that the firm's credit growth from inspected banks is higher compared to banks in the control group (i.e. eligible but not inspected).

7.2.1. *A new proxy for a firm's quality.* To test the reallocation channel hypothesis we interact our independent variables with a proxy for firm's quality. Identifying zombie firms is not so straightforward, mostly because it is difficult to distinguish whether a firm is undergoing temporary financial distress or if there are more fundamental issues.[76] Our paper

[74]Note that we focus only on committed credit instead of drawn credit. Committed credit is a variable that better represents a bank's willingness to grant a credit. Instead, drawn credit responds to a firm's business decisions – the firm decides how much/when to use the credit that was granted before (Bofondi et al., 2017).

[75]We include: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. Note that both firm-bank relationship controls and bank-level controls are computed four quarters before the banking inspection to avoid any issue related to bad controls.

[76]The literature offers different strategies. Peek and Rosengren (2005) uses a definition based on the productivity at the industry level. While this is a great first attempt, it is also true that a measure at the industry level hides a huge heterogeneity within the industry. Most recent and most credible attempts are done by Schivardi, Sette, and Tabellini (2017) and Acharya, Crosignani, Eisert, and Eufinger (2019a). The former takes advantage of a very detailed data at the firm-level. They consider a firm to be zombie if two conditions are satisfied. First, the Return on Assets (ROA) is lower than the prime rate (i.e. the interest paid to banks by the safest firm). This can be considered a proxy for a risk-free investment. Second, the leverage of the firm is higher than the median of the sample of firms. Similarly, the latter identifies a zombie if the firm is of low-quality with respect to two dimensions. If it has have operational problems, which is identified when the interest ratio is below the median and a leverage ratio above the median, and financial problems which is identified with the leverage ratio being above the median. Second, the firm obtains credit at very low

also contributes to the literature on this dimension. Leveraging the bank inspection data, we identify firms that are underperforming based on the result from bank inspections. A firm is flagged as truly underperforming if the bank reclassifies its loans from performing to non-performing within the first quarter after the inspection.[77] We believe this is a valid measure to identify "zombie firms" because this reclassification is driven by the bank supervisor and bank inspections are exactly meant to identify those loans that are "misclassified" by banks.[78] We support this assumption by confirming that 98.07% of the loans of firms that are reclassified during an inspection period by inspected banks are not reclassified by eligible but not inspected banks in the first year after the inspection.[79] Additionally, among the set of firms whose loans are reclassified as NPLs, only 0.02% are not reclassified by inspected banks.[80] Table 6 shows that firms whose loans are reclassified, are significantly different from other firms - we call them healthy firms - along several dimensions. On average they are more leveraged, have less liquidity, and are performing worse (according to different indicators such as cash flow).

To test the reallocation channel, we augment equation 7.1 with an interaction term between bank inspection and the "reclassified" status. The latter variable is a dummy variable equal to 1 if firm i has its loan reclassified as NPL as a consequence of the bank inspection.

The augmented model we use is the following:

$$\begin{aligned} credit\ growth_{ibt} \quad &= \quad \beta\Big(Post\ Inspected_{bpt}\Big) + \eta\Big(Post\ Inspected_{bpt} \times Reclassified_{ip}\Big) + \\ &\quad\ \alpha_{it} + \delta W_{b,PRE} + \gamma X_{ib,PRE} + \epsilon_{ibpt} \end{aligned} \tag{7.2}$$

interest rates, i.e., the ratio of its interest expenses relative to the sum of its outstanding loans, credit, and bonds in a given year is below the interest paid by its most creditworthy industry peers, namely AAA-rated firms in the same industry and year in our sample.

[77]We consider the first quarter, since, as it is highlighted in Panel B of Figure 2, the increase in NPLs is limited to the first quarter after the inspection. The growth rate is positive between time 0 and 1 and then goes back to 0. We use this fact as evidence that the increase in the NPLs is driven by the inspection activity.

[78]As robustness test we employ also different proxies for impaired firms such as the one used by Acharya et al. (2019b) and confirm the results.

[79]In other words, loans to the same firm are reclassified as NPLs by inspected banks and are not reclassified by banks in the control group in 98% of the cases.

[80]In other words, considering loans granted to firms that borrow from multiple inspected banks, only the 0.02% of those loans are not reclassified by some inspected banks. This is in line with the fact that banking inspectors provide only suggestions to banks. They can decide to comply with it or not.

where the outcome variable is the credit growth for firm i borrowing from bank b where bank b is included in inspection plan p.[81] The additional element in equation 7.2 is given by the interaction between $Post \times Inspected_{bpt}$ and $Reclassified_{ibp}$. This interaction term identifies those firms classified by the supervisor as unviable. Thus, this model compares the credit growth of firms that borrow from inspected and not inspected but eligible banks, and whose loan is reclassified as NPL by bank inspectors. Robust standard errors are clustered by bank.

7.3. **Results.** Table 7 shows the results on the intensive margin for the equation 7.1, while Table 8 presents the results on the extensive margin. For the intensive margin we use a sample of firms that we observe at least one quarter before and one after the inspection. For the extensive margin analysis we use only firms that we observe at least one period before the inspection. Moreover, all the analysis here considers only the sample of firms that do not have any NPLs in the two years prior the inspection.

In Table 7, column (1), we test the capital shock channel. According to this theory, we expect bank inspections to have a negative effect on the credit growth of firms. By reclassifying loans into non-performing, banks are forced to recognize losses on their balance sheets and increase the amount of write-offs, pushing them to raise capital and/or cut lending. We find a negative value of the coefficient on $Post \times inspected$. Firms borrowing from both inspected and eligible but not-inspected banks experience a negative effect on their credit growth. Their credit growth from inspected banks decreases by 0.1% compared to the credit growth from eligible but not inspected banks. The effect is not significant. This result is consistent with the findings at the bank-level. On average, inspected banks are pulling back some credit as a result of the negative shock at their capital.

Columns (2)-(3) test for the heterogeneous effect of bank inspections among different types of firms, i.e. the reallocation channel. Specifically we introduce our variable of "reclassified" based on whether the loan is reclassified as a NPL immediately after the inspection. The results are in line with the reallocation channel: we find that reclassified firms experience a

[81] The credit growth is defined in two ways. The first is the following:

$$growth(credit_{ibt}) = \frac{credit_{ibt} - credit_{ibt-1}}{0.5(credit_{ibt} + credit_{ibt-1})} \tag{7.3}$$

which is a second-order approximation of the log difference growth rate around 0; it is bounded in the range $[-2, 2]$, limiting the influence of outliers; it also accounts for changes in credit along both the intensive and extensive margins (Haltiwanger, Schuh, and Davis, 1996; Chodorow-Reich, 2013). The second measure is $\Delta \log(credit_{ibt}) = \log(credit_{ibt}) - \log(credit_{ibt-1})$. This outcome variable is a pure measure of the intensive margin.

drop in the credit growth. The coefficient on the triple interaction is negative and statistically significant and its magnitude is quite large. Reclassified firms have a drop in the credit growth of almost 66%. On the other side, the coefficient on Post$\times$inspected changes sign and increases both in magnitude and in its significance. That is, healthy firms experience a positive credit growth of 3.4%. Column (4)-(5) consider a different outcome variable, i.e. $\Delta\log(credit_{ibt}) = \log(credit_{ib,t}) - \log(credit_{ib,t-1})$. This is a pure measure of intensive margin. We find consistent result also by using this outcome variable.[82]

As a robustness test we perform a similar analysis with different proxies for a firm's quality. In Table A13 we construct the definition of zombie firms following Acharya et al. (2019b).[83] In Table A14 we use Total Factor Productivity as a proxy for firm's productivity Wooldridge, 2009.[84] We find evidence of the reallocation effect, in line with the baseline model.

Table 8 studies the effect of bank inspections on the extensive margin, namely the probability that banks cut a lending relationship. This is a linear probability model in which the outcome variable is a dummy variable equal to 1 if the bank stops lending to the firm and 0 otherwise. Columns (1)-(2) test the capital shock channel: we find that the probability of cutting a lending relationship is either *negative* for banks that are inspected (column 1) or not significant. This is somehow against the capital channel story, by which we expect that the bank capital shock increases the likelihood for a bank to cut a lending relationship. This result may be hiding a heterogeneous effect at the firm level. Columns (3)-(5) test the reallocation channel of equation 7.2. The probability of cutting a lending relationship becomes highly positive and significant for underperforming firms, while it is significant and negative for other firms.[85] This is in line with the idea that inspected banks, once they are forced to recognize loan losses (i.e. reclassify loans from performing into non-performing), are more likely to completely cut the credit lines to those firms.

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[82]In table A12 we perform a similar exercise without restricting the analysis to firms that have multiple lending relationship. The purpose is to show that the results are not driven by sample selection. However, the potential downside is that we do not control for unobserved factors affecting the credit demand (Khwaja and Mian, 2008. The estimates are consistent with the baseline results in table 7.

[83]A firm is a zombie if it satisfies two conditions. First, it is of low-quality. That is, its interest coverage ratio is below the median and its leverage ratio is above the median, where the medians are calculated at the industry-year level. Second, the firm obtains credit at very low interest rates, i.e., the ratio of its interest expenses relative to the sum of its outstanding loans, credit, in a given year is below the interest paid by its most safest peers in the same industry and year in our sample. We identify the safest firms by considering their credit score developed by the Italian Credit Agency and included in the dataset at the firm level.

[84]We compute revenue TFP with the Wooldridge method.

[85]All these regressions control for bank-firm relationship characteristics such as whether or not the bank is the main lender.

Taken together, these results show evidence that inspected banks reallocate resources towards more productive firms already in their portfolio. This is suggesting that they are changing their lending policies following an inspection. To confirm this idea, we study whether banks start credit relationships with new firms and under which conditions. To do so, we consider a similar model as equation 4.2, where the outcome variable is the change in the total number of *new* loans by bank b. We identify new loans as loans to firms that have no previous credit relationship with the bank.[86] Table A15 shows the results. We find evidence that after an inspection, audited banks are more likely to start a new credit relationship with a firm that was not previously in the bank's portfolio. The coefficient is positive and statistically significant and the results are robust to different set of controls.

We then study the characteristics of these new loans. Table A16 shows that, on average, new loans granted after an inspection are *ex-ante* less risky. To measure the risk of a firm, we use two different measures. In columns (1)-(2) we use a risk-score based on the Altman Z-score (Altman, 1968; Altman et al., 1994). This measure is computed by the Italian Credit Agency based on its proprietary algorithm and it is available to all financial intermediaries.[87] We compute the average score for firms that start a new credit relationship with bank b in quarter t.[88] In columns (3)-(4) we use a measure based on the volatility of the growth sales at the firm level, computed directly from the balance sheet of firms: following Neuhann and Saidi (2018), we construct annual growth rates that accommodate entry and exit using the measure developed in Davis et al. (2006):

$$\gamma_{i,t} = \frac{(x_{i,t} - x_{i,t-1})}{0.5 \times (x_{i,t} + x_{i,t-1})} \tag{7.4}$$

We use these growth rates to compute the standard deviation of firm i's sales growth over four years. For both measures to compute averages, and we consider only new loans created 4 quarters before and 4 quarters after the inspection. Table A16 shows that inspected banks grant new loans to firms that are less-risky. By considering the first measure of risk, the Altman Z-score we find that the average risk of firms obtaining new loans from audited banks

[86] More precisely, we consider the following empirical model:

$$\Delta \log(\#NewLoans) = \beta Post\ Inspected_{bt} + \gamma_t + \gamma_b + \gamma_{pm} + \eta X_{b,PRE} + \epsilon_{btp}$$

We include the same controls and fixed effects as in equation 4.2.

[87] This information comes from CERVED. Please refer to section 3.

[88] Formally, for each bank b in quarter t we compute the following measure: $Average\ Score_{b,t} = \frac{\sum Score_i \{\mathbb{1}_{New\ loan_{ib}=1}\}}{\sum \{\mathbb{1}_{New\ loan_{ib}=1}\}}$ where $\mathbb{1}_{New\ loan_{ib}=1}$ is an indicator that takes value 1 if firm i borrows from the first time from bank b and $Score_i$ is the Altman Z score for firm i.

is 5% lower than before an inspection. The coefficient is statistically significant and robust after controlling for a set of fixed effects and bank-level variables. We find similar results by using the second measure even if the magnitude is somehow smaller.[89]

Finally, we look at the interest rate charged on these new loans. We match these loans to the interest rate charged at origination. Similarly to the measure of risk, we compute the average interest rate charged by bank b in quarter t on the set of new loans. Table A17 shows the results of this analysis: we find that the interest rate charged by inspected banks on new loans is lower after the inspections by 1.1%. This is very much in line with a change in their lending standards by banks. We find that after an inspection, audited banks lend to safer firms and reduce the interest rate charged (Stiglitz and Weiss, 1981).

From a policy perspective, this is extremely instructive of the benefits of the banking supervision in reducing problem of zombie lending. We find that on-site bank inspections generate an effect in line with the reallocation channel. Inspected banks cut lending to zombie firms and reallocate credit either to healthy firms in their portfolio or to new firms that are, on average, less risky. Thus, bank inspections do not only uncover potential problems in bank's balance sheet by revealing loan losses (direct effect), but they also encourage banks to change their lending policies.

7.4. **Potential mechanism.** We discuss two potential mechanisms explaining the change in the lending policy by inspected banks. First, a change in their governance. Second, a forced recapitalization of inspected banks moving them away from minimal regulatory capital threshold and reducing the potential incentive of gambling for resurrection. Both of these mechanisms are consistent with banks becoming more conservative in their lending decisions.

From the previous section, we show that on-site bank supervision forces banks to clean up their balance sheet, reporting losses from their trouble loans. At the same time, we find that inspected banks adjust their portfolio towards more productive investments. They cut the lending to troubled firms while investing more in healthy or new firms. A natural question, then, is why do inspected banks change their lending policies? We show that this is related to structural changes carried out by the bank after an inspection. We explore two different mechanisms that may explain the change in their lending behavior.

7.4.1. ***Change in corporate governance.*** Changes in the governance of a bank after a scandal is not something unusual. For instance, Wells Fargo was forced by the Federal

[89]This makes sense as banks are more sensitive to the rating provided by the credit agency as it is an information immediately available to both financial intermediaries and bank supervisors.

Reserve to change four of its sixteen-member board after a fraud scandal.[90] We investigate whether inspections are a trigger for an institutional change at the audited bank. To study this question we construct a new dataset on the corporate bodies of the banks and match it with the set of inspected banks and eligible but not inspected banks.[91] We look at three different potential changes in the management of the audited bank: the change in the total number of elective members (namely the CEO, board members, executives and presidents of the board), the change in the total number of non-elective members (managers and directors) and the change in the number of employees in the internal supervisory units such as members of the supervisory committee and liquidators. Table A18 reports the results of the impact of bank audits on the governance of the bank. In column (1) we find that inspections are associated with significantly lower number of elective members one year after an inspection takes place and a significantly higher number of members of the internal supervisory unit (column 3) relative to eligible but not inspected banks. We do not find any significant effect on the total number of non-elective members. These results suggest that the change in the lending policies are driven by a substantial change in the governance and management of the audited bank. Bank audit triggers changes to the internal management practices of inspected banks, in line with the results in Granja and Leuz (2019). They show that stricter regulators are associated with an increase in turnover for board members. These results also complement a line of research in accounting showing that after a serious accounting restatement, a firm takes actions to rebuild its reputation. For instance, Chakravarthy, DeHaan, and Rajgopal (2014) shows that publicly listed firms take reputation-building actions after an accounting fraud. The actions are targeted at both capital providers and other stakeholders and are associated with improvements in the restating firm's financial reporting credibility.Accounting restatement are also economically costly. For instance, Hribar and Jenkins (2004) show that, on average, accounting restatements lead to both decreases in expected future earnings and increases in the firm's future cost of equity capital. In a similar way, audited banks have to undertake structural reforms – firing board members and strengthening the internal supervision – to regain the trust of their shareholders and to follow the guidelines of the supervisor.

[90] https://www.nytimes.com/2018/02/02/business/wells-fargo-federal-reserve.html.

[91] The starting point is the ORSO dataset. We construct a bank-year level dataset of corporate bodies and match it with the set of inspected and eligible but not inspected banks. The regression model is the same as 4.2 with the exception that the data is at the annual frequency.

7.4.2. ***Recapitalization and change in Bank incentives***. One of the potential mechanisms to interpret the distorted incentive of banks to lend to underperforming firms is risk-shifting. If a bank is undercapitalized to the point that it can default in some states of the world, the bank's shareholders start gambling. This idea called "gambling for resurrection" is based on the fact that bank shareholders care only about the states of the world in which the firm recovers. In fact, if the bank goes bankrupt, bank shareholders are still protected from potential losses due to their limited liabilities.[92] This risk-shifting leads undercapitalized banks to invest in negative NPV projects that have high variance in the outcome (Jensen and Meckling, 1976). However, if the bank has enough capital such that it does not default in any state of the world, this distorted lending incentive may disappear. We test the idea that the potential mechanism behind the change in banks' lending policies is a capital injection followed from the inspections. As discussed in section 2, inspectors can force banks to undertake corrective measures. One of these measures is capital injection. The capital injection can potentially reduce the moral hazard problem since bank shareholders also become a stakeholder in the downside state of the world. Table A19 provides some evidence of this mechanism. We find that the equity levels in inspected banks increase by about 1.3% after the inspection compared to eligible but not inspected banks. The two groups exhibit no significant differences in terms of capital ratio before the inspection as Figure A15 suggests.[93]

Overall, we find that audited banks are more likely to undergo a recapitalization. Raising equity is costly especially when banks are in financial distress (Hanson et al., 2011). The incentive to misreport losses arises as the emergence of reported losses would reduce the bank's regulatory capital position. However, existing research has shown that the bank's shareholders often resist the idea of raising new capital (Myers and Majluf, 1984; Admati et al., 2018) and prefer to find other ways to improve the regulatory capital position, for example through evergreen loans to impaired firms to keep them alive. However, once banks are forced to inject new capital to increase their regulatory capital ratio above a certain threshold, banks may review their lending policies. The increase of equity makes the bank a stakeholder not only in good times but also in the unfavorable state of the world. Thus, they stop lending to troubled firms and start lending to healthier ones. [94]

[92]Previous works have shown that this mechanism was in place in the aftermath of the European sovereign crisis in Europe (Drechsler et al., 2016; Acharya and Steffen, 2015).

[93]This last point is also confirmed by balance tests shown in table A5.

[94]This idea is related to the literature looking at the optimal level of recapitalization by the government, meaning that a minimum threshold must be reached in order to have a positive effect of recapitalization,

8. Spillover effect to the Real Economy

This section explores the consequences of bank inspections to the real economy. In the first part, we focus on the impact on firms. Our evidence suggests that bank inspections have a positive effect on the amount of credit granted to the firms, i.e. a credit channel. Healthy firms get more credit, while underperforming ones are unable to substitute credit with other banks when they experience the credit cut. We show that this has implications for real outcomes: healthy firms invest more in fixed assets, they expand their workforce and they experience an increase in their revenues. Instead, impaired firms are more likely to exit the market following a bank inspections. To perform these analysis, we match data on credit with annual information on firms' balance sheet and income statement. We also construct a firm-level measure of the degree of exposure of firms to inspected banks based on the share of credit they grant to them. The second part of this section studies the implications of bank inspections for the local economy. Consistent with previous results, we find that provinces that are more exposed to inspections experience pace of business dynamics and more entrepreneurship.

8.1. **Credit effect at the firm level.** In this section we address the following questions: are underperforming firms able to substitute the credit cut from inspected banks by borrowing from other banks? What is the impact on healthy firms? Are they able to obtain more credit? The role of zombie firms in the local economy and their impact on healthy firms is a question that is addressed in the literature without a conclusive answer.[95]

that should to be large enough to solve banks' debt overhang problems (Philippon and Schnabl, 2013; Bhattacharya and Nyborg, 2013). Diamond and Rajan (2000) and Diamond and Rajan (2001) point out that recapitalizations that are too small may even damage bank lending policies. In their setting, while recapitalizations that remedy bank capital inadequacy also restore incentives to sound lending policies, undercapitalized banks tend to evergreen bad loans to avoid writing them off and becoming officially insolvent. Capital injections allow undercapitalized banks to lend more to impaired borrowers. Such banks may even recall loans to their creditworthy borrowers, as new capital puts the goal of meeting capital requirements within reach. Thus, recapitalizations that are too small encourage banks' bad lending policies, and may even decrease the availability of loans for borrowers with valuable investment opportunities. According to the results in Acharya et al. (2019b), this is what happened in 2012 with the "Whatever it takes reform" promoted by Mario Draghi. Weak banks continuing to lend to impaired borrowers is one of the main reasons that explains stable, low economic growth in the Euro area during that period.

[95]Among the most recent works, Schivardi et al. (2017) show that even if zombie lending was a problem after the European sovereign crisis, it did not affect the ability of healthy firms to obtain new credit. On the other side, Acharya et al. (2019b) and Blattner et al. (2017) show that creditworthy firms in industries with a high zombie firm prevalence significantly suffered from this credit misallocation, which further slowed the economic recovery.

8.1.1. *Estimating equation.* To test the implication of bank inspections for the total credit allocated to firms we consider a dynamic difference-in difference (DiD) model collapsing the data at the firm level and tracking firm-level outcomes over time. Specifically, we employ the following equation:

$$\begin{aligned}\Delta\log(y_{it}) &= \beta_1 Post_{pt}\times Exposure_{i,p,PRE} + \beta_2 Post_{pt}\times Exposure_{i,p,PRE}\times Healthy_{ip} + \\ &+\alpha_i + \eta_l + \eta_t + \eta_c + \gamma S_{iPRE} + \epsilon_{itp} \qquad (8.1)\end{aligned}$$

where i, t, p, l and c are firm, quarter, inspection plan, industry and province, respectively.[96] The outcome variable $\Delta\log(y_i)$ is $\Delta\log(Tot\,Credit)_t = \log(Tot\,Credit)_t - \log(Tot\,Credit)_{t-1}$, which is a measure of intensive margin. S_{iPRE} is a set of pre-determined firm-level characteristics computed one to three quarters before the shock. These variables are the log of assets, capital over assets, interest paid over EBITDA, and the current ratio. Note that the big drawback of this specification is that we cannot fully control for credit demand as we did before. Thus, the inclusion of these firm-level controls account for potential long-term trends at the firm-level that could affect credit demand. $Healthy_{it}$ is a dummy equal to 1 if the loan of firm i is not reclassified.[97] $Exposure_{i,PRE}$ represents our main regressor of interest. It proxies for the impact of bank inspection on firm i. Following the literature (Chodorow-Reich, 2013) we construct this measure as a pre-determined exposure of firms to inspected banks as follows:

$$Exposure_{ip} = \frac{\sum_{b=1}^{b\in\mathfrak{B}^{inspected}} credit_{ibp}}{\sum_{b=1}^{b\in\mathfrak{B}^{all}} credit_{ib}} \qquad (8.2)$$

where the numerator is the sum of the credit granted to firm i by banks that are inspected included in the inspection plan p. The denominator is the sum of the credit granted to firm i by all the banks with a lending relationship with the firm. *Exposure* takes the form of a Bartik instrument.[98] $Post_{pt}$ is a dummy variable equal to 1 for all the quarters after inspection plan p. Our coefficient of interest is β, which we standardize to interpret it as the

[96] A province is the geographical area of reference in Italy, comparable to the size of a county in the US. It is also the "relevant geographic markets" according to the Antitrust Authority (Guiso, Sapienza, and Zingales, 2004; Lotti and Manaresi (2015)).

[97] In other words, it is equal to $Healthy_{ip} = 1 - Reclassified_{ip}$ where $Reclassified_{ip}$ is a dummy for whether the inspector forces the bank to reclassified loans of firm i into NPLs.

[98] Note that equation 8.1 estimates a reduced form relationship. While we interpret the main channel through which bank inspections impact firms as the firm's financing activity (i.e. the credit channel), it is not possible to disentangle it from other potential channels such as the bank's risk assessment.

percentage change in credit in response to a standard deviation increase in the borrowing share from inspected banks. ϵ_{ib} are standard errors clustered at the level of the industry.

8.1.2. *Results.* Table 9 reports the effects on the credit channel. Columns (1) and (2) consider the effect on the average firm. We include an extensive set of fixed effects such as firm, quarter, industry and province, to control for unobservable factors. We find that the growth rate of credit for the average firm is negative (column 1). One standard deviation increase in the firm's exposure to audited banks reduces the credit growth of firms by 0.2%. This result is robust to the inclusion of firm-level controls (column 2). In column (3)-(5) we include a dummy variable for whether a firm is healthy (i.e. its loan is not reclassified by the supervisor). By adding this new interaction term we shed light on an important heterogeneous effect. First, underperforming firms are not able to substitute their credit cut with different banks and their overall growth rate of total credit goes down. A one standard deviation increase in their exposure is associated with a drop in credit growth by 4.6%. Second, healthy firms more exposed to bank inspections exhibit a significant increase in their credit growth. A one standard deviation increase in the firm's exposure to inspected banks increases the credit growth for healthy firms by 3.6%.[99] Taken together, these results are in line with results in table 7. Underperforming firms suffer from a credit cut due to bank inspections and are not able to substitute the credit with other banks. On the other side, creditworthy firms have more credit available as a result of these inspections. From a policy perspective this is a powerful message as on-site inspections are able to mitigate the problem of zombie lending. While there is research showing the potential crowding out effect of zombie firms in the credit market (e.g. Acharya et al., 2019b), we document a potential solution to mitigate this problem.

8.2. **Effects on Employment and Investment.** We study how this credit supply shock is passed-through into employment, investment and sales growth at the annual firm-level. We focus on the potential spillovers to healthy firms, since there is compelling research showing that the presence of zombie firms have potential negative effects for healthy firms. For instance, Acharya et al. (2019b) show that healthy firms in industries with a high concentration of zombie firms experience negative employment and investment growth. To answer this question we rely on a dataset at the annual level of firms from Cerved.

[99]This is the sum of the two coefficients on the interaction with exposure: $-0.041 + 0.077 = 0.036$

8.2.1. *Estimating equation.* We consider the following model in first difference form:

$$\Delta y_{ipcl} = \beta Exposure_{ip} + \alpha_l + \alpha_c + \alpha_p + \gamma S_{i,PRE} + \epsilon_{ipcl} \tag{8.3}$$

where i, p, l and c are respectively firm, inspection plan, industry and province. $Exposure$ is our treatment variable as defined in equation 8.2. We include the same controls at the firm-level as in equation 8.1.[100] Our coefficient of interest is β, standardized to interpret it as the percentage change in the outcome variable in response to a standard deviation increase in the borrowing share from inspected banks. We compute robust standard errors clustered at the industry level. The outcome variable is defined as $\Delta log(y_{ipct+n}) = log(y_{ipct+n}) - log(y_{ipct-1})$ where $n = 1, 2$. In words, we compute the log change in y between the year before the inspection and one or two years after the inspection.

8.2.2. *Result.* Table 10 shows the effect on employment, fixed capital investment and sales growth. Columns (1) and (2) reports respectively the change in employment after one and two years since the inspection. Columns (3) and (4) report the change in investment in fixed capital after one and two years and column (5) and (6) reports the change in the sales after one year and two years. We find a positive effect on employment, investment in fixed capital and sales after controlling for a set of fixed effects and firm level controls. The effect is stronger in the second year after the inspection for employment and investment. Specifically for employment we find that a one standard deviation increase in the firm's exposure to inspected banks leads to 2 percentage points increase in employment and investments in fixed capital.[101] Overall, we find that healthy firms more exposed to bank inspections have a positive growth in employment, investment, and sales.

Next, we study the effect of bank inspections on the probability of firms to exit the market. Previous works show that a high share of zombie lending makes markets less dynamic. Banks, by rolling over their loans to zombie firms, keep them alive (Adalet McGowan et al., 2018). Figure 6 shows the effect of bank inspections on the probability for a firm to exit the market τ years after the inspection. We distinguish between healthy and zombie firms and track them over time.[102] We find that bank inspections do not increase the probability of exit for healthy firms. For zombie firms the result is different: in the year before the inspection takes place, the probability to exit the market is not significantly different from zero. After

[100]These variables are the natural logarithm of assets, sales growth, capital over assets, interest paid over EBITDA and the current ratio.

[101]Combining this with the effect on credit for healthy firms we can compute a back-of-the-envelope calculation. After two years, healthy firms increase their employment by about $0.036 \times 0.0200 \approx 1$ employee.

[102]Formally, our outcome is a binary variable that takes value 1 if the company goes bankruptcy.

one year, the probability becomes positive and statistically significant. It is about 6% and it grows steadily with the years. After three years from the inspection, the exit probability for a zombie firm is about 11%.

8.3. **Spillover effects to the local economy.** This section studies the impact of bank supervision on the local economy. Much of the policy debate around zombie lending is related to its impact on firm dynamics and productivity (Tracey, 2019; Adalet McGowan et al., 2018). In particular, the increasing survival of these low productivity firms at the margins of exit congests markets and constrains the growth of more productive firms (Acharya et al., 2019a). Thus, a fundamental question is whether there are positive spillovers from the reallocation channel of credit at the firm level to the local economy.[103] To shed light on this question, we construct a measure of the province's exposure to banking inspections similar to the method used in Section 8. We consider a measure based on a province's degree of dependence to the set of banks being inspected in a given year. To avoid any endogeneity problems of post-inspection sorting between bad banks and bad provinces, we compute this measure two years before the inspection. Our measure of province exposure to inspected banks is the following:

$$Exposure_{cp} = \frac{\sum_{b \in \mathfrak{B}^{inspected}} credit_{cbp}}{\sum_{b \in \mathfrak{B}^{all}} credit_{cbp}} \tag{8.4}$$

where c stands for province, p for inspection plan and b for bank. The numerator is the sum of credit granted in province c by bank b that is inspected according to the inspection plan p. The denominator is the sum of credits granted by all banks operating in province c.

8.3.1. *Identifying assumption.* The identifying assumption, as in other Bartik instruments, relies on the idea that each bank is a small contributor to a province's overall credit supply and is therefore unlikely to drive province level outcomes. Moreover, in a reduced-form model the estimation is valid if the bank-level shocks are uncorrelated with the average province-level characteristics that determine the outcome variable (i.e. employment) in the provinces most exposed to each bank (Borusyak et al., 2020).[104]

[103]With local economy, we refer to a unit of geographical aggregation. Precisely we consider a province. Provinces are about the same size as a US county. They correspond to the NUTS 3 level of Eurostat classification. In the period under exam, there were 103 provinces in Italy, with a minimum of 89 thousand and a maximum of 3.5 million inhabitants.

[104]In other words, the identifying assumption is that banks did not sort to provinces such that unobservable characteristics of the province were correlated with the bank inspections and the change in the outcome variable within that province.

Correlation between geographical characteristics and bank exposure. One potential concern is that our measure of exposure is correlated with geographical location. For instance, it may be the case that provinces more exposed to bank inspections have experienced a negative shock, and thus, they are more likely to have a larger share of banks that are inspected. A typical case that would confound the results is when provinces have experienced a bust in the pre-period and a boom in the post-period. Table A20 shows that our measure of exposure is not correlated with any covariates at the geographical level in the pre-period, such as the change in the local GDP, the importance of mutual banks in a particular province – which is computed as the share of total credit from mutual banks over total credit from any bank in province c – as well as average income in province c. This reduces concerns about a potential endogeneity problem in our independent variable.

Estimating Equation. To test the implications of banking inspections at the province level we employ the following empirical model in the first difference:

$$\Delta \log(y_{ct}) \quad = \quad \beta_1 Exposure_{c,p,PRE} + \eta_l + \eta_p + \gamma S_{c,PRE} + \epsilon_{ipt} \tag{8.5}$$

where c, p, l and t are respectively province, inspection plan, industry and year. $Exposure_{cp,PRE}$ is the measure of exposure at the province level as we define in equation 8.4. η_l are industry fixed effects, and η_p are inspection plan fixed effects.[105] $\gamma S_{c,PRE}$ are time-varying controls at the province level that are measured two years before the inspection.[106] The outcome variable is defined as in equation 8.3. We compute the log change in the outcome variable between one year before the inspection plan and n years after the inspection, with $n = 1, 2, 3$. We standardize our coefficient β_1 to interpret it as the percentage change in our outcome variable in response to a standard deviation increase in the credit exposure share from inspected banks. Standard errors are clustered by province.

8.3.2. *Result.* We start our analysis by looking at the impact of bank inspections on entrepreneurship, defined as the number of new businesses created in a given year, i.e. an extensive margin. We use the data from the Chamber of Commerce which includes *all* new type of businesses that are registered, including the single entrepreneur starting her own company. Figure 7 plots the results. We find that bank inspections have a positive effect on the local economy. Specifically, a one standard deviation increase in the treatment exposure

[105]In this analysis, inspection plan fixed effects coincide with year fixed effects as the data is at annual frequency.

[106]These consist of employment rate, average income and GDP at the province level.

causes an increase in entrepreneurship by 2.1% after the first year and by about 3% after three years. The results are statistically significant and robust to the inclusion of province level controls. Moreover, the absence of pre-trends reduce any concern that the results are driven by pre-defined differences across provinces. Overall, the results show that provinces more exposed to bank inspections can increase firm dynamics in the local economy. From a policy perspective, this speaks directly to one of the major problem experienced by the Euro zone, i.e. the lack of dynamics that the Euro zone area has been experiencing during the last decade (Adalet McGowan et al., 2018). Table 11 Panel A looks at the impact on aggregate employment. We find that bank inspections generate a cost to the local economy in the short term. Provinces more exposed to inspections have a decrease in the growth rate of employment by about 1.8 percentage point one year after inspections. The effect becomes positive after two years. This could be explained with the exit of zombie firms from the market in the short term (6 and the creation of new firms in the medium term (7).

We find a similar dynamic in the measure of aggregate productivity, measured as value added per worker.[107] Panel B of Table 11 shows the results. We find no significant effect of bank inspections on productivity after one year. However, the coefficient becomes positive and significant two and three years after the inspection. Overall, these results are in line with Bai, Carvalho, and Phillips (2018),[108] as banks can potentially be a critical factor in boosting productivity because of their role in determining which firms are financed. Eliminating potential frictions in bank's decisions and, more generally, in the credit market can strengthen the link between firm productivity and bank credit.

9. Conclusion

The recent financial crisis has shown once again the importance of a well functioning banking sector. Policymakers have focused most of their attention on the role of regulation in reducing distortions and keeping the credit market functioning properly. However, recent works have shown that the increased regulatory pressure has not prevented distortions from manifesting (Acharya et al., 2019b). This paper assesses the relevance of bank supervision as a tool to potentially complement bank regulation. There is very limited evidence on the role

[107]We don't have a measure disaggregated by industry and thus we are not able to include industry fixed effects in the regression.

[108]They study the role of local US banking markets in shifting the allocation of labor and capital within local industries towards firms with higher productivity. While the shift is due to different reasons - they consider the US bank deregulation which reduced constraints on banksâĂŹ ability to expand across geographic markets - the results point in the same direction.

of bank supervision due to endogeneity issues: we take advantage of unexpected on-site bank inspections to gauge a causal effect. The main contribution of this paper is to show that bank audits can reduce the problem of zombie lending, generating positive spillovers for the real economy. We uncover three set of results. First, there is an information disclosure effect. We find that after an inspection, audited banks increase the stock of NPLs and the loan loss provision. This effect is limited to the first quarter after the inspection. Second, there is an indirect effect on the lending activity: inspected banks cut their lending as a result of the inspection activity. However, contrary to a standard bank capital shock, we uncover an important composition effect. The credit cut is driven mainly by underperforming firms. We find evidence of a reallocation channel for which inspected banks re-optimize their portfolio of loans by investing more on healthy firms or on new firms. We show that the change in the lending policy is driven by structural changes at the inspected banks, especially in their governance structure, and they also inject new equity. Finally, we find positive spillover effects in the real economy: healthy firms in the bank's portfolio have more credit available (credit channel), increase their employment, their investment in fixed capital, and have a positive revenue growth after the inspection takes place. At the local economy, we find that inspections boost firm dynamics: provinces more exposed to bank audits experience an increase in entrepreneurship. Moreover, underperforming firms are more likely to exit the market.

There are important policy implications from this exercise. The policy debate in Europe is centered around the productivity slowdown due to various reasons: the widening productivity dispersion across firms (Andrews et al., 2016), rising capital misallocation (Gopinath et al., 2017), and declining business dynamism (Decker et al., 2016). These reasons are all related to the role of zombie lending (Banerjee and Hofmann, 2018; Acharya et al. (2019b); Blattner et al., 2017). We show that this problem can be mitigated by a more stringent role of bank supervision at the very micro-level. This result is especially important now as the European Union has undertaken an important reform in 2014 introducing a general framework in bank supervision and is still learning and employing the best practices from the different countries. Moreover, the recent pandemic outbreak and the negative implications to the real economy has increased attention to the role of bank supervision in "preventing banks to build up unrecognised non-performing loans, and eventually distinguish good customers from bad customers that are unlikely to pay."[109]

[109]Andrea Enria, Chair of the Supervisory Board of the ECB Andrea Enria in an interview on September 20, 2020. https://www.bankingsupervision.europa.eu/press/interviews/date/2020/html/ssm.in20200925~0a49bf3ea9.en.html.

References

Abbassi, P., R. Iyer, J.-L. Peydro, and P. E. Soto (2017a): "Dressing up for the regulators: evidence from the largest-ever supervisory review, mimeo," . 1

——— (2017b): "Dressing up for the regulators: evidence from the largest-ever supervisory review, mimeo," . 19, 26

Accornero, M., P. Alessandri, L. Carpinelli, and A. M. Sorrentino (2017): "Non-performing loans and the supply of bank credit: evidence from Italy," *Bank of Italy Occasional Paper*. 3.4, 5.1.2

Acharya, V. V., A. N. Berger, and R. A. Roman (2018): "Lending implications of US bank stress tests: Costs or benefits?" *Journal of Financial Intermediation*, 34, 58–90. 1, 60

Acharya, V. V., M. Crosignani, T. Eisert, and C. Eufinger (2019a): "Zombie Credit and (Dis-) Inflation: Evidence from Europe," . 1, 5.1.2, 76, 8.3

Acharya, V. V., T. Eisert, C. Eufinger, and C. Hirsch (2019b): "Whatever it takes: The real effects of unconventional monetary policy," *The Review of Financial Studies*, 32, 3366–3411. 1, 9, 1, 5.1.2, 69, 7.1, 78, 7.3, 94, 95, 8.1.2, 8.2, 9, A13

Acharya, V. V. and S. Steffen (2015): "The "greatest" carry trade ever? Understanding eurozone bank risks," *Journal of Financial Economics*, 115, 215–236. 92

Adalet McGowan, M., D. Andrews, and V. Millot (2018): "The walking dead? Zombie firms and productivity performance in OECD countries," *Economic Policy*, 33, 685–736. 1, 1, 5.1.2, 7, 8.2.2, 8.3, 8.3.2

Admati, A. R., P. M. DeMarzo, M. F. Hellwig, and P. Pfleiderer (2018): "The leverage ratchet effect," *The Journal of Finance*, 73, 145–198. 1, 4, 7.4.2

Agarwal, S., D. Lucca, A. Seru, and F. Trebbi (2014): "Inconsistent regulators: Evidence from banking," *The Quarterly Journal of Economics*, 129, 889–938. 1

Aiyar, S., C. W. Calomiris, and T. Wieladek (2014): "Does macro-prudential regulation leak? Evidence from a UK policy experiment," *Journal of Money, Credit and Banking*, 46, 181–214. 5.1.2

Albertazzi, U. and D. J. Marchetti (2010): "Credit supply, flight to quality and evergreening: an analysis of bank-firm relationships after Lehman," *Bank of Italy Temi di Discussione (Working Paper) No*, 756. 1

Altman, E. I. (1968): "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy," *The journal of finance*, 23, 589–609. 7.3

Altman, E. I., G. Marco, and F. Varetto (1994): "Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience)," *Journal of banking & finance*, 18, 505–529. 7.3

Andrews, D., C. Criscuolo, and P. Gal (2016): "The global productivity slowdown, technology divergence and public policy: a firm level perspective," in *Background Paper for OECD Global Forum on Productivity*. 9

Angrist, J. D. and J.-S. Pischke (2009): *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton: Princeton University Press. 48

Bai, J., D. Carvalho, and G. M. Phillips (2018): "The impact of bank credit on labor reallocation and aggregate industry productivity," *The Journal of Finance*, 73, 2787–2836. 68, 8.3.2

Banerjee, R. and B. Hofmann (2018): "The rise of zombie firms: causes and consequences," *BIS Quarterly Review Spetember*. 9

Bernanke, B. S., C. S. Lown, and B. M. Friedman (1991): "The credit crunch," *Brookings papers on economic activity*, 1991, 205–247. 7.1

Bernanke, B. S. et al. (2013): "Stress Testing Banks: What Have We Learned?: a speech at the" Maintaining Financial Stability: Holding a Tiger by the Tail" financial markets conference sponsored by the Federal Reserve Bank of Atlanta, Stone Mountain, Georgia, April 8, 2013," Tech. rep. 19

Bhattacharya, S. and K. G. Nyborg (2013): "Bank bailout menus," *The Review of Corporate Finance Studies*, 2, 29–61. 94

Bian, B. (2019): "Globally Consistent Creditor Protection, Reallocation, and Productivity," . 68

Bisetti, E. (2017): "The Value of Regulators as Monitors: Evidence from Banking," *SSNR Working Paper*. 1

Blattner, L., L. Farinha, and F. Rebelo (2017): "When Losses Turn Into Loans: The Cost of Undercapitalized Banks," Tech. rep., Banco De Portugal Working Paper. 1, 3, 1, 5.1.2, 7, 7.1, 69, 95, 9

Bofondi, M., L. Carpinelli, and E. Sette (2017): "Credit supply during a sovereign debt crisis," *Journal of the European Economic Association*, 16, 696–729. 3.1.1, 3.4, 7.2, 74

Bonfim, D., G. Cerqueiro, H. Degryse, and S. Ongena (2019): "On-site inspecting zombie lending," . 13

Borusyak, K., P. Hull, and X. Jaravel (2020): "Quasi-experimental shift-share research designs," Tech. rep., National Bureau of Economic Research. 8.3.1

Bottero, M., S. Lenzu, and F. Mezzanotti (2018): "Sovereign debt exposure and the bank lending channel: impact on credit supply and the real economy," . 3.1.1, 3.3, 7.1

Bruche, M. and G. Llobet (2014): "Preventing zombie lending," *The Review of Financial Studies*, 27, 923–956. 14

Caballero, R. J., T. Hoshi, and A. K. Kashyap (2008): "Zombie lending and depressed restructuring in Japan," *American Economic Review*, 98, 1943–77. 1, 1, 1, 62, 7, 69

Chakravarthy, J., E. DeHaan, and S. Rajgopal (2014): "Reputation repair after a serious restatement," *The Accounting Review*, 89, 1329–1363. 7.4.1

Chodorow-Reich, G. (2013): "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis," *The Quarterly Journal of Economics*, 129, 1–59. 1, 7.1, 81, 8.1.1

Cihák, M. M. and A. F. Tieman (2008): *Quality of financial sector regulation and supervision around the world*, 8-190, International Monetary Fund. 15

Cingano, F., F. Manaresi, and E. Sette (2016): "Does credit crunch investment down? New evidence on the real effects of the bank-lending channel," *The Review of Financial Studies*, 29, 2737–2773. 3.4

Coccorese, P. and G. Ferri (2019): "Are mergers among cooperative banks worth a dime? Evidence on efficiency effects of M&As in Italy," *Economic Modelling*. 3.1.1

Cortés, K. R., Y. Demyanyk, L. Li, E. Loutskina, and P. E. Strahan (2020): "Stress tests and small business lending," *Journal of Financial Economics*, 136, 260–279. 1, 60

Davis, S. J., J. Haltiwanger, R. Jarmin, J. Miranda, C. Foote, and E. Nagypal (2006): "Volatility and dispersion in business growth rates: Publicly traded versus privately held firms [with comments and discussion]," *NBER macroeconomics annual*, 21, 107–179. 7.3

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2016): "Declining business dynamism: What we know and the way forward," *American Economic Review*, 106, 203–07. 9

Dell'Atti, A. and M. Intonti (2006): "The Economics of Mutual Banks in Italy: Cooperation, Mutuality and Commitment to the Local Community," *SSRN Working paper*. 3.1

Detragiache, E., P. Garella, and L. Guiso (2000): "Multiple versus single banking relationships: Theory and evidence," *The Journal of Finance*, 55, 1133–1161. 70

Diamond, D. W. and R. G. Rajan (2000): "A theory of bank capital," *The Journal of Finance*, 55, 2431–2465. 94

——— (2001): "Liquidity risk, liquidity creation, and financial fragility: A theory of banking," *Journal of political Economy*, 109, 287–327. 94

Drechsler, I., T. Drechsel, D. Marques-Ibanez, and P. Schnabl (2016): "Who borrows from the lender of last resort?" *The Journal of Finance*, 71, 1933–1974. 92

Eisenbach, T. M., D. O. Lucca, and R. M. Townsend (2016): "The economics of bank supervision," Tech. rep., National Bureau of Economic Research. 1

Froot, K. A. and J. C. Stein (1998): "Risk management, capital budgeting, and capital structure policy for financial institutions: an integrated approach," *Journal of financial economics*, 47, 55–82. 5.1.2

Gan, J. (2007): "The real effects of asset market bubbles: Loan-and firm-level evidence of a lending channel," *The Review of Financial Studies*, 20, 1941–1973. 7.1

Gertner, R. and D. Scharfstein (1991): "A theory of workouts and the effects of reorganization law," *The Journal of Finance*, 46, 1189–1222. 1

Giannetti, M. and A. Simonov (2013): "On the real effects of bank bailouts: Micro evidence from Japan," *American Economic Journal: Macroeconomics*, 5, 135–67. 1

Gopinath, G., Ş. Kalemli-Özcan, L. Karabarbounis, and C. Villegas-Sanchez (2017): "Capital allocation and productivity in South Europe," *The Quarterly Journal of Economics*, 132, 1915–1967. 1, 5.1.2, 7, 9

Granja, J. and C. Leuz (2019): "The Death of a Regulator: Strict Supervision, Bank Lending and Business Activity," . 1, 4.1.3, 61, 67, 7.4.1

Guiso, L., P. Sapienza, and L. Zingales (2004): "The role of social capital in financial development," *American economic review*, 94, 526–556. 96

Haltiwanger, J., S. Schuh, and S. Davis (1996): "Job creation and destruction," . 81

Hanson, S. G., A. K. Kashyap, and J. C. Stein (2011): "A macroprudential approach to financial regulation," *Journal of economic Perspectives*, 25, 3–28. 7.1, 7.4.2

Hirtle, B., A. Kovner, and M. C. Plosser (2017): "The impact of supervision on bank performance," *Staff Report No. 768*. 1

Hribar, P. and N. T. Jenkins (2004): "The effect of accounting restatements on earnings revisions and the estimated cost of capital," *Review of accounting studies*, 9, 337–356. 7.4.1

Ivanov, I., B. Ranish, and J. Wang (2017): "Strategic Response to Supervisory Coverage: Evidence from the Syndicated Loan Market," *mimeo*. 1

Ivanov, I. T. and J. Z. Wang (2019): "The Impact of Bank Supervision on Corporate Credit: Evidence from Syndicated Loan Reviews," . 1

Jayaratne, J. and P. E. Strahan (1996): "The finance-growth nexus: Evidence from bank branch deregulation," *The Quarterly Journal of Economics*, 111, 639–670. 1

Jensen, M. C. and W. H. Meckling (1976): "Theory of the firm: Managerial behavior, agency costs and ownership structure," *Journal of financial economics*, 3, 305–360. 7.4.2

Kandrac, J. and B. Schlusche (2017): "The Effect of Bank Supervision on Risk Taking: Evidence from a Natural Experiment," *SSNR Working Paper*. 1

Khwaja, A. I. and A. Mian (2008): "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *The American Economic Review*, 98, 1413–1442. 1, 3.4, 7.2, 7.2, 82

Kok, C., C. Müller, C. Pancaro, et al. (2019): "The disciplining effect of supervisory scrutiny in banks' risk-taking: evidence from the EU wide stress test," *Macroprudential Bulletin*, 9. 1

Lenzu, S. and F. Manaresi (2019): "Sources and Implications of Resource Misallocation: New Evidence from Firm-Level Marginal Products and User Costs," Tech. rep., mimeo. 3.3, 44

Lotti, F. and F. Manaresi (2015): "Finance and creative destruction: evidence for Italy," *Bank of Italy Occasional Paper*. 96

Menand, L. (2017): "Too Big to Supervise: The Rise of Financial Conglomerates and the Decline of Discretionary Oversight in Banking," *Cornell L. Rev.*, 103, 1527. 24

Myers, S. C. and N. S. Majluf (1984): "Corporate financing and investment decisions when firms have information that investors do not have," *Journal of Financial Economics*, 13, 187–221. 1, 4, 7.4.2

Neuhann, D. and F. Saidi (2018): "Do universal banks finance riskier but more productive firms?" *Journal of Financial Economics*, 128, 66–85. 7.3

Peek, J. and E. Rosengren (1995): "Bank regulation and the credit crunch," *Journal of Banking & Finance*, 19, 679–692. 1, 60, 7.1

Peek, J. and E. S. Rosengren (2000): "Collateral damage: Effects of the Japanese bank crisis on real activity in the United States," *American Economic Review*, 90, 30–45. 60, 7.1

——— (2005): "Unnatural selection: Perverse incentives and the misallocation of credit in Japan," *American Economic Review*, 95, 1144–1166. 1, 1, 1, 62, 69, 76

Petersen, M. A. (2009): "Estimating standard errors in finance panel data sets: Comparing approaches," *The Review of Financial Studies*, 22, 435–480. 4.1.1

Petersen, M. A. and R. G. Rajan (1995): "The effect of credit market competition on lending relationships," *The Quarterly Journal of Economics*, 110, 407–443. 3.1

Philippon, T. and P. Schnabl (2013): "Efficient recapitalization," *The Journal of Finance*, 68, 1–42. 94

Rezende, M. and J. Wu (2014): "The effects of supervision on bank performance: Evidence from discontinuous examination frequencies," *Midwest Finance Association 2013 Annual Meeting Paper*. 1

Schivardi, F., E. Sette, and G. Tabellini (2017): "Credit misallocation during the European financial crisis," *mimeo*. 1, 3.3, 3.4, 5.1.2, 69, 76, 95

Schnabl, P. (2012): "The international transmission of bank liquidity shocks: Evidence from an emerging market," *The Journal of Finance*, 67, 897–932. 4.1.1, 7.1

Sette, E. and G. Gobbi (2015): "Relationship lending during a financial crisis," *Journal of the European Economic Association*, 13, 453–481. 70

SSM Supervisory Manual, d. (2018): "European banking supervision: functioning of the SSM and supervisory approach," *SSM Supervisory Manual*. 18

Stiglitz, J. E. and A. Weiss (1981): "Credit rationing in markets with imperfect information," *The American economic review*, 71, 393–410. 7.3

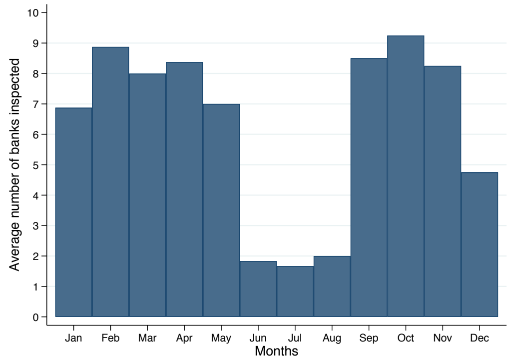
Tarullo, D. K. (2017): "Departing Thoughts: a speech at The Woodrow Wilson School, Princeton University, Princeton, New Jersey, April 4, 2017," Tech. rep., Board of Governors of the Federal Reserve System (US). 24

Tosjitaka, S., K. Keiichiro, and Y. SAITA (2003): "Forbearance lending: the case of japanese firms," *Monetary & economic Studies*, 2. 1

Tracey, B. (2019): "The real effects of zombie lending in Europe," . 8.3

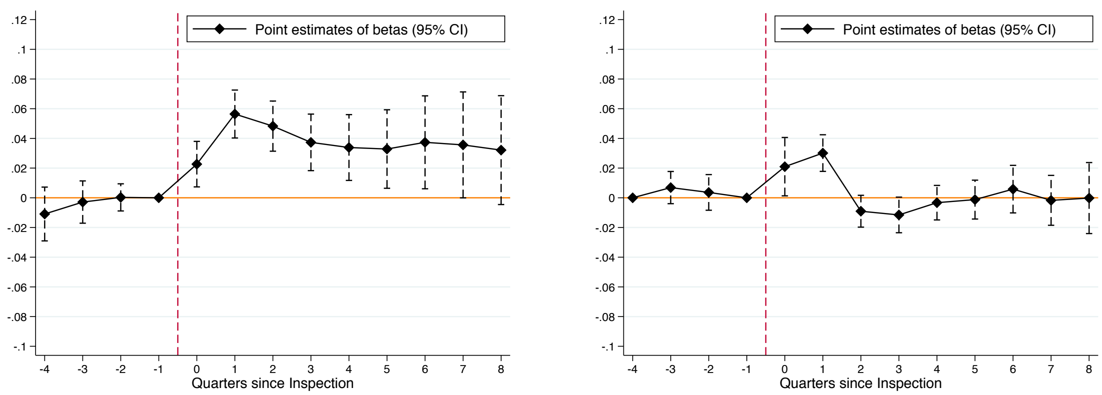
Wooldridge, J. M. (2009): "On estimating firm-level production functions using proxy variables to control for unobservables," *Economics Letters*, 104, 112–114. 9, 7.3, A14

FIGURE 1. Average Number of Banks inspected each Month



Notes: This figure shows the distribution of the average number of banks inspected every month for each inspection plan. The average number of inspections each month is 6.

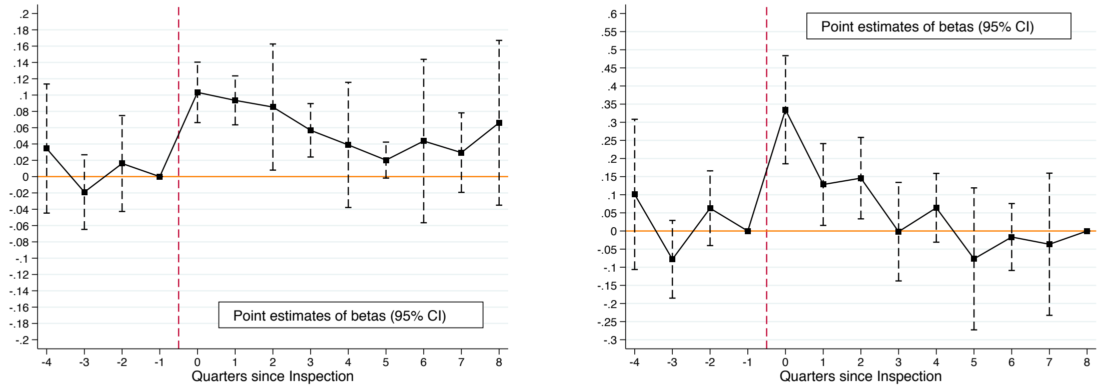
FIGURE 2. Dynamic DiD: Informational Disclosure Effect (1)



A. $\log(NPL)$ **B.** Delta log of Non-Performing Loans (NPL)

Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \{\mathbb{1}_{\tau=t}\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \{\mathbb{1}_{\tau=t}\} + \varepsilon_{btpm}$. In panel A the outcome variable is log(NPL). In panel B the outcome variable is $\Delta \log(NPL) = log(NPL_{bt+1}) - log(NPL_{bt})$. We include bank, quarter, and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. For a full description of the empirical equation refer to equation 4.1. Data comes from bank's balance sheet (Supervisory Reports).

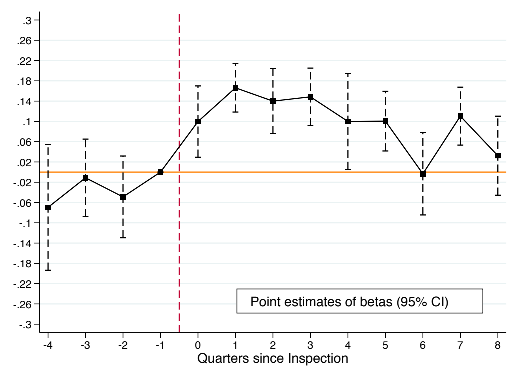
FIGURE 3. Dynamic DiD: Informational Disclosure Effect (2)



A. log(Loan Loss Provision for Bad Loans) **B.** Δ log(Loan Loss Provision for Bad Loans)

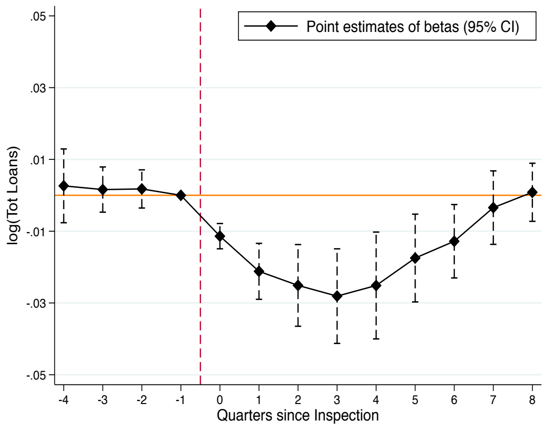
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. In panel A the outcome variable is the log of loan loss provision for bad loans. In panel B the outcome variable is the log of loan loss provision for other types of NPLs, i.e. unlikely-to-pay exposure and overdrawn/past-due exposure. We include bank, quarter, and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. For a full description of the empirical equation refer to equation 4.1. Data comes from bank's balance sheet (Supervisory Reports).

FIGURE 4. Dynamic DiD: $\log(otherNPLs)$

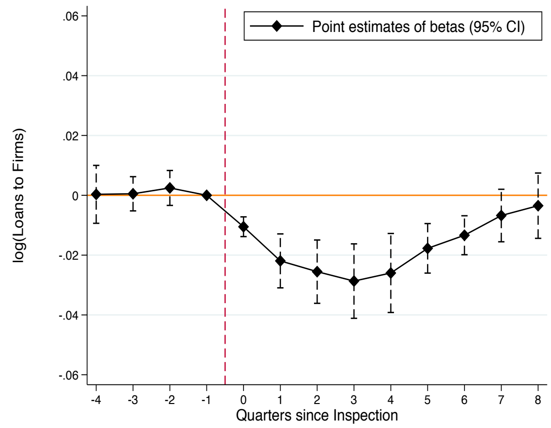


Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. The outcome variable is the log of other NPLs, i.e. unlikely-to-pay and past-due exposures. We include bank, quarter, and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. For a full description of the empirical equation refer to equation 4.1. Data comes from bank's balance sheet (Supervisory Reports).

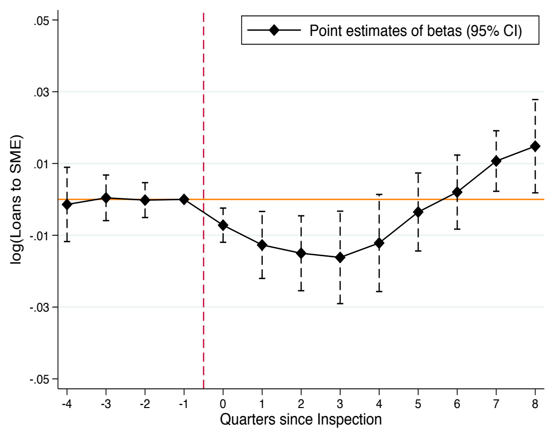
FIGURE 5. Dynamic DiD: Indirect Effect on Lending



A. log(Total Loans)



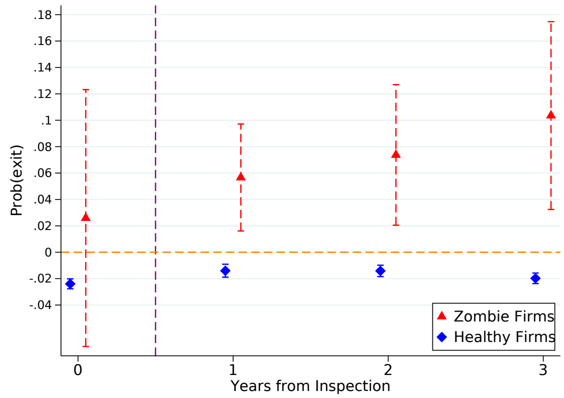
B. log(Loans to Firms)



C. log(Loans to SME)

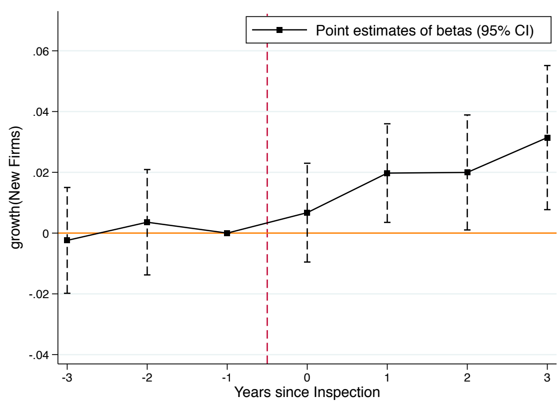
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. The outcome variable is the log of total loans. We include bank, quarter and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. In panel A the outcome variable is the log of Total Loans. In panel B the outcome variable is the log of Loans to Firms. In panel C the outcome variable is the log of loans to Small and Medium Enterprises (SME). For a full description of the empirical equation refer to equation 4.1. Data comes from bank's balance sheet (Supervisory Reports).

FIGURE 6. Effect on the Probability of Exit over time



Notes: This figure shows the results of the following regression: $Prob(exit_{i,\tau}) = \beta Exposure_{ip} + \eta_l + \eta_c + \eta_t + \gamma S_{i,PRE} + \epsilon_{itp}$. The outcome variable is $Prob(exit_{i,\tau})$ and represents the probability that the firm i exists in the market τ years after the inspection. S_{iPRE} is a set of predetermined firm-level characteristics computed one to three quarters before the shock. These variables are the natural logarithm of assets, capital/assets, interest paid/EBITDA and the current ratio. $Exposure_{i,PRE}$ is our treatment, which is the share of credit coming from inspected banks computed in the pre-period. We include province, industry, and year fixed effects. We cluster the standard errors at the industry level. Coefficients are standardized.

FIGURE 7. Effect on Entrepreneurship



Notes: This graph plots the result of the following regression: $\Delta \log(y_{ct}) = \beta_1 Exposure_{c,p,PRE} + \alpha_c + \eta_t + \eta_p + \eta_l + \gamma S_{c,PRE} + \epsilon_{ip}$ where c, p, l and t are respectively province, inspection plan, industry and year. $Exposure_{c,PRE}$ is the measure of exposure at the province level as we define in equation 8.4. α_c are province fixed effects, η_l are industry fixed effects, η_p are inspection plan fixed effects, η_t are year fixed effects. $\gamma S_{c,PRE}$ are time-varying controls at the province level that are measured two years before the inspection. They consist of employment rate, GDP at the province level. We standardize our coefficient β_1 to interpret it as the percentage change in our outcome variable in response to a standard deviation increase in the credit exposure share from inspected banks.

Table 1. Descriptive Statistics

	Mean	SD	Median	p25	p75	N
Panel A: Bank-level variables						
Total assets	582.077	788.479	362.664	161.041	692.295	438
ROA	0.001	0.006	0.002	0.001	0.004	438
ROE	0.012	0.067	0.021	0.007	0.035	438
Liquidity ratio	0.005	0.003	0.005	0.003	0.007	438
Deposit ratio	0.533	0.117	0.518	0.443	0.617	438
Capital ratio	0.133	0.037	0.128	0.107	0.153	438
NPL ratio	0.047	0.035	0.040	0.022	0.064	438
Sovereign bonds	145.204	192.665	80.219	24.178	188.155	438
Total Loans	636.978	901.254	371.789	153.792	748.949	438
log(total loans)	5.831	1.169	5.918	5.036	6.619	438
Total loans to firms	465.177	620.933	268.868	109.912	550.680	438
log(Total loans to firms)	5.510	1.184	5.594	4.700	6.311	438
Total loans to SME	183.544	208.021	116.660	54.259	232.115	438
log(Total loans to SME)	4.703	1.083	4.759	3.994	5.447	438
Panel B: Bank-firm relationship						
Maturity	9.155	13.927	0.771	0.522	12.067	1,321,312
Share of firm credit coming from bank k	0.908	0.107	0.948	0.876	0.984	1,321,312
Lead lender	0.906	0.109	0.946	0.870	0.984	1,321,312
Share of firm j in bank k's portfolio	0.001	0.001	0.001	0.000	0.001	1,321,312
Panel C: Firm variables						
Total assets	4708.192	40242.905	1010.000	376.000	2853.000	652,830
Wage bills	760.655	5680.601	202.000	73.000	513.000	652,830
Cash flow	195.525	2721.009	35.000	5.000	117.000	652,830
Return on Assets	-5.877	844.712	3.260	0.400	6.430	652,830
Profits	-5.887	1859.608	5.000	-13.000	31.000	652,830
Total credit from banks (000)	204.092	131.203	179.473	106.085	272.651	652,830
Capital ratio	0.147	3.836	0.040	0.016	0.096	652,830
Liquidity ratio	0.089	0.138	0.032	0.008	0.110	652,830
Revenue growth	8.890	489.908	0.005	-0.186	0.214	652,830
Panel D: Bank governance						
Elective members	7.262	2.327	8	5	9	5453
Non-Elective members	4.510	0.670	5	4	5	5453
Internal Supervisors	1.527	0.884	2	2	2	5453
Panel E: Local economy						
Average income	6635.939	5711.992	4554.479	2720.929	8418.939	110
Population (000)	552.021	601.083	376.182	229.413	599.654	110
Exposure	0.431	0.353	0.340	0.104	0.779	110
Aggregate productivity (000)	56.177	7.171	56.477	50.594	61.699	110

Notes: This table presents summary statistics for the main variables. Panel A reports summary statistics for the entire sample of mutual banks, i.e. eligible and not-eligible. Bank-level variables are in millions of €. Panel B presents summary statistics on bank-firm relationship. Maturity is the length of the credit relationship between the bank and the firm. Share of firm credit coming from bank k is the share of credit granted to firm j from bank k. Lead lender is a dummy variable that takes value 1 if the bank k is the primary lender to firm j in terms of size of credit granted. Share of firm j in bank k's portfolio is the share of credit granted to firm j relative to the credit granted to other firms by bank k. Panel C shows summary statistics for the sample of firms that we observe the entire period. Firm-level variables are in thousands of €. Panel D shows summary statistics for the variables related to the governance of the bank. We define: (i) elective members the CEO of the bank, board members, executive board members, presidents of the board; (ii) non-elective members managers and directors; (iii) internal supervisory members of the supervisory committee and liquidators. Panel E shows summary statistics for variables at the local economy. Local economy refers to Italian provinces. There are 110 Italian provinces.

Table 2. Inspection data

Panel A	Number of Banks	Share
Type		
Never Inspected	54	12.32
Inspected	384	87.67
Total	438	100
Number of Inspections for the same bank		
1	204	53.12
2	158	41.15
3	22	5.73

Panel B	Number of Banks	Mean	SD	Min	Max
Number of Inspections for inspected banks					
	384	1.526	0.604	1	3
Time elapsed since the last inspection (days)					
	384	1359.52	392.696	518	2710
Conditional on first inspection, time elapsed					
	180	1393.633	397.175	518	2710

Notes: This table shows the summary statistics for inspections. Panel A reports information on the share of banks inspected and the number of times each bank is inspected over the period 2010-2017. Panel B reports information on the sample of banks inspected.

Table 3. Bank-level Regression: Information Disclosure

VARIABLES	(1)	(2) NPL	(3)	(4)	(5) Loan Loss Provision on bad loans	(6)	(7)	(8) Loan Loss Provision on other NPLs	(9)
Post Inspection	0.036***	0.033***	0.036***	0.038***	0.034**	0.036***	0.006	0.037	0.012
	(0.006)	(0.006)	(0.006)	(0.008)	(0.011)	(0.010)	(0.047)	(0.028)	(0.042)
Observations	22,441	22,441	22,441	11,197	11,162	11,197	11,256	11,206	11,256
R-squared	0.979	0.979	0.979	0.965	0.968	0.963	0.925	0.933	0.921
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank-IP	Y	Y	N	Y	Y	N	Y	Y	N
Macro Area	Y	N	N	Y	N	N	Y	N	N
Quarter	Y	N	Y	Y	N	Y	Y	N	Y
Macro Area-Quarter	N	Y	N	N	Y	N	N	Y	N
Bank-IP-Macro Area	N	N	Y	N	N	Y	N	N	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{bpt} = \beta Post\ Inspection_{bpt} + \alpha_{bp} + \alpha_m + \alpha_t + \delta X_{b,PRE} + \epsilon_{ibpt}$. We include bank-inspection plan fixed effects, macro-area fixed effects and quarter fixed effects. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. Column (1)-(3) considers the log(NPL) where NPL stands for Non-Performing Loans. Column (4)-(6) considers the log(loan loss provision on bad loans). Column (7)-(9) the log(loan loss provision on other NPL). *Post Inspection* is a dummy variable taking value 1 for all quarters after bank inspection b included in inspection plan p. It takes value 0 for banks included in inspection plan p and not inspected, i.e. eligible but not inspected banks. IP stands for Inspection Plan. We consider only banks that are included in the inspection plan. We compare inspected vs. eligible but not inspected banks. Each bank included in the inspection plan p is observed 4 quarters before and 8 quarters after the inspection. Standard errors in parentheses and are two-way clustered by bank and inspection plan (IP). * p< 0.10, ** p< 0.05, *** p< 0.01.

TABLE 4. Bank-level Regression: Indirect Effect on Lending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES		Total Loans			Loan to Firms			Loans to SME	
Post Inspection	-0.023***	-0.017***	-0.023***	-0.023***	-0.016**	-0.023***	-0.012*	-0.007	-0.012*
	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Observations	22,051	22,051	22,051	22,051	22,051	22,051	22,051	22,051	22,051
R-squared	0.993	0.994	0.993	0.993	0.993	0.993	0.993	0.993	0.993
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank-IP	Y	Y	N	Y	Y	N	Y	Y	N
Macro Area	Y	N	N	Y	N	N	Y	N	N
Quarter	Y	N	Y	Y	N	Y	Y	N	Y
Macro Area-Quarter	N	Y	N	N	Y	N	N	Y	N
Bank-IP-Macro Area	N	N	Y	N	N	Y	N	N	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{bpt} = \beta Post\ Inspection_{bpt} + \alpha_{bp} + \alpha_m + \alpha_t + \delta X_{b,PRE} + \epsilon_{ibpt}$. We include bank-inspection plan fixed effects, macro-area fixed effects and quarter fixed effects. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio, and NPL ratio. Column (1)-(3) considers the log(Total Loans) where Total loans includes loans to both households and firms. Column (4)-(6) considers log(loans to firms). Column (7)-(9) the log(Small and Medium Enterprise), i.e. a subgroup of firms - SME. $Post\ Inspection$ is a dummy variable taking value 1 for all quarters after bank inspection b included in inspection plan p. It takes value 0 for banks included in inspection plan p and not inspected, i.e. eligible but not inspected banks. IP stands for Inspection Plan. We consider only banks that are included in the inspection plan. We compare inspected vs. eligible but not inspected banks. Each bank included in the inspection plan p is observed 4 quarters before and 8 quarters after the inspection. Standard errors in parentheses and are two-way clustered by bank and inspection plan (IP). * p< 0.10, ** p< 0.05, *** p< 0.01.

TABLE 5. Robustness Tests: Summary

	(1)	(2)
VARIABLES	log(NPL)	log(Loans to Firms)
1. Baseline	0.033***	-0.016**
	(0.006)	(0.005)
2. Top vs. bottom quartile	0.001	-0.010
	(0.043)	(0.017)
3. Interacting with ranking position	0.086*	-0.020**
	(0.009)	(0.008)
4. Dropping top quartile	0.054**	-0.021**
	(0.018)	(0.009)
5. Only Inspected banks	0.030***	-0.012***
	(0.008)	(0.002)
6. Propensity Score Matching	0.033***	0.034***
	(0.007)	(0.007)

Notes: This table shows a summary of the main results from robustness tests. For more details please refer to the specific tables in the Appendix. Column (1) considers the log of NPL. Column (2) considers the log of loans to firms. Row 1 shows the results from the baseline model. Row 2 shows the results comparing inspected banks in the top quartile vs. bottom quartile. Row 3 employs a specification in which we interact the main regressor with a dummy with the ranking position. Row 4 drops inspected banks in the top quartile. Row 5 considers only the sample of inspected banks. Row 6 employs a propensity score matching. * p< 0.10. ** p< 0.05, *** p< 0.01. Data comes from Cerved.

Table 6. Balance Test: Healthy vs. Reclassified

Variable	(1) Reclassified Firms	(2) Healthy Firms	(3) Difference
Total Asset	4345.544	5091.941	-746.397***
Leverage\Total Asset	1.922	1.094	0.828***
EBITDA\Total Asset	-0.315	0.002	-0.317***
Wage Bills	529.688	821.826	-292.137***
Return on Assets	-55.026	-16.154	38.872*
Return on Equity	-36147.077	-7499.595	28647.482***
Cash Flow\Total Asset	-0.298	0.013	-0.310***
Interest Coverage Ratio	-0.037	-0.001	-0.037***
Total Debt\Total Assets	2.088	1.225	0.863***
N	14,806	559,353	

Notes: This table shows summary statistics for firms that are classified as underperforming vs. healthy according to our measure. We consider a firm to be underperforming if one of its whose loans are reclassified as non-performing during an inspection. Summary statistics arecomputed one year before the inspection. Column (2) reports the mean for reclassified firms. Column (3) reports the mean for healthy firms. Column (3) reports the difference in mean and the statistical significance. * p< 0.10. ** p< 0.05, *** p< 0.01. Data comes from Cerved.

Table 7. Effect on Credit growth using our proxy for underperforming firms

VARIABLES	(1) gr(tot Loans)	(2) gr(tot Loans)	(3) gr(tot Loans)	(4) Δ log(tot Loans)	(5) Δ log(tot Loans)
Post Inspection	-0.001	0.034***	0.029**	0.037***	0.032**
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Post Inspection × reclassified		-0.668***	-0.668***	-0.714***	-0.713***
		(0.025)	(0.025)	(0.029)	(0.029)
Observations	1,837,968	1,837,968	1,837,968	1,829,005	1,829,005
R-squared	0.421	0.426	0.434	0.392	0.399
Bank FE	Y	Y	Y	Y	Y
Firm×quarter FE	Y	Y	Y	Y	Y
Bank×quarter FE	N	N	Y	N	Y
Inspection Plan FE	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y
Bank-firm relation	Y	Y	Y	Y	Y
Cluster	bank	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $y_{ibt} = \beta Post\ Inspection_{bpt} + \eta\big(Post\ Inspection_{bpt} \times reclassified_{ip}\big) + \alpha_{it} + \alpha_b + \alpha_p + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibpt}$. In columns (1)-(3) the outcome variable is $growth(credit_{ib,t}) = \frac{credit_{ibt} - credit_{ibt-1}}{0.5(credit_{ibt} + credit_{ibt-1})}$. In columns (4) and (5), the outcome variable is the following: $\Delta \log(credit_{ib,t}) = \log(credit_{ib,t}) - \log(credit_{ib,t-1})$. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p, is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $reclassified_{ip}$ is a dummy that is equal to 1 if a loan belonged to firm i is reclassified as NPL within a quarter from the inspection a bank included in the inspection plan p. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio, and NPL ratio. We include bank fixed effects, Inspection plan-macro-area fixed effects and quarter fixed effects. $W_{ib,PRE}$ is a set of pre-determined bank-firm relationship controls. These are: relationship length (number of quarters in which we observe a lending relationship between the firm and the bank; firm's credit share (i.e. share of the firm's loan balance in the bank's loan portfolio); main lender is a dummy equal to 1 if the bank is the firm's largest lender; bank share refers to the share of the bank in the firm's loan portfolio. We include the following fixed effects: bank, firm×quarter, inspection plan, quarter. The sample includes only firms that have no NPLs before the inspections and is conditional only on firms that we observe at least one period before the inspection and one period after the inspection. Standard errors in parentheses and are clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

TABLE 8. Effect on Credit Growth: Extensive Margin

VARIABLES	(1) pr(cut)	(2) pr(cut)	(3) pr(cut)	(4) pr(cut)
Post Inspection	-0.002**	-0.001	-0.007**	-0.005*
	(0.001)	(0.002)	(0.003)	(0.003)
Post Inspection × reclassif			0.056***	0.056***
			(0.010)	(0.011)
Observations	1,844,127	1,857,447	1,844,127	1,844,127
R^2	0.212	0.476	0.319	0.331
Bank FE	Y	Y	Y	Y
Firm×quarter FE	Y	Y	Y	Y
Inspection Plan FE	N	Y	N	Y
Bank controls	Y	Y	Y	Y
Bank-firm relationship	Y	Y	Y	Y
Cluster	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $pr(cut)_{ibt} = \beta Post\ Inspection_{bpt} + \eta\big(Post\ Inspection_{bpt} \times reclassified_{ip}\big) + \alpha_{it} + \alpha_b + \alpha_p + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibpt}$. The outcome variable $pr(cut)$ is a dummy variable equal to 1 if the bank-firm relationship is cut in quarter t, 0 otherwise. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p, is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $reclassified_{ip}$ is a dummy that is equal to 1 if a loan belonged to firm i is reclassified as NPL within a quarter from the inspection a bank included in the inspection plan p. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. $W_{ib,PRE}$ is a set of pre-determined bank-firm relationship controls. These are: relationship length (number of quarters in which we observe a lending relationship between the firm and the bank; firm's credit share (i.e. share of the firm's loan balance in the bank's loan portfolio); main lender is a dummy equal to 1 if the bank is the firm's largest lender; bank share refers to the share of the bank in the firm's loan portfolio. We include the following fixed effects: bank, firm×quarter, inspection plan, quarter. The sample includes only firms that have no NPLs before the inspections. Standard errors in parentheses and are clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table 9. Spillover to Healthy Firms: Credit Channel

VARIABLES	(1) Δ log(Tot Loans)	(2) Δ log(Tot Loans)	(3) Δ log(Tot Loans)	(4) Δ log(Tot Loans)	(5) Δ log(Tot Loans)
Post Exposure	-0.002***	-0.002***	-0.046**	-0.042**	-0.041**
	(0.000)	(0.000)	(0.023)	(0.017)	(0.017)
Post Exposure×Healthy			0.082***	0.078***	0.077***
			(0.025)	(0.017)	(0.017)
Post×Healthy			-0.028***	-0.021***	-0.018***
			(0.003)	(0.002)	(0.002)
H_0 : Post Exposure + Post Exposure×Healthy=0					
$\beta_1 + \beta_2$			.037	.036	.036
			(0.006)	(.002)	(0.001)
p-value			0.000	0.000	0.000
Observations	1,382,736	1,382,736	1,382,736	1,382,736	1,382,736
R-squared	0.036	0.036	0.114	0.124	0.124
Firm FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y
Inspection Plan Year FE	Y	Y	N	N	Y
Province FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Firm controls	N	Y	N	Y	Y
Cluster	industry	industry	industry	industry	industry

Notes: This table shows the results of the following equation: $\Delta\log(total\ credit_{it}) = \beta_1 Post\ Exposure_{ip,PRE} + \beta_1 Post\ Exposure_{ip,PRE} \times NonReclassified_{ip} + \alpha_i + \alpha_p + \alpha_t + \alpha_l + \alpha_c + \gamma S_{iPRE} + \epsilon_{ibtlcpt}$. The outcome variable is $\Delta\log(total\ credit_{i,t}) = \log(total\ credit_{i,t}) - \log(total\ credit_{i,t-1})$. We include firm, quarter, province, industry and inspection plan fixed effects. S_{iPRE} is a set of pre-determined firm-level characteristics computed one to three quarters before the shock. These variables are the natural logarithm of assets, sales growth, capital/assets, interest paid/EBITDA and the current ratio. $Healthy_{it}$ is a dummy equal to 1 if the loan of the firm is not reclassified. $Exposure_{ip,PRE} = \frac{\sum_{b=1}^{b\in\mathfrak{B}^{inspected}} credit_{ibp}}{\sum_{b=1}^{b\in\mathfrak{B}^{all}} credit_{ib}}$ is our treatment, which is the share of credit coming from inspected banks computed in the pre-period. Coefficients are standardized. Standard errors in parentheses and are clustered by industry. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table 10. Real Effect on Employment, Investments, and Sales for Healthy Firms

VARIABLES	(1) ΔEmploym$_{t+1}$	(2) ΔEmploym$_{t+2}$	(3) ΔFixed Assets $_{t+1}$	(4) ΔFixed Assets $_{t+2}$	(5) ΔSales$_{t+1}$	(6) ΔSales$_{t+2}$
Exposure	0.015***	0.020***	0.011***	0.019***	0.045***	0.034*
	(0.003)	(0.004)	(0.002)	(0.004)	(0.016)	(0.018)
Observations	82,296	82,296	71,668	71,668	56,668	56,668
R-squared	0.041	0.043	0.012	0.020	0.026	0.028
Province FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Inspection Plan Year FE	Y	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y	Y
Cluster	industry	industry	industry	industry	industry	industry

Notes: This table shows the results of the following regression: $\Delta y_{iplct} = \beta Exposure_{ip} + \gamma X_{i,PRE} + \alpha_i + \alpha_l + \alpha_c + \alpha_p + \gamma S_{i,PRE} + \epsilon_{iplct}$. The outcome variable is $\Delta \log(y_{ilct}) = \log(y_{iplc}) - \log(y_{ilc,t-1})$, i.e., we compute the change in y between the year before the inspection and the year after. We include province fixed effects, industry fixed effects and inspection plan year fixed effects. $S_{i,PRE}$ is a set of predetermined firm-level characteristics computed one to three quarters before the shock. These variables are the natural logarithm of assets, sales growth, capital/assets, interest paid/EBITDA and the current ratio. $Exposure_{ip,PRE}$ is our treatment, which is the share of credit coming from inspected banks included in inspection plan p computed in the pre-period. Coefficients are standardized. Standard errors in parentheses and are clustered by industry. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table 11. Effect on Local Economy

Panel A: Aggregate Employment

VARIABLES	(1) ΔAggreg Employm$_{t+1}$	(2) ΔAggreg Employm$_{t+2}$	(3) ΔAggreg Employm$_{t+3}$
Exposure	-0.018**	0.012*	0.013*
	(0.009)	(0.007)	(0.007)
Observations	39,840	31,748	23,710
R-squared	0.057	0.088	0.061
Inspection plan year FE	Y	Y	Y
Industry FE	Y	Y	Y
Province controls	Y	Y	Y
Cluster	province	province	province

Panel B: Aggregate Productivity

VARIABLES	(1) ΔValue Added per worker$_{t+1}$	(2) Δ Value Added per worker$_{t+2}$	(3) ΔValue Added per worker$_{t+3}$
Exposure	-0.003	0.005*	0.004*
	(0.003)	(0.003)	(0.002)
Observations	526	437	345
R-squared	0.397	0.498	0.490
Inspection plan year FE	Y	Y	Y
Province controls	Y	Y	Y
Cluster	province	province	province

Notes: This table shows the results of the following regression: $\Delta(y_{clt}) = \beta Exposure_{cp} + \alpha_l + \alpha_c + \alpha_p + \gamma S_{c,PRE} + \epsilon_{pcl}$. The outcome variable is $\Delta(y_{ct}) = \log(y_{c,t+n}) - \log(y_{c,t-1})$, i.e., we compute the change in y between the year before the inspection and n years after the inspection. We include whenever possible industry fixed effects, province fixed effects and inspection plan year fixed effects. $S_{c,PRE}$ is a set of predetermined province-level characteristics computed one year before the shock. These variables are the population, average income, share of deposits by mutual banks. $Exposure_{c,PRE}$ is our treatment, which is the share of credit coming from inspected banks computed in the pre-period. Standard errors in parentheses and are clustered by province. * p< 0.10, ** p< 0.05, *** p< 0.01.

10. Appendix

Robustness Tests

A1. **Balance Tests:** To reduce concerns related to selection bias, we run a battery of balance tests. First, we show that the first-step selection process of eligible banks leads to a homogeneous group of banks. Figure A7 shows a balance test comparing the group of eligible vs. not-eligible banks. Eligible banks have, on average, a higher stock of NPLs, a lower capital ratio and a lower liquidity ratio. They are also less profitable. This is in line with anecdotal evidence that the first screening is based on a bank's quality, and in line with this story, we find that eligible banks are relatively worse.[1] Second, in Figure A6 we show that, among the set of eligible banks, those that are inspected are not significantly different from those not inspected along several dimensions. They only differ in terms of profitability. In all our specifications, we include it as a control to residualize its effect on bank's activity.[2] Overall, balance tests confirm that while the first-step selection of eligible banks is based on quality, the second-step selection is not correlated with a bank's quality.

A2. **Sample of inspected banks only.** To further reduce any concern about the results driven by selection bias, we consider only the sample of banks that are inspected. We construct a monthly level dataset and compare, within the same inspection plan, banks that are inspected at different point in time. The identification strategy relies on different times in which inspected banks are inspected within the same inspection plan. As figure 1 suggested, within the same inspection plan, inspections are evenly distributed across the year. On average there are 6 banks inspected each month.

To study the impact of audits on banks' performance we consider the following parametric model:

$$y_{bptm} = \alpha_h + \alpha_{bp} + \alpha_m + \sum_{\tau=-12}^{+24} \beta_\tau Inspected_{bphm} \times \left\{\mathbb{1}_{\tau=h}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=}h\right\} + \varepsilon_{bhpm} \tag{.1}$$

where b, p, h and m stands for bank, inspection plan, month and macro-area. Similar to equation 4.1 $\left\{\mathbb{1}_{\tau=t} \times Inspected_{bptm}\right\}$ are event time indicator variables interacted with a dummy variable $Inspected$. $Inspected$ takes value 1 if bank b is included in inspection plan p and is inspected in month h. The interaction term takes value 1 if it is month τ relative to the month in which the bank is inspected and captures the relative effect of banking inspections. These indicator variables are 0 for banks not yet inspected. The specification includes the same controls as in equation 4.1.

Following equation 4.2, we consider also the parametric version of the model:

$$y_{bhpm} = \alpha_h + \alpha_b + \alpha_{pm} + \beta^{ATE} Post\ Inspection_{bph} + \gamma X_{b,PRE} + \varepsilon_{bhpm} \tag{.2}$$

where b, p, h and m stands for bank, inspection plan, month and macro-area. y_{btpm} is our outcome of interest, which refers to bank b at month h from inspection plan p located in the macro area m. The specification follows closely 4.2.

Table A3 and figure A8 shows the results of this exercise. We find that the magnitude of the effects are very similar to the baseline model and robust to different sets of fixed effects. In column (1)-(4) we consider the log of NPL as outcome variable, while columns (5)-(8) consider the log of total loans. In our preferred

[1] Table A4 shows the table counterpart of Figure A7.

[2] Table A5 shows the table counterpart of figure A6.

specification in column (2) we include pre-defined bank-level controls, bank fixed effects, month fixed effects and inspection plan-macro-area fixed effects. In this specification we control for time trend at the macro-area. In our preferred specification in column (3) we include bank, month and inspection plan-macro-area fixed effects and the magnitude of the coefficient is now 0.055. Finally in column (4) we saturate the model with bank-inspection plan-macro area fixed effects.

Column (5)-(8) show the results for total loans. We find a negative effect in all specifications which is in line with the baseline model. The coefficient ranges from 0.012 to 0.020 and it is statistically significant. This is very much in line with the results of the baseline model in table 4 where the coefficient ranges from 0.016 to 0.023.

Figure A8 Panel A shows the plot of the log of NPL while panel B shows the plot of the log of loans to firms. In both cases we find evidence of a significant effect of audits on bank's behavior. Additionally, we find that the results are not driven by pre-trends as the coefficients in the pre-period are not significantly different from zero. This exercise provides strong evidence that results we find in the baseline are not driven by selection bias.

A3. **Controlling for the ranking does not have an impact:** The ranking position of the bank could be considered as a sufficient statistic for the selection rule. Thus, by including it in the regression we can try to quantify the potential role of the selection. To do so, we conduct a similar analysis as in equation 4.2 by including an interaction term for the ranking position of inspected banks. We divide banks into quartiles according to their ranking position and interact this variable with our treatment, i.e. *post* variable. The idea of this exercise is to see if the ranking position has any significant role in predicting bank's outcomes. In particular, in this specification we can control directly for the potential bias created by the selection rule. Table A6 Panel A shows the results related to the direct effect of bank inspections. In particular, we consider NPL (column 1), loan loss provisions for bad loans (column 2) and loan loss provision for other NPL (column 3). We find that our main regressor of interest post×inspection is still statistically significant while the triple interaction has no statistical power. We perform a similar analysis by looking at the indirect effect of bank inspections on lending activity in Panel B. We find a similar pattern as before. Our main regressor on post×inspection is still statistically significant while the triple interaction with the ranking quartile has no predictive power. Also the magnitude of the coefficients are in line with the baseline results from table 4. The coefficient on the triple interactions with the ranking of the bank does not have any other significant effect. Overall, this exercise provides further evidence that the potential bias generated by the selection rule is negligible.

A4. **Placebo test ranking:** Following the same logic from before on the role of the ranking as a sufficient statistic for the selection rule, we consider only inspected banks ranked in the top quartile vs banks ranked in the bottom quartile. We consider the same specification as in equation 4.1.[3] If the ranking is picking

[3]Specifically we consider the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Top\ quartile\ Ranking_{bptm} \times \{\mathbb{1}_{\tau=t}\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \{\mathbb{1}_{\tau=t}\} + \varepsilon_{btpm}$. We include bank, quarter and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level.

differences among banks, we should see an effect comparing top-ranked banks vs bottom-ranked banks.[4] Figure A9 shows the results of this exercise. We find that inspections do not have a significant impact in the group of top-ranked banks compared to bottom-ranked banks. In addition to finding no statistical differences in the coefficients in the period before the inspection, we also find that the coefficients are not significantly different from zero in the post inspection period. This confirms once again the idea that the results are driven by the supervisory activity rather than unobserved differences among banks which are potentially represented by their ranking position.

A5. **Ranking does not predict bank's quality:** To further understand whether the ranking position of an inspected bank has any predictive power of its quality we test this idea by considering a model in which the ranking is the main regressor and the outcome variable is a bank's characteristic.[5] If ranking is correlated with a bank's quality, we may expect it to be a good predictor of a bank's health. Figure A10 shows that this is not the case. In all cases considered, the ranking position is not a good predictor of bank's quality.

A6. **Dropping top quartile of ranked banks:** We show that the results are not driven by inspected banks ranked at the top. To do so, we drop banks included in the top quartile of the ranking distributions and run the same baseline model comparing inspected banks vs. eligible but not inspected banks (Figure A9). We find similar patters compared to the baseline model where we include the full sample of inspected banks. Figure A12 plots the amount of NPL according to whether banks are included in the sample of eligible but not inspected or eligible and inspected. For the latter, we order them considering their ranking position on the x-axis. the ranking position for inspected banks anMoreover, we show that there is no clear pattern in terms on NPL according to ranking position of inspected banks. We find that there is no clear pattern in terms of NPL according to the ranking position of inspected banks.

A7. **Propensity Score Matching:** To further reduce any concerns related to selection bias we run a propensity score matching model. The idea is that we want to match inspected banks with eligible but not inspected banks that have similar probability to be inspected, or in other words similar propensity score. Based on this matched sample, we run similar regressions as before. We follow the standard approach in the literature to construct our matched sample. Specifically, for each inspection plan, we compute the propensity score by running a logit model of the following type:

$$log(insp_{b,p}) = \alpha_0 + \beta X_{b,p} + \epsilon_{b,p} \tag{.3}$$

where $X_{b,p}$ is a vector of bank-level characteristics computed three quarters before the inspections – i.e. around the time in which the supervisory authority decides the inspection plan for the next year – and we match banks in the treated group with banks in the control group based on one-to-one nearest neighbor

[4]Recall that the main limitation of this dataset is that we do not have information available on the ranking of eligible but not inspected banks. Thus, we rely on the group of banks for which we have this information to show that the selection rule is not correlated with the health of the banks.

[5]Formally, we test the following model: $Covariate_{b,p,PRE} = \beta Ranking_{b,p} + \eta_p + \epsilon_{b,p}$ where $Ranking_{b,p}$ is the ranking position assigned to the subsample of eligible and inspected banks. We include inspection plan fixed effects η_p and we two-way cluster the standard errors at the bank-inspection plan level.

matching within a caliper of 0.25 standard deviations of the estimated propensity score with replacement.[6] Figure A13 provides a visual representation of the result of the propensity score matching. Figure 14**A.** shows the common support between the treated and control group. Figure 14**B.** provides a visual inspection of the densities of propensity scores of treated and non-treated groups. From the figure, it does not seem that there are sizable differences between the maxima and the minima of the density distributions. All units from both groups lie on the same common support.

Table A10 reinforces the results found in Tables 3 and 4. In all cases, compared to the baseline regressions, the magnitude is larger as well as the statistical significance. For instance, column (1) assesses the effect of on-site bank inspections on NPL. We find that inspected banks increase their NPL by 3.3 %. This is a stronger effect compared to the 3.1 percent in the baseline model. For loans to firms we find a drop by 3.4 compared to 2.5 percent in the baseline model. The gap is especially important for loans to small and medium enterprises (SME, henceforth) for which the drop in lending activity is about 2.5 percent and it is statistically significant at the 1% level.

This empirical strategy is designed to compare pairs of banks that are exposed to a similar probability of being audited. We do this by matching banks based on observable characteristics. However, there is still some space for concern. For instance, if matched banks differ on unobserved characteristics that are known to the supervisor, and she uses them in the selection process, then their probability to be inspected may be very different. We believe this is not the case, since the selection process is done relying on algorithms and computer-based decisions. There is no space for arbitrary decisions by inspectors. Some information is factored into the scoring algorithm related to bank's organizational structure: for example, whether a bank has opened up new branches recently. But these characteristics are not directly correlated to a bank's quality. Overall, the findings confirm that selection bias is not a relevant concern. We show that by matching banks within the same inspection plan based on their propensity score (i.e. their probability to be inspected), the results are similar both in terms of magnitude and statistical significance compared to the baseline model.

A8. **Placebo Tests: unexpected inspections.** We further test the robustness of these results by confirming that audits are truly unexpected by inspected banks. We run a set of placebo tests in the pre-bank inspection period. Table A11 shows the regressions of equation 4.2 where we artificially assign the date in which the inspection is conducted either to time $t = (-2; -1)$ or $t = (-3; -2)$, rather than to period $t = -0$. In Panel A, we assume that the inspection takes place between event time -2 and -1.[7] In panel B, we assign artificial bank inspections between event time $(-3; -2)$. In both cases, we find no effect either in magnitude or significance coming from these artificial banking inspections on the outcome variables. The coefficients are very close to 0 and not statistically significant. Figure A14 plots the coefficients of equation 4.1 in the case where artificial inspection is set between event time $\tau = (-2; -1)$ (panel A) or event time $\tau = (-3; -2)$

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[6]Specifically, we use the following matching algorithm:

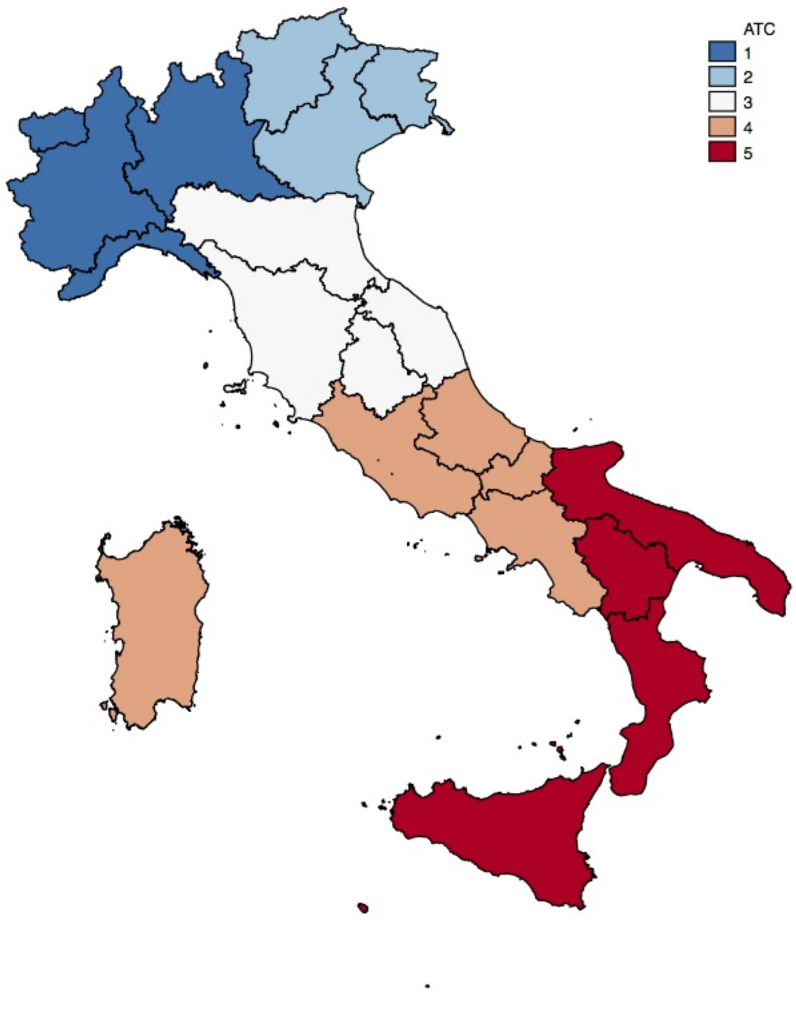
$$A_{rj} = \left\{ kj' \in I_0 : ins\hat{p}_{kj'} = \min_{kj' \in I_0} \left| ins\hat{p}_{rj} - ins\hat{p}_{kj'} \right| < 0.25\hat{\sigma}_e \right\} \tag{.4}$$

[7]Note in reality, banking inspections happen between event time $(-1; 0)$. We can't precisely set the inspection at time 0, since inspections happen continuously over the quarter. Some are performed at the beginning and some at the end.

(panel B). We normalize the coefficient in the quarter before the inspection to be equal to 0 so that we can interpret the results relative to that period. We find the coefficients in the post period to be not significantly different from zero.

Additional Figures

Figure A1. Redistribution of Regions according to their ATC - Aree Territoriali e Circoscrizionali



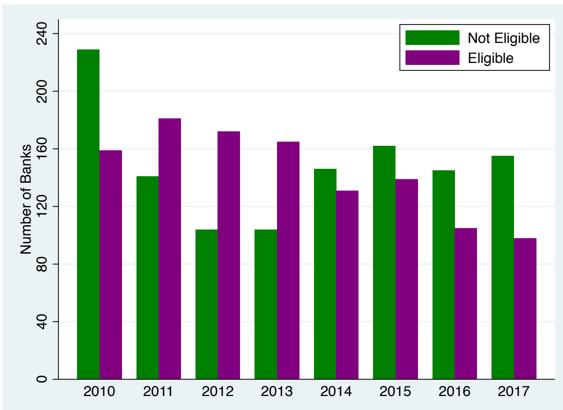
Notes: This figure shows the spatial distribution of regions according to the ATC to which they belong. There are five different ATCs: 1. North-west (Piemonte, Liguria, Valle d'Aosta, Lombardia); 2. North-East (Trentino-Alto Adige, Friuli-Venezia Giulia, Veneto); 3. North-Center (Emilia Romagna, Toscana, Umbria, Marche); 4. Center (Lazio, Campania, Molise, Sardegna, Lazio); 5. South (Sicilia, Basilicata, Calabria, Puglia)

Figure A2. Distribution of Banks according to their Legal Form

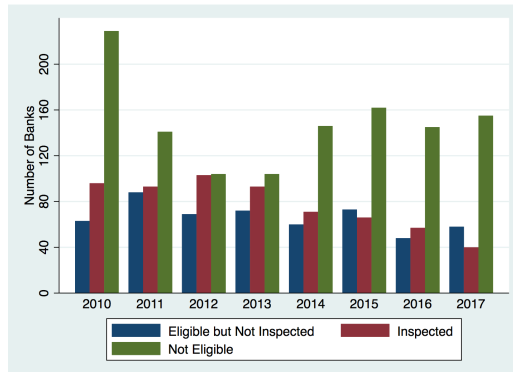
A. Frequency **B.** Total Assets **C.** Total Deposits **D.** Total Non Performing Loans

Notes: This figure shows the distribution of banks according to their type of ownership. There are four different type of banks in the Italian banking system. Public (orange) includes banks that are traded in the public market. Mutual (green) refers to mutual banks. Cooperative (yellow) stands for cooperative banks. Panel A shows the frequency of banks according to their different legal ownership. Panel B shows the distribution according to total assets. To compute this, we first take the mean of total assets for each bank for the year 2010. We then sum up the total assets according to the different legal form. The total assets of Cooperative banks account for the 5.3%. Public banks account for the 77%, Mutual banks for the 9.6% and government-owned banks for the 8.1%. Panel C show the distribution in terms of deposits. To compute this, we first take the mean of total assets for each bank for the year 2010. We then sum up the total assets according to the different legal form. The total assets of cooperative banks account for the 7.2%. Public banks account for the 66.5%, Mutual banks for the 8.1% and government-owned banks for the 18.2%. Panel D shows the distribution of Non Performing Loans (NPL). To compute it we first take the mean of total assets for each bank for the year 2010. We then sum up the total assets according to the different legal form. The total amount of Non-Performing Loans (NPL) of mutual banks account for the 20.8%; for Public banks account for the 76.9%; for Cooperative banks, for the 2.1%; and government-owned banks, for the 0.2%. *Source*: Supervisory Records and Credit Registry. Reference Year: 2010

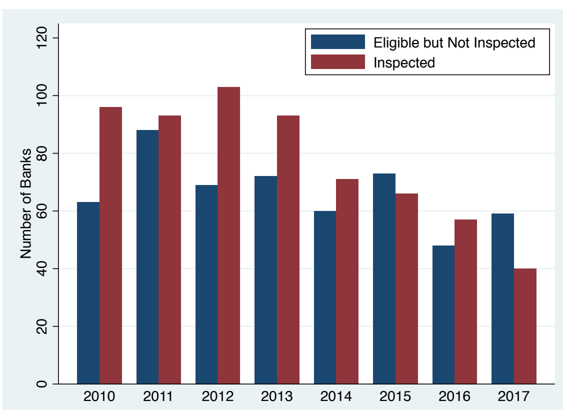
Figure A3. On-site inspections over time



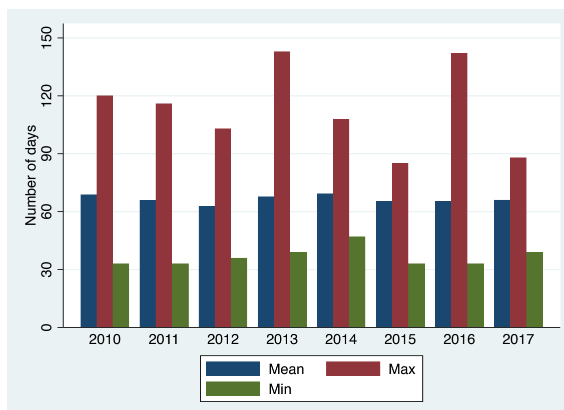
A. Eligible and Not Eligible Banks



B. Eligible and Inspected, Eligible but not-inspected and not-eligible over Time



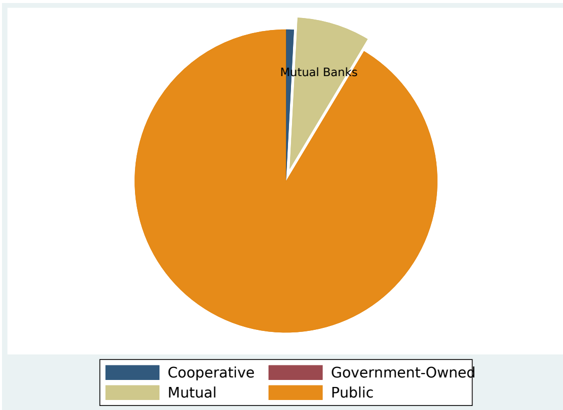
C. Inspected (Treated) and Eligible but Not Inspected (Control) over Inspection Plan



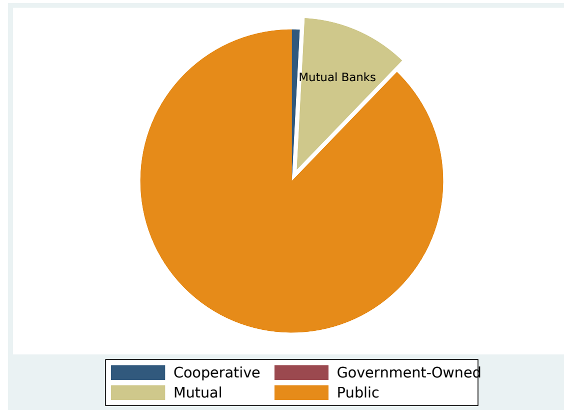
D. Length of Inspections in Days

Notes: This figure shows some descriptive statistics on bank inspections. Panel A shows the distribution of eligible banks and not-eligible banks over time. Panel B shows the distribution of banks into the three groups. The blue bar represents the group of banks that are eligible but not inspected (i.e. the control group). The red bar represents the group of banks that are inspected (i.e. treated group). The green bar represents the group of banks that are not eligible to be inspected. Panel C shows the frequency of banks in the two groups: inspected and eligible but not inspected. Each year, the Supervisor constructs these two groups based on the selection by the score system and by considering the human and other resources available to perform the on-site inspections. Panel D shows the distribution of the duration of inspections (in days) across the different years. We report by year the mean (blue bar), min (green bar) and max (red bar) in days of duration of banking inspections. *Source*: Data on on-site Inspections.

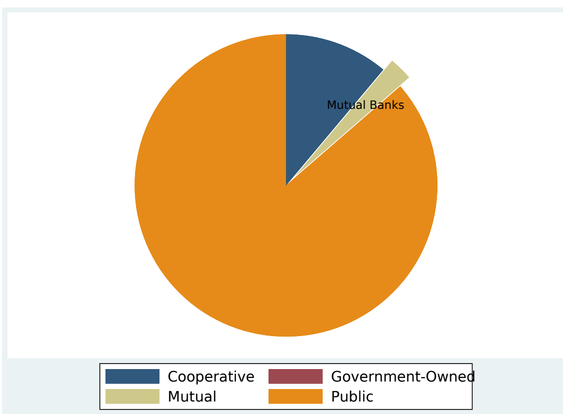
Figure A4. Distribution of Banks according to their Legal Form - Type of Credit



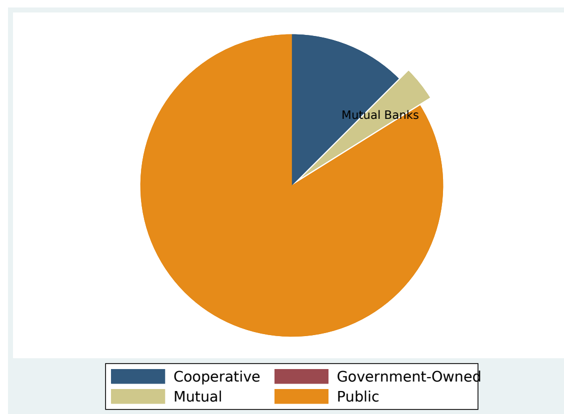
A. Loans Backed by account Receivables



B. Credit Lines



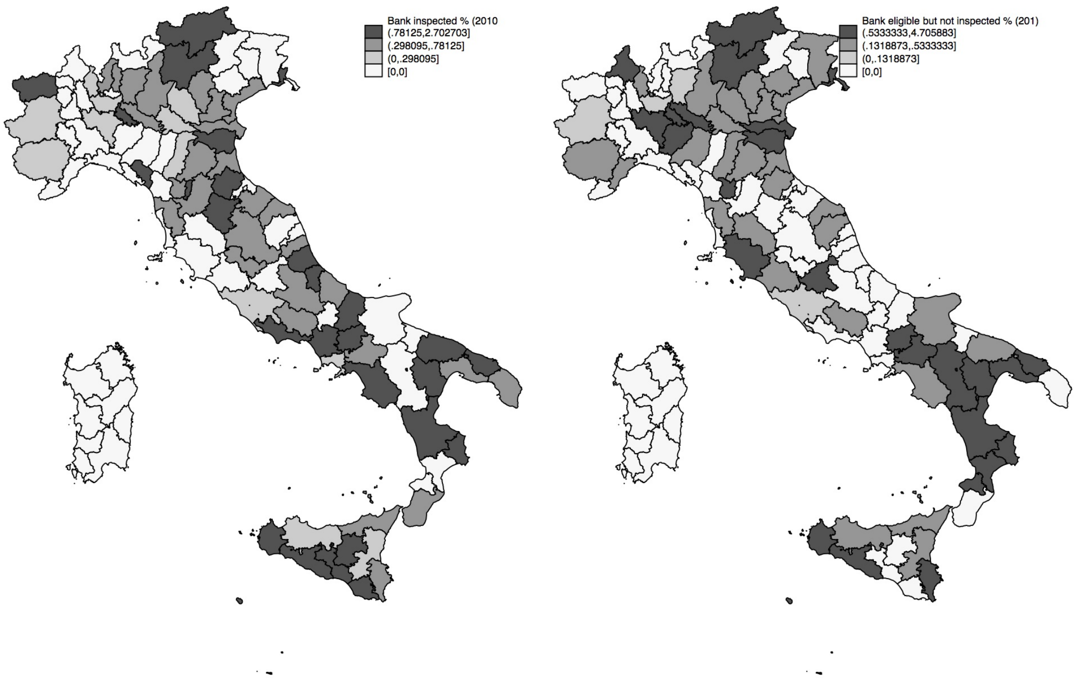
C. Term Loans



D. Total Credit

Notes: This figure shows the distribution of banks according to their types of ownership. There are four different types of banks in the Italian banking system. Public (orange) includes banks that are traded in the public market. Mutual (green) refers to mutual banks. Cooperative (yellow) stands for cooperative banks. Panel A shows the distribution of granted loans backed by account receivables by type of bank. To compute this, we first take the mean of total assets for each bank for the year 2010. We then sum up the total assets according to the different legal forms. The share of loans backed by account receivables of Cooperative banks account for the 7.6% of the total. Public banks account for 91.5%; Mutual banks, 0.8%; and government-owned banks, 0%. Panel B shows the distribution of granted credit lines by type of bank. To compute this, we first take the mean of total assets for each bank for the year 2010. The share of Cooperative bank credit lines account for 11.3% of the total; Public banks account for the 87.7%; Mutual banks, 0.9%; and government-owned banks, 0%. We then sum up the total assets according to the different legal forms. Panel C shows the distribution of total amount of term loans by type of bank. To compute this, we first take the mean of total assets for each bank for the year 2010. We then sum up the total assets according to the different legal forms. The total share of term loans of Cooperative banks account for 2.6% of the total. Public banks account for 86.3%; Mutual banks, 11.1%; and government-owned banks, 0%. Panel D shows the distribution of total credit by type of bank. Total credit consists of revocable credit lines, term loans and loans backed by account receivables (LBR). The total amount of credit of cooperative banks account the 3.6% of the total; Public banks account for 83.9%; Mutual banks, 12.4%; and government-owned banks, 0%. *Source*: Credit Registry. Reference Year: 2010

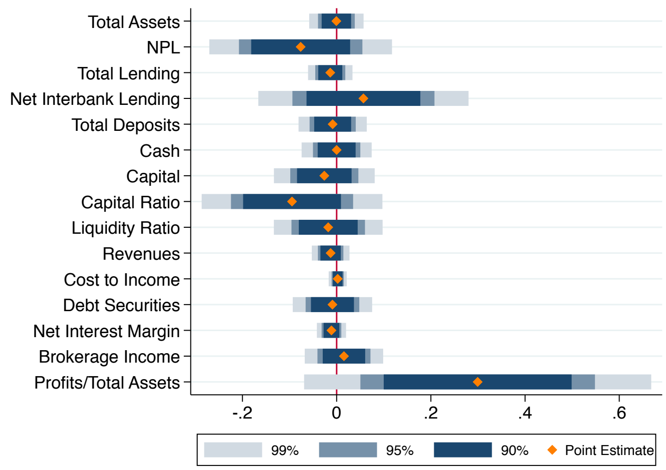
Figure A5. 2010 Inspection Plan



A. Inspected Banks **B.** Banks eligible but not inspected

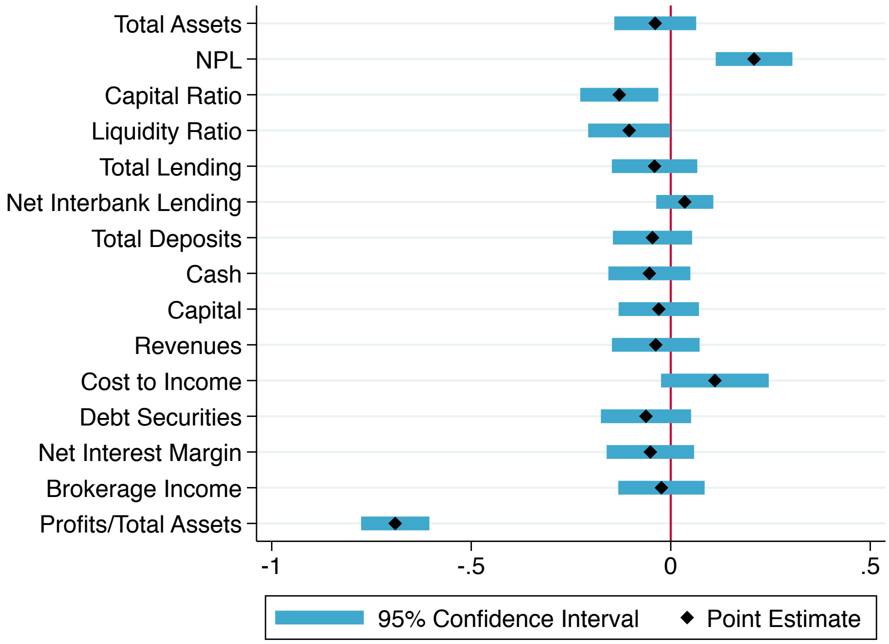
Notes: This figure shows the spatial distribution of inspected banks and eligible but not inspected banks, relative to the 2010 inspection plan. Panel A. shows the distribution of Inspected banks. Panel B. shows the distribution of Eligible but not inspected banks. Borders define provinces. A province has roughly the same size as a US county. For each province we compute the relative shares of branches belonging to either the treated or control group. The denominator is the total number of branches in that province on December 31 of the year before the inspection plan. Note that the total also includes branches of banks that are not in any of the two groups (i.e. ineligible banks). The share is multiplied by 100.

FIGURE A6. Balance Test: Inspected vs. Eligible but Not Inspected



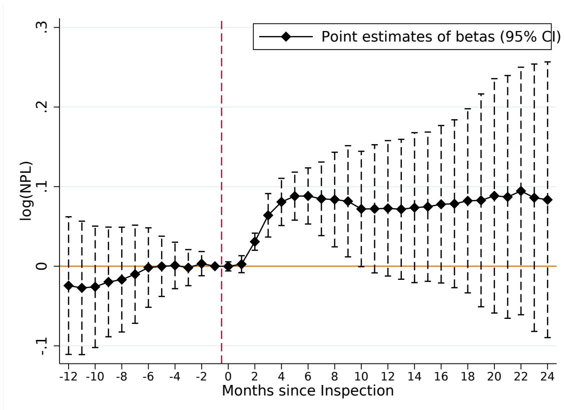
Notes: This figure shows balance tests for covariates among inspected vs. eligible but not inspected banks. The regression of interest is the following: $Y_{bp,-4} = \beta Inspected_{bp} + \gamma_p + \epsilon_{bp}$ where the outcome variables are a series of bank-level variables. The darkest shades represent 90% confidence intervals and the lightest shades represent 99% confidence intervals. This is the graphical counterpart to Table A5.

Figure A7. Balance Test: Eligible vs. Not Eligible

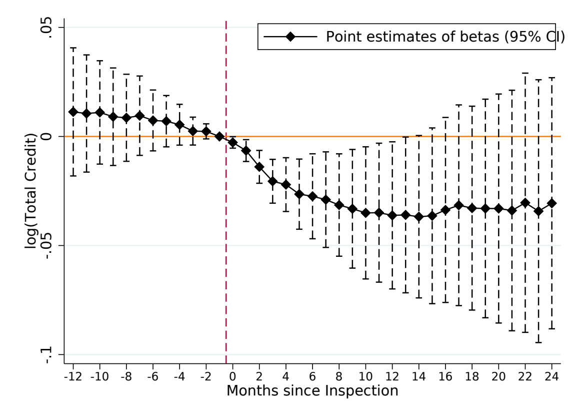


Notes: This figure shows balance tests for covariates among inspected vs. eligible but not inspected banks. The regression of interest is the following: $Y_{bp,-4} = \beta Inspected_{bp} + \gamma_p + \epsilon_{bp}$ where the outcome variable are a series of bank-level variables. This is the graphical counterpart to Table A4.

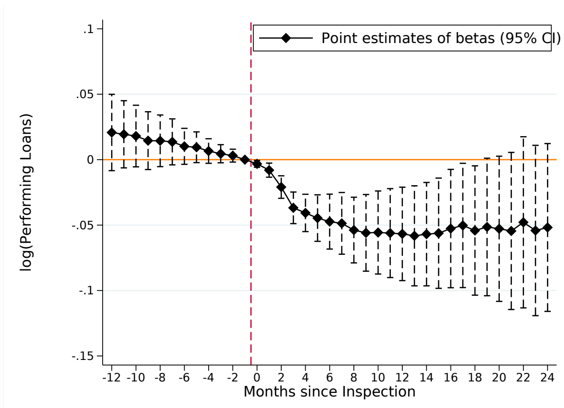
FIGURE A8. Monthly-level analysis with Only Inspected Banks



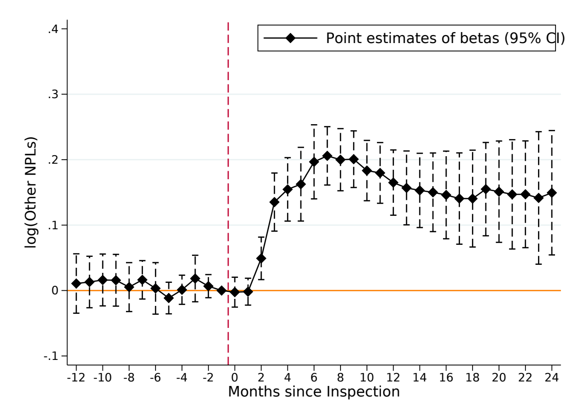
A. log(NPL)



B. log(Loans to Firms)



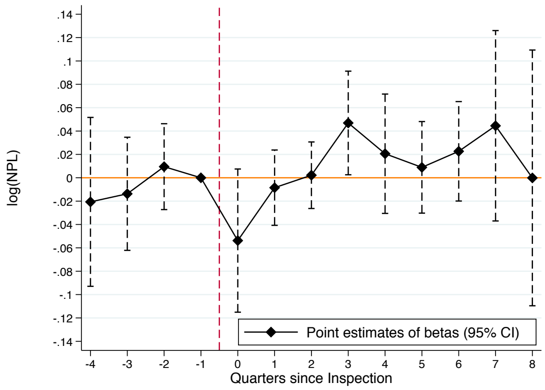
C. log(Performing Credit)



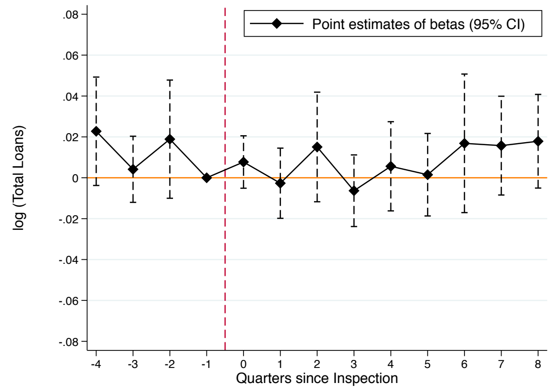
D. log(Other NPLs)

Notes: The sample includes *only* inspected banks and use monthly-level data. This figure plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-12}^{+24} \beta_\tau Inspected_{bptm} \times \{\mathbb{1}_{\tau=t}\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \{\mathbb{1}_{\tau=t}\} + \varepsilon_{btpm}$. We include bank b, month t and inspection plan-macro-area fixed effects pm. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. In panel A the outcome variable is the log of NPL (i.e. bad loans only). In panel B the outcome variable is the log of loans to firms. In panel C the outcome variable is the log of performing loans only. In panel D the outcome variable is the log of other NPLs (unlikely to pay and past due). Data comes from the Credit Registry and it is aggregate at the bank-level.

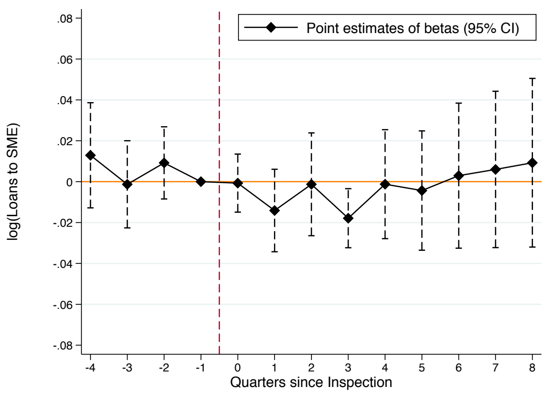
Figure A9. Comparing top-ranked inspected banks vs. bottom-ranked inspected banks



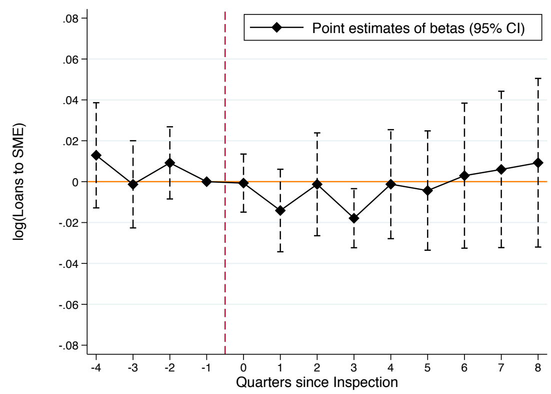
A. log(NPL)



B. log(Total Loans)



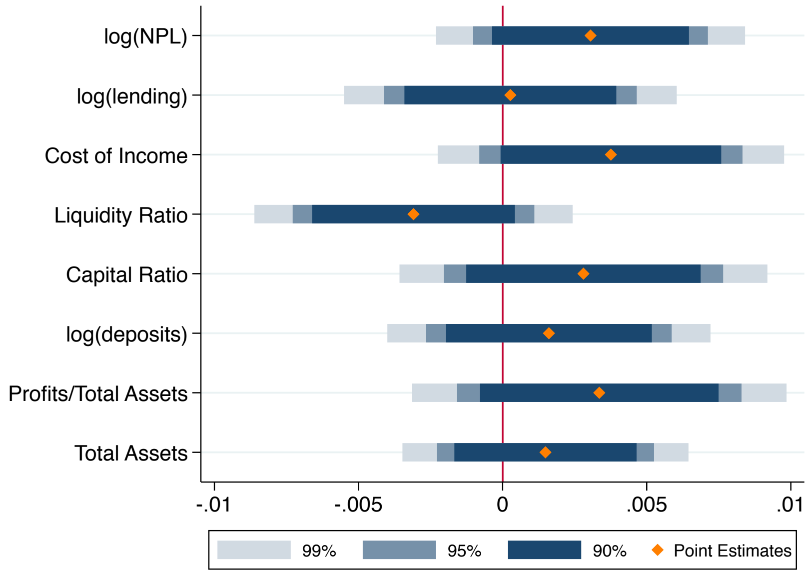
C. log(Loans to Firms)



D. log(Loans to SME)

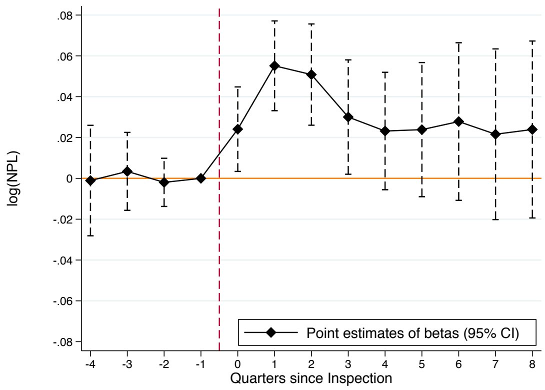
Notes: The sample includes only inspected banks ranked in the top quartile and inspected banks ranked in the bottom quartile. This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Top\ quartile\ Ranking_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. We include bank, quarter and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. In panel A the outcome variable is the log of NPL. In panel B the outcome variable is the log of total loans. In panel C the outcome variable is the log of loans to firms. In panel D the outcome variable is the log of loans to Small and Medium Enterprises (SME). Data comes from bank's balance sheet (Supervisory Reports).

FIGURE A10. Ranking Prediction

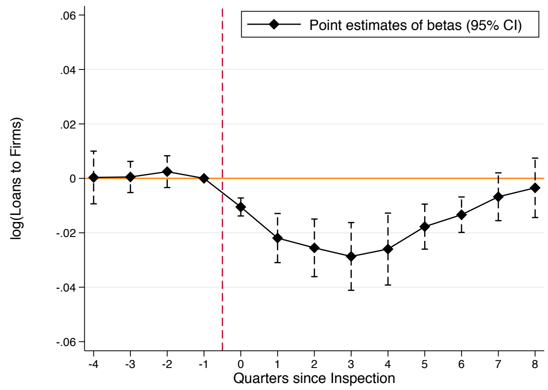


Notes: This figure shows the results of the following regression: $y_{bpa} = \beta Ranking_{bpa} + \gamma_p + \gamma_a + \epsilon_{bp}$ where γ_p are inspection plan fixed effects and γ_a are macro-area fixed effects. We consider bank-level variables 4 quarters before the inspection, which is roughly the timing when the inspection plan for the next year (and the ranking) is decided. The darkest shades represent 90% confidence intervals and the lightest shades represent 99% confidence intervals. Coefficients are standardized. This is the graphical counterpart to Table A9. Data comes from bank's balance sheet (Supervisory Reports).

FIGURE A11. Dropping the top-quartile Ranked Inspected Banks



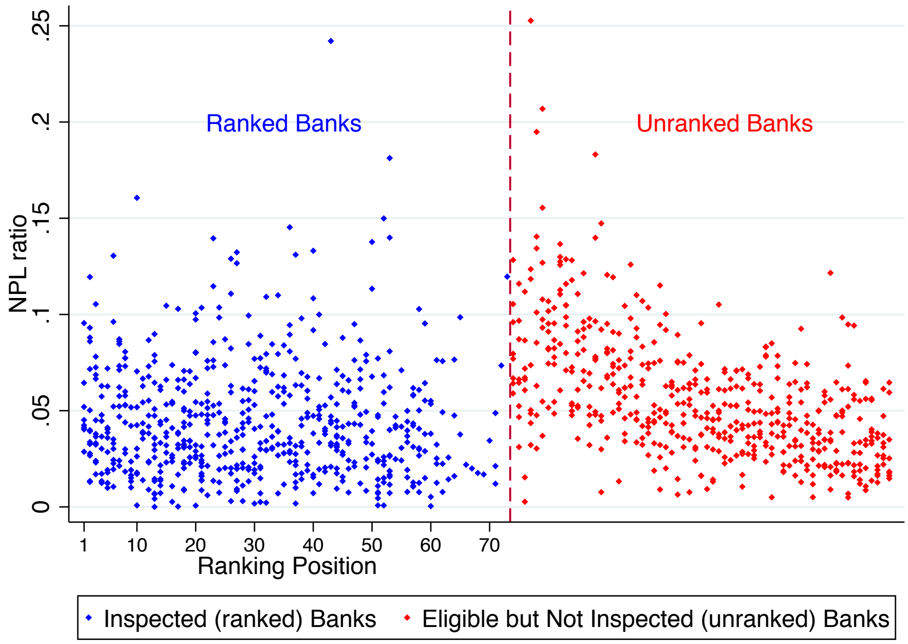
A. log(NPL)



B. log(Loans to Firms)

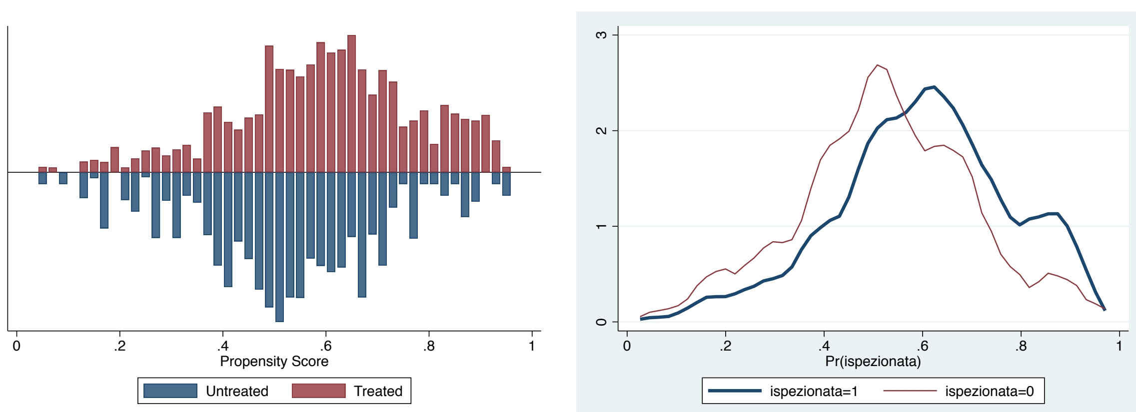
Notes: The sample does *not* include inspected banks that are ranked in the first quartile of the ranking distribution. This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Top\ quartile\ Ranking_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. The outcome variable is the log of loans to firms. We include bank, quarter and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. In panel A the outcome variable is the log of NPL. In panel B the outcome variable is the log of loans to firms. Data comes from bank's balance sheet (Supervisory Reports).

Figure A12. NPL ratio plot



Notes: This graph plots the NPL ratio of banks that are eligible. Specifically the blue dots represent inspected (ranked) banks. Top to bottom ranking is from left to right. Red dots plot the NPL ratio of eligible but not inspected banks. For the latter group there is no information available on the ranking position. Data comes from bank's balance sheet (Supervisory Reports).

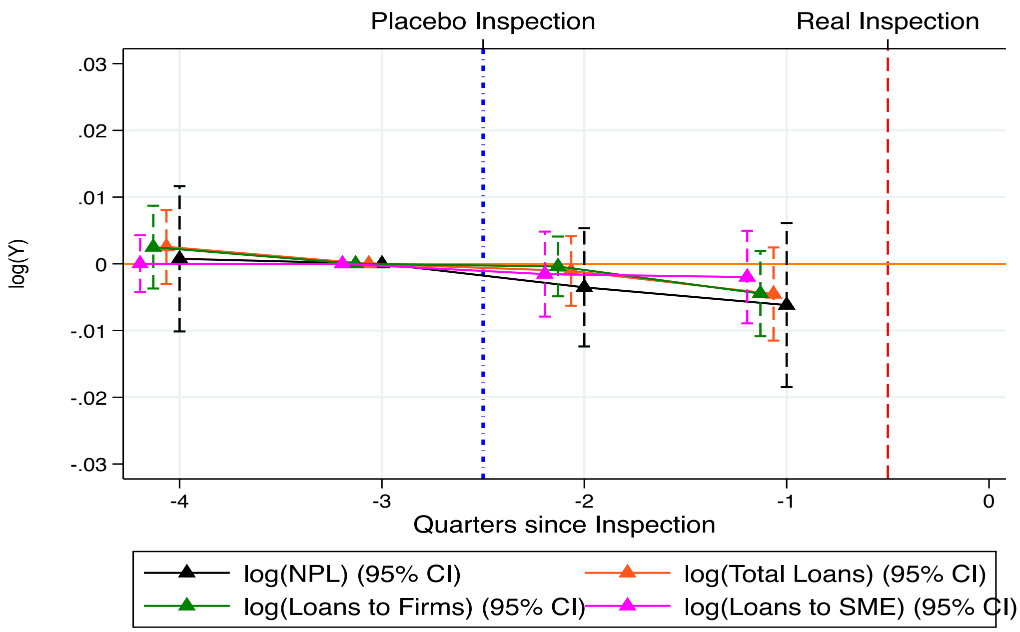
Figure A13. Propensity Score Matching



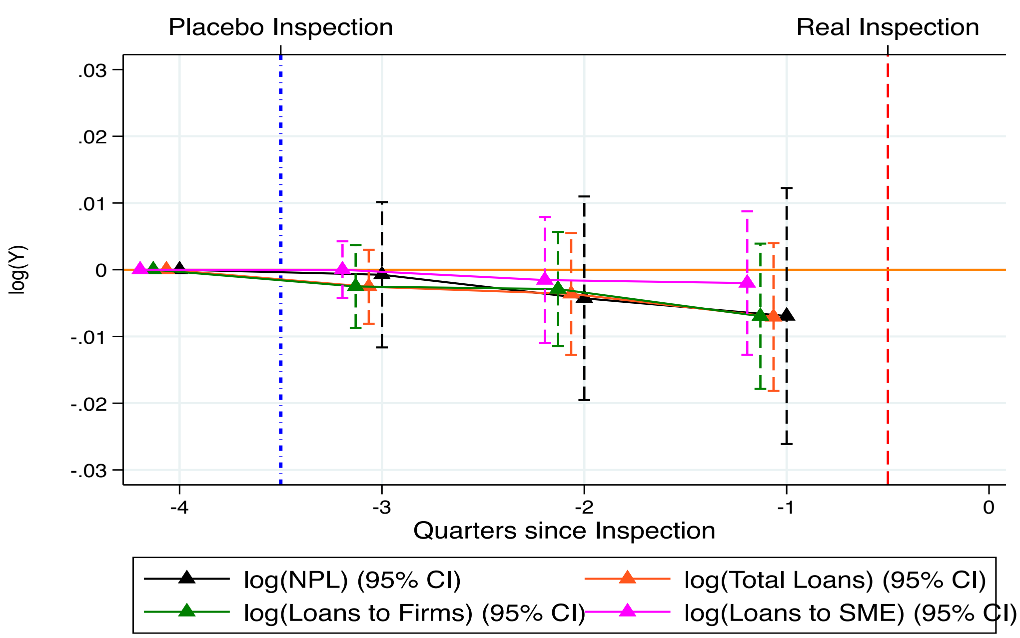
A. Common Support **B.** Density

Notes: This figure shows the common support and the density between treated and untreated banks. Panel A shows the common support between treated and untreated but eligible banks. Panel B shows the density function of the two groups.

FIGURE A14. Placebo Inspection Test



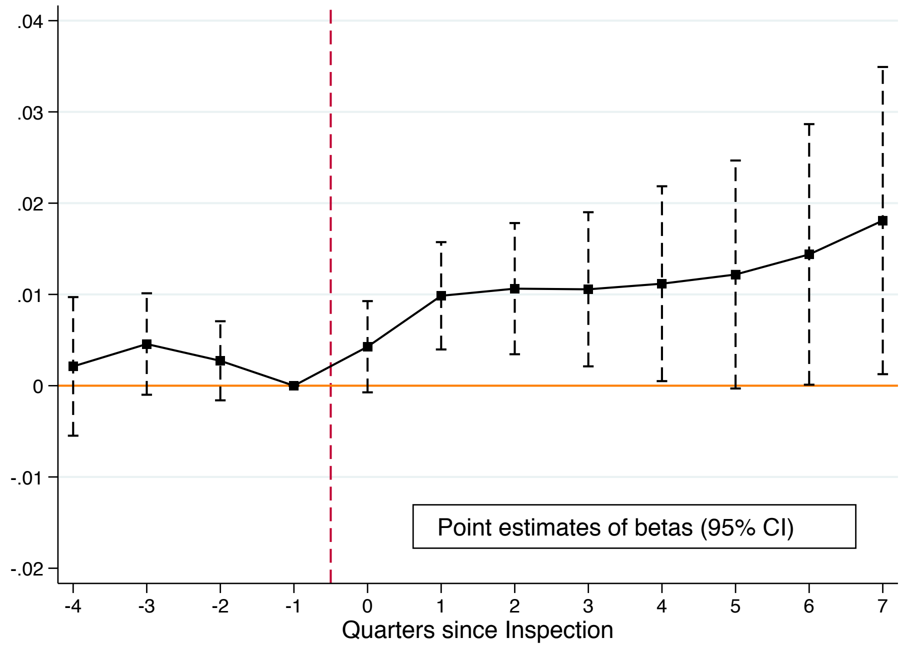
A. Placebo Inspection at $\tau = (-2; -1)$



B. Placebo Inspection at $\tau = (-3; -2)$

Notes: This figure shows a placebo test in which we create an artificial inspection in the period before the real inspection takes place. In Panel A, we assign bank inspections in period $t = (-2; -1)$ and normalize $\beta_\tau = 0$ at $\tau = -3$. In Panel B, we assign bank inspections in period $t = (-4; -3)$ and normalize $\beta_\tau = 0$ at $\tau = -4$. We compute the effect of the artificial inspections on the log(NPL), log($Total\ Loans$), log($Loans\ to\ Firms$) and log($Loans\ to\ SME$). The blue vertical line defines the starting of the artificial bank inspection while the red line shows the true timing of the bank inspection. Data comes from bank's balance sheet (Supervisory Reports).

Figure A15. Dynamic DiD: Effect on Bank Equity



Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \{\mathbb{1}_{\tau=t}\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \{\mathbb{1}_{\tau=t}\} + \varepsilon_{btpm}$. The outcome variable is the log of bank equity. We include bank, quarter and inspection plan-macro-area fixed effects. Standard errors are two-way clustered at the bank and inspection plan level. We also include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Note that we normalize $\beta_{-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. For a full description of the empirical equation, refer to equation 4.1. Data comes from bank's balance sheet (Supervisory Reports).

Additional Tables

Table A1. Bank-level Descriptive Stats

	Mean	SD	Median	p25	p75	Number Banks
NPL	30.545	41.512	15.367	6.351	36.296	397
log(NPL)	2.705	1.197	2.765	1.952	3.525	397
Tot Loans	602.288	816.406	355.785	152.694	745.070	399
log(Tot Loans)	5.789	1.135	5.867	5.020	6.580	399
Corporate Loans	441.713	547.377	265.084	113.193	574.704	399
log(Corporate Loans)	5.483	1.133	5.538	4.690	6.323	399
SME Loans	174.489	180.609	118.313	55.126	231.839	399
log(SME Loans)	4.674	1.038	4.749	3.974	5.444	399

Notes: Table A1 shows the summary statistics for eligible banks for the period 2010-2017. All variables are in millions of €. The variables are computed one year before the inspection. Data comes from bank's balance sheet (Supervisory Reports).

Table A2. Bank-level Regression: First time inspections

VARIABLES		NPL			Loan Loss Provision on bad loans			Loan Loss Provision on other NPLs	
Post×Inspection	0.052**	0.047*	0.052**	0.029**	0.028*	0.029**	0.072	0.095	0.072
	(0.019)	(0.020)	(0.019)	(0.009)	(0.013)	(0.009)	(0.102)	(0.115)	(0.102)
Observations	19,819	19,819	19,819	9,799	9,799	9,799	9,859	9,859	9,859
R-squared	0.979	0.979	0.979	0.958	0.960	0.958	0.899	0.900	0.899
Bank-IP	Y	Y	N	Y	Y	N	Y	Y	N
Macro Area	Y	N	N	Y	N	N	Y	N	N
Quarter	Y	N	Y	Y	N	Y	Y	N	Y
Macro Area-Quarter	N	Y	N	N	Y	N	N	Y	N
Bank-IP-Macro Area	N	N	Y	N	N	Y	N	N	Y
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{bpmt} = \beta Post\ Inspected_{bpmt} + \alpha_{bp} + \alpha_m + \alpha_t + \delta X_{b,PRE} + \epsilon_{ibpmt}$. The treated group includes only inspected banks audited for the first time during the sample period. We do not consider the impact of inspections for banks audited more than once. We include bank-inspection plan fixed effects, macro-area fixed effects and quarter fixed effects. We also include pre-defined bank-level controls $X_{b,PRE}$: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Column (1)-(3) considers the log(NPL) where NPL stands for Non-Performing Loan. Column (4)-(6) considers the log(loan loss provision on bad loans). Column (7)-(9) the log(loan loss provision on other NPL). * p< 0.10, ** p< 0.05, *** p< 0.01.

Table A3. Bank-level Regression: Only Inspected Banks

VARIABLES	log(NPL)				log(Loans to Firms)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Inspection	0.032***	0.030***	0.055***	0.032***	-0.012***	-0.012***	-0.020**	-0.012***
	(0.008)	(0.008)	(0.011)	(0.008)	(0.002)	(0.002)	(0.008)	(0.002)
Observations	14298	14287	14298	14298	14348	14337	14348	14348
R^2	0.980	0.980	0.963	0.980	0.998	0.998	0.992	0.998
Bank	N	N	Y	N	N	N	N	N
Month	Y	N	Y	Y	Y	N	N	Y
Macro-Area	Y	N	N	N	Y	N	N	N
IP×Bank	Y	Y	N	N	Y	Y	Y	N
IP×Macro-Area	N	N	Y	N	N	N	Y	N
Macro-Area×Month	N	Y	N	N	N	Y	N	N
Macro-Area×Bank×IP	N	N	N	Y	N	N	N	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP

Notes: Table A3 shows the results of the following equation: $y_{btpm} = \alpha_h + \alpha_b + \alpha_{pm} + \beta^{ATE} Post\ Inspection_{bph} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank fixed effects b, inspection plan-macro-area fixed effects pm, and month fixed effects h. We include pre-defined bank-level controls $X_{b,PRE}$: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Column (1)-(4) considers the log(NPL), while columns (5)-(8) considers the log(Total Loans). The sample includes *only* inspected banks. Standard errors in parentheses and are two-way clustered by bank and inspection plan (IP). * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A4. Balance Test: Eligible vs. Not Eligible

(1) Covariates	(2) Coefficient	(3) p-value	(4) Observations	(5) Mean Cont. Group	(6) Number of Banks
Total Assets	-27.829	0.532	3,174	527.823	438
NPL	8.105***	0.000	3,174	21.356	438
Total Lending	-19.318	0.533	3,174	366.012	438
Net Interbank Lending	3.419	0.418	3,174	25.484	438
Total Deposits	-16.825	0.448	3,174	253.488	438
Cash	-0.163	0.390	3,174	2.187	438
Capital	-2.314	0.624	3,174	62.868	438
Capital Ratio	-0.005**	0.030	3,174	0.130	438
Liquidity Ratio	-0.014*	0.095	3,174	0.233	438
Revenues	-0.606	0.574	3,174	12.636	438
Cost to Income Ratio	16.660	0.177	3,174	61.249	438
Debt Securities	-12.155	0.366	3,174	150.240	438
Net Interest Margin	-0.460	0.443	3,174	7.594	438
Brokerage Income	-0.334	0.723	3,174	11.465	438
Profits/Total Assets	-0.003***	0.000	3,174	0.003	438

Notes: This table shows the balance test for Eligible vs. not Eligible banks' covariates. The coefficient and p-value in columns (2) and (3) are from regressions of the covariate in column (1) on an indicator for the status Eligible (i.e. whether the score system keep or discard the bank), controlling for fixed effects (quarter, inspection plan). Regressions consider time $t = -4$ - which is roughly the time in which the banking supervisor defines the inspection plan for the subsequent year. Column (4) reports number of observation. Column (5) reports the mean of the covariate in the control group, namely banks that are discarded by the scoring system. Column (6) reports overall number of unique banks in the sample of inspection plans. Some banks are considered in multiple inspection plans. P-values are based on standard errors clustered at the inspection plan year. * p< 0.10. ** p< 0.05, *** p< 0.01. Data comes from bankâĂŹs balance sheet (SupervisoryReports).

Table A5. Balanced Test: Inspected (Treated Group) vs. Eligible but Not Inspected (Control Group)

(1) Covariates	(2) Coefficient	(3) p-value	(4) N	(5) Mean Control Group
Total Assets	-0.374	0.974	1,009	464.517
NPL	-3.096	0.211	1,009	38.28
Total Lending	-6.015	0.349	1,009	384.198
Net Interbank Lending	5.600	0.402	1,009	24.704
Total Deposits	-2.802	0.695	1,009	220.470
Cash	0.000	1.000	1,009	1.960
Capital	1.952	0.420	1,009	55.849
Capital Ratio	-0.003	0.128	1,009	0.124
Liquidity Ratio	-0.002	0.605	1,009	0.223
Revenues	-0.190	0.301	1,009	11.469
Cost to Income	0.558	0.692	1,009	82.524
Debt Securities	-1.667	0.722	1,009	130.481
Net Interest Margin	-0.093	0.253	1,009	6.801
Brokerage Income	0.214	0.535	1,009	10.331
Profits/Total Assets	0.001**	0.025	1,009	-0.001

Notes: This table shows the balanced test for inspected vs. eligible but not inspected banks' covariates. The coefficient and p-value in columns (2) and (3) are from regressions of the covariate in column (1) on an indicator for the treatment status (i.e. whether the bank is inspected or not), controlling for fixed effects (quarter, inspection plan). Regressions consider time $t = -4$ - which is roughly the time in which the banking supervisor defines the inspection plan for the subsequent year. Column (4) reports number of observation. Column (5) reports the mean of the covariate in the control group, namely banks that are eligible but not inspected. Column (6) reports overall number of unique banks in the sample of inspection plans. Some banks are considered in multiple inspection plans. P-values are based on standard errors clustered at the inspection plan year. * p< 0.10. ** p< 0.05, *** p< 0.01. Data comes from bankâĂŹs balance sheet (SupervisoryReports).

Table A6. Bank-level Regression: Placebo test ranking

Panel A: Direct effect			
	(1)	(2)	(3)
VARIABLES	NPL	Loan Loss Prov on bad loans	Loan Loss Prov on other NPLs
Post Inspection	0.028**	0.086**	-0.005
	(0.010)	(0.025)	(0.040)
Post Inspection×3rd ranking quartile	-0.030	-0.135**	0.079
	(0.022)	(0.039)	(0.054)
Post Inspection×2nd ranking quartile	0.032	0.011	0.037
	(0.024)	(0.033)	(0.089)
Post Inspection×1st ranking quartile	0.025	-0.086*	0.029
	(0.021)	(0.039)	(0.091)
Observations	21,463	12,235	11,206
R-squared	0.998	0.965	0.968
Bank FE	Y	Y	Y
IP× macro area FE	Y	Y	Y
Quarter FE	Y	Y	Y
Bank controls	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP
Panel B: Indirect effect			
VARIABLES	log(*Tot Loans*)	log(*Loans to Firms*)	log(*Loans to SME*)
Post Inspection	-0.023**	-0.020**	-0.016*
	(0.009)	(0.008)	(0.008)
Post Inspection×3rd ranking quartile	-0.005	0.008	0.001
	(0.009)	(0.008)	(0.006)
Post Inspection×2nd ranking quartile	-0.001	0.001	0.006
	(0.009)	(0.009)	(0.015)
Post Inspection×1st ranking quart	0.012	0.008	0.011
	(0.008)	(0.008)	(0.009)
Observations	21,779	21,751	21,779
R-squared	0.993	0.995	0.993
Bank FE	Y	Y	Y
IP× macro area FE	Y	Y	Y
Quarter FE	Y	Y	Y
Bank controls	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post\ Inspection_{bpt} + \delta Post\ Inspection_{bpt} \times \left\{\mathbb{1}_{ranking\ quartile=i}\right\} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank fixed effects, inspection plan-macro-area fixed effects and quarter fixed effects. The time dummy variables refer to quarters relative to the the banking inspection. $\{\mathbb{1}_{ranking\ quartile=i}\}$ is a categorical variable that takes value 1 if inspected bank b in inspection plan p belongs to the ranking quartile i. We include pre-defined bank-level controls $X_{b,PRE}$: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio. We normalize $\beta_{\tau=-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. In panel A we consider the direct effect of inspections. Column (1) considers the log(NPL). Column (2) the log(loan loss provision on bad loans). Column (3) the log(loan loss provision on other NPL). In panel B we consider the indirect effect of bank inspections on the lending activity. Column (1) considers total loans to both household and corporations. Column (2) limits the loans to only corporations. Column (3) considers only loans to Small and Medium Enterprises (SME). Standard errors in parentheses and are two-way clustered by bank and inspection plan (IP). * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A7. Bank-level Regression: Top vs. Bottom Quartile Inspected Banks

VARIABLES	log(NPL)			log(Loans to Firms)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post×Top Quartile	0.011	0.001	0.011	-0.009	-0.010	-0.009
	(0.041)	(0.043)	(0.041)	(0.016)	(0.017)	(0.016)
Observations	2,625	2,625	2,625	2,648	2,648	2,648
R-squared	0.988	0.988	0.988	0.994	0.994	0.994
Bank-IP	Y	Y	Y	Y	Y	Y
Macro Area	Y	Y	Y	Y	Y	Y
Quarter	Y	Y	Y	Y	Y	Y
Macro Area-Quarter	N	N	N	N	N	N
IP-Macro Area	N	N	N	N	N	N
Cluster	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post \times Top\ Quartile_{bpt} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank fixed effects, inspection plan-bank fixed effects, macro-area fixed effects, and quarter fixed effects. The time dummy variables refer to quarters relative to the the banking inspection. $Top\ Quartile_{bpt}$ is a dummy that takes value 1 if bank is in the top quartile in terms of ranking position. We include pre-defined bank-level controls $X_{b,PRE}$: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio. We normalize $\beta_{\tau=-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. In panel A we consider the direct effect of inspections. Column (1)-(3) considers the log(NPL). Column (4)-(6) the log of Total loans to firms. Standard errors in parentheses and are two-way clustered by bank and inspection plan (IP). The sample includes only inspected banks either in the top quartile of ranking position or bottom quartile. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A8. Bank-level Regression: Dropping inspected banks in the top quartile

VARIABLES	log(NPL)			log(Loans to Firms)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Inspection	0.057**	0.054**	0.057**	-0.021**	-0.021**	-0.024***
	(0.018)	(0.018)	(0.018)	(0.009)	(0.009)	(0.005)
Observations	19,077	19,077	19,077	19,238	19,238	19,238
R-squared	0.977	0.977	0.977	0.969	0.979	0.969
Bank-IP	Y	Y	Y	Y	Y	Y
Macro Area	Y	Y	Y	Y	Y	Y
Quarter	Y	Y	Y	Y	Y	Y
Macro Area-Quarter	N	N	N	N	N	N
IP-Macro Area	N	N	N	N	N	N
Cluster	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post \times Top\ Quartile_{bpt} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank fixed effects, inspection plan-bank fixed effects, macro-area fixed effects, and quarter fixed effects. The time dummy variables refer to quarters relative to the the banking inspection. $Top\ Quartile_{bpt}$ is a dummy that takes value 1 if bank is in the top quartile in terms of ranking position. We include pre-defined bank-level controls $X_{b,PRE}$: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio. We normalize $\beta_{\tau=-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. In panel A we consider the direct effect of inspections. Column (1)-(3) considers the log(NPL). Column (4)-(6) the log of total loans to firms. Standard errors in parentheses and are two-way clustered by bank and inspection plan (IP). The sample does *not* include inspected banks ranked in the top quartile. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A9. Ranking Prediction

(1) COVARIATES	(2) β	(3) p-value
log(NPL)	0.004	0.142
log(lending)	0.000	0.836
Cost to income ratio	0.001	0.349
Liquidity ratio	-0.003	0.148
Capital ratio	0.001	0.256
log(deposits)	0.002	0.325
Profits/Total Assets	0.000	0.146
Total Assets	1.162	0.439

Notes: Table A9 reports the results from the following regression: $Covariate_{b,p,PRE} = \beta ranking_{b,p} + \eta_p + \epsilon_{b,p}$, where $ranking_{b,p}$ is the ranking position assigned to the subsample of eligible and inspected banks. We include inspection plan fixed effects η_p and we double cluster the standard errors at the bank-inspection plan level. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A10. Propensity Score Matching Model

	(1) log(NPL)	(2) log(Total Loans)	(3) log(Loans to Firms)	(4) log(Loans to SME)
Post Inspection	0.033***	-0.028***	-0.034***	-0.025***
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	10,488	10,510	10,510	10,510
Bank FE	Y	Y	Y	Y
Inspection Plan FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table reports the result of a regression based on a propensity score matching. The matching is defined in the following way. For each inspection plan we compute a logit model of the following type:

$$\operatorname{logit}(e_{ij}) = \alpha_0 + X_{ij}\beta \tag{.5}$$

and matching algorithm

$$A_{rj} = \left\{ kj' \in I_0 : \hat{e}_{kj'} = \min_{kj' \in I_0} |\hat{e}_{rj} - \hat{e}_{kj'}| < 0.25\hat{\sigma}_e \right\} \tag{.6}$$

We use one-to-one nearest neighbor matching within a caliper of 0.25 standard deviations of the estimated PS (with replacement).

TABLE A11. Placebo Test: Testing the impact of fictitious inspections

Panel A:

VARIABLES	(1) log(NPL)	(2) log($tot\ loans$)	(3) log($Loans\ to\ Firms$)	(4) log($Loans\ to\ SME$)
Post Inspection	0.000701	-0.000947	0.000389	-0.000845
	(0.002)	(0.001)	(0.002)	(0.003)
Observations	9,833	9,954	9,954	9,954
R-squared	0.984	0.996	0.995	0.996
Bank FE	Y	Y	Y	Y
Inspection Plan FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP

Panel B:

VARIABLES	(1) log(NPL)	(2) log($tot\ loans$)	(3) log($Loans\ to\ Firms$)	(4) log($Loans\ to\ SME$)
Post Inspection	0.005868	0.000917	0.000846	0.001198
	(0.004)	(0.002)	(0.006)	(0.002)
Observations	9,833	9,954	9,954	9,954
R-squared	0.984	0.996	0.995	0.996
Bank FE	Y	Y	Y	Y
Inspection Plan FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the result of a placebo test considering equation 4.2. We construct a fictitious banking inspection and test its effect on the bank's performance. Specifically, Panel A considers an inspection that happens in event time= -1.5. Panel B considers a fictitious banking inspection in event time= -2.5. Note we allow for one period as a pre-period to have a pre- and post-period. The real inspection is at event time= -0.5.

Table A12. Effect on Credit growth without controlling for factors affecting credit demand

VARIABLES	(1) gr(tot Loans)	(2) gr(tot Loans)	(3) gr(tot Loans)	(4) Δ log(tot Loans)	(5) Δ log(tot Loans)
Post Inspection	-0.020***	0.042***	0.029**	0.044***	0.030**
	(0.010)	(0.010)	(0.012)	(0.011)	(0.014)
Post Inspection×reclassified		-0.836***	-0.834***	-0.904***	-0.904***
		(0.018)	(0.018)	(0.016)	(0.016)
Observations	1,992,936	1,992,936	1,992,936	1,983,618	1,983,618
R-squared	0.025	0.038	0.072	0.034	0.065
Firm FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Bank $\times QuarterFE$	N	N	Y	N	Y
Quarter FE	Y	N	Y	N	Y
Inspection Plan FE	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y
Bank-firm relat	Y	Y	Y	Y	Y
Cluster	bank	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $y_{ib,t} = \beta Post\ Inspected_{bp} + \alpha_i + \alpha_b + \alpha_p + \alpha_t + \eta\big(Post\ Inspected_{bpt} \times Zombie_i\big) + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp}$. In columns (1)-(3) the outcome variable is $growth(credit_{ib,t}) = \frac{credit_{ibt} - credit_{ibt-1}}{0.5(credit_{ibt} + credit_{ibt-1})}$. In columns (4) and (5), the outcome variable is the following: $\Delta \log(credit_{ib,t}) = \log(credit_{ib,t}) - \log(credit_{ib,t-1})$. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $reclassified_{ip}$ is a dummy that is equal to 1 if a loan belonged to firm i is reclassified as NPL within a quarter from the inspection. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio, and NPL ratio. We include firm fixed effects, bank fixed effects, inspection plan-macro-area fixed effects and quarter fixed effects. $W_{ib,PRE}$ is a set of pre-determined bank-firm relationship controls. These are: relationship length (number of quarters in which we observe a lending relationship between the firm and the bank; firm's credit share (i.e. share of the firm's loan balance in the bank's loan portfolio); main lender is a dummy equal to 1 if the bank is the firm's largest lender; bank share refers to the share of the bank in the firm's loan portfolio. We include the following fixed effects: bank, firm×quarter, Inspection plan, quarter. The sample includes only firms that have no NPLs before the inspections and it is conditional only on firms that we observe at least one period before the inspection and one period after the inspection. Standard errors in parentheses and are clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

TABLE A13. Effect on Credit growth using a different definition of zombie firms

VARIABLES	(1) gr(tot Loans)	(2) gr(tot Loans)	(3) Δ log(tot Loans)	(4) Δ log(tot Loans)
Post inspected	0.005**	0.008**	0.016*	0.022**
	(0.002)	(0.004)	(0.009)	(0.011)
Post inspected × Zombie	-0.008***	-0.008***	-0.019***	-0.019***
	(0.002)	(0.002)	(0.007)	(0.007)
Observations	1,523,433	1,523,433	1,515,238	1,515,238
R-squared	0.570	0.576	0.524	0.531
Bank FE	Y	N	Y	N
Firm×Quarter FE	Y	Y	Y	Y
Bank×Quarter FE	N	Y	N	Y
Inspection Plan FE	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y
Bank-firm relat	Y	Y	Y	Y
Cluster	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $y_{ib,t} = \beta Post_{bpt} \times Inspected_{bp} + \alpha_i + \alpha_b + \alpha_p + \alpha_t + \eta\big(Post_{bpt} \times Inspected_{bp} \times Zombie_i\big) + \alpha_{it} + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp}$. In columns (1)-(3) the outcome variable is $growth(credit_{ib,t}) = \frac{credit_{ibt} - credit_{ibt-1}}{0.5(credit_{ibt} + credit_{ibt-1})}$. In columns (4) and (5), the outcome variable is the following: $\Delta \log(credit_{ib,t}) = \log(credit_{ib,t}) - \log(credit_{ib,t-1})$. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after the bank is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $Zombie_i$ is a dummy that is equal to 1 if a a firm is classified as zombie according to the definition in Acharya et al. (2019b). $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio, and NPL ratio. We include bank fixed effects, inspection plan-macro-area fixed effects and firm×quarter fixed effects. $W_{ib,PRE}$ is a set of pre-determined bank-firm relationship controls. These are: relationship length (number of quarters in which we observe a lending relationship between the firm and the bank; firm's credit share (i.e. share of the firm's loan balance in the bank's loan portfolio); main lender is a dummy equal to 1 if the bank is the firm's largest lender; bank share refers to the share of the bank in the firm's loan portfolio. We include the following fixed effects: bank, firm×quarter, Inspection plan. The sample includes only firms that have no NPLs before the inspections and it is conditional only on firms that we observe at least one period before the inspection and one period after the inspection. Standard errors in parentheses and are clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

TABLE A14. Effect of Banking inspections on credit growth according to TFP

VARIABLES	(1) gr(tot Loans)	(2) gr(tot Loans)	(3) gr(tot Loans)	(4) Δ log(tot Loans)	(5) Δ log(tot Loans)
Post Inspection	0.019	-0.005	-0.006	-0.005	-0.006
	(0.016)	(0.014)	(0.014)	(0.016)	(0.016)
Post Inspection × TFP$_{pre}$		0.010***	0.009***	0.011***	0.010***
		(0.003)	(0.003)	(0.003)	(0.003)
Observations	627,823	627,823	627,823	627,823	627,823
R-squared	0.411	0.394	0.414	0.376	0.396
Firm×Quarter FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	N	Y	N
Bank×Quarter FE	N	N	Y	N	Y
Inspection Plan FE	Y	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y	Y
Bank-firm relat	Y	Y	Y	Y	Y
Cluster	bank	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $credit\ growth_{ib,t} = \beta Post\ Inspection_{bpt} + +\eta\big(Post\ Inspection_{bpt} \times TFP_{i,PRE}\big) + \alpha_{it} + \alpha_b + \alpha_p + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp}$. In columns (1)-(3) the outcome variable is $growth(credit_{ib,t}) = \frac{credit_{ibt} - credit_{ibt-1}}{0.5(credit_{ibt} + credit_{ibt-1})}$. In column (4) and (5), the outcome variable is the following: $\Delta \log(credit_{ib,t}) = \log(credit_{ib,t}) - \log(credit_{ib,t-1})$. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after the bank is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $TFP_{i,PRE}$ is a firm-level variable of total factor productivity computed according to the revenue approach (Wooldridge, 2009). $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. We include firm×quarter fixed effects, bank fixed effects, inspection plan fixed effects. $W_{ib,PRE}$ is a set of pre-determined bank-firm relationship controls. These are: relationship length (number of quarters in which we observe a lending relationship between the firm and the bank; firm's credit share (i.e. share of the firm's loan balance in the bank's loan portfolio); main lender is a dummy equal to 1 if the bank is the firm's largest lender; bank share refers to the share of the bank in the firm's loan portfolio. We include the following fixed effects: bank, firm×quarter, Inspection plan, quarter. The sample includes only firms that have no NPLs before the inspections and it is conditional only on firms that we observe at least one period before the inspection and one period after the inspection. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A15. Effect on New Bank-Firm lending Relationship

VARIABLES	(1) Δ log (New Loans)	(2) Δ log (New Loans)	(3) Δ log (New Loans)
Post Inspection	0.560***	0.483***	0.446**
	(0.190)	(0.181)	(0.177)
Observations	11,953	11,953	11,880
R-squared	0.343	0.346	0.379
Bank FE	Y	Y	Y
Quarter FE	Y	Y	Y
Province FE	Y	Y	Y
Inspection plan	Y	N	N
Inspection Plan×macro area FE	N	Y	Y
Bank Controls	N	N	Y
Cluster	bank	bank	bank

Notes: This table shows the results of the following equation: $\Delta \log(NewLoans) = \beta Post\ Inspection_{bpt} + \gamma_t + \gamma_b + \gamma_{pm} + \eta X_{b,PRE} + \epsilon_{btp}$. The outcome variable is $\Delta \log(Loans\ new\ firms_{b,t}) = \log(Loans\ new\ firms_{b,t}) - \log(Loans\ new\ firms_{b,t-1})$ which is the change in total number of loans to new firms. The variable is multiplied by 100. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after the bank is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). We include bank, quarter and inspection plan-macro area fixed effect. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. Standard errors in parentheses and clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

TABLE A16. Quality of New Loans

VARIABLES	(1) Score	(2) Score	(3) $\sigma(\widehat{growth\ sales})$	(4) $\sigma(\widehat{growth\ sales})$
Post Inspection	-0.046**	-0.050**	-0.008*	-0.009*
	(0.021)	(0.022)	(0.005)	(0.005)
Observations	11,452	11,253	10,513	10,323
R-squared	0.136	0.767	0.109	0.713
Bank FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Inspection Plan Year × macro area FE	Y	Y	Y	Y
Bank Controls	N	Y	N	Y
Cluster	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $y_{bt} = \beta Post\ Inspection_{bpt} + \gamma_b + \gamma_{pm} + \eta X_{b,PRE} + \epsilon_{bp}$. In columns (1)-(2) the outcome variable is $Average\ Score_{b,t} = \frac{\sum Score_i\{\mathbb{1}_{New\ loanib=1}\}}{\sum\{\mathbb{1}_{New\ loanib=1}\}}$ is the average score for firms that start a new brand credit relationship with bank b in quarter t. In columns (3)-(4) we consider the average volatility in sales growth in the three years before. To compute the averages, we consider only new loans created 4 quarters before the inspection and 4 quarters after the inspection. Score is the Altman-score for firm i at time t. It takes a value between 1 (safest company) and 9 (riskiest company). $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after the bank is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. Standard errors in parentheses and are clustered by bank. * $p< 0.10$. ** $p< 0.05$, *** $p< 0.01$.

Table A17. Interest rate charged on New Loans

VARIABLES	(1) Interest Rate	(2) Interest Rate
Post Inspection	-0.008*	-0.011**
	(0.004)	(0.005)
Observations	1,153	1,120
R-squared	0.146	0.587
Bank FE	Y	Y
Quarter FE	Y	Y
Inspection Plan Year × macro area FE	Y	Y
Bank Controls	N	Y
Cluster	bank	bank

Notes: This table shows the results of the following equation: $y_{bt} = \beta Post\ Inspection_{bpt} + \gamma_b + \gamma_{pm} + \eta X_{b,PRE} + \epsilon_{bp}$. The outcome variable is $Average\ interest\ rate_{b,t} = \frac{\sum interest\ rate i,t\{\mathbb{1}_{New\ loan i b=1}\}}{\sum\{\mathbb{1}_{New\ loan i b=1}\}}$ is the average interest rate charged to firms that start a new brand credit relationship with bank b in quarter t. In columns (3)-(4), we consider the average volatility in sales growth in the three years before. To compute the averages, we consider only new loans created 4 quarters before the inspection and 4 quarters after the inspection. Score is the Altman-score for firm i at time t. It takes a value between 1 (safest company) and 9 (riskiest company). We include bank, quarter, and inspection plan-macro-area fixed effects. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after the bank is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. Standard errors in parentheses and are clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

TABLE A18. Effect on the Governance of the Inspected Bank

VARIABLES	(1) Tot Elective Members	(2) Tot Not-Elective Members	(3) Tot Supervision Members
Post Inspection	-0.030**	-0.002	0.020**
	(0.011)	(0.010)	(0.007)
Observations	5,453	5,453	5,453
R-squared	0.989	0.995	0.414
bank FE	Y	Y	Y
Inspection Plan FE	Y	Y	Y
Year FE	Y	Y	Y
Bank controls	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $\Delta Tot\ Members_{b,t} = \beta Post\ Inspection_{bpt} + \gamma_t + \gamma_b + \gamma_{mp} + \gamma_m + \eta X_{b,PRE} + \epsilon_{btp}$. The outcome variable is the change in the total members belonging to a specific category between $t-1$ and $t+1$. We include bank, quarter, and inspection plan-macro-area fixed effects. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after the bank is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. Standard errors in parentheses and are clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A19. Effect of inspections on bank equity

VARIABLES	(1) log(Equity)	(2) log(Equity)	(3) log(Equity)
Post Inspection	0.010**	0.013**	0.011**
	(0.004)	(0.005)	(0.004)
Observations	9,240	9,240	9,240
R-squared	0.996	0.996	0.996
bank FE×Inspection plan	Y	Y	N
Quarter FE	Y	N	Y
Quarter×Macro Area	N	Y	N
Bank×Inspection Plan×$MacroArea$	N	N	Y
Bank controls	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} PPost\ Inspection_{bpt} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. $Post\ Inspection_{bpt}$ is a dummy variable equal to 1 for the quarters after the bank is inspected and zero otherwise. This variable is always zero for banks included in the inspection plan but not inspected (i.e eligible but not inspected banks). We include bank fixed effects, inspection plan-macro-area fixed effects and quarter fixed effects. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, equity ratio and NPL ratio. Standard errors in parentheses and are clustered by bank. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A20. Correlation

VARIABLES	(1) Exposure$_{t-1}$	(2) Exposure$_{t-1}$	(3) Exposure$_{t-1}$	(4) Exposure$_{t-1}$
$\Delta\log(GDP)_{t-2,t-1}$	0.878	0.935	-0.652	-1.088
	(0.838)	(0.933)	(1.160)	(1.136)
Share Deposits BCC$_{t-1}$	0.231	0.068	0.027	0.254
	(0.163)	(0.224)	(1.851)	(1.981)
Average Income$_{t-1}$		-0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Observations	346	274	262	262
R-squared	0.007	0.011	0.314	0.333
province FE	N	N	Y	Y
Inspection Plan FE	N	N	N	Y
Cluster	province	province	province	province

Notes: This table shows the regression of our treatment variable $Exposure_{i,PRE}$ on several variables that potentially affect the local economy. These are: the change in the GDP between $t-2$ and $t-1$, the share of deposit by Mutual banks (which is a proxy for the importance of these banks in the province, and the average income. Standard errors in parentheses and are clustered by province. * p< 0.10. ** p< 0.05, *** p< 0.01.