THE REAL EFFECTS OF BANK SUPERVISION§

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Abstract. In this paper, we show that bank supervision reduces distortions in the credit market and generates positive spillovers for the real economy. Combining a novel administrative dataset of unexpected bank inspections with a quasi-random selection of inspected banks in Italy, we show that inspected banks are more likely to reclassify loans as non performing after an audit. This behavior suggests that banks are inclined to misreport loan losses and evergreen loans to underperforming firms unless audited. We find that this reclassification of loans leads to a temporary contraction in lending by audited banks. However, this effect is completely driven by a credit cut to underperforming firms, as the composition of new lending shifts toward more productive firms. As a result, these productive firms increase employment and invest more in fixed capital. We provide evidence of a mechanisms for our results: a changes in bank governance. Finally, we find positive spillovers from inspections: entrepreneurship increases and underperforming firms are more likely to exit. 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 economic stagnation by distorting the credit market. This market failure can arise if banks misallocate credit to impaired firms.

Existing research has shown that bank regulation and policy interventions are insufficient to prevent such distortions in credit allocation and, if anything, make these distortions worse. Blattner et al. (2017) show that stricter capital requirements increase banks' incentive to distort their lending decisions. Since banks have to satisfy a higher regulatory capital ratio, they try to avoid reporting new losses by extending additional credit to support ailing firms. 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. The firms receiving these funds do not undertake real economic activity, such as employment and investment, but they use the new funds to build cash reserves. 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). 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 market failures, bank supervision. We identify the causal effect of bank supervision on credit market allocation and the subsequent spillovers to the real economy. We exploit a shock induced by randomized bank inspections to a group of eligible banks. These inspections are unexpected, intrusive and thorough audits at the supervised bank's offices. Their main goal is to validate not only the quality of banks' assets, but also their reporting activity to the supervisor.[1] When necessary, the bank inspectors may also force measures upon inspected banks.[2]

These audits are performed every year. We exploit the two-step 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 computer-based unpublished algorithm. The algorithm selects and ranks the banks that are inspected. Banks are then inspected according to this ordering.

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.

[1]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.

[2]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.

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 National Institute of Statistics ISTAT.[3] Our main empirical model is a dynamic Difference-in-Differences (DiD) model comparing 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%, which represents roughly 12% of the average of nonperforming loans across all eligible banks.[4] Moreover, inspected banks are more likely to increase loan loss provisions. These effects are limited to the first quarter following the inspection. This short time lag provides evidence that the effect is driven by audits.

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 variety of evidence 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 eligible for inspections. The selection rule depends on factors uncorrelated with banks' characteristics.[5] 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.[6]

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 following an inspection. However, the drop is temporary: after seven quarters, aggregate lending reverts to its pre-audit level. Given the supervisory-driven nature of the credit supply shock, we test whether there is a *compositional* effect. Do inspected banks

[3]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.

[4]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.

[5]We confirm the anectodal evidence of this fact.

[6]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.

readjust their portfolio? 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 estimate 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 underperforming 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 to judge the quality of a firm.[7] We find that the lending cut is driven *exclusively* by underperforming firms in the bank's portfolio.

We find evidence of a *reallocation channel*. In particular, loans are reallocated towards 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. Specifically, 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 inspections lead banks to increase their equity. This reduces moral hazard concerns as banks become important stakeholders in both upside and downside states of the world.

Our third and final set of results concerns the spillover effects of bank supervision to the real economy. We first shed light on the impact 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: they invest more in fixed assets and grow their workforce. As a result, healthy firms increase their sales. 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 bankruptcy.

[7] We validate our results by using different measures for firm's quality.

We find a small positive effect in the value added per worker at the province level.[8] Firms staying in the market or new firms entering the market are more productive.

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 (Eisenbach et al., 2016; Hirtle et al., 2017). These papers exploit different sources of variation: changes in the entity of the supervisor (Granja and Leuz, 2019; Agarwal et al., 2014), 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)). We make two contributions to this literature. First, we are the first to use data on bank audits, which provides detailed information on supervisory activity.[9] Unlike other works, we are able to estimate the causal effect of bank supervisions at the micro-level . Second, by matching this data with granular data at the loan 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. We find that there is a compositional effect, with credit pulled back from underperforming firms and reallocated to healthy firms or new firms.

Our paper is also related to a large literature documenting the real effects of credit supply shocks (Khwaja and Mian, 2008; Chodorow-Reich, 2013; Amiti and Weinstein, 2018; Bottero et al., 2018). In particular, it is related to the strand of literature considering supervisory-driven credit supply shocks. We find that the credit supply shock has an important compositional effect, and show that the credit crunch is driven by underperforming firms. 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). 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, it is silent about potential solutions. We show that bank supervision—especially intrusive on-site inspections—affect the lending policies of inspected banks and force 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

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

[9]In a contemporaneous paper Bonfim, Cerqueiro, Degryse, and Ongena (2019) use similar data on 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 event in which the largest banks are inspected. We confirm their results, i.e. inspections reducing the credit assigned to zombie firms. In addition to them, we provide evidence on the spillover effects to the real economy, as well as the mechanism driving the change in the lending policies.

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; second we document that provinces with more exposure to bank inspections experience an increase in entrepreneurship.

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 shows the spillover effects to the real economy. Section 7 concludes.

2. Institutional Background

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

2.1. **Supervision as a way to improve upon regulation.** We discuss the main distinctions between bank regulation and bank supervision. We examine the potential flaws in bank regulations and why bank supervision can reduce the potential market failure, holding fixed the regulatory system.

Bank supervision is a critical tool available to the supervisor for maintaining the stability of the banking sector. It is closely related to, but distinct from, regulation of the banking industry. Regulation involves the development and promulgation of the *rules* under which banks operate as well as their enforcement in the court of law. By their nature, regulations can be coarse. It is impossible to write a complete contract contingent to every state of the world. Within a regulation system there are always missing contingencies. These missing contingencies create the opportunity for agents to take advantage of regulatory arbitrage.[10] Theoretically, bank supervision can improve upon regulation. The core activity of the bank supervisor is to ensure that banks do not engage in unsafe and unsound practices. The relevant features of bank supervision are: (i) the assessment of the safety and soundness of banks through monitoring and exams, and (ii) the use of this information to request corrective actions from banks in the case their conditions or management are considered unsafe or unsound (Eisenbach, Lucca, and Townsend, 2016). Given the timing of supervision – after the agents take the decision – supervisors can learn about the potential missing contingencies within the regulatory system and fix them. Moreover, supervision can generate a behavioral response. Knowing that the supervisor may take corrective measures *ex-post*, agents are more likely to comply with the rules. The problem with bank supervision is that it involves judgment, for instance, in assessing whether a bank may be engaging in excessive risk. Given the highly discretionary role played by bank supervision and potential capturing problems there has been a movement in recent decades to convert many supervisory judgments about "safety and soundness" into bright-line rules, resulting in more regulation and less discretionary policy (Menand, 2017).

2.2. **A primer on bank supervision.** We provide an overview of the two types of supervisory activities, i.e. off-site and on-site inspections, as well as their targets and goals. Later, we discuss on-site inspections in detail, in the context of the Italian banking system.

[10] For instance, this is blamed as of the main factors contributing to the 2007 financial crisis, according to a sample of economists. http://www.igmchicago.org/surveys-special/factors-contributing-to-the-2008-global-financial-crisis.

Generally speaking, bank supervision can be divided into two main areas: off-site and on-site inspections.[11] 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).[12] 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. We describe in detail the selection process performed in the Italian banking system in subsection **??**. 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 (SI, henceforth).[13] 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. Specifically, we consider only a subset of Italian banks, Mutual banks, that in the period of consideration are always under the supervision of the NSA, namely the Bank of Italy.[14]

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.[15] The main goal of these inspections is to check the quality and accuracy of the data submitted and gain a better understanding of their organization and operations.[16] The main informational advantage of these audits, compared to the information obtained with off-site inspections, is the access to the complete information history of the bank-firm relationship. The supervisor can gain access to information that the supervised bank is not required to disclose for the purpose of the off-site inspection: for instance, the credit application by the firm, the documents related to the credit approval, the internal information and documents produced by the

[11]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).

[12]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.

[13]Financial institutions are selected to be part of the SI sample if at least one of the following criteria applies: 1) its total assets 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 SI under the ECB supervision (SSM Supervisory Manual, 2018).

[14]We consider the period between 2010 and 2017.

[15]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; Abbassi et al., 2017).

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

bank about the firm, as well as the email and mail exchanges between the bank and the firm. This information allows the supervisor to assess the quality of the reporting done by the supervised bank and to better understand whether the bank is assessing the risk of a specific loan in a fair way.[17] When needed, an inspector can force inspected banks to take corrective measures. The most common of these is the forced the re-evaluation of a loan, which could generate its reclassification from performing to non-performing. Additionally, the inspector 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.[18] In the latter case, i.e. actual or potential violations of criminal state laws, the Bank of Italy alerts the competent prosecutors, who have judiciary powers and may autonomously decide to start an investigation. The Bank of Italy does not have the power to start a prosecution independently.[19] There are different types of on-site bank inspections. Given the type of banks we consider, i.e. mutual banks in which shareholders are depositors and the main bank's business is the lending activity to firms, the only type of inspection performed is the "broad spectrum' inspection which covers the overall corporate situation.[20] However, for bigger and more complex financial institutions, inspections can be targeted on specific areas. There are: (1) "targeted" inspections, which focus on particular parts of the business, risk areas of governance profiles; (2) "thematic" inspections, which deal with issues of general importance for the entire credit and financial system; and (3) "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.

On-site inspections require, on average, a team of five inspectors.[21] 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 office. The latter two inspectors come from the same province where the supervised bank has its offices. The chief of the team cannot be from

[17]For instance, in a recent news report involving a firm that eventually was condemned for fraudulent bankruptcy, the inspection revealed that bank lending to the firm, *Banco di Sardegna*, was reporting a credit position characterized by "excessive tolerance and lack of transparency" (https://www.sardiniapost.it/cronaca/bancarotta-fraudolenta-le-parole-del-gip-insolvenza-del-gruppo-scanu-dal-2002/.

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

[19]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.

[20]This is the focus of our paper.

[21]The number is proportional to the size of the bank inspected. However, for mutual banks, which are of the same size (i.e. total assets) on average, the total number of inspectors is usually five.

the local branch. This composition of the team is designed in a way to achieve two goals: first, having inspectors from the central office reduce any capturing-related problem;[22] and second, local officers have a deep knowledge of the local economy – soft information – that can be used for supervisory activity. When reviewing the files on the credit application on a particular firm, they can better assess the quality of their files 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. Figure 2D shows the average, the maximum and the minimum number of days it takes to complete an auditing.[23] A large set of banks are dismissed from the pool of eligible ones and are not considered for inspection in that particular year. Figure 2A shows the number of banks eligible for on-site inspections each year, together with those that are not eligible.

2.3. **The selection process.** We discuss the selection process employed by the Italian bank supervisor to select audited banks. We argue and show that within a selected group of eligible banks, a quasi-random share are inspected. This reduces issues related to a selection bias. Moreover, audits come at a surprise, meaning that banks are unlikely to window-dress for the inspections.

It is tricky to estimate the causal impact of bank supervision; 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 they actually take place. This would confound the true effect of inspections with the anticipation effect.[24] Given these challenges, it is very hard to estimate the causal effect of bank inspections on a bank's behavior. 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.[25] Regarding the potential selection bias, we exploit the way in which on-site inspections are organized. In particular, we take advantage of a specific mechanism used by the Bank of Italy to select banks that are going to be on-site inspected.

[22]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).

[23]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.

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

[25]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.

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 aimed at discarding banks that passed standard test used in the pre-inspection phase. We refer to this group as the set of not-eligible banks.[26] Figure **3A.** shows the distribution of eligible vs. not-eligible banks across years.[27] Eligible banks are rated according to an unpublished selection rule that combines information from off-site supervision, last inspection (vintage), organizational structure of the bank and their geographical macro-area.[28]

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.[29] Higher rank position according to the rating means greater probability of being inspected. But we show that this does not translate in worse bank's performance.

The exact number of banks inspected each year within the macro area-eligible group depends on human resource constraints. Specifically, given the fact that audits are done by both inspectors from 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 inspected the year after.[30] The different macro-area-specific groups of eligible banks are then assembled together to define the inspection plan for the next year. 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 arbitrarily

[26]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. Table A4 shows balance tests for a set of covariates. We find that eligible banks have a higher stock of NPL, a lower capital ratio. and a lower liquidity ratio compared to banks that are not eligible. Figure 8 shows the graphical counterpart of it.

[27]Given that not-eligible banks are quite different from eligible banks, we drop them in all 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.

[28]One of the condition 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. An ATC is a macro area that includes from 3 to 5 different regions. There are 5 different macro areas in Italy, as shown in Figure 1. They roughly represent north-west, north-east, north-center, center, and south.

[29]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 4.1.4 that, conditional on the sample of eligible banks, inspections are as good as randomly assigned.

[30]This group of banks will consist in the control group since these banks are relatively similar to inspected banks (see Figure 7).

picked by the supervisor because the authority may have insider information.[31] 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 or it does not become public information even after the inspections are performed.[32]

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*). The datasets are described below. The period considered in 2008–2018.

3.1. **Information on bank inspections.** To identify the effect of bank inspections we use a novel proprietary dataset from the Bank of Italy. The dataset contains detailed information about on-site bank inspections performed by the National Supervisory Authority (i.e. Bank of Italy) during the period 2010–2017.[33] We only have information on the sample of Italian mutual banks, *Banche Cooperative di Credito* (BCC). Mutual banks are special banks since their depositors are also bank's shareholders. On average, they are smaller compared to public banks, but they are very popular in the Italian banking system. Moreover, by law they are supposed to lend their resources mostly to the local economy where headquarter are located.[34] Figure 3 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 Non Performing Loans.[35] Given their inability to diversify the risk as well as their legal obligation to invest locally, they are more exposed to shocks

[31]For instance, a typical case 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.

[32]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.

[33]Note that at the end of 2014 the European Union adopted the Single Supervisory Mechanism (SSM), which transferred some of the supervisory activities to the ECB and changed how supervision is performed for banks under the control of the ECB, i.e. Significant Institutions (SI). Our sample contains only banks that are Less Significant. These banks are still under the supervision of the National Supervisory Authority (NSA) and the introduction of the Single Supervisory Mechanism has not affected the ways that inspections are performed. Refer to Section 2 for more information.

[34]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

[35]Panel A highlights that mutual banks are extremely popular 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 Non Performing Loans – about 20.8%. Two things account for these results: first, they are local and, thus, find hard time to diversify their lending activity; and second, they are small and tend to lend to small, riskier firms with little or no collateral (Petersen and Rajan, 1995). Figure A2 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.

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 2 illustrate the time variation of the inspection activity. 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 to be inspected but not; and (iii) not eligible to be inspected.[36] 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 (i.e. control group). 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).[37] Figure D shows some statistics of the length of inspections. The number of days per inspection can vary greatly, from a minimum of 32 days to a maximum of 142 days. The mean is 66.43 days, and the median is 66 days.
Figure A1 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 means more concentration of bank branches belonging to the specific group in a specific province.[38]

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. We consider the data at the quarterly level. Among variables, we have total assets, capital and reserves, sovereign bonds, total loans and Non Performing Loans (NPL, henceforth). We also have data about a bank's organizational structure, such as the distribution of bank branches at the province level.[39] Table 1 provides summary statistics.

3.3. **Information on firms.** We collect detailed information on balance sheets, income statements, and registry variables from the Cerved dataset. This dataset is collected by the CERVED group SpA and contains information on the universe of only incorporated businesses

[36]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.

[37]This is also highlighted in the final year report by the Bank of Italy to the Italian Government. 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, https://www.bancaditalia.it/pubblicazioni/relazione-gestione/2010/Rel_Parlamento_Governo_2008.pdf?language_id=1.

[38]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 $t = \{\text{inspected, eligible but not inspected}\}$ and p stands for province.

[39]An Italian province is roughly the same size as a US county.

(i.e. limited liability companies, LLC), but not sole proprietorship and other-non incorporated firms. Information is collected yearly and thus the unit of observation is firm-year.[40]. Each firm has its unique identifier (i.e. Social Security Number), which allows us to link the 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). Specifically, we drop observations of firms operating in industries such as the financial and insurance sector, utilities and government-related industries.[41]

3.4. **Information on credit.** We use granular data at the borrower-technical form of credit level obtained from the Italian Credit Registry. This dataset is collected by the Bank of Italy and contains detailed information on credit exposure for all borrowers and for all the outstanding loans granted above €30,000 euros. In our analysis we focus only on non-financial borrowers. Credits are divided into three different technical forms: revocable credit lines, term loans and loans backed by account receivables (LBR). 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 a decision of banks to supply credit. We also have information about whether a loan becomes non performing. Contrary to performing loans, we do observe the universe of loans that become non-performing.

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

3.5.1. *INPS data.* First, we use data from the Italian Social Security INPS. This dataset contains yearly data on all firms with at least one employee active in manufacturing, construction, or market services, as well as their employment level and their legal form.[42] This dataset gives us a detailed picture on firm dynamics. We also use data from the Italian National Institute of Statistics ISTAT. Specifically, we obtain information on GDP, and other socio-economic indicators all measured at the province level. This data is publicly available.[43]

3.5.2. *TAXIA data.* We also use data on loan prices from the TAXIA database. This dataset is reported at quarterly frequency; it consists of granular information 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

[40]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. The drawback is that it does not include informations on companies that are not in the form of LLC.

[41]Note that we exclude firms operating in the education sectors and utilities because the government either runs them directly or indirectly subsidizes their activity. Thus, they do not respond to market incentives.

[42]The use of this dataset overcomes issues related to CERVED dataset which identifies only well-established firms, i.e. corporations.

[43]https://www.istat.it/en/.

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.

3.5.3. *ORSO data.* We obtain information on bank boards from ORgani SOciali (ORSO) dataset. ORSO contains exhaustive current and historical information on the members of the governing bodies of banks and financial intermediaries and their specific appointments (e.g. president, executive director, members of the boards of directors, members of supervisory boards, etc.).

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

The first part of our analysis is to test whether bank inspections have a direct impact on a bank's balance sheet. We run the analysis at the bank level comparing eligible and inspected banks vs. a group of eligible but not-inspected banks. We show that, following a bank inspections, audited banks are more likely to reveal losses in their balance sheet. Specifically, we show that bank inspections force inspected banks not only to reclassify loans into NPL, but also to increase loan loss provisions.[44] We call this an *informational disclosure effect* as banks are forced to review the information disclosed in their balance sheet.

4.1. **Empirical Design.** In this part, we describe in detail our experimental design and how it helps us to reduce endogeneity concerns in the estimation.

Our goal is to estimate the causal effect of bank inspections. When studying the effect of banking inspections the key identification concerns are twofold. First, the problem of selection bias. Second, the problem of anticipation. Regarding the former, by comparing the performance of banks that are inspected to that of banks that are not inspected, 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. We confirm the anecdotal evidence that the ranking is a function of many variables of a bank's characteristics and organizational structure, and it is not a predictor of bank quality.See section 4.1.4 for the tests on this condition. Thus, in our analysis, we consider that conditional on the sample of being eligible, banks are randomly selected for an inspection. Regarding the latter, given that audits come at a surprise, there is less concern that banks anticipate them and react in advance.

The empirical analysis is structured in the following way. In the first part we focus on the impact of bank inspections on a supervised bank's balance sheet. We show that these banking inspections can be reasonably considered as an exogenous shock to supervised banks.[45]

The two-step approach used by the supervisory authority to select the banks to be audited reduce concerns related to selection bias. Each year, the supervisor defines a set of homogeneous eligible banks, and within this sample, the supervisor picks some banks to be inspected. Naturally, this framework leads to a comparison of the banks inspected and banks eligible but not inspected within each inspection plan. Moreover, the fact that audits come

[44] 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.

[45] We run several robustness tests to show that our estimates are causal. See 4.1.4. Specifically, to reduce concerns about selection bias we run a set of balanced tests and show that banks in the two groups are not significantly different. To reassure that banking inspections are truly exogenous and unexpected, we show that there are no pre-trends, and we run a set of placebo tests, where we set an artificial date of the inspections and show that there is no effect (Tables A6 and Figure A5).

at surprise for supervised banks reduce any concern related to anticipation effect, i.e. banks anticipating the future inspection adjust their balance sheet beforehand.[46]

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)

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

where b, p, t and m stands for bank, inspection plan, quarter and macro-area. $\{\mathbb{1}_{\tau=t} \times Inspected_{bptm}\}$ are event time indicator variables interacted with a dummy variable $Inspected$. $Inspected$ takes value 1 if bank b 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 compare only banks that are included in the inspection plan. That is, we compare banks that are included in the inspection plan and are inspected with those that are included in the inspection plan but are not inspected. We exclude banks that are not eligible according to the first step of the selection process since these banks are very different.[47] $X_{PRE,b}$ is a set of pre-specified control variables interacted with quarter dummies. We follow the literature (Schnabl, 2012) and include in $X_{PRE,b}$ the following variables: 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. In particular, we follow banks 4 quarters before the inspection and 8 quarters after the inspection. The specification includes bank fixed effects (α_b) and quarter fixed effects (α_t), which absorb fixed differences across banks and across years. We also include inspection plan $\times$ macro area fixed effects (α_p) which takes into account differences across different inspection plans.[49] 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. We consider also the parametric version of equation 4.1. The parametric specification allows us to analyze the magnitude of the estimates. We estimate the effect at impact of bank inspections by

[46] Regarding this point both pre-trends and placebo tests show that banks do not anticipate the future audit.

[47] We confirm this in balance test. Eligible banks have a significantly higher stock of NPL, and they have lower capital ratio and liquidity ratio (Figure 8). Moreover, we run the same event study as equation 4.1 and show that indeed there is a pre-trend when we compare inspected banks with those that are not eligible (Figure A3).

[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] In some specifications, we include inspection plan-quarter fixed effects (α_{pt}) to take into account that banks are included in inspection plans multiple times. In fact, 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.

limiting the period of observation to 4 quarters before and 4 quarters after the inspection. We consider 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 stands for bank, inspection plan, quarter and macro-area respectively. y_{btpm} is our outcome of interest which refers to bank b from inspection plan p located in the macro area m.[50] $Post\ Inspection_{bpt}$ 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 banks included in inspection plan p and not inspected, i.e. eligible but not inspected banks. The parameter of interest is β^{ATE}, which measures the change in the outcome variables 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 the β^{ATE} of equation 4.2) as the causal impact of banking inspections requires two conditions. First, the timing of the bank inspection is 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. Another potential concern is that the results are driven by the demand-side instead of the supply-side. A potential situation in line with a demand-side story is that firms that borrow from inspected banks experience a shock that compromises their ability to repay the loan to the inspected banks.[51] Given that we show there are no pre-trends, this is unlikely to be the case since the timing of the credit demand shock has to coincide exactly with the start of the inspection. Second, the two set of banks (treated and control) are similar on observables. If banks that are inspected are extremely different from those 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. Third, eligible and inspected banks do not differ in their probability to be inspected compared to eligible banks. For instance, if audited banks expect to be inspected, they may react in advance to the audit, confounding the effect of bank inspections.

Our experimental design helps us to overcome these potential threats. First, bank inspections come at a surprise for inspected banks. Indeed, banks do not have any information on whether they are included in the set of eligible banks. This reduces any concern related to potential anticipation effect. Moreover, we can test it in the data by evaluating the dynamics in the

[50]Since banks can enter in multiple inspection plans over the years that is they enter in a different natural experiment – we need to take this into account in our model.

[51]In other words, 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.

$\{\beta_\tau\}$ coefficients of equation 4.1, as we show in subsection 4.1.3. 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. Additionally, we run several placebo tests in which we set a construct an artificial inspection at a different date in the pre-period and show that there is no effect.

To reduce concerns related to a potential selection bias, we again take advantage of our experimental design. First, as described in Section 2 we only consider banks with the same type of ownership, namely mutual banks. Thus, we consider banks that have a very similar business model – they have to comply to the same legal requirements, and are exposed to similar challenges.[52] Second, we rely on the selection process done by the supervisory authority to construct 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 that, according to the algorithm used by the Bank of Italy, look similar. Third, we run several balance tests to confirm that: (1) banks eligible to be inspected are very different from not-eligible banks, and (2) banks eligible and inspected are not significantly different from banks eligible but not inspected. We discuss these and additional tests in Section 4.1.3.

4.1.3. ***Result.*** The first part of our analysis investigates the impact of banking inspections on a bank's balance sheet. Specifically, we answer the question about whether the supervisor finds and reveals wrongdoing in bank's balance sheet, i.e. informational disclosure effect. We focus on two main dimensions of a bank's balance sheet: the amount of NPL and loan loss provisions. Figure 5**A.** shows the dynamic effect on the natural log of outstanding NPL.[53] We find that bank inspections force banks to reclassify some loans into NPL. As a result the levels spike after the first quarter in which the inspection is performed. Figure 6 shows similar results by looking at other types of NPL (i.e. unlikely-to-pay and past-due exposures).[54] Figure 5**B.** highlights that the timing coincides with the on-site inspections. The growth rate becomes positive just immediately after the beginning of the inspections and then goes back to zero. Overall, bank inspections force banks to truthfully disclose information on their balance sheets by reclassifying loans into NPL. Similar patterns are found when considering other NPL, i.e. unlikely to pay and past-due-exposure (Figure 6).[55] We find similar patters for loan loss provisions to bad loans (Figure 6**A.**) and to other NPL (i.e. unlikely to pay and past-due exposure (Figure 6**B.**). It is important to note that from the plot, there is no evidence of significant differences between the two groups before the inspections. This

[52]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.

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

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

[55]Data on unlikely-to-pay and past-due-exposure comes from the Supervisory reports. Unlike with bad loans, it is not from the Credit Registry.

reduces both concerns of selection and anticipation effect.

Table 2 shows the effect at impact of on-site bank inspections. Inspected banks' NPL wedge *vis-a-vis* eligible but not inspected banks is about 3.115% $(^{0.031} - 1)$. This means that for the average bank in the control group with $€NPL = 38.28$ millions this means an increase of about €1.19 millions each quarter. In other words, the total effect in the first 4 quarters – the effect at impact – is about €4.76 million, about 12% of the stock of NPL. The effect is relatively important. Column (2) considers loan loss provision for bad loans and column (3) loan loss provisions for other NPL.[56] We find similar statistically significant results for loan loss provision on bad loans but not for other types of NPLs.

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. Banks are forced to reclassify some loans into NPL and increase the resources used for future loan losses.[57]

4.1.4. *Threat to Identification.* In this part we discuss the main threats to our identification strategy, as well as how we address these concerns. We provide several robustness tests showing that, conditional on the sample of eligible banks, inspections are randomly assigned.

The main concern with our identification is that there is a selection bias. That is, inspected banks are different and in particular worse than not-inspected banks. To reduce concern about the selection driving the results, we rely on the two-step selection process. In fact, in our experiment, we only compare banks that are eligible, and within this group, some are inspected as if they are randomly picked. This is because the selection, as well as the ranking generated by the selection, are not correlated with bank's quality. Instead, it considers other components of a bank's characteristics more related to its organizational structure.We do not exactly know the components of the algorithm, because it is unpublished, private information kept by the supervisor. However, we know that it takes other information into account, such as organizational structure of the bank, and whether the bank has opened a new branch. On this point we show that the ranking, which can be consider a sufficient statistics of the selection rule, is neither a predictor of bank's quality, nor it explains the results we find.

Robustness Test. In this part, we provide a battery of robustness tests to confirm the validity of the baseline results. We find statistically significant differences among the eligible banks;

[56] Banks can account for losses on non-performing loans through two different methods. The first consists in the devaluation of the part of the exposure deemed not recoverable. The second is based on the direct "write-off" of the loss component (write-off). 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.

[57] This is in line with the result found Granja and Leuz (2019).

moreover we confirm that the ranking neither drives the results nor is correlated with a bank's health. Finally, we run a set of placebo tests to confirm that inspections come at a surprise.

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 8 shows balance test comparing the group of eligible vs. not eligible. Eligible banks have, on average a higher stock of NPL, 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.[58] Second, in Figure 7 we show that, among the set of eligible banks, those that are inspected are not significantly different from those not inspected. Inspected and eligible but not inspected banks are not significantly different along several dimensions. They only significantly differ in terms of profitability. In all our specifications, we include it as a control to residualize its effect on bank's activity.[59] 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.

Controlling for the ranking does not have an impact: We run the same regressions as in equation 4.2 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. If ranking predicts some effect, we should observe it in the triple difference. Tables 3 and 4 show that the effect of inspections is driven by whether a bank is inspected. The triple interactions with the ranking of the bank does not have any other significant effect.

Placebo test ranking: We run the same model as 4.1 but only on the set of inspected banks. In particular we compare inspected banks ranked in the top quartile according to their rating and inspected banks ranked in the bottom quartile. Figure 11 shows that ranking does not predict any effect. We find no significant differences between the two groups of banks after the inspection. This confirms once again the idea that the results are driven by supervisory activity rather than unobserved differences among banks. In other words, inspections do not have a significant different effect among inspected banks whose rating is high vs. inspected banks whose rating is low.

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

[58] Table A4 shows the table counterpart of Figure 8.

[59] Table A5 shows the table counterpart of figure 7.

model of the following type:

$$log(insp_{b,p}) = \alpha_0 + \beta X_{b,p} + \epsilon_{b,p} \tag{4.3}$$

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 matching within a caliper of 0.25 standard deviations of the estimated propensity score with replacement.[60] Figure A4 provides a visual rapresentation of the result of the propensity score matching. Figure 5**A.** shows the common support between the treated and control group. Figure 5**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 A8 reinforces the results found in Tables 2 and 5. 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 percent. 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.

Ranking does not predict bank's quality: If ranking is correlated with a bank's quality, we may expect it to be a good predictor of a bank's health. Figure 10 shows that this is

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

$$A_{rj} = \left\{ kj' \in I_0 : \hat{insp}_{kj'} = \min_{kj' \in I_0} \left| \hat{insp}_{rj} - \hat{insp}_{kj'} \right| < 0.25\hat{\sigma}_e \right\} \tag{4.4}$$

not the case. In all cases considered, the ranking position is not a good predictor of bank's quality.

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 11). We find similar patters compared to the baseline model in which we include the full sample of inspected banks. Moreover, we show that there is no clear pattern in terms on NPL according to ranking position of inspected banks (Figure 12).

Comparing Eligible vs. Not Eligible Banks: Figure A3 plots coefficients of a regression similar to equation 4.1, in which we compare eligible vs. not-eligible banks. From the figure, it is evident that the selection process employed by the supervisory authority does a great job in selecting banks that are similar. Compared to Figure 4 we find a substantial pre-trend before inspections take place. This is in line with what we find in Table 8 running balance tests among these two groups.

Bounding the size of selection bias: One way to understand the size of the selection bias due to unobserved heterogeneity is to compare banks that are arbitrarily selected by the supervisor, i.e. without the mean of the computer algorithm, with the control group. Our setting allows to do so. As pointed out in Section 2, after the computer-based selection process is completed, the supervisor still has the opportunity to select some additional banks to be included in the list of audited banks. These banks are selected arbitrarily by the supervisor according to some unobserved information.[61] We have 310 banks that are inspected without the computer-based selection process. This means that for each macro area about 7 banks are picked arbitrarily by the supervisor every year. We run the same set of regressions as in Table 2, considering only banks arbitrarily selected by the Supervisor as the treated group. Table A7 shows the result of this regression.

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 A6 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 $t = -0$. Specifically, in Panel A, we assume that the inspection takes place between event time -2 and -1.[62] 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 A5 plots the coefficients

[61]Consistent with anecdotal evidence, this can include cases of whistle-blowers within a bank who have revealed some information to the supervisor. Other cases involve banks that have undergone several changes between the time in which the supervisor finalize the inspection plan and its implementation.

[62]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.

of equation 4.1 in the case the artificial inspection is set between event time $\tau = (-2; -1)$ (panel A) or event time $\tau = (-3; -2)$ (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.

5. The indirect effect on Lending

In this section, we study the possible implications for the lending activity of inspected banks. In the first part, we examine the effect of audits on the aggregate lending. To do so, we run a bank-level analysis comparing inspected banks with the group of eligible but not-inspected banks.[63] We show that lending activity contracts in the first few quarters after the inspection. In the second part, to uncover potential heterogeneous effects based on a firm's characteristics, we conduct a bank-firm level analysis. We show that there is a compositional effect, namely, the credit cut is driven by underperforming firms.

5.1. **The effect on the aggregate lending.** *Ex-ante* it is not clear what could be the overall effect. From one side, by forcing supervised banks to reclassify loans into NPL, bank inspectors generate pressure on the bank's balance sheet. Banks 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 the lending activity.[64] From the other side, bank inspections may generate a positive effect on lending. Inspectors, by revealing wrong-doing and providing guidelines on how to improve the internal management and monitoring, can reduce moral hazard and agency frictions at the supervised bank. This theoretically could free up resources used for the lending activity.[65] Thus, what effects prevail is an empirical question.

5.1.1. *Estimating equation.* The empirical model is the same as the one explained in equation 4.1. We run a DiD model, comparing banks that are eligible and inspected to banks that are eligible but not inspected.

$$y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \{\mathbb{1}_{\tau=t}\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \{\mathbb{1}_{\tau=t}\} + \varepsilon_{btpm} \tag{5.1}$$

where b, p, t and m stands for bank, inspection plan, quarter and macro-area. $\{\mathbb{1}_{\tau=t} \times Inspected_{bptm}\}$ are event time indicator variables interacted with a dummy variable $Inspected$. $Inspected$ takes value 1 if bank b 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

[63] This is the same model as to the one used in section 4.

[64] 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.

[65] This is in line with Granja and Leuz (2019). They find that stricter supervision generates a positive credit supply shock.

relative effect of banking inspections. As before, the identification strategy relies on the fact that conditional on the set of eligible banks, inspected banks are randomly picked.

5.1.2. *Result.* Figure 13 shows the effect of the aggregate lending activity for inspected vs. eligible but not-inspected banks for the different type of borrowers. Panel 14**A.** considers the overall lending activity. Panel 14**B.** focuses only on corporate loans, while panel 14**C.** considers loans to small and medium enterprises (SME). We find that lending activity is cut after the inspection. Considering Table 5 we find that at impact total loans drop by about 2.5%. For the average bank in the control group with Tota; Loans of €384.19 millions this means a drop of about €9.61 millions each quarter; thus, the total effect for the first 4 quarters is €38.44 million. This is roughly 10% of total lending for the average bank in the control group. Looking at the plots, we do not find substantial differences between banks before the inspections take place. 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 this increase in the loan loss provision to bad loans (Accornero, Alessandri, Carpinelli, and Sorrentino, 2017). 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. They readjust their capital slowly, as suggested by Figure A7. Thus, they 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. Thus, it is natural to ask whether banks readjust to a better equilibrium after the shock. We investigate this question by considering whether inspected banks change their lending decisions. Specifically we look at whether banks reduce credit to underperforming firms.[66].

5.2. **The impact of banking inspections at the firm level: Compositional Effect.** In this section we study the heterogeneous effect of bank inspections according to firm quality. Given the supervisory-driven credit supply shock, we test whether inspected banks cut credit across all firms or whether they reallocate it to healthy firms. We introduce a novel method to identify underperforming firms based on inspectors' activity. We show that the credit cut established in the previous section is driven only by underperforming firms. Healthy firms in the inspected banks' portfolio experience a positive credit supply growth.

The previous section highlights several important facts. First, we find a substantial impact of bank inspections both in levels and in terms of growth rates. Second, the timing of the change in the NPL reassures us that the effect is driven by this micro-level channel, i.e. by inspectors' activity, rather than other indirect mechanisms. Third, the effect is not driven by either pre-inspection differences among banks or anticipation effect; that is, banks do not anticipate that they are inspected and adjust their portfolio some quarters before the

[66]This is the the content of Section 5.2

inspection takes place.[67]

Now, we study the impact of bank inspections on zombie lending. The question we answer is whether supervisory activity can reduce the misallocation of credit toward underperforming firms. Specifically, we study the effect of this "supervisory induced" shock (i.e. on-site bank inspections) on the ability of firms to obtain credit. From the previous analysis, we find that there is a drop in lending activity by banks. However, this drop may be driven by firms with particular characteristics. We therefore move to a firm-bank analysis tracking the credit relationship over time. We follow the literature and employ an empirical model in which we control for credit demand (Khwaja and Mian, 2008). Specifically, we consider the sample of firms that have multi-lending relationships.[68] Moreover, we consider only the sample of firms that have only performing credits before the inspection (Bofondi, Carpinelli, and Sette, 2017).[69] 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).[70] This is helpful, since we can control for unobserved changes in borrower characteristics.[71] We employ the following empirical model at the firm-bank level:

$$\textit{credit growth}_{ibt} = \beta \textit{Post Inspected}_{bpt} + \alpha_{it} + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp} \tag{5.2}$$

where i, b, p and t stand respectively for firm, bank, inspection plan and quarter. $\textit{credit growth}_{ibt}$ is our outcome variable and it measures the credit growth of firm i borrowing from bank b.[72] $Post_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p is inspected. $Inspected_{bp}$ is a dummy equal to 1 if bank b included in inspection plan p is inspected, 0 if it is eligible but not inspected. $X_{b,PRE}$ is a set of pre-determined bank-level controls. These are the same as the ones included in regressions in Section 4.1. [73] $W_{ib,PRE}$

[67]Inspections come at a surprise. This is different from stress tests, where the date of the assessment of a bank's assets is known by the bank.

[68]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 55.5%, in Italy the share of firms with multilending relationship is 89% (Detragiache, Garella, and Guiso, 2000; Sette and Gobbi, 2015).

[69]That is, we exclude firms with outstanding NPL at the beginning of the period and we focus only on firms that are in good standing according the the Credit Registry.

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

[71]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 can help rule out this possibility. In Section 6 we show that provinces that experience more bank inspections are not preceded by local economic downturn.

[72]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).

[73]Specifically, we follow the literature (Schnabl, 2012) and 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.

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).

5.3. **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. Indeed, 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 Rosengren, 2000, and the Japanese land market collapse (Gan, 2007).[74] The type of shock we study has a different connotation. It is driven by the supervisory activity and it aims at reducing the inefficiencies in bank's management. Thus, *ex-ante* it is not clear how the supply of credit is affected. From 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.[75] 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 side, since bank inspections are targeted to clean up a bank's balance sheet from specific unprofitable investments, this may induce banks to almost completely 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). 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,

[74]The bottom line of these papers is that a a credit supply shock derived from a period of unforeseen financial instability may reduce the ability for banks to supply credit with implications for the real economy.

[75]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.

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 ("reallocation channel").[76]

The idea behind the reallocation channel comes directly from the literature on zombie lending (Peek and Rosengren, 2005; Caballero, Hoshi, and Kashyap, 2008).[77]. The main takeaway is fro this literature is that banks (especially weak banks) have an incentive to keep lending to under-performing 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 weak banks whose capital ratio is very close to the minimum required by law. Recognizing new losses would force them to raise new capital. This would be especially costly in periods of financial instability (Hanson, Kashyap, and Stein, 2011). This ever-greening has been shown to have negative effects in the credit market with implication for 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.

5.3.1. *A new proxy for a firm's quality.* To test the reallocation channel hypothesis we interact our regressor with a variable that proxies for firm's quality. It is a bit tricky to identify zombie firms, mostly because it is difficult to identify whether a firm is going under temporary financial distress or if there are more fundamental issues.[78] Our paper contributes to the literature also on this dimension. Leveraging from the bank inspection data, we develop a new measure that is the result of bank inspections. Specifically, we identify firms that are under-performing based on the result from bank inspections. A firm is flagged as truly under-performing if the bank reclassifies its loans from performing to non-performing in the first quarter after the inspection.[79] We believe this is a valid measure to identify "zombie

[76] Bian (2019) shows that credit reallocation is an important mechanism to boost aggregate productivity in the aircraft sector.

[77] 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)

[78] 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. One recent and most credible attempt is done by Schivardi et al. (2017). By taking 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 as a proxy for a risk-free investment. Second, the leverage of the firm is higher than the median of the sample of firms.

[79] We consider the first quarter, since, as it is highlighted in Figure 5**B.**, the increase in NPL 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 NPL is driven by the inspection activity.

firms" because this reclassification is driven by the bank supervisor and bank inspections are exactly meant to identify loans that are "misclassified" by banks.[80] 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.[81] Additionally, among the set of firms whose loans are reclassified as NPL, only 0.02% are not reclassified by inspected banks.[82] Table A10 shows that reclassified firms are significantly different from other firms - we call them healthy firms - along several dimensions. On average bigger, they have more leverage, have less liquidity, are performing worse (according to different indicators such as cash flow) and invest less in intangible as well as tangible assets.

To test the reallocation channel, we augment equation 5.2 with an interaction term between bank inspection and reclassified. 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 model we use is the following:

$$\begin{aligned} credit\ growth_{ibt} &= \beta(Post\ Inspected_{bpt}) + \eta(Post\ Inspected_{bpt} \times reclassified_{ip}) + \\ &\quad \alpha_{it} + \delta W_{b,PRE} + \gamma X_{ib,PRE} + \epsilon_{ibpt} \end{aligned} \tag{5.3}$$

where the outcome variable is the credit growth for firm i borrowing from bank b where bank b is included in inspection plan p.[83] The additional element in equation 5.3 is given by the interaction between $Post \times Inspected_{bpt}$ and $Reclassified_{ibp}$. This interaction term identifies those firms classified by the supervisor as under-performing. 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 two-way clustered at the bank and inspection plan level (Petersen, 2009).

[80] As discussed, before banks do have an incentive to keep these loans as performing, because otherwise they would have to recognize losses. Recognizing losses means that banks need to raise additional capital, which is particularly costly during financial instability or in a post financial crisis.

[81] In other words, loans to the same firm are reclassified as NPL by inspected banks and are not reclassified by banks in the control group in 98% of the cases. Note also that the sample we consider in this analysis includes only firms that have no NPL in the year before the inspection. That is, firms that look good on paper according to the supervised bank.

[82] In other words, considering loans of 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.

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

$$growth(credit_{ibt}) = \frac{credit_{ibt} - credit_{ibt-1}}{0.5(credit_{ibt} + credit_{ibt-1})} \tag{5.4}$$

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; and it accounts for changes in credit along both the intensive and extensive margins. The second one is $\Delta \log(credit_{ibt}) = \log(credit_{ibt}) - \log(credit_{ibt-1})$ ((Haltiwanger, Schuh, and Davis, 1996; Chodorow-Reich, 2013). The second outcome variable is a pure measure of the intensive margin.

5.4. **Results.** Table 6 shows the results on the intensive margin for the equation 5.2, while Table 7 presents the results on the extensive margin. For the intensive margin we use a sample of firms that we observe at least one quarter in the pre-period and one quarter after the inspection. For the extensive margin analysis we use only firms that we observe at least one period before the banking inspection. Moreover, all the analysis here considers only the sample of firms that do not have any NPL in the two years before the inspection.

In Table 6, column (1), we test the capital shock channel. According to this theory, we expect that bank inspections 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. This forces them to raise capital and/or cut their lending.[84] We find a negative effect of the coefficient on $Post \times inspected$. Specifically, firms borrowing from both inspected and eligible but not-inspected banks have a positive 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.

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 NPL immediately after the inspection.[85] The results are in line with the reallocation channel. We find that reclassified firms experience a drop in the credit growth. The coefficient on the triple interaction is negative and statistically significant. The magnitude is also quite large. Reclassified banks have a drop in the credit growth of almost 66%. On the other side, the coefficient on Post×inspected changes sign and increases both in magnitude and in its significance. 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 similar results also by using this outcome variable.

Table 7 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) tests the capital shock channel. We find that the probability of cutting a lending relationship is actually *negative* for banks that are inspected (column 1) or not significant. This is somehow against the capital channel story in which we expect that the bank capital shock increases the likelihood for a bank to cut a lending relationship. Columns (3)-(5) test the reallocation channel of equation 5.3. We find that the probability of cutting a relationship becomes highly positive and significant for underperforming firms, while it is

[84]This is also found by (Cingano, Manaresi, and Sette, 2016) and (Bottero, Lenzu, and Mezzanotti, 2018) for Italian Banks. The former shows that banks that are more exposed to the dramatic liquidity drought in the interbank market that followed the 2007 financial shocks are more likely to cut credit vis-à-vis banks less exposed to it. The latter uses the European Sovereign Crisis as natural experiment, showing that banks that are more exposed to the shock (i.e. that hold more sovereign debt) are more likely to cut credit vis-à-vis banks that are less exposed. In both cases the exogenous shock generated a liquidity shock to banks.

[85]As discussed in Section 5.3 we only consider loans that are reclassified as NPL in the first quarter after the inspection by inspected banks.

significant and negative for other firms.[86] 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. Credit Table 8 provides evidence that inspected banks are more likely to start a brand-new credit relationship with a firm that was not previously in the bank's portfolio. The outcome variable is the change in the total number of new loans by bank b. The coefficient is positive and statistically significant. Moreover, we find that these loans are of better quality *ex-ante*. Table 9 shows that on average new loans initiated after the inspections are 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 information comes from CERVED. In columns (3)-(4) we use a measure based on the volatility of the growth sales of firms. Specifically, we follow (Neuhann and Saidi, 2018) and we construct annual growth rates that accommodate entry and exit using the measure developed in Davis et al. (2006):

$$\gamma_{i,t} = \frac{(x_{i,t} - x_{i,t-1})}{0.5 \times (x_{i,t} + x_{i,t-1})} \tag{5.5}$$

We use these growth rates to compute the standard deviation of firm i's sales growth over four years. The main difference between the two measures is that the Z-score is a measure available to the bank and it is likely they take this information into account when deciding whether to grant or not a new loan. The second measure instead may not be directly available to the bank. In both cases the results show that inspected banks initiate new loans with less-risky firms.

In line with this results, in table 9 we show that the interest rate charged on new loans is lower. Inspected banks lend to safer firms and thus reduce the interest charged.

From a policy perspective, this is extremely instructive of the benefits of the banking supervision in the reduction of financial frictions in the credit market. By forcing banks to recognizing losses, banks are more likely to cut these lending relationship.

In robustness tests in the Appendix we confirm these results by running similar regressions with different proxies for a firm's quality. In Table A9 we use Total Factor Productivity (TFP, henceforth), a proxy for firm's productivity which is constructed according to the revenue approach (Wooldridge, 2009).[87]

Overall, we find that on-site bank inspections generate an effect in line with the reallocation channel. Inspected banks do cut credit to underperforming firms. They reallocate this credit to either healthy firms in their portfolio or to new startups. We find evidence that after an on-site bank inspections, audited banks change their lending policies and invest more on healthy firms and new firms that are, on average, less risky.

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

[87]There are two main approaches to computing the TFP: the value-added approach and the revenue approach. We use the latter, because it reduces the number of observations that are missing.

5.5. **Potential mechanism.** We discuss the two potential mechanisms explaining the change in the lending policy by inspected banks: first, a change in the governance of the bank; and second, a forced recapitalization of the inspected bank. 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. They are forced to report losses from their trouble loans. As a consequence, there is a negative effect on a bank's profitability in the short term due to the stress put on its balance sheet. However, at the same time we find that inspected banks do adjust their portfolio toward more productive investments. They cut the lending to trouble firms and invest 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. First, on-site bank inspections lead to structural changes at the bank governance (i.e. institutional changes). Second, on-site inspections force banks to raise capital, moving them away from minimal regulatory capital threshold.

5.5.1. ***Change in corporate governance.*** Changes in the governance of a bank after a scandal is not something unusual.[88] We show that inspections reveal wrongdoing in the bank's balance sheets. This has potentially negative implications for the reputation of the bank and it may reduce the trust of their shareholder. The latter can induce them to reduce or withdraw their deposits and disinvest in the bank. Inspected banks need to make structural reforms to avoid this negative implication. Table 11 shows that the results on the impact of bank audits on the governance of the bank. We there is a decrease in the number of executive members following an inspection. Some board members are forced to exit once wrongdoing are revealed. At the same time it forces the bank to strenghten the internal monitoring by hiring more people in the internal supervisory units. We find no effect on the management side. The results complement a line of research in accounting showing that after a serious accounting restatement, a firm take reparative actions to rebuild its reputation.[89] In a similar way, audited banks have to take structural reforms – firing board members – to regain the trust of their shareholders.

5.5.2. ***Recapitalization and change in Bank incentives.*** We find that audited banks are more likely to undergo a recapitalization. Raising equity is costly when banks are in financial distress; this is one of the main reasons why banks avoid revealing their true losses and continue their evergreening. However, once they are recapitalized and their capital ratio is above the regulatory threshold, banks may change incentives in their lending policies. The

[88]For instance, Wells Fargo changed four members of its sixteen-member board after a fraud scandal (https://www.nytimes.com/2018/02/02/business/wells-fargo-federal-reserve.html).

[89] Chakravarthy et al. (2014) shows that public listed firms take reputation-building actions after an accounting fraud. The actions are targeted at both capital providers and other stakeholders are associated with improvements in the restating firm's financial reporting credibility.

increase in the equity side makes the bank a stakeholder not only in good times but also in the unfavorable state of the world. They stop lending to trouble firms and start lending to healthier ones. This idea is related to the literature looking at the optimal level of recapitalization by the government. The takeaway is that a minimum threshold must be reached in order to have a positive effect of recapitalization. In particular, this has 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, banks that remain undercapitalized 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, too small recapitalizations encourage banks' bad lending policies, and may even decrease the availability of loans for borrowers with valuable investment opportunities.[90]

Even if our setting is different since there is no active role of the government in bailing out banks, the bank supervisor indirectly force banks to inject capital. Figure A7 shows that after on-site inspections, treated banks increase the stock of their capital. The increase in capital level is high enough to reduce banks' incentives to evergreen, since now they do not have a binding condition in terms of capital ratio.

6. 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. We provide evidence that bank inspections have a positive effect for the total credit of firms, i.e. a credit channel. Healthy firms obtain more credit, while underperforming firms are not able to substitute credit with other banks. We show that this has implication for real outcomes. Specifically, healthy firms invest more in fixed assets, and they grow their workforce. Additionally, we find that this leads to increase their sales/revenues. To run 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 from 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 more exposed to inspections experience pace of business dynamics and more entrepreneurship.

6.1. **Credit effect at the firm level.** We find that inspected banks cut credit to underperforming firms. We now study two related questions. First, are underperforming firms able

[90]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 kept lending to impaired borrowers is one of the main reasons explaining stable low economic growth in the euro area in that period.

to substitute this credit cut by borrowing from not inspected banks? Second, what happens to the total credit of healthy firms? Are they able to obtain more credit? In other words we want to shed light on whether the credit supply shock highlighted in the previous section results in underperforming firms borrowing less credit from the banking system and healthy firms being able to borrow more credit.

6.1.1. *Estimating equation.* To test the implication of bank inspections for the total credit of firms we run 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:

$$\begin{aligned}(6.1)\quad \Delta\log(y_{it}) \quad = \quad & \beta_1 Post\ Exposure_{i,PRE} + \beta_1 Post\ Exposure_{i,PRE} \times Healthy_{ip} + \\ & + \alpha_i + \eta_l + \eta_t + \eta_c + \gamma S_{iPRE} + \epsilon_{itp}\end{aligned}$$

where i, t, p, l and c are respectively firm, quarter, inspection plan, industry and province.[91] The outcome variable is either the growth rate of total credit to firm i defined as $gr(TotLoans)_t = \frac{(Tot/Loans_t - Tot/Loans_{t-1}}{Tot/Loans_t}$ or a measure capturing the intensive margin, i.e. $\Delta\log(TotCredit)_t = \log(TotCredit)_t - \log(TotCredit)_{t-1}$. 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. Note that the big drawback of this specification is that we cannot fully control for credit demand as 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 the firm is not reclassified.[92] ϵ_{ib} are standard errors clustered at the level of the industry.[93] $\Delta\log(y_i)$ is the main outcome variable of interest for firm i, and it is regressed on a measure of exposure to the banking shock to firm i. We follow the literature (Chodorow-Reich, 2013) and construct our main regressor of interest as a pre-determined exposure of firms to bank inspected. Specifically our measure is constructed as follows:

$$(6.2)\qquad Exposure_{ip} = \frac{\sum_{b=1}^{b\in\mathfrak{B}^{inspected}} credit_{ibp}}{\sum_{b=1}^{b\in\mathfrak{B}^{all}} credit_{ib}}$$

where we consider the credit granted by firm i before the banking inspection. The numerator is the sum of the credit granted to firm i by banks that are inspected according to inspection plan p. The denominator is the sum of the credit granted to firm i by all banks for which the firm has a lending relationship. Our coefficient of interest is β, which we standardize to be

[91]Note that province is the geographical area of reference in Italy. it is of comparable size of a county in the USA. Province is the "relevant geographic markets" according to the Antitrust Authority (Guiso, Sapienza, and Zingales, 2004).

[92]In other words, it is equal to $Healthy_{it} = 1 - Reclassified_{it}$ where $Reclassified_{it}$ is a dummy for whether the inspector forces the bank to reclassified the loan.

[93]In robustness tests we cluster at the level of the firm and/or two-way cluster at the level of the province and industry.

able to interpret the coefficient as the percentage change in credit in response to a standard deviation increase in the borrowing share from inspected banks.

6.1.2. *Results.* Table 12 reports the effects on the credit channel. Columns (1) and (2) consider the effect on the average surviving firm. Columns (3)-(5) include an interaction term for whether or not the firm is healthy. We find that the growth rate of credit for the average firm is negative (column 1). This is true even when we control for firm-level controls and an extensive set of fixed effects (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). We find that by including this new interaction variable, the effect on the credit growth for healthy firms is positive and significant. A one standard deviation increase in the firm's exposure to inspected banks increases the credit growth for healthy firms by 3.6%.[94]

6.2. **Effects on Employment and Investment.** We study how this credit supply shock is passed-through into employment and investments at the annual firm-level.[95]

6.2.1. *Estimating equation.* We run the following model in reduced-form:

$$\Delta y_{itp} = \beta Exposure_{ip} + \alpha_i + \eta_l + \eta_c + \gamma S_{i,PRE} + \epsilon_{itp} \tag{6.3}$$

where i, t p, l and c are respectively firm, inspection plan, industry and province. *Exposure* is our treatment variable as defined in equation 6.2. We include the same controls at the firm-level as in equation 6.1.[96] Our coefficient of interest is β. We standardize it in order to interpret it as the percentage change in our 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.

6.2.2. *Result.* Table 13 shows the effect on the employment and fixed capital investments. Columns (1) and (2) reports respectively the changes in employment after one and two years from the inspection. Columns (3) and (4) report the changes in investments in fixed capital after one and two years. We find a positive effect on both employment and investments in fixed capital after controlling for a set of fixed effects and firm level controls. The effect is stronger in the second year after the inspection is performed. Specifically for employment we find that one standard deviation increase in the firm's exposure to inspected banks leads to 2 pp increase in employment and investments in fixed capital. 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. In

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

[95]We match the surviving firms used in the analysis in subsection 6.1 with balance sheet and income statement data at the annual level. This dataset is available for only incorporated businesses (limited liability companies), not sole proprietorship or other non-incorporated firms. More details on this dataset can be found in Section 3.

[96]These variables are the natural logarithm of assets, sales growth, capital/assets, interest paid/ebitda and the current ratio.

robustness tests we run the same regressions and control for the firm fixed effects estimated from the baseline regression of the credit channel in equation 6.1.

Figure 14 shows the effect of bank inspections on the probability for a firm to exit the market τ years after the market. We find that healthy firms have a consistent negative and statistically significant probability to exit the market. For zombie firms the picture is different. We find that in the year before the inspection takes place, the probability to exit the market is not significantly different from zero. After one year, the probability becomes positive and statistically significant. It is about 6%. It grows steadily with the years. After three year from the inspection, the probability of exit for a zombie firm is about 11%.[97] We find that underperforming firms more exposed to bank inspections are more likely to exit the market. The effect is statistically significant. One standard deviation increase in the exposure to bank inspections result in about 10% increase in the chances to exit the market. The result is robust after controlling for firm level controls, province, industry and year fixed effect. On the contrary, healthy firms are more likely to stay in the market. Overall, this is evidence that bank inspections have an impact on firms' dynamic.

6.3. **Spillover effects to the local economy.** This section studies the impact of bank supervision on the local economy. Precisely, we consider whether the positive effect on firms and new startups spillover to the local economy.[98] To sheds light on it, we construct a measure of province's exposure to banking inspections similarly to the method used in Section 6. 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 problem 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:

$$Exposure_{cp} = \frac{\sum_{b \in \mathfrak{B}^{inspected}} credit_{cbp}}{\sum_{b \in \mathfrak{B}^{all}} credit_{cbp}} \tag{6.4}$$

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.

6.3.1. *Identifying assumption.* The identifying assumption, as in other Bartik instruments, relies on the idea that each bank is a small contributor to a province overall credit supply and is therefore unlikely to drive province level outcomes. Moreover, in a reduced-form model the

[97]In Table A12 in the Appendix consider the probability of exit within two years. The outcome variable is equal to 1 if firm i exits the market within two years from the inspection. Column (1) and (2) consider the effect on the sample of zombie firms (i.e. firms whose loan is reclassified as NPL during the inspection). Column (3) and (4) consider the sample of other firms.

[98]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. A region corresponds to the NUTS 2 level.

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. 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 A13 shows that our measure of exposure is not correlated with any covariates at the geographical level in the pre-period, such as 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. Moreover, we show that there are no significant differences in the years before the inspection.

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

$$\Delta \log(y_{ct}) \quad = \quad \beta_1 Exposure_{c,p,PRE} + \alpha_c + \eta_t + \gamma S_{c,PRE} + \epsilon_{ip} \tag{6.5}$$

where c, p and t are respectively province, inspection plan, and year. $Exposure_{c,PRE}$ is the measure of exposure at the province level as we define in equation 6.4. 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 a year before the inspection.[99] 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.

6.3.2. *Result.* Figure 15 shows the results of banking inspection on entrepreneurship.[100] We find that bank inspections have a positive effect on the local economy. Specifically, one standard deviation increase in the treatment exposure 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 are robust to the inclusion of province fixed effect, year fixed effect, and province level controls. Moreover, we find that the effect is not driven by pre-defined differences across provinces. Overall, the results show that bank inspections can increase firm dynamics in the

[99] These consist of employment rate, and GDP at the province level.

[100] We define entrepreneurship as the number of new businesses that are created. 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.

local economy. This is a major improvement given the lack of dynamics that the Euro zone area has been experiencing during the last decade (Adalet McGowan et al., 2018). Table 14 shows that bank inspections generate a cost in the local economy in the short term. Aggregate employment goes down as a result of inspections. 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 as more firms enter the market. In line with this result we find a similar dynamics in the measure of value added per worker in table 15. Value added per worker is a proxy for the productivity and it is an outstanding measure of the extent to which you are utilizing your employeeâĂŹs strengths. We find that the productivity at the province level is increasing for those provinces more exposed to inspections.

7. Conclusion

This paper studies the effect of bank supervision. We take advantage of unexpected on-site bank inspections to estimate the causal effect of bank supervision. We uncover three set of results. First, there is an informational disclosure effect. We find that after an inspection, audited banks increase the stock of NPL 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 compositional effect. The credit cut is driven mainly by underperforming firms. We find evidence of a reallocation channel. Inspected banks re-optimize their portfolio of loans by investing more on healthy firms in their portfolio or new startups. We show that the change in the lending policy is driven by structural changes at the inspected banks; these banks set radical changes to 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 (credit channel), increasing their employment their investments in fixed capital, and their sales. At the local economy, we find an increase in entrepreneurship with underperforming firms 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 firms (Banerjee and Hofmann, 2018; Acharya et al. (2019b); Blattner et al., 2017) due to distortions in the credit market. We show that this problem can be attenuated by a more stringent role of bank supervision at the very micro-level. From the other side, it is also true that "too much" bank supervision may have potentially negative effects in the short term for the local economy. By forcing banks to stop lending to zombie firms this may results in higher rate of exit of unproductive firms and a negative effect for local aggregate employment in the short term. This can potentially affect local demand and consumption. Thus, enforcing more bank supervision may be a very costly action especially if considering the short term effects in terms of employment. Eventually it depends on how much weight is put on short-term costs vs. long-term benefits. In future work, it may be interesting to explore what is the optimal level of bank supervision.

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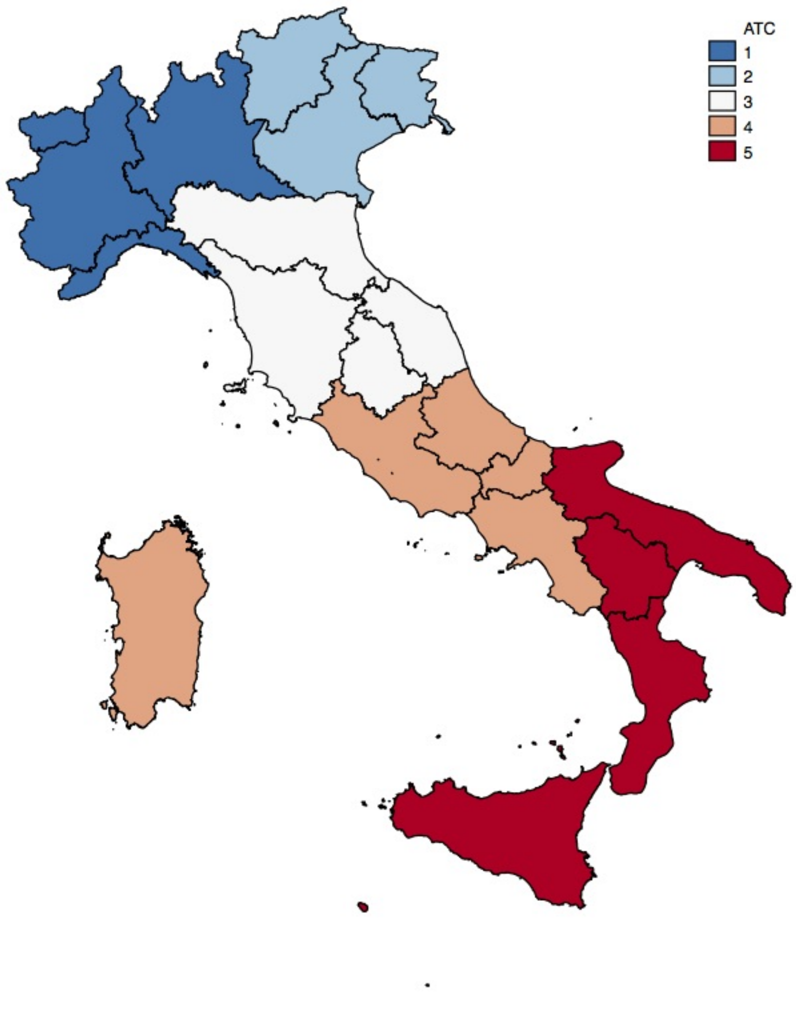
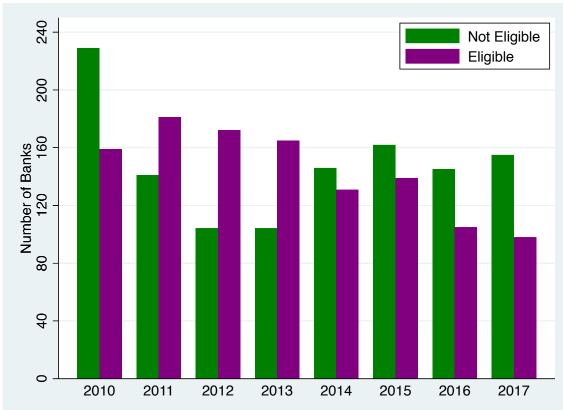
Figure 1. Redistribution of Regions according to their ATC - Aree Territoriali e Circoscrizionali

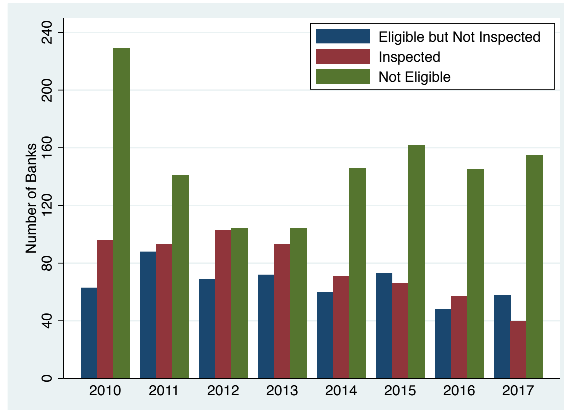


Notes: This figure shows the spatial distribution of regions according to the ATC to which belong. There are five different ATC: 1. North-west (Piemonte, Liguria, Valle d'Aosta, Lombardia); 2. North-East (Trentino-Alto Adige, Friuli-Venezia Giulia, Veneto); 3. North-Center (Emilia Romagna, Toscana, Umbria,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

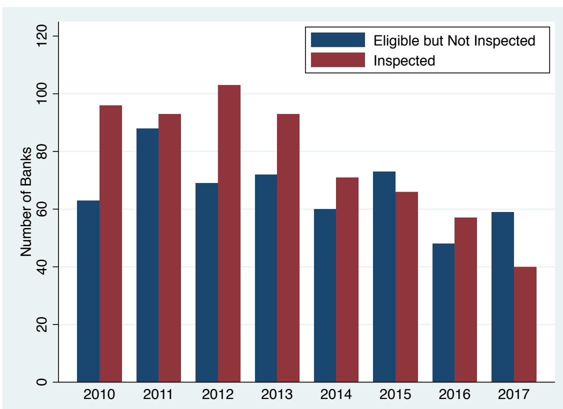
FIGURE 2. On-site inspections over time



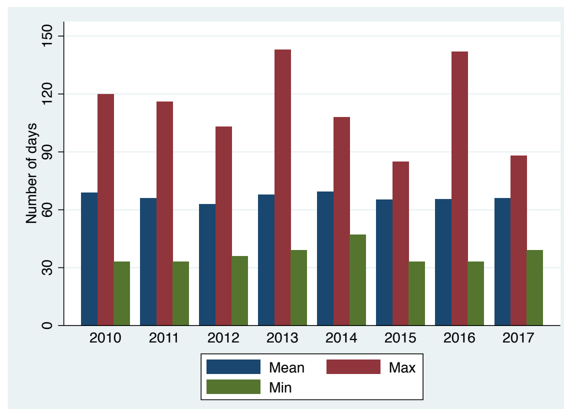
A. Eligible and Not Eligible Banks



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



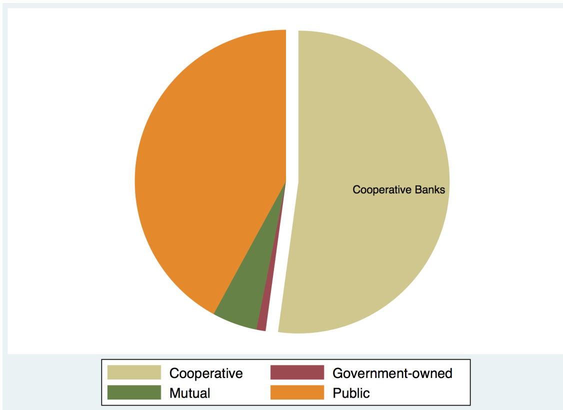
C. Inspected (Treated) and Eligible but Not Inspected (Control) over Inspection Plan



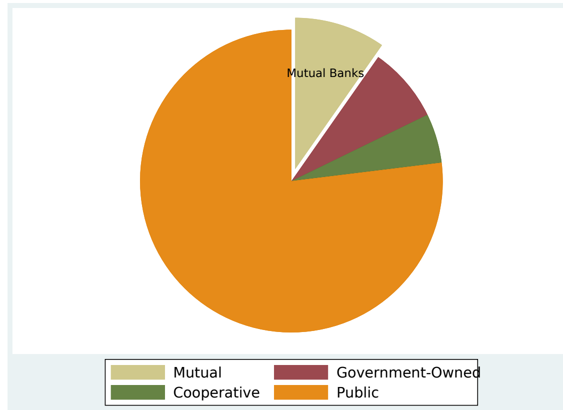
D. Length of Inspections in Days

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 to be inspected. Each year, the Supervisor construct 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.

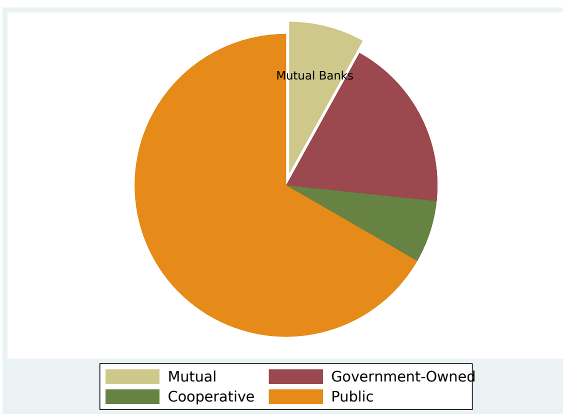
FIGURE 3. Distribution of Banks according to their Legal Form



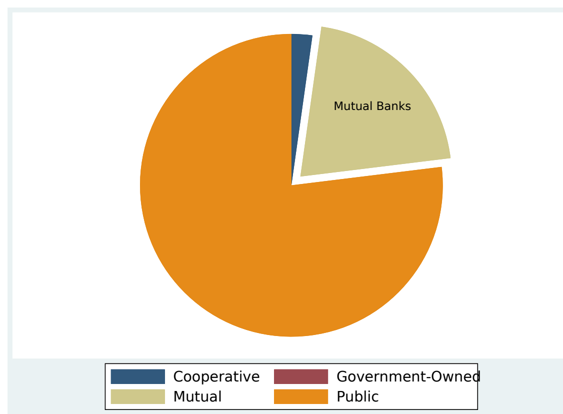
A. Frequency



B. Total Assets



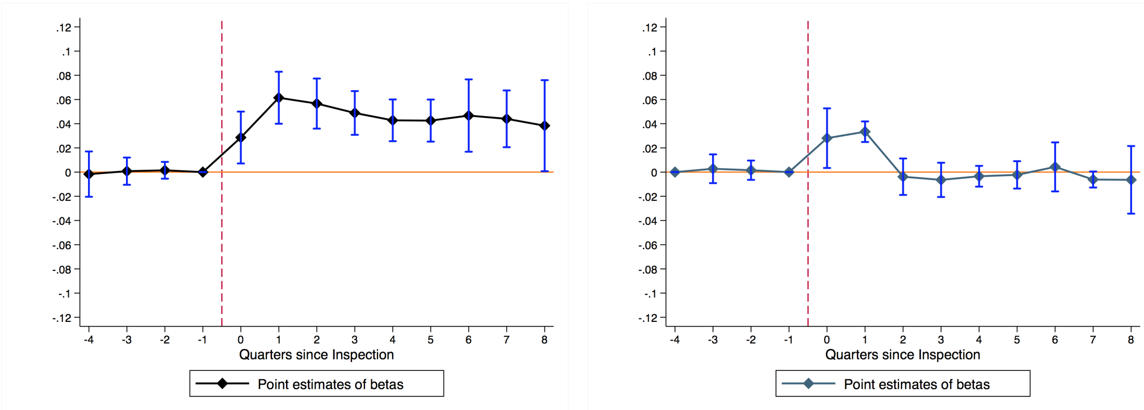
C. Total Deposits



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

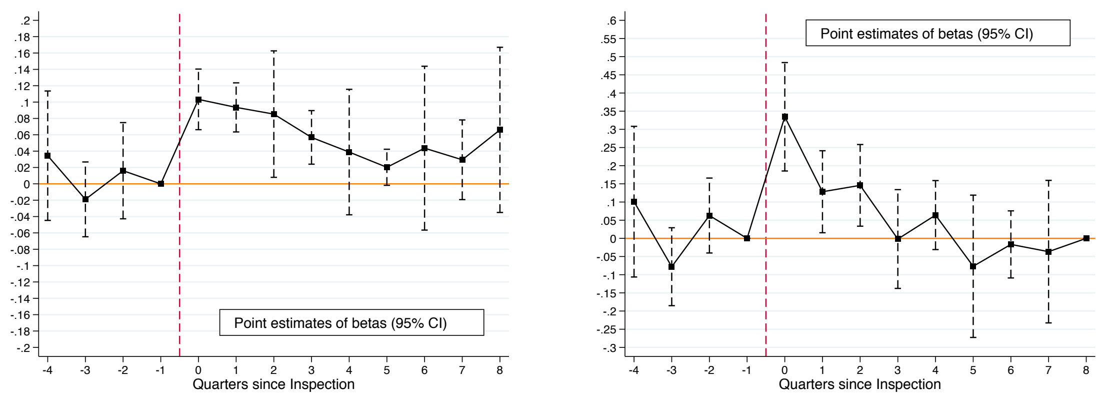
FIGURE 4. Dynamic DiD: Informational Disclosure Effect (1)



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

Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. In panel A the outcome variable is 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).

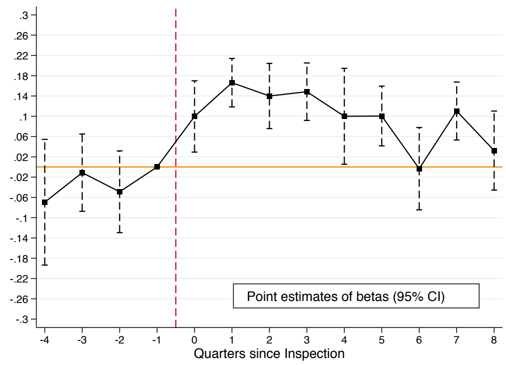
FIGURE 5. Dynamic DiD: Informational Disclosure Effect (2)



A. Loan Loss Provision for Bad Loans **B.** Delta log of Non-Performing Loans (NPL)

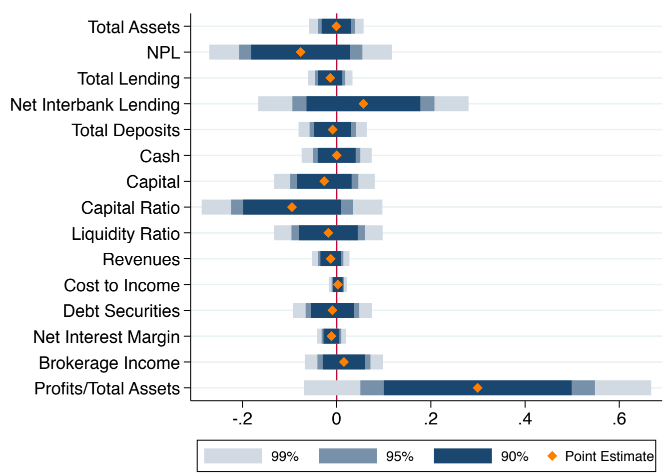
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. 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 NPL, 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 6. Dynamic DiD: $\log(otherNPL)$



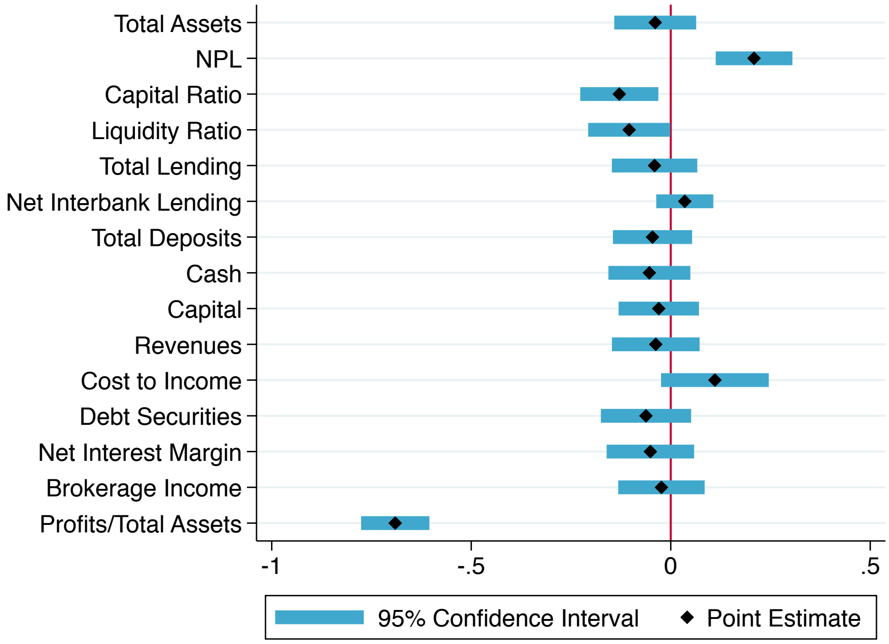
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. The outcome variable is the log of other NPL, 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 7. Balance Test: Inspected vs. Eligible but Not Inspected



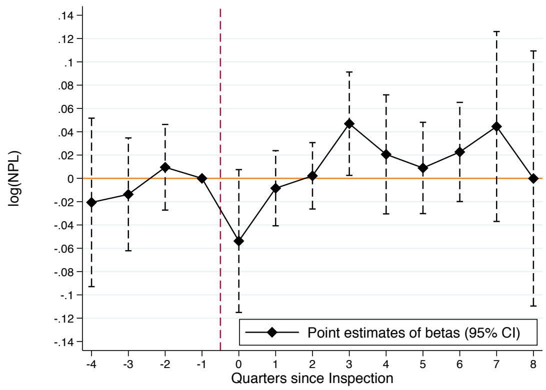
Notes: Figure 7 shows balance tests for covariates among inspected vs. eligible but not inspected. The regression of interest is the following: $Y_{bp,-4} = \beta Inspected_{bp} + \gamma_p + \epsilon_{bp}$ where the outcome variables are a series of bank-level variables. The darkest shades represent 90% confidence intervals and the lightest shades represent 99% confidence intervals. This is the graphical counterpart of Table A5.

FIGURE 8. Balance Test: Eligible vs. Not Eligible

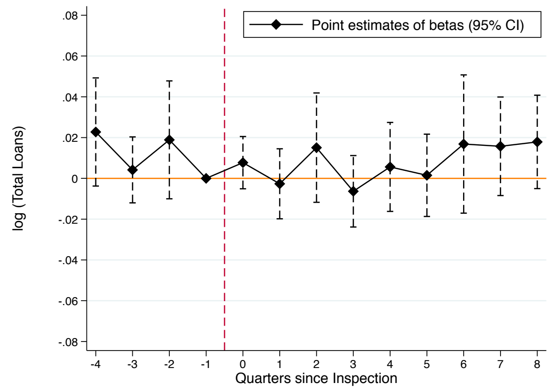


Notes: Figure 7 shows balance tests for covariates among inspected vs. eligible but not inspected. The regression of interest is the following: $Y_{bp,-4} = \beta Inspected_{bp} + \gamma_p + \epsilon_{bp}$ where the outcome variable are a series of bank-level variables. This is the graphical counterpart of Table A4.

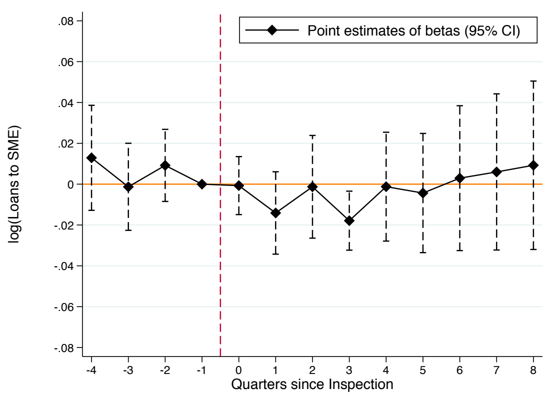
FIGURE 9. Placebo Test Ranking



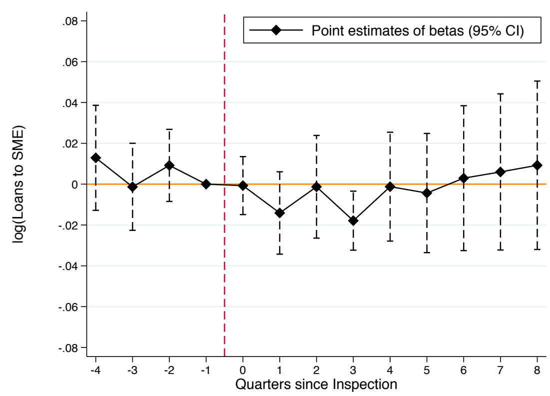
A. log(NPL)



B. log(Total Loans)



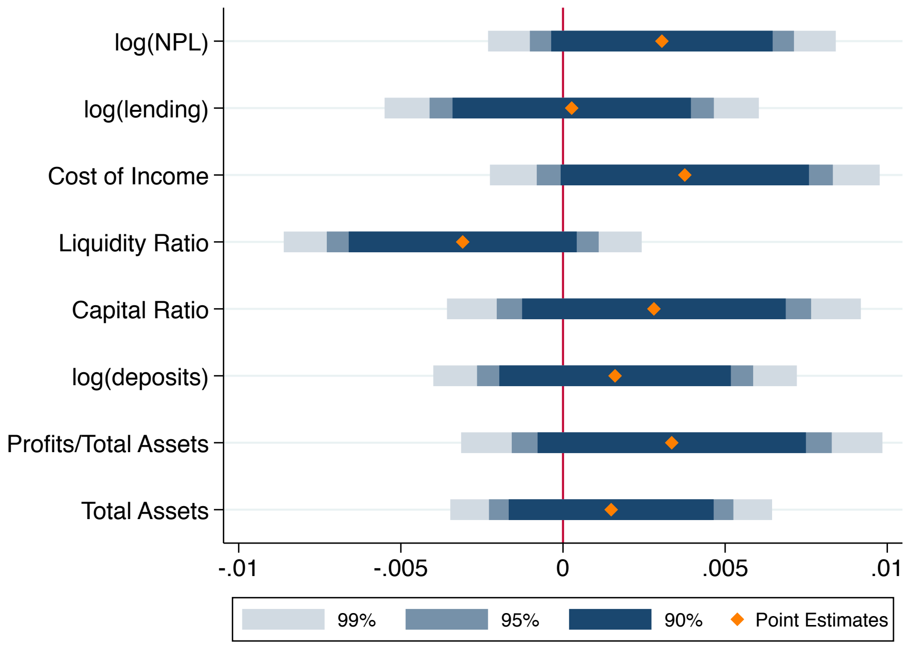
C. log(Loans to Firms)



D. log(Loans to SME)

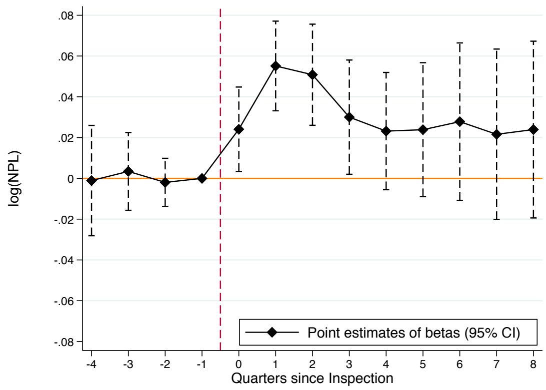
Notes: The sample includes only inspected banks ranked in the top quartile and inspected banks ranked in the bottom quartile. This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau \textit{Top quartile Ranking}_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. 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 10. Ranking Prediction

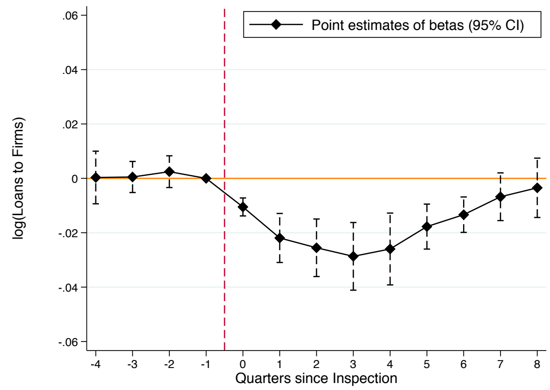


Notes: Figure 10 shows the results of the following regression: $y_{bpa} = \beta Ranking_{bpa} + \gamma_p + \gamma_a + \epsilon_{bp}$ where γ_p are inspections plan fixed effects and γ_a are ATC fixed effects. We consider bank-level variables 4 quarters before the inspection, which is roughly the timing 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 of Table A3.

FIGURE 11. Placebo Test Ranking



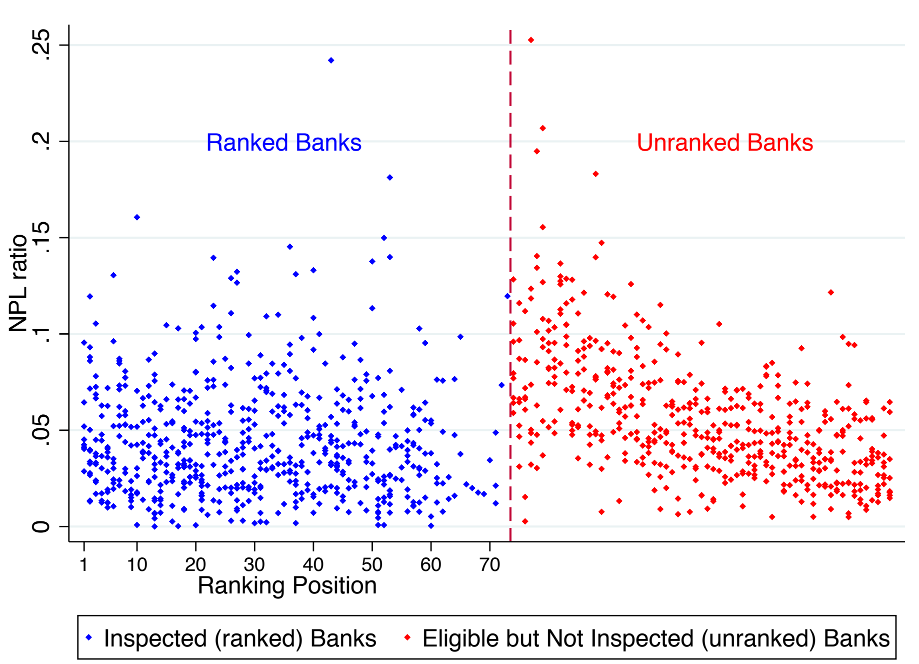
A. log(NPL)



B. log(Loans to Firms)

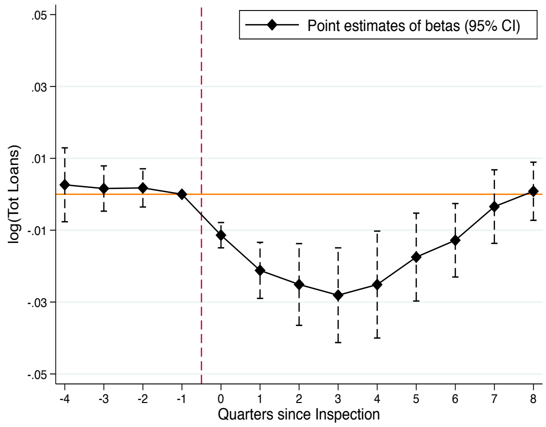
Notes: The sample does not include inspected banks that are ranked in the first quartile of the ranking distribution. This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Top\ quartile\ Ranking_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$.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 12. NPL ratio plot

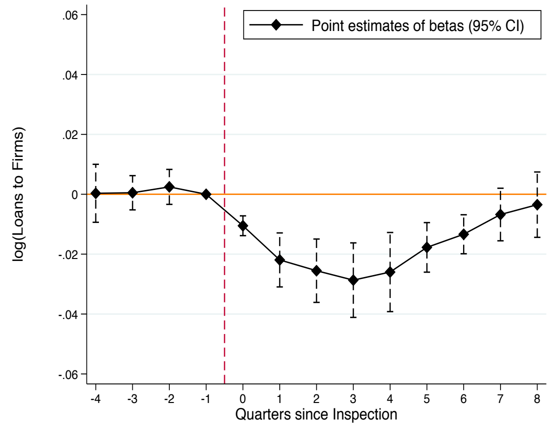


Notes: This graph plots the NPL ratio of banks that are eligible. Specifically the blue dots represent inspected (ranked) banks. Top to bottom ranking is from left to right. Red dots plot the NPL ratio of eligible but not inspected banks. For this group there is no ranking position available.

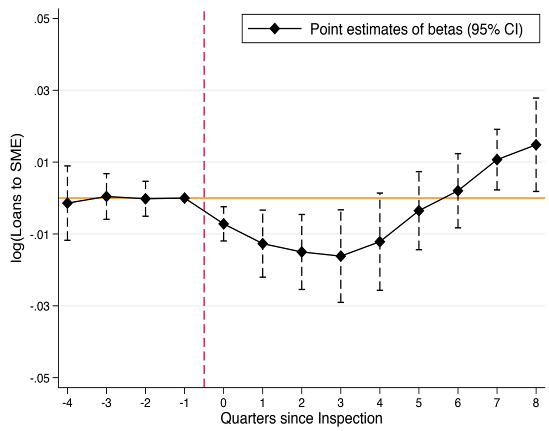
FIGURE 13. Dynamic DiD: Indirect Effect on Lending



A. log(Total Loans)



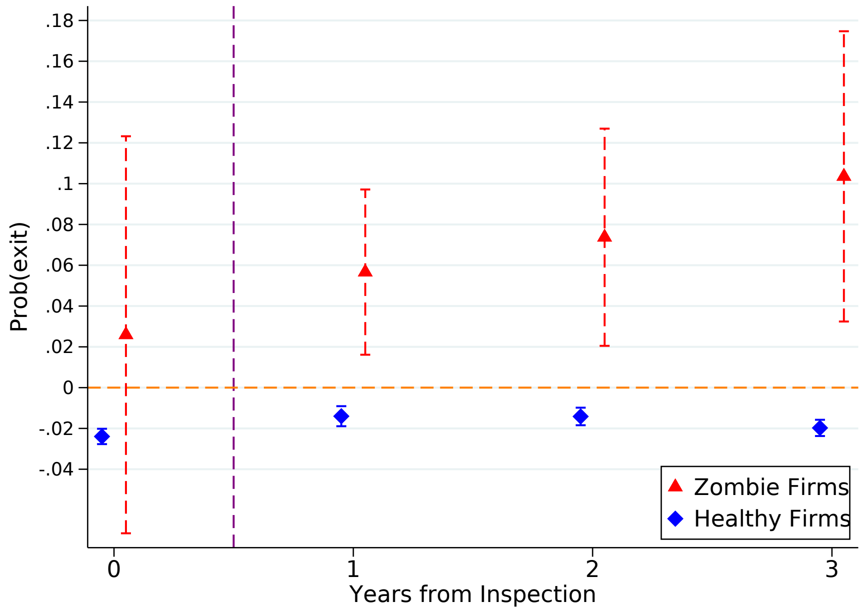
B. log(Loans to Firms)



C. log(Loans to SME)

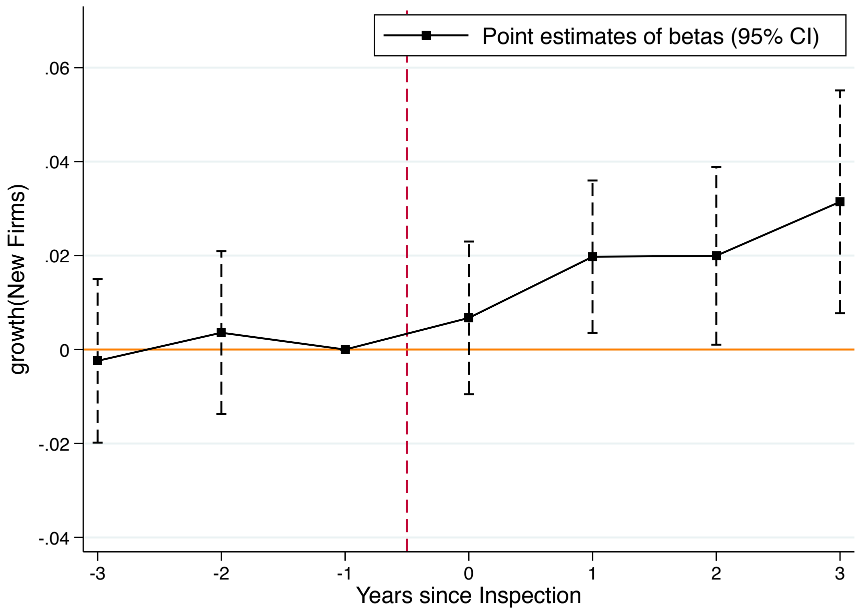
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$. 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). Data comes from bank's balance sheet (Supervisory Reports).For a full description of the empirical equation refer to equation 4.1. Data comes from bank's balance sheet (Supervisory Reports).

Figure 14. 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 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 15. Effect on Entrepreneurship



Notes: This graph plots the result of the following regression: $\Delta\log(y_{ct}) = \beta_1 Exposure_{c,p,PRE} + \alpha_c + \eta_t + \gamma S_{c,PRE} + \epsilon_{ip}$ where c, p and t are respectively province, inspection plan and year. $Exposure_{c,PRE}$ is the measure of exposure at the province level as we define in equation 6.4. 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. 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: This table shows the summary statistics for eligible banks for the period 2010-2017.

Table 2. Bank-level Regression: Informational Disclosure Effect

VARIABLES	(1) NPL	(2) Loan Loss Provision on bad loans	(3) Loan Loss Provision on other NPLs
post ×inspection	0.031***	0.038***	0.032
	(0.005)	(0.008)	(0.027)
Observations	21,870	11,197	11,206
R-squared	0.980	0.945	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

Notes: This table shows the results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post_{tb} \times Inspection_{bp} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank FE, Inspection plan-macro area FE, and quarter FE. The time dummy variables refer to quarters relative to the banking inspection. We omit event time 1. Note that we normalize $\beta_{\tau=-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. 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). IP stands for Inspection Plan. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table 3. Bank-level Regression: Placebo test ranking

VARIABLES	(1) NPL	(2) Loan Loss Prov bad Loans	(3) Loan Loss Prov other NPLs
post×inspected	0.028**	0.086**	-0.005
	(0.010)	(0.025)	(0.040)
post×inspected×3rd ranking quartile	-0.030	-0.135**	0.079
	(0.022)	(0.039)	(0.054)
post×inspected×2nd ranking quartile	0.032	0.011	0.037
	(0.024)	(0.033)	(0.089)
post×inspected×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
Cluster	bank-IP	bank-IP	bank-IP
Bank controls	Y	Y	Y

Notes: This table shows the results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post_{tb} \times Inspection_{bp} + \delta Post_{tb} \times Inspection_{bp} \times \left\{\mathbb{1}_{ranking\ quartile=i}\right\} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank FE, Inspection plan-macro area FE and quarter FE. 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: 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. 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). IP stands for Inspection Plan. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table 4. Bank-level Regression: Placebo test ranking

VARIABLES	(1) log(*tot loans*)	(2) log(*Loans to Firms*)	(3) log(*Loans to SME*)
post×inspected	-0.023**	-0.020**	-0.016*
	(0.009)	(0.008)	(0.008)
post×inspected×3rd ranking quartile	-0.005	0.008	0.001
	(0.009)	(0.008)	(0.006)
post×inspected×2nd ranking quartile	-0.001	0.001	0.006
	(0.009)	(0.009)	(0.015)
post×inspected×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: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post_{tb} \times Inspection_{bp} + \delta Post_{tb} \times Inspection_{bp} \times \left\{\mathbb{1}_{ranking\ quartile=i}\right\} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank FE, Inspection plan-macro area FE and quarter FE. 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: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio. Column (1) considers the log(total loans), column (2) the log(loans to firms) and column (3) the log(loans to Small and Medium Enterprises). IP stands for Inspection Plan. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table 5. Bank-level Regression: Indirect Effect on Lending - effect at impact

VARIABLES	(1) log(*tot loans*)	(2) log(*Loans to Firms*)	(3) log(*Loans to SME*)
post ×inspection	-0.023***	-0.025***	-0.012*
	(0.006)	(0.007)	(0.005)
Observations	22,051	22,051	22,051
R-squared	0.993	0.993	0.993
bank FE	Y	Y	Y
Inspection Plan Year × 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: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post_{tb} \times Inspection_{bp} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank FE, Inspection plan-macro area FE and quarter FE. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio. Column (1) considers the log(total loans), column (2) the log(loans to firms) and column (3) the log(loans to Small and Medium Enterprises). IP stands for Inspection Plan. We consider only the four quarters before and the four quarters after the inspection. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table 6. Effect on Credit growth - Zombie= NPL$_{post}$

VARIABLES	(1) gr(tot Loans)	(2) gr(tot Loans)	(3) gr(tot Loans)	(4) Δ log(tot Loans)	(5) Δ log(tot Loans)
inspected	-0.001	0.034***	0.029**	0.037***	0.032**
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
inspected × 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 relat	Y	Y	Y	Y	Y
Cluster	bank	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $credit\ growth_{ib,t} = \beta Post_{bpt} \times Inspected_{bp} + +\eta\Big(Post_{bpt} \times Inspected_{bp} \times reclassified_{ip}\Big) + \alpha_{it} + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp}$. 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: $\Delta\log(credit_{ib,t}) = \log(credit_{ib,t}) - \log(credit_{ib,t-1})$. $Post_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p is inspected. $Inspected_{bp}$ is a dummy equal to 1 if bank b included in inspection plan p is inspected, 0 if it is eligible but not inspected. $reclassified_{ip}$ 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 bank FE, Inspection plan-macro area FE and quarter FE. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital 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 NPL 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 7. Effect on Credit Growth: Extensive Margin

VARIABLES	(1) pr(cut)	(2) pr(cut)	(3) pr(cut)	(4) pr(cut)
inspected	-0.002**	-0.001	-0.007**	-0.005*
	(0.001)	(0.002)	(0.003)	(0.003)
inspected × reclassief			0.056***	0.056***
			(0.010)	(0.011)
Observations	1844127	1857447	1844127	1844127
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 relat	Y	Y	Y	Y
Cluster	bank	bank	bank	bank

Notes: This table shows the results of the following equation: $credit\ growth_{ib,t} = \beta Post_{bpt} \times Inspected_{bp} + +\eta\Big(Post_{bpt} \times Inspected_{bp} \times reclassified_{ip}\Big) + \alpha_{it} + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp}$. In columns (1)-(3) the outcome variable is $growth(credit_{ib,t}) = \frac{credit_{ibt} - credit_{ibt-1}}{0.5(credit_{ibt} + credit_{ibt-1})}$. The outcome variable $pr(cut)$ is a dummy variable equal to 1 if the bank-firm relationship is cut in quarter t, 0 otherwise. $Post_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p is inspected. $Inspected_{bp}$ is a dummy equal to 1 if bank b included in inspection plan p is inspected, 0 if it is eligible but not inspected. $reclassified_{ip}$ 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 bank FE, Inspection plan-macro area FE and quarter FE. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital 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 NPL before the inspections. * p< 0.10. ** p< 0.05, *** p< 0.01.

TABLE 8. Effect on New Bank-Firm lending Relationship

VARIABLES	(1) Δ log (New Loans)	(2) Δ log (New Loans)	(3) Δ log (New Loans)
Post $\times$ Inspected	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$\times$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: $\Delta \log(NewLoans) = \beta post \times Inspected_{bt} + \gamma_t + \gamma_b + \gamma_p + \gamma_m + \eta X_{b,PRE} + \epsilon_{btp}$. The outcome variable is $\Delta \log(Loans\ new\ firms_{b,t}) = \log(Loans\ new\ firms_{b,t}) - \log(Loans\ new\ firms_{b,t-1})$. The variable is multiplied by 100. We include bank, quarter and inspection plan-macro area fixed effect. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio.

TABLE 9. Quality of New Loans

VARIABLES	(1) Score	(2) Score	(3) $\widehat{\sigma(growth\ sales)}$	(4) $\widehat{\sigma(growth\ sales)}$
Post $\times$ inspected	-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 $\times$ 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: $y_{bt} = \beta post \times Inspected_{bp} + \gamma_b + \gamma_{pm} + \eta X_{b,PRE} + \epsilon_{bp}$. 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 value from 1 (safest company) to 9 (riskiest company). We include bank, quarter, and inspection plan-macro area fixed effect. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio.

TABLE 10. Quality of New Loans

VARIABLES	(1) Interest Rate	(2) Interest Rate
post inspected	-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: $y_{bt} = \beta post \times Inspected_{bp} + \gamma_b + \gamma_{pm} + \eta X_{b,PRE} + \epsilon_{bp}$. The outcome variable is $Average\ interest\ rate_{b,t} = \frac{\sum interest\ ratei,t\{\mathbb{1}_{New\ loanib=1}\}}{\sum\{\mathbb{1}_{New\ loanib=1}\}}$ 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 value from 1 (safest company) to 9 (riskiest company). We include bank, quarter, and inspection plan-macro area fixed effect. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio and NPL ratio.

TABLE 11. 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: $\Delta Tot\ Members_{b,t} = \beta post \times Inspected_{bp} + \gamma_t + \gamma_b + \gamma_{mp} + \gamma_m + \eta X_{b,PRE} + \epsilon_{btp}$. 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 effect. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio.

Table 12. 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
Province FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Firm controls	N	Y	N	Y	Y
Inspection Plan Year FE	Y	Y	N	N	Y
Cluster	industry	industry	industry	industry	industry

Notes: This table shows the results of the following equation: $\Delta \log(total\ credit_{it}) = \beta_1 Post\ Exposure_{i,PRE} + \beta_1 Post\ Exposure_{i,PRE} \times NonReclassified_{ip} + \alpha_i + \eta_l + \eta_c + \gamma S_{iPRE} + \epsilon_{itp}$. 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, and sector and inspection plan fixed effect. 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, 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. $Exposure_{i,PRE} = \frac{\sum_{b=1}^{b \in \mathfrak{B}^{inspected}} credit_{ibp}}{\sum_{b=1}^{b \in \mathfrak{B}^{all}} credit_{ib}}$ is our treatment, which is the share of credit coming from inspected banks computed in the pre-period. Standard errors are clustered at the industry level. Coefficients are standardized.

Table 13. 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: $\Delta y_{itp} = \beta Exposure_{ip} + \gamma X_{i,PRE} + \alpha_i + \eta_l + \eta_c + \gamma S_{i,PRE} + \epsilon_{itp}$. The outcome variable is $\Delta \log(y_{it}) = \log(y_{i,t}) - \log(y_{i,t-1})$, i.e., we compute the change in y between the year before the inspection and the year after. 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, sales growth, 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 cluster the standard errors at the industry level. Coefficients are standardized.

Table 14. Effect on Aggregate Employment

	(1)	(2)	(3)
VARIABLES	ΔAggreg Employm$_{t+1}$	ΔAggreg Employm$_{t+2}$	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
province FE	Y	Y	Y
Industry FE	Y	Y	Y
province controls	Y	Y	Y
Cluster	province	province	province

Notes: This table shows the results of the following regression: $\Delta(Employment_{clt}) = \beta Exposure_{cp} + \eta_l + \eta_c + \gamma S_{c,PRE} + \epsilon_{ct}$. The outcome variable is $\Delta(y_{ct}) = \log(y_{c,t}) - \log(y_{c,t-1})$, i.e., we compute the change in y between the year before the inspection and the year after. $S_{c,PRE}$ 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. We cluster the standard errors at the province level. Coefficients are standardized.

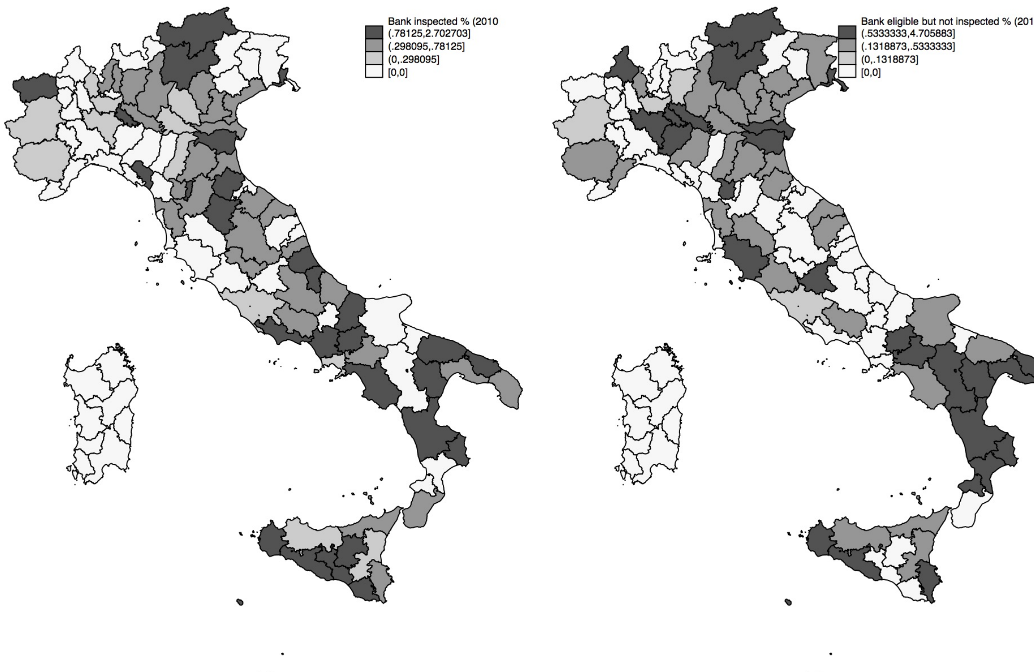
Table 15. Effect on Value Added per Worker

	(1)	(2)	(3)
VARIABLES	ΔValue Added per worker$_{t+1}$	Δ Value Added per worker$_{t+2}$	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
province FE	Y	Y	Y
province controls	Y	Y	Y
Cluster	province	province	province

Notes: This table shows the results of the following regression: Δ Value Added per Worker$_{ct} = \beta Exposure_{ip} + \eta_c + \gamma S_{i,PRE} + \epsilon_{ct}$. The outcome variable is $\Delta \log(y_{ct}) = \log(y_{c,t}) - \log(y_{c,t-1})$, i.e., we compute the change in y between the year before the inspection and the year after. S_{iPRE} 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. $Exposure_{i,PRE}$ is our treatment, which is the share of credit coming from inspected banks computed in the pre-period. We cluster the standard errors at the province level. Coefficients are standardized.

8. Appendix

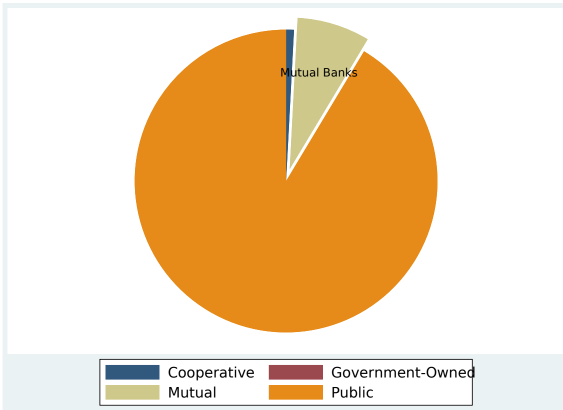
Figure A1. 2010 Inspection Plan



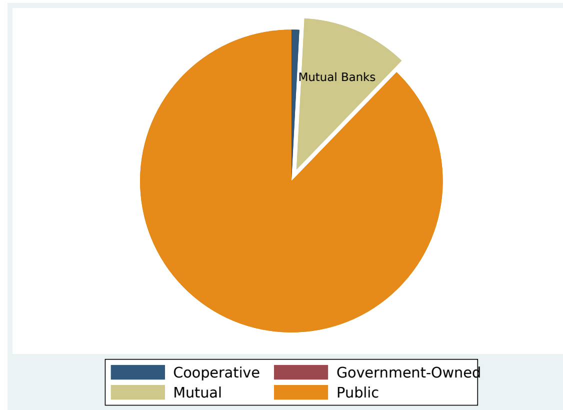
A. Inspected Banks **B.** Banks eligible but not inspected

Notes: This figure shows the spatial distribution of Inspected (Treated group) and Eligible but not inspected banks (Control group) 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 of 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 the total includes also branches of banks that are not in any of the two groups (i.e. ineligible banks). The share is multiplied by 100.

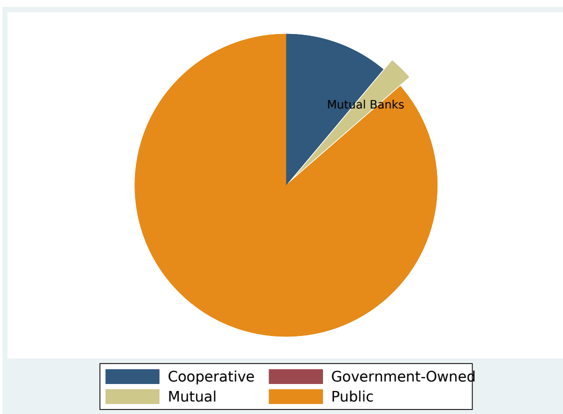
Figure A2. Distribution of Banks according to their Legal Form - Type of Credit



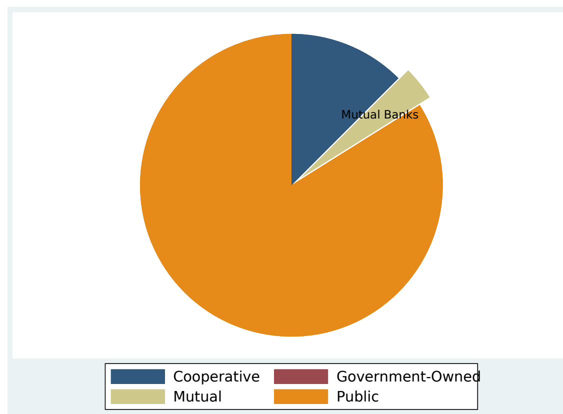
A. Loans Backed by account Receivables



B. Credit Lines



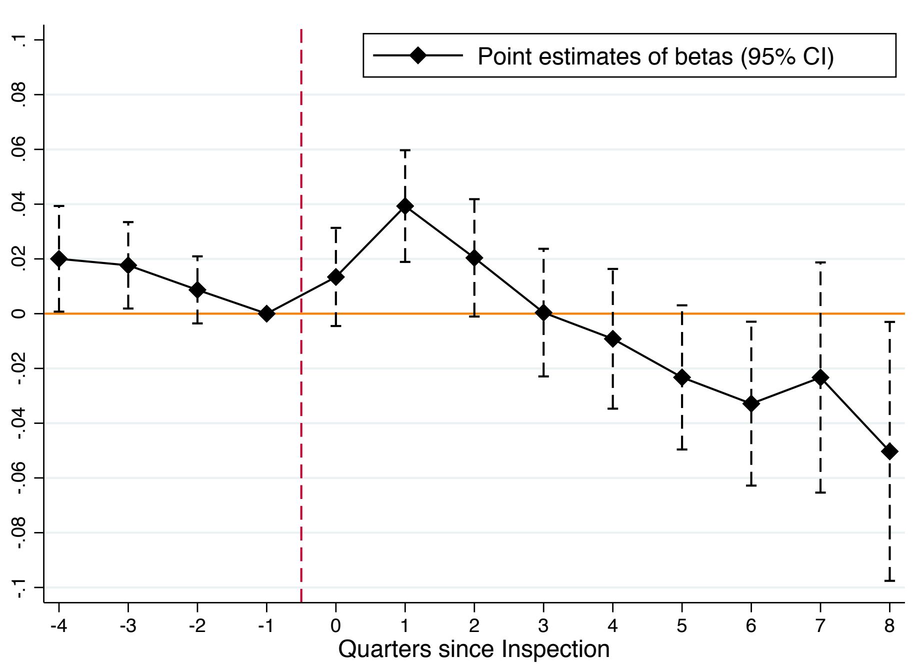
C. Term Loans



D. Total Credit

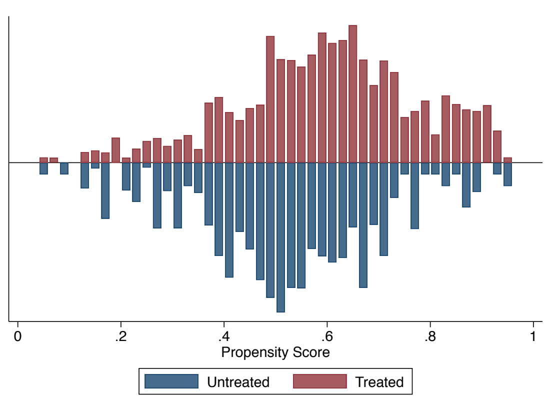
Notes: This figure shows the distribution of banks according to their types of ownership. There are four different type of banks in the Italian banking system. Public (orange) includes banks that are traded in the public market. Mutual (green) refers to mutual banks. Cooperative (yellow) stands for cooperative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

Figure A3. Eligible vs. Not Eligible Banks

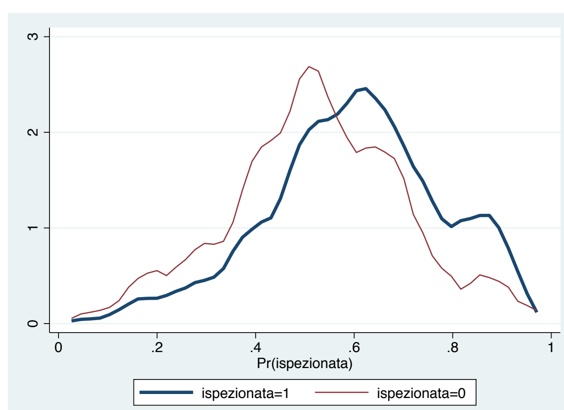


Notes: The sample includes both eligible and not eligible banks. This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$.The outcome variable is the log of loan loss provision for other types of NPL, 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 A4. Propensity Score Matching



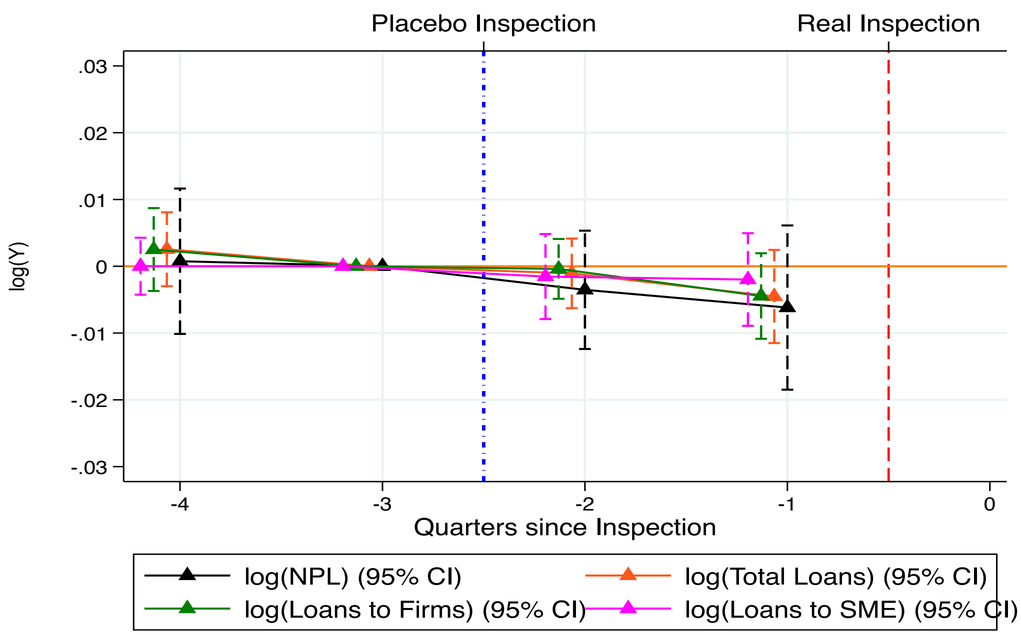
A. Common Support



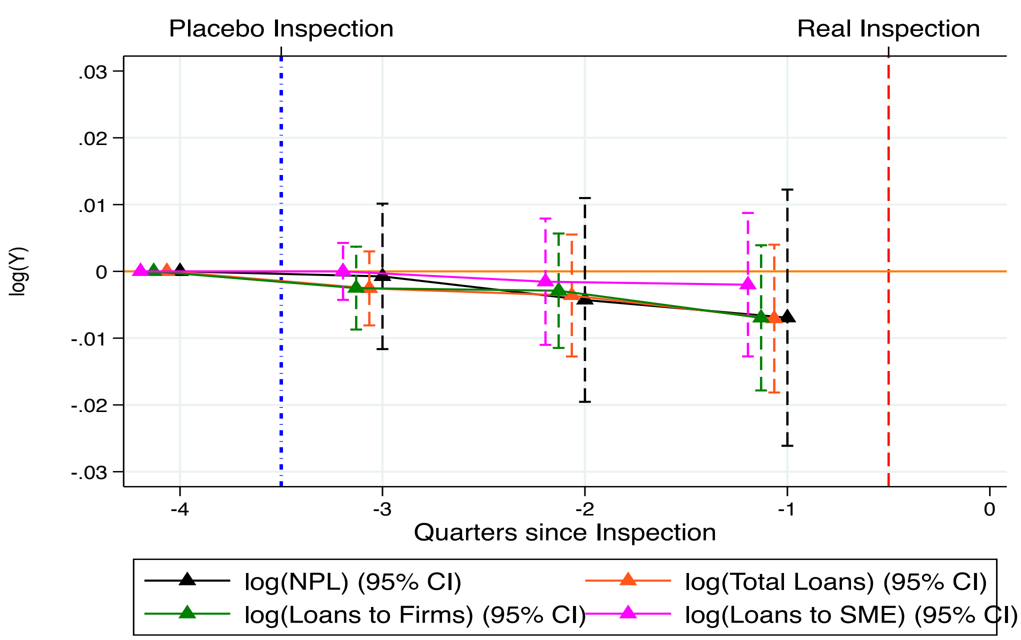
B. Density

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 A5. Placebo Test



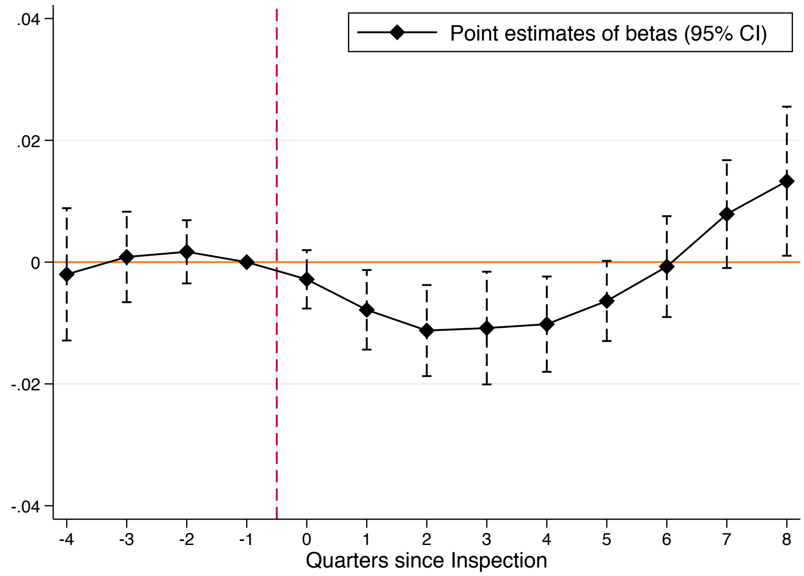
A. Placebo Inspection at $\tau = (-2; -1)$



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

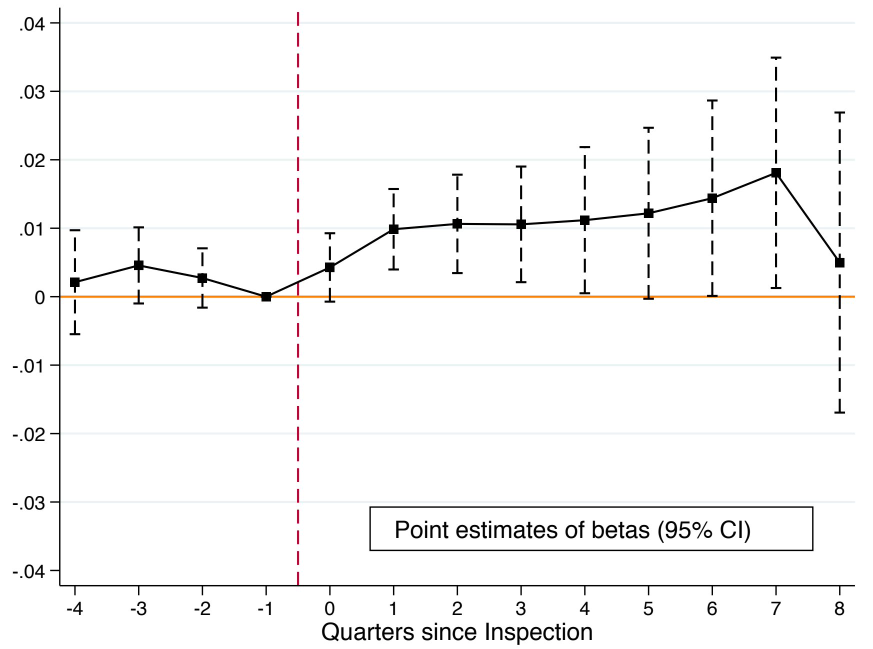
Notes:This Figure shows a placebo test. In Panel A we assign bank inspections in period $t = (-2; -1)$ and normalize $\beta_\tau = 0$ at $\tau = -3$. In Panel B we assign bank inspections in period $t = (-4; -3)$ and normalize $\beta_\tau = 0$ at $\tau = -4$. The banking inspection in period $t = -3$. We set $\beta_\tau = 0$ at $\tau = -3$. 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.

FIGURE A6. Dynamic DiD:log(deposits)



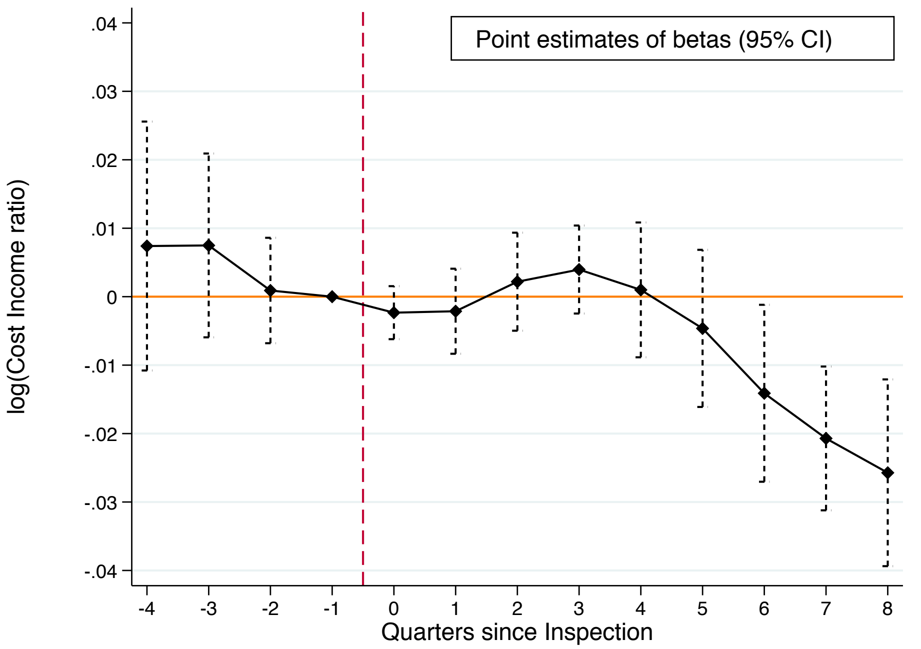
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$.The outcome variable is the log of deposits. 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 A7. Dynamic DiD: Effect on Capital



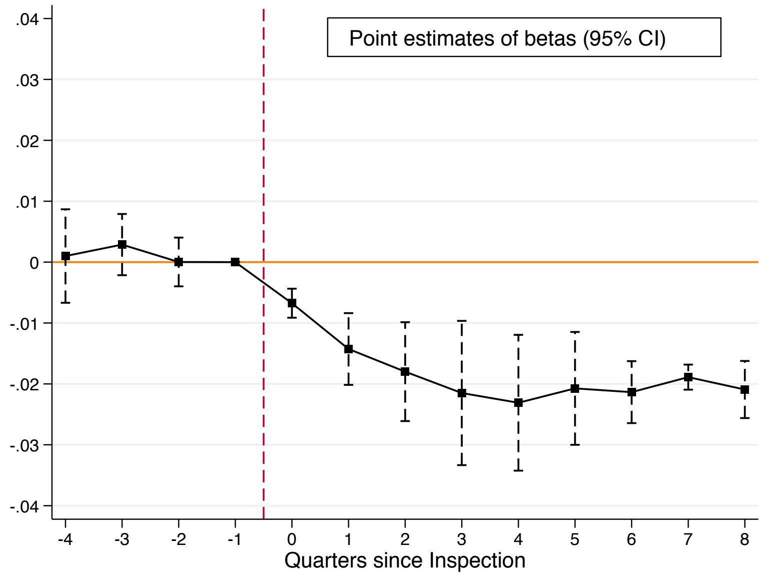
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$.The outcome variable is the log of capital. 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 A8. Dynamic DiD: Effect on Bank's Efficiency - log(cost to Income)



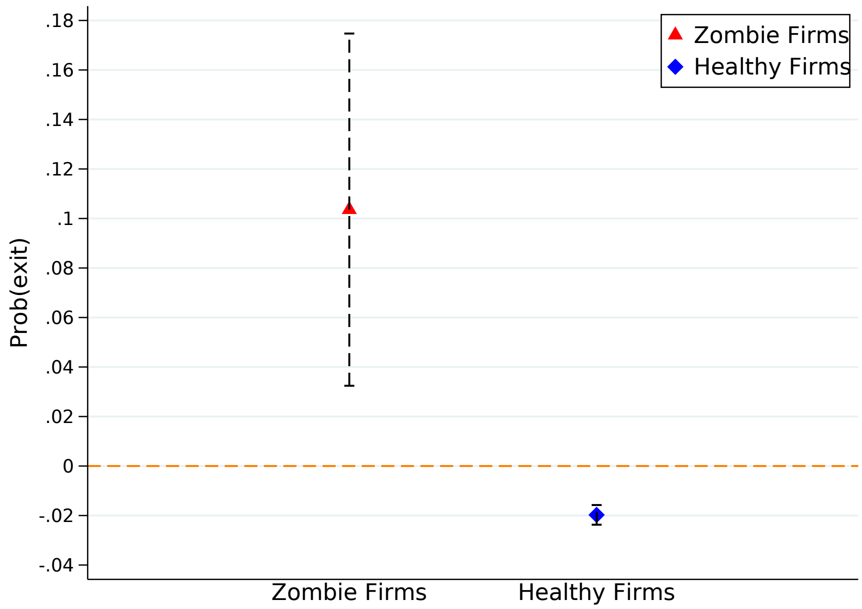
Notes: This graph plots the result of the following regression: $y_{bptm} = \alpha_t + \alpha_b + \alpha_{pm} + \sum_{\tau=-4}^{+8} \beta_\tau Inspected_{bptm} \times \left\{\mathbb{1}_{\tau=t}\right\} + \sum_{\tau=-4}^{+8} \gamma_\tau X_{PRE,b,p,m} \times \left\{\mathbb{1}_{\tau=t}\right\} + \varepsilon_{btpm}$.The outcome variable is the log of cost to income. 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 A9. Dynamic Diff-in-Diff: log(*loans to household*)



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 loans to households. 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 A10. Effect on Probability of Exit



Notes: This figure shows the results of the following regression: $Prob(exit_i) = \beta Exposure_{ip} + \eta_l + \eta_c + \eta_t + \gamma S_{i,PRE} + \epsilon_{itp}$. The outcome variable is $Prob(exit_i)$ and represents the probability that the firm exists the market within two years from 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, sales growth, 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, and industry fixed effects. We cluster the standard errors at the industry level. Coefficients are standardized.

TABLE A1. Bank-level Regression: Non Parametric model

VARIABLES	(1) log(NPL)	(2) log($tot\ loans$)	(3) log($Loans\ to\ Firms$)	(4) log($Loans\ to\ SME$)
-4	0.002	0.003	0.002	-0.001
	(0.012)	(0.005)	(0.005)	(0.005)
-3	0.007	0.002	0.001	0.000
	(0.008)	(0.003)	(0.003)	(0.003)
-2	0.004	0.002	0.002	-0.000
	(0.004)	(0.003)	(0.003)	(0.002)
0	0.024*	-0.011***	-0.012***	-0.007**
	(0.011)	(0.002)	(0.002)	(0.002)
1	0.055***	-0.021***	-0.023***	-0.013**
	(0.011)	(0.004)	(0.004)	(0.005)
2	0.046***	-0.025***	-0.026***	-0.015**
	(0.009)	(0.006)	(0.006)	(0.005)
3	0.034***	-0.028***	-0.029***	-0.016**
	(0.009)	(0.007)	(0.007)	(0.007)
4	0.025**	-0.025**	-0.025**	-0.012
	(0.008)	(0.008)	(0.008)	(0.007)
5	0.021	-0.017**	-0.016*	-0.004
	(0.012)	(0.006)	(0.007)	(0.006)
6	0.026	-0.013**	-0.012*	0.002
	(0.021)	(0.005)	(0.006)	(0.005)
7	0.023	-0.003	-0.003	0.011**
	(0.018)	(0.005)	(0.006)	(0.004)
8	0.020	0.001	0.002	0.015*
	(0.023)	(0.004)	(0.007)	(0.007)
Observations	29,855	30,054	30,054	30,054
R-squared	0.974	0.991	0.990	0.990
bank FE	Y	Y	Y	Y
IP×Macro Area FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y
Bank controls Cluster	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{bp} == \beta \sum_{\tau=-4}^{+8} Inspected_{bp} + \gamma X_b + \delta W_{b,PRE} + \epsilon_{bp}$. We include bank FE, Inspection plan FE, and quarter FE. The time dummy variables refer to quarters relative to the the banking inspection. We omit event time 1. Note that we normalize $\beta_{\tau=-1} = 0$ so that all coefficients represent the differences in outcomes relative to the quarter before the inspection. Column (1) considers the log(NPL). Column (2) the log(Total Loans). Column (3) the log(loans to firms) and column (4) the log(Small and Medium Enterprise). * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A2. Bank-level Regression: Parametric model - Long term effect

VARIABLES	(1) log(NPL)	(2) log($tot\ loans$)	(3) log($Loans\ to\ Firms$)	(4) log($Loans\ to\ SME$)
post ×inspection	0.025**	-0.014*	-0.016*	-0.004
	(0.008)	(0.006)	(0.008)	(0.006)
Observations	29,855	30,054	30,054	30,054
R-squared	0.974	0.991	0.990	0.990
bank FE	Y	Y	Y	Y
Inspection Plan Year 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 results of the following equation: $y_{bp} = \beta Post_{pt} \times Inspected_{bp} + \alpha_{ip} + \gamma X_{ib} + \delta W_{b,PRE} + \epsilon_{ibp}$. Column (1) considers the log(NPL) where NPL stands for Non-Performing Loans. Column (2) the log(Total Loans) where Total loans includes loans to both households and firms (i.e. *famiglie consumatrici* and *famiglie produttrici*). Column (3) considers the log(loans to firms) and column (4) the log(Small and Medium Enterprise), i.e. a subgroup of firms. Each bank included in the inspection plan p is observed 4 quarters before and 8 quarters after the inspection. This is the parametric version of Table A1. * p< 0.10, ** p< 0.05, *** p< 0.01.

Table A3. 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 A3 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 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 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.

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 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.

Table A6. Placebo Test:

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 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 A7. Bank-level Regression: Parametric model - arbitrary picked banks atc- Short term effect

VARIABLES	(1) log(NPL)	(2) log(Total Loans)	(3) log(Loans to Firms)	(4) log(Loans to SME)
post × inspected	-0.043	-0.068**	-0.070**	-0.034
	(0.069)	(0.024)	(0.028)	(0.026)
Observations	16,935	17,085	17,085	17,085
R-squared	0.979	0.992	0.992	0.993
bank FE	N	N	Y	Y
Quarter FE	Y	Y	Y	Y
IP ×Macro-Area FE	Y	Y	Y	Y
bank controls	Y	Y	Y	Y
Cluster	bank-IP	bank-IP	bank-IP	bank-IP

Notes: This table shows the results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post_{tb} \times Inspection_{bp} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank FE, Inspection plan-macro area FE and quarter FE. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio. The treated group (inspected) consists only of banks that are arbitrarily picked by the bank supervisor without the use of the computer algorithm. Column (1) considers the log(NPL), column (2) the log(total loans), column (3) the log(loans to firms) and column (4) the log(loans to Small and Medium Enterprises). IP stands for Inspection Plan. We consider only the four quarters before and the four quarters after the inspection. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A8. 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:

$$\operatorname{logit}(e_{ij}) = \alpha_0 + X_{ij}\beta \tag{.1}$$

and matching algorithm

$$A_{rj} = \left\{ kj' \in I_0 : \hat{e}_{kj'} = \min_{kj' \in I_0} \left| \hat{e}_{rj} - \hat{e}_{kj'} \right| < 0.25\hat{\sigma}_e \right\} \tag{.2}$$

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

Table A9. 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)
inspected	0.019	-0.005	-0.006	-0.005	-0.006
	(0.016)	(0.014)	(0.014)	(0.016)	(0.016)
inspected $\times$ 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 FE	Y	Y	Y	Y	Y
bank 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: $credit\ growth_{ib,t} = \beta Post_{bpt} \times Inspected_{bp} + +\eta\Big(Post_{bpt} \times Inspected_{bp} \times TFP_{i,PRE}\Big) + \alpha_{it} + \gamma X_{b,PRE} + \delta W_{ib,PRE} + \epsilon_{ibp}$. 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 column (4) and (5), the outcome variable is the following: $\Delta \log(credit_{ib,t}) = \log(credit_{ib,t}) - \log(credit_{ib,t-1})$. $Post_{bpt}$ is a dummy variable equal to 1 for the quarters after bank b, included in inspection plan p is inspected. $Inspected_{bp}$ is a dummy equal to 1 if bank b included in inspection plan p is inspected, 0 if it is eligible but not inspected. $TFP_{i,PRE}$ 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 bank FE, Inspection plan-macro area FE and quarter FE. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital 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 NPL 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 A10. Balance Test: Healthy vs. Reclassified

(1) Variables	(2) Healthy Firms	(3) Reclassified Firms	(4) Number of Firms	(5) Difference
Total Assets	3926.628	5320.108	334340	-1393.480***
				(232.147)
Leverage	1.279	1.857	334340	-0.579***
				(0.013)
ROA	3.380	-12.346	332072	15.726***
				(0.277)
Cash Flow	152.641	-236.979	331443	389.620***
				(12.288)
Cash\Total Assets	0.074	0.037	309429	0.036***
				(0.003)
EBIT\Revenues	-0.030	-0.607	321597	0.577***
				(0.009)
Total Debt\EBITDA	13.261	-7.571	332293	20.831***
				(2.075)
Intangible Assets\Total Assets	0.059	0.068	250241	-0.009*
				(0.004)
Tangible Assets\Total Assets	0.240	0.245	317887	-0.005
				(0.007)
Total Credit\Total Assets	0.398	0.387	331828	0.011
				(0.006)

Notes: Table A10 shows averages for firms that are subject to loss underreporting in a given year. The second column of the right panel shows differences in means relative to firms that have their loans reclassified. Column (2) shows mean for healthy firms. Column (3) reports the mean for reclassified firms. Column (5) reports the difference in means. Standard Errors are in parenthesis. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A11. Bank-level Regression: Parametric model - Treatment Group: Banks arbitrarily picked

VARIABLES	(1) log(NPL)	(2) log(Total Loans)	(3) log(Loans to Firms)	(4) log(Loans to SME)
post × inspected	-0.056	-0.071***	-0.077**	-0.038
	(0.064)	(0.017)	(0.022)	(0.023)
Observations	16,935	17,085	17,085	17,085
R-squared	0.978	0.992	0.991	0.992
bank FE	N	N	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 results of the following equation: $y_{btpm} = \alpha_t + \alpha_b + \alpha_{pm} + \beta^{ATE} Post_{tb} \times Inspection_{bp} + \gamma X_{b,PRE} + \varepsilon_{btpm}$. We include bank FE, Inspection plan-macro area FE and quarter FE. We include pre-defined bank-level controls: size (natural logarithm of lagged total assets), ROA, liquidity ratio, deposit ratio, capital ratio, and NPL ratio. The treated group (inspected) consists only of banks that are arbitrarily picked by the bank supervisor without the use of the computer algorithm. Column (1) considers the log(NPL), column (2) the log(total loans), column (3) the log(loans to firms) and column (4) the log(loans to Small and Medium Enterprises). IP stands for Inspection Plan. We consider only the four quarters before and the four quarters after the inspection. * p< 0.10. ** p< 0.05, *** p< 0.01.

Table A12. Probability of exiting the market

	exit			
	Zombie Firms		Healthy Firms	
	(1)	(2)	(3)	(4)
VARIABLES	Pr(exit)	Pr(exit)	Pr(exit)	Pr(exit)
Exposure	0.104***	0.104***	-0.024***	-0.020***
	(0.032)	(0.036)	(0.002)	(0.002)
Observations	35,143	25,854	324,295	309,554
R-squared	0.139	0.144	0.473	0.496
Province FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm controls	N	Y	N	Y
Cluster	industry	industry	industry	industry

Notes: This table shows the results of the following regression: $Prob(exit_i) = \beta Exposure_{ip} + \eta_l + \eta_c + \eta_t + \gamma S_{i,PRE} + \epsilon_{itp}$. The outcome variable $Prob(exit_i)$ is the probability that the firm exists the market within two years from 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, sales growth, 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.

Table A13. Correlation

	(1)	(2)	(3)	(4)
VARIABLES	Exposure$_{t-1}$	Exposure$_{t-1}$	Exposure$_{t-1}$	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 can 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 are clustered at the province level.

Appendix A. On-site Inspections

There are two main phases of the banking inspection process: (1) pre-inspection activity; (2) inspection activity. Both phases use a procedure called MARC (Monitoraggio Andamento Rischiosita' Creditizia - Credit Risk Trend Monitoring). The pre-inspection activity is performed during the period in which the Bank of Italy defines the inspection plan for the next year. This is generally around the spring of the year before the inspection is performed and it is used as a first screening to select banks that are eligible to be inspected. This is an evaluation of the credit positions held by the bank. The evaluation considers all problematic credits and a portion of performing credits – about 20% of performing credits in the bank's portfolio. The evaluation usually considers the largest share of credits to avoid the evaluation of too many positions. If the bank is actually selected to be inspected, there is an additional inspection phase which is performed locally at the supervised bank's office. The audit consists of an intense few weeks of field work - depending on the size of the bank and the complexity of its activity - where inspectors evaluate the vast majority of credit positions not limiting themselves to only non-performing loans (NPL).[1] After this process, the inspectors follow the MARC procedure to write a report of the audit. In their audits, inspectors combine information from the Credit Registry, the banks' balance sheet as we as information from Cerved regarding firms' balance sheet and income statement. Moreover, inspectors can have access to all private information regarding a loan available in the bank's office such as private mail between the firm and the bank, and all sort of internal information about a particular loan such as the loan application. The audits have the goal of validating a bank's quality of its assets and of its reporting activity. The audits may have several consequences. The most common consequence is an adjustment of the bank's balance sheet. The inspector can force the reclassification of a credit from performing into non performing. In some cases, it can suggest the readjustment of the expected value of the loan by writing-off some of its amount.[2] During on-site inspections, the Bank of Italy may also discover potential or actual violations of administrative laws and of secondary regulations, or of criminal state laws. In the first case, a process is initiated and the potential violations may give rise to sanctions against the bank or its administrators, statutory auditors, and directors. Sanctions are generally of pecuniary nature, but can also cause representatives administrators to temporarily or permanently lose their fit-and-proper status. The sanctions are proposed by the Banking Supervision and regulation directorate and are administered by the Board of the Bank of Italy. The sanctioned subjects have a right to be heard during the procedure. They may appeal to a court against the final decision made by the Bank of Italy. The sanctioning measures are published on the Bank of Italy's website.[3] In case of actual or potential violations of criminal state laws, the Bank of Italy alerts the competent prosecutors, who have judiciary powers and may autonomously decide to start an investigation. These cases are a subset of the sanctioning cases. The relevant data are not published, but they are available to the Bank of Italy, so we can use them in the analysis. Unfortunately, we do not have information on the final outcome of these procedures, i.e. whether these referrals do or do not end up in actual convictions.

[1]The number of days per inspection are on average 66 as reported by figure 3D..

[2]Technically this is only a "suggestion" since this is a business decision. The Bank of Italy cannot impose decisions unless it breaks the law.

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