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The Disciplining Effect of Bank Supervision: Evidence from SupTech

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Abstract

Regulators increasingly rely on supervisory technologies (SupTech) to enhance bank supervision, but their potential role in disciplining bank behavior remains unclear. We address this knowledge gap using unique data from the SupTech application of the Central Bank of Brazil. We show that, after a SupTech event, banks reveal inconsistencies in their risk reporting and tighten credit to less creditworthy firms, effectively reducing risk-taking. This credit tightening in turn has small spillovers on less creditworthy firms borrowing from affected banks. Our results can be explained by a moral suasion channel, offering novel insights into the role of SupTech in bank supervision.

JEL Classification: G21, G28

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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.*" – Broeders and Prenio (2018)

1. Introduction

Regulatory enforcement is a cornerstone of financial stability. This notion has recently regained attention, as weaknesses in the regulatory and supervisory framework played a pivotal role in establishing the conditions for the global financial crisis in 2007–2008 and the banking turmoil in 2023 (Barr 2023; Dewatripont, Rochet, and Tirole 2010; Laeven et al. 2010). In response, regulators worldwide are shifting from traditional compliance-based supervision, which merely penalizes regulatory non-compliance ex-post, to risk-based supervision, which aims to identify and resolve potential risk exposures ex-ante.

Central to this shift has been the adoption of supervisory technologies (SupTech), which leverage advanced data analytics to enhance regulators' ability to detect early risk exposures, allowing for more forward-looking, hypothesis-driven supervision (Broeders and Prenio 2018). For instance, based on a survey of 39 financial authorities, the Bank for International Settlements (BIS) reports that at least half use SupTech applications in the conduct of bank supervision (Di Castri et al. 2019). However, despite the increasing adoption of SupTech, their potential role in disciplining risky bank behavior remains unclear, posing significant challenges for policymakers tasked with designing and implementing effective supervisory frameworks.

Our paper aims to address this question using unique SupTech data from the Central Bank of Brazil (BCB)—a pioneer in the adoption of SupTech in bank supervision. Specifically, using supervisory scrutiny arising from the BCB's SupTech application—which essentially functions as an early warning system—we study how it affects banks' balance sheets and credit supply, and the potential spillover effects to the real economy.[1] This is an important

[1] Prior research has analyzed the role of off-site bank supervision in predicting bank failure (Cole and Gunther 1998; Gilbert, Meyer, and Vaughan 2002) or how off-site bank supervision influences agency frictions between bank insiders and outsiders (Bisetti 2024), but to the best of our knowledge no other study has analyzed whether and how supervisory technologies could affect credit supply and the potential spillovers to the real economy.

question because, as explained in more detail below, the supervisory scrutiny arising from SupTech differs from other supervisory actions, such as bank sanctions. For instance, unlike bank sanctions, which are imposed for regulatory violations, SupTech tools are aimed at identifying early risk exposures, even when no regulatory requirements have been violated. Consequently, the supervisory scrutiny arising from the central bank's SupTech application offers a unique opportunity to test whether moral suasion—a key element of the supervisory toolkit (Acharya et al. 2024; Adrian et al. 2023)—can discipline bank behavior.

Our paper proceeds in three steps. In the first part of the paper, we examine whether the supervisory actions ("SupTech events") arising from the central bank's SupTech application have an impact on banks' balance sheets. Specifically, we use a difference-in-differences model to analyze how SupTech events affect the balance sheets of treated versus non-treated banks, before versus after treatment. Using detailed bank balance sheet data, we find that, after a SupTech event, treated banks reclassify loans as non-performing and increase provisions for expected loan losses, particularly provisions for expected loan losses on risky loans.[2] The effects that we find are statistically and economically significant. For example, after a SupTech event, treated banks report an increase in non-performing loans and loan loss provisions of approximately 20%.[3] We do not find that the supervisory actions affect banks' capital buffer or loans-to-assets ratio, and we find only a small decrease in profitability. These results suggest that supervisory scrutiny arising from the central bank's SupTech application improves banks' regulatory reporting quality—by revealing inconsistencies in reported credit risks—without deteriorating financial soundness.

Unlike existing papers on bank supervision, we show that these results can be explained by a moral suasion channel. In essence, the idea is that supervisory scrutiny may discipline banks by improving their understanding of the regulator's supervisory views, and thereby induce them to adopt more conservative risk attitudes aligned with those views (Kok et al. 2023). More broadly, supervisory actions can change banks' perception of what the supervisory

[2]Our sample covers both bank and non-bank institutions that are active in the corporate loan market, but for simplicity we simply refer to banks in the rest of the paper.

[3]As explained below, we also find that after a SupTech event, treated banks downgrade the credit ratings of their riskiest borrowers, essentially bringing them more in line with those assigned by non-treated banks that lend to the same borrower. This suggests that, prior to the treatment event, the treated banks were under-estimating firms' credit risk (compared to non-treated banks).

authority knows and can reasonably find out, which can induce them to become more prudent. Other channels, including the capital channel or the market discipline channel, which play an important role in the context of stress tests and bank sanctions, are irrelevant in our setting given that SupTech events do not require banks to raise capital and are not publicly disclosed to market participants.[4]

We provide several pieces of evidence that our results can be attributed to a moral suasion channel. First, using information on the types of the supervisory concerns reported by the SupTech application, we distinguish between SupTech events related to regulatory non-compliance and reporting inconsistencies. Consistent with a moral suasion channel, we find that our results are driven by SupTech events related to regulatory non-compliance, which are the events that improve banks' understanding of regulators' supervisory views.

Second, we use information on the supervisory teams linked to the SupTech events, and show that our results are more pronounced for the events handled by more experienced supervisors. Assuming that more experienced supervisors are better at interpreting and explaining supervisory concerns, these results are consistent with a moral suasion channel.

Third, using information on the physical distance between banks' headquarters and the supervisory authority, we find that our results are stronger for banks located further away from the supervisory authority. In line with a moral suasion channel, this suggest that SupTech events strengthen distant banks' perception that the supervisor's ability to detect and address financial distortions is not constrained by geographical distance (Gopalan, Hann, and Mazur 2019).

Fourth, using information on the location of banks' headquarters, we show that SupTech events have within-municipality spillover effects. Specifically, inspired by the tax enforcement literature (e.g., Colonnelli and Prem 2022; Pomeranz 2015), we show that SupTech events affect not only the risk reporting of targeted banks, but also the risk reporting of non-targeted banks operating in the same municipality as the targeted banks. In line with a moral suasion channel, this suggests that SupTech events have a "deterrence effect," where increased

[4]The capital channel posits that supervisory actions may influence banks' behavior by raising their capital requirements. The market discipline channel suggests that supervisory actions may improve banks' risk management practices by increasing market discipline.

perception of regulatory enforcement in the future improves banks' regulatory compliance in the present (also see Rincke and Traxler 2011).[5] Finally, inconsistent with the capital channel and market discipline channel, we show that our results do not depend on banks' capitalization or the degree of public scrutiny that they face.

In the second part of the paper, we use granular credit register data to investigate whether the supervisory scrutiny arising from the central bank's SupTech application has an impact on banks' credit supply. Given that only a very small fraction of SupTech events is related to banks' loan portfolio, any change in lending behavior would provide further support that SupTech events have a supervisory scrutiny effect. In essence, the literature has proposed two hypotheses for the effects of supervisory scrutiny on credit supply. On the one hand, the capital shock hypothesis suggests that—by putting pressure on banks' profitability and capital ratios—supervisory scrutiny may reduce credit supply (Bernanke, Lown, and Friedman 1991; Caballero, Hoshi, and Kashyap 2008; Peek and Rosengren 2000). On the other hand, the reallocation hypothesis suggests that—by forcing banks to truthfully report problem loans and loan losses—supervisory scrutiny can mitigate evergreening behavior and lead to a reallocation of credit supply from less creditworthy to more creditworthy borrowers (Bonfim et al. 2023; Granja and Leuz 2024).

Inconsistent with the capital shock hypothesis, we do not find that treated banks reduce credit supply after a SupTech event. Instead, consistent with the reallocation hypothesis, we find that SupTech events induce treated banks to reduce credit to less creditworthy borrowers (defined as borrowers with payments in arrears). These results hold after the inclusion of high-dimensional fixed effects that control for credit demand and the endogenous matching of lenders and borrowers. In addition, we find that SupTech events also induce lenders to increase the interest rate and reduce the maturity of loans granted to less creditworthy borrowers. In terms of economic magnitude, our results indicate that, after a SupTech event, lenders reduce less creditworthy borrowers' credit by 5%, increase loan rates by 10%, and reduce loan maturities by around 15% (relative to more creditworthy borrowers). Thus, our

[5] Rincke and Traxler (2011) show that the enforcement actions of TV licensing inspectors have spillover effects on non-targeted households living in the same locality, and that this result is driven by interpersonal communication between targeted and non-targeted households. Focusing on the banking sector, Gopalan, Hann, and Mazur (2019) find that bank enforcement actions targeted at U.S. banks have spillovers effects on non-targeted banks that have the same regulator and operate in the same region.

results are consistent with the hypothesis that supervisory scrutiny induces more prudent lending behavior.

In the third part of the paper, we examine the spillover effects to the real economy. As we find that the supervisory scrutiny affects treated banks' credit supply, 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 lenders affects their leverage, employment, and revenues. While we do not find spillover effects for the average firm borrowing from treated banks, we find that less creditworthy firms cannot completely compensate for 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 employment and revenues of about 1%. Thus, while we find evidence of spillover effects to the real economy, the economic magnitude of these spillover effects is limited, which contrasts with the large, adverse spillover effects of bank sanctions (Danisewicz et al. 2018), and the positive spillover effects of on-site bank inspections (Bonfim et al. 2023). In this sense, our results suggest that the magnitude of the spillover effects of supervisory actions may be increasing in the severity of the supervisory actions.

Throughout the paper, we use difference-in-differences regressions with a large set of controls and high-dimensional fixed effects to estimate the 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.e., that treated banks are inherently different from non-treated banks). To alleviate this concern, we conduct a series of robustness tests 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, which confirms that our results are not driven by other pre-existing characteristics. Third, we show that our results are robust to falsification tests, indicating that they are not driven by other events that may have occurred at the same time as the SupTech events. Fourth, considering concerns about biased estimates from two-way fixed effects estimators, we show that our results are robust to using an alternative estimator that addresses these concerns (Baker, Larcker, and Wang 2022). Fifth, we show that our results are robust to alternative data samples and measurement choices, such as the exclusion of SupTech events related to lenders' loan portfolio.

In sum, using unique SupTech data from the Central Bank of Brazil, we show that risk-based (rather than compliance-based) supervisory actions can reveal inconsistencies in banks' risk reporting and reduce risky bank lending. Our paper therefore provides a better understanding of the role of SupTech and, more broadly, moral suasion in bank supervision. These findings also have valuable implications for policymakers and financial authorities around the world, as they suggest that SupTech tools are not merely a "check-the-box" regulatory constraint and can effectively contribute to disciplining risky bank behavior.

Our paper primarily contributes to the literature that studies how bank supervision affects bank lending, and the spillover effects to the real economy.[6] As mentioned earlier, the literature has proposed two views on the effects of bank supervision—i.e., the capital shock channel and the reallocation channel. Previous papers have however found mixed results (e.g., see Abbassi et al. 2025; Bonfim et al. 2023; Danisewicz et al. 2018; Granja and Leuz 2024; Passalacqua et al. 2022). By showing that supervisory actions arising from SupTech tools can improve the quality of banks' financial reporting and reduce risk-taking in lending, our paper 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 three types of actions: (1) bank sanctions (i.e., bank enforcement actions) (Danisewicz et al. 2018; Delis and Staikouras 2011; Delis, Staikouras, and Tsoumas 2017; Gopalan, Hann, and Mazur 2019; Roman 2016), (2) stress tests (Acharya, Berger, and Roman 2018; Cortés et al. 2020; Doerr 2021; Kok et al. 2023), and (3) on-site bank inspections (Agarwal et al. 2014; Bonfim et al. 2023; Passalacqua et al. 2022). First, although several studies on the impact of bank sanctions

[6] To estimate the causal effects of bank supervision, previous papers have used variation in the entity of the supervisory authority (Agarwal et al. 2014; Altavilla et al. 2020; Ampudia, Beck, and Popov 2021; Granja and Leuz 2024; Haselmann, Singla, and Vig 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 (Fuster, Plosser, and Vickery 2021; Ivanov and Wang 2024). In general, these studies suggest that bank supervision effectively reduces bank risk-taking and affects credit allocation, but the effects depend on the supervisory framework or the supervisory entity (also see Berger et al. 2016; Hirtle, Kovner, and Plosser 2020; Pierret and Steri 2020).

and stress tests find that such supervisory actions improve banks' financial soundness and reduce banks' risk-taking, it remains unclear whether these effects are due to supervisory scrutiny or other factors, such as monetary penalties or reputational costs in case of bank sanctions, and increased capital requirements or market discipline in case of stress tests (Degryse, Mariathasan, and Schepers 2023; Roman 2016). Second, although previous studies on the impact of on-site bank inspections find a decrease in banks' evergreening behavior, it is unclear whether this is due to moral suasion or (a mechanical outcome) due to supervisors pointing out problem loans in banks' loan portfolio (Bonfim et al. 2023). Our findings therefore provide an important step forward in the debate on whether or not moral suasion can discipline bank risk-taking.

Our paper also relates to the literature on supervisory frameworks in the banking sector. Prior research has investigated how institutional features (Agarwal et al. 2014; Beck, Silva-Buston, and Wagner 2023; Carletti, Dell'Ariccia, and Marquez 2021; Calzolari, Colliard, and Lóránth 2019; Gong, Lambert, and Wagner 2023; Haselmann, Singla, and Vig 2023), resource constraints (Eisenbach, Lucca, and Townsend 2022; Kandrac and Schlusche 2021), and incentive problems (Beck, Silva Buston, and Wagner 2024; Ganduri 2018; Lucca, Seru, and Trebbi 2014) affect the effectiveness of bank supervision. However, the literature has not paid much attention to the potential role of risk-based versus compliance-based supervision. Our paper makes a first step in this direction by showing that even risk-based supervisory actions can discipline banks, and warrants further research into the optimal combination of risk-based and compliance-based supervisory tools.

The remainder of our paper proceeds as follows. Section 2 describes the use of SupTech by supervisory agencies around the world, and the role of SupTech in 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 lenders' balance sheets, Section 5 the effect on lenders' credit supply, and Section 6 the effect on firm outcomes. Finally, Section 7 concludes.

2. Institutional setting

In the first subsection, we discuss how SupTech developed over time and across the world. After that, we discuss the supervisory framework of Brazil's financial system and position the BCB's SupTech application within that framework.

2.1. SupTech

SupTech broadly refers to innovative technologies used by supervisory agencies to support the conduct of bank supervision (BIS 2018). The development of these technologies dates from the 1990s, and was driven by the objective to remotely assess lenders' financial conditions in between on-site inspections. In those years, SupTech tools were primarily used by advanced economies and limited to financial ratio analyses (Sahajwala and Van den Bergh 2000). However, over the past decade, SupTech has become a key priority for many supervisory agencies around the world and increasingly data-oriented (FSB 2020; Hall 2022). For instance, based on a survey among 39 supervisory agencies around the world, Di Castri et al. (2019) report that in 2019 at least half of them had implemented SupTech initiatives or were in the process of doing so. One important reason for the increased use of SupTech tools is the global financial crisis, which highlighted the need for more forward-looking, hypothesis-driven supervision (World Bank 2021). Another important reason is the major improvement in technological capabilities, including data availability, data storage capacity, computer processing power, and advances in artificial intelligence and machine learning.

In recent years, most SupTech tools automatically digitize and analyze lenders' regulatory reports for previously uncovered patterns and connections, with the objective to detect early risk exposures and financial distortions.[7] For instance, the Federal Reserve's SupTech tool applies statistical analysis to hundreds of variables obtained from banks' financial statements (e.g., capital ratios, loans past due, and off-balance sheet exposures) to identify banks where risks are most likely to emerge (Bisetti 2024). The Bank of Italy and Bank of Thailand have developed SupTech tools that analyze board minutes to identify risks that are being discussed by bank management and obtain a better understanding of bank governance. Finally, the

[7] The level of sophistication of SupTech tools varies across jurisdictions (for a classification, see Di Castri et al. 2019).

Bank of Spain uses SupTech to analyze unstructured data from banks' credit files to identify credit exposures that may have been misclassified as "performing" (for a more extensive overview of existing SupTech applications, see Beerman, Prenio, and Zamil 2021). Overall, policymakers have argued that SupTech enables supervisors to become more forward-looking, data-driven, real-time supervisors.

2.2. Bank supervision in Brazil

Brazil has a robust bank supervision framework (IMF 2018). The BCB, which is responsible for the regulatory oversight of financial institutions (both banks and non-banks), monitors the financial system from a macro- and a micro-prudential perspective (BCB 2022; Vivan and Oliveira 2023).[8] In terms of macro-prudential supervision, the central bank uses various tools, including 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 SupTech tools to monitor the economic and financial conditions of individual financial institutions. Specifically, institutions are subject to periodic on-site inspections, which occur every one to three years, depending on the systemic importance of the institution. In addition to these periodic on-site inspections, since the end of 2010, 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 they could affect financial stability).[9]

Figure 1 provides a visualization of the BCB's supervisory framework, with a focus on the function of SupTech in the monitoring of financial institutions, and the supervisory units relying on SupTech to take supervisory actions. In general, the central bank's SupTech application digitizes reporting and regulatory processes, which it then analyzes to help to identify financial institutions where problems might be emerging. Specifically, the procedures

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

[9] 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, Lee, and Rosenfeld 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 financial institutions (CRS 2020).

of the SupTech application include the assessment of institutions' on- and off-balance positions from three fundamental perspectives; (1) temporal assessment, which is the evaluation of an institution's current performance compared to its own past performance; (2) comparative assessment, which is the evaluation of an institution's performance compared to its peer groups; (3) intrinsic assessment, which is the evaluation of potential inconsistencies in financial reporting. Based on these assessments, the application functions as an early warning system that generates automatic alerts for early risk exposures related to various (financial and non-financial) indicators, which is similar to the SupTech tool of the Federal Reserve, as described above.[10]

For confidentially reasons, we cannot provide details on the precise procedures of the SupTech application, but below we provide some hypothetical scenarios that might lead to an early warning signal. For the temporal assessment, an early warning can emerge if an institution's capital buffer has declined substantially over the past few months—even if the capital buffer does not fall below the regulatory minimum. For the comparative assessment, an early warning can emerge if an institution reports a decline in profitability compared to other (similar) institutions operating in the same region with the same business model, for instance. Based on this, a supervisory unit can investigate the reasons behind the decline in profitability (e.g., by analyzing which income or expense types contributed to the decline in profitability, and whether the decline in profitability is a temporary or long-term concern). For the intrinsic assessment, an early warning could occur if the sum of total deposits held by a bank's branches deviates from the total deposits reported by the parent bank.

When an early warning signal emerges, analysts of the monitoring unit (DESIG) are responsible for formally notifying the supervisory units (DESUP, DESUC, or DECON).[11] The analysts of DESIG describe the supervisory concern and explain what research may have been done related to the supervisory concern. Based on this information and additional information collected from supervised entities, the supervisory units of DESUP, DESUC, or DECON are responsible for taking the necessary actions to address the supervisory concerns.

[10] 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.

[11] DESUP is the Department of Banking Supervision. DESUC is the Department of Cooperatives and Non-Banking Institutions Supervision. DECON is the Department of Conduct Supervision.

These actions can be as formal as an on-site visit, and as informal as an email exchange between the supervisory unit and the affected institution. The supervisory actions (SupTech events) resulting from this process are the focus of our paper, and are comparable to the "Matters Requiring Attention (MRAs)" by the Federal Reserve for supervisory concerns that financial institutions should be able to resolve in the normal course of business (see Hirtle, Kovner, and Plosser 2020).

Compared to other supervisory actions, the supervisory scrutiny arising from the central bank's SupTech application offers a unique opportunity to test whether moral suasion—a key element of the supervisory toolkit (Acharya et al. 2024; Adrian et al. 2023)—can discipline bank behavior. First, unlike bank sanctions, the SupTech events that we analyze are not publicly announced and do not impose penalties, limiting the role of reputational or monetary effects. Second, unlike stress tests, SupTech events are not publicly announced and do not take place at the same point in time. Furthermore, they do not explicitly require affected institutions to raise capital, limiting the role of reputational and capital effects. Third, unlike on-site inspections, SupTech events do not involve a detailed examination of institutions' entire loan portfolio, limiting the role of mechanical effects coming from supervisors pointing out specific problem loans.[12]

3. Data

We leverage several unique datasets for our analysis. We use proprietary data on the BCB's SupTech application, balance sheet data and credit register data for banks and non-banks, and firm employment and revenue data. Below, we provide further information on the sources and composition of each individual dataset.

[12]For instance, in the study by Bonfim et al. (2023), the bank inspections were highly intrusive as 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 SupTech events analyzed in our study (which are often even unrelated to banks' lending activities).

3.1. SupTech data

We obtain detailed information from the BCB about "early warnings" arising from its SupTech application. This supervisory dataset comprises information on the date, the underlying supervisory concern, and the time needed to address the supervisory concern. Tables 1 and 2 provide information on the number of affected institutions and the number of SupTech events. Both (public and private) bank and non-bank institutions are covered by the SupTech application. We limit our sample to institutions active in the corporate loan market, resulting in 1,285 institutions of which 204 were affected at least once over the years 2010-2022. Among these institutions, 174 were affected once, 25 twice, and 5 three or more times. The average number of days needed by an affected institution to resolve a supervisory issue is about 50 days, but Figure 4 shows that this distribution is highly skewed as the median number of days needed is only 25 days (as indicated by the red vertical line).[13]

As mentioned, the supervisory dataset also contains information on the underlying supervisory concerns. Twenty different types of underlying supervisory concerns are recorded, which we group into the following two broad categories for confidentiality reasons: (1) regulatory non-compliance and (2) financial reporting inconsistencies.[14] The frequency distribution of the two categories is displayed in Figure 3. This figure shows that the majority of the supervisory concerns (60%) is related to regulatory non-compliance, supporting the idea that regulation relies on supervision for its enforcement.

3.2. Bank data

Financial statement data of the regulated financial institutions are provided by the BCB. By law, both bank and non-bank 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,

[13] As a comparison, 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.

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

we have access to detailed information on institutions' ownership structure and location from the UNICAD dataset managed by the BCB. As mentioned earlier, we limit the sample used in our empirical analysis to bank and non-bank institutions that are active in the corporate loan market.

Panel A of Table 3 provides summary statistics for the data on financial institutions used in our analysis. Our sample period runs from 2008 until 2022. Further, Table O1 in the Internet Appendix reports the difference in means for treated and non-treated institutions. This table shows that treated financial institutions are on average larger with lower capital buffers and lower profitability. In our analysis, we mitigate that our results are due to differences between treated and non-treated institutions by controlling for various characteristics and high-dimensional fixed effects, as explained in the methodology section below.

3.3. Loan 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 BCB. This dataset contains detailed information on virtually all corporate loans above BRL 5,000 (i.e., approximately USD 875 in March 2025) granted to non-financial institutions.[15] 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 quarterly frequency. The data track loan performance, which means we also have information on loan amounts in arrears and loan defaults. Panel B of Table 3 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.[16] Ultimately, our data sample covers 50% of all loans made to firms and covers all loans competitively made in Brazil from 2008 to 2022.

[15] This limit has decreased over time. Currently all loans above BRL 200 (approximately USD 40) are included in the SCR (Barroso et al. 2020).

[16] 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).

3.4. Firm data

We obtain firm employment data from the annual report of information register (Relação Anual de Informações—RAIS), which comprises information on 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 loan data from the credit register. The firm employment data contain information on the number of employees as well as the average salary of the employees, which also allows us to derive firms' wage expenses. We use the employment data at the quarterly frequency using values from the last date of each quarter. The firm revenue data are annual and part of the credit register. Further, we have information on firms' size (this is a categorical variable based on four categories; micro, small, medium, or large). Panel C of Table 3 provides summary statistics for the firm level data used in our analysis.

4. The effect on banks' balance sheets

4.1. Methodology

In our first analysis, we study how supervisory scrutiny arising from SupTech events affects banks' balance sheets, using the following difference-in-differences model:

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

where b and t refer to bank and month, respectively. The dependent variable, $y_{b,t}$, represents various bank level outcomes, including non-performing loans, loan loss provisions, capital, net income, and total loans (all scaled by total assets). $Post\ SupTech_{b,t}$ 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, liquidity, non-performing loans, deposits, and net income (all scaled by total assets). 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 which is clustered at the bank level. Note that we do not include a separate $Post$ or $SupTech$ variable as 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).[17] The coefficient of interest is β, which captures the change in the outcome of affected (relative to non-affected) banks after (relative to before) a SupTech event. The key identification assumption, which we test below, is that the outcomes of treated and non-treated banks would have evolved in parallel absent the SupTech event.

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) as the treatment effect is not perpetual obviously.[18] Further, for banks that are treated more than once, we only keep the first 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 our estimates.[19]

4.2. Results

The results from estimating Equation (1) are presented in Panels A and B of Table 4. We include bank controls in all regressions, and we gradually include bank and time fixed effects across the different columns.

Panel A of Table 4 reports results with problem loans, loan loss provisions, and loan loss provisions for risky loans as outcome variables.[20] Columns (1) to (3) show that affected banks reclassify more loans as problem loans (compared to non-affected banks) after a SupTech event (compared to before a SupTech event). The estimates are statistically as well as economically significant. The coefficient estimate in column (3), for instance, suggests that, following a SupTech event, affected banks' recognized problem loans increase by approximately 20%. In addition, columns (4) to (6) indicate that affected banks seem to cover for these problem loans by setting aside more provisions for (expected) loan losses. This result is even more

[17] 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 validity of this strategy. First, we apply a propensity score matching approach which compares affected banks to (observably similar) never-affected banks. Second, we apply a stacked difference-in-differences approach which compares affected to not-yet-affected banks.

[18] In other words, to address contamination problems related to the fact that treated banks do not remain treated, we remove treated banks two years after their treatment event date.

[19] In unreported robustness checks, we find that our results are robust to excluding banks subject to multiple SupTech events or to controlling for whether a bank has multiple SupTech events.

[20] Table O2 in the Internet Appendix also reports the coefficient estimate of *Treated*.

pronounced when we focus on loan loss provisions for risky loans, in columns (6) to (9), with an economic magnitude comparable to the one for the increase in problem loans. In Section 5.2 below, we also show that, after a SupTech event, treated banks downgrade the credit ratings of their riskiest borrowers—bringing them more in line with those assigned by non-treated banks that lend to the same firms—which supports the notion that the treated banks reveal previously unreported credit risk. Moreover, as explained in Section 4.4.2, we show that our results hold when we exclude (the few) SupTech events that are related to bank lending.

A potential financial stability concern is that, by forcing banks to set aside more loan loss provisions, supervisory scrutiny may adversely affect banks' capital position, profitability, or aggregate lending. To examine this, Panel B of Table 4 reports results with capital ratio, return on assets, and loans-to-assets as outcome variables. In general, we find statistically insignificant coefficient estimates across the different columns, suggesting that the supervisory scrutiny arising from SupTech events does not adversely affect banks' stability or lending.

Overall, our findings indicate that SupTech events have an informational disclosure effect (Passalacqua et al. 2022) in that they improve banks' risk reporting, without undermining banks' profitability or stability. In the next section, we explain the channel behind these results, followed by a series of additional tests that confirms the robustness of our findings.

4.3. Economic mechanisms

We now turn to the underlying channels that could be driving our results. In general, there are three potential channels through which supervisory actions can affect banks; (1) a capital channel, (2) a market discipline channel, and (3) a moral suasion channel. The first channel posits that supervisory actions may influence bank behavior by raising their capital requirements. The second channel argues that supervisory actions can reduce banks' risk-taking by increasing market discipline. The third channel, which is also referred to as the supervisory scrutiny channel, posits that supervisory actions may discipline banks by improving their understanding of the regulator's supervisory views, leading to more conservative risk attitudes aligned with those views. More generally, supervisory actions can change banks' perception of what the supervisory authority knows and can reasonably find out, which can induce them to become more prudent. We argue that our results can be explained by the moral suasion channel. In principle, the first two channels are irrelevant given that SupTech events do not explicitly require banks to raise capital and are not publicly disclosed (as discussed earlier in Section 2.2). Below, we first provide several pieces of evidence that support the moral suasion channel, followed by a series of results that reject the capital and market discipline channel.

First, if our results are due to a moral suasion channel, we would expect banks to react more strongly to SupTech events that improve their understanding of the regulator's supervisory views. To show that this is the case, we distinguish between supervisory concerns related to regulatory non-compliance and reporting inconsistencies. In principle, the former should enable banks to learn more about the regulator's supervisory views. We then re-estimate Equation (1) but we replace the *Post SupTech* variable by two distinct variables; one that captures the supervisory concerns related to regulatory non-compliance and one that captures the supervisory concerns related to reporting inconsistencies, represented by $Post\ SupTech_{regulatory}$ and $Post\ SupTech_{reporting}$, respectively. The results of this analysis are presented in Panel A of Table 5. For brevity, we limit our results to those for banks' non-performing loans and loan loss provisioning. The results indicate that our findings are primarily due to SupTech events related to regulatory non-compliance, consistent with a moral suasion channel.

Second, if our results are due to a moral suasion channel, we would expect our estimates to be more pronounced for SupTech events handled by more experienced supervisors (as they would arguably be better at explaining and enforcing supervisory concerns). To show that this is the case, we use information on the supervisory teams linked to the SupTech events, and distinguish the SupTech events into those handled by more and less experienced supervisory teams. We then re-estimate Equation (1) but we replace the *Post SupTech* variable by two distinct variables; one that captures events handled by more experienced supervisory teams and one that captures events handled by less experienced supervisory teams, represented by $Post\ SupTech_{experienced}$ and $Post\ SupTech_{inexperienced}$, respectively.

The results of this analysis are presented in Panel B of Table 5 and indicate that our findings are primarily due to SupTech events handled by experienced supervisors, consistent with our conjecture.

Third, we would expect banks located further away from the supervisory authority to react more strongly. Specifically, as supervisors face distance-based information frictions when monitoring geographically distant banks (e.g., Gopalan, Hann, and Mazur 2019), SupTech events may strengthen banks' perception that distance-based frictions do not impede the supervisor's ability to detect and address financial distortions. To test this, we use information on the physical distance between banks' headquarters and the supervisory authority to distinguish between SupTech events targeted at banks in cities with versus without a regional office of the Central Bank of Brazil.[21] We then re-estimate Equation (1) but we replace the *Post SupTech* variable by two distinct variables; one that captures events for geographically close banks and one that captures events for geographically distant banks, represented by $Post\ SupTech_{close}$ and $Post\ SupTech_{distant}$, respectively. The results of this analysis are presented in Panel C of Table 5 and indicate that our findings are primarily due to SupTech events targeted at geographically distant banks, which supports a moral suasion channel.

Fourth, we show that SupTech events have a "deterrence effect," a channel that has received much attention in the tax enforcement and anti-corruption literature (e.g., Advani, Elming, and Shaw 2021; Colonnelli and Prem 2022; Kleven et al. 2011; Pomeranz 2015). Specifically, we show that the SupTech events at targeted banks have spillovers on other, non-targeted banks operating in the same municipality. In line with a moral suasion channel, this result highlights that supervisory scrutiny can change banks' perception of what the supervisor knows and can reasonably find out, resulting in more prudent bank behavior, even by non-targeted banks. To show that this is the case, we restrict our sample to non-targeted banks and run the following regression model:

$$y_{b,c,t} = \beta Post \times Treated_{c,t} + \delta \boldsymbol{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,c,t} \quad (2)$$

[21] The regional offices of the Central Bank of Brazil are located in Belém, Belo Horizonte, Brasília, Curitiba, Fortaleza, Porto Alegre, Recife, Rio de Janeiro, Salvador, and São Paulo.

where $y_{b,c,t}$ is the outcome variable of non-targeted bank b operating in municipality c at time t. $Post \times Treated_{c,t}$ is an indicator variable equal to one for the 24 months following a (targeted) bank in municipality c being subject to a SupTech event. Because we only consider the non-targeted banks in this regression model and these banks do not face any direct supervisory scrutiny, this regression captures the spillovers arising from deterrence effects (Colonnelli and Prem 2022; Pomeranz 2015).[22] The results of this analysis are presented in Table 6 and confirm that SupTech events generate spillover effects on 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 12% and 10%, respectively.[23] Overall, this suggests that SupTech events increase other banks' perception of being subject to supervisory scrutiny, and thereby improves their risk reporting. Put differently, SupTech events may cause banks to think that the supervisor is "on to them" which may induce them to become more prudent (Slemrod 2019).

Finally, we rule out that our results are driven by a capital or market discipline channel. As mentioned earlier, in principle this should not be the case as SupTech events are not publicly disclosed and do not require banks to raise capital. In line with this, Table A2 in Appendix confirms that our results are similar for lowly and highly capitalized banks, and Table A3 shows that our results are not stronger for banks that face more public scrutiny, which we proxy based on banks' subordinated debt (Mishkin 2009); if anything, our results are stronger for banks that face less public scrutiny.

Taken together, the results above support that our findings can be attributed to a moral suasion channel. First, we find that our results are primarily driven by SupTech events related to regulatory non-compliance, which arguably are the events that improve banks' understanding of regulators' supervisory views. Second, we find that our results are strongest for SupTech events handled by more experienced supervisory teams, which is in line with the idea that more experienced supervisors would be better at interpreting and explaining

[22] Gopalan, Hann, and Mazur (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.

[23] To show that these spillover effects do not threaten our baseline results, Table O4 in the Internet Appendix shows that our baseline results hold if we exclude non-targeted banks operating in the same municipality as targeted banks from the control group.

supervisory concerns. Third, we find that our results are strongest for banks located further away from the supervisory authority, suggesting that SupTech events may strengthen distant banks' perception that the supervisor's ability to detect risky bank behavior is not constrained by geographical distance. Fourth, we find that SupTech events at targeted banks have spillover effects on the risk reporting of non-targeted banks located in the same municipality, in line with a deterrence effect.

4.4. Robustness

4.4.1. Dynamic analysis

To assess whether the estimated effects are attributable to supervisory scrutiny from SupTech events, we verify the parallel trends assumption underlying our difference-in-differences model. That is, we analyze whether there is a significant effect only after, and not before, the SupTech events. To do so, we estimate a dynamic version of the difference-in-differences estimator outlined in Equation (1), which can be specified as follows:

$$y_{b,t} = \sum_{\tau=-9}^{+24} \beta_\tau SupTech_{b,t} \times \{1_{\tau=t}\} + \delta \boldsymbol{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,t} \tag{3}$$

where $SupTech_{b,t} \times \{1_{\tau=t}\}$ is a dummy variable interacted with an event time indicator variable. Particularly, $SupTech_{b,t}$ 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 5a to 5f. These figures generally support the parallel trends assumption underlying our difference-in-differences regressions. For instance, for periods prior to a SupTech event, 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' problem loans and provisioning expenses significantly increase (compared to non-treated banks) after a SupTech event (compared to the pre-event period). These effects emerge almost instantly and gradually dissipate. On average, the effects become statistically insignificant after approximately fifteen to eighteen 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.

4.4.2. Excluding SupTech events related to bank lending

A potential concern could be that our baseline findings are driven by SupTech events related to bank lending. However, in reality, such events are very rare. Nevertheless, to mitigate potential concerns, Table O3 in the Internet Appendix shows that our results hold if we re-estimate Equation (1) excluding banks with SupTech events related to bank lending. Note that, for confidentiality reasons, this table does not report the number of observations.

4.4.3. Propensity score matching

As discussed earlier, a potential concern is that the supervisory actions arising from the central banks SupTech application are 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 and fixed effects in our regressions, our findings could still be (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:

$$log(y_{b,p}) = \alpha_0 + \delta \boldsymbol{X}_{b,p} + \epsilon_{b,p} \tag{4}$$

where $\boldsymbol{X}_{b,p}$ is a vector of average values of bank level variables in 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 deviation caliper of the estimated propensity score.

Based on the matched sample, we then re-estimate Equation (1). The results are presented in Table O7 in the Internet 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 increase. Further, we do not find an effect on banks' capital ratio or loans-to-assets ratio, but we do find evidence of a small decrease in treated banks' profitability after a SupTech event.

4.4.4. Placebo tests

Although the staggered nature of the SupTech events 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 sheets. These results are reported in Table O5 in the Internet Appendix. 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 around the same time as the SupTech events.

4.4.5. 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 (Baker, Larcker, and Wang 2022; 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, the weights can become negative, which can result in biased coefficient estimates.

To address this potential concern, we provide an alternative estimation method, namely a stacked difference-in-differences model (e.g., Baker, Larcker, and Wang 2022; Deshpande and Li 2019). To estimate this model, we start by creating separate datasets for each of the SupTech event dates. In each dataset, banks that are affected during the current SupTech event 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 SupTech event period. Finally, we stack all the datasets of treatment and control banks for each period into one dataset and we estimate the following equation:

$$y_{b,p,t} = \beta Treated_{b,p} + \gamma(Treated_{b,p} \times Post_{p,t}) + \alpha_{b,p} + \alpha_{p,t} + \epsilon_{b,p,t} \tag{5}$$

where $y_{b,p,t}$ is a bank level outcome of bank b at time t for SupTech event period (cohort) p. $Treated_{b,p}$ is a dummy variable equal to one if bank b is a treated bank for event 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 SupTech event period p at time t (i.e., the interaction of treatment with post SupTech event 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 (Joaquim, Doornik, and Ornelas 2019). The standard errors are represented by $\epsilon_{b,p,t}$ and clustered by SupTech event period (cohort) as these represent the level of variation in this regression (but the results are robust to clustering at the bank×cohort level).[24]

The results are reported in Table O6 in the Internet Appendix. Overall, these results are quantitatively equivalent to our baseline estimates from Table 4, indicating that the supervisory actions induce banks to reclassify loans as problem loans and to set aside more provisions for potential loan losses.

5. The effect on banks' lending behavior

5.1. Methodology

In our second analysis, we examine the effect of SupTech events on bank lending using granular loan data from the corporate credit register. As mentioned earlier, SupTech events are generally unrelated to banks' loan portfolio (and our results hold when we exclude those events), meaning that any effect on bank lending would provide further support that our results can be explained by a moral suasion channel.

The literature has proposed two views on how supervisory scrutiny could affect bank

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

lending. On the one hand, the capital shock hypothesis posits that supervisory scrutiny puts pressure on banks' capital ratios which may force them to reduce credit supply (Bernanke, Lown, and Friedman 1991; Caballero, Hoshi, and Kashyap 2008; Peek and Rosengren 2000). On the other hand, the reallocation hypothesis suggests that supervisory scrutiny may reduce banks' risk-taking and lead to a reallocation of credit supply from less creditworthy to more creditworthy borrowers (Bonfim et al. 2023). First, we test for the capital shock hypothesis using the following firm-bank level regressions:

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

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.[25] As before, $Post\ SupTech_{b,t}$ is a dummy 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 deposit ratio; firms' size and industry; and the (proprietary) credit rating assigned by the lender to the borrower, which essentially captures lenders' private information about the borrower and mitigates concerns that our results are biased by confounding factors that are observable to the lender but unobservable to the econometrician.[26] In addition, 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 $\alpha_{f,b}$, 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 growth opportunities, that proxies 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., Paligorova and Santos 2017). The error term corresponds to $\epsilon_{f,b,t}$ and is clustered at the bank level. In this equation, the coefficient of interest is β, which captures the change in credit supply from treated banks (relative to non-treated banks) in the post-supervision period (relative to the

[25]Following Bonfim et al. (2023), loans include outstanding exposures, undrawn credit lines, and unreleased credit lines of a bank to a firm. We compute credit growth as follows: $Credit\ growth_{f,b,t} = \frac{Credit_{f,b,t} - Credit_{f,b,t-1}}{0.5 \times (Credit_{f,b,t} + Credit_{f,b,t-1})}$ (Davis and Haltiwanger 1992). This transformation is widely used as it is symmetric and bounded.

[26]Resolution 2,682/1999 of the BCB stipulates 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.

pre-supervision period).[27]

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

$$\begin{aligned} y_{f,b,t} = & \gamma_1 Arrears_{f,b,t-1} + \gamma_2 (Post\ SupTech_{b,t} \times Arrears_{f,b,t-1}) + \\ & \delta \boldsymbol{X}_{f,b,t-1} + \alpha_{b,t} + \alpha_{f,t} + \alpha_{f,b} + \epsilon_{f,b,t} \end{aligned} \tag{7}$$

where $Arrears_{f,b,t-1}$ is a dummy variable equal to one for less creditworthy firms, which we define as firms that had payment in arrears for loans outstanding at bank b in quarter $t-1$ (similar to, e.g., Abbassi et al. 2025). 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 proxies for changes in overall credit supply.[28] In this regression, the coefficient of interest is γ_2, 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 borrowers (relative to more creditworthy borrowers).

Note that, Equations (6) and (7) allow us to establish the causal relationship between SupTech events 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. Hence, we are able to measure the causal effect on banks' lending behavior. This assertion is supported by the fact that—prior to a SupTech event—affected banks' lending behavior is similar to that of non-affected banks (as discussed in Section 5.3.1 below).

5.2. Results

Table 7 shows the results of estimating Equation (6) to test the capital shock hypothesis. We include the vector of controls in all regressions, and gradually saturate the model with different sets of fixed effects to gauge their effects on the robustness of our findings. The standard errors are clustered at the bank level. The results from Table 7 show statistically

[27] Note that, as in Equation (1), we drop treated banks from the sample after their corresponding post-treatment period (i.e., two years after the SupTech event). Further, for banks that are treated more than once, we only keep the first SupTech event (similar to the approach of Roman 2020).

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

insignificant coefficient estimates across the different columns, suggesting that, on average, SupTech events do not affect banks' credit supply. Stated differently, inconsistent with the capital shock hypothesis, we do not find that treated banks cut credit after a SupTech event.

Turning to the reallocation hypothesis, Table 8 show the results of estimating Equation (7). As before, we gradually saturate the model with different sets of fixed effects. In line with the reallocation hypothesis, the results from Table 8 indicate that treated banks reduce credit supply to less creditworthy borrowers after a SupTech event. More precisely, the coefficient estimates indicate that, after a SupTech event, less creditworthy borrowers experience a 3–5% reduction in credit supply from treated banks. This effect is economically relevant but (unsurprisingly) smaller than the estimates from Bonfim et al. (2023) and Passalacqua et al. (2022), who find that on-site bank inspections—which are much more intrusive and include a detailed evaluation of banks' loan portfolio—cause treated banks to reduce credit to unproductive borrowers by 20% and 60%, respectively.

We also examine whether treated banks change other loan terms after a SupTech event. To this end, we use the regression models from Equations (6) and (7) to examine the effect on loan rates, maturities, collateral requirements, and credit ratings. The regression results on loan rates are presented in Tables A4 and A5 in Appendix, respectively. The results in Table A4 show that treated banks in general do not change interest rates after a SupTech event. However, in line with our results on the reallocation of credit, Table A5 shows that treated banks increase interest rates charged to less creditworthy borrowers. Column (5) from Table A5 for example implies that treated banks increase loan rates charged to less creditworthy borrowers by roughly 9% after a SupTech event. We find a similar pattern for loan maturities. In particular, Table A6 in Appendix shows that, on average, treated banks do not change loan maturities after a SupTech event, while Table A7 shows that treated banks reduce the loan maturities of loans to less creditworthy borrowers. For instance, column (5) of Table A7 indicates that, after a SupTech event, treated banks reduce the loan maturity of loans granted to less creditworthy borrowers by around 17%. Tables A8 and A9 in Appendix indicate that SupTech events do not affect collateral requirements (independent of borrowers' creditworthiness), which may be due to the fact that firms cannot easily increase pledged collateral.[29] Finally, Tables A10 and A11 in Appendix show that after a SupTech event, treated banks bring the credit ratings assigned to their riskiest borrowers more in line with those assigned by non-treated banks, suggesting that they become more conservative in their credit risk assessment.[30]

In sum, our results show that, after a SupTech event, treated banks increase the interest rate and reduce the loan amount and maturity of loans granted to less creditworthy borrowers. Since SupTech events are generally unrelated to banks' loan portfolio, and supervisors do not force treated banks to cut credit to any particular borrowers in any case, these findings provide further support that our results are due to a supervisory scrutiny channel.

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:

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

where $SupTech_{b,t} \times \{1_{\tau=t}\}$ 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 6a 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' average credit supply.

Similarly, we verify the parallel trends assumption underlying the regression model from Equation (7), by including an interaction term between $SupTech_{b,t} \times \{1_{\tau=t}\}$ and

[29] One observation in line with this argument is that 60% of loans in our sample is already collateralized (see Table 3).

[30] Note that the number of observations is lower for the regression results reported in Tables A8 and A9 as we need at least two banks to lend to a borrower in order to be able to compute credit rating deviations.

the $Arrears_{f,b,t-1}$ variable from Equation (7). The result is presented in Figure 6b, which seems 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 4.4.1, the effect seems to dissipate after five to six quarters (i.e., after fifteen to eighteen months).

5.3.2. Excluding SupTech events related to bank lending

As in Section 4.4.2, Tables O8 and O9 in the Internet Appendix show that our results hold if we exclude banks with SupTech events related to bank lending. This further resolves any concerns that our estimated effects on bank lending would be driven by SupTech events related to banks' loan portfolio. As before, for confidentiality reasons, these tables do not report the number of observations.

5.3.3. Placebo tests

To ensure that our results are not driven by other events that may have occurred at the same time as the SupTech events, 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 events on banks' credit supply. These results are reported in Tables O10 and O11 in the Internet Appendix. The falsification tests based on the placebo events show no statistically significant effects. That is, placebo events 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

Finally, we assess whether SupTech events have real effects by analyzing the potential spillovers on firm outcomes. For this purpose, we estimate the following difference-in-differences models:

$$y_{f,t} = \beta Exposure_{f,pre} + \lambda Post\ Exposure_{f,pre} + \delta \boldsymbol{X}_{f,t-1} + \alpha_f + \alpha_{j,t} + \alpha_{m,t} + \epsilon_{f,t} \tag{9}$$

where $y_{f,t}$ represents different firm level outcomes, including total leverage, employment, and revenues. $Exposure_{f,pre}$ represents the credit exposure of firm f to treated bank(s) right before treatment.[31] $\boldsymbol{X}_{f,t-1}$ 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.[32] The error term corresponds to $\epsilon_{f,t}$ and is clustered at the firm level. In this equation, the coefficient of interest is λ, 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:

$$\begin{aligned} y_{f,t} = & \gamma_1 Exposure_{f,pre} + \gamma_2 Post\ Exposure_{f,pre} + \gamma_3 Arrears_{f,pre} + \\ & \gamma_4 (Arrears_{f,pre} \times Exposure_{f,pre}) + \gamma_5 (Post\ Exposure_{f,pre} \times Arrears_{f,pre}) + \\ & \delta \boldsymbol{X}_{f,t-1} + \alpha_f + \alpha_{j,t} + \alpha_{m,t} + \epsilon_{f,t} \end{aligned} \tag{10}$$

where $Arrears_{f,pre}$ is a dummy variable equal to one if firm f had payment in arrears at the treated bank(s) and zero otherwise (including if the firm had payments in arrears at other non-treated bank(s) that the firm may be borrowing from). This equation allows us to assess whether the real effects of being exposed to a treated bank were different for less creditworthy firms, for instance, because treated banks cut credit to less creditworthy firms,

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

[32] 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.

as our earlier results indicate. γ_5 thus identifies the differential impact of borrowing from treated banks (compared to non-treated banks) in the post-treatment period (compared to the pre-treatment period) for a less creditworthy borrower (compared to a more creditworthy borrower).

6.2. Results

Table 9 shows the results of estimating Equation (9). Across the different columns, the table reports the effect on firms' total leverage, employment, and revenues. The estimated effects in column (1) indicate that, on average, supervisory scrutiny does not have spillover effects on the outcomes of firms borrowing from treated banks. This is not surprising as the results from Table 7 earlier show that, on average, treated banks do not tighten credit conditions after a SupTech event. Accordingly, in columns (2) and (3), we do not find spillover effects on firms' employment or revenues.

Table 10 presents the results of estimating Equation (10), where we focus on the spillover effects to less creditworthy firms. First, the interaction term in column (1) points to a significant decrease in the leverage of less creditworthy firms (compared to more creditworthy firms), indicating that less creditworthy firms cannot completely compensate the reduction in credit from treated banks. Columns (2) and (3) further suggest that this has real spillover effects on less creditworthy firms in the form of reduced employment and revenues. For instance, a one standard deviation increase in a less creditworthy firm's exposure to a treated bank decreases the firm's employment and revenues by approximately 1%, on average. 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).[33]

In sum, the spillover effects of SupTech events on firms borrowing from treated banks seem small and concentrated among less creditworthy firms. This contrasts with prior research, which has found large negative spillovers for bank sanctions (Danisewicz et al. 2018) and large positive spillovers for on-site bank inspections (Bonfim et al. 2023; Passalacqua et al. 2022), but accords with the idea that moral suasion has a more limited impact.

[33] 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 0.70 percentage points and increase the unemployment rate by 0.16 percentage points (compared to average growth rates averaging 1.5% on the county level).

7. Conclusion

Despite the importance of bank regulation, bank supervision is essential to detect and prevent financial distortions and regulatory non-compliance (Stiglitz 2009). To this end, regulators increasingly rely on SupTech tools that identify banks where weaknesses are most likely to be found, in order to prevent early risk exposures from materializing and affecting financial stability. Although policymakers have argued that this allows for more forward-looking, hypothesis-driven supervision, the fact that the supervisory scrutiny arising from SupTech tools is preventive rather than punitive raises a fundamental question: can this type of supervisory scrutiny discipline risky bank behavior?

In this paper, we address this question using unique data from the SupTech tool implemented by the Central Bank of Brazil. We uncover three sets of results. First, we find that SupTech events seem to have an informational disclosure effect, as treated banks reclassify loans as non-performing and increase provisions for expected loan losses. Consistent with the notion that SupTech tools enable supervisors to help banks in addressing early risk exposures, we show that these results can be explained by a moral suasion channel, according to which supervisory scrutiny improves banks' understanding of the regulator's supervisory views, inducing them to adopt more conservative risk attitudes in line with those views. Second, we find that SupTech events reduce risk-taking in bank lending, as treated banks reduce credit to less creditworthy borrowers after the events. Given that, in general, SupTech events are unrelated to banks' lending activities and supervisors do not explicitly force banks to change their lending behavior, this finding provides further support that our results can be attributed to supervisory scrutiny. Finally, we find that the change in lending behavior of treated banks has negative (albeit small) spillover effects on the economic performance of their less creditworthy borrowers.

Overall, our findings provide novel evidence that SupTech and, more broadly, moral suasion can discipline bank risk-taking. These results have valuable policy implications, suggesting that SupTech is more than just a "check-the-box" regulatory constraint, and warrant further research into the role of risk-based versus compliance-based supervision in the optimal design of supervisory frameworks.

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Figures

Figure 1: The Central Bank of Brazil's supervisory framework

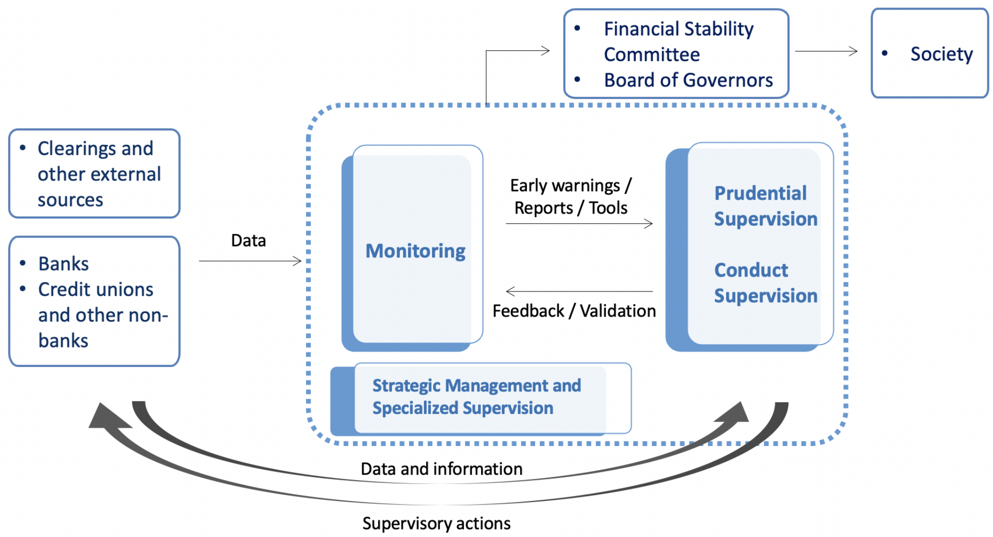


Figure 2: Number of SupTech events per year

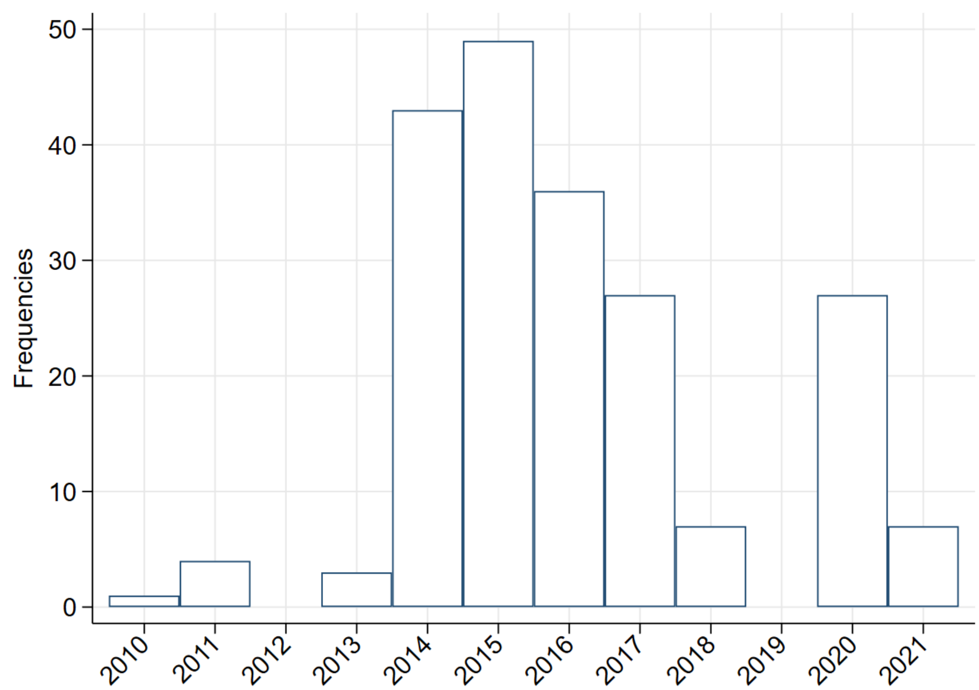


Figure 3: Distribution of the types of supervisory concerns underlying the SupTech events

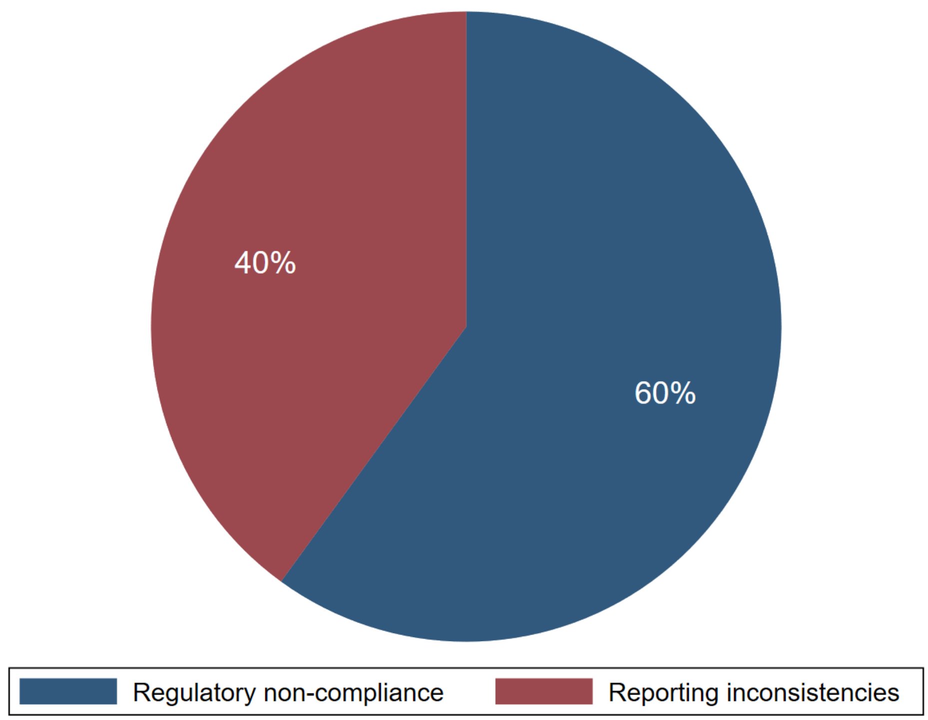
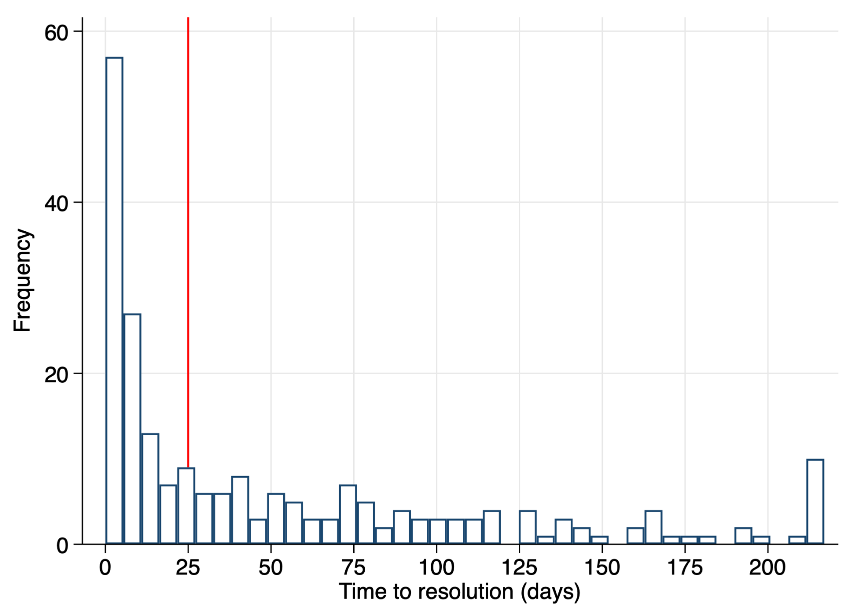
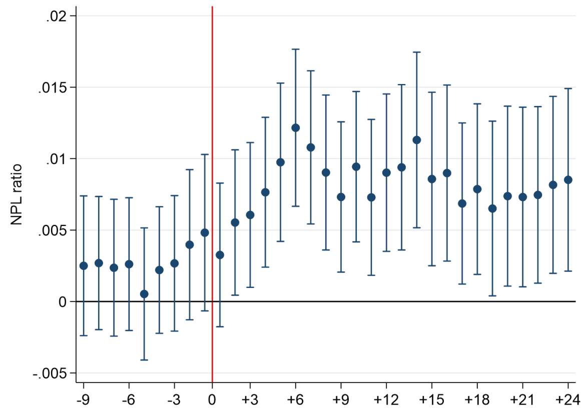


Figure 4: Distribution of the number of days needed to resolve the supervisory concerns underlying the SupTech events

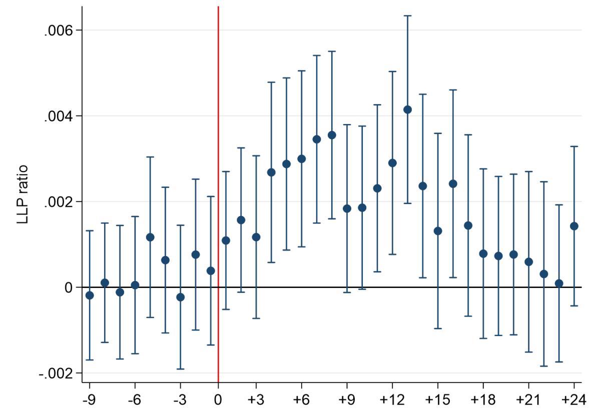


Note: The red vertical line corresponds to the median.

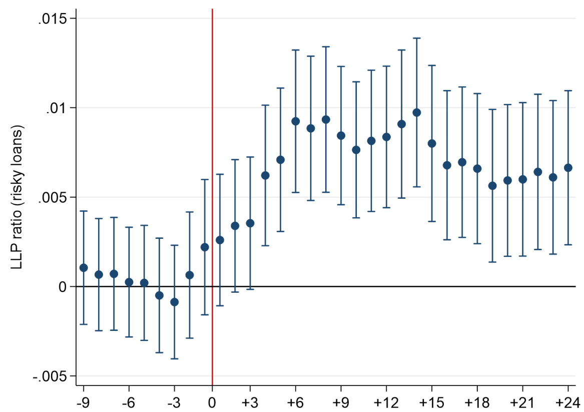
Figure 5: Dynamic difference-in-differences estimates for the effect of SupTech events on banks' balance sheet items



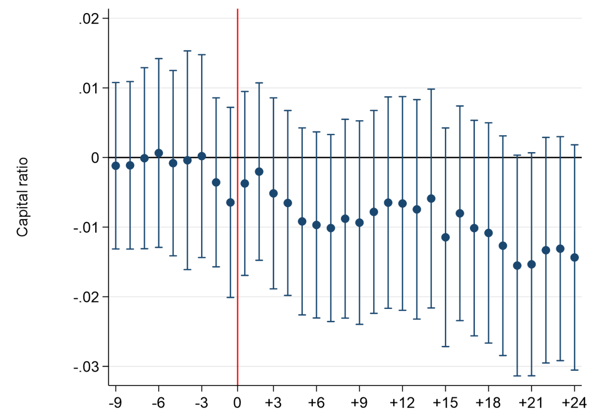
(a) Problem laons/TA



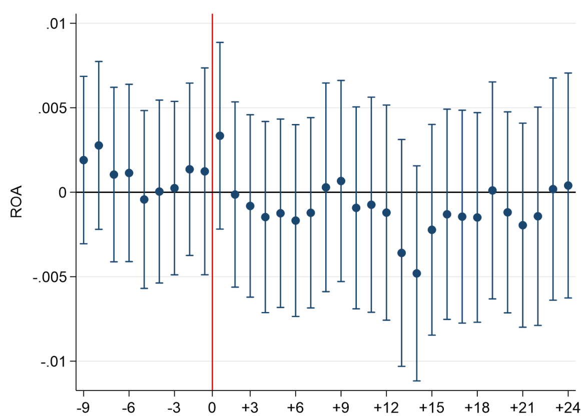
(b) LLP/TA



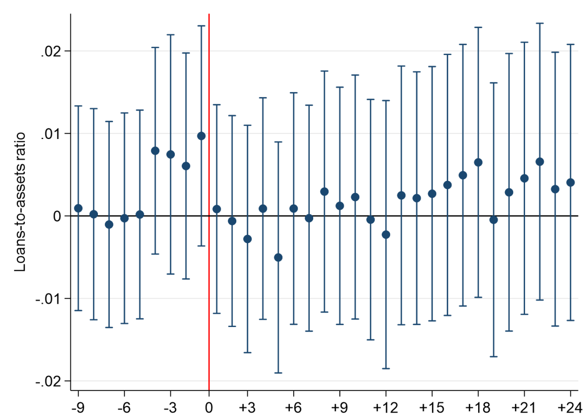
(c) $\text{LLP}_{\text{risky}}$/TA



(d) Capital/TA



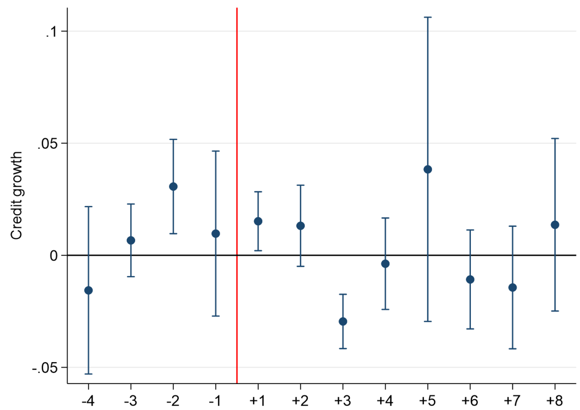
(e) ROA



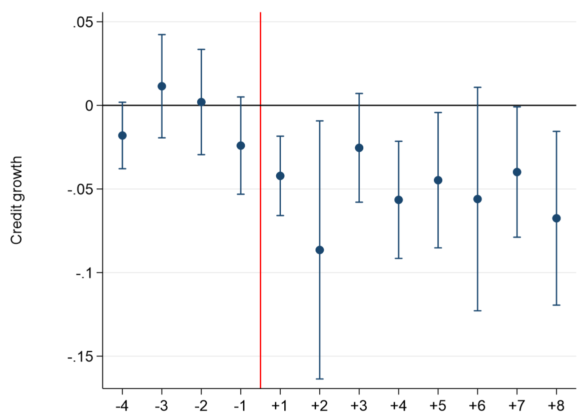
(f) Loans/TA

Note: This figure presents the dynamic difference-in-differences estimates of the effect of SupTech events on banks' balance sheet items. The y-axis corresponds to the coefficient estimates of β from Equation (3). The x-axis corresponds to months relative to the time of a SupTech event. The outcome variable is indicated at the bottom of each figure. A constant is included in all regressions but not reported. The bars represent confidence intervals at the 95% level.

Figure 6: Dynamic difference-in-differences estimates for the effect of SupTech events on bank lending



(a) Baseline



(b) Less creditworthy firms

Note: This figure presents the dynamic difference-in-differences estimates of the effect of SupTech events on bank lending. The y-axis corresponds to the coefficient estimates of β from Equations (8) and (7). The x-axis corresponds to quarters relative to the time of a SupTech event. The outcome variable is the change in total credit of bank b to firm f from quarter $t-1$ to quarter t. Panel 6a presents the effects for average credit supply. Panel 6b presents the effects for credit supply to less creditworthy borrowers (defined as borrowers with payments in arrears). A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the bank level. The bars represent confidence intervals at the 95% level

Tables

Table 1: Distribution of treated vs. non-treated banks

	Frequency	Percentage	Cumulative Percentage
Treated	204	15.87	15.87
Non-treated	1,081	84.12	100.00
Total	1,285	100.00	

Table 2: Number of SupTech events per treated bank

	Frequency	Percentage	Cumulative Percentage
0	1,081	84.12	84.12
1	174	13.54	97.66
2	25	1.95	99.61
3+	5	0.00	100.00
Total	1,285	100.00	

Table 3: Summary statistics

	N	Mean	Median	SD	P10	P90
Panel A: Bank variables						
Treated	120,567	0.15	0.00	0.36	0.00	1.00
ln(TA)	120,567	18.67	18.57	2.42	15.64	22.09
Loans/TA	120,567	0.56	0.59	0.23	0.23	0.83
Deposits/TA	120,567	0.48	0.54	0.26	0.00	0.80
Equity/TA	120,567	0.26	0.19	0.21	0.11	0.58
Liquid assets/TA	120,567	0.34	0.33	0.19	0.09	0.61
NPL/TA	120,567	0.04	0.03	0.05	0.00	0.10
LLP/TA	120,567	0.01	0.01	0.02	0.00	0.03
LLP_{risky}/TA	120,567	0.03	0.02	0.03	0.00	0.06
ROA	72,773	0.03	0.03	0.04	-0.01	0.07
Panel B: Firm-bank variables						
Credit growth	14,938,873	0.31	0.00	0.81	-0.28	2.00
ln(Loan amount)	14,938,873	10.08	10.07	1.61	8.00	12.20
ln(Maturity)	14,938,873	2.61	3.04	1.28	0.62	3.93
Collateral	14,938,873	0.60	1.00	0.49	0.00	1.00
ln(Loan rate)	13,255,159	3.65	3.48	1.19	2.48	5.36
Arrears	14,938,873	0.21	0.00	0.41	0.00	1.00
Credit rating	14,938,873	0.11	0.00	0.26	0.00	0.50
N(Bank relationships)	14,938,873	2.20	2.00	1.49	1.00	4.00
Panel C: Firm variables						
Size	3,219,677	1.86	2.00	0.66	1.00	3.00
Δ ln(Credit)	3,219,677	-0.02	-0.02	0.50	-0.53	0.53
Δ ln(Employment)	3,219,677	-0.01	0.00	0.18	-0.22	0.21
Δ ln(Revenue)	3,219,677	0.05	0.00	1.06	-0.75	0.91

Note: This table presents summary statistics for the variables used in our empirical analysis. Variable definitions are provided in Table A1 in Appendix.

Table 4: The effect of SupTech events on banks' balance sheets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A		NPL/TA			LLP/TA			LLP_{risky}/TA	
Post SupTech	0.016***	0.011***	0.008***	0.002**	0.003***	0.002***	0.013***	0.011***	0.007***
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	96,617	96,617	96,614	96,617	96,617	96,614	96,617	96,617	96,614
Adjusted R-squared	0.163	0.189	0.676	0.062	0.165	0.530	0.100	0.112	0.628
Panel B		Equity/TA			ROA			Loans/TA	
Post SupTech	-0.008	-0.008	-0.009	0.001	-0.004	-0.001	0.024**	0.010	0.001
	(0.010)	(0.011)	(0.007)	(0.003)	(0.003)	(0.002)	(0.011)	(0.012)	(0.007)
Observations	96,617	96,617	96,614	67,837	67,837	67,835	96,617	96,617	96,614
Adjusted R-squared	0.471	0.476	0.867	0.053	0.107	0.582	0.614	0.619	0.876
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 sheets. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, and the ratio of loan loss provisions for risky loans in Panel A, and the capital ratio, return on assets, and loans-to-assets ratio in Panel B. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 5: The effect of SupTech events on banks' balance sheets: Heterogeneity in supervisory issues, supervisory experience, and distance from the supervisory authority

	(1)	(2)	(3)
	NPL/TA	LLP/TA	LLP_{risky}/TA
Panel A			
Post $SupTech_{regulatory}$	0.010***	0.002**	0.008***
	(0.003)	(0.001)	(0.003)
Post $SupTech_{reporting}$	0.002	0.001	0.003
	(0.004)	(0.001)	(0.003)
Observations	96,614	96,614	96,614
Adjusted R-squared	0.676	0.530	0.628
Panel B			
Post $SupTech_{experienced}$	0.008***	0.002***	0.007***
	(0.003)	(0.001)	(0.002)
Post $SupTech_{inexperienced}$	0.000	-0.002	0.003
	(0.004)	(0.003)	(0.002)
Observations	96,614	96,614	96,614
Adjusted R-squared	0.676	0.530	0.629
Panel C			
Post $SupTech_{distant}$	0.008***	0.002***	0.008***
	(0.003)	(0.001)	(0.002)
Post $SupTech_{close}$	0.004	0.001	-0.005
	(0.011)	(0.003)	(0.008)
Observations	96,614	96,614	96,614
Adjusted R-squared	0.676	0.530	0.629
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' balance sheets. In Panel A, we distinguish between SupTech events related to regulatory non-compliance and reporting inconsistencies. In Panel B, we distinguish between SupTech events handled by more and less experienced supervisors. In Panel C, we distinguish between banks located in cities with versus without an office of the Central Bank of Brazil. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, and the ratio of loan loss provisions for risky loans. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 6: The effect of SupTech events on banks' balance sheets: Within-municipality spillovers

	(1)	(2)	(3)	(4)	(5)	(6)
	NPL/TA	LLP/TA	LLP_{risky}/TA	Capital/TA	ROA	Loans/TA
Post × Treated	0.005**	0.002***	0.003*	-0.008	-0.004	-0.003
	(0.002)	(0.001)	(0.001)	(0.008)	(0.003)	(0.007)
Observations	61,819	61,819	61,819	61,819	41,427	61,819
Adjusted R-squared	0.674	0.532	0.630	0.882	0.628	0.888
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. Targeted banks are excluded from the estimation sample. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, and the ratio of loan loss provisions for risky loans in Panel A, and the capital ratio, return on assets, and loans-to-assets ratio in Panel B. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 7: The effect of SupTech events on banks' lending behavior: Credit growth

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth
Post SupTech	0.012	0.004	0.010	0.020
	(0.015)	(0.018)	(0.017)	(0.021)
Observations	12,515,254	12,462,072	6,227,401	6,108,925
R-squared	0.013	0.098	0.425	0.510
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	No
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 outcome variable is the change in total credit of bank b to firm f from quarter $t-1$ to quarter t. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 8: The effect of SupTech events on banks' lending behavior to less creditworthy firms: Credit growth

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth	(5) Credit growth
Post SupTech	0.009	0.021	0.031	–	–
	(0.020)	(0.020)	(0.023)	(–)	(–)
Post SupTech × Arrears	-0.021*	-0.044**	-0.037**	-0.040*	-0.026**
	(0.013)	(0.021)	(0.015)	(0.021)	(0.012)
Observations	12,462,072	6,227,401	6,218,787	6,108,925	6,099,907
R-squared	0.098	0.426	0.444	0.510	0.527
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Bank × Time FE	No	No	No	Yes	Yes
Firm × Time FE	No	Yes	Yes	Yes	Yes
Bank × Firm FE	No	No	Yes	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior. The outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 9: The effect of SupTech events on firm outcomes

	(1)	(2)	(3)
	Δ Credit	Δ Employment	Δ Revenue
Exposure_{pre}	-0.021***	0.000	0.004
	(0.003)	(0.001)	(0.006)
Post Exposure_{pre}	0.003	-0.001	0.003
	(0.003)	(0.001)	(0.004)
Observations	3,217,577	3,217,577	3,217,577
R-squared	0.130	0.165	0.168
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry $\times$ Time FE	Yes	Yes	Yes
Municipality $\times$ Time FE	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on firm outcomes. The dependent variables across the different columns are the change in total bank credit, the change in employment, and the change in revenue. Variable definitions are provided in Table A1 in Appendix. A constant is included in all regressions but not reported. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 10: The effect of SupTech events on firm outcomes of less creditworthy firms

	(1)	(2)	(3)
	Δ Credit	Δ Employment	Δ Revenue
Exposure$_{pre}$	-0.021***	-0.000	0.037
	(0.003)	(0.000)	(0.036)
Post Exposure$_{pre}$	-0.003	-0.002**	0.010
	(0.003)	(0.001)	(0.008)
Post Exposure$_{pre}$ $\times$ Arrears	-0.026***	-0.006***	-0.012*
	(0.003)	(0.001)	(0.007)
Observations	3,217,577	3,217,577	3,217,577
R-squared	0.130	0.165	0.168
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry $\times$ Time FE	Yes	Yes	Yes
Municipality $\times$ Time FE	Yes	Yes	Yes

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

Appendix

Table A1: Variable definitions

Variable	Description
Treated	A dummy variable equal to one if a bank is subject to a SupTech event over our sample period.
ln(TA)	The natural logarithm of banks' total assets.
Loans/TA	The ratio of banks' loans to total assets.
Deposits/TA	The ratio of banks' deposits to total assets.
Liquidity/TA	The ratio of banks' liquid assets to total assets.
Capital/TA	The ratio of banks' equity to total assets.
NPL/TA	The ratio of banks' non-performing loans to total assets.
LLP/TA	The ratio of banks' loan loss provisions to total assets.
$\text{LLP}_{\text{risky}}$/TA	The ratio of banks' loan loss provisions for risky loans to total assets.
ROA	The ratio of banks' net revenue to total assets.
Credit growth	The change in credit from bank b to firm f from quarter $t-1$ to quarter t.
Collateral	A dummy variable equal to one if the loan relationship between firm f and bank b has underlying collateral.
ln(Loan amount)	The natural logarithm of the total loan amount of firm f from bank b in quarter t.
ln(Loan rate)	The natural logarithm of the loan rate on the loans of firm f from bank b in quarter t.
ln(Maturity)	The natural logarithm of the loan maturity on the loans of firm f from bank b in quarter t.
Credit rating	Credit rating varying from 0 to 1, where 0 represents the best rating a loan can achieve (lowest credit risk) and 1 represents the worst rating a loan can be assigned (highest credit risk).
N(Bank relationships)	The natural logarithm of the number of bank lending relationships that firm f has in quarter t.
Arrears	A dummy variable equal to one if the loans of firm f have payments in arrears on the loans from bank b.
Δ Employment	The change in the total number of employees working at firm f from quarter $t-1$ to quarter t.
Δ Revenue	The change in the total revenue of firm f from quarter $t-1$ to quarter t.

Table A2: The effect of SupTech events on banks' balance sheets: Heterogeneity in banks' capitalization

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post $SupTech_{low\ capital}$	0.006**	0.001*	0.005***	-0.012*	-0.003	0.005
	(0.003)	(0.001)	(0.002)	(0.007)	(0.002)	(0.008)
Post $SupTech_{high\ capital}$	0.013**	0.004***	0.010**	-0.001	0.003	-0.010
	(0.005)	(0.001)	(0.004)	(0.017)	(0.006)	(0.013)
Observations	96,614	96,614	96,614	96,614	67,835	96,614
Adjusted R-squared	0.676	0.530	0.629	0.867	0.582	0.876
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 sheets. We distinguish between bank with below- and above-median capital buffers. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for risky loans, the capital ratio, return on assets, and loans-to-assets ratio. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 A3: The effect of SupTech events on banks' balance sheets: Heterogeneity in banks' exposure to public scrutiny

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post $SupTech_{without\ subordinated\ debt}$	0.009***	0.002***	0.008***	-0.005	-0.001	-0.005
	(0.003)	(0.001)	(0.002)	(0.008)	(0.003)	(0.007)
Post $SupTech_{with\ subordinated\ debt}$	-0.001	-0.000	-0.001	-0.026	-0.001	0.031
	(0.005)	(0.001)	(0.003)	(0.017)	(0.003)	(0.022)
Observations	96,614	96,614	96,614	96,614	67,835	96,614
Adjusted R-squared	0.676	0.530	0.629	0.868	0.582	0.876
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 sheets. We distinguish between bank with and without subordinated debt. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for risky loans, the capital ratio, return on assets, and loans-to-assets ratio. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 A4: 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 SupTech	-0.478***	0.218	0.216	0.169
	(0.139)	(0.159)	(0.191)	(0.112)
Observations	11,191,300	11,137,012	5,253,313	5,131,113
R-squared	0.071	0.551	0.639	0.841
Controls	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No
Firm FE	No	Yes	No	No
Time FE	No	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 outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 A5: The effect of SupTech events on banks' lending behavior to less creditworthy firms: Loan rates

	(1)	(2)	(3)	(4)	(5)
	ln(Loan rate)	ln(Loan rate)	ln(Loan rate)	ln(Loan rate)	ln(Loan rate)
Post SupTech	0.176	0.141	0.130	–	–
	(0.172)	(0.201)	(0.117)	(–)	(–)
Post SupTech × Arrears	0.167*	0.276***	0.138***	0.202**	0.095**
	(0.089)	(0.082)	(0.037)	(0.086)	(0.040)
Observations	11,137,012	5,253,313	5,131,113	5,244,555	5,121,896
R-squared	0.552	0.640	0.841	0.686	0.865
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Bank × Time FE	No	No	Yes	No	Yes
Firm × Time FE	No	Yes	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior. The outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 A6: The effect of SupTech events on banks' lending behavior: Loan maturity

	(1) ln(Maturity)	(2) ln(Maturity)	(3) ln(Maturity)	(4) ln(Maturity)
Post SupTech	0.719***	0.153***	0.098	0.032
	(0.187)	(0.048)	(0.072)	(0.026)
Observations	14,870,060	12,452,655	6,219,594	6,100,998
R-squared	0.5218	0.5318	0.6226	0.8550
Controls	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No
Firm FE	No	Yes	No	No
Time FE	No	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 outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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: The effect of SupTech events on banks' lending behavior to less creditworthy firms: Loan maturity

	(1) ln(Maturity)	(2) ln(Maturity)	(3) ln(Maturity)	(4) ln(Maturity)	(5) ln(Maturity)
Post SupTech	0.219***	0.157*	0.075***	–	–
	(0.046)	(0.080)	(0.020)	(–)	(–)
Post SupTech × Arrears	-0.288***	-0.248***	-0.154***	-0.292***	-0.174***
	(0.106)	(0.079)	(0.058)	(0.084)	(0.059)
Observations	12,462,072	6,227,401	6,108,925	6,218,787	6,099,907
R-squared	0.543	0.626	0.856	0.639	0.860
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Bank × Time FE	No	No	Yes	No	Yes
Firm × Time FE	No	Yes	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes	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 outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 A8: The effect of SupTech events on banks' lending behavior: Loan collateral

	(1) Collateralized	(2) Collateralized	(3) Collateralized	(4) Collateralized
Post SupTech	0.033	-0.009	-0.023	-0.011
	(0.085)	(0.052)	(0.040)	(0.034)
Observations	12,515,254	12,462,072	6,227,401	6,108,925
R-squared	0.028	0.493	0.603	0.822
Controls	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No
Firm FE	No	Yes	No	No
Time FE	No	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 outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 A9: The effect of SupTech events on banks' lending behavior to less creditworthy firms: Loan collateral

	(1) Collateralized	(2) Collateralized	(3) Collateralized	(4) Collateralized	(5) Collateralized
Post SupTech	0.000	-0.018	0.002	–	–
	(0.047)	(0.041)	(0.032)	(–)	(–)
Post SupTech × Arrears	-0.036	-0.020	-0.043*	-0.001	-0.008
	(0.041)	(0.023)	(0.024)	(0.021)	(0.014)
Observations	12,462,072	6,227,401	6,108,925	6,218,787	6,099,907
R-squared	0.496	0.605	0.822	0.693	0.867
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Bank × Time FE	No	No	Yes	No	Yes
Firm × Time FE	No	Yes	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior. The outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 A10: The effect of SupTech events on banks' credit risk assessment

	(1) Rating deviation	(2) Rating deviation	(3) Rating deviation	(4) Rating deviation
Post SupTech	-0.048	-0.026	-0.033	-0.043
	(0.086)	(0.045)	(0.046)	(0.046)
Observations	7,399,360	7,370,721	6,227,401	6,108,925
R-squared	0.097	0.224	0.462	0.687
Controls	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No
Firm FE	No	Yes	No	No
Time FE	No	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' credit risk assessment. The outcome variable is the difference between the proprietary credit rating assigned by bank b to firm f and the average credit rating assigned by all banks that lend to firm f. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 A11: The effect of SupTech events on banks' credit risk assessment of less creditworthy firms

	(1) Rating deviation	(2) Rating deviation	(3) Rating deviation	(4) Rating deviation	(5) Rating deviation
Post SupTech	0.013	0.011	0.058	–	–
	(0.055)	(0.064)	(0.043)	(–)	(–)
Post SupTech × Arrears	-0.197**	-0.210**	-0.151**	-0.206**	-0.145**
	(0.087)	(0.098)	(0.069)	(0.098)	(0.066)
Observations	7,370,721	6,227,401	6,108,925	6,218,787	6,099,907
R-squared	0.233	0.486	0.700	0.514	0.710
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No	No
Firm FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Bank × Time FE	No	No	Yes	No	Yes
Firm × Time FE	No	Yes	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' credit risk assessment. The outcome variable is the difference between the proprietary credit rating assigned by bank b to firm f and the average credit rating assigned by all banks that lend to firm f. Arrears is a dummy variable equal to one if firm f has payments in arrears on loans at bank b. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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.

Internet Appendix

The Disciplining Effect of Bank Supervision: Evidence from SupTech

Hans Degryse, Cédric Huylebroek, and Bernardus Van Doornik

Table O1: Treated and non-treated banks: difference in means

	Non-treated		Treated		
	Mean	SD	Mean	SD	Difference
ln(Total assets)	18.51	2.38	19.62	2.45	1.11***
Deposits/TA	0.49	0.26	0.45	0.28	-0.04***
Loans/TA	0.56	0.23	0.57	0.24	0.01***
Equity/TA	0.27	0.22	0.27	0.21	-0.00***
ROA	0.03	0.04	0.02	0.05	-0.00***
NPL/TA	0.04	0.05	0.05	0.06	0.01***
LLP/TA	0.01	0.02	0.01	0.02	-0.00***
LLP_{risky}/TA	0.03	0.03	0.03	0.04	0.01***
Liquid assets/TA	0.35	0.19	0.30	0.20	-0.04***
Observations	102,405		18,162		

Note: This table reports a difference in means test for treated and non-treated banks. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O2: The effect of SupTech events on banks' balance sheets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	NPL/TA			LLP/TA			LLP_{risky}/TA		
Treated	0.012***	0.012***	–	0.002**	0.001	–	0.004	0.005*	–
	(0.004)	(0.004)	(–)	(0.001)	(0.001)	(–)	(0.002)	(0.003)	(–)
Post SupTech	0.016***	0.011***	0.008***	0.002**	0.003***	0.002***	0.013***	0.011***	0.007***
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	96,617	96,617	96,614	96,617	96,617	96,614	96,617	96,617	96,614
Adjusted R-squared	0.163	0.189	0.676	0.062	0.165	0.530	0.100	0.112	0.628
Panel B	Equity/TA			ROA			Loans/TA		
Treated	0.021	0.026*	–	-0.002	-0.003	–	-0.019	-0.010	–
	(0.013)	(0.014)	(–)	(0.003)	(0.003)	(–)	(0.015)	(0.016)	(–)
Post SupTech	-0.008	-0.008	-0.009	0.001	-0.004	-0.001	0.024**	0.010	0.001
	(0.010)	(0.011)	(0.007)	(0.003)	(0.003)	(0.002)	(0.011)	(0.012)	(0.007)
Observations	96,617	96,617	96,614	67,837	67,837	67,835	96,617	96,617	96,614
Adjusted R-squared	0.471	0.476	0.867	0.053	0.107	0.582	0.614	0.619	0.876
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 sheets. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, and the ratio of loan loss provisions for risky loans in Panel A, and the capital ratio, return on assets, and loans-to-assets ratio in Panel B. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 O3: The effect of SupTech events on banks' balance sheets: Excluding SupTech events related to bank lending

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post SupTech	0.007***	0.002**	0.007***	-0.009	-0.001	0.001
	(0.003)	(0.001)	(0.002)	(0.007)	(0.002)	(0.007)
Adjusted R-squared	0.676	0.530	0.628	0.867	0.582	0.876
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 sheets. We exclude banks with SupTech events related to bank lending. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for risky loans, the capital ratio, return on assets, and loans-to-assets ratio. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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. For confidentiality reasons, this table does not report the number of observations.

Table O4: The effect of SupTech events on banks' balance sheets: Excluding local (non-targeted) banks

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post SupTech	0.006**	0.002***	0.005***	-0.014**	0.002	-0.003
	(0.003)	(0.001)	(0.002)	(0.007)	(0.002)	(0.007)
Observations	58,702	58,702	58,702	58,702	38,925	58,702
Adjusted R-squared	0.706	0.553	0.653	0.888	0.624	0.883
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 sheets. The sample excludes local (non-targeted) banks. The outcome variables are the ratio of non-performing loans, the ratio of loan loss provisions, the ratio of loan loss provisions for risky loans, the capital ratio, return on assets, and loans-to-assets ratio. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 O5: The effect of SupTech events on banks' balance sheets: Placebo test

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post SupTech	-0.001	0.000	-0.002	0.000	-0.001	-0.000
	(0.002)	(0.001)	(0.002)	(0.007)	(0.003)	(0.007)
Observations	103,970	103,970	103,970	103,970	74,388	103,970
Adjusted R-squared	0.687	0.532	0.638	0.868	0.578	0.872
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 sheets. The outcome 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. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 O6: The effect of SupTech events on banks' balance sheets: Stacked difference-in-differences

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Treated × Post	0.007***	0.000	0.006***	-0.007	-0.008**	-0.001
	(0.002)	(0.001)	(0.002)	(0.006)	(0.003)	(0.008)
Observations	85,013	85,013	85,013	85,013	60,127	85,013
Adjusted R-squared	0.776	0.640	0.779	0.881	0.655	0.911
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 sheets. The outcome 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. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 O7: The effect of SupTech events on banks' balance sheets: Propensity score matching

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post SupTech	0.007**	0.002**	0.007***	0.005	-0.005*	-0.017
	(0.003)	(0.001)	(0.002)	(0.009)	(0.003)	(0.013)
Observations	20,947	20,947	20,947	9,244	14,472	20,947
Adjusted R-squared	0.714	0.562	0.672	0.919	0.543	0.855
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 sheets. The outcome 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. Depending on the outcome variable, the control variables include lagged values of banks' size, capital ratio, deposit ratio, liquidity ratio, and non-performing loans ratio. Variable definitions are provided in Table A1 in Appendix. 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 O8: The effect of SupTech events on banks' lending behavior: Excluding SupTech events related to bank lending

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth
Post SupTech	0.012	0.004	0.010	0.020
	(0.015)	(0.018)	(0.017)	(0.021)
R-squared	0.013	0.098	0.425	0.510
Controls	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No
Firm FE	No	Yes	No	No
Time FE	No	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. We exclude banks with SupTech events related to bank lending. The outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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. For confidentiality reasons, this table does not report the number of observations.

Table O9: The effect of SupTech events on banks' lending behavior to less creditworthy firms: Excluding SupTech events related to bank lending

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth	(5) Credit growth
Post SupTech	0.009	0.021	0.032	–	–
	(0.020)	(0.020)	(0.023)	(–)	(–)
Post SupTech × Arrears	-0.021	-0.044**	-0.037**	-0.040*	-0.026**
	(0.014)	(0.021)	(0.015)	(0.021)	(0.012)
R-squared	0.098	0.426	0.510	0.444	0.527
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	No	No
Firm FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Bank × Time FE	No	No	No	Yes	Yes
Firm × Time FE	No	Yes	Yes	Yes	Yes
Bank × Firm FE	No	No	Yes	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior. We exclude banks with SupTech events related to bank lending. The outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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. For confidentiality reasons, this table does not report the number of observations.

Table O10: The effect of SupTech events on banks' lending behavior: Placebo test

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth
Post SupTech	0.007	0.001	0.009	0.003
	(0.013)	(0.012)	(0.012)	(0.012)
Observations	10,619,040	10,569,077	4,821,121	4,723,055
R-squared	0.012	0.101	0.433	0.519
Controls	Yes	Yes	Yes	Yes
Bank FE	No	Yes	Yes	No
Firm FE	No	Yes	No	No
Time FE	No	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 using placebo events. The outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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 O11: The effect of SupTech events on banks' lending behavior to less creditworthy firms: Placebo test

	(1) Credit growth	(2) Credit growth	(3) Credit growth	(4) Credit growth	(5) Credit growth
Post SupTech	0.001	0.012	0.005	–	–
	(0.011)	(0.013)	(0.013)	(–)	(–)
Post SupTech × Arrears	0.001	-0.015	-0.010	-0.011	-0.007
	(0.013)	(0.014)	(0.010)	(0.014)	(0.009)
Observations	10,569,077	4,821,121	4,723,055	4,812,354	4,713,800
R-squared	0.101	0.434	0.520	0.449	0.534
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	No	No
Firm FE	Yes	No	No	No	No
Time FE	Yes	No	No	No	No
Bank × Time FE	No	No	No	Yes	Yes
Firm × Time FE	No	Yes	Yes	Yes	Yes
Bank × Firm FE	No	No	Yes	No	Yes

Note: This table presents the difference-in-differences estimates of the effect of SupTech events on banks' lending behavior using placebo events. The outcome variable 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. The control variables are the lagged value of banks' size, banks' non-performing loan ratio, banks' capital ratio, banks' deposit ratio, firms' size, and firms' industry. Variable definitions are provided in Table A1 in Appendix. 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.

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