The Disciplining Effect of Bank Supervision: Evidence from SupTech

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Note: The views expressed in this project are those of the authors and do not necessarily reflect those of the Banco Central do Brasil or the Bank for International Settlements.

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→ **We address this research gap using unique SupTech data from the Central Bank of Brazil**

Research Objective and Approach

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  1. **banks' balance sheets**
  2. **banks' corporate lending decisions**
  3. **firms' outcomes**

- We employ **difference-in-differences models** to compare the outcomes of treated (versus non-treated) banks before (versus after) a SupTech event

Preview of findings

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- We provide evidence that these findings can be explained by a **supervisory scrutiny channel**

Contribution

1. **The real effects of regulatory enforcement in the banking sector** (Abbassi et al., 2024; Bonfim et al., 2022; Cortés et al., 2020; Danisewicz et al., 2018; Fuster et al., 2021; Granja and Leuz, 2018; Haselmann et al., 2023; Hirtle et al., 2020; Kandrac and Schlusche, 2021; Kok et al., 2023; Passalacqua et al., 2022; Roman, 2016)

→ The effect of SupTech

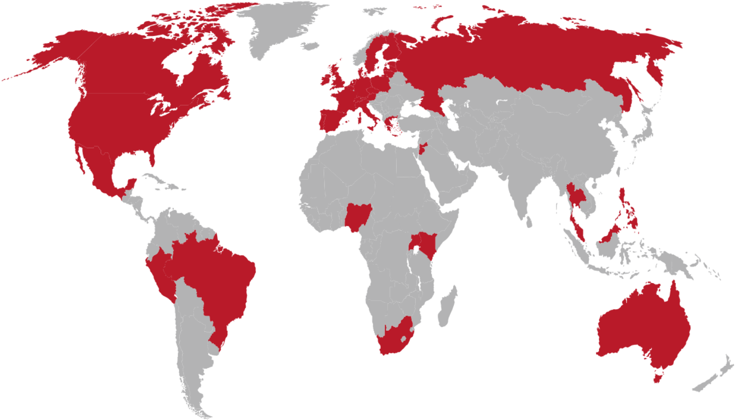
2. **The design of supervisory frameworks in the banking sector** (Agarwal et al., 2014; Carletti et al., 2021; Eisenbach et al., 2022; Ganduri, 2018; Haselmann et al., 2023; Lucca et al., 2014)

→ The effect of formal (punitive) versus informal (non-punitive) regulatory enforcement

SupTech

- SupTech = innovative technologies used by supervisory agencies to support the conduct of bank supervision (BIS, 2018b)
- In the 1990s, SupTech was primarily used by advanced economies and limited to financial ratio analyses Examples
- In recent years, SupTech has become a key priority for many supervisory agencies around the world and increasingly data-oriented (FSB, 2020)
  - Data collection
  - Data processing

SupTech around the world

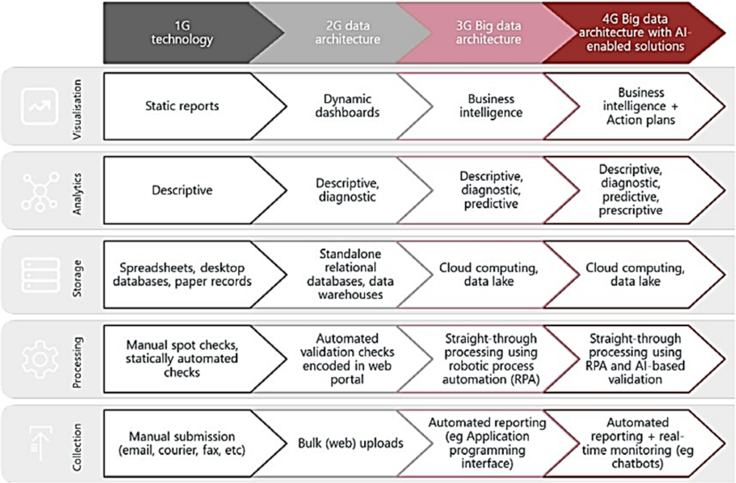


(a) Countries with SupTech initiatives in 2019 in red (source: Di Castri et al., 2019)

SupTech: Drivers?

1. The global financial crisis, which highlighted the need for more proactive and hypothesis-driven supervision (World Bank, 2021)
2. Recent improvements in technological capabilities, including data storage capacity, computer processing power, availability and usability of data, and advances in artificial intelligence

SupTech: different generations



(a) SupTech classification (source: Di Castri et al., 2019)

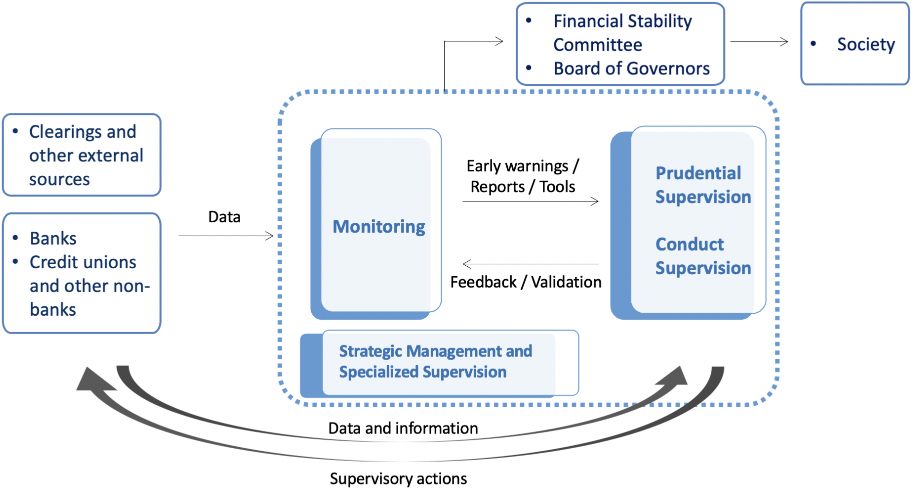
Central Bank of Brazil (BCB): SupTech within supervisory framework

- BCB supervises financial institutions (banks and non-banks (e.g., credit unions))
- BCB relies on both on-site and off-site monitoring of financial institutions
  - $\rightarrow$ On-site bank inspections
  - $\rightarrow$ Off-site SupTech application – generates "automatic alerts" ("SupTech events")

Central Bank of Brazil: SupTech application

- The SupTech application from the BCB automatically analyzes banks' on- and off-balance sheet positions from 3 different perspectives (temporal, comparative, and intrinsic) Example
- The application can generate "automatic alerts" that suggest the need for further investigation to the supervisory departments
  - Human intervention remains indispensable (BIS, 2018b)
- In general, this leads to "more focused supervision that allows the supervisor to act more preemptively" (BCB, 2022)
  - This differs from other regulatory enforcement actions, such as bank sanctions and on-site bank inspections

Central Bank of Brazil: Supervisory framework



Institutional setting

Data

The effect on banks' balance sheet

The effect on banks' lending behavior

The effect on firms' outcomes

Conclusion

Data

- SupTech data Details
- Bank data Details
- Loan data Details
- Firm data Details

→ The ultimate dataset covers 1,325 financial institutions (including 221 treated institutions) and 870,000 firms over the period 2008-2021

Methodology

- First, we study how SupTech events affect banks' balance sheets:

$$y_{b,t} = \beta^{ATE} Post\ SupTech_{b,t} + \delta \boldsymbol{X}_{b,t-1} + \alpha_b + \alpha_t + \epsilon_{b,t} \quad (1)$$

where β^{ATE} captures the difference in the outcome variable of treated (versus non-treated) banks after (versus before) a SupTech event

Results

- Banks reclassify loans as problem loans (NPL) and increase loan loss provisions (LLP)

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA
Post SupTech	0.0060***	0.0014**	0.0044***
	(0.0020)	(0.0006)	(0.0014)
Observations	100,194	99,257	99,257
Adjusted R^2	0.6751	0.5398	0.6326
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

→ Treated banks increase LLP by 20% for risky loans

Results

- There is no (statistically significant) impact on bank capital (Capital), profitability (ROA), or credit (Loans)

	(4) Capital/TA	(5) ROA	(6) Loans/TA
Post SupTech	-0.0055	-0.0036	0.0030
	(0.0066)	(0.0029)	(0.0069)
Observations	99,257	54,833	99,257
Adjusted R^2	0.8644	0.5657	0.8966
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Robustness

- A potential concern is that our results are due to the non-random assignment of the SupTech events
- To alleviate this concern, we use four methods to ensure that our estimates are well-identified:
  - → Parallel trends assumption Details
  - → Propensity score matching Details
  - → Falsification tests Details
  - → Alternative estimator Details (Baker et al., 2022)

Channel

- The literature has proposed 3 channels through which bank supervision can affect banks' balance sheets:

  1. Capital channel
  2. Market discipline channel
  3. Supervisory scrutiny channel (moral suasion)

Supervisory scrutiny channel: The types of SupTech events

- First, we show that the effects are stronger for SupTech events related to regulatory non-compliance
  - $\rightarrow$ These events are the ones that allow banks to learn about regulators' supervisory views

Supervisory scrutiny channel: The types of SupTech events

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA
Post $SupTech_{regulatory}$	0.00810***	0.00178***	0.00544***
	(0.00225)	(0.00064)	(0.00159)
Post $SupTech_{reporting}$	0.00267	0.00009	0.00059
	(0.00375)	(0.00109)	(0.00247)
Observations	101,194	99,257	99,257
Adjusted R-squared	0.63737	0.53892	0.63206
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

The length of SupTech events

Supervisory scrutiny channel: Within-municipality spillovers

- Second, we show that SupTech events have within-municipality spillovers on non-treated banks
  - $\rightarrow$ This suggests that SupTech has a "deterrence effect" (Colonnelli and Prem, 2022; Pomeranz, 2015; Rincke and Traxler, 2011)

Supervisory scrutiny channel: Within-municipality spillovers

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA
Post × Treated	0.0033**	0.0013**	$0.0015^{\dagger}$
	(0.0015)	(0.0006)	(0.0009)
Observations	66,220	62,323	62,323
Adjusted R-squared	0.6505	0.5554	0.6361
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

(Sample: non-treated banks)

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

where $Post \times Treated_{c,t}$ is equal to one after another bank operating in municipality c was treated

In a nutshell

- We find that SupTech events induce financial institutions to reveal unreported credit risks, in line with an informational disclosure effect (Delis et al., 2018; Bonfim et al., 2022; Passalacqua et al., 2022)
- These results can be rationalized by a supervisory scrutiny channel

Bank lending: possible channels

- Second, we study the effect of SupTech events on banks' lending behavior
- The literature has proposed 2 potential channels through which bank supervision can affect bank lending (Granja and Leuz, 2018):
  1. Capital shock channel
  2. Reallocation channel

Bank Lending: Methodology

- We first test the capital shock channel:

$$\Delta Credit_{f,b,t} = \beta^{ATE} Post\ SupTech_{b,t} + \delta \boldsymbol{X}_{f,b,t-1} + \alpha_{f,t} + \alpha_{b,f} + \epsilon_{f,b,t} \quad (3)$$

with $\Delta Credit_{f,b,t} = \frac{Credit_{f,b,t} - Credit_{f,b,t-1}}{0.5 \times (Credit_{f,b,t} + Credit_{f,b,t-1})}$ (Davis and Haltiwanger, 1992)

Results

- On average, we do not find a change in credit supply

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

Methodology

- We then extend the previous model to test the reallocation channel:

$$\Delta Credit_{f,b,t} = \beta^{ATE}(Post\ SupTech_{b,t} \times Credit\ risk_{f,b,t-1}) + \delta \boldsymbol{X}_{f,b,t-1} + \alpha_{b,t} + \alpha_{f,t} + \alpha_{b,f} + \epsilon_{f,b,t} \quad (4)$$

where *Credit risk*$_{f,b,t}$ is a dummy variable equal to 1 if a borrower has a bad credit (*Subprime*) rating or has outstanding payments in arrears (*Arrears*)

Results

- We do find a reallocation in credit supply

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

Robustness

- After a SupTech event, treated banks also increase interest rates and reduce the maturity of loans granted to less creditworthy borrowers Details

- The results are robust to a set of additional checks:
  - $\rightarrow$ Parallel trends assumption Details
  - $\rightarrow$ Falsification tests Details

In a nutshell

- SupTech events reduce bank lending to less creditworthy firms (Delis et al., 2017; Bonfim et al., 2022)
- These results are consistent with a reallocation channel, indicating that SupTech events reduce banks' risk-taking and enhance banks' loan portfolio quality

Methodology for firms' outcomes

- Third, we study whether SupTech events generate spillover effects to the real economy (based on firms' exposure to treated banks)
- We test this using the following regression model:

$$
\begin{aligned}
y_{f,t} =& \beta_1 Post_{f,t} + \beta_2 Exposure_{f,t-1} + \beta^{ATE}(Post_{f,t} \times Exposure_{f,t-1}) \\
& + \delta \boldsymbol{X}_{f,t-1} + \alpha_f + \alpha_{j,t} + \alpha_{m,t} + \epsilon_{f,t}
\end{aligned}
\tag{5}
$$

with $Exposure_{f,t-1} = \frac{\sum_{i=1}^{N_{treated}} Exposure_{f,b,t-1} \times Treated_b}{\sum_{i=1}^{N_{all}} Exposure_{f,b,t-1}}$

Results

- There are some spillover effects for less creditworthy firms

	(1) Δ Credit	(2) Δ Employment	(3) Δ Revenue	(4) Δ Productivity
Panel A:				
Post $\times$ Exposure $\times$ Arrears	-0.0349*	-0.0081*	-0.0093	-0.0025
	(0.0201)	(0.0041)	(0.0120)	(0.0121)
R-squared	0.1329	0.1903	0.1393	0.0950
Panel B:				
Post $\times$ Exposure $\times$ Subprime	0.0174	-0.0056	-0.0544**	-0.0529*
	(0.0150)	(0.0055)	(0.0259)	(0.0272)
R-squared	0.1340	0.1902	0.0844	0.0950
Observations	2,581,598	2,466,176	2,664,410	2,493,510
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry $\times$ Time FE	Yes	Yes	Yes	Yes
Municipality $\times$ Time FE	Yes	Yes	Yes	Yes

In a nutshell

- SupTech events generate small spillover effects to less creditworthy firms
- These firms cannot compensate the reduction in credit from treated banks, leading to a reduction in firm performance

Institutional setting

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- **Supervisors increasingly rely on SupTech** to identify banks where weaknesses are most likely to be found
- We provide **novel insights** that SupTech can help to **improve banks' risk reporting** and **reduce risk-taking in bank lending**
- Our findings warrant further research into SupTech, and its role in the **optimal design of supervisory frameworks**

Thank you!

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Appendix

Historical SupTech applications

Table 1: Supervisory risk assessment and early warning systems in selected G10 countries

Country	Supervisory Authority	System	Year of implementation	System type
France	Banking Commission	ORAP (Organisation and Reinforcement of Preventive Action)	1997	Off-site Supervisory bank rating system
		SAABA (Support System for Banking Analysis)	1997	Early warning model - Expected loss
Germany	German Federal Supervisory Office	BAKIS (BAKred Information System)	1997	Financial ratio and peer group analysis system
Italy	Bank of Italy	PATROL	1993	Off-site Supervisory bank rating system
		Early Warning System	Planned	Early warning model - failure and timing to failure prediction
Netherlands	Netherlands Bank	(RAST) Risk Analysis Support Tool	1999	Comprehensive bank risk assessment system
		Observation system	Planned	Financial ratio and peer group analysis system
United Kingdom	Financial Services Authority	RATE (Risk Assessment, Tools of Supervision and Evaluation)	1998	Comprehensive bank risk assessment system
	Bank of England	TRAM (Trigger Ratio Adjustment Mechanism)	Developed 1995 – not implemented	Early warning model
United States	All three supervisory authorities	CAMELS	1980	On-site examination rating
	Federal Reserve System	Individual Bank Monitoring Screens	1980s	Financial ratio analysis
		SEER Rating (System for Estimating Exam Ratings)	1993	Early warning model - Rating estimation
		SEER Risk Rank	1993	Early warning model- Failure prediction
	FDIC	CAEL	1985 (withdrawn December 1999)	Off-site supervisory bank rating system
		GMS – Growth Monitoring System	mid 1980s (refined recently)	Simple early warning model - tracking high growth banks
		SCOR (Statistical CAMELS Off-site Rating)	1995	Early warning model - Rating downgrade estimation
	OCC	Bank Calculator	Planned	Early warning model Failure prediction

SupTech example: ADAM

Box 5

Central Bank of Brazil (BCB) ADAM

Tool classification: Risk identification

Tool description: The BCB is using ADAM to examine the entire credit portfolio of a supervised firm and identify credit exposures with inadequately recognised expected loss (EL).

Supervisory use and deployment: The BCB requires banks to classify credit exposures based on their EL ranges. ADAM identifies credit exposures with high ELs (ie 50-100%) but that banks incorrectly classified.

ADAM has impressive scale and results in a huge time gain. It can analyse 3 million exposures to customers in just 24 hours, while a team of 10 experienced inspectors would take 30 years to do the same. ADAM was first used by non-banking supervision teams and then increasingly used for banking supervision. Now all inspectors have access to it and can continuously enhance it.

ADAM was initially trained using data from credit portfolio analyses by inspectors in 2015 (and also some in 2013 and 2014). Training data are regularly updated with field inspection data.

Status: Operational

Who developed? Internally developed

↑

Summary statistics

Summary statistics: Bank data

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

↑

Summary statistics

Summary statistics: Bank data

	Non-treated		Treated		
	Mean	SD	Mean	SD	Difference
ln(Total assets)	18.678	2.267	19.768	2.214	1.090***
Deposits/TA	0.489	0.267	0.474	0.292	-0.015***
Loans/TA	0.536	0.239	0.522	0.258	-0.014***
Equity/TA	0.265	0.205	0.244	0.198	-0.021***
ROA	0.030	0.038	0.023	0.033	-0.007***
NPL/TA	0.033	0.037	0.041	0.044	0.008***
LLP/TA	0.012	0.016	0.012	0.015	0.000
LLP_{risky}/TA	0.023	0.023	0.027	0.026	0.004***
Liquid assets/TA	0.358	0.198	0.340	0.211	-0.017***
Observations	114,962		30,178		145,140

↑

Summary statistics

Summary statistics: Loan data

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

↑

Summary statistics

Summary statistics: Firm data

	N	Mean	SD	Min	Max
$\Delta\ln$(Credit)	8,603,946	0.008	0.664	-2.991	3.891
$\Delta\ln$(Employment)	3,685,596	0.000	0.207	-0.977	1.203
$\Delta\ln$(Wage/hour)	3,684,614	0.011	0.073	-0.409	0.655
$\Delta\ln$(Hours worked)	3,685,596	-0.001	0.270	-1.244	1.592
$\Delta\ln$(Revenue)	4,649,900	0.035	1.318	-13.106	13.700

↑

Summary statistics

Table: Distribution of treated vs. non-treated banks

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

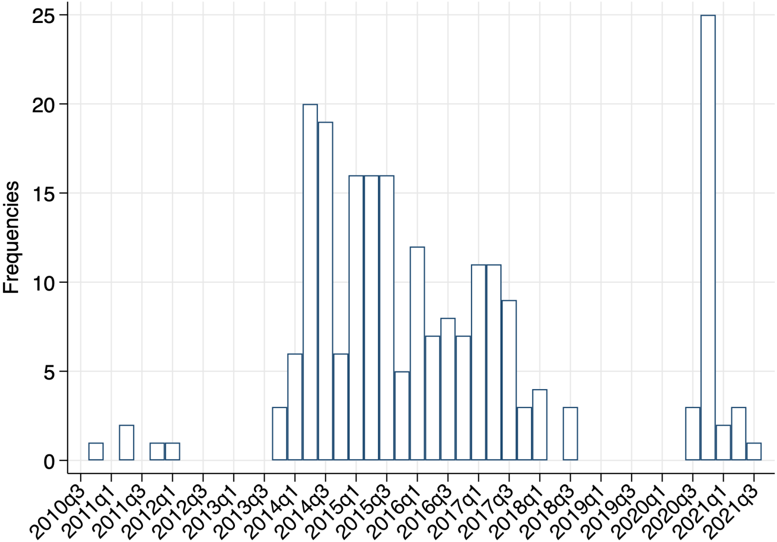
↑

Summary statistics

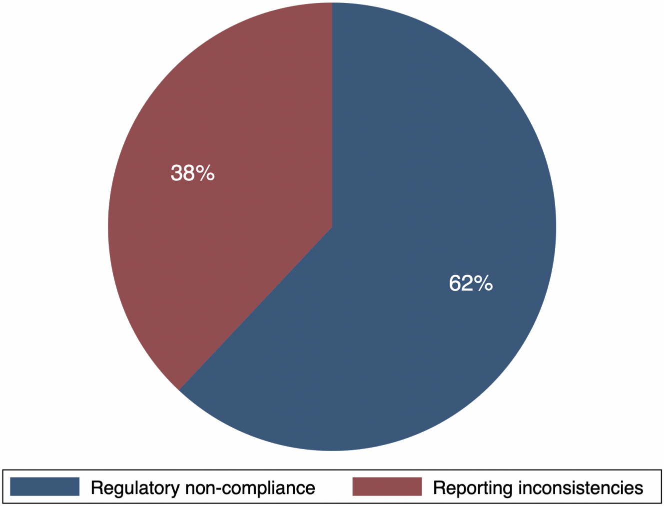
Table: Number of SupTech events per treated bank

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

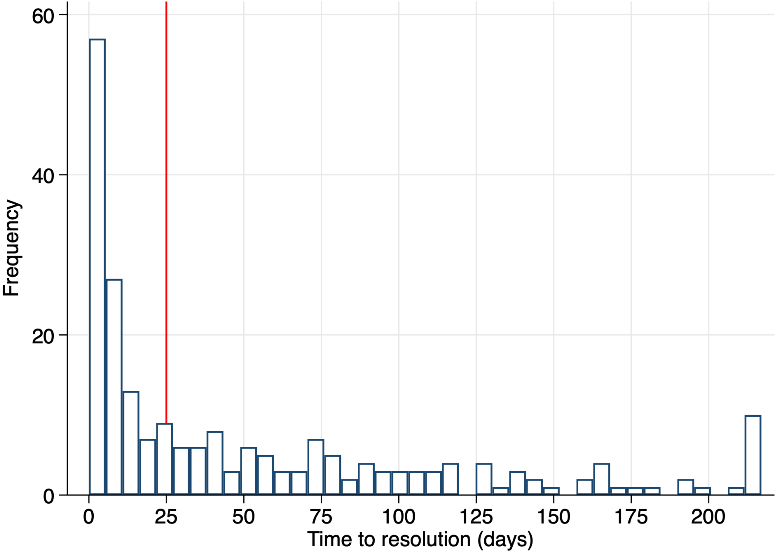
Summary statistics



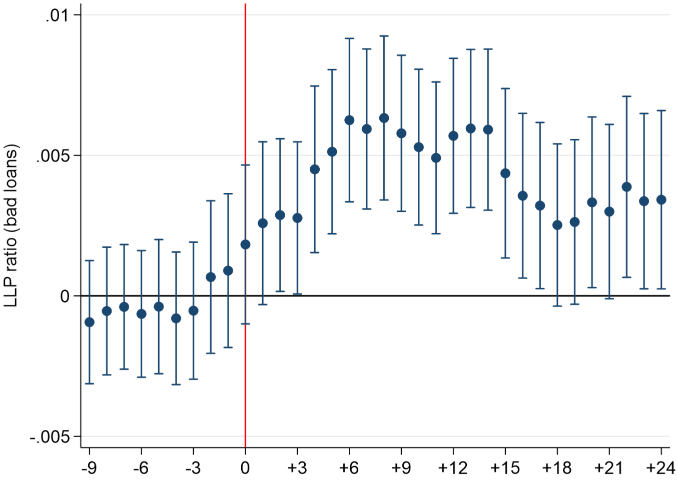
Summary statistics



Summary statistics



The effect on banks' balance sheet: Dynamic



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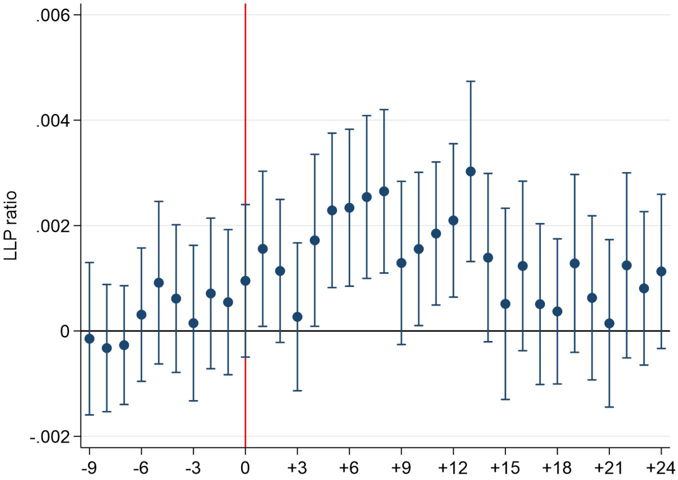
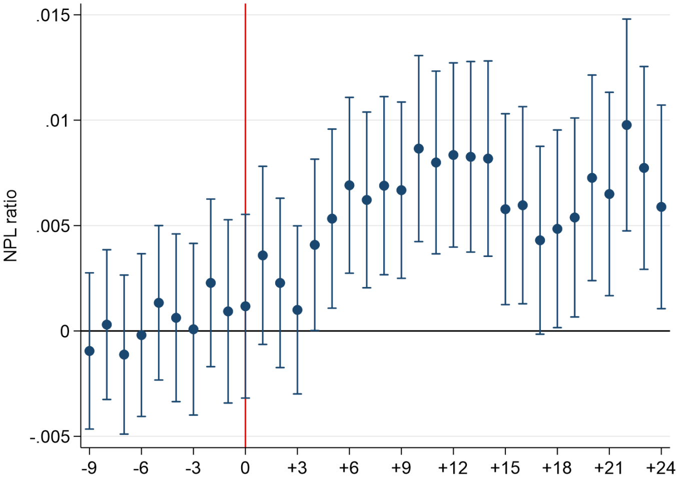
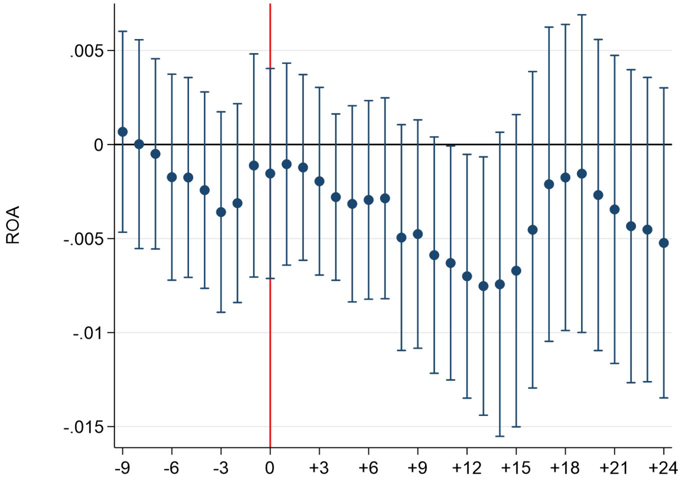
The effect on banks' balance sheet: Dynamic



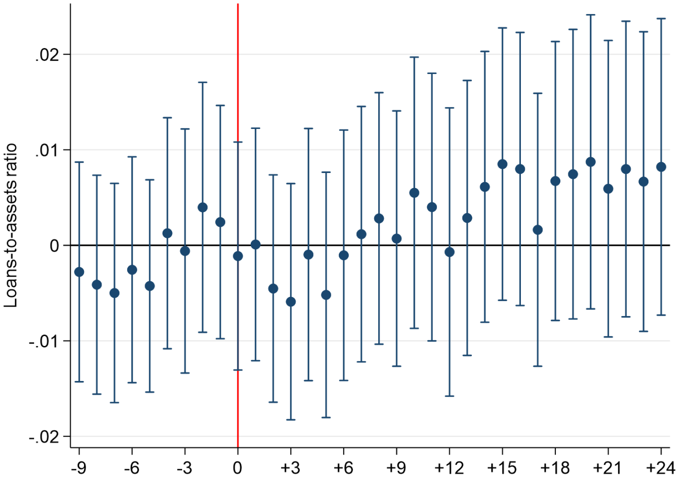
The effect on banks' balance sheet: Dynamic



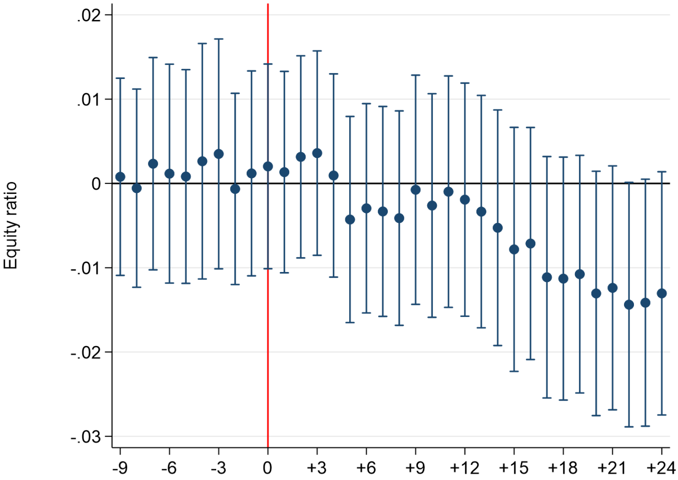
The effect on banks' balance sheet: Dynamic



The effect on banks' balance sheet: Dynamic



The effect on banks' balance sheet: Dynamic



The effect on banks' balance sheet: PSM

- To create a matched sample, we follow the standard approach in the literature: for a bank b inspected at period p, we compute the propensity score by running a logit model of the following form:

$$log(y_{b,p}) = \alpha_0 + \delta \boldsymbol{X}_{b,p} + \epsilon_{b,p} \tag{6}$$

- We then match (with replacement) an inspected bank with a non-inspected bank based on one-to-one nearest neighbor matching within a 0.25 standard deviations caliper of the estimated propensity score
- Based on the matched sample, we then re-estimate the regressions from Equation (1)

↑

The effect on banks' balance sheet: PSM

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

The effect on banks' balance sheet: Falsification

- Although the staggered nature of 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, coinciding events
- Specifically, we assign a random date in the pre-enforcement period to the bank's supervisory intervention, and then estimate the effect of these placebo interventions on banks' balance sheet

↑

The effect on banks' balance sheet: Falsification

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

↑

The effect on banks' balance sheet: Stacked

- 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 (e.g., Baker et al., 2022).
- To alleviate this concern, we provide an alternative estimation method, a stacked difference-in-differences model, that addresses this concern (see Deshpande and Li, 2019; Joaquim et al., 2019):

$$\begin{aligned} y_{b,p,t} = &\beta Treated_{b,p} + \gamma^{post}(Treated_{b,p} \times Post_{p,t}) + \\ &\alpha_{b,p} + \alpha_{p,t} + \epsilon_{b,p,t} \end{aligned} \tag{7}$$

↑

The effect on banks' balance sheet: Stacked

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

Channel: The length of SupTech events

	(1) NPL/TA	(2) LLP/TA	(3) LLP_{risky}/TA
Post SupTech_{short}	0.0064**	0.0018***	0.0047***
	(0.0026)	(0.0007)	(0.0017)
Post SupTech_{long}	0.0072***	0.0015***	0.0047
	(0.0026)	(0.0007)	(0.0037)
Observations	100,194	99,257	99,257
Adjusted R-squared	0.6751	0.5398	0.6326
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

↑

The effect of SupTech events on banks' lending behavior

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

↑

The effect of SupTech events on banks' lending behavior

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

The effect of SupTech events on banks' lending behavior

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

↑

The effect of SupTech events on banks' lending behavior

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

↑

The effect of SupTech events on banks' lending behavior

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

↑

The effect of SupTech events on banks' lending behavior

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

↑

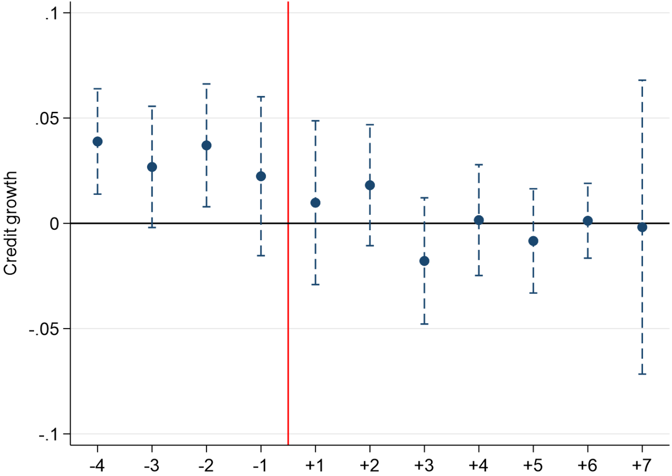
The effect of SupTech events on banks' lending behavior

	(1) Rating deviation	(2) Rating deviation	(3) Rating deviation	(4) Rating deviation
Post SupTech	-0.02618	-0.02051	-0.03432	0.01538
	(0.02835)	(0.03102)	(0.05257)	(0.03192)
Observations	14,871,421	12,453,694	6,220,155	6,101,470
R-squared	0.0812	0.0877	0.1417	0.6109
Controls	No	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

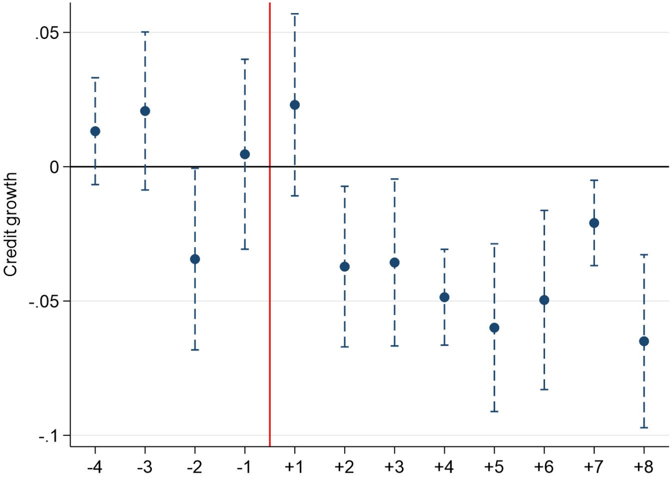
The effect of SupTech events on banks' lending behavior

	(1) Rating deviation	(2) Rating deviation	(3) Rating deviation	(4) Rating deviation
Panel A:				
Post SupTech × Arrears	-0.1307**	-0.3567***	-0.3492***	-0.2470***
	(0.0574)	(0.1096)	(0.1122)	(0.0709)
R-squared	0.1048	0.1935	0.2321	0.6194
Panel B:				
Post SupTech × Subprime	-0.0841	-0.1585	-0.1504	-0.0659
	(0.1379)	(0.1172)	(0.1188)	(0.1045)
R-squared	0.1741	0.5609	0.5914	0.7771
Observations	12,453,694	6,220,155	6,211,525	6,101,470
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No
Firm FE	Yes	No	No	No
Time FE	Yes	No	No	No
Bank × Time FE	No	No	Yes	No
Firm × Time FE	No	Yes	Yes	Yes
Bank × Firm FE	No	No	No	Yes

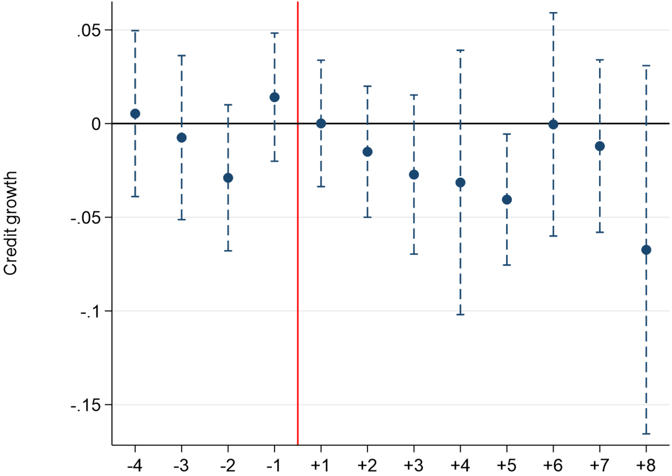
The effect of SupTech events on banks' lending behavior: Dynamic



The effect of SupTech events on banks' lending behavior: Dynamic



The effect of SupTech events on banks' lending behavior: Dynamic



The effect of SupTech events on banks' lending behavior: Falsification

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

↑

The effect of SupTech events on banks' lending behavior: Falsification

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