The Disciplining Effect of Bank Supervision: Evidence from SupTech

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Abstract

Regulators around the world increasingly rely on supervisory technologies (SupTech) to support bank supervision, but little is known about how SupTech could affect the banking sector. To address this knowledge gap, we use confidential data from the Central Bank of Brazil to analyze how supervisory actions arising from the central bank's SupTech application affect bank balance sheets and bank lending, and the potential spillover effects to the real economy. We find that the supervisory actions induce banks to reveal inconsistencies in their reported credit risk and to tighten credit to less creditworthy firms, thereby reducing bank risk-taking. In turn, this credit tightening affects the performance of less creditworthy firms that borrow from affected banks, indicating that there are spillover effects to the real economy. Further tests suggest that these results are due to the disciplining effect of supervisory scrutiny, which induces bank to become more prudent. Overall, our findings provide novel insights into the role of SupTech in bank supervision.

Keywords: Bank supervision, SupTech, Bank risk-taking, Bank lending, Real effects

PRELIMINARY WORK, PLEASE DO NOT CITE OR CIRCULATE

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"Supervisory technology (SupTech) is the use of innovative technology by supervisory agencies to support supervision. It helps supervisory agencies to digitize reporting and regulatory processes, resulting in more efficient and proactive monitoring of risk and compliance at financial institutions." (Financial Stability Institute, 2018)

1. Introduction

Regulatory enforcement is a cornerstone of financial stability. This notion has regained attention, as weaknesses in the regulatory and supervisory framework played a pivotal role in establishing the conditions for the global financial crisis (Dewatripont et al., 2010; Laeven et al., 2010). In the past decade, regulators around the world have therefore advocated tighter bank regulation and supervision, with a focus on the *prevention* of regulatory non-compliance and financial distortions (BCBS, 2015; BIS, 2018).

To this end, regulators increasingly rely on supervisory technologies (SupTech) for the early detection and prevention of potentially risky bank behavior. For instance, based on a survey covering 39 financial authorities, the Bank for International Settlements (BIS) finds that at least half of financial authorities use SupTech applications in the conduct of bank supervision (BIS, 2019). In general, SupTech applications digitize and analyze banks' regulatory reports to identify financial distortions or regulatory non-compliance, allowing for more proactive bank supervision targeted at banks where weaknesses are most likely to be found (Financial Stability Institute, 2018). Thus, by allowing for more proactive bank supervision, SupTech is meant to prevent regulatory non-compliance and financial distortions.

Despite the use of SupTech by supervisory agencies around the world, there is no empirical evidence on the role of SupTech as a supervisory tool. In this study, we use administrative data from the Central Bank of Brazil to address this gap in the literature. Particularly, we study how supervisory actions arising from the central bank's SupTech application (SupTech events) affect banks' balance sheet and lending decisions, and the potential spillover effects to the real economy.[1] This is important to study because, as explained in more detail below, the supervisory actions arising from SupTech differ from other supervisory actions, such as bank sanctions. Unlike bank sanctions, for instance, SupTech is aimed at preventing (rather than penalizing) regulatory non-compliance, and this preventive motive makes it unclear whether SupTech events are merely a "check-the-box"

[1] In the rest of the paper, we will use supervisory actions and SupTech events interchangeably.

regulatory constraint or whether SupTech events can discipline banks.

Our paper proceeds in three steps. In the first part of the paper, we examine whether the supervisory actions arising from the central bank's SupTech application have an impact on banks' balance sheet. In particular, using financial statement data on banks operating in Brazil, we analyze the impact on various balance sheet items, including banks' non-performing loans, loan loss provisions, capitalization, profitability, and aggregate lending. We find that, after a SupTech event, treated banks reclassify loans as non-performing and increase provisions for expected loan losses, particularly for risky loans. The effects that we find are economically significant. Our results for instance indicate that, after a SupTech event, treated banks' reported non-performing loans and provisions for expected loan losses increase by approximately 20%. We do not find that the actions affect banks' capital position, profitability, or aggregate lending. Taken together, these results suggest that supervisory scrutiny arising from the central bank's SupTech application improves banks' financial reporting quality—by revealing inconsistencies in banks' reported credit risk—without deteriorating banks' financial stability (Delis et al., 2018; Passalacqua et al., 2022).

To identify the potential drivers underlying this effects, we run three tests. First, we use information on the types of issues reported by the SupTech application and show that the effects are not driven by a subset of issues related to regulatory non-compliance, i.e., the more severe issues. Second, we use information on the time to resolution and show that the effects are not driven by a subset of issues that takes longer to be resolved by the affected banks, i.e., larger or more complicated issues. Third, we use information on the location of banks' headquarters to show that SupTech events have within-municipality spillover effects. Specifically, we show that SupTech events do not only affect the risk reporting of targeted banks, but also the risk reporting of non-targeted banks operating in the same municipality as the targeted banks. Based on the tax enforcement literature (e.g., see Colonnelli and Prem, 2022; Pomeranz, 2015), this suggests that there is a "deterrence effect", where increased perception of regulatory enforcement in the future improves banks' regulatory compliance in the present (also see Gopalan et al., 2019). In other words, SupTech events—which are completely unanticipated—might change banks' perception of what the regulator knows and can reasonably find out, and thereby improve banks' regulatory compliance. Conceptually, this channel is similar to the "supervisory scrutiny channel" documented by Kok et al. (2023) in the context of the EU-wide stress test.[2]

[2] Kok et al. (2023) show that banks that participated in the EU-wide banking sector stress test in 2016 reduced

In the second part of the paper, we use granular firm-bank-loan data to investigate whether the supervisory actions arising from the central bank's SupTech application have an impact on banks' credit supply. In essence, the literature has proposed two hypotheses for the effects of bank supervision on bank lending. On the one hand, the capital shock channel suggests that—by putting pressure on banks' capital ratios—supervisory scrutiny may reduce banks' credit supply (Bernanke et al., 1991; Caballero et al., 2008; Peek and Rosengren, 2000). On the other hand, the reallocation channel suggests that—by forcing banks to truthfully report problem loans and loan losses—supervisory scrutiny can mitigate banks' evergreening behavior and lead to a reallocation of credit supply from less creditworthy to more creditworthy borrowers (Bonfim et al., 2022; Granja and Leuz, 2018). Inconsistent with the capital shock channel, we do not find that treated banks reduce credit supply after a SupTech event. Instead, consistent with the reallocation channel, we find that SupTech events induce treated banks to reduce credit to less creditworthy borrowers. These results hold for different proxies of borrowers' creditworthiness and for the inclusion of high-dimensional fixed effects that control for credit demand and the endogenous matching of banks and borrowers. Similarly, we find that supervisory scrutiny induces banks to increase the interest rate and to reduce the maturity of loans granted to less creditworthy borrowers. In terms of economic magnitude, our results indicate that the SupTech events induce banks to reduce less creditworthy borrowers' credit by five percent, increase loan rates by twenty percent, and reduce loan maturities by five percent (relative to more creditworthy borrowers). Together, these results are consistent with the hypothesis that supervisory scrutiny induces more prudent bank lending.

In the third part of the paper, we examine the spillover effects to the real economy. As we find that the supervisory scrutiny changes treated banks' lending behavior, we study the impact of SupTech events on the outcomes of firms borrowing from treated banks. In particular, we analyze how firms' credit exposure to treated banks affects firms' leverage, employment, profitability, and productivity. While we do not find spillover effects for the average firm borrowing from a treated bank, we do find that less creditworthy firms cannot completely compensate the reduction in credit from treated banks with credit from non-treated banks, and that this reduction in credit results in a small deterioration in the economic activity of less creditworthy firms. For instance, after a SupTech event, less creditworthy borrowers report a decrease in profitability and productivity of about one percent. Thus, while we find evidence of spillover effects to the real economy, the

their credit risk compared to banks that did not participate. In additional analyses, they show that this effect is due to the fact that the supervisory scrutiny associated with the stress test has a disciplining effect on banks.

economic magnitude of these spillover effects is limited. Importantly, this is in contrast with the large, adverse spillover effects of bank sanctions (Danisewicz et al., 2018), and the positive spillover effects of on-site bank inspection programs (Bonfim et al., 2022). In this sense, our results suggest that there is a trade-off between the severity and the impact of supervisory actions, with formal supervisory actions having larger effects than informal supervisory actions.

Throughout the paper, we use difference-in-differences regressions with a large set of controls and fixed effects to estimate the real effects of supervisory scrutiny arising from the central bank's SupTech application. Nevertheless, a potential concern is that our results are due to the non-random assignment of SupTech events (i.a., that treated bank are inherently different from non-treated banks). To alleviate this concern, we use four methods to ensure that our estimates are well-identified. First, we estimate dynamic difference-in-differences models and show that the parallel trends assumptions are not violated. Second, we show that our results are robust to a propensity score matching approach, suggesting that our results are not driven by other pre-existing bank characteristics. Third, we show that our results are robust to falsification tests, suggesting that our results are not driven by other events that may have occurred at the same time as the supervisory actions. Finally, considering concerns about biased estimates from two-way fixed effects estimators (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021), we show that our results are robust to using an alternative estimator that addresses these concerns.

In sum, our paper provides evidence that supervisory actions arising from SupTech applications can reduce inconsistencies in banks' risk reporting and reduce risk-taking in banks' lending decisions. This implies that the SupTech events are not merely a "check-the-box" regulatory constraint (Kok et al., 2023), but that supervisory scrutiny from SupTech events has a disciplining effect on the banking sector.

Related Literature. Our paper primarily contributes to the literature on the real effects of bank supervision. Several studies have examined the effect of bank supervision on bank risk-taking, bank lending, and the spillover effects to the real economy.[3] This literature has put forward two possible effects of increased supervisory scrutiny on bank lending. On the one hand, the capital

[3]To estimate the causal effects of bank supervision, previous papers have used variation in the entity of the supervisory authority (Agarwal et al., 2014; Ampudia et al., 2021; Granja and Leuz, 2018; Haselmann et al., 2023), the location of the supervisor (Kandrac and Schlusche, 2021), the quasi-random selection of bank inspections (Passalacqua et al., 2022), the frequency of the supervisory actions (Rezende and Wu, 2014), and variation in supervisory intensity (Ivanov et al., 2019). In general, these studies suggest that bank supervision effectively reduces bank risk-taking and affects credit allocation, but the effects depends on the supervisory framework or the supervisory entity (also see Berger et al., 2016; Hirtle et al., 2020; Pierret and Steri, 2020).

shock channel suggests that supervisory actions may reduce credit supply (Bernanke et al., 1991; Caballero et al., 2008; Peek and Rosengren, 2000). By forcing banks to recognize problem loans, supervisors put pressure on banks' capital ratios so that banks either have to raise capital or cut lending to make sure they do not fall short of the regulatory requirements. As raising capital tends to be more costly than reducing risk exposures, the capital shock channel posits that bank supervision induces banks to reduce credit supply. On the other hand, the reallocation channel suggests that supervisory scrutiny may lead to a reallocation of credit supply from less creditworthy to more creditworthy borrowers (Granja and Leuz, 2018). By forcing banks to truthfully report loan losses, supervisors can mitigate banks' evergreening behavior (i.e., banks' incentive to roll over credit to impaired borrowers), leading to a reallocation of credit from unproductive to productive borrowers (Bonfim et al., 2022). Previous papers that study the real effects of bank supervision have however come to different conclusions (e.g., see Bonfim et al., 2022; Danisewicz et al., 2018; Granja and Leuz, 2018; Passalacqua et al., 2022). Consequently, by showing that supervisory actions arising from the Central Bank of Brazil's SupTech application can improve the quality of banks' financial statements and reduce bank risk-taking, our paper directly contributes to a better understanding of the real effects of bank supervision.

More particularly, our paper contributes to the literature on the effects of supervisory actions in the banking sector, which has primarily focused on two types of actions: (1) bank sanctions (i.e., bank enforcement actions) (Danisewicz et al., 2018; Delis et al., 2017; Gopalan et al., 2019; Roman, 2016) and (2) on-site bank inspection programs (Agarwal et al., 2014; Bonfim et al., 2022; Passalacqua et al., 2022). First, the literature on bank sanction has focused on the effects of formal enforcement actions against U.S. banks, and shows that bank sanctions improve banks' financial soundness and reduce banks' risk-taking (Delis et al., 2017; Delis and Staikouras, 2011). However, it remains unclear whether these effects are due to supervisory scrutiny or other factors, such as monetary penalties or reputational costs of bank sanctions (Degryse et al., 2023; Roman, 2016).[4] Second, the literature about on-site bank inspections is limited and has primarily focused on periodic on-site bank inspection programs. Bonfim et al. (2022) and Passalacqua et al. (2022), for instance, study the effect of on-site bank inspection programs carried out by the Central Bank of Portugal and the Central Bank of Italy, respectively, and show that the inspections reduce banks' incentive to provide credit to unproductive firms. These bank inspections programs are however periodic, predetermined

[4]Banks sanctions sometimes require banks to pay fines or to make a monetary restitution to affected parties. Bank sanctions may also impose reputational costs because they tend to be announced publicly.

supervisory actions and, unlike the SupTech events studied in our paper, not necessarily geared towards preventing regulatory non-compliance. Our paper contributes to the literature by analyzing the effect of supervisory actions arising from the regulator's SupTech application developed to detect and prevent early risk exposures, and by showing that these supervisory actions can discipline bank risk-taking.

Our paper also relates to the literature on supervisory frameworks in the banking sector. This literature has investigated how institutional features (Agarwal et al., 2014; Carletti et al., 2021; Calzolari et al., 2019; Haselmann et al., 2023), resource constraints (Eisenbach et al., 2022; Kandrac and Schlusche, 2021), and incentive problems (Ganduri, 2018; Lucca et al., 2014) affect the effectiveness of bank supervision. However, little is known about the potentially different effects between formal (punitive) actions, such as bank sanctions, and informal (non-punitive) supervisory actions, such as SupTech events. Our paper makes a first step in this direction by showing that even informal supervisory actions can discipline banks.

The remaining part of this paper proceeds as follows. Section 2 describes the institutional background of the regulatory oversight of Brazil's financial system. Section 3 introduces the datasets used in the analysis. Section 4 discusses the effect of supervisory scrutiny on banks' balance sheet, Section 5 the effect on banks' lending decisions, and Section 6 the effect on firm outcomes. Finally, Section 7 concludes the analysis.

2. Background

Brazil has a robust bank supervision framework (IMF, 2018). The Central Bank of Brazil, who is responsible for the regulatory oversight of financial institutions, monitors the financial system from a macro- and a micro-prudential perspective (Banco Central do Brasil, 2022; Vivan et al., 2023).[5] In terms of macro-prudential supervision, the central bank uses various tools, such as macroeconomic stress tests, to monitor the stability of the financial system in its entirety. In terms of micro-prudential supervision, the central bank uses both on-site inspections and off-site supervisory technologies to monitor the economic and financial situation of individual financial institutions. Specifically, financial institutions are subject to periodic on-site bank inspections, which occur every one to three years, depending on the systemic importance of the institution. In addition to

[5] A comprehensive overview of the supervisory processes of the Central Bank of Brazil can be found at https://www3.bcb.gov.br/gmn/visualizacao/listarDocumentosManualVinculadoPublico.do?method=pesquisarManualVinculadoPublico&idManualVinculado=2&idManual=1.

these periodic bank inspections, the central bank relies on a SupTech application that continuously monitors the financial sector with the aim to preemptively correct unsafe and unsound practices (i.e., before it could affect bank stability).[6]

Figure A1 illustrates the Central Bank of Brazil's supervisory framework, with a focus on the function of SupTech in the monitoring of financial institutions, and the supervisory units relying on this to take proactive supervisory actions. In general, the central bank's SupTech application digitizes reporting and regulatory processes, which it then analyzes to help to identify banks where problems might be emerging. Specifically, the procedures of the SupTech application include the assessment of banks' on- and off-balance positions from three fundamental perspectives, namely (1) temporal assessment (i.e., evaluation of past changes in banks' balance sheet items in order to provide insight into future trends), (2) comparative assessment (i.e., evaluation of banks' performance compared to its peer groups), and (3) intrinsic assessment (i.e., evaluation of the bank in relation to itself according to objective analysis parameters). Based on these three assessments, the application functions as an early warning system which generates automatic alerts for variations in various (financial) indicators and ratios.[7] These automatic alerts (or irregularities) are reviewed by analysts of the monitoring unit (DESIG), who are responsible for formally notifying the supervisory units (DESUP, DESUC, or DECON). The analysts of DESIG then describe the particular concern and explain what research may have been done to examine or address the irregularity. Based on this information and additional information collected from supervised entities, the supervisory units of DESUP, DESUC, or DECON can take the necessary actions to address the supervisory concerns. These actions be as formal as an on-site visit, and as informal as an email exchange between the supervisory unit and the affected bank. The supervisory actions (SupTech events) resulting from this process are the focus of our paper, and are comparable to the informal supervisory actions taken by the Federal Reserve to induce banks to rectify potential problems (see Hirtle et al., 2020).

Compared to formal on-site bank inspections and bank sanctions, the supervisory scrutiny arising from the central bank's SupTech events is unique along two dimensions.[8] First, on-site bank

[6]Note that the micro-prudential supervision process of Brazil is relatively similar to that of the United States and other developed economies. For instance, in the US, bank supervisors conduct at least one full-scope, on-site examination of each bank every twelve months, with poorly-rated banks being examined more frequently (Kupiec et al., 2017). In addition to these periodic inspections, US regulators rely on supervisory monitoring procedures, which are based on information reported under banks' regulatory reporting requirements, in order to identify weaknesses in the operations of individual institutions (CRS, 2020).

[7]The reliability of the information used in the SupTech application is automatically verified by internal consistency tests and validation rules developed by the central bank.

[8]Clearly, the supervisory actions that we analyze are also different from stress-tests. First, unlike stress tests, the SupTech application employed by the Central Bank of Brazil does not tests whether banks could withstand a

inspections occur on a predetermined basis and involve a detailed examination of banks' entire operations,[9] while the SupTech events that we analyze are unplanned and focused on a particular part of banks' operations (related to the specific issue that has been reported). Second, bank sanctions correspond to publicly announced penalties imposed due to bank misconduct, while the SupTech events that we analyze are not publicly announced and aimed at preemptively resolving potential distortions, without imposing penalties. In sum, the SupTech application of the Central Bank of Brazil helps to direct supervisors towards banks where weaknesses are most likely to be found, resulting in "more focused supervision" that "allows the supervisor to act preemptively" (Banco Central do Brasil, 2022).

3. Data

We leverage several unique datasets for our analysis. We use proprietary data on the Central Bank of Brazil's SupTech application, bank financial statement data, corporate credit register data, and firm financial statement data. Below, we provide further information on the sources and composition of each individual dataset.

3.1. SupTech data

We obtain detailed information from a proprietary dataset of the Central Bank of Brazil about "early warnings" and supervisory actions arising from the central bank's SupTech application. This supervisory dataset comprises information on the date, the underlying issue (or motive), and the time needed by the affected bank to resolve the SupTech event. Tables A1 and A2 provides information on the number of affected banks and the number of SupTech events. In total, 221 of the 1,325 financial institutions in our data sample were affected at least once over the years 2008-2021. Among these banks, 187 banks were affected once, 28 twice, and 6 three or more times. The average number of days needed by an affected bank to resolve a supervisory issue is about 50 days, but Figure A3

(hypothetical) negative economic shock. Second, unlike stress tests, the supervisory actions studied in our paper are not publicly announced (meaning that there could not be reputation effects, for instance).

[9] In the study by Bonfim et al. (2022), the bank inspections involved a cooperation between the IMF, the European Commission, the European Central Bank, and the Banco de Portugal. These inspections were very intensive in terms of the coordination efforts between the different parties involved and the human resources used. In addition, these inspections were highly intrusive in the sense that supervisors could not only analyze loans on a one-by-one basis and talk to loan officers, but also directly talk to the treated banks' borrowers (possibly eroding the reputational capital of the treated banks). Similarly, the on-site inspections analyzed by Passalacqua et al. (2022) were remarkably intrusive as supervisors from the Bank of Italy could, for instance, review a bank's mail exchanges with a borrower to assess the bank's reporting quality. This is not the case for the inspections analyzed in our study.

shows that this distribution is highly skewed as the median number of days needed is only 25 days (indicated by the red vertical line).[10]

As mentioned, the supervisory dataset also contains detailed information on the underlying supervisory concerns. Twenty different types of underlying supervisory concerns have been recorded, which can be grouped into two broad topics: (1) regulatory non-compliance and (2) financial reporting inconsistencies.[11] The frequency distribution of the two topics is displayed in Figure A2, which shows that the majority of the supervisory concerns (62%) is related to regulatory non-compliance, which confirms the notion that regulation relies on supervision for its enforcement.

3.2. Bank financial statement data

Accounting data of the regulated financial institutions is provided by the Central Bank of Brazil. By law, financial institutions operating in Brazil have to provide balance sheet files on a monthly or quarterly basis (depending on their institutional structure). These files contain the balance sheet data for the individual institutions as well as the financial consolidates at a monthly frequency. Variables include, among others, total assets, deposits, equity, liquid assets, gross loans, non-performing loans, and loan loss provisions. In addition, we have access to detailed information on banks' ownership structure from the UNICAD dataset managed by the Central Bank of Brazil. We restrict our sample to financial institutions active in the Brazilian credit market, which results in a sample of 1,325 financial institutions. Table A3 provides summary statistics.

3.3. Credit register data

We use quarterly data on bank lending at the bank-firm-loan level from the supervisory credit register (Sistema de Informações de Crédito—SCR) administered by the Central Bank of Brazil. This dataset contains detailed information on virtually all corporate loans above BRL 5,000 (i.e.,

[10] In the analysis of Passalacqua et al. (2022), the mean and median number of days that a team of supervisors spends per on-site bank inspection corresponds to 66 days. In our case, 50% of the SupTech events are resolved in less than 25 days, with supervisors spending only a fraction of that period on actually resolving a SupTech event. This implies that the supervisory actions analyzed in our study are much less labor intensive, which in line with the idea that SupTech leads to more efficient bank supervision (Financial Stability Institute, 2018).

[11] Due to confidentiality restrictions, we cannot provide detailed statistics on each of he twenty underlying supervisory concerns.

approximately USD 1,000 in May 2023)[12] granted to non-financial institutions in the Brazilian financial system. Specifically, the SCR includes information on the contractual loan amount, loan type, interest rate, initial and due dates, collateral value, collateral type, and credit risk classification of every particular loan at a monthly frequency. The data tracks loan performance, which means we also have information on loan amounts in arrears and loan defaults. Table A4 provides summary statistics of the credit data used in our analysis. To compute the loan size, we use the sum of the outstanding loan amount, unreleased credit, and credit lines, which together make up the total amount available for the firm. We also exclude government-funded loans from our data sample as most of the terms of these loans are not decided by banks themselves.[13] Ultimately, our data sample covers roughly 50% of all corporate loans competitively made to firms in Brazil from 2008 to 2021.

3.4. Firm data

We obtain firm employment and profitability data from RAIS (Relação Anual de Informações), which essentially comprises all tax-registered firms operating in Brazil. The dataset is administered by the Brazilian Ministry of Labor and Employment and can easily be linked to the credit register data. The firm employment data contains quarterly information on the number of employees as well as the average salary of the employees, which also allows us to derive firms' quarterly wage expenses. The firm profitability data contains quarterly information on firms' profits. Further, we also have information on firm's size (this is a categorical variable based on four categories; micro, small, medium, or large). Table A5 provides summary statistics on the firm level data used in our analysis.

4. The effect on banks' balance sheet

4.1. Methodology

In our first analysis, we estimate the overall effect of SupTech events on banks' balance sheet. Following the empirical approach from Granja and Leuz (2018) and Passalacqua et al. (2022), we estimate the following difference-in-differences model:

[12] This limit has decreased over time and currently all loans above BRL 200 (i.e., approximately USD 40) are included in the SCR (Barroso et al., 2020).

[13] In Brazil, government-funded loans are allocated through public as well as private banks and make up around 50% of all loans. Importantly, government-funded loans are not decided by banks themselves as more than 80% of these loans are subject to interest rate caps and industry targets (see Santos, 2016).

$$y_{b,t} = \beta^{ATE} Post\ supervision_{b,t} + \delta \boldsymbol{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,t} \tag{1}$$

where b and t refer to bank and month, respectively. The dependent variable, $y_{b,t}$, represents various bank level outcomes, namely non-performing loans, loan loss provisions, capitalization, return on assets, and loan-to-assets.[14] $Post\ supervision_{b,t}$ is a dummy variable equal to one for the 24 months after bank b is treated. $\boldsymbol{X}_{b,t-1}$ is a vector of lagged control variables which, depending on the outcome variable, controls for banks' size, capital ratio, liquidity ratio, non-performing loans ratio, deposits ratio, and profitability. Further, α_b and α_t are bank and time fixed effects, respectively, to control for unobserved heterogeneity, and $\epsilon_{b,t}$ is the error term. Note that we do not include a separate $Post$ or $Supervision$ variable because the bank fixed effects already control for differences between affected and non-affected banks, while the time fixed effects control for unobserved aggregate fluctuations (Bertrand and Mullainathan, 2003).[15] The coefficient of interest is β^{ATE}, which captures the change in a bank level outcome of an affected bank (relative to a non-affected bank) after supervision (relative to the pre-supervision period).

Note that, in estimating the average treatment effect, we drop treated banks from the sample after their corresponding post-treatment period (i.e., two years after the SupTech event). The reason for this is that the effect of a bank supervision is not perpetual (i.e., treated banks do no remain treated). We omit this contamination problem by removing treated bank observations after the first SupTech event. Further, for banks that are treated more than once, we only keep the first bank SupTech event (as in Roman, 2020). The reason for this is that, in case subsequent SupTech events were included, it could occur that the pre-supervision window of the second SupTech event overlaps with the post-treatment window of the previous SupTech events, and this overlap could confound the estimations.[16]

4.2. Results

The estimates of Equation 1 are presented in Tables A8 and A9. We include bank controls in all regressions, and we gradually include bank and time fixed effects across the different columns. The

[14] All bank level variables are scaled by a bank's total assets.

[15] Our empirical strategy is designed such that the control group consists of never-affected as well as not-yet-affected banks. In robustness checks, we verify the reliability of this strategy. First, by applying a propensity score matching approach which compares affected banks to (observably similar) never-affected banks. Second, by applying a stacked differences-in-differences approach which compares affected to not-yet-affected banks.

[16] In a first robustness check, we exclude banks subject to multiple bank SupTech events and find that the results are robust. In a second robustness check, we run regressions controlling for whether a banks has multiple SupTech events and the results continue to hold.

standard errors are clustered by bank.

Table A8 presents regressions with problem loans, loan losses provisions, and loan loss provisions for risky loans as outcome variables.[17] Columns (1) to (3) show that affected banks reclassify more loans as problem loans (compared to non- banks) after supervision (compared to the pre-supervision period). The estimates are statistically as well as economically significant. The coefficient estimate in column (3), for instance, suggests that supervisory scrutiny leads to an approximately 20% increase in banks' recognized problem loans after a SupTech event. In addition, in line with evidence by Passalacqua et al. (2022), we find that banks are forced to cover for these problem loans by setting aside more provisions for (expected) loan losses. Particularly, the coefficient estimates in columns (4) to (6) show that the supervisory scrutiny lead to an increase in banks' loan loss provisioning expenses. When we distinguish between overall loan loss provisions and loan loss provisions for risky loans, columns (6) to (9) show that the effect of supervisory scrutiny on banks' loan loss provisions for bad loans is more pronounced than the effect on overall loan loss provisions. More specifically, treated banks set aside 20% more provisions for risky loans in the post-supervision period.

A financial stability concern is that, by forcing banks to set aside more loan loss provisions, bank supervision may adversely affect banks' capital position, profitability, or aggregate lending. Table A9 presents regressions with capital ratio, return on assets, and loans-to-assets as outcome variables.[18] Overall, we find statistically insignificant coefficient estimates across all columns. Hence, our results do not indicate that the supervisory scrutiny arising from the central bank's SupTech application adversely affect banks' stability or lending.

Overall, our results are in line with previous studies (e.g., Granja and Leuz, 2018; Passalacqua et al., 2022) and imply that bank supervision reveals a more accurate level of bank risk, thus enhancing banks' financial statement quality (Delis et al., 2018), without deteriorating bank' profitability or stability.

4.3. Robustness

4.3.1. Dynamic analysis

To assess whether the estimated effects are attributable to supervisory scrutiny, we verify the parallel trends assumption underlying our difference-in-differences model. That is, we verify whether there

[17] Table A10 also reports the coefficient estimate of *Treated*.

[18] Table A11 also reports the coefficient estimate of *Treated*.

is a significant effect only after, and not before, the supervisory actions. To do so, we estimate a dynamic version of the difference-in-differences estimator outlined in Equation 1, which can be specified as follows:

$$y_{b,t} = \sum_{\tau=-8}^{+24} \beta_\tau Supervision_{b,t} \times \{1_{\tau=t}\} + \delta \boldsymbol{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,t} \quad (2)$$

where $Supervision_{b,t} \times \{1_{\tau=t}\}$ is a dummy variable interacted with an event time indicator variable. Particularly, $Supervision_{b,t}$ is a dummy variable equal to one if bank b is treated at time t, so that the interaction term equals one if it is month τ relative to the month in which the bank is treated.

The results are presented in Figures 5(a) to 5(f) and generally support that the parallel trends assumption that underlies our difference-in-differences regressions is satisfied. Indeed, for periods prior to bank supervision, the coefficients are close to zero and statistically insignificant, which suggests that affected banks were not significantly different relative to non-affected banks before the supervisory actions took place. In line with our earlier findings, the results further indicate that treated banks' NPLs and provisioning expenses significantly increase (compared to non-treated banks) after supervision (compared to the pre-supervision period). These effects emerge almost instantly and gradually dissipate. On average, the effects become statistically insignificant after approximately fifteen months. We also find, consistent with our earlier estimates, that banks' capital position, profitability, and loans-to-assets do not significantly change after a supervisory action.

4.3.2. Propensity score matching

As discussed earlier, a potential concern is that the supervisory actions arising from the central bank's SupTech application is non-random, i.e., that the supervisory actions are not unrelated to (observable) bank characteristics. Although we control for a large set of bank variables in our regressions, concerns remain that our results are partly driven by differences between treated and non-treated banks. To address this endogeneity concern, we use a propensity score matching approach to construct a control group of non-treated banks that is observably similar to treated banks across a wide set of observable bank characteristics. To create this matched sample, we follow the standard approach in the literature. Specifically, for a bank b treated in period p, we compute the propensity score by running a logit model of the following form:

$$log(y_{b,p}) = \alpha_0 + \delta \boldsymbol{X}_{b,p} + \epsilon_{b,p} \quad (3)$$

where $\boldsymbol{X}_{b,p}$ is a vector of average values of bank-level variables the year prior to the supervisory actions. We then match (with replacement) a treated bank with a non-treated bank based on one-to-one nearest neighbor matching within a 0.25 standard deviations caliper of the estimated propensity score.

Based on the matched sample, we then re-estimate the regressions from Equation 1. The result are presented in Table A12 in Appendix. Overall, the propensity score matched difference-in-differences estimation confirms our baseline results as we find that banks' reported problem loans and loan loss provisions increases. Further, in line with our baseline estimates (from Table A8 and A9), we do not find an effect on banks' capital ratio, profitability, or loans-to-assets ratio. Note that the coefficient estimates in columns (1) to (3) of Table A12 are also larger than those in columns (1) to (9) of Table A8, implying that the matching procedure strengthens our results.

4.3.3. Placebo tests

Although the staggered nature of the supervisory actions makes it unlikely that our results are driven by other events, we run falsification tests to ensure that our results are not driven by other, unrelated events. Specifically, we assign a random date in the pre-enforcement period to the bank's treatment event, and then estimate the effect of these placebo events on banks' balance sheet. These results are reported in Table A13. Overall, none of the falsification tests show statistically significant effects of the placebo events, suggesting that our main results are not driven by other events that may have occurred at the same time as the supervisory actions.

4.3.4. Difference-in-differences with variation in treatment timing

Recently, researchers have raised concerns about the use of standard two-way fixed effects estimators for difference-in-differences estimates with variation in treatment timing (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). The general concern is that—when treatment effects are dynamic and there exists variation in treatment timing—the difference-in-differences coefficient represents a weighted average of the dynamic effects. In this case, it has been shown that weights can become negative, which can results in biased coefficient estimates.

To address this potential concern, we provide an alternative estimation method, namely a stacked difference-in-differences model (e.g., Deshpande and Li, 2019; Joaquim et al., 2019). To estimate this model, we start by creating separate datasets for each of the bank supervision dates. In each dataset, banks that are affected during the current bank supervision period are labeled as treated, while banks that are affected more than two years in the future are labeled as control (thus, we take banks that are currently affected as treated banks, and banks that are affected in the future as control banks). We then specify event quarter indicator variables relative to the quarter of the bank supervision. Finally, we stack all the datasets of treatment and control banks for each period into one dataset and we estimate the following equation:

$$y_{b,p,t} = \beta Treated_{b,p} + \gamma(Treated_{b,p} \times Post_{p,t}) + \alpha_{b,p} + \alpha_{p,t} + \epsilon_{b,p,t} \tag{4}$$

where $y_{b,p,t}$ is a bank level outcome of bank b at time t for supervision period (cohort) p. $Treated_{b,p}$ is a dummy variable equal to one if bank b is a treated bank for supervision period p. The interaction term $Treated_{b,p} \times Post_{p,t}$ is a dummy variable equal to one if bank b is already treated in supervision period p at time t (i.e., the interaction of treatment with post supervision period). $\alpha_{b,p}$ are bank×cohort fixed effects, and $\alpha_{p,t}$ are cohort×time fixed effects. The former control for unobserved bank heterogeneity within a cohort, and the latter control for the unobserved time-specific events within a cohort (e.g., Joaquim et al., 2019). The standard errors are represented by $\epsilon_{b,p,t}$ and clustered by supervision period (cohort) since the supervision periods represent the level of variation in this regression (but the results are robust to clustering at the bank×cohort level).[19]

The results are reported in Table A14. Overall, these results are quantitatively equivalent to our baseline estimates from Tables A8 and A9, indicating that the supervisory actions induce banks to reclassify loans as problem loans and to set aside more provisions for potential loan losses.

4.4. Drivers

In this section, we investigate the underlying factors that could be driving the effects generated by the supervisory actions triggered based on the central bank's SupTech application. To shed light on this, we run three tests. First, we use information on the types of supervisory concerns reported by the application to study whether the effects are driven by issues related to regulatory non-compliance. To do so, we classify supervisory concerns as concerns related to regulatory non-compliance or concerns related to reporting inconsistencies, and we include an interaction term

[19] As mentioned earlier, the stacking method uses future supervisory actions as controls for current supervisory actions, which results in the same bank appearing multiple times in the data. Clustering at the supervision period (cohort) level effectively takes into account the repeated appearance of banks.

$Post\ supervision \times Regulatory\ non-compliance$ in the regression model outlined in Equation 1, where $Regulatory\ non-compliance$ is a dummy variable equal to one if the supervisory concern is related to regulatory non-compliance. The results of this analysis are presented in Table A15 and confirm that our results are not driven by regulatory concerns only, which are considered the most severe type of supervisory issues. This result is in line with the findings from Roman (2016), who shows that the severity of bank sanctions also does not play a significant role.

Second, we use information on the time to resolution needed by the bank to resolve the underlying issue. We then include an interaction term $Post\ supervision \times Time\ to\ resolution$ in the regression model outlined in Equation 1, where $Time\ to\ resolution$ represents the number of days needed by the bank to resolve the supervisory concern reported by the SupTech application. The results of this analysis are presented in Table A16 and show that our results are not driven by a susbset of issues that require more time to be resolved, which could be considered more complicated issues. That is, issues that require more time to be resolved do not generate larger effects.

Third, we use information on banks' organizational structure to test whether supervisory scrutiny has a "deterrence effect", a channel that has received much attention in the tax enforcement literature (e.g., Advani et al., 2021; Kleven et al., 2011) and the anti-corruption literature (e.g., Colonnelli and Prem, 2022; Pomeranz, 2015). This channel is based on the idea that supervisory scrutiny can increase the perception of the probability of regulatory non-compliance being detected in the future, for instance through a change in the perception of what an auditor knows and can reasonably find out, which can result in increased regulatory compliance in the present. To test this, we examine whether a supervisory action targeted at a particular bank has spillover effects on other, non-targeted banks operating in the same municipality (also see Pomeranz, 2015). To this end, we run the following regression model for the sample of non-targeted banks:

$$y_{b,c,t} = \beta Treated_c + \gamma Post \times Treated_{c,t} + \delta \boldsymbol{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,c,t} \tag{5}$$

where $y_{b,c,t}$ is the outcome variable of non-targeted bank b operating in municipality c at time t. $Treated_c$ is an indicator variable equal to one if at least one bank of municipality c was targeted over the sample period, and $Post \times Treated_{c,t}$ is an indicator variable equal to one for the two years after a bank in municipality c was targeted by the supervisor. Because we only consider the non-targeted banks in this regression model and the non-targeted banks do not face any direct supervisory scrutiny, this regression captures the spillovers arising from deterrence effects (Colonnelli and Prem, 2022; Pomeranz, 2015).[20] The results of this analysis are presented in Table A17 and suggest that the central bank's supervisory scrutiny generates spillover effects to non-targeted banks operating in the same municipality. In particular, we find that after a supervisory action at a targeted bank, non-targeted banks operating in the same municipality increase problem loans and loan loss provisions by 10% and 20%, respectively. Further, in line with our previous estimates, we do not find supervisory scrutiny to affect banks' capitalization, profitability, or loans-to-assets ratio.

Based on these three tests, we essentially rule out that our estimated effects are driven by the severity or complexity of the issues underlying the SupTech events. Instead, we find that supervisory scrutiny at targeted banks has a spillover effect to non-targeted banks, suggesting that there is a deterrence effect, where supervisory scrutiny increase banks' perception of being subject to future future enforcement initiatives,[21] and thereby improve banks' risk reporting.

5. The effect on banks' lending behavior

5.1. Methodology

In our second analysis, we examine the effect of supervisory scrutiny on bank lending. To do so, we turn to the bank-firm level using the data from the corporate credit register. As mentioned before, the literature provides two hypotheses on the effect of bank supervision on bank lending. On the one hand, the capital shock hypothesis posits that supervisory actions put pressure on banks' capital ratios and induces banks to reduce credit supply (Bernanke et al., 1991; Caballero et al., 2008; Peek and Rosengren, 2000). On the other hand, the reallocation hypothesis posits that supervisory scrutiny may mitigate banks' evergreening behavior and lead to a reallocation of credit supply from less creditworthy to more creditworthy borrowers (Bonfim et al., 2022). First, we test for the capital shock hypothesis using the following firm-bank level regressions:

$$y_{f,b,t} = \beta^{ATE} Post\ supervision_{b,t} + \delta \boldsymbol{X}_{f,b,t-1} + \alpha_b + \alpha_{f,t} + \alpha_{b,f} + \epsilon_{f,b,t} \tag{6}$$

where f, b, and t refer to firm, bank, and quarter, respectively. $y_{f,b,t}$ represents the credit growth from quarter t to $t+1$ within a specific firm-bank pair,[22] As before, $Post\ supervision_{b,t}$ is a dummy

[20] Gopalan et al. (2019) use a similar strategy to show that U.S. banks that share a common regulator react to the enforcement actions imposed by that regulator on other banks operating in the same region.

[21] Another way to see this is that supervisory scrutiny may cause banks to think that the regulator is "on to them" (Slemrod, 2019), which may induce banks to become more cautious.

[22] Following Bonfim et al. (2022), loans include outstanding exposures, undrawn credit lines, and unreleased credit

variable equal to one for the eight quarters (24 months) after bank b is treated. $\boldsymbol{X}_{f,b,t-1}$ is a vector of lagged control variables which includes banks' size, capital ratio, liquidity ratio, non-performing loans ratio, and deposits ratio, as well as firms' size and industry. In the most saturated models, we include bank, firm×time, and bank×firm fixed effects, which are represented by α_b, $\alpha_{f,t}$, and $\alpha_{b,f}$, respectively. The bank fixed effects account for unobserved heterogeneity across banks. The firm×time fixed effects account for time-varying unobserved heterogeneity across firms, such as risk and growth opportunities, that proxy for credit demand (Khwaja and Mian, 2008). The bank×firm fixed effects control for potential biases arising from the endogenous matching of banks and firms (e.g., see Paligorova and Santos, 2017). The error term corresponds to $\epsilon_{f,b,t}$ and is dually clustered at the firm and bank level. In this equation, β^{ATE} captures the change in credit supply from a treated bank (relative to a non-treated bank) in the post-supervision period (relative to the pre-supervision period).

Second, to test for the reallocation hypothesis, we estimate the following regression model:

$$\begin{aligned} y_{f,b,t} = &\beta_1 Creditworthiness_{f,b,t-1} + \gamma^{ATE}(Post\ supervision_{b,t} \times Creditworthiness_{f,b,t-1}) + \\ &\delta \boldsymbol{X}_{f,b,t-1} + \alpha_{b,t} + \alpha_{f,t} + \alpha_{b,f} + \epsilon_{f,b,t} \end{aligned} \tag{7}$$

where $Creditworthiness_{f,b,t-1}$ is a dummy variable equal to one for less creditworthy firms, which we proxy based on two different methods. In particular, this dummy variable is equal to one if firm f has payment in arrears for loans outstanding at bank b, or if the credit rating of firm f assigned by bank b is equal to or below C.[23] In the most saturated models, we also include bank×time fixed effects represented by $\alpha_{b,t}$ (in addition to firm×time and bank×firm fixed effects), in order to account for time-varying unobserved heterogeneity across banks that proxy for changes in overall credit supply.[24] In this regression, the coefficient of interest is γ^{ATE}, which captures the change in credit supply from treated banks (relative to non-treated banks) in the post-supervision period (relative to the pre-supervision period) to less creditworthy firms (relative to more creditworthy firms).

Note that, in the spirit of Bonfim et al. (2022), regressions 6 and 7 allow to establish the causal

lines of a bank to a firm. We compute credit growth as follows: $Credit\ growth_{f,b,t} = \frac{Credit_{f,b,t} - Credit_{f,b,t-1}}{0.5 \times (Credit_{f,b,t} + Credit_{f,b,t-1})}$. This transformation is widely used because it is symmetric and bounded.

[23]Resolution 2,682/1999 of the Central Bank of Brazil outlines that banks have to classify their credit exposures into nine levels of risk, varying from AA to H. Rating AA should be assigned to loans with the lowest credit risk, and rating H should be assigned to loans with the highest credit risk.

[24]Note that the inclusion of the bank×time fixed effects absorbs the $Post\ supervision_{b,t}$ term.

relationship between supervisory scrutiny and bank lending (credit supply) because supervisors do not oblige treated banks to cut credit to any particular borrowers. Consequently, changes in lending behavior are ultimately the decision of the affected bank so that we are able to measure the causal effect on banks' lending behavior. This assertion is supported by the fact that—prior to a a supervisory action—affected banks' lending behavior is similar to that of non-affected banks, as discussed in Section 5.3.1 below.

5.2. Results

Table A18 shows the results of Equation 6 which is used to test the capital shock hypothesis. Across the different columns, we saturate the model with different sets of fixed effects to gauge their effects and the robustness of our findings. The standard errors are clustered at the bank level. The results from Table A18 consistently show statistically insignificant coefficient estimates, indicating that SupTech events do not affect banks' credit supply. Stated differently, on average, we do not find that treated banks cut credit after a supervisory action, thus rejecting the capital shock hypothesis.

Turning to the reallocation hypothesis, Panel A and B of Table A19 shows the results of Equation 7. Across the different columns, we saturate the model with different sets of fixed effects. The results from Table A19 suggest that, in line with the reallocation hypothesis (e.g., see Granja and Leuz, 2018), treated banks reduce credit supply to less creditworthy borrowers after a supervisory action.[25] Particularly, the coefficient estimates of column (4) of Panel A from Table A19 indicate that, after a supervisory action, less creditworthy borrowers experience a 5% reduction in credit supply from treated bank. This effect is economically relevant but (as expected) smaller than the estimates from Bonfim et al. (2022) and Passalacqua et al. (2022), who find that on-site bank inspection programs cause treated banks to reduce credit to unproductive borrowers by 20 and 60 percent, respectively.

We also examine whether treated banks change other loans terms after supervisory actions. To this end, we use the regression models from 6 and 7 to examine the effect of supervisory actions on the loan rate, loan maturity, and collateral requirements of loans granted by treated banks. These regression results on loan rates are presented in Tables A20 and A21, respectively. In line with our results on credit supply, the results in Table A20 show that treated banks in general do not change interest rates. However, in line with our results on the reallocation of credit, we find that

[25] As explained before, by forcing banks to truthfully report loan losses, supervisory scrutiny may have a disciplining effect and induce banks to reallocate credit from unproductive to productive borrowers.

treated banks increase interest rates charged to less creditworthy borrowers. In particular, based on the estimates in column (4) of Panel A from Table A21, we find that treated banks increase loan rates charged to less creditworthy borrowers by roughly 20% (compared to the average loan rate) after a supervisory action. We find a similar pattern for loan maturities. In particular, Table A22 shows that, on average, treated banks do not change loan maturities after a SupTech event, while Table A23 shows that treated banks reduce the loan maturities of loans to less creditworthy borrowers. For instance, column (4) of Table A22 indicates that, after a SupTech event, treated banks reduce the loan maturity of loans granted to less creditworthy borrowers by five percent. Further, Tables A24 and A25 indicate that SupTech events do not affect collateral requirements (independent of borrowers' creditworthiness), which could be due to the fact that firms cannot easily increase pledged collateral.[26]

In sum, our results show that, after a SupTech event, banks increase the interest rate and reduce the loan amount and maturity of loans granted to less creditworthy borrowers. These results are in line with previous papers on regulatory enforcement in the banking sector (Delis and Staikouras, 2011), indicating that supervisory actions reduce risk-taking in bank lending. However, the economic magnitudes of our estimated effects are smaller than those of more severe supervisory actions documented by previous papers (Bonfim et al., 2022; Danisewicz et al., 2018; Passalacqua et al., 2022), such as bank sanctions and on-site bank inspections, which suggests that there is a trade-off between the severity and the impact of supervisory actions.

5.3. Robustness

5.3.1. Dynamic analysis

To assess whether the estimated effects are attributable to the SupTech events, we verify the parallel trends assumption underlying our difference-in-differences models. To this end, we estimate a dynamic version of the difference-in-differences estimator outlined in Equation 6, which can be specified as follows:

$$y_{f,b,t} = \sum_{\tau=-4}^{+8} \beta_\tau Supervision_{b,t} \times \{1_{\tau=t}\} + \delta \boldsymbol{X}_{f,b,t-1} + \alpha_b + \alpha_{f,t} + \alpha_{f,b} + \epsilon_{f,b,t} \tag{8}$$

[26] In line with this idea, the summary statistics presented in Table A4 show that already 60% of loans in our sample is collateralized.

where $Supervision_{b,t} \times \{1_{\tau=t}\}$ is a dummy variable interacted with an event time indicator variable, which is equal to one if bank b is treated at time t, so that the interaction term equals one if it is quarter τ relative to the quarter in which the bank is treated.

The results are presented in Figure 6(a) and support the parallel trends assumption underlying our difference-in-differences regressions. That is, in general, the coefficient estimates before and after the supervisory actions are stable and statistically insignificant, which suggests that SupTech events do not cause a change in banks' total credit supply.

Similarly, we verify the parallel trends assumption underlying the regression model from Equation 7, by including an interaction term between $Supervision_{b,t} \times \{1_{\tau=t}\}$ and the $Creditworthiness_{f,b,t-1}$ variable from Equation 7. Figures 6(b) and 6(c) present the results using $Arrears$ and $Subprime$ as a measure of creditworthiness, respectively. These results also seem to support the parallel trends assumptions underlying our difference-in-differences regressions. Particularly, prior to the SupTech events there is little significant difference in credit supply between treated and non-treated banks to less creditworthy borrowers, but after the supervisory actions there is a significant decrease in credit supply to less creditworthy borrowers from treated banks. Similar to the results discussed in Section 4.3.1, the effect seems to dissipate after five to six quarters (i.e., fifteen to eighteen months).

5.3.2. Placebo tests

To ensure that our results are not driven by other events that may have occurred at the same time as the supervisory actions, we again run falsification tests. As before, we assign a random date in the pre-enforcement period to the bank's SupTech event, and then estimate the effect of these placebo supervisory actions on banks' credit supply. These results are reported in Tables A26 and A27. The falsification tests based on the placebo supervisory actions show no statistically significant effects. That is, placebo supervisory actions do not have an effect on banks average credit supply or banks' credit supply to less creditworthy borrowers. Unreported regression results show insignificant effects for other loan terms as well. This implies that our main results are not driven by other, unrelated events.

6. The effect on firm outcomes

6.1. Methodology

In our third analysis, we aim to identify the real spillover effects of supervisory scrutiny on firm outcomes. For this purpose, we estimate the following difference-in-differences models:

$$\begin{aligned} y_{f,t} =& \beta_1 Post_{f,t} + \beta_2 Exposure_{f,pre} + \gamma^{ATE}(Post_{f,t} \times Exposure_{f,pre}) + \delta \boldsymbol{X}_{f,t-1} + \\ & \alpha_f + \alpha_{j,t} + \alpha_{m,t} + \epsilon_{f,t} \end{aligned} \tag{9}$$

where $y_{f,t}$ represents different firm-level outcomes, including total leverage, employment, revenue, and productivity (defined as revenue over total number of employees). *Post* is a dummy variable equal to one for the eight quarters (24 months) after bank b is treated and $Exposure_{f,t}$ represents the exposure of firm f to the treated bank(s) right before treatment.[27]. $\boldsymbol{X}_{f,t-1}$ is a vector of lagged control variables. α_f, $\alpha_{j,t}$, and $\alpha_{m,t}$ represent firm, industry×time, and municipality×time fixed effects, respectively. [28] The error term corresponds to $\epsilon_{f,t}$ and is clustered at the firm level. In this equation, the coefficient of interest is γ^{ATE}, which captures the change in firm outcomes attributable to a firm's credit exposure to treated banks.

As in the previous analysis, we extend this regression to examine whether the effect depends on the creditworthiness of the borrower:

$$\begin{aligned} y_{f,t} =& \beta_1 Post_{f,t} + \beta_2 Exposure_{f,pre} + \beta_3 Creditworthiness_{f,t-1} + \beta_4(Post_{f,t} \times Exposure_{f,pre}) + \\ & \beta_5(Post_{f,t} \times Creditworthiness_{f,t-1}) + \beta_6(Exposure_{f,pre} \times Creditworthiness_{f,t-1}) + \\ & \gamma^{ATE}(Post_{f,t} \times Exposure_{f,pre} \times Creditworthiness_{f,t-1}) + \delta \boldsymbol{X}_{f,t-1} + \alpha_f + \alpha_{j,t} + \\ & \alpha_{m,t} + \epsilon_{f,t} \end{aligned} \tag{10}$$

[27]Particularly, $Exposure_{f,pre} = \frac{\sum_{i=1}^{N_{treated}} Exposure_{f,b,pre} \times Treated_b}{\sum_{i=1}^{N_{all}} Exposure_{f,b,pre}}$ where $Treated_b$ is equal to one if bank b is treated and zero otherwise.

[28]Note that we collapse the data from the firm-bank-time level to the firm-time level in this regression, meaning that we cannot fully control for credit demand factors (as we cannot include firm × time fixed effects). However, we do include industry×time and municipality×time fixed effects to control for time-varying shocks across industries and municipalities, respectively.

where $Creditworthiness_{f,t-1}$ is a dummy variable equal to one if firm f has payment in arrears or a bad credit rating at the treated bank(s). Note that this indicator is only equal to one if the firm is identified as less creditworthy by the treated bank(s), not if the firm is identified as less creditworthy by other (non-treated) banks that the firm may be borrowing from. This equation allows to assess whether the real effects of being exposed to an supervised bank were stronger for less creditworthy firms, for instance, because supervised banks cut credit to less creditworthy firms, as our earlier results indicate. Thus, γ^{ATE} identifies the differential impact of borrowing from a treated bank (compared to a non-treated bank) in the post-supervision period (compared to the pre-supervision period) for a less creditworthy firm (compared to more creditworthy borrowers).

6.2. Results

Table A28 shows the results of Equation 9. Across the different columns, this Table shows the effect on firms' total leverage, employment, revenue, and productivity. The estimated effects in column (1) indicate that supervisory scrutiny does not have spillover effects on firm outcomes of firms borrowing from treated banks (i.e., the three estimated coefficients cancel each other out). This is not surprising as the results from Table A18 and A20 show that, on average, treated banks do not tighten credit after a SupTech event. Accordingly, in columns (2) to (4), we do not find substantial spillover effects to employment, revenue, or productivity.

Table A29 shows the results of Equation 10, where we focus on the spillover effects to less creditworthy firms. First, the triple interaction estimate in column (1) points to a significant decrease in the leverage of less creditworthy firms (compared to more creditworthy firms), indicating that these firms cannot completely compensate the reduction in credit from treated banks. Column (2) to (4) further suggest that this has real spillover effects on less creditworthy firms in the form of reduced employment, profitability, and productivity. Columns (3) and (4) of Panel B for instance indicate that, for a less creditworthy firm, a one standard deviation increase in the firm's exposure to a treated bank decreases the firm's revenue and productivity by 1.3%, on average. Note that the economic magnitude of these effects is non-negligible but small compared to the economic magnitude of the negative spillover effects of bank sanctions (see Danisewicz et al., 2018).[29]

In sum, our results suggest that the spillover effects of the supervisory actions to firms borrowing

[29] Danisewicz et al. (2018) for instance find that bank sanctions imposed on single-market banks operating in U.S. counties reduce personal income growth rates by 0.7 percentage points and increase the unemployment rate by 0.157 percentage points (compared to average growth rates averaging 1.5% on the county level).

from treated banks are limited and concentrated among less creditworthy firms. In contrast, previous research has shown that bank sanctions have large negative spillover effects on the real economy (Danisewicz et al., 2018), and on-site bank inspections have large positive spillover effects on the real economy (Bonfim et al., 2022; Passalacqua et al., 2022). Thus, our results support the notion that SupTech events are distinct from other supervisory actions.

7. Conclusion

Despite the importance of bank regulation, bank supervision is essential to detect and prevent regulatory non-compliance (Stiglitz, 2009). To this end, regulators increasingly rely on SupTech applications to identify banks where weaknesses are most likely to be found, and to preemptively correct unsafe and unsound practices (i.e., before they could affect financial stability). In this paper, we use data from the SupTech application employed by the Central Bank of Brazil to assess the effects of supervisory scrutiny on banks' balance sheet and bank lending, as well as the potential spillover effects to the real economy.

We uncover three sets of results. First, we find that the supervisory actions induce banks to reclassify loans as non-performing and increase provisions for expected loan losses, meaning that the supervisory actions reveal and mitigate inconsistencies in banks' reported (credit) risk. A potential explanation for this effect is that supervisory scrutiny increases banks' perception of being subject to future future enforcement initiatives, inducing them to become more prudent. Second, we find that the supervisory actions reduce risk-taking in bank lending, as treated banks reduce credit to less creditworthy borrowers after the supervisory actions. Similarly, treated banks increase loan rates and reduce loan maturities of loans granted to less creditworthy borrowers, consistent with the idea that the supervisory scrutiny leads to more prudent bank lending. Third, we find that this credit reallocation generates some spillover effects to the real economy, although the economic magnitude of these spillover effects is limited.

In sum, we provide novel evidence on how SupTech affects the banking sector and the real economy. We find that SupTech events—which are meant to prevent rather than penalize regulatory non-compliance—have a disciplining effect on the banking sector, which indicates that SupTech is more than just a "check-the-box" regulatory constraint and has important implications for regulatory agencies around the world.

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Appendix

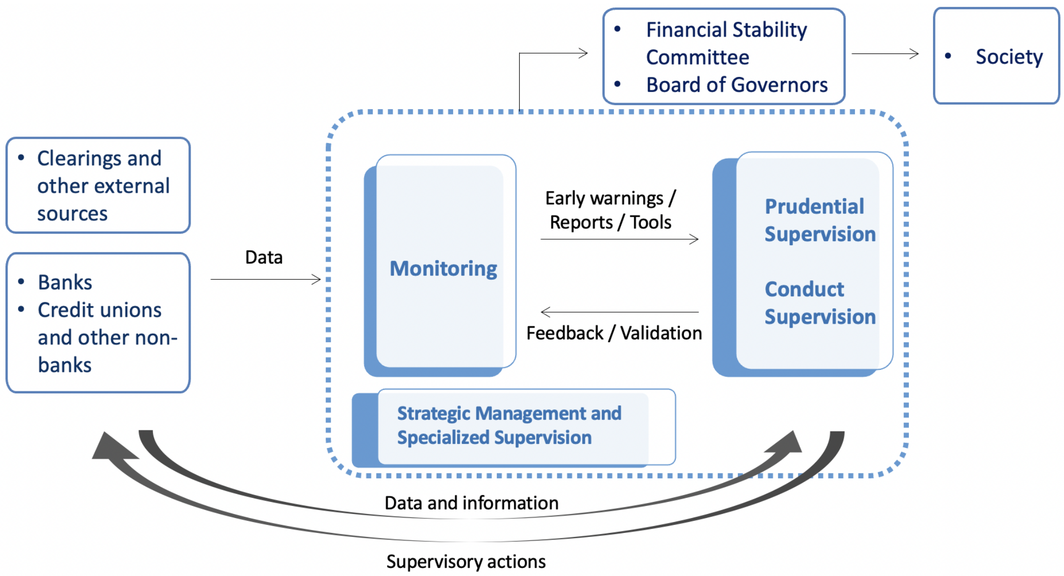


Figure A1: The Central Bank of Brazil's supervisory framework

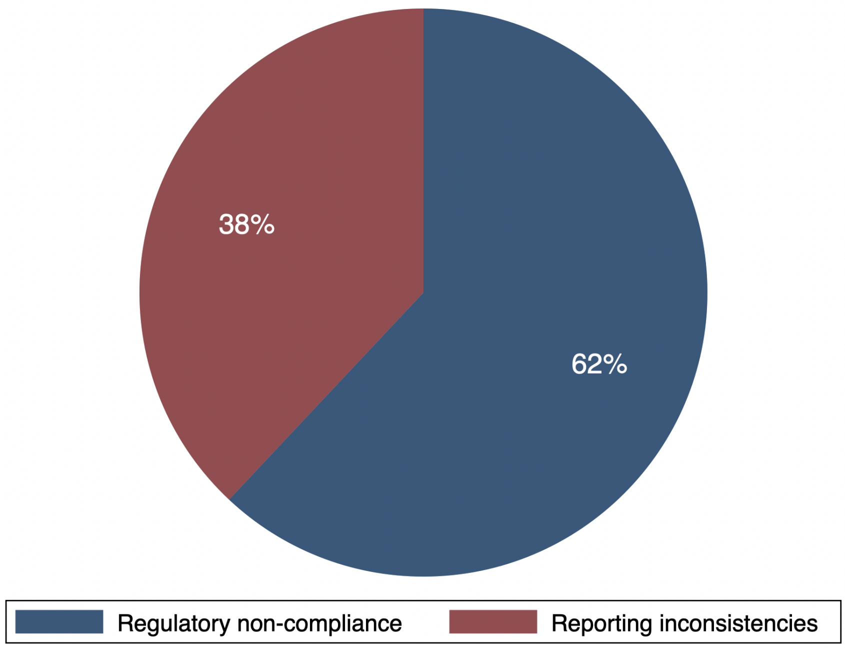


Figure A2: Distribution of the types of issues underlying the SupTech events

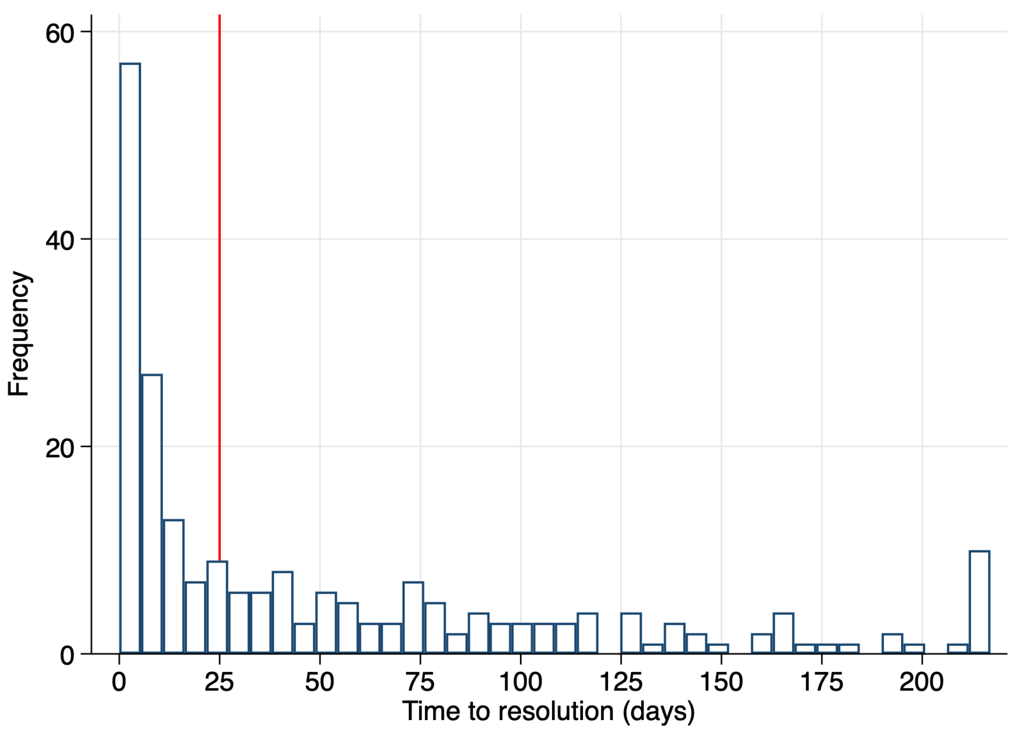
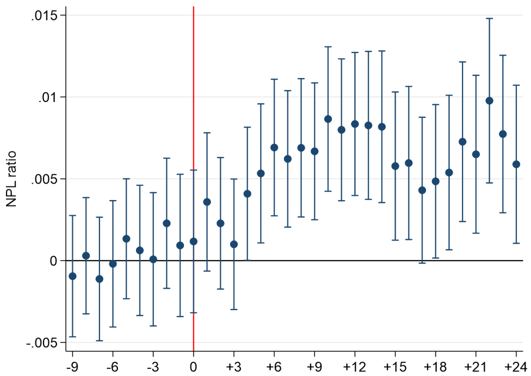
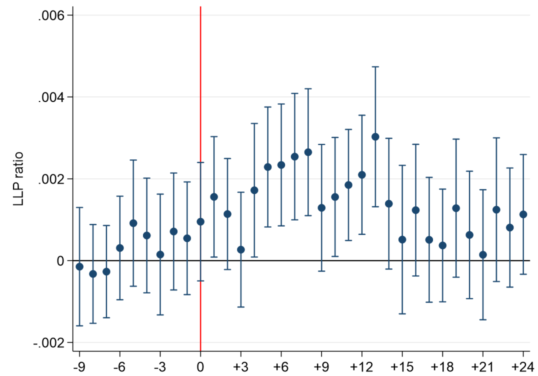


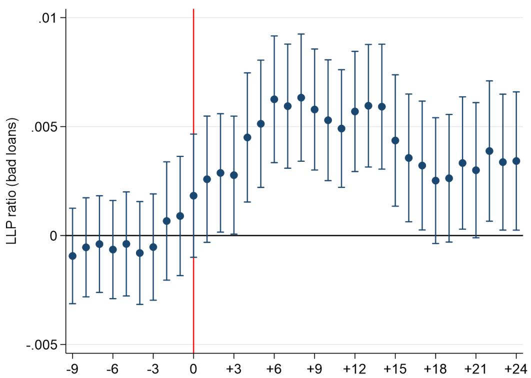
Figure A3: Distribution of the number of days needed to resolve the issue underlying the SupTech events
Note: The red vertical line corresponds to the median.



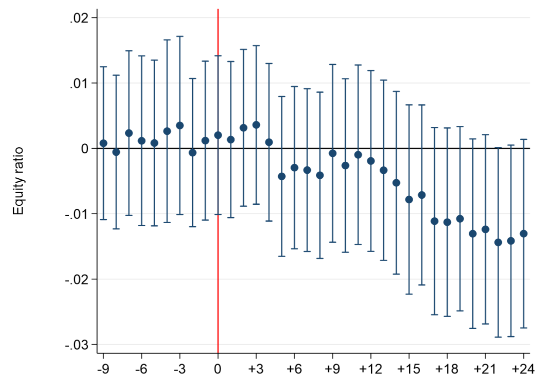
((a)) NPL/TA



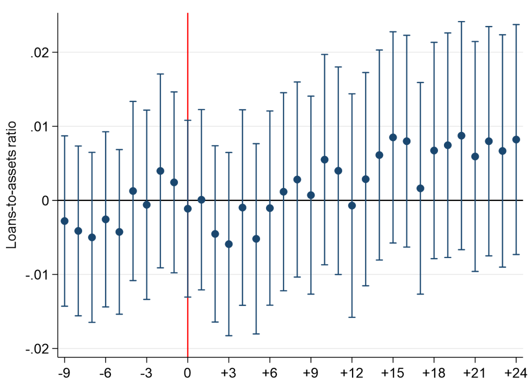
((b)) LLP/TA



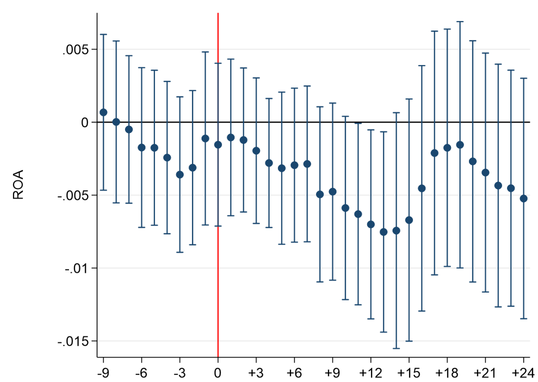
((c)) $\text{LLP}_{\text{risky}}$/TA



((d)) Capital/TA

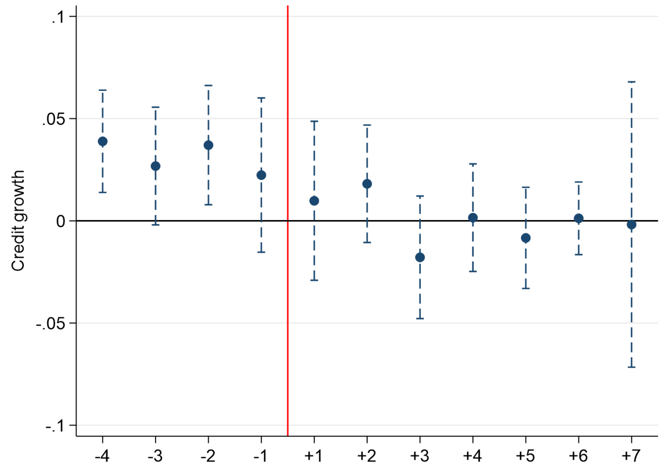


((e)) Loans/TA

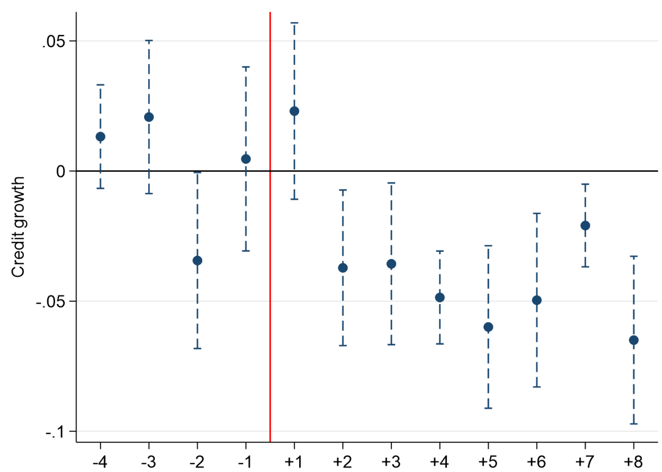


((f)) ROA

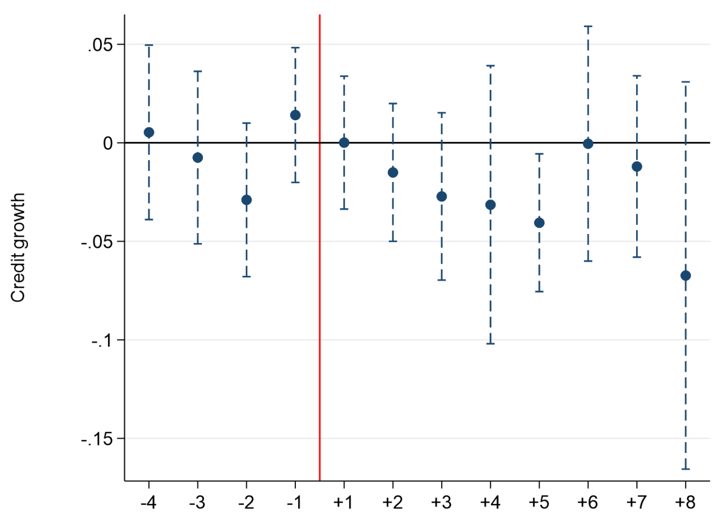
Figure A5: Dynamic difference-in-differences estimates for the effect of SupTech events on banks' balance sheet items



((a)) Baseline



((b)) Less creditworthy firms (Arrears)



((c)) Less creditworthy firms (Subprime)

Figure A6: Dynamic difference-in-differences estimates for the effect of SupTech events on banks' balance sheet items

Table A1: Distribution of treated vs. non-treated banks

	Frequency	Percentage	Cumulative Percentage
Treated	221	16.86	16.86
Non-treated	1,104	83.32	100.00
Total	1,325	100.00	

Table A2: Number of SupTech events per treated bank

	Frequency	Percentage	Cumulative Percentage
0	1,104	83.32	83.32
1	187	14.11	97.43
2	28	2.11	99.55
3+	6	0.45	100.00
Total	1,325	100.00	

Table A3: Bank-level summary statistics

	N	Mean	SD	Min	Max
ln(TA)	131,928	18.824	2.469	13.604	25.213
Loans/TA	131,928	0.532	0.243	0.000	0.958
Deposits/TA	131,928	0.482	0.264	0.000	0.807
Liquidity/TA	131,928	0.334	0.213	0.020	0.957
Capital/TA	131,928	0.261	0.218	0.040	0.930
NPL/TA	131,928	0.036	0.036	0.000	0.198
LLP/TA	131,928	0.011	0.012	0.123	0.000
$\mathrm{LLP}_{\mathrm{risky}}$/TA	131,928	0.023	0.024	0.117	0.000
ROA	62,267	0.022	0.040	-0.114	0.184
Treated	131,928	0.211	0.410	0.000	1.000

Note: This table presents summary statistics for the bank-level variables derived from banks' financial statements. ln(TA) is the natural logarithm of banks' total assets, Loans/TA is banks' loans over total assets, Deposits/TA is banks' deposits over total assets, Liquidity/TA is banks' liquid assets over total assets, Capital/TA is banks' equity over total assets, NPL/TA is banks' non-performing loans over total assets, LLP/TA is banks' loans loss provisions over total assets, $\mathrm{LLP}_{\mathrm{risky}}$ is banks' loan loss provisions for risky loans over total assets, ROA is banks' net revenue over total assets, Treated is a dummy variable equal to one if a bank is ever treated.

Table A4: Bank-firm-level summary statistics

	N	Mean	SD	Min	Max
Credit growth	15,630,592	-0.028	0.473	-2.000	2.000
Pr(New Loan)	15,630,592	0.358	.479	0.000	1.000
ln(Amount)	15,630,592	10.363	1.969	0.010	26.047
ln(Rate)	15,630,592	2.506	2.924	-4.605	5.521
ln(Maturity)	15,630,592	2.811	1.271	0.000	7.375
Collateral	15,630,592	0.607	0.489	0.000	1.000
N(Relationships)	15,630,592	2.235	1.715	1.000	31.000
Subprime	15,630,592	0.133	0.340	0.000	1.000
Arrears	15,630,592	0.206	0.404	0.000	1.000

Note: This table presents summary statistics for the bank-firm-level variables derived from the credit register. Credit growth is the change in credit from bank b to firm f from quarter $t-1$ to quarter t. Collateral is a dummy equal to one if the loan relationship between firm f and bank b has underlying collateral. ln(Amount) is the natural logarithm of the total loan amount of firm f from bank b in quarter t. ln(Rate) is the natural logarithm of the loan rate on the loans of firm f from bank b in quarter t. ln(Maturity) is the natural logarithm of the loan maturity on the loans of firm f from bank b in quarter t. N(Relationships) is the natural logarithm of the number of bank lending relationships that firm f has in quarter t. Subprime is a dummy variable equal to one if the loans of firm f from bank b have a bad credit rating (i.e., a credit rating of C or lower). Arrears is a dummy variable equal to one if the loans of firm f has payments in arrears on the loans from bank b.

Table A5: Firm-level summary statistics

	N	Mean	SD	Min	Max
Δ Credit	8,603,946	0.008	0.664	-1.949	1.920
Δ Employment	3,685,596	0.000	0.207	-0.977	1.203
Δ Wage	3,684,614	0.011	0.073	-0.409	0.655
Δ Hours worked	3,685,596	-0.001	0.270	-1.244	1.592
Δ Revenue	4,649,900	0.018	0.651	-1.998	1.999
Δ Productivity	3,685,596	0.032	0.736	-1.998	1.993

Note: This table presents summary statistics for the bank-firm-level variables derived from the credit register. Credit growth is the change in total credit of firm f from quarter $t-1$ to quarter t. Employment growth is the change in total number of employees working at firm f from quarter $t-1$ to quarter t. Wage growth is the change in average wage (per hour) paid by firm f from quarter $t-1$ to quarter t. Hours worked growth is the change in the total number of hours worked at firm f from quarter $t-1$ to quarter t. Revenue growth is the change in the total revenue of firm f from quarter $t-1$ to quarter t. Productivity growth is the change in the total revenue scaled by total employees of firm f from quarter $t-1$ to quarter t

Table A6: Balance sheet variables that predict SupTech events

	2008	2012	2016
ln(Total assets)	0.03709	0.10889	0.22036**
	(0.11084)	(0.10233)	(0.08345)
Deposit ratio	0.74300	1.00972	0.34641
	(1.03424)	(0.98259)	(0.89796)
Liquidity ratio	-2.09360	-2.37243	-0.57022
	(1.57724)	(1.49018)	(1.24756)
NPL ratio	-3.27675	-0.98205	-12.34053**
	(6.99084)	(6.58098)	(5.70395)
LLP ratio	17.98419	8.58158	-2.36949
	(23.00112)	(21.18354)	(18.13961)
Equity ratio	0.91313	1.16182	0.54864
	(1.40816)	(1.30345)	(1.22240)
Loans-to-assets ratio	-1.55852	-1.76877	0.90568
	(1.32643)	(1.21750)	(1.01168)
Observations	139	134	64
R-squared	0.02319	0.04211	0.26025

Note: This table presents (observable) bank balance sheet variables that predict the timing of SupTech events for the banks that are not treated yet by the year indicated in the column heading. The sample consists of all banks that were treated at least once during the sample period, and the dependent variable is the year in which the bank was treated for the first time. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A7: Treated and non-treated banks: difference in means

	Non-treated		Treated		
	Mean	SD	Mean	SD	Difference
Bank log assets	18.678	2.267	19.768	2.214	1.090***
Bank deposits/TA	0.489	0.267	0.474	0.292	-0.015***
Bank loans/TA	0.536	0.239	0.522	0.258	-0.014***
Bank equity/TA	0.265	0.205	0.244	0.198	-0.021***
Bank ROA	0.030	0.038	0.023	0.033	-0.007***
Bank NPL/TA	0.033	0.037	0.041	0.044	0.008***
Bank LLP/TA	0.012	0.016	0.012	0.015	0.000
Bank $\text{LLP}_{\text{risky}}$/TA	0.023	0.023	0.027	0.026	0.004***
Bank liquid assets/TA	0.358	0.198	0.340	0.211	-0.017***
Observations	114,962		30,178		145,140

Note: This table shows a difference in means test for treated banks and non-treated banks.

Table A8: The effect of SupTech events on banks' balance sheet

	NPL/TA			LLP/TA			LLP_{risky}/TA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post supervision	0.0106***	0.0065**	0.0060***	0.0004	0.0019***	0.0014**	0.0091***	0.0071***	0.0044***
	(0.0026)	(0.0027)	(0.0020)	(0.0007)	(0.0007)	(0.0006)	(0.0016)	(0.0017)	(0.0014)
Observations	100,197	100,197	100,194	99,260	99,260	99,257	99,260	99,260	99,257
Adjusted R-squared	0.1721	0.2109	0.6751	0.0731	0.2115	0.5398	0.1166	0.1329	0.6326
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' balance sheet. The dependent variables are the ratio of non-performing loans, the ratio of loan loss provisions, and the ratio of loan loss provisions for risky loans. A constant is included in all regressions but not reported. The control variables correspond to lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and a dummy variables equal to one for banks that are part of a financial conglomerate. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A9: The effect of SupTech events on banks' balance sheet

	Equity/TA			ROA			Loans/TA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post supervision	-0.0040	-0.0045	-0.0055	0.0015	-0.0029	-0.0036	-0.0029	-0.0014	0.0030
	(0.0101)	(0.0107)	(0.0066)	(0.0033)	(0.0032)	(0.0029)	(0.0105)	(0.0111)	(0.0069)
Observations	99,260	99,260	99,257	54,836	54,836	54,833	99,260	99,260	99,257
Adjusted R-squared	0.4538	0.4595	0.8644	0.0937	0.1475	0.5657	0.6431	0.6444	0.8966
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' balance sheet. The dependent variables are the capital ratio, return on assets, and loans-to-assets ratio. A constant is included in all regressions but not reported. The control variables in columns (1) to (3) correspond to lagged values of banks' size, non-performing loans ratio, deposit ratio, liquidity ratio, and a dummy variables equal to one for banks that are part of a financial conglomerate. The control variables in columns (4) to (9) correspond to lagged values of banks' size, capital ratio, non-performing loans ratio, deposit ratio, liquidity ratio, and a dummy variables equal to one for banks that are part of a financial conglomerate. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A10: The effect of SupTech events on banks' balance sheet

	NPL/TA			LLP/TA			LLP_{risky}/TA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.0076**	0.0080**	–	0.0016*	0.0001	–	0.0021	0.0029	–
	(0.0031)	(0.0032)	(–)	(0.0009)	(0.0009)	(–)	(0.0018)	(0.0018)	(–)
Post supervision	0.0106***	0.0065**	0.0060***	0.0004	0.0019***	0.0014**	0.0091***	0.0071***	0.0044***
	(0.0026)	(0.0027)	(0.0020)	(0.0007)	(0.0007)	(0.0006)	(0.0016)	(0.0017)	(0.0014)
Observations	100,197	100,197	100,194	99,260	99,260	99,257	99,260	99,260	99,257
Adjusted R-squared	0.1721	0.2109	0.6751	0.0731	0.2115	0.5398	0.1166	0.1329	0.6326
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' balance sheet. The dependent variables are the ratio of non-performing loans, the ratio of loan loss provisions, and the ratio of loan loss provisions for risky loans. A constant is included in all regressions but not reported. The control variables correspond to lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and a dummy variables equal to one for banks that are part of a financial conglomerate. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A11: The effect of SupTech events on banks' balance sheet

	Equity/TA			ROA			Loans/TA		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.0102	0.0162	–	-0.0056**	-0.0035	–	-0.0233*	-0.0236*	–
	(0.0129)	(0.0134)	(–)	(0.0028)	(0.0027)	(–)	(0.0134)	(0.0140)	(–)
Post supervision	-0.0040	-0.0045	-0.0055	0.0015	-0.0029	-0.0036	-0.0029	-0.0014	0.0030
	(0.0101)	(0.0107)	(0.0066)	(0.0033)	(0.0032)	(0.0029)	(0.0105)	(0.0111)	(0.0069)
Observations	99,260	99,260	99,257	54,836	54,836	54,833	99,260	99,260	99,257
Adjusted R-squared	0.4538	0.4595	0.8644	0.0937	0.1475	0.5657	0.6431	0.6444	0.8966
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	No	No	Yes	No	No	Yes
Time FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' balance sheet. The dependent variables are the capital ratio, return on assets, and loans-to-assets ratio. A constant is included in all regressions but not reported. The control variables in columns (1) to (3) correspond to lagged values of banks' size, non-performing loans ratio, deposit ratio, liquidity ratio, and a dummy variables equal to one for banks that are part of a financial conglomerate. The control variables in columns (4) to (9) correspond to lagged values of banks' size, capital ratio, non-performing loans ratio, deposit ratio, liquidity ratio, and a dummy variables equal to one for banks that are part of a financial conglomerate. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A12: The effect of SupTech events on banks' balance sheet: Propensity score matching

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post supervision	0.0102***	0.0039*	0.0069**	0.0013	-0.0071	0.0003
	(0.0031)	(0.0024)	(0.0028)	(0.0081)	(0.0045)	(0.0090)
Observations	26,280	26,037	26,037	26,037	14,279	26,037
Adjusted R-squared	0.6393	0.3481	0.6050	0.8657	0.4547	0.8852
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the matched difference-in-differences estimates of the effect of SupTech events on banks' balance sheet. The dependent variables are the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for low-rated loans, the capital ratio, return on assets, and loans-to-assets ratio. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A13: The effect of SupTech events on banks' balance sheet: Placebo test

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post supervision	0.0024	0.0002	0.0002	-0.0093	-0.0020	0.0095
	(0.0020)	(0.0006)	(0.0014)	(0.0086)	(0.0038)	(0.0083)
Observations	92,462	91,634	91,634	91,634	51,508	91,634
Adjusted R-squared	0.6834	0.5747	0.6379	0.8689	0.5919	0.8913
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the falsification tests of the effect of SupTech events on banks' balance sheet. The dependent variables are the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for low-rated loans, the capital ratio, return on assets, and loans-to-assets ratio. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A14: The effect of SupTech events on banks' balance sheet: Stacked difference-in-differences

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Treated × Post	0.0077***	0.0014***	0.0043***	0.0036	-0.0007	-0.0015
	(0.0022)	(0.0005)	(0.0015)	(0.0045)	(0.0015)	(0.0050)
Observations	382,337	378,465	378,465	378,465	204,891	378,465
Adjusted R-squared	0.8373	0.6414	0.8392	0.9499	0.6852	0.9563
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Time × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the stacked difference-in-differences estimates of the effect of SupTech events on banks' balance sheet. The dependent variables are the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for low-rated loans, the capital ratio, return on assets, and loans-to-assets ratio. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A15: The effect of SupTech events on banks' balance sheet: Heterogeneity in the type of events

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post supervision	0.0030	0.0015**	0.0035*	0.0013	-0.0033	0.0060
	(0.0028)	(0.0008)	(0.0020)	(0.0094)	(0.0035)	(0.0095)
Post supervision × Regulatory non-compliance	0.0056	-0.0003	0.0015	-0.0122	-0.0015	-0.0055
	(0.0039)	(0.0011)	(0.0027)	(0.0127)	(0.0055)	(0.0128)
Observations	100,194	99,257	99,257	99,257	54,833	99,257
Adjusted R-squared	0.6752	0.5398	0.6326	0.8644	0.5657	0.8966
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' balance sheet, including an interaction term with the type of SupTech event. The dependent variables are the natural logarithm of the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for low-rated loans, the capital ratio, return on assets, and the loans-to-assets ratio. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A16: The effect of SupTech events on banks' balance sheet: Heterogeneity in the duration of events

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post supervision	0.0064**	0.0018***	0.0047***	-0.0090	0.0002	-0.0021
	(0.0026)	(0.0007)	(0.0017)	(0.0080)	(0.0027)	(0.0079)
Post supervision × Time to resolution	-0.0009	-0.0013	-0.0010	0.0010	-0.0106	0.0142
	(0.0040)	(0.0011)	(0.0030)	(0.0131)	(0.0068)	(0.0141)
Observations	100,194	99,257	99,257	99,257	54,833	99,257
Adjusted R-squared	0.6751	0.5398	0.6326	0.8644	0.5661	0.8967
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' balance sheet, including an interaction term with the time to resolution of the supervisory issue. The dependent variables are the natural logarithm of the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for low-rated loans, the capital ratio, return on assets, and the loans-to-assets ratio. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A17: The effect of SupTech events on banks' balance sheet: Within-municipality spillovers

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post × Treated	0.0033**	0.0013**	0.0015	-0.0113	-0.0045	0.0021
	(0.0015)	(0.0006)	(0.0010)	(0.0089)	(0.0032)	(0.0062)
Treated	0.0000	0.0029	0.0011	-0.0794	-0.0055	-0.0053
	(0.0128)	(0.0025)	(0.0083)	(0.0710)	(0.0087)	(0.0688)
Observations	66,220	62,323	62,323	62,323	41,790	62,323
Adjusted R-squared	0.6505	0.5554	0.6361	0.8892	0.6441	0.9059
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on non-targeted banks located in the same municipality as targeted banks. The dependent variables are the natural logarithm of the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for low-rated loans, the capital ratio, return on assets, and the loans-to-assets ratio. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A18: The effect of SupTech events on banks' lending behavior: Credit growth

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth
Post supervision	-0.0005	0.0004	0.0138	0.0144
	(0.0330)	(0.0305)	(0.0270)	(0.0362)
Observations	10,478,565	10,466,282	5,371,450	5,243,909
R-squared	0.0842	0.0845	0.4239	0.4976
Controls	No	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Time FE	Yes	Yes	No	No
Firm × Time FE	No	No	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior. The dependent variables is the change in total credit of bank b to firm f from quarter $t-1$ to quarter t. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A19: The effect of SupTech events on banks' lending behavior: Credit growth

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth
Panel A:				
Post supervision × Arrears	-0.0386***	-0.0604***	-0.0341**	-0.0542***
	(0.0136)	(0.0199)	(0.0163)	(0.0199)
Post supervision	0.0095	0.0303	0.0337	
	(0.0269)	(0.0243)	(0.0298)	
R-squared	0.0868	0.4260	0.5023	0.4434
Panel B:				
Post supervision × Subprime	-0.0421	-0.0583**	-0.0499*	-0.0538*
	(0.0248)	(0.0296)	(0.0294)	(0.0315)
Post supervision	0.0048	0.0189	0.0210	
	(0.0307)	(0.0267)	(0.0340)	
R-squared	0.0903	0.4245	0.5013	0.4420
Observations	10,219,038	5,196,395	5,069,598	5,189,108
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	No
Firm FE	Yes	No	No	No
Time FE	Yes	No	No	No
Bank × Time FE	No	No	No	Yes
Firm × Time FE	No	Yes	Yes	Yes
Bank × Firm FE	No	No	Yes	No

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms. The dependent variables is the change in total credit of bank b to firm f from quarter $t-1$ to quarter t. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. Subprime is a dummy variable equal to one if firm f has been assigned a bad credit rating by bank b. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A20: The effect of SupTech events on banks' lending behavior: Loan rates

	(1)	(2)	(3)	(4)
	ln(Loan rate)	ln(Loan rate)	ln(Loan rate)	ln(Loan rate)
Post supervision	0.2774	0.2390	0.1765	0.3541**
	(0.3771)	(0.2917)	(0.3254)	(0.1560)
Observations	14,870,060	12,452,655	6,219,594	6,100,998
R-squared	0.5313	0.5455	0.6281	0.8369
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	Yes
Firm FE	Yes	No	No	No
Time FE	Yes	No	No	No
Bank × Time FE	No	No	Yes	No
Firm × Time FE	No	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms. The dependent variables is the logarithmic value of the interest rate of loans of bank b to firm f. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A21: The effect of SupTech events on banks' lending behavior: Loan rates

	(1)	(2)	(3)	(4)
	ln(Loan rate)	ln(Loan rate)	ln(Loan rate)	ln(Loan rate)
Panel A:				
Post supervision × Arrears	0.5166**	0.8615***	0.7554**	0.3485**
	(0.265)	(0.3209)	(0.3470)	(0.1672)
R-squared	0.5378	0.6176	0.6561	0.8364
Panel B:				
Post supervision × Subprime	0.4391***	0.8934***	0.7249*	0.4013**
	(0.1375)	(0.3363)	(0.3703)	(0.1830)
R-squared	0.5380	0.6177	0.6560	0.8362
Observations	10,219,038	5,196,395	5,189,108	5,069,598
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	Yes
Firm FE	Yes	No	No	No
Time FE	Yes	No	No	No
Bank × Time FE	No	No	Yes	No
Firm × Time FE	No	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms. The dependent variables is the logarithmic value of the interest rate of loans of bank b to firm f. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. Subprime is a dummy variable equal to one if firm f has been assigned a bad credit rating by bank b. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A22: The effect of SupTech events on banks' lending behavior: Loan maturity

	(1) ln(Maturity)	(2) ln(Maturity)	(3) ln(Maturity)	(4) ln(Maturity)
Post supervision	0.1921***	0.1644***	0.1007	0.0354
	(0.0422)	(0.0460)	(0.0665)	(0.0255)
Observations	14,870,060	12,452,655	6,219,594	6,100,998
R-squared	0.5218	0.5318	0.6226	0.8550
Controls	No	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Time FE	Yes	Yes	No	No
Firm × Time FE	No	No	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms. The dependent variables is the logarithmic value of the maturity of loans of bank b to firm f. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A23: The effect of SupTech events on banks' lending behavior: Loan maturity

	(1) ln(Maturity)	(2) ln(Maturity)	(3) ln(Maturity)	(4) ln(Maturity)
Panel A:				
Post supervision × Arrears	-0.2872**	-0.2475***	-0.2928***	-0.1506***
	(0.1097)	(0.0636)	(0.0675)	(0.0469)
R-squared	0.5386	0.6256	0.6386	0.8251
Panel B:				
Post supervision × Subprime	-0.2778*	-0.2996***	-0.3117***	-0.1810**
	(0.1680)	(0.0984)	(0.1004)	(0.0731)
R-squared	0.5382	0.6235	0.6364	0.8552
Observations	12,452,655	6,219,594	6,211,012	6,100,998
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	Yes
Firm FE	Yes	No	No	No
Time FE	Yes	No	No	No
Bank × Time FE	No	No	Yes	No
Firm × Time FE	No	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms. The dependent variables is the logarithmic value of the maturity of loans of bank b to firm f. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. Subprime is a dummy variable equal to one if firm f has been assigned a bad credit rating by bank b. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A24: The effect of SupTech events on banks' lending behavior: Loan collateral

	(1)	(2)	(3)	(4)
	Pr(Collateral)	Pr(Collateral)	Pr(Collateral)	Pr(Collateral)
Post supervision	0.0073	-0.0088	-0.0222	-0.0108
	(0.0477)	(0.0538)	(0.0422)	(0.0329)
Observations	14,870,060	12,452,655	6,219,594	6,100,998
R-squared	0.4738	0.4928	0.6035	0.8220
Controls	No	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Time FE	Yes	Yes	No	No
Firm × Time FE	No	No	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms. The dependent variables is the probability that the loans of bank b to firm f are collateralized. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A25: The effect of SupTech events on banks' lending behavior: Loan collateral

	(1)	(2)	(3)	(4)
	Pr(Collateral)	Pr(Collateral)	Pr(Collateral)	Pr(Collateral)
Panel A:				
Post supervision × Arrears	-0.0365	-0.0214	-0.0013	-0.0441*
	(0.0417)	(0.0231)	(0.0186)	(0.0238)
R-squared	0.4952	0.6049	0.6928	0.8223
Post supervision × Subprime	-0.0736	-0.0470	-0.0149	-0.1011**
	(0.0594)	(0.0295)	(0.0217)	(0.0462)
R-squared	0.4929	0.6035	0.6917	0.8221
Observations	10,219,038	5,196,395	5,189,108	5,069,598
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	Yes
Firm FE	Yes	No	No	No
Time FE	Yes	No	No	No
Bank × Time FE	No	No	Yes	No
Firm × Time FE	No	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms. The dependent variables is the probability that the loans of bank b to firm f are collateralized. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. Subprime is a dummy variable equal to one if firm f has been assigned a bad credit rating by bank b. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A26: The effect of SupTech events on banks' lending behavior: Placebo test with credit growth

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth
Post supervision	-0.0159	0.0081	-0.0017	0.0057
	(0.0249)	(0.0072)	(0.0050)	(0.0044)
Observations	10,478,565	10,466,282	5,371,450	5,243,909
R-squared	0.0059	0.0755	0.4418	0.5108
Controls	No	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Time FE	Yes	Yes	No	No
Firm × Time FE	No	No	Yes	Yes
Bank × Firm FE	No	No	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior with placebo events. The dependent variables is the change in total credit of bank b to firm f from quarter $t-1$ to quarter t. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. Subprime is a dummy variable equal to one if firm f has been assigned a bad credit rating by bank b. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A27: The effect of SupTech events on banks' lending behavior: Placebo test with credit growth

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth
Panel A:				
Post supervision × Arrears	0.0200	-0.0207	0.0124	-0.0313
	(0.0240)	(0.0081)	(0.0192)	(0.0199)
Post supervision	0.0045	0.0031	0.0037	
	(0.0093)	(0.0081)	(0.0072)	
R-squared	0.0756	0.4441	0.5120	0.4589
Panel B:				
Post supervision × Subprime	0.0118	-0.0121	-0.0103	-0.0209
	(0.0295)	(0.0187)	(0.0137)	(0.0156)
Post supervision	0.0346	0.0539**	0.0504	
	(0.0244)	(0.0223)	(0.0376)	
R-squared	0.0799	0.4410	0.5092	0.4560
Observations	10,219,038	5,196,395	5,069,598	5,189,108
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	No
Firm FE	Yes	No	No	No
Time FE	Yes	No	No	No
Bank × Time FE	No	No	No	Yes
Firm × Time FE	No	Yes	Yes	Yes
Bank × Firm FE	No	No	Yes	No

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior to less creditworthy firms with placebo events. The dependent variables is the change in total credit of bank b to firm f from quarter $t-1$ to quarter t. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. Subprime is a dummy variable equal to one if firm f has been assigned a bad credit rating by bank b. A constant is included in all regressions but not reported. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposits ratio, firms' size, and firms' industry. Standard errors (in parentheses) are clustered at the bank and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A28: The effect of SupTech events on firm outcomes

	(1) Δ Credit	(2) Δ Employment	(3) Δ Revenue	(4) Δ Productivity
Post	0.1516***	0.0008	0.0110	0.0102
	(0.0274)	(0.0016)	(0.0160)	(0.0169)
Exposure	-0.0147*	0.0042***	-0.0071	-0.0125*
	(0.0083)	(0.0010)	(0.0068)	(0.0069)
Post × Exposure	-0.0912***	-0.0052***	.03900	0.0487
	(0.0194)	(0.0014)	(0.0291)	(0.0335)
Observations	2,604,159	2,487,823	2,687,711	2,515,362
R-squared	0.1325	0.1895	0.0840	0.0946
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm × Industry FE	Yes	Yes	Yes	Yes
Firm × Municipality FE	Yes	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on firm outcomes of firms borrowing from treated banks. The dependent variables across the different columns are the change in total bank credit, the change in employment, the change in revenue, and the change in productivity. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the firm and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A29: The effect of SupTech events on firm outcomes

	(1) Δ Credit	(2) Δ Employment	(3) Δ Revenue	(4) Δ Productivity
Panel A:				
Post	0.1480***	0.0006	-0.0004	0.0060
	(0.0271)	(0.0020)	(0.0018)	(0.0177)
Exposure	-0.0247***	0.0040***	0.0039***	-0.0120*
	(0.0075)	(0.0011)	(0.0012)	(0.0062)
Arrears	0.0021	-0.0194	-0.0191***	0.0013
	(0.0052)	(0.0011)	(0.0011)	(0.0032)
Post × Exposure	-0.0820***	-0.0041**	-0.0032*	0.0507
	(0.0202)	(0.0015)	(0.0017)	(0.0324)
Post × Arrears	0.0111	0.0037	0.0148*	0.0123
	(0.0151)	(0.0036)	(0.0075)	(0.0086)
Exposure × Arrears	0.0442***	0.0047**	0.0040	-0.0028
	(0.0099)	(0.0020)	(0.0018)	(0.0073)
Post × Exposure × Arrears	-0.0349*	-0.0081*	-0.0093	-0.0025
	(0.0201)	(0.0041)	(0.0120)	(0.0121)
R-squared	0.1329	0.1903	0.1393	0.0950
Panel B:				
Post	0.1518***	0.0023	-0.0009	0.0090
	(0.0272)	(0.0018)	(0.0143)	(0.0176)
Exposure	-0.0164*	0.0042***	-0.0039	-0.0141*
	(0.0086)	(0.0010)	(0.0076)	(0.0072)
Subprime	-0.1045***	-0.0204***	-0.0457***	-0.0055
	(0.0072)	(0.0031)	(0.0054)	(0.0061)
Post × Exposure	-0.0910***	-0.0049***	0.0353	0.0531
	(0.01988)	(0.0016)	(0.0365)	(0.0351)
Post × Subprime	-0.0036	-0.0117***	0.0090	0.0150
	(0.0149)	(0.0049)	(0.0087)	(0.0135)
Exposure × Subprime	0.0288***	0.0021	0.02174	0.0175*
	(0.0079)	(0.0025)	(0.0087)	(0.0089)
Post × Exposure × Subprime	0.0174	-0.0056	-0.0544**	-0.0529*
	(0.0150)	(0.0055)	(0.0259)	(0.0272)
R-squared	0.1340	0.1902	0.0844	0.0950
Observations	2,581,598	2,466,176	2,664,410	2,493,510
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Firm × Industry FE	Yes	Yes	Yes	Yes
Firm × Municipality FE	Yes	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on firm outcomes of firms borrowing from treated banks. The dependent variables across the different columns are the change in total bank credit, the change in employment, the change in revenue, and the change in productivity. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. Subprime is a dummy variable equal to one if firm f has been assigned a bad credit rating by bank b. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the firm and time level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.