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Quo Vadis? Evidence on New Firm-Bank Matching and Firm Performance Following "Sin" Bank Closures*

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February 2022

Abstract

In this paper, we analyze how firms search for new lenders after a financial regulator forcibly closes their prior banks, and what happens to the firms' performance during this transition period. In 2013, the Central Bank of Russia launched a large-scale bank closure policy and started detecting fraudulent (sin) banks and revoking their licenses. By 2020, two-thirds of all operating banks had been shuttered. We analyze this unique period in history using credit register data. First, we establish that before sin bank closures, there was no informational leakage and the borrowing firms remain unaffected. After the closures, there is a clear sorting pattern: poorly-performing firms rush to other (not-yet-detected) sin banks, while profitable firms transfer to financially solid banks. We find that the coupling of poorly-performing firms and not-yet-detected sin banks occurs more frequently when the two sin banks (the prior and the next lender) are commonly owned or when the local banking market is unconcentrated. Finally, we show that during the transition period (i.e., after the sin bank closures and before matching to new banks), poorly-performing firms shrink in size and experience a sharp decline in borrowings and market sales, whereas profitable firms strengthen in terms of employment, investment, and market sales. A potential mechanism involves *credit risk underpricing* by sin banks: we find that poorly-performing firms (especially commonly owned) received loans at lower interest rates than profitable firms prior to sin bank closures. (**JEL**: G21, G28)

Keywords: Credit register, Bank clean-up, Regulatory forbearance, Credit risk underpricing, Common ownership.

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1. INTRODUCTION

Firms derive value from bank credit beyond the benefit of obtaining external financing. Banks can help mitigate information asymmetries between lenders and borrowers through screening (Leland and Pyle, 1977), and to reduce moral hazard through monitoring (Holmstrom and Tirole, 1997). Through a lending relationship with a borrowing firm, a bank can gain proprietary information about the firm and potentially influence decisions taken by the firm's management (Petersen and Rajan, 1995), and the firm may expect support from the relationship bank in times of distress (Bolton et al., 2016; Schäfer, 2019). Thus, losing an established relationship with a bank due to the bank's failure can have negative effects on a firm. However, the negative consequences of such an event are less clear if banks are forcibly closed by a financial regulator due to fraudulent activities revealed. In this paper, we explore the phenomenon of fraudulent ("sin") banks to understand what happens to firms borrowing from these banks after the financial regulator breaks the sin bank-firm relationships.

We analyze how firms match with new banks when their prior lenders are forcibly closed by the regulator. We examine what happens to the firms' performance during the transition period, i.e., after their sin banks are closed and before they match with new banks. Moreover, we investigate whether there are differences between poorly-performing, loss-making firms ("bad" firms, hereinafter) and well-performing, profitable firms ("good" firms) in this respect, given that both could have had relationships with the same closed bank.

How firms fare after the closure of their banks remains an open question of sizable academic and policy-making interest. Empirical studies have examined how firms are affected by negative credit supply shocks (Chodorow-Reich, 2014; Gropp et al., 2018; Degryse et al., 2019a; Greenstone et al., 2020), the closure of their bank branches (Bonfim et al., 2020), and the failure of their distress banks (Liaudinskas and Grigaite, 2021). However, to the best of our knowledge, there are no studies that examine the effect of pre-emptive regulatory closure of banks on firms' consequent matches with new banks and performance. It is vitally important to understand these effects to design optimal bank clean-up policies.

We analyze the recent—and rather dramatic—series of bank closures undertaken by the Central Bank of Russia (CBR), which began in 2013. Its intent was to clean up the banking system by closing banks engaged in fraudulent activities (see historical and institutional details in Section 2). This new regime of intensified fraud intolerance followed a period of widespread regulatory forbearance from 2006 to 2013. Over the seven years between 2013 and early 2020—which were characterized by primarily calm economic times—the CBR effectively revoked around two-thirds of all banking licenses in the country. As a result, almost 650 banks were briskly closed when fraud was detected in their operations.

Three characteristics of the policy make it particularly informative. First, the policy began unexpectedly following a prolonged period of regulatory forbearance, which resulted in a large fraction of the banking system being contaminated with fraudulent banks. Second, the active phase of the policy continued for over five years, which allows for the possibility of new matches between firms and not-yet-detected fraudulent banks following the closure of the firms' prior sin bank. Finally, the bulk of the policy was enacted during a period of mostly normal economic times, which provides a clean setting for identifying the real effects of the policy.[1]

We employ loan-level data provided by the Bureau of Credit History (BCH) from 2008 until 2018, and the CBR's credit register, which is available to us from 2017 onward. The former data contain a monthly firm-bank match and the number of days during which a firm was delinquent in its payment of interest and/or principal of a loan. Hereinafter, we refer to this indicator as the *days of NPLs* (Non-Performing Loans), for simplicity. The latter data are unique in their coverage and comprehensiveness and were made accessible to independent academic research for the first time in this study. We merge these data with the balance sheet characteristics of firms, taken from the SPARK-Interfax database, and of banks, as gleaned from the CBR website. We also manually collect data on all bank owners and directors during the last decade from a nationwide banking media source. We employ this information to assess whether firms, following the closure of their sin bank, match with a new bank that has the same or different owners as the closed bank.

We begin our empirical analysis by exploring the determinants of firms' matching with new banks following their prior banks' closures. Many such closures were motivated by the detection of bank fraud, and we apply a duration model to analyze if the closure of such sin banks results

[1]The policy was launched in mid-2013—six months before the Russian economy entered another (local) recession and was hit by Western economic sanctions (Ahn and Ludema, 2020). The recession was relatively mild, peaking at–3.1% of GDP growth by 2015Q2 (for comparison, during the world economic crisis of 2007-2009, the Russian economy declined by 11.2% at its peak in 2009Q2). The effect of the sanctions was muted by the preceding largely negative oil price shock in 2014 and because the targeted (state-owned or controlled) banks were largely supported by the government, which allowed them to simply reshuffle credit flows from firms to households (Mamonov et al., 2021).

in firms of different quality engaging with banks of different standing. We proxy the quality of the firms with two variables: (i) whether the firms have negative profits (firm-level); or (ii) the number of days of NPLs firms had in closed banks (firm-bank level). We find that the lower the quality of loans the firms had in the closed banks, the more likely it is that those firms again matched with (not-yet-detected) sin banks and the less likely that the firms end up at "saint" banks (all other peers survived till the end of the sin bank closure policy). The firms' profitability always has a positive effect on matching.

We also show that the average time to match with another sin bank equals 19 months, while the time to match with a saint bank takes much longer, at 42 months. Our duration regression analysis also shows that compared to a firm with 0 days of NPLs, a firm with 90 days of NPLs is 35% more likely to match with another sin bank and 16% less likely to join a saint bank.

We then investigate several channels through which firm-bank matching may work. First, with our unique data on bank owners and directors, we find that among the 956 banks present after 2010, as many as 238 banks have interlocks with other banks through their bank holding company and/or through owners and/or directors. Following sin bank closure, 50 to 75% of the bad firms again match with a sin bank owned by the *same* owners. It takes only a year and a half to establish such matches. In contrast, establishing a new firm–saint bank match takes about three years.[2] Excluding banks with common ownership, we find that following sin bank closure, bad firms are *no more* likely to match with another (not-yet-detected) sin bank. In most instances, good firms match with a new saint bank, regardless of whether the new bank shares common owners and/or directors with the firms' closed bank.

Second, apart from common ownership, we hypothesize that not all sin bank closures are equally predictable by economic agents. Some may be more *predictable* than others, based on publicly observable data reported in the banks' balance sheets. If detection of bank fraud is predictable from its balance sheet we conjecture that the related bad firms will experience difficulties engaging a new bank, even if it is a sin bank. To assess this effect of *surprising* bank closures on firm-bank matching, we follow a two-stage procedure. In the first stage, we run a loop of logit regression models using a six-month rolling window to predict bank fraud

[2] After a sin bank is closed, its firms continue repaying loans to a receiver (CBR or the Deposit Insurance Agency) until the loans either mature or are sold to other entities (financial or non-financial). Firm-level data reveals that the treated firms with a single bank-firm relationship raise funding from other (non-banking) sources, e.g., through trade credit, before matching with a new bank.

detection and flexibly capture the regulator's learning about misreporting approaches employed by fraudulent banks. We sort the closed sin banks into two categories: *surprising* closures contain those with the predicted probability of fraud detection being below the unconditional threshold, and *expected* closures consist of those with the predicted probability being above the same threshold. In the second stage, we re-run the duration model for the two subsamples of firms: those that experienced surprising bank closures and those whose lenders' fraud detection was expected. Our results clearly show that new banks pay attention to where the firms come from: firms whose prior banks were predictably fraudulent do not match easily with new banks, and the sorting of bad firms to new (not-yet-detected) sin banks only works when closures of the bad firms' prior sin banks were surprising.

Third, we show that the concentration of regional credit markets matters for the matching of bad firms and saint banks. The higher the market concentration, the more likely a saint bank operating in this market will engage a bad firm coming from a closed sin bank. This result is consistent with the information acquisition hypothesis in Petersen and Rajan (1995), who argue that banks in more concentrated markets are more willing to finance opaque firms because future retention of the firm is more likely and therefore intertemporal subsidization is possible.

To confirm the validity of our estimates, we perform a placebo test to check whether firms switch from about-to-fail banks in advance. Importantly, our results show that bad firms do not increase their loan delinquencies, nor do they switch in advance from their current lenders.[3]

We proceed to a difference-in-differences analysis of firm performance conditional on sin bank closure. We examine whether the closure of sin banks results in deterioration of firm performance, which could be due to the destruction of the bank-firm match, or whether it leads to improvement of firm performance, which may happen due to the break-up of the lock-in effect (Liaudinskas and Grigaite, 2021). Our estimation results show that the policy had a *cleansing* effect (Gropp et al., 2022) on the performance of good firms that experienced sin bank closures: firms' employment and total size increase, total revenues improve, default rates decrease. We find the opposite for bad firms after sin bank closures. Using credit register data on loan interest rates, we show that a potential explanation involves *credit risk underpricing*

[3] In general, the latter result is consistent with the literature highlighting a firm's cost of switching from one bank to another (Ioannidou and Ongena, 2010; Bonfim et al., 2020; Liaudinskas and Grigaite, 2021).

by sin banks, especially in the case of bad firms: bad firms enjoy a lower rate at a sin bank than they would at a saint bank. When the sin bank is closed, bad firms lose their "subsidized" loans, which in combination with the lack of opportunities and incentives to improve further deteriorates the state of bad firms.

Our paper contributes to several strands of the literature. First, to the literature that examines the effects of bank clean-up policies (Acharya et al., 2018; Cortés et al., 2020; Chopra et al., 2020; Diamond and Rajan, 2011; Philippon and Schnabl, 2013). In advanced economies, clean-up policies often take the form of a combination of capital infusions (Calomiris and Khan, 2015), stress testing (Acharya et al., 2018), and/or asset quality reviews. Clean-up policies often take place as a response to a crisis.[4] To the best of our knowledge, our paper is the first one to analyze the real effects of a clean-up policy that takes the form of many sin bank closures. This is of particular interest to emerging economies, which are more likely to suffer from widespread malpractice in their banking systems.

Second, our paper contributes to the literature on the real effects of bank distress on firms (Chodorow-Reich, 2014; Gropp et al., 2018; Degryse et al., 2019a; Greenstone et al., 2020). A recent study by Bonfim et al. (2020) shows, for example, that if firms purposely switch banks, unconditional on bank closure, they likely receive a lower interest rate on loan, i.e., a discount to the market price. However, if firms are forced to switch due to their current bank's decision to close the nearest-by branch, the firms receive no discount and pay the same interest as before. A study by Liaudinskas and Grigaite (2021) further documents that firms that had relationships with distressed banks that eventually failed were charged a higher loan rate than the competitive market price prior to the banks' failure (hence possibly locked-in by these banks). After the banks' failure, the firms generally benefit by obtaining a lower loan rate from a new bank. Yet, despite the impact of a branch or bank closure on loan rates, work by Greenstone et al. (2020) finds no significant impact of bank switching itself (which has been shown to involve costs) on the firms' employment, during crises or normal times. Our analysis shows that following the closure of a fraudulent sin bank, bad (good) firms are more likely to end up in a match with a sin (saint) bank, and that the performance of a bad (good firm) worsens (improves).

Third, our paper contributes to the literature on regulatory forbearance (Acharya and Yorul-

[4] A notable exception is the Indian Asset Quality Review program analyzed in Chopra et al. (2020).

mazer, 2007; Brown and Dinç, 2011; Morrison and White, 2013; Agarwal et al., 2014; Kang et al., 2014; Gropp et al., 2022). The literature usually rationalizes the presence of regulatory myopia in closing distressed banks by the Too-Many-To-Fail concerns (Acharya and Yorulmazer, 2007; Brown and Dinç, 2011), reputational contagion (Morrison and White, 2013), competition between regulators at different levels (Agarwal et al., 2014), political pressure, and/or avoidance of damage to the local economy (Kang et al., 2014). Our results show that, through a well-designed closure policy (pre-emptive and exogenous with respect to bank and firm expectations), regulators can overcome reputational risk and the risk of declining economic activity when closing distressed banks, thus exhibiting a complete reversal of regulatory forbearance.

Fourth, we contribute to the literature on relationship lending (Degryse and Ongena, 2005; Petersen and Rajan, 1995; Bolton et al., 2016; Degryse et al., 2019a; Schäfer, 2019). We show that a relationship can be caused by common ownership: following bank closures, firms can often establish new relationships with banks owned/governed by the same persons/entities. We show that this effect weakens as the concentration of local credit markets rises.

The rest of the paper is structured as follows. Section 2 describes the policy experiment undertaken by CBR in mid-2013. Section 3 introduces the loan-level, firm- and bank-level data. In Section 4, we perform our duration analysis to investigate how bad and good firms switch to new sin or saint banks. In Section 5, we explore the channels of firm-bank matching. In Section 6, we present the difference-in-differences estimation of the real effects of sin bank closure on firm performance. Section 7 concludes.

2. REGULATORY FORBEARANCE AND BANK CLEAN-UP POLICY IN RUSSIA

Following the collapse of the USSR in 1991, the centrally-planned Russian economy began to transition to a market economy. Russia witnessed rapid growth in the number of privately-owned banks.[5]

During the "dashing" 1990s, the number of banks expanded to nearly 2,500. These were mainly very small credit institutions, short-lived, created to finance non-financial businesses of their owners ('pocket' banks) at lower interest rates than the market would otherwise offer,

[5] During the Soviet time the banking system comprised the "Big-4" state banks. These are still operational, and even 30 years after the collapse of the USSR, they dominate the banking landscape of Russia, with a share of more than 50%.

which was especially important during hyperinflation (Svejnar, 2002). Many of these banks were involved either in outright criminal activities or employed questionable practices (Degryse et al., 2019b).

With the start of the new millennium, the number of operating banks shrank by half; nevertheless, many were still pursuing illegal or questionable practices. In 2006, the CBR attempted a clean-up of the banking system, which resulted in the closure of two large banks involved in illegal activities. However, the clean-up policy came to an effective halt with the assassination of the Deputy Head of the CBR, Andrey Kozlov, the key figure behind the clean-up policy. The so-called "Kozlov affair" shocked the banking community in Russia and led to an extreme form of regulatory forbearance: bank closures became rare and took place primarily when the owners of failed banks simply had no interest to continuing, irrespective of whether their business was fully legal or not.[6]

Until the global financial crisis of 2007–2009, the Russian banking system had been expanding at a two-digit growth a year per year, mainly due to expanding corporate and retail lending, thus satisfying a large demand for loans.[7] The financial crisis exposed serious inefficiencies in the Russian banking system and necessitated large-scale government interventions to provide support to the largest banks. The number of operating banks continued to decline after the crisis, to around 1,100 banks by the beginning of 2013. Overall, the regulatory stigma over auditing and closing fraudulent banks following the assassination of Andrey Kozlov remained, and the period between 2006-2013 was characterized by a large degree of regulatory forbearance.

This forbearance effectively ended in 2013 with the appointment of a new head of the Central Bank.[8] Though the intention to conduct an active clean-up of the banking system was not explicitly mentioned in the inauguration speech of the new head of the Bank, in a sequence of consequent interviews, the new head stressed her intention to tighten regulatory oversight over illegal and questionable banking practices.[9]

[6] See the history of the process at The Guardian's article: https://www.theguardian.com/business/2006/sep/14/russia.internationalnews.

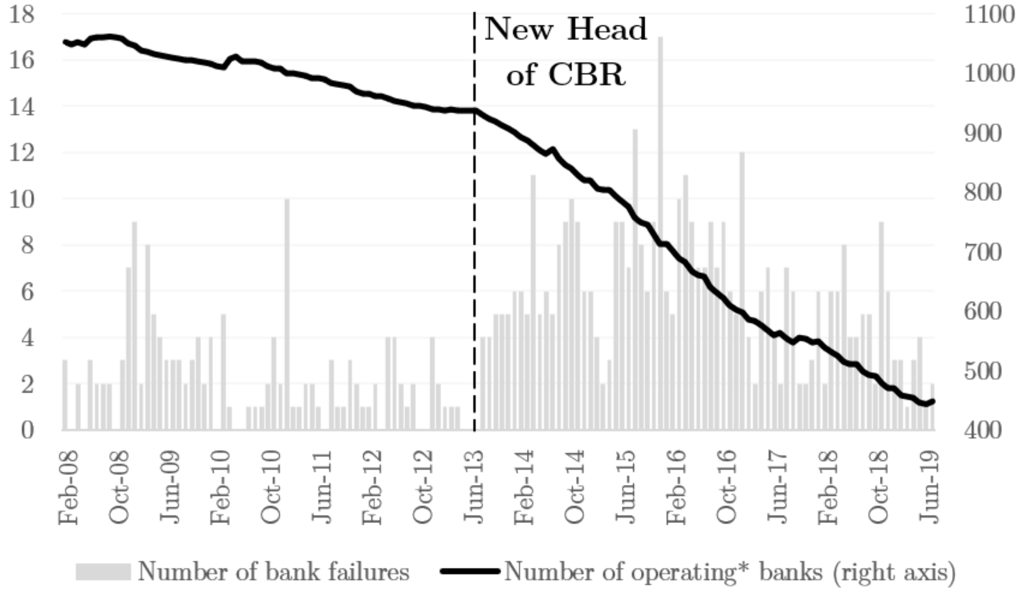
[7] For example, commercial loans grew up by nearly 70% in 2007, on the eve of the crisis in Russia.

[8] The change of the head of the Bank was announced rather unexpectedly: Elvira Nabiullina, the head of the Ministry of Economic Development, was to replace the head of the Bank, Sergey Ignatiev, who had held the post for the previous 13 years.

[9] In her inauguration speech, the new head of the CBR mainly stressed that the primary aims of the Bank would include switching from a fixed to a flexible exchange rate regulation and establishing an inflation targeting regime, in which the key instrument of monetary policy would be the regulated interest rate. The main purpose of the new policy, as the new head announced, was in curbing double-digit inflation in the country to the target of 4%. There was no apparent discontinuity over the policy following the appointment of the new head: for

However, it soon became clear that the CBR had rather rapidly swung from its regulatory forbearance regime towards a strict intolerance of fraud. Overall, during the period of 2013–2020, the number of operating banks in Russia had declined from around 1,000 to about 350, due to the tightened policy (Figure 1). The average annual frequency of fraud-induced license revocation rose from 29 (on average during 2008–2013) to nearly 70 (on average during 2013–2020). The dramatic fall in the number of operating banks is nearly linear, irrespective of the changing phases of the business cycle during that time.[10] In February 2018, the CBR officially announced that the active phase of the cleansing policy was over, given the large number of fraudulent banks discovered and closed.

Figure 1. Bank Closures and the New Head of CBR
Note: This figure depicts the time series of monthly bank closures (the left y-axis) and the monthly number of operating banks (the right y-axis) during February 2008 and June 2019. The new head of the Central Bank of Russia (CBR) was appointed in Jun 2013.



The geography of the cleansing policy is summarized in Figure 2. The policy was not limited to Moscow and Saint-Petersburg—where more than 75% of the banking system in terms of total asset size is concentrated—but in fact affected every region up to the Far East, with the largest number of license revocations taking place in the West and in the South, near the Black Sea. In almost every case, forced license revocations were associated with hidden negative capital revealed during on-site inspections of the banks, ranging between 10% and 50% of affected banks' total liabilities, throughout all of Russia.[11] As can be inferred from Figure 3, the bank-

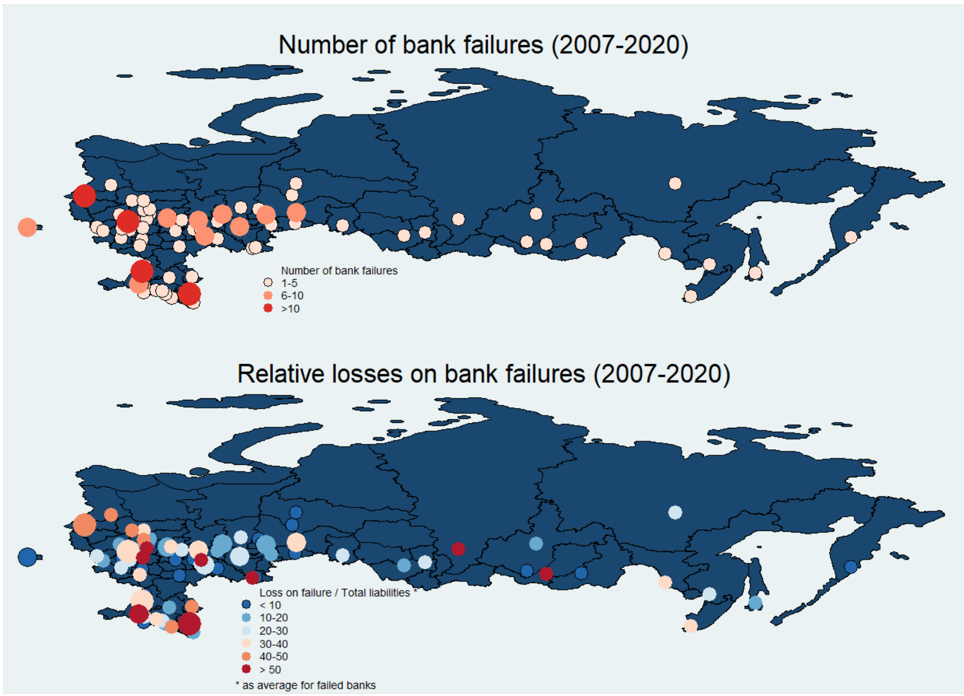
example, the previous head of the bank took up the post of the new head's adviser.

[10]The Russian economy experienced a local recession during 2014-2015 and subsequent recovery in 2016–2019.

[11]By negative capital, we mean negative owners' equity—that is, when the total value of a bank's assets is

level data shows that during the active phase of the policy in 2013–2018, operating banks: (a) created additional loan loss reserves, (b) disclosed more NPLs in their loan portfolios, (c) reduced the stock of (possibly opaque) loans to firms, and (d) slowed down new loan issuance, compared to before the policy, and irrespective of the business cycle phase. Overall, despite closing 2/3rds of all operating banks, the policy did *not* lead to a shrinking of the financial system. According to the World Bank statistics, the ratio of domestic private credit to GDP increased from 81% in 2012 to 99% in 2020, i.e., the banking sector was rising rapidly during the years of the CBR's tight policy.[12]

Figure 2. Geography of bank fraud and bank closures



3. DATA

Our bank-firm level data come primarily from three sources. First, the annual frequency firm-level data covering the period from 2007 to 2020 come from financial statements provided in SPARK database.[13] Second, the monthly (balance sheets items) and quarterly (P&L account) frequency bank-level data come from the CBR's reporting forms 101 and 102, respectively, available from 2004 to 2021.[14] Third, to identify the bank-firm lending relationships, we employ

less than the sum total of its liabilities.

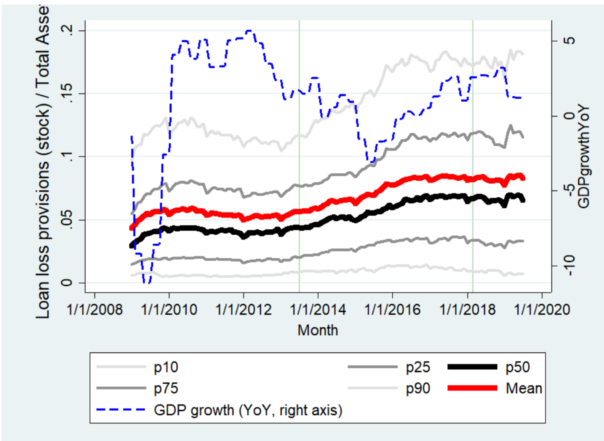
[12] See https://data.worldbank.org/indicator/FD.AST.PRVT.GD.ZS.

[13] https://spark-interfax.ru/.

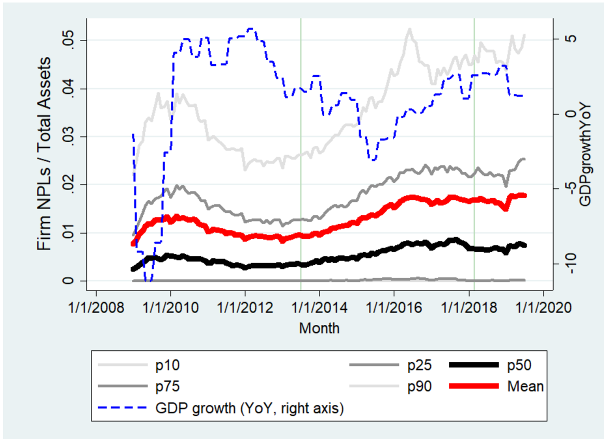
[14] https://www.cbr.ru/banking_sector/otchetnost-kreditnykh-organizaciy/.

Figure 3. Time evolution of selected bank variables before and during the active phase of the tight regulation policy (Jul.2013–Feb.2018)

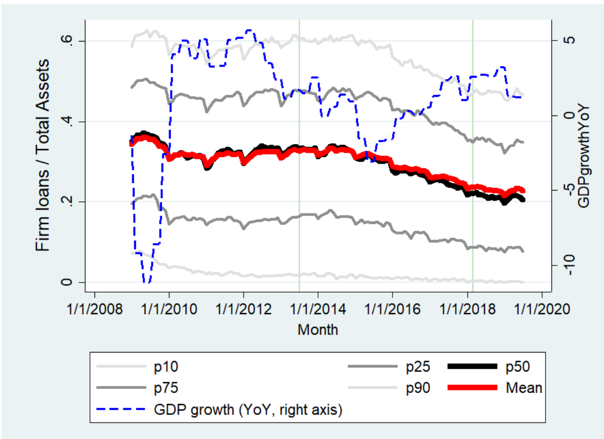
Note: The figure depicts the time evolution of selected bank characteristics at the bank-month level before, during, and after the active phase of the tight regulatory policy against the background of the annual GDP growth rates in Russia. The active phase of the policy is marked with two vertical green lines.



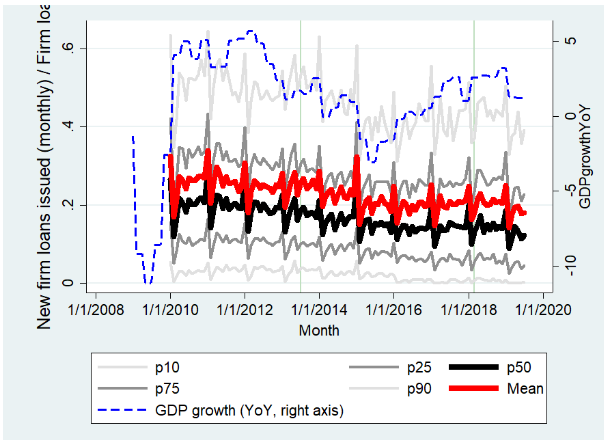
(a) Loan loss reserves



(b) NPLs of firms



(c) Loans to firms



(d) New loans issued

monthly data from two Russian credit registries. For the period from July 2013 to December 2017, we use the Credit History Bureaus (CHB), which only provides data on the number of days during which the loans are overdue, the *days of NPLs*, while for the period from January 2018 to October 2020, we employ data from the credit registry of the CBR (reporting form No. 0409303).

3.1 Credit History Bureau and Credit Registry Data

The Credit History Bureaus database (the CHB hereafter) is compiled from three credit history bureaus: the United Credit Bureau, the National Bureau of Credit Histories, and the

Equifax Credit History Bureau. These three credit history bureaus are the largest of 14 bureaus registered with the State Register of Credit History Bureaus maintained by the CBR (https://www.cbr.ru/ckki/restr/). For each bank and each corporate borrower, the CHB contains information on the maximum number of days loan payment is overdue at the reporting date (the *days of NPLs*, for simplicity). That is, if a firm has multiple loans at a bank, the CHB provides the maximum number of days of payment overdue across these multiple loans (it is possible that only one of several loans is delinquent).

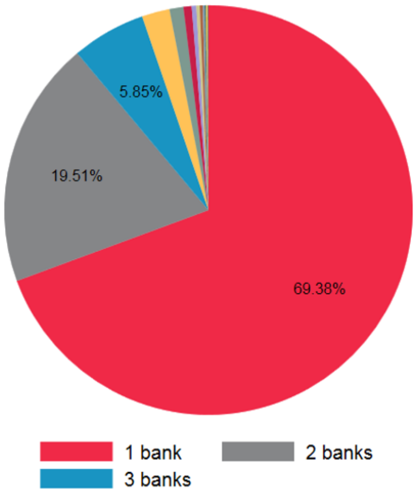
The days of NPLs indicator is a categorical variable denoting the time intervals of overdue dates. For example, days overdue is equal to 0 if there are no delayed payments, 30 for all delays in payments from 1 to 30 days, 60 for delays from 31 to 60 days, and so on. Loans with days overdue equal to 150 or 200 routinely include loans that were labeled as "hopeless," paid by collateral, contested in courts, or written off.

The CHB covers the period from 2007 to 2017. We use the CHB from July 2013 to 2017 to identify bank-firm relationships during the active phase of the cleansing policy. To identify the firm-bank relationships starting from 2017, we employ the credit registry database (Form 0409303). This database contains detailed information about credit: currency and amount of loans, lending rates, maturity, collateral attached, borrower-lender affiliation, and the amounts of debt repayment including interest payments and the amortization of the principal amount of debt. Here, we use the days of NPLs indicator.

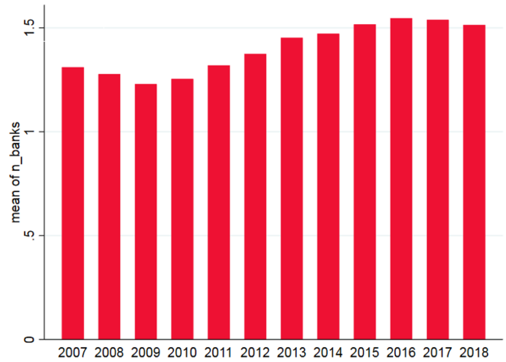
Our database (CHB merged with credit registry) of matched bank-firm relationships initially consists of 655,300 firms and 906 banks at the start of the sample in July 2013 and covers almost 90% of Russian banks by net assets. More than 70% of firms in the CHB data are micro-firms (with fewer than 15 employees), another 20-25% are SMEs, while the rest are medium and large firms.

The majority of Russian firms obtain loans from just one bank. 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 4). 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).

Figure 4. Bank–firm relationships



(a) Distribution of bank-firm relationships (as of 2017)



(b) Time evolution of the mean number of bank-firm relationships, by year

3.2 Bank-Level Data

We merge the bank-level data from the banks' balance sheets and P&L accounts with the firm-bank relationships database (the CHB and credit registry). The bank-Level data is at the monthly frequency for balance sheet items and at the quarterly frequency for the P&L account. The data come from the CBR forms 101 and 102 and cover the period from 2004 to 2021.

As discussed earlier, around 650 banks were shut down by the regulator during the active phase of the cleansing policy (July 2013–February 2018), of which 85% were due to fraud revealed during the audit. We refer to those banks that had their licenses revoked due to fraud as sin banks, while those that were permitted to continue their activities we dub saint banks.

3.3 Firm-Level Data

The firm-level data includes information from firms' financial statements extracted from the SPARK database, which is provided by the Interfax Group. Matching the SPARK database with the firm-bank relationships database (CHB and credit registry) covers about 60% of the total number of firms operating in the Russian economy. For a detailed list of variables we use from firms' financial statements, refer to Table A.I.

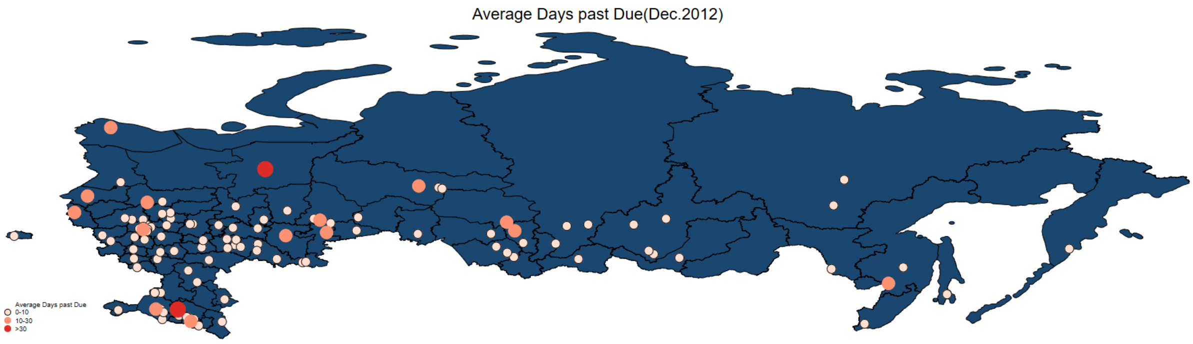
We refer to a firm as a "bad" firm if it suffered losses during at least the prior two years (three and four years for robustness). In other cases, we refer to a firm as a "good" firm. In addition, we proxy for the quality of firm by the days of NPLs variable from the CHB database.

3.4 Bank-Firm Relationships: Descriptive Statistics

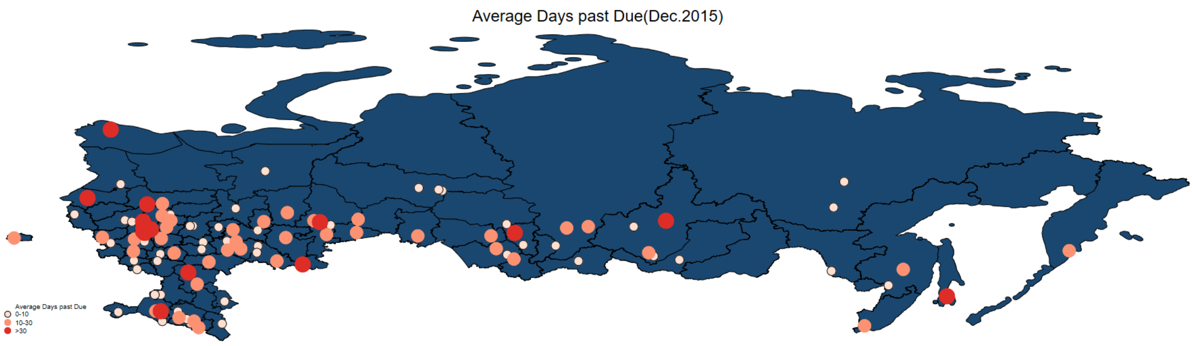
We focus on the subset of firms that were borrowing from sin banks and, thus, experienced bank shutdowns during the cleansing period. In our sample, 13,373 firms had relationships with at least one of the sin banks detected and closed by the CBR. Firm-level data are not available for 6,062 of these firms. After we trim our data for outliers (1 and 99 percentiles), we lose 80 more firms. Adjusting for a one-month lag of all regressors in our analysis, our effective sample consists of 262.6 thousand observations with 6,267 firms and 645 banks. If we focus on the case in which a firm has relationships with more than one bank, our sample includes 287.1 thousand observations with 6,061 firms.

Regarding the geography of firm-bank relationships, our final dataset is representative, covering the whole territory of Russia, with the densest frequency of relationships observed in the west, central, and south regions of the country (Figure 5).

Figure 5. Geographical variation in the number of firm-bank relationships



(a) Before the regulatory shock (as of December 2012)



(b) After the regulatory shock (as of December 2015)

We present the descriptive statistics at the firm-bank-month and firm-year levels in Table 1. We consider three groups of switching firms: firms that switch to a saint bank, firms that switch to a sin bank, and firms that never switch (i.e., are not recorded in the credit register anymore) following their prior sin bank closures. Of 6,267 firms in our sample, the overwhelming majority (85%) are the never-switchers.[15] Those firms that manage to switch to a new bank (15%) mostly establish a connection with a saint bank (11% or 715 firms). The rest (3.2%) borrow from a new sin bank, which is not-yet-detected by the CBR. Firms that switch to a saint bank are generally in better financial shape, with an average ROA of 5%, smaller leverage, and higher liquidity ratios.

Table 1. Descriptive statistics for the firms matching with either *sin* or *saint* banks following closures of their prior banks

	Mean	Median	SD	Min	Max
Panel 1: Firms matching with new *saint* banks:					
Match with saint vs never match	0.25	0.00	0.43	0.00	1.00
Months in search	45.77	46.00	25.39	2.00	139.00
Days of NPLs in the closed sin bank	14.87	0.00	42.07	0.00	200.00
Whether had negative profit when the sin bank closed	0.05	0.00	0.23	0.00	1.00
Whether had a negative profit when matched with new 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
Liquid assets	0.17	0.19	0.70	–8.57	1.00
Return on assets	0.05	0.03	0.23	–2.37	0.91
Panel 2: Firms matching with new *sin* banks:					
Match with sin vs never match	0.06	0.00	0.23	0.00	1.00
Months in search	17.86	13.00	14.34	1.00	73.00
Days of NPLs in the closed sin bank	15.73	0.00	41.75	0.00	200.00
Whether had negative profit when the sin bank closed	0.02	0.00	0.13	0.00	1.00
Whether had a negative profit when matched with new 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
Liquid assets	0.06	0.12	0.90	–9.52	1.00
Return on assets	–0.02	0.00	0.29	–2.73	0.90
Panel 3: Firms that *never* match with new banks:					
Days of NPLs in the closed sin bank	14.19	0.00	39.52	0.00	200.00
Whether had negative profit when the sin bank closed	0.05	0.00	0.21	0.00	1.00
Whether had a negative profit when matched with new bank	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
Liquid assets	0.03	0.14	1.01	–11.93	1.00
Return on assets	0.00	0.01	0.27	–3.14	0.91

Though we observe that firms matching with new saint banks reported fewer days of NPLs in the prior sin banks than firms matching with new sin banks, the difference between the two is not large. This may indicate that both good and bad firms match with either of the two types of banks. However, we do observe that matching with new saint banks takes much longer

[15]These firms generally rely on either their own funds, borrowings from other non-financial firms inside Russia, or from foreign banks abroad. We do not have detailed data on the breakdown of the firms' borrowing outside the Russian credit registry.

(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 saint bank. Another characteristic that delivers substantial differences across the three types of matching firms is their overall size (in terms of total assets). In contrast to an expectation that larger firms may find it easier to borrow from new saint banks, we observe a different picture in our data. The average size of a firm that switches to a sin bank is almost three times larger than the average size of a firm that switches to a saint bank (85 vs. 29 mln rubles), and almost two times larger than the average size of those that never switch (85 vs. 44 mln rubles). Thus, we can describe a firm that switches to a sin bank as a large financially constrained firm (higher leverage and lower liquidity than for an average firm that switches to a saint bank).

Table 2 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%) are for firms from the North Caucasian FD. The majority of observations (from 78 to 94%) contain no information about delays in credit payments. The only notable exception is the North Caucasian FD, where the share of "no delays" is less than 70%.

Table 2. Regional structure of observations, by Federal Districts (FD)

	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 days of NPLs 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

The regional dimension of our data allows us to look into the spatial concentration of the Russian regional credit markets by calculating the Herfindahl-Hirschman index (HHI). We construct the index as the sum of squared shares of newly issued loans for firms in the region r

by bank b in the total volume of new loans in the region r for each month t. We report means and standard deviations of HHI across federal districts in the lower panel of Table 2.

4. FIRM-BANK MATCHING FOLLOWING SIN BANK CLOSURES

4.1 Baseline Results

We begin our analysis by examining the determinants of a firm's matching with a new bank following the closure of the firm's prior sin bank, and conditional upon the firm's survival to the moment in time when the new match is established.[16] The duration regression approach ("survival" model) is a natural methodological framework for this analysis, because it takes into account the duration of the spell, i.e., the time it takes the firm to match with a new bank.[17] We focus on *single* firm-sin bank relationships, i.e., when a firm obtained loans from only one bank, which, at some point in time, is closed for fraud.[18] Appealing to the title of our paper, we are interested in *where* the firm goes to after the closure of its prior sin bank: to another (not-yet-detected) sin bank, or to a saint bank. The rationale for focusing on single firm-bank relationships at the moment of sin bank closure is that the CBR's tight regulation policy is likely to affect single firm-bank pairs much more than firms with multiple-bank relationships, in which the firms may have more opportunities to substitute the flow of borrowed funds across existing lenders.

Among the determinants of new firm-bank matching, we focus on the *quality* of firms. One may expect that when a sin bank is closed, good firms have more chances to find new bank matches than bad firms. We start by employing a *single-failure duration analysis*, in which the duration of the spell for a firm f begins with the closure of its prior sin bank b at time t^*_f (t^*, for simplicity) and ends with the firm being matched with a new bank at time $t^* + k$, where k is the firm-specific duration of the spell (in the data mean $k = 35$ months). Following the standard terminology of duration analysis, we refer to the time $t^* + k$ event as a "failure." If $t^* + k$ is never observed in the sample—that is, if firm f never matches with a new bank—we treat the corresponding failure as right-censored, leaving all such firms in the sample. The instantaneous rate at which firms "exit," i.e., match with new banks conditional on survival to the current

[16]As discussed in Section 3, we define a sin bank as a bank that is closed due to fraud at some later point in time in our sample.

[17]"Survival" regressions have been previously adopted to study bank failures in, e.g., (Brown and Dinç, 2011).

[18]Recall from Section 3 that single firm-bank relationships cover 70% of the sample.

moment in time, is described by the following hazard function $\lambda(\cdot)$:

$$\lambda\left(t, \mathbf{X}_{f,t-1};\Theta\right) = \lambda_0\left(t\right)\cdot\exp\Big(\alpha + \alpha_{bc} + \alpha_r + \alpha_i + \text{Firm.Quality}_{f,t-1}\text{B} + \mathbf{C}_{f,t-1}\Gamma\Big), \tag{1}$$

where $\text{Firm.Quality}_{f,t-1}$ is firm f quality proxy at time $t-1$, which is measured by either (i) the log of days of NPLs accumulated in the prior sin bank before its closure—that is, by $t^*_{f,b}$—or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b}+k$. $\mathbf{C}_{f,t}$ is a set of control variables including the firm's size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios (see definitions in Table A.I; all controls are taken with a one year lag to eliminate simultaneity). $\alpha_{bc}, \alpha_r, \alpha_i$ are bank-closure event fixed effects, fixed effects of the region in which the firm operates, and industry fixed effects. Θ is the set of parameters to be estimated $(\alpha, \alpha_b c, \alpha_r, \alpha_i, B, \Gamma)$. $\lambda_0\left(t\right)$ is the baseline hazard function. We use the exponential distribution function to specify the baseline hazard: $\lambda_0\left(t\right) = \lambda > 0$.[19]

Table 3 reports the estimation results of equation (1). In columns (1)–(2) the firm quality measure is proxied by the log of days of NPLs the firm had accumulated in the closed sin bank prior to its closure at t^*, log $DNPL_{f,t^*}$. Here, the sample consists of 6,249 firms, 413 bank closures, and 915 "failures," i.e., new firm-bank matches. We obtain negative but largely insignificant estimates on the log $DNPL_{f,t^*}$ variable, moreover, the estimated coefficient is close to zero. Next, in columns (3)–(4) we replace this granular measure with the binary variable of whether a firm has negative profits, $Profit_{f,t^*} < 0$, at the bank closure date t^*. Due to limitations with firm-level data on profits, the sample slightly reduces. Similar to the previous case, we observe negative and largely insignificant estimates on the $Profit_{f,t^*} < 0$ variable.

Finally, in columns (5)–(6) we add an indicator variable of whether a firm had negative profits at the time it matched with a new bank, $Profit_{f,t^*+k} < 0$, to the specification considered in the two previous columns, because although a firm might suffer losses at t^* when its sin bank was closed, the firm might also have improved by the time it matched with a new bank at t^*+k. Indeed, while the estimates on the $Profit_{f,t^*} < 0$ variable are still insignificant, we find negative and highly significant estimates on the $Profit_{f,t^*+k} < 0$ variable. Economically,

[19]Under the exponential distribution, the hazard does not change as time passes (the memoryless property of the exponential distribution function). We test the constant duration dependence using the Weibull distribution.

Table 3. Survival regression results: firm-bank match based on firm quality

Note: The table reports estimates of new firm-bank matching following the firms' f prior sin banks closure, as implied by equation (1). Dependent variable $\lambda(t, \mathbf{X}_{f,t-1}; \Theta)$ is an instantaneous rate at which firms "exit," i.e., match with new sin or saint banks, conditional on survival to the current month t. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure–that is, by $t^*_{f,b}$–or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include firm size, as measured by the log of total assets and its square, leverage-to-total assets, and liquidity-to-total assets ratios. We perform the estimations for the period starting with the active phase of the tight regulation policy, i.e., from 2013M7 till 2020M10. Coefficients are reported instead of subhazard ratios. The constant term is included but not reported to save space.

Firm.Quality$_{f,t}$:	*Days of NPLs at t^**		*Negative profit at t^**		*Negative profit at t^* and $t^* + k$*	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Firm quality:						
log DNPL$_{f,t^*}$	–0.009	–0.024				
	(0.024)	(0.031)				
Profit$_{f,t^*} < 0$			–0.117	–0.240	0.046	–0.066
			(0.212)	(0.253)	(0.213)	(0.252)
Profit$_{f,t^*+k} < 0$					–0.391***	–0.403***
					(0.129)	(0.136)
Panel 2: Other controls:						
Firm size$_{f,t-1}$	1.600***	1.590***	2.053***	2.062***	2.071***	2.096***
	(0.261)	(0.290)	(0.304)	(0.335)	(0.306)	(0.338)
Firm size$^2_{f,t-1}$	–0.043***	–0.042***	–0.055***	–0.056***	–0.056***	–0.057***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
Leverage$_{f,t-1}$	–0.271**	–0.342**	–0.479***	–0.597***	–0.482***	–0.607***
	(0.118)	(0.140)	(0.141)	(0.174)	(0.144)	(0.179)
Liquidity$_{f,t-1}$	–0.061	–0.088	–0.132	–0.142	–0.166	–0.188
	(0.105)	(0.123)	(0.121)	(0.143)	(0.124)	(0.147)
Bank closure event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs		Yes		Yes		Yes
N obs	262,648	262,648	182,197	182,197	182,120	182,120
N firm-bank new matches	915	915	705	705	705	705
N firms	6,249	6,249	4,280	4,280	4,277	4,277
log L	–4,015.3	–3,680.6	–3,096.5	–2,791.0	–3,091.4	–2,785.8

***, **, * 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.

the underlying effect is sizeable: as compared to a profitable (good) firm, a firm that still has losses after the closure of its prior sin bank (bad firm) is 33.2% less likely to match with a new bank.[20]

The regression results suggest an absence of an empirical relationship between the time t^* measures of firm quality and the chances to match with a new bank in the future at some random

[20]The effect is computed as $exp(-0.403 * 1) - exp(-0.403 * 0) = -0.332$.

time $t^* + k$. In other words, more severe loan payment delinquencies and low profitability when the firm's sin bank is closed do not predict whether the firm finds a new bank match in the future.

We further hypothesize that it may be important to distinguish cases in which the firm matches with a new sin bank—that has not yet been shut down—from those with a saint bank. We hypothesize that bad firms are more likely to be sorted to sin banks and good firms are more likely to match with saint banks. Because the CBR's cleansing policy stretched over five years, it gave firms that were separated from sin banks an opportunity to be matched again with another (not yet shut down) sin bank.

To test these hypotheses we slightly modify the duration regression we applied above. Specifically, we consider two hazard functions instead of one: $\lambda_1(\cdot)$ for the firm's decision to match with a new sin bank vis-a-vis never match and $\lambda_2(\cdot)$ for when the firm seeks to match with a new saint bank vis-a-vis never match:

$$\lambda_j\left(t, \mathbf{X}_{f,t-1}; \Theta\right) = \lambda_0\left(t\right) \cdot \exp\Big(\alpha_j + \alpha_{j,bc} + \alpha_{j,r} + \alpha_{j,i} + \text{Firm.Quality}_{f,t-1}\mathrm{B}_j + \mathbf{C}_{f,t-1}\Gamma_j\Big), \qquad (2)$$

where $j = 1$ stands for regression with sin bank matching and $j = 2$ for saint bank matching. Other notations, including sample size and time span, remain the same.

Table 4 reports the estimation results on the duration regressions with the sample split in equation (2). Columns (1)–(3) present the estimates from regressions of the matching with sin banks and columns (4)–(6) with saint banks, for different measures of firm quality. For the duration analysis of matching with sin banks, the sample consists of 6,069 firms and nearly 200 new sin matches, and the average duration of the spell changes from 35 months, which was true across all matches, to 18 months. For the matches with saint banks, the sample comprises 6,080 firms and 715 matches with new saint banks, and the average duration of the spell rises to 46 months. Note that the 200 new sin matches and 715 new saint matches constitute the 915 matches we considered above before splitting the sample.

Strikingly, our split estimates suggest that the insignificant effect of log $DNPL_{f,t^*}$ obtained above now turns *positive* and is highly significant in the regressions of matching with sin banks (column 1). Conversely, in the regressions of matching with saint banks, the respective estimate is negative and also highly significant (column 4). Jointly, these estimates support our

Table 4. Survival regression results: splitting the firm-bank matches

Note: The table reports estimates of new firm-bank matching following the firms' f prior sin banks closure, as implied by equation (2). Dependent variable $\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta)$ is an instantaneous rate at which firms "exit," i.e., match with new banks, sin ($j = 1$) or saint ($j = 2$) vis-a-vis never match, conditional on survival to the current month t. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure—that is, by $t^*_{f,b}$—or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include a firm's size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. The sample includes those firms that have a *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy, i.e., from 2013M7 to 2020M10. Coefficients instead of subhazard ratios are reported. The constant term is included but not reported to save space.

	Match with a sin bank			Match with a saint bank		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Firm quality:						
log DNPL$_{f,t^*}$	0.155***			–0.091**		
	(0.058)			(0.037)		
Profit$_{f,t^*} < 0$		–1.742*	–1.475*		0.041	0.204
		(0.908)	(0.895)		(0.247)	(0.248)
Profit$_{f,t^*+k} < 0$			–0.534*			–0.384**
			(0.297)			(0.151)
Panel 2: Other controls:						
Firm size$_{f,t-1}$	2.627***	2.229***	2.263***	1.422***	2.036***	2.069***
	(0.760)	(0.783)	(0.786)	(0.313)	(0.371)	(0.374)
Firm size$^2_{f,t-1}$	–0.069***	–0.061***	–0.061***	–0.038***	–0.055***	–0.056***
	(0.020)	(0.021)	(0.021)	(0.009)	(0.010)	(0.010)
Leverage$_{f,t-1}$	–0.275	–0.289	–0.292	–0.353**	–0.730***	–0.745***
	(0.222)	(0.265)	(0.262)	(0.165)	(0.188)	(0.192)
Liquidity$_{f,t-1}$	–0.151	–0.248	–0.303	–0.057	–0.094	–0.135
	(0.208)	(0.243)	(0.251)	(0.144)	(0.164)	(0.168)
Bank closure event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N obs	257,190	178,447	178,372	257,681	178,833	178,758
N firm-bank new matches	200	168	168	715	537	537
N firms	6,069	4,198	4,195	6,080	4,203	4,200
log L	–1,066.0	–853.7	–851.8	–2,921.0	–2,169.1	–2,165.4

***, **, * 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.

hypothesis on endogenous sorting of firms: conditional on sin bank closure, bad firms tend to match with another (not-yet-detected) sin banks, while good firms are more likely to establish relationships with saint banks. Economically, both estimates imply large effects: compared to a firm with 0 days of NPLs, a firm with 90 days of NPLs is 35.4% more likely to match with another sin bank and 16.2% less likely to join a saint bank in the future.[21]

[21] The effects are computed as (i) $exp(0.155{\cdot}90) - exp(0.155{\cdot}0) = 0.354$ and (ii) $exp(-0.091{\cdot}90) - exp(-0.091{\cdot}0) =$

Next, we replace the log $DNPL_{f,t^*}$ variable by $Profit_{f,t^*} < 0$ to check whether having negative profits also predicts the sorting of bad firms to sin banks and good firms to saint banks, as we find above. However, as can be inferred from columns (2) and (5) of Table 4, this is not the case. Indeed, in the regression of matching with sin banks, we obtain a negative, not positive, coefficient on the $Profit_{f,t^*} < 0$ variable, meaning that firms that had negative profits at the moment their sin bank closed are not more likely to establish a match with another sin banks in the future. Economically, the underlying effect is very large: a firm with negative profits at t^* has a 77.1% smaller chance to match with another sin bank. However, we treat this result with caution: the estimated coefficient itself is only marginally significant, and thus uncertainty is large, as opposed to the highly significant coefficient on the loan payment delinquencies variable obtained above.

In the regression of matching with saint banks, we obtain a near zero and insignificant coefficient on the $Profit_{f,t^*} < 0$ variable, reflecting that firms that were facing losses during the closure of their sin banks are *not* less likely to match with saint banks in the future. This estimate is also in stark contrast to what we obtained for the loan delinquencies variable above.

Finally, we consider whether a firm had negative profits not only at t^* when the firm's sin bank fails but at $t^* + k$ when the firm matches with another sin bank, column (3), or with a saint bank, column (6). As can be observed from the two columns, we obtain negative and significant estimates in both cases. The underlying effects imply that a firm with negative profit at the moment of establishing a new match is 41.4% less likely to join a new sin bank and 31.9% less likely to join a saint bank, as compared to a profitable firm.

4.2 Robustness Checks

One concern regarding splitting duration regressions is that we separately study matching with sin and with saint banks. To address this concern, we run a *multinomial regression model* in which we have all three options for a firm: never switch (0), match with a sin bank (1), and match with a saint bank (2). As Table B.I shows, the estimation results are qualitatively and even quantitatively very close to the baseline.[22]

Another concern is that we omit *macroeconomic and regional characteristics*, which both

−0.162.

[22]The estimates are performed with the multinomial logit model instead of a competing risks duration model. This is because of the issues with the convergence of the likelihood function.

might affect the CBR's intention to close problem banks.[23] We thus include GDP growth rates (moving averages across four quarters) to capture the turning points of the business cycle and concentration of regional credit markets, as measured by the Herfindahl-Hirschman Index (HHI) using the bank branch-level data, to control for the observed differences in banks' market power across Russia. As we show in Table C.I, neither of the two forces has an effect on our baseline results. This supports the view that the CBR conducted its tight policy exogenously, i.e., not because of the recession/sanctions and not because of the dramatically large concentration of regional credit markets that could have led to higher risk-taking by small banks.

Further, one could doubt that our baseline effects are valid only for firms that have single-bank relationships. We re-run our splitting duration regressions on the sample of firms that have *multiple bank relationships*, with at least one of them being a sin bank. Table D.I clearly indicates that there are no significant effects of the firm quality on the likelihood, and *direction*, of new bank matching. The estimates on the log $DNPL_{f,t^*}$ and $Profit_{f,t^*} < 0$ are insignificant in both regressions of matching with sin and saint banks. The only effect that remains is the one describing the negative relationship between a firm's losses after the firm's prior bank is closed, i.e., at $t^* + k$, and the chance to match with a new saint bank on the same date. Jointly, these results imply that firms behave *strategically*: if they establish multiple bank relationships, they may use sin banks to store the worst part of their debt and service the best parts in saint banks. When their sin banks are closed, the firms tend to substitute the lost credit at their other banks rather than searching for new lenders.

Finally, one could argue that not all days of NPLs are equally important, given the internationally applied 90-day threshold. Recall that the days of delinquencies in loan repayment reported for each firm-bank match at the Bureau of Credit History (BCH) varies from 0 to more than 200 days, thus covering qualitatively different cases. When choosing between two firms to establish a match, it is likely that new banks pay less attention to the cases when one firm had, say, 30 days and the other had 60 days—both are well below the threshold of 90 days. However, if one of the firms had, say, 120 days, not 30 or 60, then a saint bank may strongly prefer to reject the firm.

We begin with testing the 90 days threshold by substituting our initial variable log $DNPL_{f,t^*}$

[23] In 2014–2015, the Russian economy experienced a double shock: internal factors led the economy into yet another recession, and external forces, e.g., deterioration of the commodities terms of trade and Western economic sanctions (Ahn and Ludema, 2020), intensified the internal factors.

with a binary version in which it equals 1 if $DNPL_{f,t^*} \geq 90$ and 0 if else. We find that the estimated coefficient on the new binary variable is insignificant for matching with sin banks and remains negative and highly significant for matching with saint banks.

We then re-categorize the $DNPL_{f,t^*}$ variable on the following seven bins: $0 \leq DNPL_{f,b,t} < 30$ (bin 1, reference), $30 \leq DNPL_{f,b,t} < 60$ (bin 2),..., $DNPL_{f,b,t} \geq 180$ (bin 7). The estimation results appear in Table E.I. In column (1) where we analyze matching with new sin banks, the estimated coefficients on the categorical variables $30 \leq DNPL_{f,b,t} \leq 60$ (bin 2) and $60 \leq DNPL_{f,b,t} \leq 90$ (bin 3) are both positive and highly significant. The estimated coefficients for bins 4 and 5 are also positive but insignificant. Before categorizing, we were unable to see the striking estimated coefficient on $150 \leq DNPL_{f,b,t} \leq 180$ (bin 6) and $DNPL_{f,t^*} \geq 180$ (bin 7), which turns *negative* and also highly significant in the last case. Jointly, these results imply that *intensity really matters*: the effect of the days of NPLs on matching with new sin banks is positive for small and moderate magnitudes of loan delinquencies (below 90 days), but turns negative for very large delinquencies (above 150 days). Sin banks, despite being sin, are evidently unwilling to match with "hopeless" firms.

In column (2) with the results on matching with new saint banks, we obtain negative coefficients on mostly all categorical variables, with those for $30 \leq DNPL_{f,b,t} \leq 60$ (bin 2), $120 \leq DNPL_{f,b,t} \leq 150$ (bin 5), and $150 \leq DNPL_{f,b,t} \leq 180$ (bin 6) being significant. Therefore, saint banks really prefer to establish matches with firms that had virtually no bad debts in closed sin banks.

Regarding the other control variables at the firm level, our estimates indicate that all else being equal, size has a non-linear relationship with the likelihood of matching with both sin and saint banks, with mid-sized firms having the largest likelihoods.[24] We also find that more leveraged firms are less likely to find a new match, conditional on surviving to the moment, whereas liquidity seems to have no effect on the hazard rate.

Overall, our regression analysis has shown that firms with more days of NPLs accumulated when their sin bank is closed are *more* likely to match with another (not-yet-detected) sin

[24] This is consistent with the observation that small firms usually experience more problems obtaining credit, while large firms may either use their own sources of funds or substitute domestic credit with funds raised from international financial markets. Indeed, there is a large body of anecdotal evidence that during the 2010s largest Russian companies, mainly exporters of natural resources, reduced their demand for *domestic* loans and were actively using either international (at least before the Western sanctions in 2014) or local financial markets to place their debts. As is shown by Bruno and Shin (2017), borrowing from abroad is cheaper for large companies operating in EMEs than getting finance in domestic markets.

banks and are *less* likely to establish relationships with saint banks. This favors endogenous firm-bank matching that appears under a stretched-in-time regulation policy targeting sin banks detection. Turning from the granular level, i.e., loan-month, to a more aggregated level, i.e., firm-year, does not lead to the same result. Firms with negative annual profits, either at the moment of sin bank closure or the moment of matching with new banks, are always *less* likely to establish new relationships with banks, regardless of their sin or saint type.

5. CROSS-SECTIONAL VARIATION IN NEW FIRM-BANK RELATIONSHIPS

In this section, we examine how our baseline result on differential sorting of good and bad firms across sin and saint banks depends on common ownership between the old and new banks, how well anticipated the closures of sin banks are, and concentration of regional credit markets.

5.1 Common Bank Ownership

One potential explanation for our baseline results is that having experienced the closure of their sin banks, bad firms consequently matched with another (not-yet-detected) sin banks that have *the same* directors or owners as the closed sin banks. Several banks may constitute a bank holding group, or the same individuals may appear on the board of directors in different (formally unrelated) banks. We refer to this channel as *common bank ownership*, for simplicity.

To examine the efficacy of common bank ownership we re-estimate our duration regressions (2) on a subsample of firms that only match with those new banks that do not share common persons on the board of directors or owners with detected and closed sin banks. To construct such a subsample, we exploit the nation-wide banking media source banki.ru and manually collect data on the ownership structure of the banks that operated in the Russian banking system over the 2010s, which is publicly disclosed through this web-site. The data contains personal information on every member of the board of directors or owners of these banks, including name, surname, and the share in the capital owned.[25]

Overall, we find that among the 956 banks in our database, as many as 238 had overlapping ownership or control structures. In fact, more than half of all firms that had relationships with sin banks later matched with another (not-yet-detected) sin banks owned or controlled by *the*

[25] We disclose our *common ownership database* through our websites for further research.

same persons.

Table 5 presents estimation results of the duration regressions (2) on the reduced sample without common ownership of "old" (i.e., closed) and "new" (i.e., not-yet-detected) sin banks. Columns (1)-(3) summarize the results of matching with a new sin bank, while columns (4)-(6) present the results of matching with a new saint bank. As can be inferred from column 1 of Table 5, the estimated coefficient on the log $DNPL_{f,t^*}$ remains positive, as before, but the size of the coefficient drops by a factor of 2 and, more importantly, the estimate is no longer significant. This clearly indicates that the baseline result on the endogenous sorting of firm-bank matches is fueled by the common ownership phenomenon. It is remarkable that the estimated coefficient is still not negative, as one might expect. We think that this may reflect either inferior expertise in sin banks or the sin banks' exposure to adverse selection of borrowers, intentional or forced by the conduct of market rivals. Further, in columns (2) and (3), we find that the estimated coefficient on the $Profit_{f,t^*} < 0$ and $Profit_{f,t^*+k} < 0$ variables are also insignificant. By contrast, in columns (4)-(6) we show no qualitative differences with our baseline result; quantitatively, the estimates imply even stronger effects than in the respective part of the baseline result.

Overall, our estimation results highlight the importance of common ownership for matching between bad firms and (not-yet-detected) sin banks after the closure of the firms' prior sin banks. In fact, in the subsample without common ownership, our estimation no longer predicts that bad firms are more likely to end up in a new match with a (not-yet-detected) sin bank. In contrast, good firms are more likely to match with new saint banks regardless of whether there is common ownership between their old and new banks.

5.2 Surprising Bank Closures

With such a large number of sin bank closures, it is natural that not all of them were perceived as equally likely to happen: while some were more predictable, others were more surprising. The more predictable closures are indicative of more severe or, at least, more transparent bank fraud. Intuitively, following a relatively more anticipated sin bank closure, the firms must have had a harder time finding new matches, regardless of their perceived quality based on their credit history or profitability. Therefore, we examine how our baseline results are affected by

Table 5. Channels of endogenous firm-bank matching: Common bank group owners

Note: The table reports estimates of new firm-bank matching following the firms' f prior sin banks closure, as implied by equation (2) and conditional on the new bank not sharing owners or governors with the closed sin bank. Dependent variable $\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta)$ is an instantaneous rate at which firms "exit," i.e., match with new banks, sin ($j = 1$) or saint ($j = 2$) vis-a-vis never match, conditional on survival to the current month t. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure–that is, by $t^*_{f,b}$–or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include a firm's size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and its liquidity-to-total assets ratios. The sample includes those firms that have *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy, i.e., from 2013M7, and till 2020M10. Coefficients instead of subhazard ratios are reported. The constant term is included but not reported to save space.

	Switch to a sin bank w/out common owners			Switch to a saint bank w/out common owners		
	(1)	(2)	(3)	(4)	(5)	(6)
log DNPL$_{f,t^*}$	0.082			–0.125***		
	(0.082)			(0.046)		
Profit$_{f,t^*} < 0$		–0.886	–0.589		0.341	0.512
		(0.912)	(0.902)		(0.305)	(0.314)
Profit$_{f,t^*+k} < 0$			–0.483			–0.418**
			(0.384)			(0.202)
Other firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank closure event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N obs	107,220	76,235	76,160	107,434	76,371	76,296
N firm-bank new matches	116	99	99	361	274	274
N firms	2,757	1,965	1,962	2,764	1,969	1,966
log L	–590.8	–471.9	–470.9	–1,489.1	–1,134.7	–1,132.2

***, **, * 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.

how well specific bank closures could have been predicted.

To capture the effect of the degree of surprise regarding closures of sin banks on new firm-bank matching, we apply the following two-stage approach. First, we run a simple predictive logit regression of bank closures and sort all failed banks by their respective predicted probabilities into two groups: well-predicted closures and surprise closures. Second, we re-estimate our duration regression (2) separately for these two groups of closures.

The details in the first stage—that is, the estimation of the predictive model—are presented in Appendix F and in Table F.I. We define well-predicted closures as those with a predicted probability of closure above threshold $\bar{p}$, while surprise closures are those with a predicted probability of closure below the threshold $\bar{p}$. We set the threshold $\bar{p} = 0.5\%$, which is the mean of the predicted monthly probability of bank closure in the sample.[26] As a result of this sorting, we classify about 250 bank closures as surprises and about 150 ones as well predicted. In Figure 6, we plot the evolution of predicted probabilities of closure in time. The predicted probabilities are close to zero prior to implementation of the policy, and increase dramatically during the active phase of the policy (i.e., between 2013M7 and 2018M2).[27]

Figure 6. Time evolution of selected bank variables before and during the active phase of the tight regulation policy (Jul.2013–Feb.2018)

Note: The figure depicts the time evolution of the predicted probabilities of fraud detection at the bank-month level before, during, and after the active phase of the tight regulatory policy against the background of annual GDP growth rates in Russia. The active phase of the policy is marked with two vertical green lines.

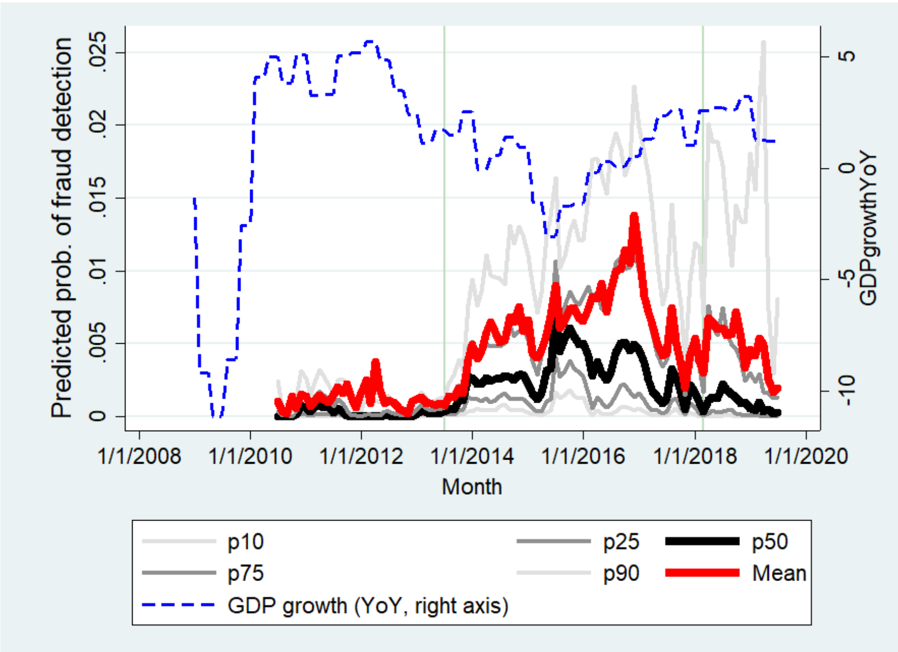


Table 6 presents the results of estimating the duration regression (2) separately for surprise closures in columns (1)-(2) and for well-predicted ones in columns (3)-(4). Panel 1 of Table 6 demonstrates that our baseline results are fully driven by the surprise bank closures. In the duration regressions of matching with new sin banks, the estimated coefficient on log $DNPL_{f,t^*}$ is positive and highly significant in the case of surprise closures (column 1) and is negative and insignificant in the case of well-predicted closures (column 3). Moreover, in the case of surprise closures, the magnitude of the effect rises by about 30% compared to the baseline

[26]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.

[27]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 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.

estimation results. Similarly, in the duration regressions of matching with saint banks, the estimated coefficient on the log $DNPL_{f,t^*}$ variable is negative and highly significant under the surprise condition (column 2), but is insignificant under the other condition (column 4). Again, the magnitude of the coefficient increases by about 30% compared to the baseline estimation results.

In Panel 2 of Table 6, we replace the log $DNPL_{f,t^*}$ with the firm's profitability as an alternative proxy of its quality variable—that is, with $Profit_{f,t^*} < 0$ and $Profit_{f,t^*+k} < 0$. The estimation results in Panel 2 are consistent with those in Panel 1. We obtain significant coefficients on the negative profits variables only in the case of the surprise closures—columns (1) and (2).

Overall, our results suggest that when the closure of a sin bank is more predictable, the quality of its firms measured by accounting information does not help to predict the sorting of new firm-bank matches. If we interpret higher closure predictability as evidence of more severe fraud, then one potential explanation behind this result is that the firm's past accounting information is viewed by banks as being less reliable if it was generated in a relationship with a more fraudulent bank.

5.3 Regional Credit Market Concentration

Next, we examine the effect of regional bank market concentration on our baseline results. The CBR's cleansing policy was associated with a rising market concentration, because many banks were closed. Following a sin-bank closure, firms have fewer opportunities to find a new bank match. Bad firms become increasingly more restricted in their ability to match with *not-yet-detected* sin banks. Saint banks, however, may be less willing to lend to bad firms to protect their market power from the uncertainty associated with financing bad firms. Thus, in need of credit, bad firms could be effectively forced to improve to be accepted by saint banks.

To examine the effect of regional bank market concentration on our baseline results, we slightly modify our duration regressions by introducing a cross-product of the regional HHI

Table 6. Channels of endogenous firm-bank matching: surprising bank closures

Note: The table reports the estimates of new firm-bank matching following the firms' f prior sin banks closure, as implied by equation (2) and conditional on the sin bank closure being less predictable (*Surprise*) or more predictable (*Not a surprise*). Dependent variable $\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta)$ is an instantaneous rate at which firms "exit," i.e., match with new banks, sin ($j = 1$) or saint ($j = 2$) vis-a-vis never match, conditional on survival to the current month t. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure–that is, by $t^*_{f,b}$–or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include a firm's size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. *Surprise* indicates that the estimations are performed on the subsample of only those banks for which the predicted probability of fraud detection is *below* the unconditional threshold of 0.5% monthly (or 6% annually). *Not a surprise*, in contrast, means *above* the threshold. Details on modeling the probability of fraud detection are in Appendix F. The sample includes those firms that have a *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy, i.e., from 2013M7, and till 2020M10. Coefficients instead of subhazard ratios are reported. The constant term is included but not reported to preserve space.

Previous sin bank closure:	*Surprise*		*Not a surprise*	
Match with a new bank:	sin bank	saint bank	sin bank	saint bank
	(1)	(2)	(3)	(4)
Panel 1: Firm quality: Days of NPLs				
log DNPL_{f,t^*}	0.204***	–0.118***	–0.072	–0.019
	(0.065)	(0.044)	(0.143)	(0.069)
Other firm controls	Yes	Yes	Yes	Yes
Bank closure event FEs	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
N obs	224,821	225,274	32,369	32,407
N firm-to-bank switches	168	611	32	104
N firms	5,193	5,203	876	877
log L	–893.6	–2,479.7	–157.4	–428.7
Panel 2: Firm quality: Negative profits				
$\text{Profit}_{f,t^*} < 0$	–2.039*	0.124	0.385	0.443
	(1.202)	(0.279)	(1.822)	(0.701)
$\text{Profit}_{f,t^*+k} < 0$	–0.711**	–0.364**	0.095	–0.614
	(0.350)	(0.164)	(0.744)	(0.389)
Other firm controls	Yes	Yes	Yes	Yes
Bank closure event FEs	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
N obs	154,007	154,382	24,365	24,376
N firm-to-bank switches	143	459	25	78
N firms	3,545	3,551	650	649
log L	–719.0	–1,827.8	–112.5	–319.8

***, **, * 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.

concentration measure with a firm quality proxy:

$$\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta) = \lambda_0(t) \cdot \exp\Big(\alpha_j + \alpha_{j,bc} + \alpha_{j,r} + \alpha_{j,i} + \beta_{j,1}\text{Firm.Quality}_{f,t-1} + \mathbf{C}_{f,t-1}\Gamma_j + \beta_{j,2}HHI.credit_{r,t-1} + \beta_{j,3} \cdot \text{Firm.Quality}_{f,t-1} \times HHI.credit_{r,t-1}\Big), \quad (3)$$

The estimation results are presented in Table 7, where Panel 1 contains the results with firm quality proxied with the days of NPLs, while in Panel 2, firm quality is proxied with negative profits.

Table 7. Channels of endogenous firm-bank matching: regional credit market concentration

Note: The table reports the estimates of new firm-bank matching following the firms' f prior sin banks closure, as implied by equation (3). Dependent variable $\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta)$ is an instantaneous rate at which firms exit, i.e., match with new banks, sin (j = 1) or saint (j = 2) vis-a-vis never match, conditional on survival to the current month t. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure–that is, by $t^*_{f,b}$–or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. $HHI.credit_{r,t}$ is the Herfindahl-Hirschman index of regional credit market concentration. Other controls include a firm's size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. The sample includes those firms that have a *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy, i.e., from 2013M7, and till 2020M10. Coefficients instead of subhazard ratios are reported. The constant term is included but not reported to preserve space.

	Switch to a sin bank	Switch to a saint bank
	(1)	(2)
Panel 1: Firm quality: Days of NPLs		
log $\text{DNPL}_{f,t^*} \times \text{HHI.credit}_{r,t-1}$	0.501	1.430***
	(1.017)	(0.425)
log $\text{DNP}L_{f,t^*}$	0.223***	–0.107**
	(0.068)	(0.043)
$\text{HHI.credit}_{r,t-1}$	1.406	5.625***
	(1.405)	(0.649)
N obs	222,837	223,290
N firms	5,159	5,169
N firm-to-bank switches	168	611
log L	–891.0	–2,434.6
Panel 2: Firm quality: Negative profits		
$\text{Profit}_{f,t^*} < 0 \times \text{HHI.credit}_{r,t-1}$	–6.860	4.364*
	(8.042)	(2.487)
$\text{Profit}_{f,t^*+k} < 0 \times \text{HHI.credit}_{r,t-1}$	2.946	2.399**
	(3.977)	(1.138)
$\text{Profit}_{f,t^*} < 0$	–2.221*	–0.036
	(1.143)	(0.311)
$\text{Profit}_{f,t^*+k} < 0$	–0.681*	–0.405**
	(0.349)	(0.171)
$\text{HHI.credit}_{r,t-1}$	–0.721	3.110***
	(2.036)	(0.811)
N obs	152,735	153,110
N firms	3,526	3,532
N firm-to-bank switches	143	459
log L	–718.7	–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.

As can be seen in Panel 1, the estimated coefficient on the interaction of log $DNPL_{f,t^*}$ and

$HHI.credit_{r,t-1}$ is insignificant in column (1) and positive and highly significant in column (2). Qualitative, the same result is in Panel 2. These results suggest that the rising concentration of credit markets was unlikely to prevent bad firms from matching with not-yet-detected sin banks but that it did facilitate new matches between bad firms and saint banks. One possible interpretation is that the saint banks could extract rent from relationships with bad firms by setting higher interest rates. Furthermore, saint 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, helping them to improve.

6. SIN BANK CLOSURE AND FIRM PERFORMANCE

In this section, we examine the real effects of sin bank closures on firm performance and explore the corresponding mechanisms.

6.1 The real effects of sin bank closure

Closure of a (sin) bank can be viewed as a *credit supply shock*. The literature typically considers the effects of credit supply shocks on firm employment (Chodorow-Reich, 2014), investment and sales (Gropp et al., 2018; Degryse et al., 2019a; Chopra et al., 2020), among other measures of performance. We employ similar characteristics of performance except for investment.[28] We also use firm profits and firm default rates as our measures of firm performance.

There is one potential issue with evaluating the effect of sin bank closures on firm performance. If firms anticipate the closure of their sin banks in advance, they could make preemptive adjustments. If so, the effect of a sin bank closure per se could be distorted by firm's preemptive actions. We conduct two tests to examine whether firms could anticipate the closure of their sin banks in advance. We test whether firms preemptively leave sin banks in anticipation of regulatory closure, and whether firms strategically delay loan repayments around the closure date. These tests are based on the conjectured heterogeneous responses of high and low-quality firms to the prospect of sin bank closure, and are presented in Appendix G. These tests do not support the hypothesis that firms anticipated the closure of their sin banks.

[28] Our firm-level data (provided by SPARK-Interfax) unfortunately contains a very large number of missing values on investment. Thus, using the data on investment will result in the total number of observations shrinking by a factor of 10, at least.

Specifically, we want to understand what happens to firm performance *after* the firms experience the closure of their prior sin banks, but *before* they find new bank matches. On the one hand, one might expect that firm performance deteriorates because, by losing their bank, firms become more financially constrained (Chodorow-Reich, 2014; Chopra et al., 2020). On the other hand, firm performance could improve due to the termination of the hold-up problem (Liaudinskas and Grigaite, 2021).

To answer this question, we employ the difference-in-differences approach with the time-varying imposition of treatment (TV-DID, Goodman-Bacon, 2021). The *treatment group* consists of all those firms, bad and good, that experienced sin bank closures at some point in time during 2013–2020. Specifically, we define treatment as the closure of sin bank b that affects firm f at time $t^*_{b,f}$. Thus, our treatment variable is $Sin.Bank_{b,f}$ which equals 1 if firm f's bank b is closed due to fraud detection at $t^*_{b,f}$. Furthermore, for each firm f, let $POST_{\{t \geq t^*_{b,f}\}}$ define an indicator variable equals 1 for all t following $t^*_{b,f}$, and 0 otherwise.

The *control group* is constructed by matching firms on the set of observable characteristics using the nearest neighborhood estimator of Abadie and Imbens (2011). The following set of observable characteristics is employed: firm size, leverage, liquidity, return on assets, and annual growth of total assets. We follow the so-called 1:4 rule of thumb and match firm f that has experienced bank closure at $t^*_{b,f}$ (i.e., a *treated* firm) with four similar (*control*) firms that (i) also have relationships with sin banks and (ii) have not experienced closures of their sin banks within two years before and after firm f.[29]

Acknowledging that any real effect of sin bank closure on a firm's performance can be mitigated if the firm has more than one bank relationship (i.e., borrows from more than one bank), we focus only on *single*-bank firms (Degryse et al., 2019a). We thus run our TV-DID regressions for the subsamples of firms that had only one (sin) bank at the moment of the bank's closure.

[29]That is, we consider a moving window of $[t^*_{b,f} - 2, t^*_{b,f} + 2]$. Our treatment group includes firms that experienced closures of their sin banks between 2011 (beginning of the sample period) and 2018. Because our sample ends in 2020, the last treated firm appears at the end of 2018 since, by construction, we require that it is matched with four control firms that did not experience their sin bank closures between 2016 and 2020 (end of the sample period).

Formally, we specify the following TV-DID regression:

$$
\begin{aligned}
Y_{f,t} = \alpha_f + \alpha_t + \beta_1\Big(Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}}\Big) + \\
+ \beta_2\Big(Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}} \times Bad.Firm_{f,t}\Big) \\
+ X'_{f,b,t}\Psi + \varepsilon_{f,t}, \text{ if } t \in [t^*_{b,f} - 2, t^*_{b,f} + 2]
\end{aligned}
\tag{4}
$$

where $Y_{f,t}$ is a measure of firm f's performance, among which we consider (i) firm size (the log of total assets), (ii) the ratio of debt to total assets, (iii) the ratio of total revenue to total assets, (iv) the ratio of the number of workers to total revenue, (v) the ratio of profit to total assets, and (vi) a binary variable which equals 1 if firm f defaults in year t and 0 otherwise. $X_{f,b,t}$ includes various control variables including firm size and its square, leverage, and liquidity ratios to total assets, where appropriate, to capture any residual differences between the treated and control firms remaining after the 1:4 nearest neighborhood matching. Equation (4) is estimated with logit when the dependent variable is binary (i.e., case (vi)) and with panel FE estimator otherwise (cases (i)-(v)).[30] We require firms to not default between $t^*_{b,f} - 2$ and $t^*_{b,f}$ in logit regression (case (vi)) and we require firms to survive until at least $t^*_{b,f} + 2$ in panel FE regressions (cases (i)-(v)) to control for the survivorship bias (Brown et al., 1992).

The estimation results of equation (4) are summarized in Table 8. After the nearest neighborhood matching and restricting the sample of firms by imposing condition $t \in [t^*_{b,f} - 2, t^*_{b,f} + 2]$ years, we have only about 10,745 to 18,613 observations at the firm-year level for different dependent variables.

Column (1) of Table 8 starts with firm size as the dependent variable in equation (4). The estimated coefficient β_1 on $Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}}$ is positive and highly statistically significant, whereas the coefficient β_2 on the $Sin.Bank_{b,f} \times \text{POST}_{\{t \geq t^*_{b,f}\}} \times Bad.Firm_{f,t}$ is negative and statistically significant at 5%. This implies that while good firms tend to grow in size following sin bank closure (but before they start borrowing from a new bank), bad firms tend to shrink in size. Economically, these effects and their differences are significant. Regressions in the next columns of the table shed light on why we obtain these differential effects.

In column (2) of Table 8, we turn to results on firm leverage. The estimated coefficient β_1

[30]Those observations for which a new firm-bank match is created before $t^*_{b,f} + 2$ are censored, to insure that we are analyzing firm performance before the firm finds a new bank.

Table 8. Difference-in-differences estimation results: firm performance after sin bank closures

Note: The table reports the estimates of firm performance after a firm experiences closure of its prior sin bank and before it establishes a relationship with a new bank, as implied by equation (4). Firm performance is proxied with the following dependent variables $Y_{f,t}$: firm size, as captured by the log of total assets (*log(TA)*, column 1), the ratio of borrowed funds to total assets (*Borrow/TA*, column 2), revenue to total assets (*Revenue/TA*, column 3), number of workers to total revenue ratio (*Employ/Revenue*, column 4), profit after taxes to total assets (*Profit/TA*, column 5), a binary indicator of whether a firm f defaults at year t (*Default=1*, column 6). $Sin.Bank_{b,f}$ = 1 if bank b that has a relationship with firm f is closed for fraud at some point in time within the sample period, and 0 if it survives till the end of the sample. $POST_{\{t\geq t^*_{b,f}\}}$ = 1 if $t \geq t^*_{b,f}$, and 0 if else. $Bad.Firm_{f,t}$ is a binary variable that equals 1 for firms with losses, and 0 for profitable firms. We run our regressions for $t \in [2011, 2020]$ on a panel of matched firms that experienced sin bank closures and only had relationships with a single bank at the moment of its forced closure. We also restrict the panel so that it only includes observations up to two years before and after $t^*_{b,f}$, i.e., firm-bank-specific windows $[t^*_{b,f} - 2, t^*_{b,f} + 2]$ years. We employ 1:4 nearest neighborhood matching of firms prior to $t^*_{b,f}$ using the five observables: firm size, leverage, liquidity, annual growth of total assets, and profitability. All regressions contain all necessary sub-products of the triple interaction variable $Sin.Bank_{b,f} \times \text{POST}_{\{t\geq t^*_{b,f}\}} \times Bad.Firm_{f,t}$, firm and year fixed effects, and the set of firm controls to capture any residual differences across treated and control firms after 1:4 matching (firm size, except (1); leverage, except (2); and liquidity).

$\text{Y}_{f,t} :=$	log(TA)	$\frac{Borrow}{TA}$	$\frac{Revenue}{TA}$	$\frac{Employ}{Revenue}$	$\frac{Profit}{TA}$	Default
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Focus variables:						
$\text{Sin.Bank}_{b,f} \times \text{POST}_{\{t\geq t^*_{b,f}\}}$	0.205***	0.011	0.384***	–4.408*	0.006	–2.566*
	(0.043)	(0.018)	(0.140)	(2.365)	(0.017)	(1.468)
$\text{Sin.Bank}_{b,f} \times \text{POST}_{\{t\geq t^*_{b,f}\}} \times \text{Bad.Firm}_{f,t}$	–0.320**	0.101*	–0.770**	10.553**	–0.017	n/a
	(0.136)	(0.060)	(0.325)	(4.239)	(0.030)	
Panel 2: Key components of the triple interaction variable:						
$\text{Sin.Bank}_{b,f}$	–0.091**	–0.009	–0.210**	1.994**	0.000	2.356***
	(0.040)	(0.011)	(0.101)	(0.921)	(0.014)	(0.319)
$\text{POST}_{\{t\geq t^*_{b,f}\}}$	0.082**	–0.030	–0.184	4.940*	–0.028	0.595
	(0.037)	(0.025)	(0.162)	(2.852)	(0.018)	(1.500)
$\text{Bad.Firm}_{f,t}$	–0.008	0.085***	–0.316***	8.703**	–0.180***	0.607
	(0.029)	(0.031)	(0.120)	(3.599)	(0.014)	(0.717)
N obs	17,174	18,861	17,835	11,683	18,613	10,745
N firms	3,226	3,261	3,234	2,869	3,258	3,237
R^2 (pseudo / LSDV)	0.3	0.7	0.1	0.0	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.

on $Sin.Bank_{b,f} \times POST_{\{t\geq t^*_{b,f}\}}$ is positive, but it is not statistically significant. Thus, we do not find any effect on a treated firm's leverage-to-total assets ratio. The estimated coefficient β_2 on the $Sin.Bank_{b,f} \times \text{POST}_{\{t\geq t^*_{b,f}\}} \times Bad.Firm_{f,t}$ is, however, positive and marginally significant. Therefore, our results suggest that the leverage of bad firms increases by as much as 10 p.p. relative to good firms. This is a sizeable effect, given that the mean leverage ratio of the firms in our sample lies between 75 and 95%. Further estimations show that the absolute amount of borrowing by low-quality treated firms declines, but by less than their total assets (see column (2) of Table H.I in Appendix H).

Column (3) of Table 8 presents the result for firm total revenue. We obtain a positive and highly significant coefficient β_1 on $Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}}$ and a negative and significant coefficient β_2 on $Sin.Bank_{b,f} \times \text{POST}_{\{t \geq t^*_{b,f}\}} \times Bad.Firm_{f,t}$. In absolute terms, β_2 exceeds β_1 by a factor of 2, which implies a heterogeneous treatment effect on firm revenue-to-total assets depending on firm quality. Following their sin bank closures, good firms have rising revenue, while the revenue of bad firms declines, relative to the total assets of respective firms. The result on firm revenue is in line with the result on leverage. It provides evidence of a cleansing effect of sin bank closure: good firms improve while bad firms deteriorate.

In column (4) of Table 8, we present our results on firm employment. We obtain a negative and marginally significant coefficient β_1 on $Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}}$ while coefficient β_2 on the $Sin.Bank_{b,f} \times \text{POST}_{\{t \geq t^*_{b,f}\}} \times Bad.Firm_{f,t}$ is estimated to be positive and significant. In absolute terms, β_2 exceeds β_1 by a factor of 2. That is, the treatment effect on firm employment-to-total revenue is also heterogeneous. Following their sin bank closures, good firms reduce their labor force to total revenue ratio, whereas bad firms expand the labor force loading on their total revenue, compared to control firms. Given that good firms also raise their total revenues—column (3)—we find that their revenues grow faster than the number of workers employed. This is also confirmed by our additional regressions, in which we replace the revenue-to-total assets ratio with the log of revenue and employment-to-revenue with the log of employment: the estimated semi-elasticity of revenue exceeds that of the number of workers by a factor of two (compare columns (3) and (4) of Table H.I in Appendix H).

In column (5) of Table 8, we examine the effect on profits. We obtain a positive but insignificant coefficient β_1 on the $Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}}$ variable and negative and insignificant coefficient β_2 on the $Sin.Bank_{b,f} \times \text{POST}_{\{t \geq t^*_{b,f}\}} \times Bad.Firm_{f,t}$ variable. The signs are consistent with the firm improvement hypothesis for good firms and the firm deterioration hypothesis for bad firms. However, since the effects are insignificant, we interpret these results with caution.

Finally, column (6) presents the estimation result when the dependent variable is *firm defaults*. In this case, we obtain a negative and marginally significant coefficient on the

$Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}}$ variable. That is, following the closure of a sin bank, the failure risk of a good firm *decreases.* At the same time, the variable $Sin.Bank_{b,f} \times POST_{\{t \geq t^*_{b,f}\}} \times Bad.Firm_{f,t} = 1$ perfectly predicts firm defaults, and thus this variable is dropped from the estimations (marked as "n/a" in the table). Our results thus suggest that while the stability of high-quality firms improves following the closure of a sin bank, the opposite result holds for low-quality firms. This result is consistent with the findings in previous columns and indicates the cleansing effect of sin bank closure on firms.

6.2 *Exploring the mechanisms: credit risk underpricing*

Next, we investigate why good firms may improve while bad firms may deteriorate following their sin bank closures. We hypothesize that sin banks may underprice credit risk when lending to firms, thus effectively subsidizing firm credit. The loss of such a subsidy would naturally pose a larger problem to a bad firm. Thus, underpricing of the credit risk by sin banks could explain why bad firm performance is likely to deteriorate following the closure of its sin bank—the loss of the subsidy combined with fewer opportunities and incentives to improve will further deteriorate the state of bad firms. On the other hand, good firms have better incentives and abilities to improve following the closure of their sin banks, which helps to decrease their cost of credit in the future.

To test this hypothesis, we employ credit registry loan-level data on interest rates available from 2017 at a monthly frequency. The credit register contains data on loan contracts and includes the interest rate, loan amount, loan maturity, type of credit, and ex-ante assessment of the borrower's credit risk on a scale of 1 to 5, with 1 being the lowest risk and 5 being the highest.

First, we examine a linear regression model of the interest rate that a bank b sets to firm f at month t on the sin bank indicator variable (bank level), credit risk category from 1, lowest risk, to 5, highest risk (firm-bank-month level), and the product of the two, controlling for firm and firm*month fixed effects, log of loan volumes, loan maturities, relevant bank-level controls, and regional and macroeconomic characteristics:

$$r^L_{f,b,t} = \sum_{j=1}^{5} \beta_j \cdot \left(Sin.Bank_{b,f} \times Credit.Risk^{(j)}_{f,b,t}\right) + \gamma Sin.Bank_{b,f} + Loan.Control'_{f,b,t}\Xi$$
$$+ Bank.Control'_{b,t}\Psi + Macro.Control'_t\Phi + \alpha_f + \alpha_{f,t} + \epsilon_{f,b,t} \quad (5)$$

With this composition of variables, we have up to 1,774,379 loan-level observations. We obtain a positive and highly significant coefficient on the $Sin.Bank_{b,f}$ variable, meaning that sin banks charge 1.5 p.p. higher interest rates on loans than the saint banks (see Table 9). However, we further obtain a negative and highly significant coefficient on the interactions of the sin bank variable and credit risk category, and the magnitudes of the estimates range from –1.6 to –0.5 p.p. This means that within *the same* sin bank, firms with poorer quality *pay less* on their loans, while firms with better quality *pay more*. These results hold on the sample of all loans issued and for the subsample of multiple loans, i.e., for the firms that obtained at least two loans within the 2017-2020 period. The latter subsample allows us to shut down demand effects by including firm*month fixed effects. Overall, our regression results here are consistent with the hypothesis that sin banks underprice risk, especially in the case of low-quality firms.

Second, we proceed to a linear regression of the credit risk category on the bad firm and sin bank indicator variables, the product of the two, controlling for the same characteristics as in the interest rate regression above. The credit risk regression reads as:

$$Credit.Risk_{f,b,t} = \beta \cdot \left(Sin.Bank_{b,f} \times Bad.Firm_{f,t}\right) + \gamma Sin.Bank_{b,f} + \delta Bad.Firm_{f,t}$$
$$+ Loan.Control'_{f,b,t}\Xi + Bank.Control'_{b,t}\Psi + Macro.Control'_t\Phi + \alpha_f + \alpha_{f,t} + \epsilon_{f,b,t} \quad (6)$$

With this composition of variables, we have up to 1,263,970 loan-level observations. We obtain a negative and highly significant coefficient on the sin bank variable, meaning that the same borrower is given higher credit quality ex-ante assessment by sin banks than by saint banks (see Table 10). Further, we obtain a negative and highly significant coefficient on the interaction of the sin bank and bad firm indicators, which implies that within a given sin bank, bad firms receive relatively higher, not lower, credit quality assessments. As in the case of interest rate regressions, these results hold for both the sample of all loans and the subsample of multiple loans.

Table 9. Interest rates and amount of loans in sin banks: regression estimation results

Note: The table reports the estimates of equation (5), where the dependent variable is either the loan interest rate (columns 1–2) or the log of the loan amount (columns 3–4) at the firm-bank-month level, $t \in$ 2017M1–2020M9. $Sin.Bank_{b,f}$ is an indicator variable of a sin bank, i.e., a bank that ever experienced license revocation due to fraud detection. $Credit.Risk_{f,b,t}$ is a categorical variable ranging from 1 (the lowest risk, or the best quality, reference) to 5 (the highest risk, or the worst quality) to reflect a bank's ex-ante assessment of the loan credit risk. $Loan.Control_{f,b,t}$ includes loan quality, log of the loan amount (columns 1–2), the interest rate on the loan (columns 3–4), maturity of the loan, and loan type (credit lines, overdraft, etc.). $Bank.Control_{b,t}$ includes the structure of bank assets (loans to firms, loans to households), the structure of bank liabilities (equity capital, deposits of firms, households, and government), all as % of bank total assets, bank size (log of total assets), and the ex-post quality of bank loans (NPL ratio), which are not reported to save space. $Macro.Control_t$ is GDP growth rate (YoY) and regional credit market concentration, as proxied with $HHI_{r,t}$. α_f is firm fixed effects and $\alpha_{f,t}$ is firm*month fixed effect (capturing firm demand on loans). *All loans* means each and every loan from the credit register is included in the regression ($\alpha_{f,t}$ is not included), whereas *Multiple loans* involves a subsample of those firms that obtain credit at least twice in the time period considered ($\alpha_{f,t}$ is included). *n/a* means the effect is absorbed by (month) fixed effects. The sample includes those firms that have a *single* bank relationship.

	Interest rate on loan, $Interest.Rate_{f,b,t}$		log of loan amount, log $Loan_{f,b,t}$	
	All loans	Multiple loans	All loans	Multiple loans
	(1)	(2)	(3)	(4)
$\text{Sin.Bank}_{b,f}$	1.579***	1.519***	–0.104***	–0.270***
	(0.091)	(0.181)	(0.037)	(0.084)
$\text{Credit.Risk}_{f,b,t} = 1$ (*reference*)				
$\text{Credit.Risk}_{f,b,t} = 2$	0.029**	0.191***	–0.060***	–0.075***
	(0.012)	(0.023)	(0.006)	(0.015)
$\text{Credit.Risk}_{f,b,t} = 3$	0.593***	1.228***	–0.045***	–0.024
	(0.029)	(0.080)	(0.012)	(0.034)
$\text{Credit.Risk}_{f,b,t} = 4$	0.045	0.594***	–0.282***	–0.217**
	(0.036)	(0.127)	(0.026)	(0.105)
$\text{Credit.Risk}_{f,b,t} = 5$	–0.052	0.713***	–0.040	0.235*
	(0.069)	(0.257)	(0.045)	(0.135)
$\text{Sin.Bank}_{b,f} \times \text{Credit.Risk}_{f,b,t} = 2$	–0.502***	–0.786***	0.095***	0.259***
	(0.083)	(0.189)	(0.035)	(0.088)
$\text{Sin.Bank}_{b,f} \times \text{Credit.Risk}_{f,b,t} = 3$	–1.036***	–1.648***	0.104**	0.680***
	(0.116)	(0.307)	(0.050)	(0.154)
$\text{Sin.Bank}_{b,f} \times \text{Credit.Risk}_{f,b,t} = 4$	–0.718***	–0.194	0.310***	1.345***
	(0.149)	(0.826)	(0.092)	(0.484)
$\text{Sin.Bank}_{b,f} \times \text{Credit.Risk}_{f,b,t} = 5$	–0.750***	–0.930	–0.222	0.271
	(0.259)	(0.688)	(0.223)	(0.232)
log $\text{Loan}_{f,b,t}$	–0.056***	–0.032***		
	(0.002)	(0.005)		
$\text{Interest.Rate}_{f,b,t}$			–0.031***	–0.022***
			(0.001)	(0.004)
GDP.Growth_t	–0.229***	n/a	0.005***	n/a
	(0.002)		(0.001)	
$\text{HHI.Credit}_{r,t}$	–0.001***	n/a	–0.000***	n/a
	(0.000)		(0.000)	
Firm FEs	Yes	Yes	Yes	Yes
Firm × month FEs	No	Yes	No	Yes
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.

Table 10. Loan quality in sin and saint banks: regression estimation results

Note: The table reports estimates of the following loan-level regressions: $Credit.Risk_{f,b,t} = \beta \cdot \Big(Sin.Bank_{b,f} \times Bad.Firm_{f,t}\Big) + \gamma Sin.Bank_{b,f} + \delta Bad.Firm_{f,t} + Loan.Control'_{f,b,t}\Xi + Bank.Control'_{b,t}\Psi + Macro.Control'_t\Phi + \alpha_f + \alpha_{f,t} + \epsilon_{f,b,t}$, where $Credit.Risk_{f,b,t}$ is a categorical variable ranging from 1 (the lowest risk, or the best quality, reference) to 5 (the highest risk, or the worst quality) to reflect a bank's ex-ante assessment of the loan credit risk, $t \in$ 2017M1–2020M9. $Sin.Bank_{b,f}$ is an indicator variable of a sin bank, i.e., a bank that ever experienced license revocation due to fraud detection. $Bad.Firm_{f,t}$ is a binary variable that equals 1 for firms with losses, and 0 for profitable firms. $Loan.Control_{f,b,t}$ includes the log of the loan amount, maturity of the loan, and loan type (credit lines, overdraft, etc.). $Bank.Control_{b,t}$ includes the structure of bank assets (loans to firms, loans to households), the structure of bank liabilities (equity capital, deposits of firms, households, and government), all as a % of bank total assets, bank size (log of total assets), and the ex-post quality of bank loans (NPL ratio), which are not reported to save space. $Macro.Control_t$ is GDP growth rate (YoY) and regional credit market concentration, as proxied with $HHI_{r,t}$. α_f is firm fixed effects and $\alpha_{f,t}$ is firm*month fixed effect (capturing firm demand on loans). *All loans* means each and every loan from the credit register is included in the regression ($\alpha_{f,t}$ is not included), whereas *Multiple loans* involves a subsample of firms that obtain credit at least twice in the time period considered ($\alpha_{f,t}$ is included). *n/a* means the effect is absorbed by (month) fixed effects. The sample includes firms that have a *single* bank relationship.

$Y_{f,b,t}$:=	Loan quality	
	All loans	Multiple loans
	(1)	(2)
$\text{Sin.Bank}_{b,f}$	–0.073***	–0.062***
	(0.011)	(0.019)
$\text{Bad.Firm}_{f,t}$	0.026***	0.003
	(0.003)	(0.007)
$\text{Sin.Bank}_{b,f} \times \text{Bad.Firm}_{f,t}$	–0.047**	–0.192***
	(0.021)	(0.055)
$\log \text{Loan}_{f,b,t}$	–0.003***	–0.002***
	(0.000)	(0.001)
GDP.Growth_t	0.007***	n/a
	(0.000)	
$\text{HHI.Credit}_{r,t}$	0.000***	n/a
	(0.000)	
Firm FEs	Yes	Yes
Firm × month FEs	No	Yes
Obs	1,263,970	679,904
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.

7. CONCLUSION

Our study shows that following sin bank closures, bad firms are more likely to match with any remaining sin banks, especially if the remaining banks are held by the same owners or operate in relatively less concentrated regional credit markets. Good firms, on the other hand, match with saint banks. The tight policy of the Central Bank of Russia (CBR) in the 2010s against fraud committed by banks had cleansing effects on the performance of firms during the transition period, i.e., after their prior sin banks were closed and before they matched with any remaining banks.

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. These heterogeneous effects on firm performance are channeled through credit risk underpricing by sin banks, especially in the case of low-quality firms.

REFERENCES

Abadie, Alberto, and Guido W. Imbens, 2011, Bias-Corrected Matching Estimators for Average Treatment Effects, *Journal of Business & Economic Statistics* 29, 1–11.

Acharya, Viral, and Tanju Yorulmazer, 2007, Too many to fail–an analysis of time-inconsistency in bank closure policies, *Journal of Financial Intermediation* 16, 1–31.

Acharya, Viral V., Allen N. Berger, and Raluca A. Roman, 2018, Lending Implications of U.S. Bank Stress Tests: Costs or Benefits?, *Journal of Financial Intermediation* 34, 58–90, Assessing Banking Regulation During the Obama Era.

Agarwal, Sumit, David Lucca, Amit Seru, and Francesco Trebbi, 2014, Inconsistent Regulators: Evidence from Banking *, *The Quarterly Journal of Economics* 129, 889–938.

Ahn, Daniel P., and Rodney Ludema, 2020, The sword and the shield: The economics of targeted sanctions, *European Economic Review* 130, S0014292120302178.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli, 2016, Relationship and Transaction Lending in a Crisis, *The Review of Financial Studies* 29, 2643–2676.

Bonfim, Diana, Gil Nogueira, and Steven Ongena, 2020, "Sorry, We're Closed" Bank Branch Closures, Loan Pricing, and Information Asymmetries*, *Review of Finance* 25, 1211–1259.

Brown, Craig O., and I. Serdar Dinç, 2011, Too Many to Fail? Evidence of Regulatory Forbearance When the Banking Sector Is Weak, *The Review of Financial Studies* 24, 1378–1405.

Brown, Stephen, William Goetzmann, Roger Ibbotson, and Stephen Ross, 1992, Survivorship bias in performance studies, *The Review of Financial Studies* 5, 553–580.

Bruno, Valentina, and Hyun Song Shin, 2017, Global Dollar Credit and Carry Trades: A Firm-Level Analysis, *The Review of Financial Studies* 30, 703–749.

Calomiris, Charles W., and Urooj Khan, 2015, An Assessment of TARP Assistance to Financial Institutions, *Journal of Economic Perspectives* 29, 53–80.

Chodorow-Reich, Gabriel, 2014, The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008–9 Financial Crisis, *The Quarterly Journal of Economics* 129, 1–59.

Chopra, Yakshup, Krishnamurthy Subramanian, and Prasanna L Tantri, 2020, Bank Cleanups, Capitalization, and Lending: Evidence from India, *The Review of Financial Studies* hhaa119.

Cortés, Kristle R., Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E. Strahan, 2020, Stress Tests and Small Business Lending, *Journal of Financial Economics* 136, 260–279.

Degryse, Hans, Olivier De Jonghe, Sanja Jakovljević, Klaas Mulier, and Glenn Schepens, 2019a, Identifying credit supply shocks with bank-firm data: Methods and applications, *Journal of Financial Intermediation* 40.

Degryse, Hans, Alexei Karas, and Koen Schoors, 2019b, Relationship lending during a trust crisis on the interbank market: A friend in need is a friend indeed, *Economics Letters* 182, 1–4.

Degryse, Hans, and Steven Ongena, 2005, Distance, lending relationships, and competition, *Journal of Finance* 60, 231–266.

DeYoung, Robert, and Gokhan Torna, 2013, Nontraditional banking activities and bank failures during the financial crisis, *Journal of Financial Intermediation* 22, 397–421.

Diamond, Douglas W., and Raghuram G. Rajan, 2011, Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes, *The Quarterly Journal of Economics* 126, 557–591.

Goodman-Bacon, Andrew, 2021, Difference-in-differences with variation in treatment timing, *Journal of Econometrics* .

Granja, Joao, Gregor Matvos, and Amit Seru, 2017, Selling failed banks, *The Journal of Finance* 72, 1723–1784.

Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen, 2020, Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and "normal" economic times, *American Economic Journal: Economic Policy* 12, 200–225.

Gropp, Reint, Thomas Mosk, Steven Ongena, and Carlo Wix, 2018, Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment, *The Review of Financial Studies* 32, 266–299.

Gropp, Reint, Steven Ongena, Joerg Rocholl, and Vahid Saadi, 2022, The cleansing effect of banking crises, *Economic Inquiry* Forthcoming.

Holmstrom, Bengt, and Jean Tirole, 1997, Financial Intermediation, Loanable Funds, and the Real Sector, *The Quarterly Journal of Economics* 112, 663–691.

Ioannidou, Vasso, and Steven Ongena, 2010, "Time for a Change": Loan Conditions and Bank Behavior when Firms Switch Banks, *The Journal of Finance* 65, 1847–1877.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, 2014, Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?, *Econometrica* 82, 463–505.

Kang, Ari, Richard Lowery, and Malcolm Wardlaw, 2014, The Costs of Closing Failed Banks: A Structural Estimation of Regulatory Incentives, *The Review of Financial Studies* 28, 1060–1102.

Keeley, Michael C, 1990, Deposit insurance, risk, and market power in banking, *American Economic Review* 80, 1183–1200.

Leland, Hayne E., and David H. Pyle, 1977, Informational Asymmetries, Financial Structure, and Financial Intermediation, *The Journal of Finance* 32, 371–387.

Liaudinskas, Karolis, and Kristina Grigaite, 2021, Estimating firms' bank-switching costs, *Norges Bank Working Paper* 4/2021, 1–57.

Mamonov, Mikhail, Anna Pestova, and Steven Ongena, 2021, "Crime and Punishment?" How Russian Banks Anticipated and Dealt with Global Financial Sanctions, *CEPR Discussion paper* 16075.

Morrison, Alan D., and Lucy White, 2013, Reputational contagion and optimal regulatory forbearance, *Journal of Financial Economics* 110, 642–658.

Petersen, Mitchell A., and Raghuram Rajan, 1995, The effect of credit market competition on lending relationships, *The Quarterly Journal of Economics* 110, 407–443.

Philippon, Thomas, and Philipp Schnabl, 2013, Efficient Recapitalization, *The Journal of Finance* 68, 1–42.

Schäfer, Larissa, 2019, "Forgive but Not Forget": The Behavior of Relationship Banks When Firms Are in Distress, *Review of Finance* 23, 1079–1114.

Svejnar, Jan, 2002, Transition economies: Performance and challenges, *Journal of Economic Perspectives* 16, 3–28.

APPENDIX

Appendix A. DESCRIPTION OF THE DATA

Table A.I. The list of financial statement variables for the survival analysis and difference-in-difference analysis

Name	Definition	Source
Survival regression analysis		
Size	$\ln(\text{Total assets})$	Balance sheet
Leverage	$\dfrac{\text{Short-term liabilities} + \text{Long-term liabilities}}{\text{Total assets}}$	Balance sheet
Liquidity	$\dfrac{\text{Current liabilities} - (\text{Accounts payable} + \text{Short-term loans})}{\text{Total assets}}$	Balance sheet
Profit	Gross profit	Income statement
Difference-in-difference analysis		
Default	$= 1$ if firm is bankrupt at t	Register of Legal Entities
Employ	$\dfrac{\text{Number of workers}}{\text{Sales}}$	Balance sheet
Revenue	$\dfrac{\text{Sales}}{\text{Total assets}}$	Income statement, Balance Sheet
Profit	Gross profit	Income statement
Borrowed funds	Short-term liabilities+Long-term liabilities	Income statement
Total assets	Sum of all assets	Balance Sheet

Table B.I. Multinomial logit regression results: splitting the firm-bank matches

Note: The table reports estimates of a multinomial logit model of new firm-bank matching that follows the closure of firm f's prior sin bank b, as an analog to the duration regression (2). Differently from equation (2) that splits the match option to "match with sin bank" or "match with saint bank," conditional on surviving till month t, the multinomial regression here assembles all the three outcomes: never match, match with sin or saint banks ($\jmath = 0, 1, 2$): $\mathbf{Pr}(Match_{f,t} = \jmath \,|\, \mathbf{X}_{f,t-1}; \Theta) = \Lambda\Big(\alpha_\jmath + \alpha_{\jmath,bc} + \alpha_{\jmath,r} + \alpha_{\jmath,i} + \text{Firm.Quality}_{f,t-1}\mathrm{B}_\jmath + \mathbf{C}_{f,t-1}\Gamma_\jmath\Big)$, where the dependent variable $Match_{f,t}$ is a categorical variable that equals zero if a firm that experienced closure of its prior bank never finds a new bank match (*reference*, 1 if a firm finds a new match with a *sin* bank (columns 1–3), 2 if with a *saint* bank (columns 4–6). Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure—that is, by $t^*_{f,b}$—or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include a firm's size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. The sample includes those firms that have *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy, i.e., from 2013M7, and till 2020M10. Coefficients instead of marginal effects are reported. Constant is included but not reported to save space.

	Switch to a sin bank			Switch to a saint bank		
	(1)	(2)	(3)	(4)	(5)	(6)
log DNPL$_{f,t^*}$	0.126***			–0.063**		
	(0.041)			(0.029)		
Profit$_{f,t^*} < 0$		–1.278*	–1.029		0.104	0.245
		(0.722)	(0.711)		(0.211)	(0.210)
Profit$_{f,t^*+k} < 0$			–0.568**			–0.328**
			(0.268)			(0.143)
Other firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank closure event FEs	No	No	No	No	No	No
Regional FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N obs	263,502	183,166	183,088	263,502	183,166	183,088
N firm-bank new matches	200	168	168	715	537	537
N firms	6,921	4,770	4,767	6,253	4,327	4,324
log L	–6,428	–4,879	–4,874	–6,428	–4,879	–4,874

***, **, * 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 C. BANK-FIRM MATCHING MODEL WITH MACROECONOMIC AND REGIONAL CREDIT MARKET CONTROLS

Table C.I. Survival regression results with aggregate controls: splitting the firm-bank matches

Note: The table reports estimates of new firm-bank matching that follows the closure of firm f's prior sin bank b, as implied by equation (2), with GDP growth rates (YoY) and concentration at regional credit markets (HHI) included as additional controls: $\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta) = \lambda_0(t) \cdot \exp\Big(\alpha_j + \alpha_{j,bc} + \alpha_{j,r} + \alpha_{j,i} + \text{Firm.Quality}_{f,t-1}\text{B}_j + \mathbf{C}_{f,t-1}\Gamma_j + \delta_{j,1}GDP.growth_{t-1} + \delta_{j,2}HHI.credit_{r,t-1}\Big)$, where the dependent variable $\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta)$ is an instantaneous rate at which firms exit, i.e., match with new banks, sin ($j = 1$) or saint ($j = 2$) vis-a-vis never match, conditional on survival to the current month t. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure—that is, by $t^*_{f,b}$—or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include firm size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. The sample includes firms with a *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy in 2013M7 and till 2020M10. Coefficients are reported instead of subhazard ratios. Constant is included but not reported to preserve space.

	Switch to a sin bank			Switch to a saint bank		
	(1)	(2)	(3)	(4)	(5)	(6)
log DNPL$_{f,t^*}$	0.156***			–0.085**		
	(0.058)			(0.036)		
Profit$_{f,t^*}$ < 0		–1.729*	–1.469*		0.021	0.182
		(0.893)	(0.882)		(0.245)	(0.246)
Profit$_{f,t^*+k}$ < 0			–0.532*			–0.394***
			(0.298)			(0.150)
GDP.growth$_{t-1}$	0.141	–0.110	–0.107	–0.277***	–0.267***	–0.265***
	(0.230)	(0.200)	(0.198)	(0.062)	(0.071)	(0.071)
HHI.credit$_{r,t-1}$	1.187	–0.244	–0.245	4.900***	3.865***	3.935***
	(1.420)	(2.030)	(2.071)	(0.574)	(0.707)	(0.713)
Other firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank closure event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N obs	255,152	177,121	177,046	255,643	177,507	177,432
N firm-bank new matches	200	168	168	715	537	537
N firms	6,034	4,178	4,175	6,045	4,183	4,180
log L	–1,065.0	–853.4	–851.5	–2,876.6	–2,149.4	–2,145.6

***, **, * 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 D. BANK-FIRM MATCHING MODEL: MULTIPLE FIRM-BANK RELATIONSHIPS WITH AT LEAST ONE SIN BANK WITHIN

Table D.I. Survival regression results with multiple firm-bank relationships: splitting the firm-bank matches

Note: The table reports estimates of new firm-bank matching that follows the closure of firm f's prior sin bank b, as implied by equation (2). Dependent variable $\lambda_j\left(t, \mathbf{X}_{f,t-1}; \Theta\right)$ is an instantaneous rate at which firms exit, i.e., match with new banks, sin (j = 1) or saint (j = 2) vis-a-vis never match, conditional on survival to the current month t. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure—that is, by $t^*_{f,b}$—or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include firm size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. The sample includes those firms that have *multiple* bank relationships. The estimations are performed for the period starting with the active phase of the tight regulation policy in 2013M7 and till 2020M10. Coefficients are reported instead of subhazard ratios. Constant is included but not reported to preserve space.

	Switch to a sin bank			Switch to a saint bank		
	(1)	(2)	(3)	(4)	(5)	(6)
log DNPL$_{f,t^*}$	–0.013			–0.033		
	(0.068)			(0.039)		
Profit$_{f,t^*} < 0$		–0.816	–0.558		–0.771*	–0.576
		(0.727)	(0.759)		(0.428)	(0.423)
Profit$_{f,t^*+k} < 0$			–0.453			–0.344**
			(0.307)			(0.166)
Other firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank closure event FEs	Yes	Yes	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
N obs	235,231	160,843	160,802	235,562	161,124	161,082
N firm-bank new matches	171	142	142	502	423	422
N firms	5,368	3,671	3668	5,405	3,704	3,701
log L	–928.9	–722.1	–720.8	–2,259.4	–1,814.7	–1,808.1

***, **, * 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 E. BANK-FIRM MATCHING MODEL: CATEGORIZATION OF LOAN QUALITY IN CLOSED BANKS

Table E.I. Categorizing the days of non-performing loans: splitting the bank-firm matches

Note: The table reports estimates of new firm-bank matching that follows the closure of firm f's prior sin bank b, as implied by equation (2). Dependent variable $\lambda_j(t, \mathbf{X}_{f,t-1}; \Theta)$ is an instantaneous rate at which firms exit, i.e., match with new banks, sin ($j = 1$) or saint ($j = 2$) vis-a-vis never match, conditional on survival to the current month t. Firm quality is proxied by the log of days of NPLs accumulated in the closed sin bank before its closure—that is, by $t^*_{f,b}$. The days of NPLs were categorized into seven 30-day bins: $0 \leq DNPL_{f,t-1} \leq 30$ (*reference*), $30 < DNPL_{f,t-1} \leq 60$, ..., $DNPL_{f,t-1} > 180$. Other controls include firm size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. The sample includes firms with a *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy in 2013M7 and till 2020M10. Coefficients are reported instead of subhazard ratios. Constant is included but not reported to preserve space.

	Switch to a sin bank	Switch to a saint bank
	(1)	(2)
Bin 1: $0 < DNPL_{f,t-1} \leq 30$ (*reference*)		
Bin 2: $30 < DNPL_{f,t-1} \leq 60$	0.779***	–0.377*
	(0.302)	(0.212)
Bin 3: $60 < DNPL_{f,t-1} \leq 90$	1.425***	0.053
	(0.421)	(0.286)
Bin 4: $90 < DNPL_{f,t-1} \leq 120$	0.016	–0.616
	(0.991)	(0.502)
Bin 5: $120 < DNPL_{f,t-1} \leq 150$	0.193	–0.653**
	(0.483)	(0.287)
Bin 6: $150 < DNPL_{f,t-1} \leq 180$	–0.910	–17.399***
	(1.086)	(1.431)
Bin 7: $DNPL_{f,t-1} > 180$	–16.140***	–0.721
	(0.770)	(1.090)
N obs	257,190	257,681
N firms	6,069	6,080
N firm-to-bank switches	200	715
log L	–1,060.1	–2,918.9

***, **, * 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 F. IN-ADVANCE DETECTION OF SIN BANKS

When developing a logit model of bank failures to capture bank fraud, we need to account for the following stylized facts. A large body of anecdotal evidence, as well as our consultations with the Central Bank of Russia, shows that gambling banks, having observed that the regulator switched to the tight regime in mid-2013, turned to permanently update their tools for balance sheet falsification (artificially raising the quality of their assets to lower loan loss provisions and keep the capital above the regulatory threshold).[31] the Central Bank of Russia itself was, and is, constantly learning these tools through the process of revoking sin banks' licenses. Thus, we need to account for updating of falsification schemes and the regulator's learning process in our logit models. In addition, our models have to accommodate not only standard bank failure determinants, as captured by CAMELS (see, e.g., DeYoung and Torna, 2013), but also fraud-specific indicators.

We account for fraudulence updating and the regulator's learning processes by running a loop of logit regressions on a 6-month rolling window starting from 2010M6, i.e., three years before the regulator switched to the tight regime, to 2020M12, i.e., nearly three years after the announcement of the end of the active phase of the tight policy (see the description of the timing of the policy in Section 2).

As for fraud-specific indicators, after our consultations with the Central Bank of Russia, we choose (i) a variable that captures those situations in which a bank has higher-than-average loan loss reserves but lower-than-average NPLs of firms (both as % of the bank's total assets), (ii) a variable that captures the cases in which a bank has a large portion of assets in corresponding accounts of banks outside Russia (greater than 30%, for concreteness) and no operations with these funds, (iii) a variable that captures the cases when a bank predominantly attracts funds from households and lends them to non-financial firms rather than to households.

As for the variables within the CAMELS approach, we use (i) capital adequacy ratio (C), NPL ratios in the loans to firms and to households, loan loss reserves to total assets ratio, growth of total assets and its square (A), operating cost-to-income ratio (M), the annual return on total assets (E), the ratio of cash and government securities in total assets (L), net inter-bank exposure in the domestic banking system and net foreign assets abroad, both as % of total assets (S). We also include bank size to control for too-big-to-fail considerations.

We also incorporate macroeconomic controls to account for the state of the business cycle, cross-regional differences in bank competition, and distance from a bank headquarters to the center of Moscow to capture geographical differences across banks.

The 6-month rolling window logit estimates appear in Table F.I.[32] The table contains a snapshot of results extracted for the following four sub-periods: before the tight policy, during the first months of the tight policy (2013M7), at the midpoint of the policy (2016M1), and around the end of the policy (2018M2). The dependent variable is a binary variable that equals

[31] See an early review of these falsification tools here: https://www.banki.ru/news/daytheme/?id=6609791 (In Russian; for English, one may use automated web-translation tools).

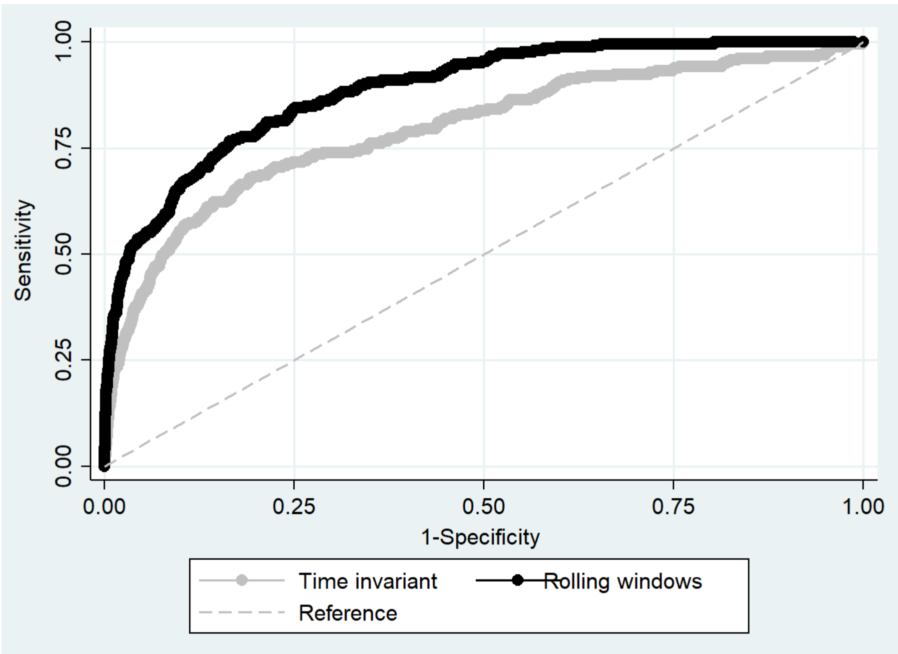
[32] We also tested the 12-month window and found no qualitative changes compared to the baseline.

1 if a bank b was shut down at month t for fraud.[33] All explanatory variables are taken with a one-month lag.

The logit estimation results show that, depending on the sub-period, banks with greater capital, lower NPL ratios, higher returns, and greater net inter-bank loans were less likely to be closed for fraud. These are within the CAMELS approach. With our fraud-specific indicators, we find strong evidence that greater LLR together with lower NPLs is a significant predictor of fraud in the near future. Regarding regional controls, we find that banks operating in regions with higher regional bank concentration, as measured by the regional Herfindahl-Hirschman Index (HHI), are less likely to be closed for fraud. This can be viewed as reminiscent of the "market power–stability" concept (see, e.g., Keeley, 1990). At the macro level, we find that banks are less likely to be closed for fraud during an expansionary phase of the business cycle. Overall, the results are in line with the broad literature on bank failures.

Regarding the in-sample quality of the estimated logit models, we compute two ROC curves—one for models with only CAMELS variables and the other for models in which we add our fraud-specific variables. The results are reported in Fig. F.I. The area under the ROC curve equals 0.78 for the models with CAMELS and 0.88 for models with added fraud indicators. This indicates the high in-sample quality of the models and a high added value of the fraud indicators.

Figure F.I. The in-sample quality of logit models (Area under ROC-curves): CAMELS alone and with fraudulent indicators



[33]The data on fraud-related closures come from the Central Bank of Russia's official press releases from 2010 to 2020.

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

Note: The table reports estimates of the following logit model: $Pr\left(Fraud.Detection_{b,t} = 1 \,|\, \mathbf{X}_{b,t-1}\right) = \Lambda\Big(\mathbf{X}'_{b,t-1}\Psi$, where the dependent variable $Pr\left(Fraud.Detection_{b,t} = 1 \,|\, \mathbf{X}_{b,t-1}\right)$ 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 using 6-month rolling windows starting from 2010M1, i.e., before the active phase of the tight regulation policy began, and finishes at the end of the sample period in 2019M6. The constant term is not reported.

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.

Appendix G. DID FIRMS ANTICIPATE CLOSURE OF THEIR SIN BANKS?

In this section, we examine whether firms anticipated the closure of their sin banks. We consider two possible endogenous adjustments by firms as evidence of such anticipation. 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.

G.1 Preemptive Switching

There are at least three reasons why firms could consider leaving their about-to-fail sin bank preemptively. First, a firm obtaining loans from an about-to-fail bank may decide to leave the bank preemptively to *signal* to other banks that it seeks long-term stable relationships with its lender(s). Second, if the firm does not switch to a different bank in advance, its payment obligation can be transferred to a new bank through an auction during the resolution process of the sin bank, in which case the firm has no control over which new bank this may be (Granja et al., 2017). Third, the closure of the firm's bank can have a disruptive effect on a firm's day-to-day operations.

On the other hand, even if the firms obtaining loans from an about-to-fail sin bank wanted to preemptively switch to a new bank, they may actually do so. The empirical literature provides evidence of the existence of switching costs, which leads to a hold-up problem—a situation in which the firm stays with its current bank despite being able to obtain better conditions at another one.[34]

We are interested in whether firm quality determines preemptive switching to a new bank. One could expect that, because of higher outside options, better quality firms are less subject to the hold-up problem and, thus, are more likely to switch to a new bank preemptively. Likewise, lower quality firms are likely to be more constrained by the hold-up problem and, thus, are less likely to leave the about-to-fail bank preemptively.

To find whether firm quality helps to explain preemptive switching, we examine if firms switch to a new bank within some time period h before the sin bank closure date. We define the indicator variable $Switch_{f,t}$ which equals 1 if firm f switches to a new bank during the time interval $[t^*_{f,b} - h, t^*_{f,b})$, where $t^*_{f,b}$ is sin bank b closure date, and zero otherwise.[35] We set $h = 6$—that is, we consider a time interval of 6 months to identify evidence of preemptive switching. We then estimate the following logit model:

$$\mathbf{Pr}(Switch_{f,t} = 1 \mid \mathbf{X}_{f,t-1}; \Theta) = \Lambda\Big(\alpha_j + \alpha_{j,bc} + \alpha_{j,r} + \alpha_{j,i} + \text{Firm.Quality}_{f,t-1}\mathrm{B}_j + \mathbf{C}_{f,t-1}\Gamma_j\Big). \quad (7)$$

[34] Ioannidou and Ongena (2010) provide evidence on the existence of switching costs. Bonfim et al. (2020) show that switching costs are primarily due to information asymmetries. Liaudinskas and Grigaite (2021) also provide the estimates of switching cost and evidence on the hold-up problem.

[35] A firm may decide to switch in advance from an about-to-fail bank *occasionally*, because the firm's loan will mature at some time $\tilde{t} \in [t^*_{f,b} - h, t^*_{f,b})$ and the firm is simply not willing to continue with the same bank. Unfortunately, with information only on the days of NPLs at the loan lever and no access to either maturity or other relevant information until 2017—we cannot distinguish these cases from the in-advance switching based on information leakages.

Table G.I. Logit regression results: do firms switch to sin or saint banks in anticipation of their current sin bank closure?

Note: The table reports estimates of the logit model (7) of new firm-bank matching *prior* to the closure of firm f's current sin bank b, as an analog to the duration regression (2) that considers the matching *after* the sin bank closure. The dependent variable $\mathbf{Pr}(Switch_{f,t} = 1 | \mathbf{X}_{f,t-1}; \Theta)$ is the indicator variable which equals 1 if firm f switches to a new bank during the time interval $[t^*_{f,b} - h, t^*_{f,b})$, where $t^*_{f,b}$ is sin bank b closure date, and zero otherwise. Firm quality is proxied by either (i) the log of days of NPLs accumulated in the closed sin bank before the closure—that is, by $t^*_{f,b}$—or (ii) the binary variables of whether the firm had negative profits at $t^*_{f,b}$ or $t^*_{f,b} + k$. Other controls include a firm's size, as measured by the log of total assets and its square, the firm's leverage-to-total assets, and liquidity-to-total assets ratios. The sample includes firms with a *single* bank relationship. The estimations are performed for the period starting with the active phase of the tight regulation policy, i.e., from 2013M7, and till 2020M10. Coefficients instead of marginal effects are reported. The constant term is included but not reported to preserve space.

	Match with a sin bank		Match with a saint bank	
	(1)	(2)	(3)	(4)
Panel 1: Firm quality:				
log DNPL_{f,t^*-6}	0.010		0.095	
	(0.080)		(0.131)	
$\text{Profit}_{f,t^*-6} < 0$		0.362		0.035
		(0.267)		(0.069)
$\text{Profit}_{f,t} < 0$		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 FEs	Yes	Yes	Yes	Yes
Regional FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
N obs	4,645	4,253	26,287	25,519
N firm-bank new matches	619	606	1,331	1,317
N firms	854	818	2,336	2,314
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.

The estimation results are reported in Table G.I. Our sample now consists of only about 30,000 firm-month observations, which is less than in the reference by a factor of 10. We have about 3,190 firms and the number of preemptive switches is about 1,950. Estimation of the preemptive switching regressions delivers no significant coefficients on the log $DNPL_{f,t^*-6}$ or $Profit_{f,t^*-6} < 0$ variables. This is true for switching to new (not-yet-detected) sin banks in columns 1 and 2, and switching to saint banks regressions in columns 3 and 4. The signs of the estimated coefficients are reversed compared to the baseline.

Regarding the other firm controls, we find that the coefficients on firm size and its square are insignificant, meaning that *larger* and *smaller* firms are not more likely to switch preemptively. The estimated coefficient on firm leverage is negative and significant in the case of in-advance switching to saint banks. Finally, liquidity negatively and significantly affects the likelihood of in-advance switching to sin banks.

Overall, the logit estimation results reveal that firms' preemptive switching from about-to-fail banks is not affected by firms' quality. One potential interpretation of this is the lack of evidence that firms could easily anticipate bank closures. That is, preemptive switching is 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 was strong enough even for high-quality firms.

G.2 Strategic Loan Repayment Delay

An alternative way to examine whether firms anticipate sin bank closures is to investigate loan repayments during the run-up to sin bank closure. Troubled firms that struggle more to meet their loan obligations may find it optimal to delay their payments if they anticipate that their bank is about to fail. In this case, they can be transferred to a new creditor, thus, opening up the possibility for debt restructuring.

We hypothesize that bad firms, as proxied with negative profits, may act strategically and thus raise loan delinquencies. We explore empirically if a change in loan repayment delay relates negatively to the firm's quality proxy during some time period before the sin bank closure. Specifically, we estimate the following model:

$$\Delta DNPL_{f,b,t} = \alpha_f + \alpha_b + \alpha_{b,f} + \alpha_t + \alpha_r + \alpha_i + \alpha_{bc} + \beta \cdot \mathbf{1}\{Profit_{f,t^*-h} < 0\} + \varepsilon_{f,b,t}, \qquad (8)$$

where $\Delta DNPL_{f,b,t}$ is a one-month change in the days of NPLs reported by a firm f that has a relationship with (not-yet-detected) sin bank b at month $t \in [t^* - h, t^*)$, $h = 12, 9, 6, 3$ months prior to the bank b closure. α_f, α_b, $\alpha_{b,f}$, α_t, α_r, α_i, α_{bc} are respectively FEs for firm, bank, firm*bank (relationship), month, region, industry, and bank closure events.

We aim to capture the effect of $Profit_{f,t^*-h} < 0$ on $\Delta DNPL_{f,b,t}$ that works *beyond* those stemming from intrinsic features of the firm's and bank's business models, the $bank \times firm$ relationships, aggregate shocks affecting the economy of the whole country or its particular regions, industry-specific shocks that may force even a profitable firm to delay repayment on loans, and the cascade of bank closures witnessed in the active phase of the tight policy.

The estimation results of regression (8) are presented in Panel 1 of Table G.II. We do not find any statistical evidence that a firm's quality relates to the delay of loan repayments—that is, the estimated coefficient on $Profit_{f,t^*-h} < 0$ is insignificant at any considered horizon h prior to the bank closures. Thus, we do not find evidence that bad firms increase their loan delinquencies before the closures of their sin banks.

Panel 2 of Table G.II, further presents the result of estimation equation (8) when we allow

Table G.II. Panel estimation results: do bad firms increase delays in repaying loans before their banks are closed?

Note: The table reports estimates of 1-month changes in the days of NPLs prior to sin bank closure, as implied by equation (8), where the dependent variable $\Delta DNPL_{f,b,t}$ is a one-month change in the days of NPLs a firm f has in bank b at month t. The estimations are performed in a window of h months before a sin bank closure, i.e., $t \in [t^*_{f,b} - h, t^*_{f,b})$, where $t^*_{f,b}$ is firm-specific date of ending a relationship with the firm f's current sin bank b and h is set at 6 months. $Profit_{t^*-h}$ is the binary variable of whether the firm had negative profits at $t^*_{f,b} - h$. *Single "firm–sin bank"* indicates those cases in which a firm has a relationship only with one bank and this bank is a sin bank. *Multiple "firm–(sin) bank"* indicates cases in which a firm has relationships with more than one bank and (at least) one of these banks is a sin bank. All regressions include bank, firm, firm*month, month, regional, industry, and bank closure events fixed effects.

Months h before sin bank closure:	$h = 12$	$h = 9$	$h = 6$	$h = 3$
	(1)	(2)	(3)	(4)
Panel 1: single "firm–sin bank" relationship (*baseline*)				
$\text{Profit}_{f,t^*-h} < 0$	1.063	0.761	1.197	–0.711
	(0.720)	(0.949)	(1.174)	(1.565)
N obs	78,645	62,519	44,749	24,768
R^2 (within)	0.091	0.111	0.143	0.255
Panel 2: multiple "firm–(sin) bank" relationship				
$\text{Profit}_{f,t^*-h} < 0$	0.219	0.414	0.937	0.379
	(0.450)	(0.786)	(0.591)	(0.500)
$\text{Sin.Bank}_b \times \text{Profit}_{f,t^*-h} < 0$	0.111	–0.644	–1.165	–1.589
	(0.791)	(1.200)	(1.367)	(1.955)
N obs	213,229	163,688	111,957	60,140
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 firm level and appear in the brackets under the estimated coefficients.

for *multiple* firm-bank relationships.[36] The results are qualitatively similar in that we do not find evidence that firm quality affects loan delinquencies before the closures of their 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 repayments delay.

[36]For this purpose, equation (8) is modified so that a firm may have relationships with at least one (not-yet-detected) sin bank and at least one saint bank simultaneously. In this case, the variable of interest is not only $Profit_{f,t^*-h} < 0$, but also its product with the sin bank indicator variable, $Sin.Bank_b$, which is equal to 1 if a bank ever fails due to fraud, and 0 if survives till the end of the sample. For strategic reasons, firms are likely to hold the worst part of their debts in sin banks and serve their best-quality debts in saint banks. If firms anticipate sin bank closures, then bad firms could start to increase loan delinquencies in the sin banks rather than saint ones.

Appendix H. FIRM PERFORMANCE: ADDITIONAL RESULTS

Table H.I. Difference-in-differences estimation results: firm performance after sin bank closures

Note: The table reports estimates of firm performance after firms experience closures of their prior sin banks and before they match with new banks, as implied by equation (4). Firm performance is proxied with the following dependent variables $Y_{f,t}$: firm size, as captured by the log of total assets (*log(TA)*, column 1), log of borrowed funds (*log(Borrow)*, column 2), log of total revenue (*log(Revenue)*, column 3), log of number of workers (*log(Employ)*, column 4), log of profit after taxes (*log(Profit)*, column 5). $Sin.Bank_{b,f} = 1$ if bank b that has a relationship with firm f ever fails for fraud, and 0 if it survives till the end of the sample. $POST_{\{t \geq t^*_{b,f}\}} = 1$ if $t \geq t^*_{b,f}$, and 0 if else. $Bad.Firm_{f,t}$ is a binary variable that equals 1 for firms with losses, and 0 for profitable firms. The estimations are performed for $t \in [2011, 2020]$ on a panel of matched firms that experienced sin bank closures during the sample period and only had single bank relationships at $t^*_{b,f}$, and the panel is restricted so that it includes the observations in only up to two years before and after $t^*_{b,f}$, i.e., firm-bank-time specific windows $[t^*_{b,f} - 2, t^*_{b,f} + 2]$ years. 1:4 nearest neighborhood matching of firms is performed prior to $t^*_{b,f}$ using the five observables: firm size, leverage, liquidity, annual growth of total assets, and profitability. All regressions contain all necessary sub-products of the triple interaction variable $Sin.Bank_{b,f} \times \text{POST}_{\{t \geq t^*_{b,f}\}} \times Bad.Firm_{f,t}$, firm and year fixed effects, and the set of firm controls to capture any residual differences across treated and control firms after 1:4 matching (firm size, except (1); leverage, except (2); and liquidity). The sample includes those firms that have a *single* bank relationship.

$\text{Y}_{f,t} :=$	log(TA)	log(Borrow)	log(Revenue)	log(Employ)	log(Profit)
	(1)	(2)	(3)	(4)	(5)
Panel 1: Focus variables:					
$\text{Sin.Bank}_{b,f} \times \text{POST}_{\{t \geq t^*_{b,f}\}}$	0.205***	0.164***	0.342***	0.158**	0.267***
	(0.043)	(0.058)	(0.063)	(0.069)	(0.080)
$\text{Sin.Bank}_{b,f} \times \text{POST}_{\{t \geq t^*_{b,f}\}} \times \text{Bad.Firm}_{f,t}$	–0.320**	–0.259**	–0.028	0.307	n/a
	(0.136)	(0.121)	(0.168)	(0.197)	
Panel 2: Key components of the triple interaction variable:					
$\text{Sin.Bank}_{b,f}$	–0.091**	–0.045	–0.129***	–0.120**	–0.093
	(0.040)	(0.052)	(0.045)	(0.060)	(0.059)
$\text{POST}_{\{t \geq t^*_{b,f}\}}$	0.082**	0.122**	–0.072	–0.131*	0.006
	(0.037)	(0.054)	(0.068)	(0.068)	(0.082)
$\text{Bad.Firm}_{f,t}$	–0.008	0.099**	–0.390***	–0.041	n/a
	(0.029)	(0.043)	(0.081)	(0.056)	
N obs	17,174	17,065	16,344	10,336	13,016
N firms	3,226	3,225	3,190	2,647	2,932
R^2 (pseudo / LSDV)	0.3	0.2	0.2	0.3	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.

Abstrakt

V tomto článku analyzujeme, jak firmy hledají nové věřitele poté, co finanční regulátor násilně zavře jejich předchozí banky, a co se stane s výkonností firem během tohoto přechodného období. V roce 2013 zahájila Centrální banka Ruska rozsáhlou politiku uzavírání bank a začala odhalovat podvodné (hříšné) banky a odebírat jim licence. Do roku 2020 byly uzavřeny dvě třetiny všech bank, které byly v provozu. Toto jedinečné období v historii analyzujeme pomocí údajů z úvěrového registru. Za prvé zjišťujeme, že před uzavřením bank nedocházelo k žádnému úniku informací, a společnosti, které si půjčují, zůstávají nedotčeny. Po uzavření existuje jasná tendence třídění: špatně výkonné firmy spěchají do jiných (dosud nezjištěných) hříšných bank, zatímco ziskové firmy přecházejí do finančně stabilních bank. Zjišťujeme, že ke spojení slabě výkonných firem a dosud neodhalených hříšných bank dochází častěji, když jsou obě hříšné banky (předchozí a další věřitel) ve společném vlastnictví, nebo když je místní bankovní trh nekoncentrovaný. Nakonec ukazujeme, že během přechodného období (tj. po uzavření bank a před přizpůsobením se novým bankám) se špatně výkonné firmy zmenšují a zažívají prudký pokles půjček a prodeje na trhu, zatímco ziskové firmy posilují, pokud jde o zaměstnanost, investice a prodej na trhu. Potenciální mechanismus zahrnuje podceňování úvěrového rizika ze strany hříšných bank: zjišťujeme, že špatně výkonné firmy (zejména společně vlastněné) dostávaly půjčky za nižší úrokové sazby než ziskové firmy před uzavřením hříšných bank.

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