Quo Vadis? Bank Closures, Firm Performance, and New Bank-Firm Relationships*

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Abstract

How do firms respond to sudden and forcible closures of their lenders? Using unique credit register data from a setting where two-thirds of banks were closed within a decade, we find that neither bad nor good firms delay repayments or switch lenders before closures. Afterward, bad firms lose subsidized credit and experience sharp declines in employment, borrowing, and sales, while good firms improve performance. This divergence stems from banks' prior underpricing of bad firms' credit risk. Ultimately, good firms match with new solid banks, while bad firms gravitate toward not-yet-detected weak banks—especially where boards overlap or markets are unconcentrated. (100 words)

Keywords: Firms, Financial Fraud, Regulatory forbearance, Bank clean-up policies, Credit risk underpricing, Common board membership, Real effects.

JEL: F51, G41, H81, L25.

*For insightful comments, we would like to thank David Andolfatto, Klenio Barbosa (discussant), Thorsten Beck (discussant), Indraneel Chakraborty, Ralph De Haas, Reint Gropp, Olena Havrylchyk (discussant), Hans Degryse, Francois Derrien, Balinth Horvath, Alexei Karas, Charles Khan, Sotirios Kokas, Michael Koetter, Florencio Lopez-de-Silanes, Raoul Minetti, Mrinal Mishra, Alexander Morozov, Volker Nitsch (discussant), Jose-Luis Peydro, Anthony Saunders, and seminar participants at BOFIT (Helsinki), CInSt HSE University (Moscow), the Florence School of Banking and Finance at the European University Institute (Florence), the IWH Halle Institute for Economic Studies (Halle), Toulouse Business School, and the Universities of Leuven (KU Leuven), Miami, Pompeu Fabra, and Zurich, and conference participants at the 2024 Paris School of Business Workshop on Banks and Financial Markets, 2023 Econometric Society European meeting (Barcelona), the 2022 European Economic Association Meetings (Milano), and the 2022 International Conference on Macroeconomic Analysis and International Finance (Rethymno). Daria Kolesnik provided excellent research assistance. Mamonov acknowledges financial support by the NPO "Systemic Risk Institute" no. LX22NPO5101, funded by European Union – Next Generation EU (Ministry of Education, Youth and Sports, NPO: EXCELES) and GEOCEP (both from the Czech Republic). Ongena acknowledges financial support from ERC ADG 2016 - GA 740272 lending. The views expressed in this paper are solely those of the authors and do not necessarily reflect the official position of the Central Bank of Ireland, the Eurosystem, or the Central Bank of Russia.

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1. Introduction

> *"He had thought that he would die, but he had survived. The wounds which had torn his heart would be healed, and life would begin again, though it would never be as it had been before."*
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> — "Quo Vadis" by Henryk Sienkiewicz, the winner of the Nobel Prize in Literature (1905)

A well-established line of research explores what happens to firms when their lending banks experience financial distress or fail—whether during financial crises (Ongena et al., 2003), recessions (Chodorow-Reich, 2014; Huber, 2018; Blattner et al., 2023), or even in normal times (Slovin et al., 1993; Gropp et al., 2018; Amiti and Weinstein, 2018; Chopra et al., 2020; Beck et al., 2021). These studies consistently find that firms borrowing from financially distressed banks generally suffer: they reduce employment and investment and eventually experience declines in productivity and sales. Importantly, the severity of these real effects varies substantially across firms, depending on characteristics such as size, liquidity, and other fundamentals. For instance, Beck et al. (2021) show that firms with high liquidity are better able to cushion negative credit supply shocks, while Greenstone et al. (2020) find that small firms are surprisingly less affected by those shocks.

However, a crucial gap remains: we know relatively little about how firms of differing *quality*—henceforth "good" and "bad" firms—respond to the *closure* of their financially distressed banks. It is also unclear to what extent these closures are anticipated by the firms and their banks. This gap is particularly surprising given the vast "flight to quality" literature, which shows that in times of financial distress, lenders tend to reallocate credit away from risky and less profitable firms toward safer and more profitable firms (Lang and Nakamura, 1995; Caballero and Krishnamurthy, 2008; Giannetti and Laeven, 2012; De Jonghe et al., 2019). And much of the existing work has been focused on bank branch closures rather than entire bank closures. In such cases, firms are often simply transferred to other branches of the same or different banks, losing only the switching discount in loan pricing (Ioannidou and Ongena, 2010; Barone et al., 2011; Stein, 2015; Xu et al., 2020; Bonfim et al., 2020; Cao et al., 2024; Gong et al., 2024). A smaller set of studies, such as Liaudinskas (2023), investigate how loan pricing responds to forced firm transitions, but are silent about broader real effects. We aim to close the gap by analyzing the role of firm quality in the context of forced bank closures.

What makes the behavior of good versus bad firms around their bank closures particularly interesting—and, as we elaborate later, analytically non-trivial—are the strong incentives that weak banks have to conceal their true financial condition to avoid unexpected regulatory intervention. These incentives can lead to distortive credit allocation, such as preferential lending to bad firms over good ones. Specifically, weak banks may engage in "turning losses into loans"— the phenomenon that has recently been documented by Blattner et al. (2023), which implies that weak banks extend credit to risky, informationally opaque borrowers to delay the recognition of losses. Such behavior is often driven by the desire to escape regulatory punishments—ranging from activity restrictions to license revocation—and is enabled by the widespread (and routinely criticized) practice of regulatory forbearance (Acharya and Yorulmazer, 2007; Huizinga and Laeven, 2012; Morrison and White, 2013; Agarwal et al., 2014; Kang et al., 2015; Matta and Perotti, 2023). This forbearance, defined as the intentional delay in shutting down already-recognized weak banks, has been shown to exacerbate welfare losses, especially under political interference in banking (Khwaja and Mian, 2005; Brown and Dinc, 2005, 2011; Koetter and Popov, 2020; Bircan and Saka, 2021; Chari et al., 2021).

To better understand how good versus bad firms borrowing from not-yet-recognized weak lenders—those we refer to as "sin banks"—respond to the closure of their lenders, we require a setting in which the regulatory environment changes from tolerance to enforcement.[1] It is not easy to find such settings due to the widespread regulatory forbearance across both advanced and developing economies, but we have (at least) one recent exception, which comes from Russia in the 2010s. As a prototypical emerging market, Russia experienced extensive financial fraud amid regulatory myopia and systemic corruption (Mironov, 2013; Schulze et al., 2016; Ananyev and Guriev, 2018; Enikolopov et al., 2020).[2] However, in mid-2013—prior to the Russo-Ukrainian war (Korovkin and Makarin, 2023) and the subsequent Western sanctions (Ahn and Ludema, 2020)—Russia's President appointed Elvira Nabiullina as Head of the Central Bank of Russia (CBR), who immediately initiated a crackdown on sin banks. Over subsequent seven years, the CBR intensified inspections and shut down about 600 banks—around

[1] Recent high-profile bank failures—including Silicon Valley Bank (SVB), First Republic Bank in the United States, and Credit Suisse in Switzerland—have reignited interest in understanding bank soundness as a policy concern (Jiang et al., 2023; Correia et al., 2024; Metrick, 2024). These episodes underscore the need to better understand how preemptive closures affect firms relying on poorly performing or mismanaged lenders.

[2] According to the IMF, Russia is classified as an "Emerging Market and Developing Economy," see http://www.imf.org/external/pubs/ft/weo/2015/02/pdf/text.pdf.

two-thirds of the total number of banks in the system (Figure 1). Most closures were triggered by capital depletion from misreported corporate loan losses. Importantly, the underlying type of financial fraud is not Russia-specific (other examples include, e.g., Portugal in Blattner et al. (2023) and the US in James (1991)), ensuring our analysis is globally relevant.

In such a setting, we ask three core questions. (1) *Before closure*: Are sin banks and their borrowers aware of impending license revocation (e.g., through regulatory leaks), and do they act strategically? For instance, do default rates increase or repayments slow in anticipation of closure? (2) *After closure, during the transition*: How do good and bad firms differ in their performance responses after the closure but before establishing new lending relationships? (3) *After the transition*: Do good and bad firms end up with strong lenders, or do they become entangled again with not-yet-detected sin banks?

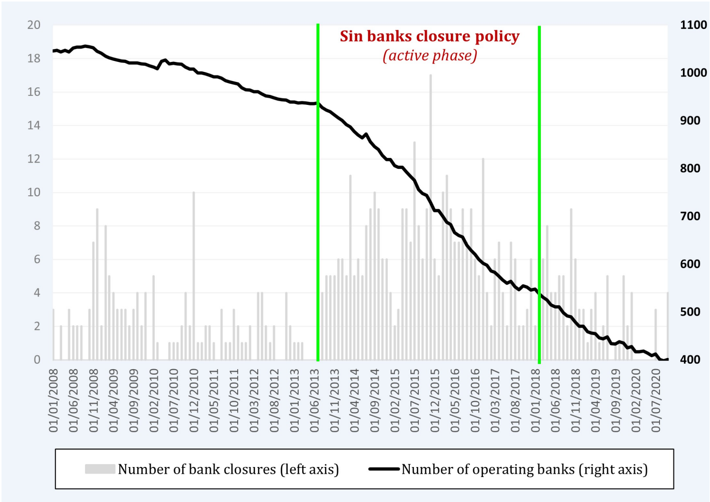
Although sin banks may often lend to bad firms—as in zombie lending (Caballero and Krishnamurthy, 2008; Acharya et al., 2021; Bonfim et al., 2023)—there are several reasons to expect they also serve good firms. First, to maintain the appearance of financial strength, sin banks may also deliberately extend credit to solid borrowers. Second, good firms may be locked into sin bank relationships due to credit rationing (Berger and Udell, 1992; Cenni et al., 2015), high switching costs (Hasan et al., 2019), or a lack of viable alternatives in concentrated or underbanked credit markets (Ashcraft, 2005; Bircan and De Haas, 2020). Some may not even know their lender is a sin bank. These heterogeneities make preemptive bank closures far more nuanced in their real effects than outright bank failures. In fact, closures may free good firms from entanglement with poor lenders—improving their performance rather than "sealing their fate" (much like the protagonists in Sienkiewicz's Quo Vadis narrowly escaping death).[3]

Before Closure: Were Bank Failures Predictable? We first investigate whether sin bank closures were anticipated by banks and firms. From the bank side, we analyze monthly balance sheet data for 1,152 banks (2004–2020) using CAMEL-based panel logit models over six-month rolling windows. While cross-sectional fraud detection probabilities rose sharply post-2013, we find that more than 90% of all sin bank closures are characterized by very low levels of predicted probabilities—lower than the unconditional mean of 2%.

[3]This is what the "Quo Vadis?" in our title refers to: Latin for "Where are you going?", it captures the uncertain path borrowers face after the closure of their lender. The phrase, famously spoken by Saint Peter to the risen Christ, was later popularized by Henryk Sienkiewicz's novel and its cinematic adaptations—and now, metaphorically, applies to borrowers navigating the aftermath of sin bank closures.

Figure 1. Preemptive bank closures before and after the change of the Head of the Central Bank of Russia in 2013

Note: The figure depicts the monthly frequency of bank closures (left Y-axis) and the monthly number of operating banks (right Y-axis) from February 2008 to July 2020. The first green vertical line marks the replacement of the head of the Central Bank of Russia (CBR) in June 2013 and the start of the sin bank closure policy. The second vertical green line marks the end of the active phase of the policy as the bulk of the financial problems were announced to be resolved in February 2018. We use official press releases of the CBR throughout 2008–2020 to distinguish preemptive bank closures initiated by the CBR from bank failures due to market developments and bank liquidations launched by bank owners due to various reasons (M&A, termination of business, etc.).



From the firm side, we are the first to exploit the bank-firm matched data from the CBR's Credit History Bureau (CHB), covering 669,035 relationships (2008–2020), including 93,661 firm–sin-bank pairs. Merging this data to firms' balance sheets retrieved from the SPARK-Interfax database, we classify firms as bad if they report losses in at least two consecutive years; all others are assumed good. We also consider delinquency-based credit history measures. Using this data, we find no evidence that bad or good firms anticipated bank closures: neither were they more likely to switch lenders, nor did they show worse delinquency trends in the six months prior to closure. These findings, robust to extensive fixed effects and validated via single-bank firm analysis (Degryse et al., 2019a), suggest no strategic firm behavior, reinforcing the view that bank closures were unanticipated.

During Transition: How Did Bank Closures Affect Firm Performance? We further focus on the period after bank closure but before firms establish new lending relationships. We estimate a difference-in-differences (DiD) model at the firm-year level, comparing firms whose sin banks were closed between 2013–2018 (early treated) to firms whose sin banks were closed at least two years later (late treated). Our DiD estimates reveal that good firms responded to closures with strong gains: employment rose by 18.5%, assets by 22.8%, sales by 42.7%, and profits by 37.5% over two subsequent years. They also increased borrowing from non-financial firms by 17.8%. By contrast, bad firms borrowing from the same sin banks experienced sharp declines in the same margins: employment collapsed by 12.2%, assets by 10.9%, sales by 25.2%, losses jumped by 38.2%, and borrowings from other firms decreased by 9.1%. These diverging outcomes—emerging from the same policy—indicate a cleansing effect: while sin bank closures deteriorated the performance of bad firms, good firms recovered and grew.

We further explore the mechanisms that could explain these strikingly different real effects of the sin bank closure policy. We run regressions at the bank-firm-month level and reveal that sin banks *underpriced credit risk*: bad firms were charged 0.5–1.0 pp lower interest and received 36% larger loan amounts than good firms within the same bank. Thus, sin bank closures eliminated these implicit loan subsidies in the economy, reallocating resources more efficiently.

After Closure: Where Do Firms Go? Finally, we investigate how firms reallocated across the banking system. Two key facts from the data emerge: (1) only 0.15% of new banks assume existing loans, implying that new lending relationships involve fresh credit; and (2) firms reappear in the credit register with another (not-yet-detected) sin banks in 18 months and with financially solid banks in only 42 months during 2010–2020. Employing a three-outcome survival model (0 = no rematch, 1 = match with a new sin bank, 2 = match with a new solid bank) and treating good firms with clean credit histories as a reference group, we find that *good firms with poor credit histories* are 66% faster in matching with new sin banks and 38% slower in matching with new solid ones. This makes them overall 2.7 times slower in accessing solid banks. Further, *bad firms with clean credit histories* are 91% slower in matching with new sin banks and only 24% slower in matching with new solid banks. And finally, *bad firms with poor credit histories* are 22% slower in matching with new sin banks and 33% slower in matching with new solid banks. These sorting patterns suggest sin banks prefer bad firms with poor credit histories, while solid banks prefer cleaner histories, even among bad firms.

To rationalize these findings, we analyze cross-sectional and spatial variation in the estimated sorting patterns and explore the following two channels. *Common board members*: We manually collect unique personal data on all bank owners and managers for each Russian bank during the 2010s and find that over 50% of firms reconnect with banks sharing the same owners or managers with their previous sin banks. We re-run the survival analysis on the subsample that excludes common board members and reveal that sin banks are no longer willing to match with bad firms having poorer credit histories if there are no common board members. This result is consistent with the anticompetitive and risk-inducing effects of common ownership (Backus et al., 2020; Gilje et al., 2020). *Local market concentration*: We show that in areas with high local credit market concentration, solid banks are more likely to match with bad firms compared to the baseline result. This supports the idea that retention incentives increase willingness to finance risky borrowers, which is consistent with Petersen and Rajan (1995).

Beyond the two mechanisms we examine—common board membership and local market concentration—other potential drivers may also help explain the observed firm-bank sorting patterns. First, following the closure of sin banks, firms may suffer from the loss of accumulated soft information, especially in cases where lending was highly relationship-based. This disruption can hinder credit access even for good firms, as solid banks may lack the informational foundation to accurately assess borrower quality in the short run (Boot, 2000; Berger and Udell, 1998). Second, solid banks themselves may exhibit heightened regulatory caution in the wake of a sweeping policy crackdown. Concerned with preserving charter value and avoiding reputational spillovers, they may become more selective and risk-averse toward borrowers previously associated with fraudulent banks—even those with clean credit histories (Keeley, 1990; Peek and Rosengren, 2005). While these frictions are consistent with the broader banking literature, their empirical investigation is beyond the scope of the current paper and offers a promising direction for future research.

Our study contributes to several strands of the literature. First, the vast research on regulatory forbearance in banking shows that delayed regulatory action is often driven by concerns about systemic risk, reputational contagion, or political pressures (Acharya and Yorulmazer, 2007; Brown and Dinc, 2011; Morrison and White, 2013; Agarwal et al., 2014; Kang et al., 2015; Cole and White, 2017; Matta and Perotti, 2023). We provide a rare counterexample: a central bank (CBR) that preemptively closed two-thirds of the banking system due to financial fraud. While proactive regulatory policies as the Prompt Corrective Action (PCA) in the US or more recent efforts in the EU and India exist (Benston and Kaufman, 1997; Gropp et al., 2018; Chopra et al., 2020), none have resulted in such a sweeping, preemptive closure wave. Our case is unique and offers lessons for other countries, suggesting that credible and well-designed interventions can overcome the typical costs associated with forceful bank closures. Moreover, our finding that sin bank closures, in our setting, come as a surprise to both the borrowing firms and their banks is novel in the literature. This unexpected nature sharpens the identification of the real effects of bank closures and helps us better understand how firms subsequently sort into new banking relationships.

Second, we contribute to the literature on the real effects of bank clean-up policies (Diamond and Rajan, 2011; Philippon and Schnabl, 2013; Acharya et al., 2018; Cortés et al., 2020; Chopra et al., 2020; Beck et al., 2021; Bonfim et al., 2023; Liaudinskas, 2023). While most studies document average negative effects on firm outcomes due to credit supply shocks, they overlook borrower heterogeneity. We show that distinguishing between good and bad firms is crucial: after sin bank closures, good firms improve performance while bad ones deteriorate. We also uncover a novel credit risk underpricing mechanism within closed banks: bad borrowers were charged lower interest rates than good borrowers—unlike prior studies that focus on comparisons to market benchmarks (Liaudinskas, 2023).

Third, our findings extend the relationship lending literature (Petersen and Rajan, 1995; Degryse and Ongena, 2005; Bolton et al., 2016; Degryse et al., 2019a; Schafer, 2019). We show that ties based on common board membership allow bad firms to reconnect with weak but surviving lenders. Meanwhile, market structure also matters: solid banks may take on bad borrowers if local market concentration is high enough.

Finally, our results deliver a new perspective on why post-2022 Western financial sanctions have had limited impact on Russia's banking system (Itskhoki and Mukhin, 2022; Cipriani et al., 2023). The CBR's earlier purge of private banks shifted deposit shares to state-owned banks, consolidating control and limiting contagion risk. Surviving private banks—and their corporate borrowers—were stronger and better prepared to absorb shocks.

The remainder of the paper is organized as follows. Section 2 describes the Russian banking system and the sin bank closure policy. Section 3 presents the data. Section 4 analyzes bank and firm behavior prior to closures. Section 5 examines firm performance during the transition period. Section 6 explores credit risk underpricing as a mechanism. Section 7 investigates post-closure firm-bank matching and the role of common ownership and market concentration. Section 8 concludes.

2. Bank Clean-Up Policy: Institutional Details

During the Soviet era, the centrally planned Russian economy operated with only one bank—the Gosbank of the USSR (Bircan and De Haas, 2020). After the USSR collapsed in 1991 and Russia began its market transition, Gosbank was split into what are now the Big-4 government-owned banks,[4] and a surge of private banks followed. By the end of the "dashing" 1990s, there were nearly 2,500 banks, mostly small, short-lived institutions established to fund their owners' non-financial ventures at preferential rates—particularly important during the period's hyperinflation (Svejnar, 2002). Many of these banks were engaged in criminal or dubious activities (Degryse et al., 2019b).

In the 2000s, the number of active banks halved, yet fraudulent practices remained common. A 2006 attempt at system-wide reform by the Central Bank of Russia (CBR) led to the closure of two major banks for criminal activity, including terrorism financing. However, the assassination of the campaign's lead, Deputy CBR Head Andrey Kozlov, effectively halted the effort. The "Kozlov affair" instilled deep regulatory stigma, making authorities hesitant to act. Bank closures became rare and typically occurred only when owners had no incentive to continue operations—regardless of legality.[5]

The turning point came in 2013 with the appointment of Elvira Nabiullina as CBR Governor. In her inaugural address on June 24, she acknowledged the stigma from the Kozlov affair and announced a fraud-intolerant bank clean-up policy: "*...It is necessary to create the rules that will increase the transaction costs of this kind [fraudulent] of activity. Step by step. This is the priority.*"[6]

Even before implementation, each forced license withdrawal was publicly announced on the CBR's website, detailing detected fraud and refined post-closure balance sheets. The average annual number of fraud-induced closures rose sharply—from 29 (2008 to mid-2013) to nearly 70 (mid-2013 to 2020) (Figure 1). Most fraud involved hiding corporate loan losses stemming from aggressive, high-risk lending.

[4] Sberbank, VTB, Gazprombank, and the Russian Agricultural Bank.

[5] Before the 2007–2009 Global Financial Crisis, Russia's banking sector grew at double-digit annual rates, driven by pent-up demand for loans. For instance, commercial lending rose by nearly 70% in 2007. The crisis exposed inefficiencies, prompting state interventions worth 2.5% of GDP. Bank numbers gradually declined afterward, reaching 1,000 by early 2013.

[6] https://www.kommersant.ru/doc/2218708 (in Russian).

Analysis of refined balance sheets shows staggering hidden losses. A quarter before closure, fraudulent banks reported capital adequacy ratios (CAR) averaging 18%—well above the regulatory minimum (10% pre-2016, 8% post-2016, per Basel III).[7] Within one quarter after closure, average CAR dropped to –51%, revealing that half of reported assets were fictitious. These losses equaled 5% of GDP annually, justifying the term "sin banks."

Geographically, the policy was nationwide, not limited to Moscow and Saint Petersburg (which together hold over 75% of banking assets). Every region—including the Far East—was affected, with the most closures occurring in the West and South (near the Black Sea), and the largest hidden losses revealed in the South, Siberia, and West (Figure 2).

In February 2018, the CBR declared the active phase of the clean-up complete, having eliminated the most egregious fraud cases. Although the policy continued beyond that date, its intensity declined, with the majority of major closures occurring between 2013 and 2018 (Figure A.I in Appendix A). Overall, we document the following four stylized facts.

Stylized Fact 1: *Major frauds are revealed gradually.* As Figure A.I shows, the largest closures occurred in the middle to late phase, suggesting sophisticated fraud schemes can delay detection.

Stylized Fact 2: *Preemptive closures have a sobering effect.* Between 2013–2018, remaining banks increased loan-loss reserves, disclosed more non-performing loans (NPLs), reduced opaque lending, and slowed credit issuance—regardless of the economic cycle (Figure A.II).

Stylized Fact 3: *The policy bolstered government-owned banks.* During the active phase, these banks gained nearly 20 percentage points of deposit market share, previously held by domestic private banks, while foreign banks' share remained stable (Figure A.III).

Stylized Fact 4: *Banking system depth increased.* According to the World Bank, the ratio of domestic private credit to GDP rose from 72% in 2012 to 91% in 2020—despite private bank discrimination and ongoing Western sanctions (Figure A.IV).[8]

By 2020, the number of operating banks had fallen from ~ 1,000 to ~ 350. This decline was steady, unaffected by the business cycle or sanctions, underscoring the CBR's firm commitment to rooting out banking fraud—even at the cost of lender disruption for sin banks' clients.

[7] CAR = total capital / risk-weighted assets.

[8] https://data.worldbank.org/indicator/FD.AST.PRVT.GD.ZS.

Figure 2. Geography and scope of sin bank closures, *2007–2020*

Note: The figure shows total preemptive bank closures by region from 2007–2020 due to detected fraud (*a*) and hidden losses as a share of pre-closure assets (*b*), based on CBR press releases and balance sheets.

(a) Number of bank closures

(b) Relative losses on bank closures, %

3. Data

We compile a unique dataset that retrieves and merges bank-, firm-, and loan-level information from the following five sources: the CBR's credit register of corporate loans, SPARK-Interfax database on firms' balance sheets and financial statements, the CBR's database on banks' balance sheets and their profit and loss accounts, the CBR's official press-releases on bank closures, and the nation-wide media banki.ru containing personal data on banks' board members.

3.1 The credit register data on corporate loans

Our primary data need is observing the evolution of bank-firm relationships over time. Russian credit register data containing comprehensive loan-level details (such as the loan contract date, bank and firm IDs, loan amount, interest rate, maturity, etc.) is only available from January 2017 onwards. However, to cover the bank closure policy period, we require data starting at least in mid-2013. In 2020–2021, the CBR granted us access to the so-called *Credit History Bureau* (CHB) database. While the CHB contains only partial information on corporate loans, it covers bank-firm relationships at the monthly frequency from January 2007 to January 2018. This data granularity is sufficient for our analysis.

Specifically, the CHB is compiled from three major sources: the United Credit Bureau, the National Bureau of Credit Histories, and the Equifax Credit History Bureau. These three are the largest among the fourteen bureaus officially recognized by the State Register of Credit History Bureaus maintained by the CBR.[9] For each bank and each corporate borrower, the CHB provides three key pieces of information: (*i*) the dates when bank-firm relationships are established, (*ii*) the quality of loans in every bank-firm pair in subsequent months until the end of the corresponding relationships, and (*iii*) the size of borrowing firms (micro, SME, or large). The quality of loans is reported as the maximum number of days the loan payment is past due at the reporting date.[10] In addition, if a firm has multiple loans at a bank, the CHB provides only the maximum number of days of payment past due across all these multiple loans (it is clearly possible that just one of the multiple loans is delinquent).

The CHB's loan quality indicator (hereafter DPD, which is *days past due*) is a categorical variable representing different overdue time intervals. For instance, $DPD = 0$ if there are no delayed payments, 30 for all delays in payments from 1 to 30 days, 60 for delays from 31 to 60 days, and so forth. Loans with $DPD \geq 150$ typically include those classified as hopeless, paid by collateral, disputed in courts, or written off.

To identify the bank-firm relationships beyond January 2018, we employ the credit register database.[11] To ensure comparability with the CHB database, we manually calculate DPD using the full loan-level data contained in the credit register. Since the credit register is available from January 2017, we leverage the resulting twelve-month overlap with the CHB to cross-validate our calculations.

By appending the credit register to the CHB, we construct a dataset covering 483,512 unique firms and 906 unique banks from January 2010 to October 2020, resulting in 669,035 unique bank-firm relationships. Among these, 93,661 cases involve firms borrowing from sin banks—private domestic banks whose financial fraud had been detected by the CBR and whose licenses were revoked during the sample period. The remaining 570,179 cases pertain to firms borrowing

[9]See https://www.cbr.ru/ckki/restr/.

[10]Unfortunately loan quality information does not include the ratio of past due payments to the total amount of loans. This may limitation our analysis somewhat.

[11]The credit register is compiled by the CBR using the monthly Form 0409303, see www.cbr.ru/eng/statistics/pdko/sors/summary_methodology/).

from banks that remained operational until the end of the sample period, with approximately 75% of these cases belonging to government-owned banks. Preliminary descriptive analysis shows that more than 70% of firms in the appended dataset are micro-firms (with less than 15 employees), another 20-25% are SMEs, and the rest are large firms. Further, the majority of Russian firms obtain loans from just one bank. For instance, in 2017, the share of such single-bank firms equaled 69.4%, and another 19.5% of firms obtained loans from at least two banks (Figure B.I in Appendix B). These patterns are similar to, e.g., Belgium where 84% of firms are single-bank firms (Degryse et al., 2019a) but are different from, e.g., Spain, where 86% of loans are granted to multiple-bank firms (Jiménez et al., 2014).

3.2 Merging the credit register to bank- and firm-level data

Bank-level data. Since our analysis of firms' responses to the sin bank closure policy depends on the predictability of bank fraud detection, we require detailed bank-level data. This data comes from the CBR's Forms 101 and 102, which contain banks' balance sheets and income statements at monthly and quarterly frequencies, respectively, and are publicly accessible from 2004 to 2020.[12] This dataset covers over 1,100 unique banks, representing 95% of the banking system's total assets. We extend this data with the CBR's official press releases on bank closures, from which we infer that up to 589 banks were preemptively closed due to financial fraud detected during on-site inspections—accounting for 85% of all bank closures during the sample period. Based on this inference, we construct the *sin bank* binary variable that equals 1 for these sin banks and 0 for those that survived until the end of the sample period.

In addition, we manually collect personal data on the composition of banks' boards throughout the 2010s using the library of all Russian banks publicly disclosed by the nation-wide media banki.ru. We provide an example of this information in Appendix C. We use this source to detect board member overlaps across different banks and construct the *common ownership* binary variable that equals 1 if at least one board member also served on the board of another bank operating during the same year, and equals 0 otherwise.

Firm-level data. Further, our analysis also requires detailed firm-level data to evaluate the real effects of the sin bank closure policy. This data emerges from the SPARK-Interfax database that delivers firms' balance sheets and income statements at the annual frequency,

[12]See https://www.cbr.ru/banking_sector/otchetnost-kreditnykh-organizaciy/.

and we retrieve the data from this database for the period of 2010–2020.[13] Over this period, the SPARK-Interfax database contains data for 500,431 companies in Russia, which is a minor fraction of the total number of companies but whose sales nonetheless represent more than 90% of GDP. We exploit a wide range of variables from this database, including gross profits, market sales, income taxes, employment, etc. (see the full list in Table D.I of Appendix D). We also use this data to complement our baseline measure of firm quality—the DPD variable from the CHB–credit register database—by constructing the *Firm Losses* binary variable that equals 1 if a firm reported losses for two consecutive years and 0 in all other cases.

The final dataset. We merge the CHB–credit register data on corporate loans, SPARK-Interfax data on firm characteristics, and the extended CBR's dataset on bank variables. Intersecting the CHB–credit register (483,512 unique firms) with SPARK-Interfax (500,431 unique firms) yields 106,998 firms, which is a yield of about 20%.[14] As a result, the total number of unique bank-firm relationships shrinks from 669,035 to 181,783 and the number of sin-bank–firm relationships drops from 93,661 to 22,801. Notably, this shrinkage affects only the number of firms, not the number of sin banks covered: we still have the general population of 589 sin banks within these 22,801 lending relationships, with the same 70% share of single-(sin)bank firms as before. Moreover, the geographical distribution of bank-firm relationships remains unchanged, covering the entire Russian territory, with the highest concentrations in the western, central, and southern regions (Figure B.II in Appendix B).[15]

From this point forward, we focus exclusively on the 22,801 lending relationships involving the 589 closed sin banks. Within this set, we specifically examine the subset of $0.70 \cdot 22,801 = 15,961$ relationships that pertain to single-(sin)bank firms. We will explore the remaining $6,840$ relationships, which involve multiple-(sin)bank firms, later as part of the sensitivity analysis.

At various points during our sample period, each of the $15,961$ single-(sin)bank firms encounters the closure of its current sin banks and faces a choice: either remain unbanked, relying

[13]The SPARK-Interfax database is a comprehensive resource that aggregates information from over 65 official sources, including the Federal Tax Service, Federal State Statistics Service, and the Central Bank of Russia, among others. It contains data on approximately 24 million legal entities operating in Russia and the CIS countries. See https://spark-interfax.ru/.

[14]For comparison, Laeven and Popov (2023) report a 10% intersection rate when merging the DealScan database on syndicating loans with the Compustat dataset on (large) firms across the world.

[15]In addition, Table B.I in Appendix B describes the regional structure of our data. In more than half of the observations, the firms that experienced bank closures were registered in the Central Federal District (FD), and observations with firms from Volga, Northwestern, and Siberian FDs account for 10% each. Ural, Southern, and Far Eastern FDs add another 15% together, and the rest of the observations (less than 1%) pertain to firms from the North Caucasian FD.

on its own funds or alternative financing sources (trade credit, bond financing, etc.), or seek a new bank. From an ex-post perspective, we can track whether these new banks turn out to be sin banks again (but not yet detected) or solid banks. Table 1 presents summary statistics on the three resulting subgroups of single-(sin)bank firms:

- $3,990$ **firms** (25% of the focused sample, *Panel 1*) that eventually matched with new solid banks,
- 958 **firms** (6%, Panel 2) that matched with not-yet-detected sin banks, which were later closed within our sample period, and
- $11,013$ **firms** (the rest 69%, *Panel 3*) that did not reappear in the credit register until the end of the sample period, if survived, or their own exiting from the economy before the end of the sample period, if closed for any reason.

Comparing the three subsets of firms that encounter the closure of their sin banks, we first document that the largest portion of them (two-thirds) remained unbanked in the future. From the firms' balance sheets, however, we do not observe systematic declines in their aggregate leverage, which implies a substitution between the types of borrowed funds—from banks to non-banks. Second, we document that the composition of firms that match to new banks in the future is dominated by firms that managed to establish lending relationships with solid rather than other sin banks. This implies that the stability of lending relationships is perceived by (majority of) firms as a crucial determinant of their own survival and market success.

Further, we observe that firms that match with new solid banks in the future reported fewer DPD in the prior sin banks than firms matching with new sin banks. However, the difference between the two is not large, thus likely indicating that both good and bad firms may match eventually with either one of the two types of banks, solid or sin. The time it takes differs drastically across the new lending relationships: matching with new solid banks takes much longer (46 months) than matching with new sin banks (18 months). Apparently, it is less difficult to persuade a not-yet-detected sin bank to accept a firm than to persuade a solid bank. As the data indeed shows, at the moment when a new lending relationship is set, a firm that matches with a new sin bank is: (i) 1.5 times more likely to bear losses on its balance sheet, (ii) in a worser financial shape in terms of returns on assets (ROA), and (iii) operate with much larger leverage and much lower liquidity ratios than a firm that matches with a new solid bank.

Table 1. Description of firms in the final dataset

Note: The table reports the summary statistics for the final dataset of 15,961 firms that had lending relationships with the 589 sin banks that had been detected and closed by the CBR during the period from January 2010 to October 2020. The firms are split into three categories depending on whether they establish new lending relationships with solid banks (Panel 1) or another (not-yet-detected) sin banks (Panel 2), or remain unbanked until the end of the sample period (Panel 3). In each panel, the DPD variable, match with a new bank, and the time till new bank matching are sourced from the merged CHB-credit register on corporate loans provided by the Central Bank of Russia in 2020–2021. The rest of the variables—losses, size, leverage, liquidity, and ROA—are retrieved from the SPARK-Interfax database on firms' balance sheets and income statements.

	Mean	Median	SD	Min	Max
Panel 1: Firms matching with new solid banks ($N = 3,990$):					
Days of loan repayments past due (DPD) in the closed sin bank	14.87	0.00	42.07	0.00	200.00
Match with solid bank after current sin bank's closure	0.25	0.00	0.43	0.00	1.00
Time till new bank matching (in months)	45.77	46.00	25.39	2.00	122.00
Whether have losses when matching with new solid bank	0.10	0.00	0.30	0.00	1.00
Log of total assets	17.19	17.23	2.03	10.04	23.38
Leverage	0.75	0.73	0.80	0.00	9.78
Liquidity	0.17	0.19	0.70	–8.57	1.00
Return on assets (ROA)	0.05	0.03	0.23	–2.37	0.91
Panel 2: Firms matching with new sin banks ($N = 958$):					
Days of loan repayments past due (DPD) in the closed sin bank	15.73	0.00	41.75	0.00	200.00
Match with new sin bank after current sin bank's closure	0.06	0.00	0.23	0.00	1.00
Time till new bank matching (in months)	17.86	13.00	14.34	1.00	73.00
Whether have losses when matching with new sin bank	0.15	0.00	0.35	0.00	1.00
Log of total assets	18.26	18.45	2.07	9.39	23.44
Leverage	0.95	0.89	1.25	0.00	18.46
Liquidity	0.06	0.12	0.90	–9.52	1.00
Return on assets (ROA)	–0.02	0.00	0.29	–2.73	0.90
Panel 3: Firms that never match with new banks ($N = 11,013$):					
Days of loan repayments past due (DPD) in the closed sin bank	14.19	0.00	39.52	0.00	200.00
Time till exiting the sample (in months)	28.73	29.00	31.80	1.00	125
Whether have losses in the end of the sample period	0.12	0.00	0.33	0.00	1.00
Log of total assets	17.60	17.71	2.52	9.31	23.63
Leverage	0.99	0.86	1.34	0.00	18.71
Liquidity	0.03	0.14	1.01	–11.93	1.00
Return on assets (ROA)	0.00	0.01	0.27	–3.14	0.91

And finally, another characteristic that delivers substantial differences across the three types of single-(sin)bank firms is their overall size (in terms of total assets). In contrast to the expectation that larger firms may find it easier to borrow from new solid banks, we observe a different picture in our data. Firms that match with new sin banks in the future are on average almost three times larger than firms that match with a solid bank, and almost two times larger than firms that remain unbanked. Thus, we can describe an average firm that matches with a not-yet-detected sin bank in the future as a large, financially constrained, low-liquidity firm.

4. Before Sin Bank Closure: Predictable Closures and Strategic Firm Behavior?

The empirical design in our paper follows the chronological sequence of events, with a focus on how borrowing firms adapt at each of the three stages: (1) before the closure of their sin banks; after the closure of their sin banks but before matching with any new banks; and, (3) after matching with any new banks. Figure 3 illustrates the key steps of the empirical design and the corresponding sections that effectuate them. In the figure, $t^*_{b,f}$ is the moment when a bank b is recognized as sin by the CBR and preemptively closed, which breaks the bank's lending relationships with its borrowing firms f. Further, $t^*_{b,f} + k_f$ is a moment when a firm f matches with new banks, which may be financially solid or not-yet-detected sin. The parameter k_f represents the firm-specific transition period. Our analysis across the three stages addresses the following issues:

- **Before the closure** $t < t^*_{b,f}$: (i) how predictable is sin bank detection and closure and whether firms internalize this predictability by strategically delaying loan repayments or switching to other lenders (Section 4) and (ii) whether sin banks artificially lower the interest rates on loans to bad firms (Section 6),
- **transition period** $t^*_{b,f} \leq t < t^*_{b,f} + k_f$: what happens to performance of good vs. bad firms (Section 5),
- **After the matching with new banks** $t \geq t^*_{b,f} + k_f$: how do good vs. bad firms sort across new lenders and what determines the cross-sectional variation in this sorting (Section 7).

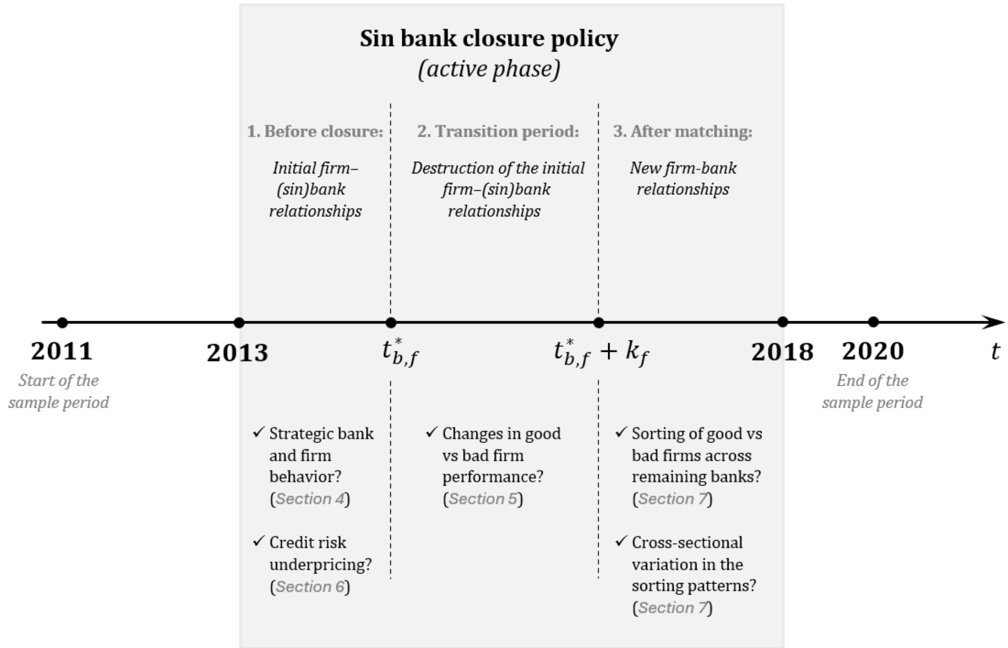
In the current section, we begin by examining whether banks anticipated their closures and whether firms anticipated the closure of their sin banks. We consider two possible endogenous adjustments by firms. First, we conjecture that firms could preemptively leave sin banks in anticipation of their closure. Second, we conjecture that firms, especially low-quality ones, could delay their loan repayments.

4.1 Predictable bank closures?

To determine whether the detection and closure of sin banks came as a surprise to the economy, we apply the traditional CAMELS rating system approach to predicting bank failures (DeYoung

Figure 3. Empirical design along the timeline of the sin bank closure policy

Note: The figure depicts the key steps of our empirical design in the context of the sin bank closure policy in Russia (2013–2018) and the corresponding section of the paper that effectuates those steps. In the figure, $t^*_{b,f}$ is the moment when a bank b is recognized as sin by the CBR and preemptively closed, which breaks the bank's lending relationships with its borrowing firms f. Further, $t^*_{b,f} + k_f$ is a moment when a firm f transfers to another bank, which may be financially solid or not-yet-detected sin.

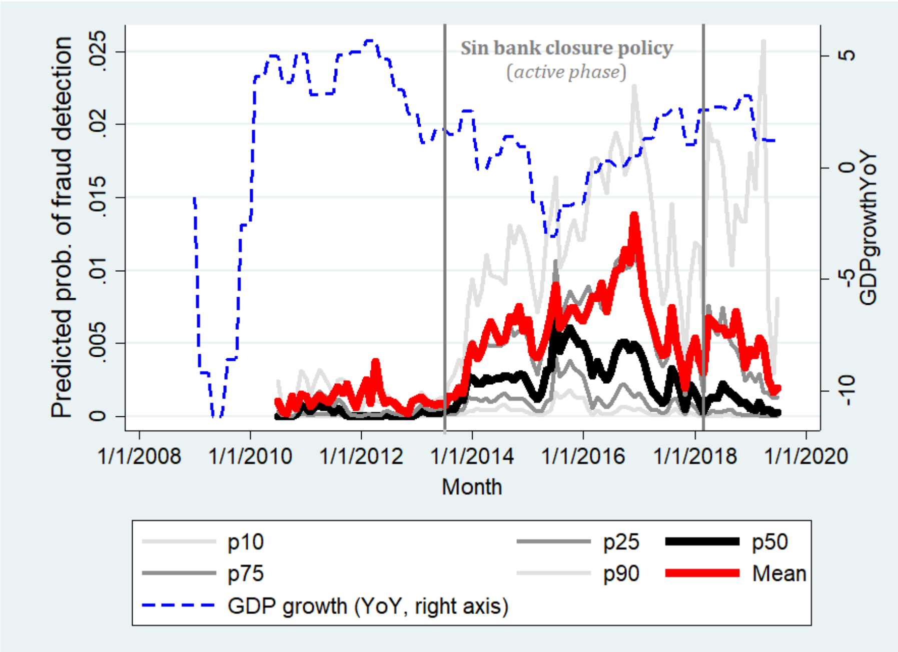


and Torna, 2013). Additionally, to account for extensive anecdotal evidence suggesting that sin banks continuously updated their balance-sheet falsification techniques to conceal losses—and that the central bank adapted its learning correspondingly—we run our CAMELS-based logit regressions using a six-month rolling window from January 2010 (well before the policy was introduced) to January 2020. Our primary objective is to classify all banks—both closed and operating—based on their (in-sample) predicted probabilities of sin detection and closure in a given month, dividing them into two groups: high and low predicted probability. Importantly, we are not interested in whether we can predict bank closures per se, we aim to compare the predicted probabilities of closures for actually closed banks vs. the banks that survived until the end of the sample. Specifically, we examine whether the banks that were actually closed fell into the low-predicted-probability group. If they did, we conclude that the closures were surprising; if not, we assert the opposite.

The logit estimations are presented in Table E.I and thoroughly discussed in Appendix E. Overall, our estimates are characterized by sufficiently large area under the ROC-curve (Figure E.I), indicating our logit regression models do capture the majority of actually closed banks.

Figure 4. Predicted probabilities of sin bank detection and closure

Note: The figure depicts the time evolution of the (in-sample) predicted probabilities of sin bank detection and closure at the bank-month level. The probabilities are obtained from the CAMELS-based logit regression models ran on a six-month rolling window from January 2010 to January 2020. The probabilities are predicted for both the actually closed sin banks and the banks that survived until the end of the sample period. We report the mean predicted probability across all banks in the corresponding month ($Mean$) as well as the probabilities in selected percentiles of the bank-month distribution ($p10, p25, p50, p75, p90$). In the background, we report the annual GDP growth rates in Russia. The active phase of the policy is marked with two vertical grey lines (June 2013 and February 2018). The data is sourced from the CBR's press-releases on sin bank detection and closure during the sample period as well as banks' balance sheets (Form 101) and P&L accounts (Form 102).



However, as our analysis of the magnitudes of the predicted probabilities shows, it is indeed the case that majority of the closed banks have lower probabilities than the survived banks.[16]

Specifically, in Figure 4 below, we plot the time evolution of the corresponding predicted probabilities of sin bank detection and closure in time for both the actually closed and operating banks. We obtain the predicted probabilities that —in line with expectations— are close to zero before implementation of the policy and then soar during the active phase of the policy.[17] For classification purposes, let us consider a threshold $\bar{p} = 0.5\%$, which is the unconditional mean of the predicted monthly probability of bank closure in the sample.[18] It appears that

[16]In theory, the area under the ROC Curve can be high (> 0.8) while the predicted probabilities for False Positives are, on average, larger than those for True Positives. This is because the ROC Curve is based on ranking, not probability magnitude.

[17]Note that the predicted probabilities are at the monthly frequency. It is also notable that the probabilities peak in 2016–2017, at least one year before the end of the active phase. We also observe no clear pattern of correlations between the predicted probabilities and annual real GDP growth rates. This suggests that the policy and macroeconomic conditions were fairly orthogonal to each other.

[18]Annualized, the average predicted probability of closure is about 6%. As a part of robustness checks, we also consider substantially higher values for the threshold $\bar{p}$ of 1% and 1.5%. Qualitatively, our results are robust to these higher values of the threshold.

about 90% of all bank closure cases have $p < 0.5\%$, that is, they are correctly captured by the model but the estimated magnitudes of the probability of their detection is lower than those for the solid banks that survived until the end of the sample period. In this sense, we can claim that the probability of sin bank closures is low.

4.2 Preemptive switching of lenders on the eve of sin bank closure?

Though the predictability of sin bank closures is low, as we have just established, this conclusion has been based so far solely on the information contained in banks' balance sheets. However, firms borrowing from sin banks may possess information from different sources and well anticipate the banks' closures. There are at least three reasons why some firms could consider leaving their sin banks in this case. First, good firms may be willing to signal to other banks that they are seeking stable long-term relationships with their lender(s). Second, if firms do not switch to other banks in advance, their debts can be transferred to new banks through auctions during the resolution process launched by a receiver (Granja et al., 2017), in which case firms may have little control in determining who acquires their debts. Third, bank closures can have a disruptive effect on firms' daily transactions causing payment delays and harming their reputation.

Of course, some firms can switch to new lenders on the eve of their existing sin banks' closure coincidentally, i.e., not because they anticipate the closures but because their current loan contracts mature and the firms find better credit deals (from other banks, from the bond market, etc.). In this case, we should not observe any predictive power of the firm quality characteristics—i.e., whether a firm is a good or bad one—on the likelihood of lender switching in a reasonably short period before sin banks' closures. In the data, we indeed observe that only a tiny fraction of firms switched lenders some six months before the closure of their existing sin banks: 1.4% (5.3%) of the total number of firms that ever matched with new sin banks (new solid banks) in the future.

To formally test for whether firm quality predicts preemptive lender switching, we construct a set of binary variables $Switch_{f,t}^{(\jmath)}$ reflecting firms' switching to new (sin or solid) lenders at $t \in [t_{b,f}^{*} - h, t_{b,f}^{*})$ and run the following panel logit regression models:

$$\mathbf{Pr}(Switch_{f,t}^{(\jmath)} = 1 \,|\, \mathbf{X}_{f,t-1}) = \Lambda\Big(\beta_\jmath \cdot Firm\,Quality_{f,t-1} + \alpha_{\jmath,bce} + \gamma_{\jmath,r} + \mu_{\jmath,s} + \tilde{\mathbf{X}}_{f,t-1}\Theta_\jmath'\Big), \qquad (1)$$

where $t^*_{b,f}$ is the moment in time when a (sin)bank-firm relationship breaks due to the closure of sin bank b and h is a parameter determining the 'reasonably' short estimation window prior to the closure. We set $h = 6$ for the baseline estimates. The dependent variable $Switch^{(\jmath)}_{f,t}$ takes one of the two following forms: either $Switch\,to\,Sin\,Bank_{f,t}$ ($\jmath = 1$) or $Switch\,to\,Solid\,Bank_{f,t}$ ($\jmath = 2$), so that it equals 1 if a firm f switches in month $t \in [t^*_{b,f} - 6, t^*_{b,f})$ to a new sin bank (new solid bank) and 0 if not. The $Firm\,Quality_{f,t-1}$ is either (i) the log of the maximum number of days during which the loan repayments in the existing sin banks were past due (DPD), as had been accumulated by $t^*_{b,f} - 6$ or (ii) the binary variables of whether firms reported losses for at least two consecutive years at $t^*_{b,f} - 6$ or $t^*_{b,f}$ (*Firm Losses*, proxy for bad firm). $\tilde{\mathbf{X}}_{f,t-1}$ contains other controls, such as (i) the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, (ii) firm $Leverage$ (short- and long-term debts over the total assets), and (iii) firm $Liquidity$ (current liabilities net of accounts payable and short-term debts over the total assets).

The logit regression models (1) also include the following fixed effects. First, $\alpha_{\jmath,bce}$ is bank-closure-event fixed effect, as captured by a binary variable that equals 1 if there are sin bank closures in a given month t and 0 if not. Detection and closure of a portion of sin banks may produce spillover effects on firms borrowing from other—not-yet-detected—sin banks, forcing the firms to switch to other lenders irrespective of whether they are good or bad. Second, $\gamma_{\jmath,r}$ and $\mu_{\jmath,s}$ are region and sector fixed effects aimed at removing differences across firms operating in poor vs. rich regions and in more vs. less procyclical industries.

We conjecture that firm quality does not predict a firm's preemptive switching to a new bank on the eve of its current sin bank closure. The alternative hypothesis would be that good firms are more likely to switch to new banks preemptively, as they are less subject to the hold-up problem Ioannidou and Ongena (2010), while bad firms are less likely to do so.

The estimation results appear in Table 2. In columns (1)–(2), the dependent variable is $Switch\,to\,Sin\,Bank_{f,t}$ and the sample is restricted to those 958 firms that at some point switched from their existing sin banks to new sin banks, of which 13 did so preemptively (on average, three months before the corresponding sin banks' closures). This gives us $13 \cdot 3 + 944 \cdot 6 = 5,706$ firm*month observations. In columns (3)–(4), the dependent variable is $Switch\,to\,Solid\,Bank_{f,t}$ and the sample is restricted to those 3,990 firms that at some point switched from their existing

Table 2. Logit estimation results: Do firms switch to new banks in anticipation of their existing sin banks' closure?

Note: The table reports the estimates of the panel logit regression model (1). In columns (1)–(2), the dependent variable $Switch\,to\,Sin\,Bank_{f,t}$ equals 1 if a firm f switches in month $t \in [t^*_{b,f} - 6, t^*_{b,f})$ to a new *sin* bank and 0 if not, where $t^*_{b,f}$ is the point in time when the firm's f previous sin bank b is detected and closed. In the sample, there are 13 firms that did these preemptive switchings to new sin banks on the eve of their previous sin banks' closure and 945 firms that stayed with their existing sin banks till their closure and switched to new sin banks only after. Analogously, in columns (3)–(4), the dependent variable $Switch\,to\,Solid\,Bank_{f,t}$ equals 1 if a firm f switches in month $t \in [t^*_{b,f} - 6, t^*_{b,f})$ to a new *solid* bank and 0 if not. In the data, there are 210 firms that preemptively switched to new solid banks on the eve of their previous sin banks' closure and 3,780 firms that stayed with their existing sin banks till their closure and switched to new solid banks only after. Only single-(sin)bank firms are considered. The estimates are performed over the period from January 2010 to January 2020 encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. By rows, Panel 1 contains firm quality proxies we are focused on: (i) the log of the maximum number of days during which the loan repayments in the existing sin banks were past due (DPD), as had been accumulated by $t^*_{b,f} - 6$, (ii) the binary variables of whether firms reported losses for at least two consecutive years at $t^*_{b,f} - 6$ or $t^*_{b,f}$ ($Firm\,Losses$). Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm $Leverage$ (short- and long-term debts over the total assets), and firm $Liquidity$ (current liabilities net of accounts payable and short-term debts over the total assets). Coefficients instead of marginal effects are reported. The constant term is included but not reported to preserve space.

Dependent variable:	$Switch\ to\ Sin\ Bank_{f,t}$		$Switch\ to\ Solid\ Bank_{f,t}$	
	(1)	(2)	(3)	(4)
Panel 1: Firm quality:				
ln DPD_{f,t^*-6}	0.010		0.095	
	(0.080)		(0.131)	
Firm Losses_{f,t^*-6}		0.362		0.035
		(0.267)		(0.069)
Firm $\text{Losses}_{f,t}$		0.038		0.052
		(0.153)		(0.047)
Panel 2: Other controls:				
Firm $\text{size}_{f,t-1}$	0.406	0.521	0.013	0.074
	(0.417)	(0.431)	(0.134)	(0.145)
Firm $\text{size}^2_{f,t-1}$	–0.012	–0.015	0.000	–0.001
	(0.011)	(0.011)	(0.004)	(0.004)
$\text{Leverage}_{f,t-1}$	–0.264	–0.293	–0.252***	–0.228***
	(0.194)	(0.203)	(0.066)	(0.068)
$\text{Liquidity}_{f,t-1}$	–0.411**	–0.361**	–0.090	–0.049
	(0.166)	(0.172)	(0.059)	(0.061)
Bank closure event FE	✓	✓	✓	✓
Regional FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
N obs	5,706	5,706	23,312	23,312
N firm switches	13	13	210	210
N firms	958	958	3,990	3,990
log L	–2,916	–2,676	–16,010	–15,557
R^2 (pseudo)	0.035	0.034	0.006	0.005

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

sin banks to new solid banks, of which 210 did so preemptively (on average, again three months before the corresponding sin banks' closures). This gives us $210 \cdot 3 + 3,780 \cdot 6 = 23,312$ firm*month observations.

In columns (1) and (3) we obtain insignificant and close-to-zero estimates of the β_1 and β_2 coefficients when the firm quality is proxied with the log of DPD. This means that neither poorer quality of firm debts can predict the firm's preemptive switching to new sin banks, nor higher quality can do so when it comes to preemptive switching to new solid banks. When we replace the log of DPD by the two firm losses variables in columns (2) and (4), we reach the same conclusion.

Regarding the other firm controls, we find that the coefficients on firm size and its square are insignificant, meaning that neither *larger* nor *smaller* firms are more likely to switch preemptively. The estimated coefficient on firm leverage is negative and highly significant in columns (3) and (4), implying that low-leverage firms are more likely to switch to solid banks on the eve of the current sin banks' closure. As we control for firms' DPDs and $Firm\,Losses$ in the same regressions, lower leverage is unlikely to reflect any strategic reasons for lenders' switchings (in fact, if the corresponding coefficients were positive, this could reflect high-leverage firms' strategic behavior aimed at ensuring operational stability by transferring debt to solid banks). Finally, the estimated coefficients on firm liquidity are negative and also significant in columns (1) and (2), suggesting that low-liquidity firms are more likely to switch to new sin banks on the eve of their current sin banks' closure. This in turn can reflect firms' strategic behavior contrasting our baseline story but the scope of this behavior is strictly limited, as we discussed above (recall that only 13 out of 958 firms preemptively switched to new sin banks).

Overall, the panel logit estimation results reveal that firms' preemptive switching from existing sin banks is not affected by firms' quality. One potential interpretation of this is the lack of evidence that firms could easily anticipate bank closures (no information leakage). Preemptive switching, if any, is thus more likely to take place for other common reasons (expiration/full repayment of loans, etc.). An alternative explanation is that firms could anticipate closures, but the hold-up problem is strong enough to keep them in place, even for high-quality firms.

4.3 Strategic loan repayment delays?

Even if the majority of firms stay with their existing sin banks until the banks' closure, this does not necessarily mean that the firms are unaware of the upcoming closures and are not trying to reap benefits from it. For example, bad firms struggling to meet their loan obligations may find it optimal to strategically delay their payments if they anticipate that their banks will soon be closed. The bank closure means that the firms' debts will be transferred to new creditors, which opens up the possibility for debt restructuring.

To test for this hypothesis, we specify the following regression model:

$$\Delta DPD_{b,f,t} = \beta_1 \cdot Firm\,Losses_{f,t^*-h} + \beta_2 \cdot Firm\,Losses_{f,t^*-h} \times Sin\,Bank_b \qquad (2)$$
$$+ \mathbf{X}_{b,t-1}\mathbf{\Theta}' + \alpha_{bce} + \gamma_r + \mu_s + \nu_{b,f} + \lambda_t + \varepsilon_{b,f,t},$$

where $\Delta DPD_{f,b,t}$ is a one-month change in the days past due (DPD) accumulated by firm f borrowing from a sin bank b in time $t \in [t^*_{b,f} - h, t^*_{b,f})$, where the parameter h determines the estimation window ($h = 12, 9, 6, 3$ months prior to the bank b closure). $Sin\,Bank_b$ is a binary variable that equals 1 if a bank is ever closed for fraud (i.e., sin bank) and 0 if it survives until the end of the sample. Control variables $\mathbf{X}_{b,t-1}$ include: bank size, the ratio of household credit to total assets, equity capital to total assets, corporate and household deposits to total assets, and non-performing loans to total assets. The model features the following fixed effects. First, α_{bce} and λ_t are the bank-closure-event fixed effects and month t fixed effects, capturing the specific circumstances surrounding each closure event in time and the aggregate shocks that affect all banks in the same month t, respectively. Second, γ_r and μ_s are the region and sector fixed effects, as before. Third, $\nu_{b,f}$ is a high-dimensional bank-firm fixed effect that captures unobserved features of bank-firm relationships that may affect the schedule of loan repayments and bank tolerance to their delinquencies.

In the baseline (single sin bank-firm relationships), β_2 is redundant because the condition $Sin\,Bank_b = 1$ always holds. In this case, we hypothesize that $\beta_1 > 0$: bad firms (i.e., $Firm\,Losses_{f,t^*-h} = 0$) raise their loan delinquencies. In the robustness check (multiple bank-firm relationships involving at least one sin bank), we hypothesize that $\beta_1 = 0$ and $\beta_2 > 0$: firms repay their loans in full at solid banks but they raise loan delinquencies at sin banks.

Table 3. Linear estimation results: Do firms strategically increase delays in repaying loans before their sin banks are closed?

Note: The table reports the estimates of regression (2), where the dependent variable $\Delta DPD_{b,f,t}$ is a one-month change in the days past due (DPD) accumulated by firm f borrowing from a sin bank b in time $t \in [t^*_{b,f} - h, t^*_{b,f})$, where $t^*_{b,f}$ is firm-bank-specific date of ending a relationship between firm f and its existing sin bank b. The parameter h determines the estimation window ($h = 12, 9, 6, 3$ months prior to the bank b closure). In Panel 1, there are 15,961 unique single (sin) bank-firm relationships. In Panel 2, there are 6,840 multiple bank-firm relationships involving at least one sin bank. $Firm\,Losses_{f,t^*-h}$ is a binary variable that equals 1 if firm f reported losses for at least two consecutive years at $t^*_{b,f} - h$ (bad firm) and 0 if else. $Sin\,Bank_b$ is a binary variable that equals 1 if a bank is ever closed for fraud (i.e., sin bank) and 0 if it survives till the end of the sample. Fixed effects as specified.

Months h before sin bank closure:	$h = 12$	$h = 9$	$h = 6$	$h = 3$
	(1)	(2)	(3)	(4)
Panel 1: single (sin) bank-firm relationship (*baseline*)				
Firm Losses$_{f,t^*-h}$	1.063	0.761	1.197	−0.711
	(0.720)	(0.949)	(1.174)	(1.565)
Bank closure event FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Bank × firm FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
N obs	190,859	142,977	95,095	47,213
R^2 (within)	0.091	0.111	0.143	0.255
Panel 2: Multiple bank-firm relationships				
Firm Losses$_{f,t^*-h}$	0.219	0.414	0.937	0.379
	(0.450)	(0.786)	(0.591)	(0.500)
Firm Losses$_{f,t^*-h}$ × Sin bank$_b$	0.111	−0.644	−1.165	−1.589
	(0.791)	(1.200)	(1.367)	(1.955)
Bank closure event FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
Bank × firm FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
N obs	82,084	61,563	41,042	20,521
R^2 (within)	0.081	0.100	0.135	0.232

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank level and appear in the brackets under the estimated coefficients.

The estimates of regression (2) are presented Table 3, with Panel 1 devoted to the baseline case of single (sin) bank-firm relationships and Panel 2 multiple bank-firm relationships. From Columns (1) to (4) we shrink the estimation window from 12 to 3 months before sin bank closures. At the intersection of Column (1) and Panel 1 we have 190,859 bank-firm-month observations, which result from 15,961 unique single (sin) bank-firm pairs, of which 13+210 = 223 last on average for 9 out of 12 months (recall these are those firms that switch preemptively to new sin and solid banks, respectively) and the rest 15,738 last till the sin banks' closure in 12 months. The number of observations in the rest of columns are produced analogously.

Across the four columns of Panel 1 we consistently obtain very small and insignificant estimates of the β_1 coefficient, whose size barely exceeds 1.2 additional days of payments past due. This means that the firms that suffer losses did not raise loan repayment delinquencies at any reasonably small horizons prior to their sin banks closure. The same results emerge from Panel 2, in which we obtain very small and insignificant estimates of both β_1 and β_2 coefficients. These estimates imply that firms borrowing from multiple banks did not raise loan repayment delinquencies neither at solid banks nor existing sin banks. Overall, our results show little evidence that firms anticipated sin bank closures. The firms neither left their sin banks preemptively nor did they engage in strategic loan repayment delays.

5. The Real Effects of Sin Bank Closures

5.1 Baseline results

In this section, we examine the real effects of sin bank closures on firm performance. Specifically, we aim to understand what happens to firms in the transition period—*after* they experience the sin bank closure and *before* they establish new bank-firm relationships. On the one hand, one might expect that firm performance should deteriorate because, by losing their bank (even if it was a sin bank), firms become more financially constrained (Chodorow-Reich, 2014; Chopra et al., 2020). On the other hand, firm performance may improve due to the termination of a situation with hold-up (Ioannidou and Ongena, 2010; Liaudinskas and Grigaite, 2021), especially if new lenders offer lower interest rates, collateral requirements, etc. We further conjecture that the negative effects may dominate the positive ones for bad firms and the other way around for good firms.

To formally explore the differential real effects of sin bank closures on the performance of good and bad firms during the transition period, we formulate the following difference-in-differences regression model:

$$Y_{f,t} = \alpha_f + \gamma_{s,t} + \beta_1 \cdot Sin\,Bank_{f,t} \times Post\,Closure_{f,t} \quad (3)$$
$$+ \beta_2 \cdot Sin\,Bank_{f,t} \times Post\,Closure_{f,t} \times Firm\,Losses_{f,t}$$
$$+ \mathbf{X}_{f,t-1}\mathbf{\Theta}' + \varepsilon_{f,t},$$

where for firm f in year t the dependent variable $Y_{f,t}$ is either (1) the firm size, proxied by the log of total assets ($\ln TA_{f,t}$), (2) the log of total borrowed funds, which by the definition of the transition period implies non-bank borrowings ($\ln Debt_{f,t}$), (3) the ratio of sales revenue to total assets, which reflects the firm's ability to generate income out of one ruble of assets ($Sales_{f,t}/TA_{f,t}$), (4) the negative of the ratio of the total number of workers to the sales revenue, which proxies for the firm's efficiency by capturing how many workers it needs to generate one ruble of income ($Workers_{f,t}/Sales_{f,t}$), or (5) the ratio of the gross profit to the total assets, which summarizes the real effects of sin bank closure on the cost and income sides of the firm's balance sheet ($Profit_{f,t}/TA_{f,t}$).

The three key variables in equation (3) are as follows.

First, $Sin\,Bank_{f,t}$ is our focus variable that determines treatment: it is a binary variable that equals 1 for each year $t \in [t^*_{f,b} - 2, t^*_{f,b} + 2]$ if firm f had a lending relationship with sin bank b that had been closed at $t^*_{f,b}$ (*earlier-treated*) and 0 over the same time interval if firm f had a lending relationship with bank $\tilde{b}$ which was also sin but had been closed at a sufficiently later point in time, i.e., $t^*_{f,\tilde{b}} > t^*_{f,b} + 2$ (*later-treated*). To guarantee the pre-treatment comparability of treated and control firms, we employ the 1:4 nearest-neighbor matching estimator of Abadie and Imbens (2011) using pre-treatment firm size, the annual growth of total assets, leverage, and liquidity as observables. Importantly, as we are interested in the transition period, we restrict our treatment to only those $958 + 3,990 = 4,949$ entities that managed to establish new lending relationships until the end of the sample period in 2020. But we do employ the whole population of the 15,961 unique single (sin)bank-firms for drawing control firms when we do the matching. We intentionally restrict the time window by two years before and after each sin bank closure to lower the potential contamination from other shocks that may affect firms during the sample period.[19] This means that we have to exclude the 223 firms that had

[19] Recall from Table 1 that the average time it takes for good firms to establish new lending relationships is

been treated in the last two years of our sample, i.e., in 2019 and 2020.[20] To control for the survivorship bias (Brown et al., 1992), we also require treated firms to survive until at least $t^*_{b,f} + 2$.

Second, the timing of treatment is captured by $Post\,closure_{f,t}$, which is a binary variable that equals 1 if firm f is an earlier-treated firm and $t \geq t^*_{f,b}$; in all the other cases, the timing variable equals 0 (that is, for earlier-treated firms before sin bank closures and for later-treated firms when they are used as controls).

Third, $Firm\,Losses_{f,t}$ is a binary variable that equals 1 if firm f reported losses for at least two consecutive years (proxy for a bad firm) and 0 if else. Each regression contains the other two sub-products of the triple interaction variable (not reported to save space), the fixed effects as specified, and the four firm-specific characteristics we used for matching to capture any residual differences across earlier- and later-treated firms.

The rest of notations in equation (3) involve the matrix $\mathbf{X}_{f,t-1}$ that accommodates all the sub-products of the triple interaction term that we estimate but do not report to save space, as well as the four firm-level characteristics that we used for matching to capture residual differences observable across firms, if any. The variables α_f and $\gamma_{s,t}$ are the firm and sector × year fixed effects that eliminate unobserved differences across firms and any time-specific shocks to the industries in which firms operate, respectively. Finally, $\varepsilon_{f,t}$ is the regression error.

Using equation (3), we can formalize the two hypotheses we discussed above as follows:

Hypothesis **H1** "*Good firms improve*": $\beta_1 > 0$.

Hypothesis **H2** "*Bad firms deteriorate*": $\beta_1 + \beta_2 < 0$.

The estimates of equation (3) appear in Table 4. The regression analysis is based on 4,725 unique single (sin)bank-firms in the treatment group and 14,175 non-unique counterparts in the control group. The treatment group is composed of 543 bad firms ($Firm\,Losses_{f,t} = 1$) and 4,182 good firms ($Firm\,Losses_{f,t} = 0$). And given that we require all these firms to survive within the (rolling) five-year estimation window (two years before the treatment, the treatment year, and the two years after the treatment), the total number of firm*year observations reaches 94,503.

more than 42 months, and that for bad firms it is 18 months.

[20] Recall that the active phase of the policy had been finished in 2018, explaining why we lose only a minor fraction of treated firms in 2019–2020.

Table 4. Difference-in-differences estimation results: Firm performance after sin bank closures and before establishing new bank-firm relationships

Note: The table reports the estimates of equation (3), where the dependent variable $Y_{f,t}$ reflects for each firm f in year t (1) the firm size, as captured by the log of total assets ($\ln TA_{f,t}$), (2) the log of total borrowed funds ($\ln Debt_{f,t}$), (3) the ratio of sales revenue to total assets ($Sales_{f,t}/TA_{f,t}$), (4) the ratio of the total number of workers to the sales revenue ($Workers_{f,t}/Sales_{f,t}$), or (5) the ratio of the gross profit to the total assets ($Profit_{f,t}/TA_{f,t}$). $Sin\,Bank_{f,t}$ is a binary variable that equals 1 for each year $t \in [t^*_{f,b} - 2, t^*_{f,b} + 2]$ if firm f had a lending relationship with sin bank b that had been closed at $t^*_{f,b}$ (*earlier-treated*) and 0 over the same time interval if firm f had a lending relationship with bank $\tilde{b}$ which was also sin but had been closed at a sufficiently later point in time, i.e., $t^*_{f,\tilde{b}} > t^*_{f,b} + 2$ (*later-treated*). To guarantee the pre-treatment comparability of affected firms, we employ the 1:4 nearest-neighbor matching estimator of Abadie and Imbens (2011) using firm size, the annual growth of total assets, leverage, and liquidity as observables. $Post\,closure_{f,t}$ is a binary variable that equals 1 if firm f is an earlier-treated firm and $t \geq t^*_{f,b}$ and 0 in all the other cases. $Firm\,Losses_{f,t}$ is a binary variable that equals 1 if firm f reported losses for at least two consecutive years and 0 if else (proxy for bad firm). Each regression contains the other two sub-products of the triple interaction variable (not reported to save space), the fixed effects as specified, and the four firm-specific characteristics we used for matching to capture any residual differences across earlier- and later-treated firms.

	Dependent variable $Y_{f,t}$:				
	$\ln \text{TA}_{f,t}$	$\ln \text{Debt}_{f,t}$	$\frac{\text{Sales}_{f,t}}{\text{TA}_{f,t}}$	$-\frac{\text{Workers}_{f,t}}{\text{Sales}_{f,t}}$	$\frac{\text{Profit}_{f,t}}{\text{TA}_{f,t}}$
	(1)	(2)	(3)	(4)	(5)
Sin bank$_{f,t}$ × Post closure$_{f,t}$	0.205***	0.164***	0.384***	4.408*	0.006
	(0.043)	(0.058)	(0.063)	(2.365)	(0.017)
Sin bank$_{f,t}$ × Post closure$_{f,t}$ × Firm Losses$_{f,t}$	–0.320**	–0.259**	–0.770**	–10.553**	–0.017
	(0.136)	(0.121)	(0.325)	(4.239)	(0.030)
Sin bank$_{f,t}$	–0.091**	–0.045	–0.210**	–1.994**	0.000
	(0.040)	(0.052)	(0.101)	(0.921)	(0.014)
Post closure$_{f,t}$	0.082**	0.122**	–0.184	–4.940*	–0.028
	(0.037)	(0.054)	(0.162)	(2.852)	(0.018)
Firm Losses$_{f,t}$	–0.008	0.099**	–0.316***	–8.703**	–0.180***
	(0.029)	(0.043)	(0.120)	(3.599)	(0.014)
Other firm controls	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓	✓
N obs	94,503	94,503	94,503	94,503	94,503
N treated firms	4,725	4,725	4,725	4,725	4,725
N control firms	14,175	14,175	14,175	14,175	14,175
R^2 (pseudo / LSDV)	0.3	0.2	0.1	0.1	0.1

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

In column (1) of Table 4, we obtain a positive and highly statistically significant estimate of the β_1 coefficient and a negative and statistically significant estimate of the β_2 coefficient. The first estimate indicates that following their sin bank closures and before establishing new lending relationships, good earlier-treated firms increased the size of their total assets by $e^{0.205} - 1$, or

22.8 percent, more compared to good later-treated firms. The second estimate further implies that in the similar situation, bad earlier-treated firms encountered a squeeze of their total assets that was by $|e^{0.205-0.320}-1|$, or 10.9 percent, more intensive compared to bad later-treated firms.

In column (2), we similarly obtain a positive and highly significant estimate of the β_1 coefficient and a negative and significant estimate of the β_2 coefficient. The first estimate implies that compared to good later-treated firms, good earlier-treated firms raised additional $e^{0.164}-1$, or 17.8 percent, borrowed funds from non-banks during the transition period. The second estimate then indicates that bad earlier-treated firms suffered from an additional $|e^{0.164-0.259}-1|$, or 9.1 percent, reduction of their total borrowed funds during the same period, as compared to bad later-treated firms.

Column (3) also reports a positive and highly significant estimate of the β_1 coefficient and a negative and significant estimate of the β_2 coefficient, meaning that the ratio of sales revenue to total assets grew for good earlier-treated firms and plummeted for bad earlier-treated firms. From the summary statistics, we know that the average sales revenue of good firms equals 68.9 bn rubles, which implies the pre-treatment ratio of sales revenue over total assets being equal 2.36. Given the average total assets of good firms before the treatment (29 bn rubles) and after the treatment ($29 \cdot 1.205 = 36$), we can uncover the average sales revenue of good earlier-treated firms after the treatment as $(0.384 + 2.36) \cdot 35.9 = 98.4$ bn rubles. This figure implies a 42.7 percent jump in the average sales revenue of good earlier-treated firms during the transition period, as compared to good later-treated firms. Similar computations for bad earlier-treated firms lead us to an estimate of a 25.4 percent additional drop in the sales revenues of bad earlier-treated firms during the same time, as compared to bad later-treated firms.

Column (4) then introduces the estimates for firm efficiency. We obtain a positive and marginally highly significant estimate of the β_1 coefficient and a negative and significant estimate of the β_2 coefficient, meaning that the negative of the ratio of the number of workers to sales revenue increased for good earlier-treated firms and fell for bad earlier-treated firms. From the summary statistics, we observe that the pre-treatment average number of workers at good firms was equal 1,792, implying that its ratio over the pre-treatment sales revenue was equal 26.0. We can thus compute that after the treatment, the number of workers at good earlier-treated firms increased to $(-4.408 + 26.0) \cdot 98.4 = 2,132$. This implies an additional 18.5

percent of employment growth at good earlier-treated firms during the transition period, as compared to good later-treated firms. Analogous computations for bad earlier-treated firms result in 12.2 percent of the additional decline in employment over the same time span, as compared to bad later-treated firms.

Finally, column (5) delivers insignificant estimates of both β_1 and β_2 coefficients, which implies that the profitability ratios of both good and bad earlier-treated firms remained relatively fixed. Given the estimated post-treatment assets (the denominator of the profitability ratio) and the pre-treatment profitability ratios (0.05 for good firms and −0.02 for bad firms), we can finally compute that good earlier-treated firms witnessed an additional 37.5 percent growth of their gross profits during the transition period, as compared to good later-treated firms. By contrast, bad earlier-treated firms suffered from an additional 38.2 percent growth of their gross losses over the same time period, as compared to bad later-treated firms.

Overall, our estimation results largely support the H1–H2 hypotheses as we establish that at least along the five different margins—from firm size to employment and market sales—the performance of good firms improves and the performance of bad firms deteriorates. These differential real effects are caused by the closure of sin lenders, and they are materializing during the transition period, i.e., before the affected firms establish new lending relationships.

5.2 Sensitivity analysis

We address the following two concerns regarding the way we construct the control group of firms for the baseline analysis. The first one is that we ignore the never-treated firms, i.e., those entities that had been borrowing from solid banks over our sample period. Recall that the intersection of the SPARK-Interfax and the CHB databases produced 106,998 unique firms, with a 70% ratio of single-bank firms. We thus have $0.7 \cdot 106{,}998 - 958 - 3{,}990 = 69{,}950$ unique never-treated single-bank firms. We use these observations to re-run the 1:4 matching (Abadie and Imbens, 2011) and re-construct the control group. We then re-run the difference-in-differences regressions reported in Table 4 above and report the resultant estimates in Appendix Table F.I. We consistently obtain largely insignificant and close-to-zero estimates of β_1 and β_2 coefficients (the results are not reported to save space). The only partial exception is the estimated β_1 coefficient in the 'employment' regression (column 4), which appears to be very close to the one in the baseline (3.908) and also statistically significant. Overall, this exercise indicates that never-treated firms are bad controls for earlier-treated firms, which presumably arises from the heterogeneous nature of the new control set.

Further, we address the issue of multiple-bank firms that had at least one sin bank in their network. Recall that we have $6,840$ lending relationships involving multiple-bank firms. We now consider them for the treatment group, and we re-do the 1:4 matching exercise. We then re-run the difference-in-differences analysis and obtain no significant estimates of β_1 and β_2 coefficients (see Appendix Table F.II). The only exception is the β_1 estimate in the 'sales revenue' regression (column 3), which is positive and significant as in the baseline, but whose magnitude is nonetheless an order of magnitude lower than in the baseline. Overall, this exercise favors the view that multiple-bank firms are able to effectively cope with negative credit supply shocks (Degryse et al., 2019a) by attracting additional funds from the other banks in the existing network, thus substituting for the lost part of credit provided by sin banks before their closure.

6. Mechanisms of the Differential Real Effects: Credit Risk Underpricing

In the previous section, we have established the differential real effects of sin bank closures on the subsequent performance of good and bad firms. We now explore the mechanisms through which these differences may arise. One potential mechanism is that sin banks underprice credit risk when lending to firms, effectively subsidizing corporate credit. This may occur, for example, when weak banks attempt to offset losses by shifting their borrower composition from healthier (more transparent) firms to weaker (more opaque) ones, thereby artificially easing their regulatory capital constraints (Blattner et al., 2023). When regulators reveal the gamble and close a sin bank, firms lose these implicit subsidies—a disruption that likely affects bad firms more severely than good firms.

To test this mechanism, we need to rely on the full credit register data (rather than the CHB), which is only available from January 2017 onward (see Section 3.1). While this provides only 14 months of coverage within the five-year active phase of the sin bank closure policy, we argue that the analysis is still informative. The key argument is that the regulator's approach to detecting and closing sin banks remained consistent throughout the active phase, as evidenced by the nearly linear time trend in monthly closures (recall Figure 1). Furthermore, although at a lower frequency, closures of sin banks continued beyond February 2018. Over the period from January 2017 to September 2020, we have $1,774,379$ observations pertaining to single-bank firms and another $679,356$ observations on multiple-bank firms.

A particularly valuable feature of the credit register data is that it provides credit risk scores at the bank-firm-month level. These scores are an ex-ante assessment of borrower quality at the contractual date and are subsequently reassessed by banks each month depending on the borrower's performance. This granularity allows us to test the credit risk underpricing mechanism by directly linking the price and amount of loans to credit risk scores in sin vs. solid banks. As Figure B.III in Appendix B shows, the credit risk score variable ranges from **1** (lowest credit risk, or best borrower quality) to **5** (highest credit risk, or worst quality). Jointly for single- and multiple-bank firms, the category 1 accounts for 21% of the total number of loans and category 2 represents another 75%. This means that the highest-risk loans (categories 3-5) make up no more than 4% of the total. In terms of loan amounts, however, category 1 dominates, representing 60% of total corporate lending in Russia, with category 2 covering another 37%, thus leaving the highest-risk loans with a share of no more than 4%. Descriptive statistics of the key variables we source from the credit register for our analysis are reported in Table B.II.

To understand how sin versus solid banks assign credit risk scores to good versus bad firms, we run a preliminary regression of these scores on the $Sin\,Bank_b$ and $Firm\,Losses_{f,t}$ variables and their interaction, controlling for the bank-closure-event, region, sector, firm and month fixed effects. As Table G.I in Appendix G shows, we obtain a negative and highly significant coefficient on the sin bank variable, meaning that the same borrower would be assigned to a higher-quality bucket by sin banks than by solid banks. Further, when interacting with the firm losses variable, we also obtain a negative and highly significant coefficient, which indicates that within a given sin bank, bad firms would be assigned to even higher-quality buckets compared to good firms. The key outcome that we get from this preliminary analysis is that bad firms receive relatively higher, not lower, credit quality assessments than good firms within the same sin bank, and the corresponding gap between the bad and good firms' scores constitutes about

20% of the observed variation of the credit risk scores in the full sample.

With these preliminaries at hand, we specify the following linear regression model at the bank b, firm f, and month t level:

$$Y_{b,f,t} = \beta_0 \cdot Sin\,Bank_b + \sum_{k=1}^{5} \beta_k \cdot Sin\,Bank_b \times Credit\,Risk\,Score^{(k)}_{b,f,t} \tag{4}$$
$$+ \mathbf{X}_{b,f,t-1}\mathbf{\Theta}' + \alpha_{bce} + \gamma_r + \mu_s + \lambda_{f,t} + \epsilon_{b,f,t}$$

where the dependent variable $Y_{b,f,t}$ is either the interest rate on a loan or the log of the loan amount. $Sin\,Bank_b$ is a binary variable that equals 1 if a bank is ever closed for fraud and 0 if it survives until the end of the sample. $Credit\,Risk\,Score_{b,f,t}$ is a categorical variable that reflects a bank's ex-post (re)assessment of a borrowing firm's quality (1 is set as the reference). Control variables $\mathbf{X}_{b,f,t-1}$ include: other loan characteristics (maturity and whether term credit, credit line, or overdraft), bank-level characteristics (bank size, the ratio of household credit to total assets, equity capital to total assets, corporate and household deposits to total assets, and non-performing loans to total assets), and regional credit market concentration (the Herfindahl-Hirschman Index, see the lower panel of Table B.I for descriptive statistics).

Table 5 presents the estimates of equation (4). The dependent variable is the interest rate on loans in columns (1) and (2) and the log of the loan amount in columns (3) and (4). The sample contains only single-bank firms in columns (1) and (3) and only multiple-bank firms in the other two columns.

Focusing on the single-bank firms, we first obtain a positive and highly significant coefficient on the sin bank variable in column (1) and a negative and highly significant coefficient in column (3). This indicates that sin banks charge on average 1.58 pp higher interest rates on loans to the best category of borrowers and offer them on average a $e^{-0.104} - 1$, or 9.88%, lower amount of loan than solid banks do. Furthermore, we obtain negative and highly significant coefficients on the interactions of the sin bank variable and each of the remaining four credit risk categories in column (1) and, vice versa, positive and highly significant coefficients in column (3), except for the fifth category. This implies that lower-quality categories of borrowers are charged on average 0.50 to 1.04 pp lower interest rates on loans than the best category of borrowers within the same sin banks. And these lower-quality borrowers get on average $e^{0.095} - 1$ to $e^{0.310} - 1$, or

Table 5. Regression estimation results: The price and amount of loans in sin vs. solid banks depending on the credit risk score of corporate borrowers

Note: The table reports the estimates of equation (4), where the dependent variable $Y_{b,f,t}$ is either the interest rate on a loan (columns 1–2) or the log of the loan amount (columns 3–4) at the bank-firm-month level. *Single-bank firms*: "*Yes*" means that the sample contains (good and bad) firms that have lending relationships with only one bank (sin or solid); "*No*" means that the sample comprises (good and bad) firms borrowing from at least two banks (sin and/or solid). $Sin\,Bank_b$ is a binary variable that equals 1 if a bank is ever closed for fraud (i.e., sin bank) and 0 if it survives till the end of the sample. $Credit\,Risk\,Score_{b,f,t}$ is a categorical variable that reflects a bank's ex-post assessment of a borrowing firm's quality ranging from **1** (the lowest realized credit risk, or the best quality, reference category) to **5** (the highest realized credit risk, or the worst quality). Control variables ($\mathbf{X}_{b,f,t-1}$) include: other loan characteristics (maturity, whether term credit, credit line, or overdraft), bank-level characteristics (bank size, the ratio of household credit to total assets, equity capital to total assets, corporate and household deposits to total assets, and non-performing loans to total assets), and regional credit market concentration (the Herfindahl-Hirschman Index). Fixed effects as specified. In columns (1) and (3), the sample contains $25,614$ firms having single lending relationships with 151 sin banks closed in between January 2017 and September 2020 and $157,353$ firms borrowing from 390 solid banks. In columns (2) and (4), $3,650$ firms borrow from at least one of 151 sin banks and $21,178$ firms borrow from 390 solid banks. The data is sourced from the corporate credit register of the Bank of Russia and banks' balance sheets.

Dependent variable:	Interest $\text{Rate}_{b,f,t}$		ln $\text{Loan}_{b,f,t}$	
Single-bank firms:	Yes	No	Yes	No
	(1)	(2)	(3)	(4)
Sin Bank_b	1.579***	1.519***	–0.104***	–0.270***
	(0.091)	(0.181)	(0.037)	(0.084)
Sin Bank_b × Credit Risk $\text{Score}_{b,f,t}$ = 2	–0.502***	–0.786***	0.095***	0.259***
	(0.083)	(0.189)	(0.035)	(0.088)
Sin Bank_b × Credit Risk $\text{Score}_{b,f,t}$ = 3	–1.036***	–1.648***	0.104**	0.680***
	(0.116)	(0.307)	(0.050)	(0.154)
Sin Bank_b × Credit Risk $\text{Score}_{b,f,t}$ = 4	–0.718***	–0.194	0.310***	1.345***
	(0.149)	(0.826)	(0.092)	(0.484)
Sin Bank_b × Credit Risk $\text{Score}_{b,f,t}$ = 5	–0.750***	–0.930	–0.222	0.271
	(0.259)	(0.688)	(0.223)	(0.232)
Credit Risk $\text{Score}_{b,f,t}$ = 2	0.029**	0.191***	–0.060***	–0.075***
	(0.012)	(0.023)	(0.006)	(0.015)
Credit Risk $\text{Score}_{b,f,t}$ = 3	0.593***	1.228***	–0.045***	–0.024
	(0.029)	(0.080)	(0.012)	(0.034)
Credit Risk $\text{Score}_{b,f,t}$ = 4	0.045	0.594***	–0.282***	–0.217**
	(0.036)	(0.127)	(0.026)	(0.105)
Credit Risk $\text{Score}_{b,f,t}$ = 5	–0.052	0.713***	–0.040	0.235*
	(0.069)	(0.257)	(0.045)	(0.135)
ln $\text{Loan}_{b,f,t}$	–0.056***	–0.032***		
	(0.002)	(0.005)		
Interest $\text{Rate}_{b,f,t}$			–0.031***	–0.022***
			(0.001)	(0.004)
Bank closure event FE	✓	✓	✓	✓
Region FE, Sector FE	✓	✓	✓	✓
Firm FE	✓		✓	
Month FE	✓		✓	
Firm × Month FE		✓		✓
N Obs	1,774,379	679,356	1,774,379	679,356
R^2 (adj.)	0.9	0.8	0.7	0.6

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

10.0 to 36.3% larger amount of loans.

If we then consider the sample of multiple-bank firms in columns (2) and (4), for which we can completely account for the demand effects by saturating the regression models with firm*month fixed effects, we obtain even stronger quantitative results.

Overall, the estimation results in this section provide strong evidence of the credit risk underpricing by sin banks when lending to bad firms. In other words, before being recognized and shut down, sin banks charge lower interest rates and grant more credit to corporate borrowers that report losses on their balance sheets for at least two consecutive years. These findings shed light on the mechanism of the differential real effects of sin bank closures: when the regulator intervenes and dissolves the (sin)bank-firm relationships, bad firms lose access to their "subsidized" loans, while good firms are no longer burdened by unfairly high borrowing costs.

7. The End of the Transition Period: New Bank-Firm Relationships

In this final section, we explore how good and bad firms establish lending relationships with new banks, sin or solid, following their current sin banks' closure. We will start with a purely descriptive model of bank-firm matching in Section 7.1. We will then attempt to explain the observed patterns of firm-bank matching through common bank board members in Section 7.3 and differences in local credit market concentration in Section 7.4.

7.1 Average effects

Having established that good firms improve while bad firms deteriorate their performance following the closure of their sin banks—and that these outcomes result from the breakdown of the credit risk underpricing mechanism—we finally examine the time it takes for good and bad firms to establish new lending relationships and relax their borrowing constraints.

It is highly likely that new lenders—no matter whether they are (not yet detected) sin or solid—request balance sheets and income statements from potential borrowers, and also access the credit bureau(s) to retrieve their credit performance in the past.[21] In the data, we have

[21] Of course, banks also take into account political connections of the applicants (Khwaja and Mian, 2005), common ownership (Gilje et al., 2020; Azar et al., 2022), and other hard and soft information.

$Firms\,Losses_{f,t^*}$ to proxy for the balance sheet's strength of a firm and DPD_{f,t^*} to capture a firm's past credit performance.[22]

When we analyze the data on $Firms\,Losses_{f,t^*}$ and DPD_{f,t^*} for firms that had relationships with closed sin banks, we reveal the following three striking regularities.

1. Firms with more DPDs in the past tend to establish new lending relationships in the future much faster than firms with fewer DPDs in the past (Figure H.I in Appendix Appendix H).
2. Even bad firms may have very little DPDs: indeed, as Figure H.II shows, 81% of all bad firms in the sample had DPDs in between 0 and 30 days. This is very close to, though still lower than, the share of good firms in the corresponding DPD bucket (89%).[23]
3. Though in the majority (75%) of cases the matching patterns are aligned with expectations (good firms match with solid banks, bad firms sort to sin banks), in the rest 25% cases we have type-I and type-II "errors": 399 bad firms matched with new solid banks and 800 good firms matched with new (not yet detected) sin banks following their respective sin banks' closure.

In our subsequent regression analysis, we aim to investigate how DPD_{f,t^*}, $Firms\,Losses_{f,t^*}$, and their interaction, may explain both the expected and the seemingly erratic patterns of new bank-firm matching. Focusing on the time it takes a good or bad firm to establish new lending relationships, we appeal to the duration regression approach (i.e., "survival" models), which provides a natural methodological framework for this analysis. This approach accounts for the duration of the spell—that is, exactly the time it takes a firm to "exit" from the transitional period, i.e., establish a new lending relationship, conditional on the firm's survival to the current moment in time.[24]

We conduct a *multiple-failure duration analysis*, in which the duration of the spell for a firm f begins with the closure of its sin bank b in time $t^*_{b,f}$ and ends with the firm being matched with a new sin bank or a new solid bank in time $t^*_{b,f} + k_f$, where k is the firm-specific duration

[22] We do not rely here on the $Credit\,Risk\,Score_{b,f,t}$ as it is available only from January 2017, while DPD has been recorded since 2010.

[23] This, in turn, echoes another observation in the data that the correlation between DPDs and $Firms\,Losses_{f,t^*}$ is positive, as one may expect, but is very small, barely exceeding 5% in the full sample.

[24] "Survival" regressions have been previously adopted to study bank failures (Brown and Dinc, 2011), bank decisions to issue CoCo bonds (Goncharenko et al., 2021), and the likelihood of firms to switch banks (Ongena and Smith, 2001), for example.

of the spell. Following the standard terminology of duration analysis, we refer to the time $t^*_{b,f} + k_f$ as a "failure" event. To sharpen the identification, we consider only the first episodes of bank-firm matching, neglecting all the subsequent such episodes for each firm f, if any. If $t^*_{b,f} + k_f$ is never observed in the sample—that is, if firm f never matches with a new bank and remains unbanked—we treat the corresponding failure as right-censored, leaving all such firms in the sample. The instantaneous rate at which firms exit by matching with either a new sin bank ($\jmath = 1$) or a new solid bank ($\jmath = 2$), conditional on survival to the current moment in time, is described by the following hazard function:

$$\begin{aligned}\lambda_\jmath\left(t \,|\, \mathbf{X}_{f,t-1}\right) = \lambda_0(t) \cdot \exp\Big(\ & \beta_{\jmath,1} \cdot \ln DPD_{f,t^*} \\ & + \beta_{\jmath,2} \cdot Firm\, Losses_{f,t^*} \\ & + \beta_{\jmath,3} \cdot \ln DPD_{f,t^*} \times Firm\, Losses_{f,t^*} \\ & + \alpha_{\jmath,bce} + \gamma_{\jmath,r} + \mu_{\jmath,s} + \tilde{\mathbf{X}}_{f,t-1}\Theta'_\jmath\Big),\end{aligned} \tag{5}$$

where $\lambda_0(t) = \lambda \cdot \alpha t^{\alpha-1}$ is the common specification of the baseline hazard function, with α reflecting the duration time-dependence. For the baseline estimations, we set $\alpha = 1$ and thus consider the exponential distribution function: $\lambda_0(t) = \lambda > 0$.[25] Other notations, as well as the sample size and time span, remain the same.

Our underlying hypotheses are as follows:

Hypothesis **H1** "*Poor credit history*": $\beta_{1,1} > 0$ and $\beta_{2,1} < 0$. That is, a greater magnitude of DPD_{f,t^*} increases the speed at which firm f matches with a new sin bank, while reducing the speed of its matching with a new solid bank. Sin banks may be more inclined than solid banks to accept firms with weaker loan performance in the past, as they may then turn their current losses into loans to these (likely financially opaque) firms (Blattner et al., 2023). Solid banks, in contrast, may be too concerned with protecting their charter value to accept firms with weak loan performance in the past (Keeley, 1990).

Hypothesis **H2** "*Lack of balance sheet strength*": $\beta_{2,1} < 0$ and $\beta_{2,2} < 0$. Firm losses reduce the speed of establishing new lending relationships with both not-yet-detected sin banks and

[25] Under the exponential distribution, the baseline hazard does not change as time passes (reflecting the memoryless property of the exponential distribution function). We tested for constant duration dependence by assessing the estimated value of the relevant parameter in the Weibull distribution.

solid banks. It makes little sense even for sin banks to accept a firm that transparently reports losses on its balance sheet.[26]

Hypothesis **H3** "*Amplification/Attenuation*": $\beta_{1,3} \geq 0$ and $\beta_{2,3} \leq 0$. Sin banks (solid banks) may be relatively more (less) willing to accept bad firms with higher levels of DPD, for the reasons outlined in **H1**, thus partially attenuating (amplifying) the negativity of the $Firm\,Losses$ effect described in **H2**.

Table 6 reports the estimates of the duration regression (5). Columns (1)–(3) contain results for the case of firms' matching with new sin banks, and Columns (4)–(6) contain results for the other case, i.e., matching with new solid banks. Columns (1) and (4) report the estimates of a model that has only $\ln DPD_{f,t^*}$ as the focus explanatory variable. Columns (2) and (5) replace it with $Firm\,Losses_{f,t^*}$. Finally, Columns (3) and (6) accommodate both variables and their interaction term. In Columns (1)–(3) ((4)–(6)), the sample contains $333,398$ $(490,297)$ firm-month observations on 944 $(3,770)$ firms that eventually matched with new sin banks (new solid banks), with the average duration of the spell being 18 (46) months, and $11,013$ firms that remain unbanked, with their corresponding duration of the spell equaled 28.7 months.[27]

In Columns (1) and (4), we obtain a positive and a negative estimate on the $\ln DPD_{f,t^*}$ variable, respectively, both being statistically significant at the 1% level. These estimates suggest that a firm with a higher level of DPDs establishes new lending relationships with (not yet detected) sin banks faster than with solid banks, compared to a firm with lower DPDs, and conditional on both firms' survival to the current moment in time. This sorting pattern favors the **H1** hypothesis.

In Columns (2) and (5), we further obtain negative estimates on the $Firm\,Losses_{f,t^*}$ variable, significant at 1% and 10%, respectively. These estimates imply that bad firms are slower in establishing new lending relationships with both sin and solid banks compared to good firms. This evidence supports the **H2** hypothesis.

Finally, in Columns (3) and (6), we obtain positive estimates on the $\ln DPD_{f,t^*} \times Firm\,Losses_{f,t^*}$ variable, both significant at the 1% level. The estimate in Column (3) indicates an attenua-

[26] In a similar vein, the existing studies consistently find that a firm's lower profitability leads to shorter lending relationships (Sapienza, 2002; Bharath et al., 2007; Degryse et al., 2011).

[27] For the unbanked firms, we trace the last year when they report their balance sheets and assume it to be their "exit."

Table 6. Duration regression results: New bank-firm matches

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered. In the sample, there are 944 firms that eventually matched with new sin banks (average $k_f = 18$ months, see Table 1), 3,780 firms that matched with new solid banks (average $k_f = 46$ months), and 11,013 firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\ln DPD_{f,t^*}$ is the log of the maximum number of days of firm's f loan delinquency in the closed sin banks, as of the beginning of the spell at $t^*_{b,f}$. $Firm\,Losses_{f,t^*}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t^*_{b,f}$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm $Leverage$ (short- and long-term debts over the total assets), and firm $Liquidity$ (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank			Match with a new solid bank		
	(1)	(2)	(3)	(4)	(5)	(6)
ln DPD$_{f,t^*}$	0.167***		0.112***	–0.094***		–0.106***
	(0.057)		(0.038)	(0.036)		(0.041)
Firm Losses$_{f,t^*}$		–1.844***	–2.396***		–0.205*	–0.276*
		(0.520)	(0.619)		(0.121)	(0.144)
ln DPD$_{f,t^*}$ × Firm Losses$_{f,t^*}$			0.365***			0.078***
			(0.125)			(0.030)
Firm controls	✓	✓	✓	✓	✓	✓
Bank closure event FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N obs	333,398	333,398	333,398	490,297	490,297	490,297
N new firm-bank matches	944	944	944	3,780	3,780	3,780
N firms	11,957	11,957	11,957	14,793	14,793	14,793
log L	–1,109.1	–1,146.4	–928.3	–2,960.6	–3,915.1	–2,435.2

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

tion of the negative effect of $Firm\,Losses_{f,t^*}$, meaning that new sin banks are relatively more likely to accept a bad firm if this firm has higher levels of DPDs, as our hypothesis **H3** postulates. However, in Column (6), we obtain the same attenuation—rather than amplification—mechanism in the case of matching with solid banks, which is contrary to the **H3** hypothesis. In the next two subsections, we will investigate this (seemingly) controversial evidence.

Let us now focus on the economic effects of the underlying estimates in Columns (3) and (6). Suppose we have four firms: a good and a bad firm with $DPD = 0$ and a good and a bad firm with $DPD = 90$. In this setting, the hazard rate for the good firm with $DPD = 0$

can serve as a reference as $\lambda\Big(t \mid Firm\,Losses_{f,t^*} = 0, \ln(1 + DPD_{f,t^*}) = 0\Big) = \exp(0.112 \cdot 0) = \exp(-0.106 \cdot 0) = \exp(0) = 1$. We then have the following three outcomes.

Outcome #1. Good firms with poorer credit history *(type-1 "error")*. For a good firm ($Firm\,Losses_{f,t^*} = 0$), an increase in DPD from 0 to 90 days raises the odds of matching with a new sin bank by about 66% ($\jmath = 1$) and slows down the process of matching with new solid bank by 38% ($\jmath = 2$), conditional on surviving to the current moment in time and relative to a good firm with perfect credit history:

$$\lambda_{\jmath=1}\Big(t \mid Firm\,Losses_{f,t^*} = 0, DPD_{f,t^*} = 90\Big) = \exp\Big(0.112 \cdot \ln(1 + 90)\Big) = 1.66 > 1 \tag{6}$$

$$\lambda_{\jmath=2}\Big(t \mid Firm\,Losses_{f,t^*} = 0, DPD_{f,t^*} = 90\Big) = \exp\Big(-0.106 \cdot \ln(1 + 90)\Big) = 0.62 < 1 \tag{7}$$

These hazards imply that a good firm with 90 days of DPD is 1.66/0.62 = 2.7 times faster in matching with a new sin bank than with a new solid bank. This roughly corresponds to the time matching gap we observe in the data (recall Table 1).

Outcome #2. Bad firms with stronger credit history *(type-2 "error")*. For a firm with $DPD = 0$, turning from good ($Firm\,Losses_{f,t^*} = 0$) to bad ($Firm\,Losses_{f,t^*} = 1$) almost eliminates any chance of matching with a new sin bank, with the underlying odds plummeting by 91%, and also reduces the hazard of matching with a new solid bank, but to a much lesser extent, only by 24%, conditional on surviving to the current moment in time and relative to a good firm with perfect credit history:

$$\lambda_{\jmath=1}\Big(t \mid Firm\,Losses_{f,t^*} = 1, DPD_{f,t^*} = 0\Big) = \exp(-2.396) = 0.09 \ll 1 \tag{8}$$

$$\lambda_{\jmath=2}\Big(t \mid Firm\,Losses_{f,t^*} = 1, DPD_{f,t^*} = 0\Big) = \exp(-0.276) = 0.76 < 1 \tag{9}$$

These hazards, in turn, indicate that a bad firm with 0 days of DPD is 0.76/0.11 = 8.4 times faster in establishing new lending relationships with solid banks than with sin banks.

Outcome #3. Bad firms with poorer credit history. Finally, a bad firm ($Firm\,Losses_{f,t^*} = 1$) with $DPD = 90$ is estimated to have a 22% lower chance to match with a new sin bank and a 33% lower odd of matching with a new solid bank:

$$\lambda_{j=1}\Big(t\,|Firm\,Losses_{f,t^*} = 1, DPD_{f,t^*} = 90\Big) \tag{10}$$
$$= \exp\Big(0.112 \cdot \ln(1+90) - 2.396 + 0.365 \cdot \ln(1+90)\Big) = 0.78 < 1$$
$$\lambda_{j=2}\Big(t\,|Firm\,Losses_{f,t^*} = 1, DPD_{f,t^*} = 90\Big) \tag{11}$$
$$= \exp\Big(-0.106 \cdot \ln(1+90) - 0.276 + 0.078 \cdot \ln(1+90)\Big) = 0.67 < 1$$

These hazards also imply that a bad firm with 90 days of DPD is slightly faster, by 0.78/0.67 = 1.14 times, in matching with new sin banks than with new solid banks.

Overall, our analysis has shown that past credit history is crucial for both good and bad firms when it comes to establishing new lending relationships after experiencing their current sin banks' closures. For good firms, poorer credit history substantially reduces the odds of matching with new solid banks, while dramatically raising the odds of matching with new sin banks. For bad firms, poorer credit history brings the same qualitative outcomes. But bad firms are not doomed to match with sin banks only: if they have a better credit history, they are more likely to establish lending relationships with solid rather than sin banks. After elaborating on the sensitivity of these results in the next subsection, we will show how common bank board members and variation in the local credit market concentration shape these patterns of establishing new bank-firm relationships.

7.2 Robustness checks

Multinomial logit. We run our baseline analysis using the duration regression approach that is based on hazard rates. A natural test is to check whether greater (lower) hazard rates of firms' matching with new banks map into greater (lower) probabilities of establishing new lending relationships. To run this test, we specify a *multinomial logit regression* with the same three outcomes: 0 if a firm remains unbanked, 1 if it matches with a new sin bank, and 2 if it matches with a new solid bank. As Appendix Table H.I shows, the multinomial logit estimates are fully in line with the duration results and are preserving the 1% statistical significance in the case of matching with new sin banks, except for the linear effect corresponding to the $Firm\,Losses_{f,t^*}$ variable. In the case of matching with new solid banks, the estimates are also significant but at the 5% only (again except for the linear effect of the $Firm\,Losses_{f,t^*}$, which is still negative in the final specification but is no longer significant at any conventional levels).

A simpler measure of firm performance. In the baseline results, we exploit a measure of a firm's balance sheet strength, $Firm\,Losses_{f,t^*}$, which is equal to one if a firm reported losses for two consecutive years at the moment of its sin bank closure. We now replace it with a simpler, a time-varying measure of returns on assets (ROA) and repeat all the analyses. As Table H.II, this replacement does not alter our results qualitatively: firms with greater magnitudes of ROA have higher chances to match with new sin banks and new solid banks, compared to less profitable firms, but less so if they have poorer credit histories.

Allowing for time-variation in firm losses. In the baseline approach, we fix the composition of bad and good firms at the moment of their corresponding sin banks' closure. One potential concern is that bad firms may improve and good firms may deteriorate during the transitional period, thus contaminating our estimated patterns of new bank-firm matching. We replace $Firm\,Losses_{f,t^*}$ by $Firm\,Losses_{f,t-1}$ and re-run the duration analysis. The results presented in Table H.III clearly indicate that all our baseline estimates survive qualitatively. The only visible difference is that now the magnitude of the estimated coefficient on the firm losses variable shrinks substantially in the case of matching with new sin banks, meaning that improvements during the transitional period also matter.

Discretizing the DPD_{f,t^*} variable. Another concern is that our credit history measure, DPD, is a categorical variable with eight different levels, and these levels are not all equally important from the credit scoring perspective. We now discretize it using the 120 days threshold—beyond non-performing—and report updated estimates in Table H.IV. As one can infer, all the results remain the same, except for the coefficient on the discretized DPD in the case of matching with new sin banks, which changed its sign from positive to negative and lost statistical significance. However, even in this case, we still obtain positive and significant estimate on the product of the discretized DPD and the firm losses variable, suggesting that bad firms with poorer credit histories have higher odds of matching with new sin banks than with new solid banks.

Multiple-bank firms. Finally, we check the sensitivity of our estimated patterns of new bank-firm matching to the composition of firm lenders. In the baseline analysis, we stick to single-bank firms, and we now replace them with multiple-bank firms, with the condition that at least one of them is a sin bank. We expect to see no significant results as multiple-bank firms have an option to raise additional loans within the existing lenders' network in the case of sin bank's closure. As Table H.V demonstrates, this is indeed the case: the majority of estimated coefficients shrank to near-zero levels and lost their statistical significance. The only exception is the coefficient on the firm losses variable in the case of matching with new solid banks, which is still negative and highly significant, indicating that bad multiple-bank firms may have troubles in substituting for the lost credit within existing lenders' network and attempt to establish new lending relationships after encountering sin banks' closure, but these attempts are much less successful compared to good firms in a similar situation.

7.3 Exploring the channels: common bank board membership

In the previous section, we show that bad firms with poorer credit histories are significantly more likely to match with another (not-yet-detected) sin bank—compared to bad firms with cleaner credit histories—after the closure of their existing sin banks. In this section, we examine a potential channel behind this matching pattern: common board memberships between the closed and the new sin banks. Specifically, several sin lenders may belong to the same bank holding group, or the same individuals may sit on the boards of different, formally unrelated, sin banks. If at least one such bank lends to bad firms with weaker credit histories, its closure could accelerate these firms' transition to other sin banks within the same informal network.

As described in Section 3.2, we manually construct a dataset capturing all owner and manager overlaps across banks in Russia. Descriptive statistics in Appendix Table I.I show that 20% of all closed sin banks shared at least one board member with another bank—some with up to five such overlaps. Interestingly, the corresponding figure for solid banks is nearly twice as high, averaging at 39%. Thus, common board membership is widespread, not only among sin banks but even more so among solid banks. In absolute terms, we find that over half of the firms that lost ties with closed sin banks subsequently matched with other sin banks owned or managed by the same individuals.

We re-estimate our duration regressions (5) on the subsample of firms that only match with those new banks that do not share common board members with the firms' previous lenders that had been closed. In the subsample, there are 548 firms that eventually matched with new sin banks (average $k_f = 25$ months, which is 7 months longer than in the full sample, see Table 1), 1,909 firms that matched with new solid banks (average $k_f = 46$ months, as in the full sample), and 4,558 firms that remained unbanked until the end of the sample period.

Table 7 presents the estimation results. Column (1) reports the estimated coefficients for the case of matching with new sin banks, while Column (2) contains the results for the case of matching with new solid banks.

As can be inferred from Column (1), the estimated coefficient on the $\ln DPD_{f,t^*}$ variable remains positive, as before, but it completely loses its statistical significance and, what is also important, the size of the coefficient drops by a factor of three, approaching zero. This suggests that good firms with poorer credit histories are not matching with new sin banks, following their existing sin banks' closures, if the existing and the new sin banks have no overlaps on their boards. We further obtain a positive estimate on the $\ln DPD_{f,t^*} \times Firm\,Losses_{f,t^*}$ variable, as before, but again it is no longer statistically significant. This, in turn, implies that bad firms with poorer credit histories are also unlikely to match with new sin banks, if these banks share no common members with the firms' existing sin banks. Finally, the coefficient on the $Firm\,Losses_{f,t^*}$ variable appears negative, as in the baseline, but only marginally significant. Overall, these results clearly indicate that the common board membership determines the baseline result, and that in the absence of boards' overlaps a firm's poor credit history is no longer potent when it comes to the formation of new sin bank-firm relationships.[28]

Column (2) delivers the opposite results for the case of matching with new solid banks. As in the baseline, we obtain a negative estimate on the $\ln DPD_{f,t^*}$ variable and a positive estimate on the $\ln DPD_{f,t^*} \times Firm\,Losses_{f,t^*}$ variable, both being highly statistically significant. Moreover, the corresponding coefficient magnitudes rise by one-third and two-thirds, suggesting much stronger relationships than in the baseline. Therefore, even in the absence of common board members, there is a strong force that raises the odds of matching with new solid banks for bad firms with poorer credit histories compared to good firms with the same credit histories. The next subsection will shed light on the nature of this force.

[28]In Appendix Table I.II, we further show that these results hold if we discretize the DPD variable.

Table 7. Duration regression results: New bank-firm matches in the absence of common board members

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered, as in the baseline (Table 6), but now we also require that the closed sin banks did not have overlaps with other banks in the composition of the board members. In the sample, there are 548 firms that eventually matched with new sin banks (average k_f = 25 months, which is 7 months longer than in the full sample, see Table 1), $1,909$ firms that matched with new solid banks (average k_f = 46 months, as in the full sample), and $4,558$ firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\ln DPD_{f,t^*}$ is the log of the maximum number of days of firm's f loan delinquency in the closed sin banks, as of the beginning of the spell at $t^*_{b,f}$. $Firm\,Losses_{f,t^*}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t^*_{b,f}$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm $Leverage$ (short- and long-term debts over the total assets), and firm $Liquidity$ (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank	Match with a new solid bank
	(1)	(2)
ln DPD$_{f,t^*}$	0.035	–0.144***
	(0.035)	(0.053)
Firm Losses$_{f,t^*}$	–1.619*	–0.133
	(0.874)	(0.233)
ln DPD$_{f,t^*}$ × Firm Losses$_{f,t^*}$	0.316	0.129***
	(0.313)	(0.047)
Firm controls	✓	✓
Bank closure event FE	✓	✓
Region FE	✓	✓
Sector FE	✓	✓
Banks with common board members	No	No
N obs	144,631	218,739
N new firm-bank matches	548	1,909
N firms	5,105	6,466
log L	–928.3	–2,435.2

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

7.4 Exploring the channels: local credit market concentration

Finally, we examine how local credit market concentration affects our baseline results. After sin bank closures, firms face fewer opportunities to match with new banks, potentially increasing the market power of solid banks over prospective borrowers. Drawing on Petersen and Rajan (1995), we hypothesize that solid banks may be more willing to match with bad firms or those with poorer credit histories when operating in more concentrated local credit markets. Solid banks could extract rent from relationships with such firms by setting higher interest rates and taking control over them in the longer run.[29]

To test for this hypothesis, we aggregate the bank-firm-month data to the bank-region-month level and compute the Herfindahl-Hirschman Index (HHI) at the region-month level as the sum of the squared shares of each bank's loans extended to all firms operating in the corresponding region in a given month in the total corporate loans in that region in that month.[30] Table B.I shows that the average magnitude of HHI across the federal districts ranges between $1,265$ and $1,885$, thus indicating moderate levels of credit market concentration at the district level. However, at the region level, the HHI variable peaks at the maximum possible magnitude of $10,000$, suggesting the presence of local monopolistic banks. With this data at hand, we slightly modify our duration regressions (5) by introducing the $HHI_{r,t-1}$ variable and its interactions with both $\ln DPD_{f,t^*}$ and $Firm\,Losses_{f,t^*}$ variables. We also subtract the unconditional mean from the HHI variable so that the coefficients on the DPD and firm losses variables reflect their effects in markets with average credit concentration.

Table 8 presents the estimation results. Panel 1 reports estimates from the regression including the $HHI_{r,t-1} \times \ln DPD_{f,t^*}$ interaction term, while Panel 2 shows estimates from the regression with the $HHI_{r,t-1} \times Firm\,Losses_{f,t^*}$ interaction.

In Column (1), we still obtain a positive and highly significant coefficient on the $\ln DPD_{f,t^*}$ variable (*Panel 1*) and a negative and significant coefficient on the $Firm\,Losses_{f,t^*}$ variable (*Panel 2*), consistent with the baseline results. We also obtain a positive coefficient on the $\ln DPD_{f,t^*} \times HHI_{r,t-1}$ interaction, suggesting that firms with poorer credit histories have higher odds to match with new sin banks in more concentrated regions—an amplification that is in line with our hypothesis above. However, this estimate is statistically insignificant and should be interpreted with caution. Similarly, the coefficient on the $Firm\,Losses_{f,t^*} \times HHI_{r,t-1}$ interaction is negative, implying that bad firms have lower chances to match with new sin banks in more concentrated regions—likely due to the dominance of solid banks in such markets. Yet this estimate too is insignificant and should also be treated cautiously.

[29] Alternatively, solid banks operating in regions with highly concentrated credit markets may be more skilled in evaluating projects, and thus they might be able to provide valuable expertise to bad firms or firms with poorer credit histories, helping them to improve.

[30] As of 2020, Russia had 83 internationally recognized regions grouped into the 8 federal districts.

Table 8. Duration regression results: New bank-firm matches depending on the local credit market concentration

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching, which is similar to (5), except that it explicitly explores differences in the bank-firm matching depending on the local credit market concentration across the 85 regions in which Russian banks operate. A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (column 1) or matching with a new solid bank (column 2), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered. In the sample, there are 944 firms that eventually matched with new sin banks (average k_f = 18 months, see Table 1), 3,780 firms that matched with new solid banks (average k_f = 46 months), and 11,013 firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\ln DPD_{f,t^*}$ is the log of the maximum number of days of firm's f loan delinquency in the closed sin banks, as of the beginning of the spell at $t^*_{b,f}$. $Firm\,Losses_{f,t^*}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t^*_{b,f}$. $HHI_{r,t-1}$ is the concentration of the credit market in region r in month $t-1$ (Herfindahl-Hirschman Index). Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm *Leverage* (short- and long-term debts over the total assets), and firm *Liquidity* (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank	Match with a new solid bank
	(1)	(2)
$\ln \text{DPD}_{f,t^*}$	0.223***	–0.107**
	(0.068)	(0.043)
$\ln \text{DPD}_{f,t^*} \times \text{HHI}_{r,t-1}$	0.501	1.430***
	(1.017)	(0.425)
$\text{HHI}_{r,t-1}$	1.406	5.625***
	(1.405)	(0.649)
Firm controls	✓	✓
Bank closure event FE	✓	✓
Region FE, Sector FE	✓	✓
N obs	333,398	490,297
N new firm-bank matches	944	3,780
N firms	11,957	14,793
log L	–891.0	–2,434.6
$\text{Firm Losses}_{f,t^*}$	–2.510**	–0.195
	(1.149)	(0.308)
$\text{Firm Losses}_{f,t^*} \times \text{HHI}_{r,t-1}$	–4.646	5.257**
	(7.188)	(2.600)
$\text{HHI}_{r,t-1}$	–0.389	3.417***
	(1.939)	(0.749)
Firm controls	✓	✓
Bank closure event FE	✓	✓
Region FE, Sector FE	✓	✓
N obs	333,398	490,297
N new firm-bank matches	944	3,780
N firms	11,957	14,793
log L	–721.6	–1,808.0

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Finally, in Column (2), we find a negative and significant coefficient on the $\ln DPD_{f,t^*}$ variable (*Panel 1*) and a negative but insignificant coefficient on the $Firm\, Losses_{f,t^*}$ variable (*Panel 2*), both consistent with the baseline results. Strikingly, and in contrast with the evidence in Column (1), we then obtain a positive and highly significant coefficient on the $\ln DPD_{f,t^*} \times HHI_{r,t-1}$ interaction, indicating that firms with poorer credit histories have higher, not lower, odds to establish lending relationships with new solid banks in more concentrated markets. A similar pattern holds for the $Firm\, Losses_{f,t^*} \times HHI_{r,t-1}$ interaction, which is likewise positive and highly significant. Furthermore, the effect of $HHI_{r,t-1}$ variable itself is positive and highly significant. These findings support our hypothesis above that solid banks in more concentrated markets may have larger incentives to lend to bad firms and firms with poorer credit histories. Overall, our results in this section imply that the average effects reported in Table 6 for the case of matching with new solid banks are driven by the observations that pertain to more concentrated local credit markets.

8. Conclusion

Leveraging rich credit register data from an environment where two-thirds of all banks exited the market within a decade, we examine how firms respond to the regulatory-induced collapse of weak lenders. We find that weak banks systematically underprice credit risk, extending cheaper credit to financially weaker firms. We establish that, despite impending closures, firms neither shift lenders nor delay repayments. Once these banks close, we find that bad firms experience steep declines in borrowing, employment, and sales, while good firms show improved outcomes. In the aftermath, we reveal that good firms with strong credit histories transfer to solid banks, while bad firms gravitate toward not-yet-closed sin banks—especially when board overlaps exist or market concentration is low.

Overall, our analysis of sin bank closures provides evidence of heterogeneous treatment effects on firm performance. Closing sin banks improves the state of good firms and has the opposite effect on bad firms, especially if bad firms also have poorer credit history.

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Appendix A. Further details on the sin bank closure policy in Russia

Figure A.I. The recognition of sin banks before, during, and after the active phase of the policy

Note: For each month from 2007 to 2020, the figure depicts the total (stacked) amount of assets held by sin banks that were detected and closed by the CBR during that month. The two vertical green lines mark the beginning and the end of the active phase of the sin bank closure policy. *LCU* stands for local currency unit (Ruble). The data is sourced from the CBR's official press-releases devoted to each and every case of bank closures and the corresponding banks' balance sheets.

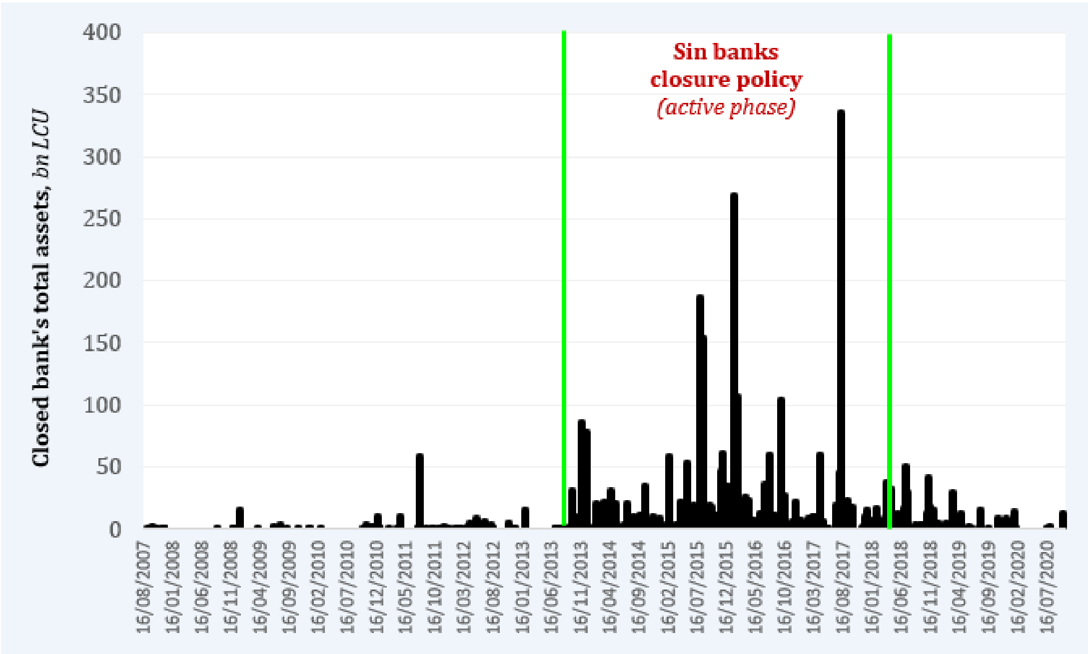
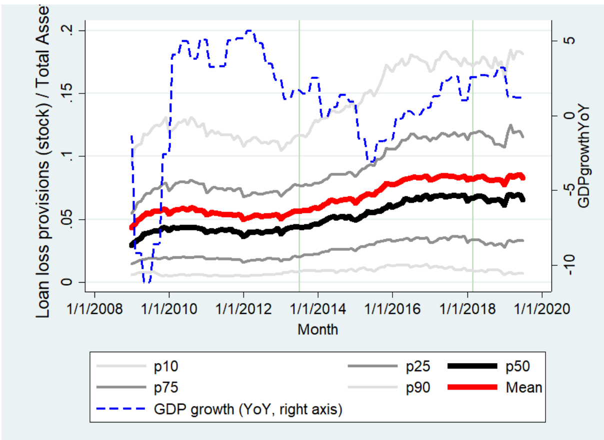
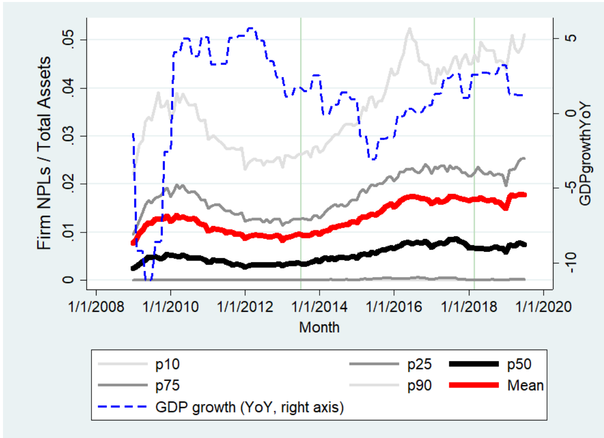


Figure A.II. The performance of operating banks before, during, and after the active phase of the policy

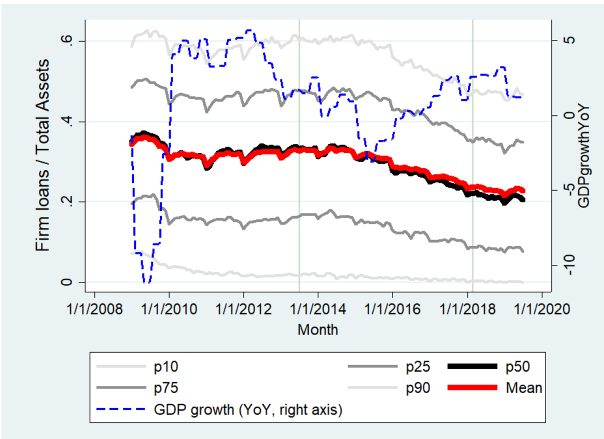
Note: The figure depicts the time evolution of selected bank characteristics at the bank-month level before, during, and after the active phase of the sin bank closure policy against the background of the annual GDP growth rates in Russia. The two vertical green lines mark the beginning and the end of the active phase of the sin bank closure policy. *p10* to *p90* denote the corresponding percentiles of banks' distribution by the respective balance sheet characteristic in each month. The data is sourced from the CBR's official press-releases devoted to each and every case of bank closures and the corresponding banks' balance sheets.



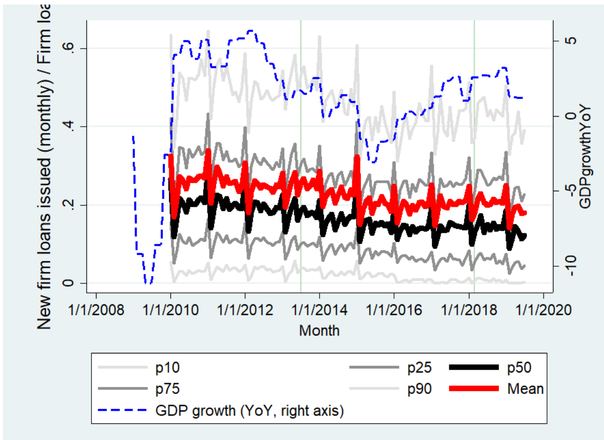
(a) Loan loss reserves



(b) NPLs of firms



(c) Loans to firms



(d) New loans issued

Figure A.III. The banking market structure before, during, and after the active phase of the policy

Note: The figure depicts shares in the total banking system's household deposits held by the four groups of banks: the Big-4 government-owned banks (Sberbank, VTB, Gazprombank, and the Russian Agricultural Bank), the other government-controlled banks, private domestic banks, and foreign bank subsidiaries in Russia. The two vertical green lines mark the beginning and the end of the active phase of the sin bank closure policy. The data is sourced from the CBR's official press-releases devoted to each and every case of bank closures and the corresponding banks' balance sheets.

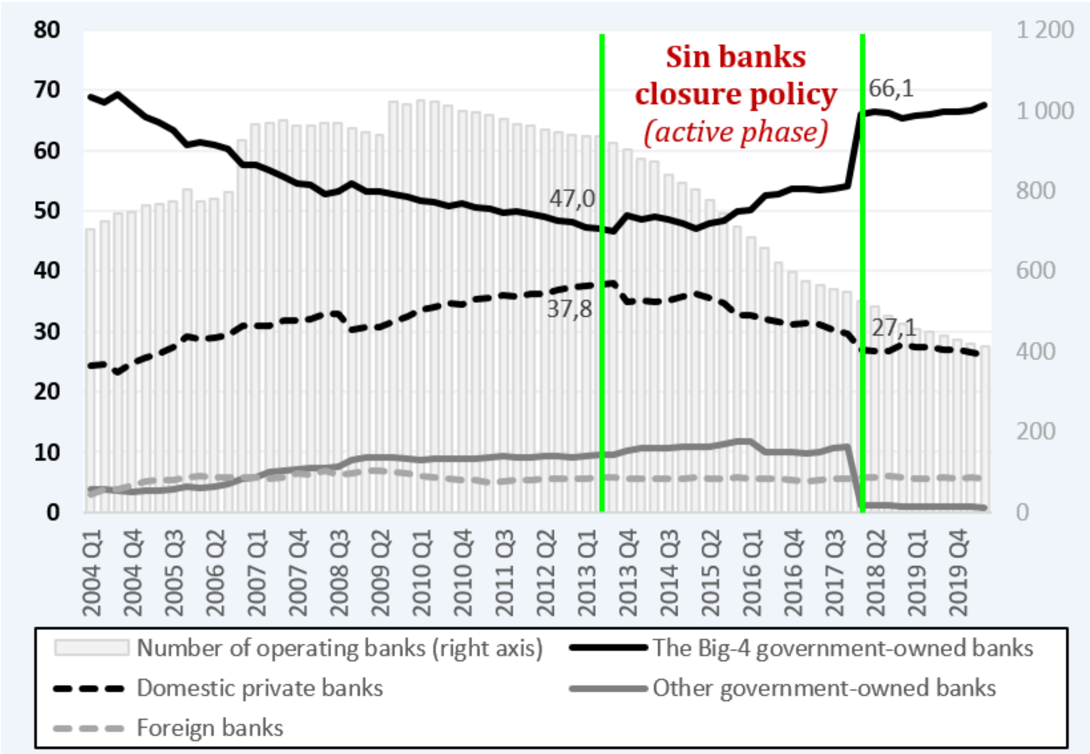
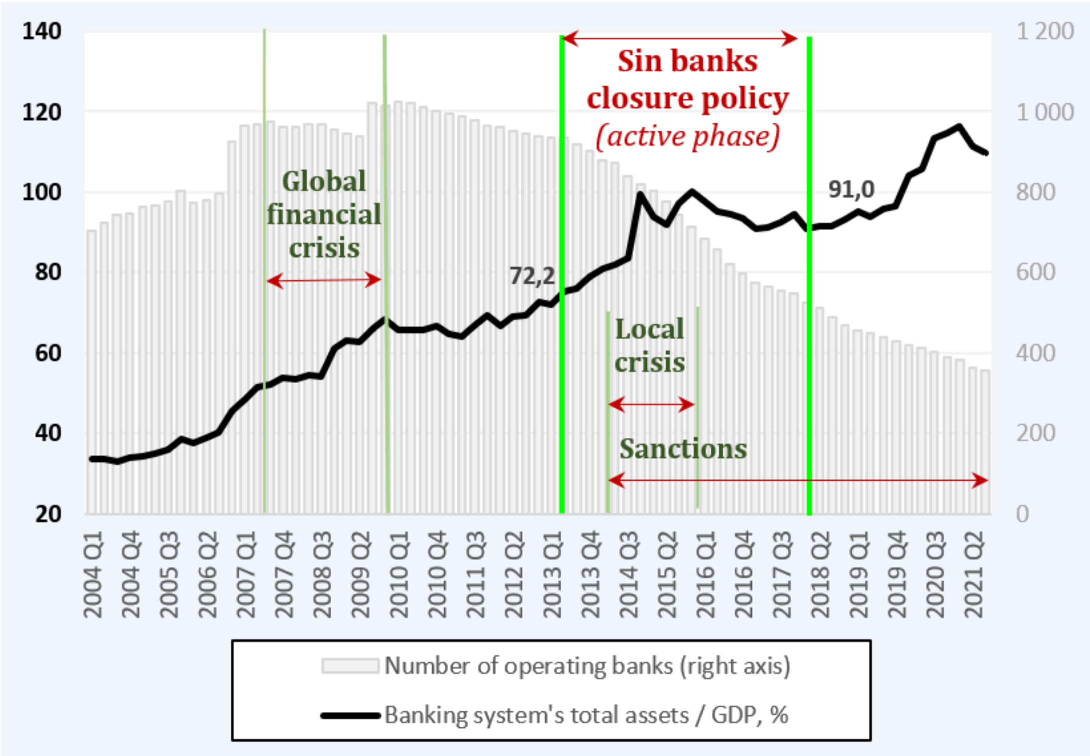


Figure A.IV. The depth of the banking system before, during, and after the active phase of the policy

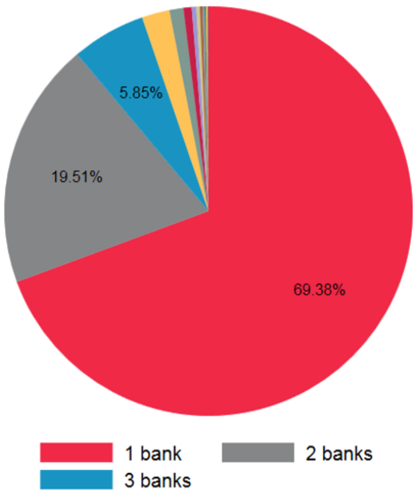
Note: The figure depicts time evolution of the banking system's depth, as measured by the ratio of its total assets to GDP, against the background of the number of operating banks in Russia. The vertical green lines around 2007 and 2009 mark the beginning and the end of Global Financial Crisis. The vertical green lines around 2013 and 2018 mark the active phase of the sin bank closure policy. The vertical green line around 2014 marks the onset of the sanctions era in Russia and the beginning of the local economic crisis induced by the world oil price collapse, and the vertical green line around 2016 marks the end of the local economic crisis. The data is sourced from the CBR's official press-releases devoted to each and every case of bank closures, the US Office of Foreign Asset Control (OFAC) press-releases containing sanctions announcements against Russian banks, and the World Bank's World Development Indicators.



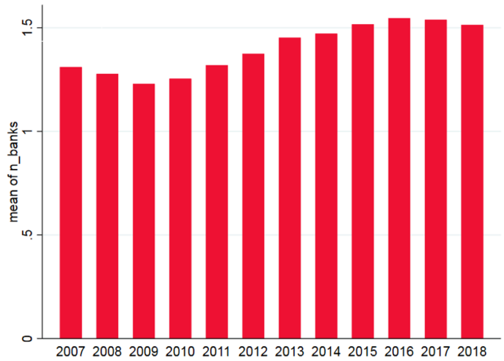
Appendix B. Details on the data

Figure B.I. Bank–firm relationships

Note: The subfigure (*a*) depicts the structure of bank-firm relationships in terms of the number of banks lending to a single firm (as of 2017). Subfigure (*b*) shows the time evolution of the average number of banks lending to a single firm (2007–2018). The data is sourced from the Credit History Bureau (CHB) of the Central Bank of Russia in 2020–2021.



(a) Structure of relationships (in 2017)



(b) Time evolution

Figure B.II. Geographical variation in bank-firm relationships and the quality of loans in the final dataset

Note: The figure depicts the loan quality indicator (*DPD*, *days past due*) which is a categorical variable representing different overdue time intervals, aggregated from the bank-firm-month to the city level across Russia, as of before the sin bank closure policy (*a*) and after (*b*). For instance, $DPD = 0$ if there are no delayed payments on average at the city level for a given date, 30 if the average delay in payments is from 1 to 30 days, 60 for delays from 31 to 60 days, and so forth. The sample data is the product of merging of the CBR's Credit History Bureau (CHB) containing the information on bank-firm relationships, the SPARK-Interfax database on firm balance sheets, and the CBR's database on bank balance sheets.

(a) Before the sin bank closure policy (as of December 2012)

(b) During the active phase of the sin bank closure policy (as of December 2015)

Table B.I. The distribution of firms, aggregate loan quality indicator (DPD), and credit market concentration across the Federal Districts of Russia

Note: The table reports the distribution of firms in the CBR's Credit History Bureau (CHB) across the eight Federal Districts in Russia, as well as the loan quality indicator (DPD, *days past due*) and local credit market concentration (HHI, *Herfindahl-Hirschman Index*), as averages across January 2010 – January 2018. DPD is a categorical variable representing different overdue time intervals, aggregated from the bank-firm-month to the district level across Russia. For instance, $DPD = 0$ if there are no delayed payments on average, 30 if the average delay in payments is from 1 to 30 days, 60 for delays from 31 to 60 days, and so forth. HHI is the sum of the squared shares of each bank's loans to all firms operating in a district in a given month in the total corporate loans in that region in that month. The sample data is the product of merging of the CBR's Credit History Bureau (CHB) containing the information on bank-firm relationships, the SPARK-Interfax database on firm balance sheets, and the CBR's database on bank balance sheets.

	Sib.	Far East.	Volga	N-West.	N.Caucas.	Ural	Central	South	Total
Share of firms, %	9,47	2,27	10,45	10,13	0,66	6,49	54,70	5,84	100
The DPD accumulated by firms in their sin banks in each FD:									
0	85,14	91,58	78,24	92,41	69,69	82,51	84,71	82,78	84,66
30	6,54	1,53	7,67	1,93	7,25	2,68	4,9	4,19	5,12
60	1,55	1,54	3,61	0,75	2,35	1,54	1,96	3,6	2,12
90	1,14	0,02	1,91	0,18	0,03	0,49	0,91	1,99	1,02
120	0,44	0,62	0,82	0,10	0,03	0,37	0,36	0,85	0,44
150	3,98	4,27	6,61	4,09	5,9	11,47	6,24	5,94	5,56
≥180	1,21	0,44	1,14	0,54	14,75	0,94	0,92	0,65	1,06
Mean HHI	1 265,3	1 822,9	1 457,5	1 651,6	1 885,5	1 763,9	1 205,8	1 769,2	1 371,5
SD HHI	459,8	796,0	1 051,6	596,7	485,7	995,6	737,3	821,7	802,5

Figure B.III. Credit risk score

Note: The figure depicts empirical frequencies of the number of loans and loan amounts across borrowers' credit risk scores. The credit risk score is a categorical variable that ranges from 1, if a bank attributes a borrower to the highest category in terms of the borrower's loan performance, to 5, if a borrower has been assigned to the lowest category. The sample data is the product of merging of the CBR's credit register (January 2017 – October 2020) containing the full information on bank-firm relationships, the SPARK-Interfax database on firm balance sheets, and the CBR's database on bank balance sheets.

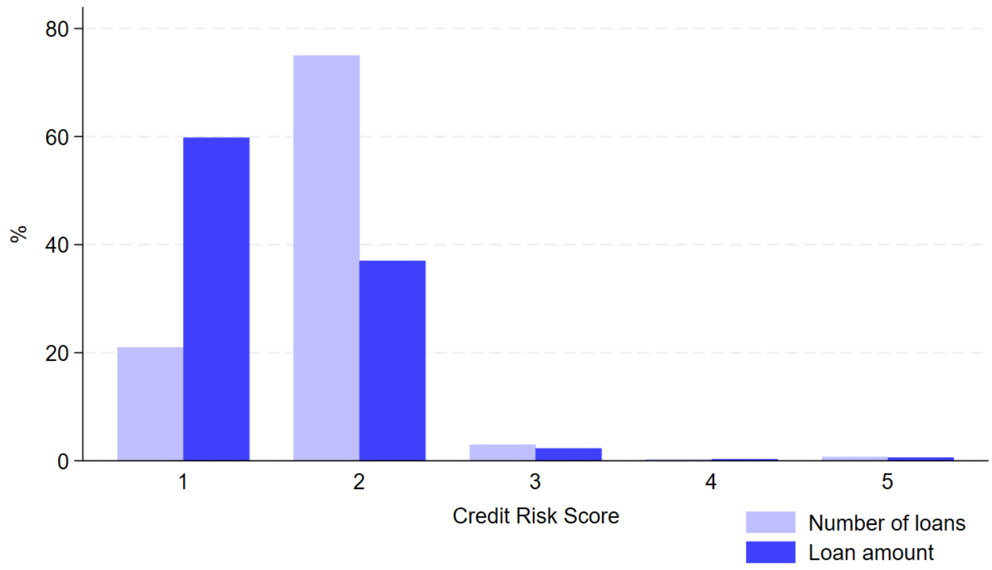


Table B.II. Summary statistics on corporate loans

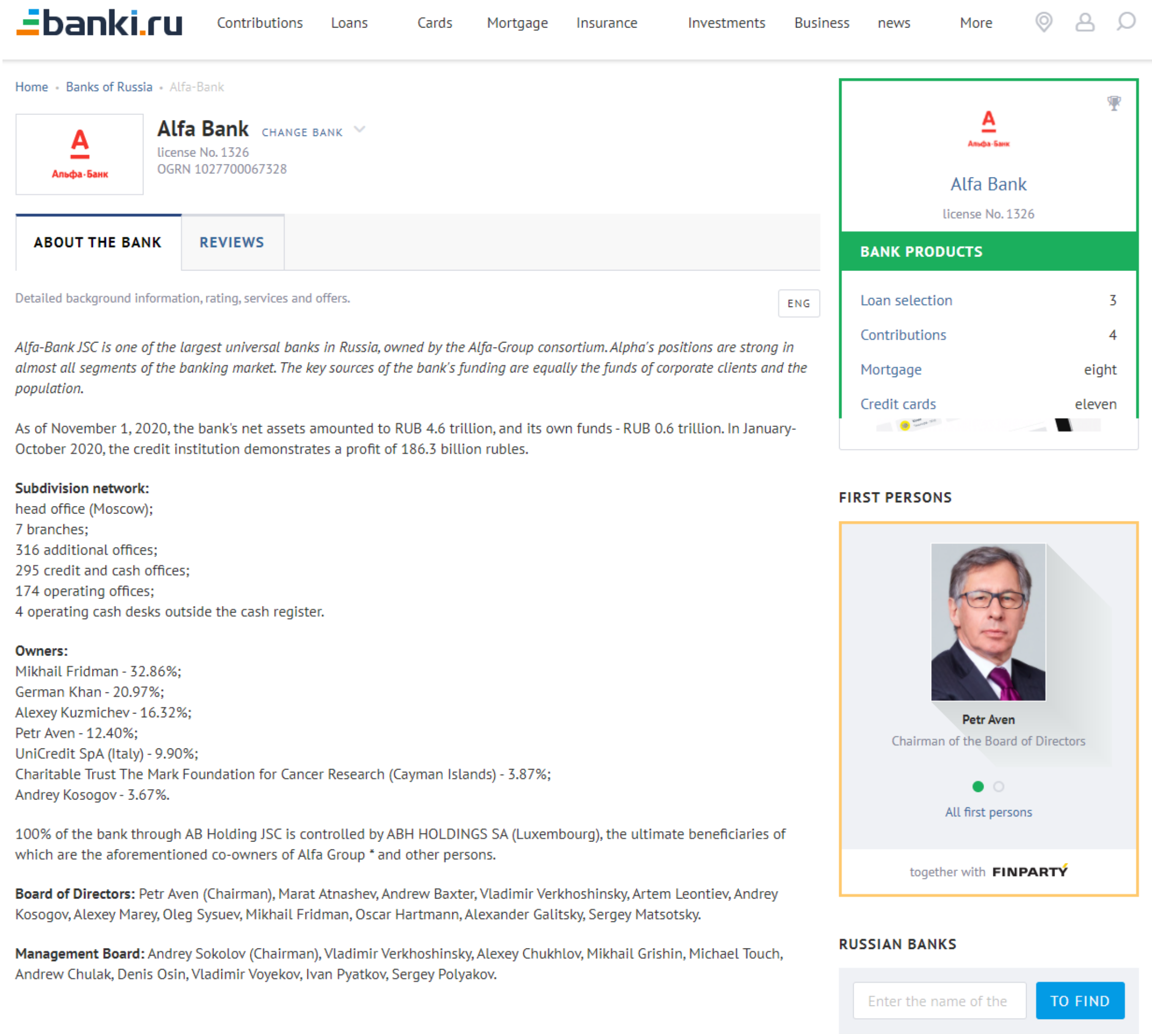
Note: The table reports the summary statistics on the key variables at the bank-firm-month level, including the interest rate, log of loan amount, the credit risk score, and the loan maturity (N obs is $1,774,379$). The credit risk score is a categorical variable that ranges from 1, if a bank attributes a borrower to the highest category in terms of the borrower's loan performance, to 5, if a borrower has been assigned to the lowest category. The sample data is the product of merging of the CBR's credit register (January 2017 – October 2020) containing the full information on bank-firm relationships, the SPARK-Interfax database on firm balance sheets, and the CBR's database on bank balance sheets.

	Mean	Median	SD	Min	Max
Interest rate$_{b,f,t}$	11.5	11.8	4.5	0.01	35.4
ln loan$_{b,f,t}$	15.2	15.3	2.2	4.1	20.7
Credit risk score$_{b,f,t}$	1.85	2.0	0.54	1	5
Loan maturity$_{b,f,t}$	428	317	412	0	3,399

Appendix C. Composition of bank boards: An example

Figure C.I. Bank board composition: An example of a bank from top-10 largest banks in terms of size

Note: The figure depicts a screenshot from a section of the national media banki.ru devoted to Alfa-Bank, the largest privately-held financial institution in Russia. The section contains the information on owners of the banks, with their corresponding shares, the board of directors, and the management board, as of 2021. The same sections are available for all the other banks in Russia—both as of 2021 and in the historical perspective since 1991. We use this individual information to create our database on common bank boards as individuals' overlaps across different banks.



Appendix D. Definition of the variables

Table D.I. Variables and their sources

Name	Definition	Source	Unit
Firm-level variables:			
Total assets	Total assets at the firm-year level, as reported in balance sheets	SPARK-Interfax	bn Rub
Leverage	Sum of short- and long-term liabilities, as % of total assets	SPARK-Interfax	%
Liquidity	The sum of current liabilities and short-term loans ($\leq 1 year$) net of accounts payable, as % of total assets	SPARK-Interfax	%
Return on assets (ROA)	Gross profit over total assets	SPARK-Interfax	%
Workers	The number of workers	SPARK-Interfax	Persons
Sales	Total value of market sales	SPARK-Interfax	bn Rub
Firm losses	A binary variable equaled 1 if a firm reported losses in its balance sheets for at least two consecutive years	SPARK-Interfax	0/1
Bank-level variables			
Sin bank	A binary variable equaled 1 if a bank had been recognized as sin (engaged in financial fraud that entails deterioration of own capital below the thresholds imposed by capital regulation) and closed by the Central Bank of Russia, and 0 if a bank	CBR's official press-releases	0/1
Common board membership	A binary variable equaled 1 for a bank that shares at least one person on its board with other bank(s).	National media banki.ru	0/1
Total assets (TA)	The sum of all assets reported in the balance sheet	CBR	bn Rub
CAR	Capital adequacy ratio, the ratio of tiers 1 and 2 capital to risk-weighted assets	CBR	%
NPL (households, firms)	Non-performing (households, firms) loans, as % of total (households, firms) loans	CBR	%
ROA	Returns on assets, the ratio of gross profit (a moving sum over the last 12 months) to TA	CBR	%
Liquidity	The ratio of liquid assets (cash, reserves) to TA	CBR	%
Growth of total assets	Growth of rate of TA over 12 moving months	CBR	%
Net interbank loans	Interbank loans granted minus interbank deposits attracted, as % of TA	CBR	%
Net foreign assets	Foreign assets (Rub equivalent) minus foreign liabilities (Rub equivalent), as % of TA	CBR	%
LLR	Loan loss provisions over the four moving quarters, as % of TA	CBR	%
Distance to Moscow	Distance between a bank's headquarters and the Kremlin	geopy.readthedocs.io	ths km
Bank-firm level variables			
DPD	Days of loan repayments past due (0, 30, ..., $\geq$ 200)	Credit History Bureau (CHB)	Day
Match with a bank	A binary variable equaled one if a firm re-appears in the credit register or CHB in some time after its current sin bank closure and zero if the firm remains unbanked	Credit History Bureau (CHB), credit register	0/1
Time till new bank matching	Number of months it takes a firm to re-appear in the credit register or CHB after its current sin bank closure	Credit History Bureau (CHB), credit register	Months
Loan	Loan amount aggregated to the bank-firm-month level	Credit register	bn Rub
Interest rate	Interest rate on loan aggregated to the bank-firm-month level	Credit register	%
Maturity	Time until the loan is matured, as aggregated to the bank-firm-month level	Credit register	Months
Credit risk score	A categorical variable ranging from 1 (the highest credit score) to 5 (the lowest credit score), as aggregated to the bank-firm-month level	Credit register	Months

Appendix E. Predictability of sin bank closure: Details

When developing a logit model of bank failures to detect bank fraud, we need to account for a large body of anecdotal evidence suggesting that gambling banks, upon realizing that the regulator had shifted to a stricter regime in mid-2013, began continuously updating their balance-sheet falsification techniques. These methods artificially improved the quality of their assets, reducing loan loss provisions and keeping capital above the regulatory threshold.[31] Meanwhile, the Central Bank of Russia was learning and adapting to these evolving schemes through the process of revoking the licenses of fraudulent banks. Thus, our logit models must account for both the evolution of falsification techniques and the regulator's learning process. Additionally, our models must incorporate not only standard bank failure determinants, as captured by the CAMELS framework (see, e.g., DeYoung and Torna, 2013), but also fraud-specific indicators.

We account for fraud evolution and regulatory adaptation by estimating logit regressions using a six-month rolling window from January 2010—more than three years before the central bank initiated the sin bank closure policy—until October 2020, nearly three years after the active phase of the policy was declared complete (see Section 2 for details on policy timing).

As for *fraud-specific indicators*, we exploit:

- A variable that captures cases where a bank has higher-than-average loan loss reserves (LLR) but lower-than-average non-performing loans (NPLs) for firms (both expressed as a percentage of the bank's total assets),
- A variable identifying banks that hold a large share of assets (greater than 30%) in correspondent accounts at foreign banks but engage in no actual transactions with these funds,
- A variable capturing banks that predominantly collect deposits from households but lend mainly to non-financial firms instead of households.

As for the *CAMELS-based variables*, we use:

- (C) Capital adequacy ratio,
- (A) Asset quality: NPL ratios for firm and household loans, loan loss reserves as a percentage of total assets, total asset growth, and its square,

[31] For an early review of these falsification tools, see: `https://www.banki.ru/news/daytheme/?id=6609791`.

- (M) Management efficiency: operating cost-to-income ratio,
- (E) Earnings: annual return on total assets,
- (L) Liquidity: ratio of cash and government securities to total assets,
- (S) Sensitivity to market risk: net interbank exposure within the domestic banking system and net foreign assets abroad (both as a percentage of total assets). We also include bank size to control for too-big-to-fail considerations.

We also incorporate macroeconomic and regional controls to account for broader economic conditions, cross-regional differences in banking competition, and geographic disparities. Specifically, we control for the state of the business cycle, the regional banking concentration, measured by the Herfindahl-Hirschman Index (HHI), and the distance from a bank's headquarters to central Moscow to capture regional variations.

The six-month rolling window logit estimates are presented in Table E.I.[32] The table provides a snapshot of results for four key sub-periods: before the implementation of the strict policy, during its early months (July 2013), at the policy's midpoint (January 2016), and near its conclusion (February 2018). The dependent variable is a binary indicator that equals 1 if bank b was shut down in month t due to fraud. All explanatory variables are lagged by one month (three months deliver the same results, not reported to save space).

The logit results indicate that, depending on the sub-period, banks with greater capital, lower NPL ratios, higher returns, and larger net interbank loans were less likely to be closed for fraud, aligning with findings from the CAMELS framework. Regarding fraud-specific indicators, we find strong evidence that high LLR combined with low NPLs is a significant predictor of fraud in the near future. In terms of regional factors, banks operating in areas with higher levels of banking concentration (larger HHIs) were less likely to be closed for fraud, consistent with the "market power–stability" hypothesis (see, e.g., Keeley, 1990). At the macroeconomic level, our findings suggest that banks were less likely to be shut down for fraud during expansionary phases of the business cycle. Overall, our results align with the broader literature on bank failures and highlight the importance of incorporating fraud-specific risk factors alongside traditional CAMELS-based indicators in predicting fraudulent bank closures.

[32] We also tested a 12-month rolling window and found no qualitative differences compared to the baseline results.

Table E.I. Probability of sin banks detection and closure: logit regression results

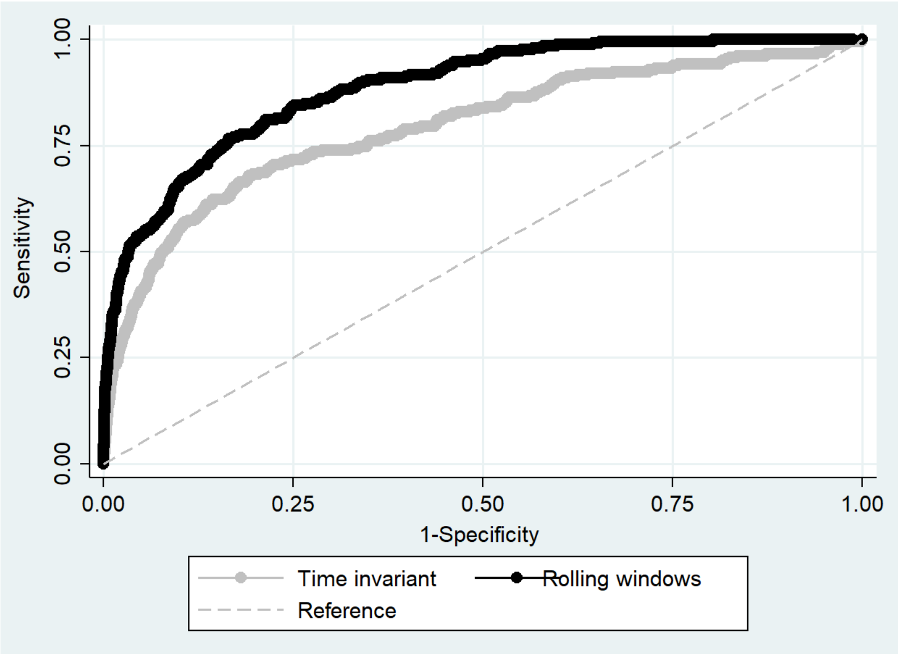
Note: The table reports estimates of the following logit model: $Pr\left(Fraud\,Detection_{b,t} = 1|\mathbf{X}_{b,t-1}\right) = \Lambda\Big(\mathbf{X}_{b,t-1}\Psi'\Big)$, where the dependent variable is a binary variable that equals 1 if an operating bank b is closed for fraud at month t, and 0 if the bank continues to operate. $\mathbf{X}_{b,t-1}$ includes capital adequacy ratio (CAR), the NPL ratios in the credit to households and credit to firms, return-to-assets (ROA), cash and reserves at the corresponding accounts at the Central Bank of Russia to total assets ratio (liquidity), growth of total assets (YoY) and its square, inter-bank loans minus inter-bank debts to total assets ratio, foreign assets minus foreign liabilities to total assets ratio, log of total assets, a censored variable equals loan loss reserves (LLR) if LLR exceeds median across all banks at a given month and equals 0 if else, the product of the censored variable and NPLs of firms, the distance of bank headquarters location to Moscow, regional credit market concentration (HHI), and GDP growth rates (YoY). The estimations are performed in six-month rolling windows starting from 2010M6, i.e., before the active phase of the sin bank closure policy began, and finishes at the end of the sample period in 2019M6. The constant term is not reported. The data is sourced from the CBR's database on bank balance sheets.

Period:	Before the policy	During the active phase of the policy		
		≤2013M7	≤2016M1	≤2018M2
	(1)	(2)	(3)	(4)
CAR	–0.003	0.003	–0.002	–0.021**
	(0.018)	(0.018)	(0.008)	(0.010)
NPLs households	–2.660	24.488***	–1.337	–4.167
	(11.869)	(8.027)	(6.085)	(4.414)
NPLs firms	5.943	–22.104	9.264	8.187**
	(4.146)	(104.406)	(7.044)	(3.382)
ROA	–7.664***	–35.742***	–8.069***	–10.415***
	(2.053)	(9.724)	(2.981)	(1.852)
Liquidity	–1.376	3.422	–1.375	–2.863*
	(1.681)	(5.235)	(1.475)	(1.490)
Growth of total assets	–0.946	–0.664	–1.053	–0.575
	(0.775)	(3.559)	(0.666)	(0.490)
Growth of total assets ^{2}	0.545*	0.448	0.467*	0.348*
	(0.295)	(1.311)	(0.252)	(0.185)
Net inter-bank loans	–3.342***	3.878	–3.632***	–3.852***
	(0.845)	(3.695)	(1.399)	(0.848)
Net Foreign assets	0.165	5.464**	1.040	0.038
	(1.077)	(2.402)	(1.124)	(0.865)
Bank size	–0.614**	–0.049	–0.416***	–0.525***
	(0.294)	(0.413)	(0.122)	(0.098)
LLR > 50%*tile*	7.367***	–3.977	5.654***	6.497***
	(1.781)	(7.210)	(1.393)	(0.910)
LLR > 50%*tile* × NPLs firms	–22.147	–66.891	–63.950**	–53.920***
	(16.286)	(476.620)	(27.815)	(16.016)
Distance to Moscow	0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Regional HHI		0.001	–0.000	–0.000*
		(0.000)	(0.000)	(0.000)
Annual GDP growth	0.083	–1.038	–0.158**	–0.143***
	(0.110)	(0.682)	(0.077)	(0.055)
N obs	37,889	1,550	19,568	31,836
R^2-pseudo	0.117	0.274	0.080	0.120

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank level and appear in the brackets under the estimated coefficients.

Figure E.I. In-sample quality of the logit regression models: rolling windows versus the full sample estimates

Note: The figure depicts ROC curves (Receiver Operating Characteristics) for two logit regression models of sin bank detection and closures: one for the version of the model estimated over the full sample of 2010M6 to 2019M6 (*Time invariant*) and the other estimated in a loop of six-month rolling windows over the same horizon (*Rolling windows*). See Table E.I for the details on the models.



Regarding the in-sample quality of the estimated logit models, we compute two ROC curves—one for the models estimated in a six-month rolling window and the other for a model estimated over the whole time span. The results are reported in Fig. E.I. The area under the ROC curve equals 0.88 in the first case and 0.78 in the other, thus suggesting our 'learning' approach outperforms the full-time-span model.

Appendix F. The Real Effects of Sin Bank Closure: Additional Estimates

Table F.I. Difference-in-differences estimates: Never-treated firms as additional controls

Note: The table reports the estimates of equation (3), where the dependent variable $Y_{f,t}$ reflects for each firm f in year t (1) the firm size, as captured by the log of total assets ($\ln TA_{f,t}$), (2) the log of total borrowed funds ($\ln Debt_{f,t}$), (3) the ratio of sales revenue to total assets ($Sales_{f,t}/TA_{f,t}$), (4) the ratio of the total number of workers to the sales revenue ($Workers_{f,t}/Sales_{f,t}$), or (5) the ratio of the gross profit to the total assets ($Profit_{f,t}/TA_{f,t}$). $Sin\,Bank_{f,t}$ is a binary variable that equals 1 for each year $t \in [t^*_{f,b} - 2, t^*_{f,b} + 2]$ if firm f had a lending relationship with sin bank b that had been closed at $t^*_{f,b}$ (*earlier-treated*) and 0 over the same time interval if firm f either never had lending relationships with sin banks or had a lending relationship with bank $\tilde{b}$ which was also sin but had been closed at a sufficiently later point in time, i.e., $t^*_{f,\tilde{b}} > t^*_{f,b} + 2$ (*later-treated*). To guarantee the pre-treatment comparability of affected firms, we employ the 1:4 nearest-neighbor matching estimator of Abadie and Imbens (2011) using firm size, the annual growth of total assets, leverage, and liquidity as observables. $Post\,closure_{f,t}$ is a binary variable that equals 1 if firm f is an earlier-treated firm and $t \geq t^*_{f,b}$ and 0 in all the other cases. $Firm\,Losses_{f,t}$ is a binary variable that equals 1 if firm f reported losses for at least two consecutive years and 0 if else (proxy for bad firm). Each regression contains the other two sub-products of the triple interaction variable (not reported to save space), the fixed effects as specified, and the four firm-specific characteristics we used for matching to capture any residual differences across earlier- and later-treated firms.

	Dependent variable $Y_{f,t}$:				
	$\ln \text{TA}_{f,t}$	$\ln \text{Debt}_{f,t}$	$\frac{\text{Sales}_{f,t}}{\text{TA}_{f,t}}$	$-\frac{\text{Workers}_{f,t}}{\text{Sales}_{f,t}}$	$\frac{\text{Profit}_{f,t}}{\text{TA}_{f,t}}$
	(1)	(2)	(3)	(4)	(5)
Sin bank$_{f,t}$ × Post closure$_{f,t}$	0.039	0.030	0.162	3.908**	0.012
	(0.025)	(0.019)	(0.134)	(1.772)	(0.017)
Sin bank$_{f,t}$ × Post closure$_{f,t}$ × Firm Losses$_{f,t}$	0.070	0.057	0.336	−2.131	0.052
	(0.088)	(0.078)	(0.302)	(4.301)	(0.042)
Other firm controls	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓	✓
N obs	94,503	94,503	94,503	94,503	94,503
N treated firms	4,725	4,725	4,725	4,725	4,725
N control firms	14,175	14,175	14,175	14,175	14,175
R^2 (pseudo / LSDV)	0.3	0.7	0.1	0.1	0.1

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Table F.II. Difference-in-differences estimates: Multiple-bank firms as treated

Note: The table reports the estimates of equation (3), where the dependent variable $Y_{f,t}$ reflects for each firm f in year t (1) the firm size, as captured by the log of total assets ($\ln TA_{f,t}$), (2) the log of total borrowed funds ($\ln Debt_{f,t}$), (3) the ratio of sales revenue to total assets ($Sales_{f,t}/TA_{f,t}$), (4) the ratio of the total number of workers to the sales revenue ($Workers_{f,t}/Sales_{f,t}$), or (5) the ratio of the gross profit to the total assets ($Profit_{f,t}/TA_{f,t}$). $Sin\,Bank_{f,t}$ is a binary variable that equals 1 for each year $t \in [t^*_{f,b} - 2, t^*_{f,b} + 2]$ if a multiple-bank firm f had a lending relationship with at least one sin bank b that had been closed at $t^*_{f,b}$ (*earlier-treated*) and 0 over the same time interval if a multiple-bank firm f also had a lending relationship with at least one sin bank $\tilde{b}$ but this sin bank but had been closed at a sufficiently later point in time, i.e., $t^*_{f,\tilde{b}} > t^*_{f,b} + 2$ (*later-treated*). To guarantee the pre-treatment comparability of affected firms, we employ the 1:4 nearest-neighbor matching estimator of Abadie and Imbens (2011) using firm size, the annual growth of total assets, leverage, and liquidity as observables. $Post\,closure_{f,t}$ is a binary variable that equals 1 if firm f is an earlier-treated firm and $t \geq t^*_{f,b}$ and 0 in all the other cases. $Firm\,Losses_{f,t}$ is a binary variable that equals 1 if firm f reported losses for at least two consecutive years and 0 if else (proxy for bad firm). Each regression contains the other two sub-products of the triple interaction variable (not reported to save space), the fixed effects as specified, and the four firm-specific characteristics we used for matching to capture any residual differences across earlier- and later-treated firms.

	Dependent variable $Y_{f,t}$:				
	$\ln \text{TA}_{f,t}$	$\ln \text{Debt}_{f,t}$	$\frac{\text{Sales}_{f,t}}{\text{TA}_{f,t}}$	$-\frac{\text{Workers}_{f,t}}{\text{Sales}_{f,t}}$	$\frac{\text{Profit}_{f,t}}{\text{TA}_{f,t}}$
	(1)	(2)	(3)	(4)	(5)
Sin bank$_{f,t}$ × Post closure$_{f,t}$	0.022	0.028	0.043**	−2.874	0.129
	(0.015)	(0.112)	(0.021)	(3.140)	(0.136)
Sin bank$_{f,t}$ × Post closure$_{f,t}$ × Firm Losses$_{f,t}$	−0.032	−0.001	0.076	−5.344	−0.231
	(0.022)	(0.001)	(0.051)	(3.843)	(0.288)
Other firm controls	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Sector × Year FE	✓	✓	✓	✓	✓
N obs	24,807	24,807	24,807	24,807	24,807
N treated firms	1,418	1,418	1,418	1,418	1,418
N control firms	3,544	3,544	3,544	3,544	3,544
R^2 (pseudo / LSDV)	0.3	0.7	0.1	0.1	0.1

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Appendix G. Credit risk scores, firm losses, and sin banks

Table G.I. Regression estimation results: Credit risk scores assigned for good vs. bad firms by sin vs. solid banks

Note: The table reports the estimates of the following regression: $Credit\,Risk\,Score_{b,f,t} = \beta_1 \cdot Firm\,Losses_{f,t} + \beta_2 \cdot Sin\,Bank_b + \beta_3 \cdot Sin\,Bank_b \times Losses_{f,t} + \mathbf{X}_{b,f,t-1}\mathbf{\Theta'} + \alpha_{bce} + \gamma_r + \mu_s + \lambda_f + \nu_t + \epsilon_{b,f,t}$, where the dependent variable $Credit\,Risk\,Score_{b,f,t}$ is a categorical variable that reflects a bank's ex-post assessment of a borrowing firm's quality ranging from **1** (the lowest realized credit risk, or the best quality) to **5** (the highest realized credit risk, or the worst quality). *Single-bank firms*: "*Yes*" means that the sample contains (good and bad) firms that have lending relationships with only one bank (sin or solid); "*No*" means that the sample comprises (good and bad) firms borrowing from at least two banks (sin and/or solid). $Sin\,Bank_b$ is a binary variable that equals 1 if a bank is ever closed for fraud (i.e., sin bank) and 0 if it survives till the end of the sample. $Firm\,Losses_{f,t}$ is a binary variable that equals 1 if firm f reported losses for at least two consecutive years and 0 if else (proxy for bad firm). Control variables ($\mathbf{X}_{b,t-1}$) include bank size, the ratio of household credit to total assets, equity capital to total assets, corporate and household deposits to total assets, and non-performing loans to total assets and regional credit market concentration (the Herfindahl-Hirschman Index). Fixed effects include bank closure events α_{bce}, region γ_r, sector μ_s, firm λ_f and month ν_t (column 1) or firm*month $\lambda_{f,t}$ (column 2). In column (1), the sample contains $25,614$ firms having single lending relationships with 151 sin banks closed in between January 2017 and September 2020 and $157,353$ firms borrowing from 390 solid banks. In column (2), $3,650$ firms borrow from at least one of 151 sin banks and $21,178$ firms borrow from 390 solid banks. The data is sourced from the corporate credit register of the Bank of Russia and banks' balance sheets.

Dependent variable:	Credit Risk Score$_{b,f,t}$	
Single-bank firms:	Yes	No
	(1)	(2)
Firm Losses$_{f,t}$	0.026***	
	(0.003)	
Sin Bank$_b$	–0.073***	–0.062***
	(0.011)	(0.019)
Firm Losses$_{f,t}$ × Sin Bank$_b$	–0.047**	–0.192***
	(0.021)	(0.055)
ln Loan$_{f,b,t}$	–0.003***	–0.002***
	(0.000)	(0.001)
Bank closure event FE	✓	✓
Region FE	✓	✓
Sector FE	✓	✓
Firm FE	✓	
Month FE	✓	
Firm × Month FE		✓
N Obs	1,774,379	679,356
R^2 (adj.)	0.7	0.8

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank-firm level and appear in the brackets under the estimated coefficients.

Appendix H. Duration regression analysis: Details

Figure H.I. Loan quality indicator (DPD) and duration of the transition period

Note: The figure depicts a scatterplot in which the loan quality indicator (DPD, *days past due*) is along the Y axis and the duration of the transition period—time it takes to match with a new bank (or duration of the spell, k_f)—is along the X axis. The time span is from January 2010 to October 2020. DPD is a categorical variable representing different overdue time intervals at the bank-firm-month level fixed at the moment of a sin bank's recognition and closure ($t^*_{b,f}$). For instance, $DPD = 0$ if there are no delayed payments on average, 30 if the average delay in payments is from 1 to 30 days, 60 for delays from 31 to 60 days, and so forth. The sample data is the product of merging of the CBR's Credit History Bureau (January 2010 – January 2018) and credit register (January 2017 – October 2020) containing the full information on bank-firm relationships, the SPARK-Interfax database on firm balance sheets, and the CBR's database on bank balance sheets.

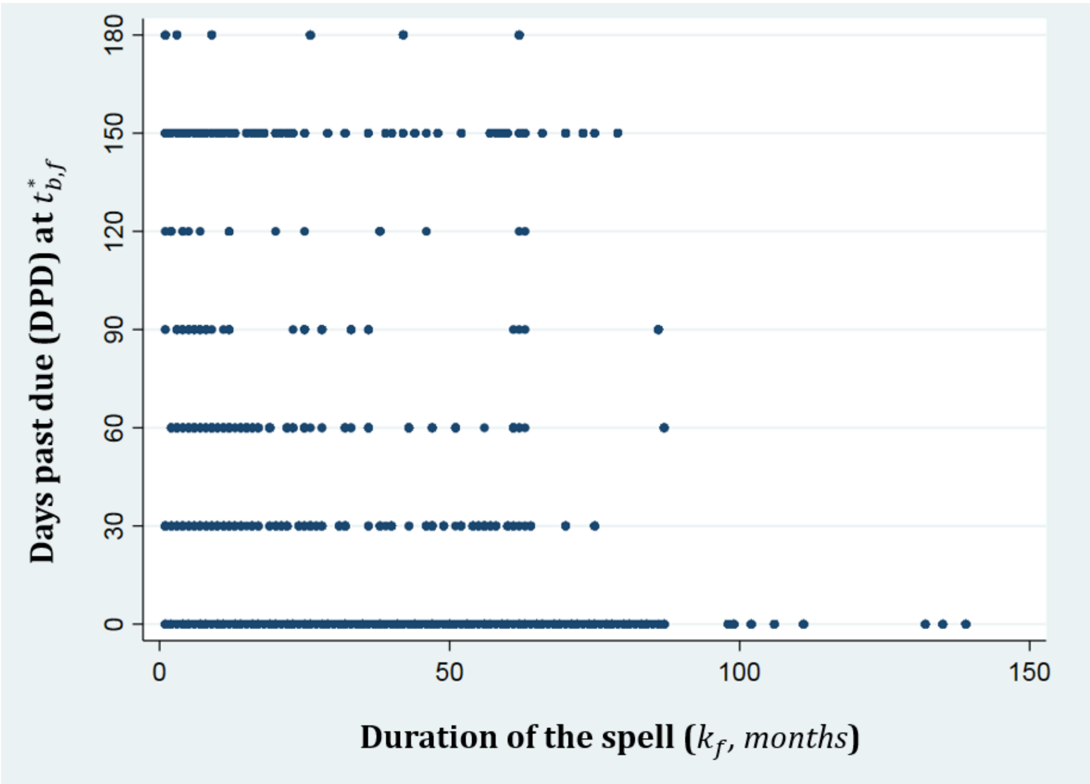


Figure H.II. Quality of loans in bad vs. good firms

Note: The figure depicts empirical frequencies of the loan quality indicator (DPD, *days past due*) across bad firms (a) and good firms (b). DPD is a categorical variable representing different overdue time intervals at the bank-firm-month level fixed at the moment of a sin bank's recognition and closure ($t^*_{b,f}$). For instance, DPD = 0 if there are no delayed payments on average, 30 if the average delay in payments is from 1 to 30 days, 60 for delays from 31 to 60 days, and so forth. *Bad firms* are those with $Firm\,Losses_{f,t}$ equal to 1 and *Good firms* are those with $Firm\,Losses_{f,t}$ equal to 0, where $Firm\,Losses_{f,t}$ is a binary variable that equals 1 if firm f reported losses for at least two consecutive years and 0 if else. The sample data is the product of merging of the CBR's Credit History Bureau (January 2010 – January 2018) and credit register (January 2017 – October 2020) containing the full information on bank-firm relationships, the SPARK-Interfax database on firm balance sheets, and the CBR's database on bank balance sheets.

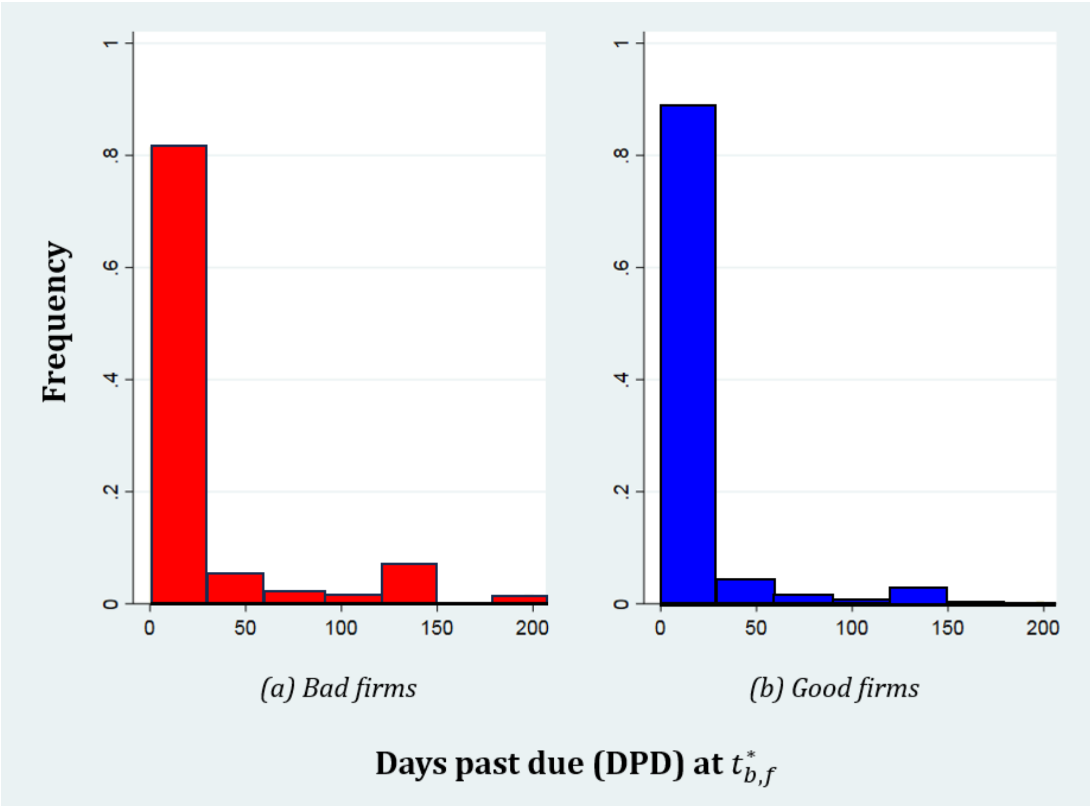


Table H.I. Multinomial logit regression results: New bank-firm matches

Note: The table reports the estimates of a multinomial logit model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered. In the sample, there are 944 firms that eventually matched with new sin banks (average $k_f = 18$ months, see Table 1), $3,780$ firms that matched with new solid banks (average $k_f = 46$ months), and $11,013$ firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\ln DPD_{f,t^*}$ is the log of the maximum number of days of firm's f loan delinquency in the closed sin banks, as of the beginning of the spell at $t^*_{b,f}$. $Firm\,Losses_{f,t^*}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t^*_{b,f}$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm *Leverage* (short- and long-term debts over the total assets), and firm *Liquidity* (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank			Match with a new solid bank		
	(1)	(2)	(3)	(4)	(5)	(6)
ln DPD$_{f,t^*}$	0.126***		0.085***	–0.063**		–0.071**
	(0.041)		(0.028)	(0.029)		(0.033)
Firm Losses$_{f,t^*}$		–1.278*	–1.611*		0.104	–0,191
		(0.722)	(0.859)		(0.211)	(0.200)
ln DPD$_{f,t^*}$ × Firm Losses$_{f,t^*}$			0.275***			0.053**
			(0.090)			(0.024)
Firm controls	✓	✓	✓	✓	✓	✓
Bank closure event FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N obs	333,398	333,398	333,398	490,297	490,297	490,297
N new firm-bank matches	944	944	944	3,780	3,780	3,780
N firms	11,957	11,957	11,957	14,793	14,793	14,793
log L	–6,428	–4,879	–3,950	–6,428	–4,879	–3,950

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Table H.II. Duration regression results: The role of firm profitability

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered. In the sample, there are 944 firms that eventually matched with new sin banks (average $k_f = 18$ months, see Table 1), 3,780 firms that matched with new solid banks (average $k_f = 46$ months), and 11,013 firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\ln DPD_{f,t^*}$ is the log of the maximum number of days of firm's f loan delinquency in the closed sin banks, as of the beginning of the spell at $t^*_{b,f}$. $ROA_{f,t-1}$ is the the ratio of firm's f gross profit to total assets at $t-1$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm *Leverage* (short- and long-term debts over the total assets), and firm *Liquidity* (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank		Match with a new solid bank	
	(1)	(2)	(3)	(4)
$\mathrm{ROA}_{f,t-1}$	0.034	0.153***	0.070	0.136***
	(0.042)	(0.015)	(0.054)	(0.049)
$\ln \mathrm{DPD}_{f,t^*}$		0.189***		–0.084***
		(0.065)		(0.032)
$\ln \mathrm{DPD}_{f,t^*} \times \mathrm{ROA}_{f,t-1}$		–0.441***		–0.194***
		(0.151)		(0.074)
Firm controls	✓	✓	✓	✓
Bank closure event FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓
N obs	333,398	333,398	490,297	490,297
N new firm-bank matches	944	944	3,780	3,780
N firms	11,957	11,957	14,793	14,793
log L	-1,140.0	–1,111.5	–3,910.1	–2,925.1

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Table H.III. Duration regression results: Time-varying firm losses after sin bank closures

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered. In the sample, there are 944 firms that eventually matched with new sin banks (average $k_f = 18$ months, see Table 1), $3,780$ firms that matched with new solid banks (average $k_f = 46$ months), and $11,013$ firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\ln DPD_{f,t^*}$ is the log of the maximum number of days of firm's f loan delinquency in the closed sin banks, as of the beginning of the spell at $t^*_{b,f}$. $Firm\,Losses_{f,t-1}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t-1$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm $Leverage$ (short- and long-term debts over the total assets), and firm $Liquidity$ (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank	Match with a new solid bank
	(1)	(2)
ln DPD$_{f,t^*}$	0.092***	–0.115***
	(0.031)	(0.044)
Firm Losses$_{f,t-1}$	–0.760**	–0.554***
	(0.321)	(0.174)
ln DPD$_{f,t^*}$ × Firm Losses$_{f,t-1}$	0.503***	0.138***
	(0.172)	(0.053)
Firm controls	✓	✓
Bank closure event FE	✓	✓
Region FE	✓	✓
Sector FE	✓	✓
N obs	333,398	490,297
N new firm-bank matches	944	3,780
N firms	11,957	14,793
log L	–892.1	–2,196.4

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Table H.IV. Duration regression results: Fixing firm losses at the moment of sin bank closures and discretizing the loan delinquency variable

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered. In the sample, there are 944 firms that eventually matched with new sin banks (average $k_f = 18$ months, see Table 1), 3,780 firms that matched with new solid banks (average $k_f = 46$ months), and 11,013 firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\mathbb{1}\{\text{DPD}_{f,t^*} \geq 120\}$ is the binary variable that equals 1 if the maximum number of days of firm's f loan delinquency in the closed sin banks at $t^*_{b,f}$ exceeded 120 and 0 if else. $Firm\,Losses_{f,t^*_{b,f}}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t^*_{b,f}$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm *Leverage* (short- and long-term debts over the total assets), and firm *Liquidity* (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank	Match with a new solid bank
	(1)	(2)
$\mathbb{1}\{\text{DPD}_{f,t^*} \geq 120\}$	–0.178	–1.022***
	(0.560)	(0.363)
Firm Losses_{f,t^*}	–2.953***	–0.225*
	(1.017)	(0.136)
$\mathbb{1}\{\text{DPD}_{f,t^*} \geq 120\} \times$ Firm Losses_{f,t^*}	3.309**	1.121*
	(1.381)	(0.621)
Firm controls	✓	✓
Bank closure event FE	✓	✓
Region FE	✓	✓
Sector FE	✓	✓
N obs	333,398	490,297
N new firm-bank matches	944	3,780
N firms	11,957	14,793
log L	–921.9	–2,421.7

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Table H.V. Duration regression results: Multiple-bank firms

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only multiple-bank firms with at least one sin bank in the respective network are considered. In the sample, there are 130 firms that eventually replaced their closed sin banks with new sin banks (average k_f = 18 months, as in the case of single-bank firms, see Table 1), 541 firms that replaced their closed sin banks with new solid banks (average k_f = 46 months), and 1,494 firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\ln DPD_{f,t^*}$ is the log of the maximum number of days of firm's f loan delinquency in the closed sin banks, as of the beginning of the spell at $t^*_{b,f}$. $Firm\,Losses_{f,t-1}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t-1$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm *Leverage* (short- and long-term debts over the total assets), and firm *Liquidity* (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank			Match with a new solid bank		
	(1)	(2)	(3)	(4)	(5)	(6)
ln DPD$_{f,t^*}$	0.020		0.016	–0.027		–0.043
	(0.060)		(0.049)	(0.038)		(0.061)
Firm Losses$_{f,t^*}$		–0.795	–1.000		–0.744*	–0.957***
		(0.711)	(0.870)		(0.230)	(0.214)
ln DPD$_{f,t^*}$ × Firm Losses$_{f,t^*}$			0.024			0.108
			(0.073)			(0.152)
Firm controls	✓	✓	✓	✓	✓	✓
Bank closure event FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓
N obs	45,273	45,273	45,273	67,841	67,841	67,841
N new firm-bank matches	130	130	130	541	541	541
N firms	1,624	1,624	1,624	2,046	2,036	2,036
log *L*	–979.6	–769.2	–625.0	–2,315.1	–1,865.8	–1,118.5

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.

Appendix I. Common bank board members: Data description and additional regression results

Table I.I. Description of common bank board members in the final dataset

Note: The table reports the summary statistics for the 550 out of 589 sin banks that had been detected and closed by the CBR during the period from January 2010 to October 2020 (*Panel 1*) and 232 solid banks as of October 2020. The data is sourced from banki.ru.

	N	Mean	SD	Min	Max
Panel 1: Sin banks					
Common managers	550	0.065	0.255	0	2
Common owners	550	0.138	0.417	0	4
Total	550	0.204	0.521	0	5
Panel 1: Solid banks					
Common managers	232	0.267	0.556	0	2
Common owners	232	0.125	0.380	0	2
Total	232	0.392	0.743	0	4

Table I.II. Duration regression results: Discretizing the loan delinquency variable and removing common board members

Note: The table reports the estimates of a competing risk proportional hazard model of new bank-firm matching (5). A typical spell begins at $t^*_{b,f}$ when bank b is recognized as sin and closed, and firm f observes the destruction of its lending relationship with b. The duration of the spell k_f is firm-specific. There are two types of firm "exit": matching with a new not-yet-detected sin bank (columns 1–3) or matching with a new solid bank (columns 4–6), conditional on survival to the current month $t = t^*_{b,f} + k_f$. Only single-(sin)bank firms are considered, as in the baseline (Table 6), but now we also require that the closed sin banks did not have overlaps with other banks in the composition of the board members. In the sample, there are 944 firms that eventually matched with new sin banks (average $k_f = 25$ months, which is 7 months longer than in the full sample, see Table 1), $3,780$ firms that matched with new solid banks (average $k_f = 46$ months), and $11,013$ firms that remained unbanked until the end of the sample period. The estimates are performed over the period from January 2010 to January 2020, encompassing the active phase of the sin bank closure policy from July 2013 to February 2018 as well as before and after it. A positive estimated coefficient denotes a rising hazard of firm exit through the corresponding type of exit event. $\mathbb{1}\{\text{DPD}_{f,t^*} \geq 120\}$ is the binary variable that equals 1 if the maximum number of days of firm's f loan delinquency in the closed sin banks at $t^*_{b,f}$ exceeded 120 and 0 if else. $Firm\,Losses_{f,t^*_{b,f}}$ is the binary variable of whether firms reported losses for at least two consecutive years at $t^*_{b,f}$. Other controls include the linear and quadratic components of $Firm\,size$, as measured by the log of total assets and its square, firm *Leverage* (short- and long-term debts over the total assets), and firm *Liquidity* (current liabilities net of accounts payable and short-term debts over the total assets). Fixed effects as specified. Coefficients instead of subhazard ratios are reported.

	Match with a new sin bank	Match with a new solid bank
	(1)	(2)
$\mathbb{1}\{\text{DPD}_{f,t^*} \geq 120\}$	–0.198	–1.274***
	(0.639)	(0.446)
Firm Losses$_{f,t^*}$	–2.441**	–0.342*
	(1.028)	(0.192)
$\mathbb{1}\{\text{DPD}_{f,t^*} \geq 120\}$ × Firm Losses$_{f,t^*}$	2.273	1.467**
	(1.627)	(0.711)
Firm controls	✓	✓
Bank closure event FE	✓	✓
Region FE	✓	✓
Sector FE	✓	✓
N obs	144,631	218,739
N new firm-bank matches	548	1,909
N firms	5,105	6,466
log L	–673.1	–1,452.7

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the firm level and appear in the brackets under the estimated coefficients.