Invisible Lines: How Banks Use Firm Networks to Blunt Supervisory Tightening *

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Abstract

This paper introduces a novel approach to measuring fraud in banking and to evaluating its cross-sectional and aggregate implications. I explore unique evidence of declining regulatory forbearance from the Russian banking system in the 2010s, when the central bank forcibly closed roughly two-thirds of all operating banks for fraudulent activities. I first introduce an empirical model of the regulatory decision rule that determines whether a regulator is likely to run an unscheduled on-site inspection of a suspicious bank in the near future. I estimate the model using unique data on asset losses hidden by commercial banks and discovered by the Central Bank of Russia during unscheduled on-site inspections in the last two decades. I find that the average size of hidden asset losses detected by the rule equals 38% of the total assets of not-yet-closed fraudulent banks, and that the likelihood of fraud detection soared by a factor of 5 after 2013. With quarter-by-quarter predictions from the estimated rule, I form a "treatment" group of likely-to-be-inspected banks and then run a "fuzzy" difference-in-differences (FDID) regression to estimate the effects of the tightened regulation. FDID estimates show that likely-to-be-inspected banks substantially reduced credit to households and firms after the policy started in 2013, compared to similar untreated banks. Interpreting the FDID estimates of credit contraction as a credit supply shock and evaluating the macroeconomic implications of this shock using a VAR model of the Russian economy, I find that Russia's GDP could have been larger by 7.3% cumulatively by the end of 2016 in the absence of the policy. This is the price the economy pays for reducing fraud in the banking system.

JEL classifications: D22, G21, G28, G33, H11.

Keywords: Bank misreporting, Regulatory forbearance, Bank closure, Credit Supply Shocks, Heckman selection model, Fuzzy difference-in-differences, VAR.

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1 Introduction

Central banks are typically perceived as planners that can prevent financial crises by setting proper bank regulation, thus avoiding associated welfare losses. However, in practice, central banks usually do not achieve this ideal picture due to a myriad of confounders, including (*i*) uncertainty regarding the banks' assets choices, which undermines planners' ability to recognize problem banks (Boot and Thakor, 1993), (*ii*) reputational issues when problem banks are detected and must be closed (Morrison and White, 2013), (*iii*) a lack of commitment to optimal policy per se (Acharya and Yorulmazer, 2007), and (*iv*) inconsistency in bank closure decisions at different levels of regulation (Agarwal et al., 2014). These issues cause not only the "too big to fail" problem (O'Hara and Shaw, 1990) but also lead to *regulatory forbearance* in bank closure decisions. Regulatory forbearance is shown to be pervasive both in developed countries (Wheelock and Wilson, 2000; Kang et al., 2015) and in emerging economies (Brown and Dinc, 2011). Though regulatory forbearance can be optimal in specific situations (Morrison and White, 2013; Kang et al., 2015), it can also be costly for society (Cole and White, 2017). Regulatory forbearance adds to banks' incentives to misreport losses when they face negative shocks to their assets, which results in greater fraud in banking (James, 1991; Nagel and Purnanandam, 2019). In this paper, I suggest a novel approach to measure bank fraud and its implications for the real economy. I explore a unique example of what can happen to privately-held operating banks when regulatory forbearance suddenly disappears.

The example comes from the Russian banking system in the 2010s, when substantial organizational changes were made in the structure and responsibility of its key regulatory authority, the Central Bank of Russia (CBR). In mid-2013, a new head of the CBR, Elvira Nabiullina, launched an aggressive policy of fraud detection and license revocation to deal with a large body of asset falsifications inherited from the past.[1] This policy resulted in forced bank closures of more than 600 of 950 privately-held financial institutions during the following six years.[2] Be-

[1] The myopia of the CBR before 2013 has roots in 2006, when the first deputy chairman of the CBR, Andrei Kozlov, was murdered after he revealed and blocked an illegal withdrawal of funds from Russia by a coalition of domestic and foreign subsidiary banks, see https://www.theguardian.com/business/2006/sep/14/russia.internationalnews. This episode provoked a large depressive effect on the subsequent quality of prudential regulation in Russia and stimulated not only further expansion of illegal activities, but also less stringent credit risk management by Russian banks and more bank misreporting.

[2] In 2015, *Euromoney* awarded Nabiullina a top central banker award, after the Reserve Bank of India's governor Raghuram Rajan was awarded one year before; see https://www.forbes.com/sites/kenrapoza/2015/09/16/and-the-worlds-best-central-banker-is-not-yellin/#4223182550d3. In 2016, Nabiullina received another award, by *The Banker*. See also an overview of the Nabiul-

fore 2013, the number of banks had also been permanently decreasing, but at a much lower rate, and due to more market-based reasons (losing market shares during the global recession of 2007–2009, the exit of a number of foreign banks, and others) than to changes in bank regulation. Conversely, starting from exactly mid-2013, the rate of license revocation increased dramatically and remained very high throughout the next six years.[3]

During the period of 2013-2018, in addition to regular on-site inspections of each bank every two years, the CBR was conducting *unscheduled* in-site inspections of suspicious banks and reporting the size of losses discovered in the closed banks' assets, i.e., *hidden negative capital* (HNC).[4] According to the CBR official press releases, in the majority of cases, banks were closed for illegal activities (e.g., money laundering) and excessive risk-taking that resulted in large-scale asset losses that were artificially hidden by means of balance sheet falsifications.[5] Importantly, the CBR was not publicly disclosing its upcoming targets after discovering and closing fraudulent banks: uncertainty remained as to which banks can be inspected next, and when this could happen. This environment provides a rich, unique laboratory to test the effects of declining regulatory forbearance on the operations of and risk perception by "gambling" commercial banks.

More formally, my research questions are as follows. First, what is the *empirical rule* according to which the central bank distinguishes those banks engaged in misreporting from those that report the state of their balance sheets truthfully?[6] Put differently, I suggest an empirical approach to capturing which banks are likely to be *suddenly* inspected by a regulator. Second, do likely-to-be-inspected banks increase or decrease their equity capital, and do they shrink their liabilities and assets after the empirical rule signals that they are in the red zone? Specifically, I am interested in whether such banks reduce their deposits from households and

lina's license revocation policy by *Bloomberg* via https://www.bloomberg.com/news/features/2017-02-14/putin-s-central-banker-purges-100-banks-a-year-in-epic-crackdown.

[3]Note that this decreasing trend materialized at least six months before the Russian economy entered the (local) recession of 2014–2015, and at least three quarters before the first wave of financial sanctions against Russian banks were imposed (in March 2014); see Ahn and Ludema (2020) and Mamonov et al. (2021).

[4]For convenience reasons, and because the banks were forcibly closed due to (eventually) revealed misreporting, I refer to this measure of losses as "hidden negative capital".

[5]Typically, after facing negative idiosyncratic shocks to their assets, the banks turned to falsify the actual quality of these assets to prevent accruing additional loss reserves, so that the falsified capital adequacy ratios still satisfy official requirements. Before 2016, the regulatory threshold on the minimal capital to risk-weighted assets equaled 10%, and after 2016—8%, plus a counter-cyclical component depending on the state of the business cycle (as a part of the Basel III recommendations).

[6]In this respect, I act similarly to empirical macroeconomists who proxy for monetary policy rule with actual data on inflation and GDP.

non-financial firms and whether they decrease lending to the economy. I refer to these as *scale effects* of tightened regulation. Third, what are the *composition effects* of tightened regulation, i.e., whether likely-to-be-inspected banks change the structure of their balance sheets towards specific type(s) of liabilities and assets (more or less prone to falsification and opaqueness, in the spirit of Song and Thakor (2007))? Fourth, what happens to the prices these banks set for their services? Finally, what are the macroeconomic implications of tightened prudential regulation? If the identified misreporting banks reduce their credit supply to the economy, how large could it be economically?

The first challenge I face is how to identify misreporting banks that are likely to be inspected by the regulator in an unscheduled mode. Note that these are not-yet-failed credit institutions—they continue their operations until they either recover their financial health (by drawing a positive idiosyncratic shock) or they are detected by the regulator. Thus, standard logit/probit analysis applied in the literature on bank failures is not appropriate here. One option is to compute some balance sheet characteristics that reflect bank risk exposure, rank the banks, and identify those at the bottom of the list, as is done, e.g., in DeYoung and Torna (2013). Though I also follow this direction, I argue that there is a more appropriate alternative. Specifically, if a regulator publishes official reports on the reasons for closing failed banks, one can extract the necessary information from these reports. As noted, the CBR publishes detailed reports, from which I obtain all cases of bank misreporting—fair evaluation of (remaining) assets, and the actual size of HNC.[7] I thus can keep track of not only whether a bank was closed for misreporting or not (*extensive margin*), but also the size of the losses on the closed banks' assets (*intensive margin*). The press releases containing these data, "*Vestniki Banka Rossii*", are irregular, and I manually collect them from 2007 till the end of 2019, case by case. I construct a binary indicator that equals one if a bank appears in press releases as closed for misreporting, and I use the difference between remaining assets and liabilities as a measure of losses associated with misreporting. For the rest, I rely on the monthly balance sheets and quarterly profit and loss accounts of Russian banks disclosed publicly through the CBR official website from January 2004 till February 2022, when the data was closed due to Russia's invasion of Ukraine.

I first identify likely-to-be-inspected banks among those not yet detected by the CBR using

[7]Typically, the CBR inspection committee works for 1-2 months evaluating the real quality of assets reported by the banks on the eve of license revocation. Further, all the necessary asset loss provisions are accrued, and the remaining equity capital (usually negative) is reported as the difference between remaining assets and liabilities.

the Heckman selection approach (Heckman, 1979), which encompasses both the binary indicator of misreporting bank closure and the size of HNC in a tractable way.[8] I know which banks were already forcibly closed for misreporting, and I use this information to estimate (i) the probability that a given operating bank is likely to be inspected in the next quarter for misreporting and (ii) the size of HNC conditional on misreporting being detected by the CBR.

When identifying misreporting banks, the idea is that a researcher does not know *how* a regulator makes decisions on whether to audit a suspicious bank or not, and thus she is agnostic regarding *which part* of the banking system the regulator inspects each and every period.[9] To formalize this idea, I assume the regulator inspects a bank if the predicted probability of misreporting reaches the red zone. For convenience, I assume that the threshold between green and red zones is the median value across all banks in the respective period (quarter). I also modify this assumption in several directions and discuss it in the robustness section.

Further, the researcher may also be agnostic about *the degree of regulatory suspicion*, i.e., for how long a bank with misreporting detected at a given date is treated by the regulator as continuing its misreporting practices afterward. It is natural to assume that under declining regulatory forbearance, once detected, a bank could operate under the watchful eye of the regulator for longer than just one quarter. In my regression analysis, I nonetheless start with one quarter, then proceed with four quarters, and finally assume that a suspicious bank remains under the regulator's control forever. Therefore, I construct various versions of the treatment group by assuming that different parts of the banking system will be inspected, and by changing the presumed degree of regulatory suspicion. Technically, from the standpoint of a standard difference-in-differences implementation, it is important that the treated objects remain in the treated group during the whole estimation window. In my case, this holds if I assume suspicious banks remain under the regulator's control forever. However, this does not hold in the other two cases. However, I show that the results are qualitatively the same across all these cases—though they are stronger for the 'forever' assumption.

The control group includes all not-treated banks in my baseline estimates, i.e., the banks in the green zone. In additional estimates, I reduce the control group by using the bias-adjusted

[8] I am not the first to exploit this technique in banking studies. Jiménez et al. (2014) also apply the Heckman selection approach when analyzing which loan applications were approved and which were rejected, and how an otherwise standard bank lending channel of monetary policy works when it is conditioned on approved loan applications.

[9] As I mention above in the case of Russia, the CBR does not disclose this information.

matching estimator of Abadie and Imbens (2011) to find the nearest neighbors to treated banks. For this purpose, I employ certain bank-specific characteristics (asset size, structure of assets and liabilities, quality of assets, profitability, etc.), as suggested by Gropp et al. (2018).

Given the estimated nature of my constructed treatment and control groups, I next follow a "fuzzy" difference-in-differences approach (de Chaisemartin and D'Haultfoeuille, 2017) to estimate whether the tightened prudential regulation shrank the size of treated banks after mid-2013 and forced them to adjust their assets and liabilities, compared to control banks. I then analyze the role of aggregate banking sector concentration (Boyd and De Nicolo, 2005) and cross-sectional variation in bank risk-taking (Laeven and Levine, 2009), as proxied by non-performing loan (NPL) and bank equity capital ratios, in propagating the effects of tightened regulation. Finally, I aggregate the microeconomic estimates to the macroeconomic level. I estimate the elasticity of GDP with respect to loan volumes during periods of loan supply shocks using a VAR model of the Russian economy with the sign restrictions scheme developed by Gambetti and Musso (2017) and the narrative sign restrictions approach of Antolin-Diaz and Rubio-Ramirez (2018).

In a nutshell, my results indicate that the CBR policy was efficient in restricting the scope and structure of activities of treated banks in the 2010s, i.e., before the war against Ukraine in 2022, on both intensive and extensive margins. My estimates suggest that in one quarter after the predicted probability of unscheduled in-site inspection hits the red zone, the treated banks reduced loans to households by 3.9 billion rubles and to non-financial firms by another 3.0 billion rubles, on average.[10] These are the estimated amounts of credit that could have been granted to borrowers if the banks continued to overstate their creditworthiness after 2013. This shows that tightened regulation can have considerable scale effects, echoing the result obtained by Kupiec et al. (2017), who show that lower ratings assigned by regulators to weak banks led to a significant decline in these banks' lending to the economy. At the same time, treated banks raised the share of (expensive) household deposits by 2.3 p.p. of their total liabilities and increased the share of (cheaper) firm credit by the same amount. In other words, they became more dependent on the fully insured funds and more specialized on informationally opaque assets, thus engaging in a greater asset-liability mismatch (Song and Thakor, 2007)—

[10]For comparison reasons, these are equivalent to 79 and 61 million US dollars, respectively (applying the average US dollar-to-ruble exchange rate for 2014–2016).

an unintended effect of the CBR policy. This also proves that tightened bank regulation can entail unintended composition effects. I then show that the banking sector concentration, which was rising in the 2010s due to the growing share of state-owned banks, was amplifying the scale effects of the tightened regulation. My cross-sectional estimates also show that the scale effects were larger for the banks with larger NPLs and lower equity capital. From the VAR analysis, I infer that the policy-induced reduction of credit to households and to non-financial firms by the banks in the red zone could entail a decrease in GDP by 4.1% and 3.2%, respectively. These are the estimated macroeconomic effects of the policy-induced negative credit supply shock, which are clearly large.

My results survive a battery of robustness checks, including variations of the regulation rule and the degree of regulatory suspicion, applying the bias-adjusted matching estimator of Abadie and Imbens (2011) to construct a matched sample of treated and control banks, modifications to the composition of the Heckman selection model (Lennox et al., 2012), and applying a popular measure of a bank in distress (Z-score) to constructing the treatment group, as, e.g., in DeYoung and Torna (2013).

This paper contributes to several strands of the literature. First, I suggest an empirical approach to capture a prudential regulation rule setting unscheduled on-site inspections of potentially fraudulent banks. My approach is based on a combination of the Heckman selection model and fuzzy difference-in-differences. It is applicable to many banking systems that are subject to bank fraud, and it requires only standard bank balance sheet characteristics rather than proprietary loan-level data (Blattner et al., 2023). The approach complements traditional ways of measuring bank risk exposures usually applied in the literature—Z-score of the distance to default (Beck et al., 2013) and logit/probit-based probabilities of default that exploit CAMELS indicators (DeYoung and Torna, 2013). As stated by Nagel and Purnanandam (2019), "*solvency problems may not be immediately apparent when bad shocks are realized. Deterioration in asset values may be hidden for a while, perhaps facilitated by regulatory forbearance, and short-term debt may be rolled over even if the bank is actually insolvent.*" My approach, distinct from Z-scores and predicted probabilities of default, is able to capture hidden deterioration in asset values.

Second, I add to studies on regulatory forbearance (Acharya and Yorulmazer, 2007; Brown and Dinc, 2011; Morrison and White, 2013; Kang et al., 2015, among others). The Russian banking system provides an empirical example of the theory of optimal regulatory forbearance developed by Morrison and White (2013). Although as many as 600 of 950 banks were closed by the CBR within six years after the appointment of a new head in mid-2013, there were no systemic episodes of contagious runs on other (healthy) banks, which could have potentially been initiated by banks' creditors because of the overall loss of trust. The reputation of the CBR after detecting and closing misreporting banks was not diminished. Self-interested regulation (Boot and Thakor, 1993) seems also not to have played a role. As can be inferred from the figures, the "too many to fail" effect (Acharya and Yorulmazer, 2007; Brown and Dinc, 2011) was absent in the Russian banking system. To make things even more complicated, the "too big to fail" effect (O'Hara and Shaw, 1990) was also rather limited, because the CBR refused to forbear losses of a bank from the top-30 in terms of assets (Bank Trust) and revoked its license after discovering that the bank had hidden negative capital.[11]

Third, my results contribute to the literature on relationship lending and asset-liability mismatch (Song and Thakor, 2007, among others) by showing that misreporting banks tend to increase the relative weights of less monitored funding (from the liability side) and more informationally opaque lending (from the asset side).

Finally, given Russia's war against Ukraine in 2022, it is important to understand the strength of the Russian banking system. This is a key sector that transmits financial sanctions to the rest of the economy (Mamonov et al., 2021). My results indicate that due to the CBR policy, the banking sector became stronger than before in terms of the degree of fraud but, at the same time, it also became more state-oriented. Lower fraud can reduce the overall impact of sanctions due to more trust from local investors, whereas larger government ownership can increase the impact of sanctions through capital misallocation (Nigmatulina, 2022).

The remainder of the paper is organized as follows. Section 4 presents the empirical design of the paper. In Section 3, I describe the bank-level data. Section **??** then presents the baseline estimation results. I perform sensitivity analysis in Section **??**, and Section 6 concludes.

[11]The "too big to fail" effect appeared in 2017 when the CBR detected hidden negative capital in three banks from the top-10 or top-20 in terms of assets (Binbank, Promsvyazbank, and Otkrytie, the so-called banks of the "*Moscow Gold Ring*"), and initiated their resolution through the Banking sector consolidation fund rather than closing them; see https://www.rbc.ru/finances/02/07/2019/5d1b858c9a7947ed0ee3c54f.

2 Institutional background

After the 2014 financial crisis, sanctions, and the sharp depreciation of the ruble, the Central Bank of Russia (CBR) under Governor Elvira Nabiullina initiated a sweeping program of banking-sector reform. The CBR's aim was to restore financial stability, reinforce supervisory credibility, and strengthen the transmission of monetary policy through a smaller and more solvent banking system (IMF, 2019). These reforms were enabled by institutional changes in 2013 that consolidated financial supervision within the CBR, transforming it into a "mega-regulator" overseeing banks, insurance firms, and nonbank intermediaries (BIS, 2016).

Prior to reform, Russia's banking system suffered from overcapacity, weak capitalization, and widespread related-party lending. Many small and medium-sized institutions operated as "pocket banks" for corporate owners, facilitating regulatory arbitrage and money-laundering rather than efficient intermediation (Euromoney, 2015). The CBR therefore framed its supervisory overhaul as a precondition for sustainable credit allocation and effective inflation targeting, which it formally adopted in 2014 alongside a floating exchange rate.

From 2014 onward, the CBR implemented a shift toward risk-based supervision, emphasizing asset quality, governance, and anti–money-laundering (AML) compliance (Bank of Russia, 2018). It developed more advanced off-site analytics to detect concealed losses and related-party exposures and applied stricter early-intervention triggers. Institutions unable to meet prudential standards faced license withdrawal. Between 2014 and 2018, the CBR revoked over 380 banking licenses, removing a large number of weakly capitalized and non-compliant banks. As shown in Figure 1, the number of operating credit institutions fell from 834 in 2014 to 484 by end-2018, representing a contraction of more than 40 percent in only four years.

Figure 2 illustrates the annual pace of license revocations, which peaked in 2016 at 97 banks, before declining to 51 and 60 in 2017 and 2018 respectively. Common reasons cited for enforcement actions included falsification of financial statements, asset-quality misreporting, and repeated AML breaches. While critics argued that the campaign favored state-owned incumbents, it markedly improved transparency and depositor confidence in the surviving institutions.

A very consequential institutional reform occurred in 2017, when Federal Law No. 84-FZ established the Banking Sector Consolidation Fund (BSCF) and its asset-management company

(Bank of Russia, 2017). The BSCF gave the central bank direct powers to intervene, recapitalize, and restructure insolvent institutions without relying solely on the Deposit Insurance Agency. This framework was applied rapidly to three large private banks—Otkritie, BN Bank, and Promsvyazbank—which together accounted for roughly one-tenth of system assets. Under the new mechanism, shareholders were bailed-in, while deposits and critical functions were preserved (Yale JFC, 2019). These interventions contained contagion risks and demonstrated the CBR's capacity to execute complex resolutions within weeks rather than months, but it also revealed how well-connected banks could dodge resolution for a long time, as for example Otkritie was connected in several ways to the state energy giant Rosneft. (Not sure this is a good idea)

To support the supervisory overhaul, the CBR also reformed market infrastructure and communication. The withdrawal of international credit-rating agencies from national-scale operations in 2015 prompted the establishment of the Analytical Credit Rating Agency (ACRA), ensuring continued domestic ratings coverage (BIS, 2016). Simultaneously, the CBR enhanced policy transparency through regular press conferences, inflation reports, and detailed supervisory bulletins, aligning with best practices in central-bank communication (IMF, 2019).

By 2018, the Russian banking landscape had consolidated dramatically. Asset quality and capitalization indicators improved among surviving banks, while the volume of "dubious transactions" linked to money-laundering fell by more than 80 percent relative to 2013 (Bank of Russia, 2018). However, the resolution of large private banks temporarily increased state ownership: the share of state-controlled institutions in total banking assets rose from 60 percent in 2015 to approximately 62–68 percent in 2018, depending on the source (World Bank, 2018; Vernikov, 2019). The CBR has stated its intention to re-privatize rehabilitated banks once market conditions permit.

The 2014–2018 reform episode thus combined three reinforcing elements: (1) a rigorous supervisory purge eliminating unsound institutions; (2) a modern resolution framework allowing rapid, centralized interventions; and (3) structural modernization in ratings, communication, and prudential tools. While these measures increased the state's footprint in the short run, they significantly enhanced systemic resilience and laid the foundation for a credible, rules-based supervisory regime. This institutional transformation forms the empirical backdrop for the analysis that follows.

3 Data description

3.1 Bank-level data

I use several sources of statistics at the bank level. First, data on bank misreporting come from official press releases of the CBR ("*Vestniki Banka Rossii*") from 2007 till mid-2019. These data deliver information on which banks were closed by the CBR for misreporting and what size of associated losses (HNC) that entailed. Second, I collect all relevant data on bank assets and liabilities from monthly balance sheets ("*Form 101*") and data on bank income and expenses from quarterly profit and loss accounts ("*Form 102*"), which were freely disclosed through the CBR website from 2004 to 2022.[12] Publishing these forms is not mandatory for banks; however, from 2007 (the beginning of my sample due to the availability of the data on misreporting), these forms covered about 95% of the Russian banking system's total assets.

I exclude from the sample the top-5 largest banks in the Russian banking system in terms of assets because these are state-owned national giants that are unlikely to be inspected.[13] I also exclude the subsequent 6 banks in the asset ranking, because they—together with the top-5—are officially recognized by the CBR as SIFI, i.e., systemically important financial institutions, and thus are also unlikely to be closed.[14] For each relative bank-specific indicator discussed in the previous section (except bank size as measured by the log of total assets), I winsorize all observations below the 1st and above the 99th percentiles in respective distribution, by each quarter. Overall, I have 925 banks that reported their forms publicly in January 2007 (the beginning of the sample), 937 banks in June 2013 (the time of Nabiullina's appointment as the head of the CBR), and 448 banks in June 2019 (the end of the sample).

I do not report the descriptive statistics of the full sample of banks here. I first run the Heckman selection model and, based on the results, construct treatment and control groups, and then, before proceeding to the DID analysis, I report descriptive statistics for the two

[12] The forms can be accessed through https://www.theCBR.ru/banking_sector/otchetnost-kreditnykh-organizaciy/.

[13] These include (in order of size): Sberbank, VTB, Gazprombank, Russian Agricultural Bank, and the Bank of Moscow.

[14] https://www.theCBR.ru/press/PR/?file=14102019_191000ik2019-10-14T19_03_50.htm.

groups in comparison.

3.2 Firm networks

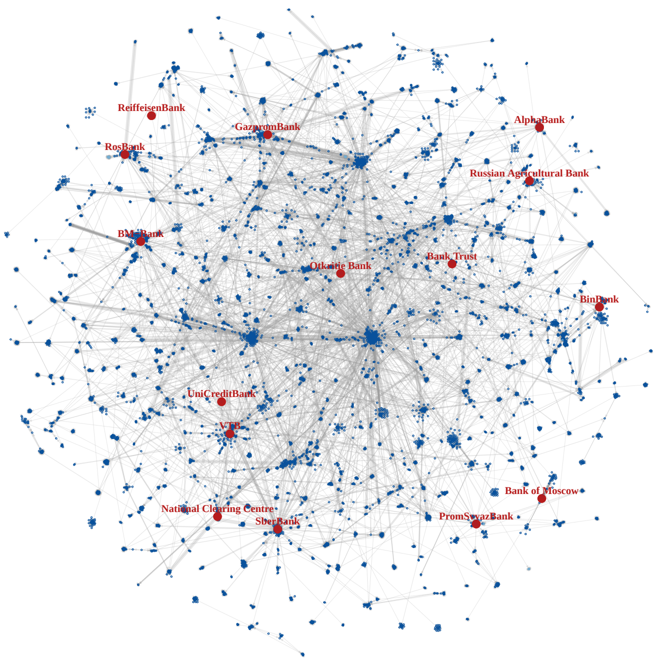
The network measures used for analysis are based on the ownership data, which comes from the Unified State Register of Legal Entities ('EGRUL'[15]) maintained by the Federal Tax Service of Russia (FTS). For each ownership relation, the registry reports identifiers, counterparty type (legal entity, individual entrepreneur, or natural person), either the owned *share* or the contributed *amount* in RUB (or both), and the period through which the ownership relationship has been valid. We use the taxpayer ID (INN) as the unique key for entities throughout. The sample covers 2004Q1–2025Q3[16]. The registry data has been obtained from the web by the means of web-crawling of each entity's ownership information. Rather than reconstruct the full national ownership graph each quarter, we iteratively expand each *bank*'s ego network up to fourth network 'handshake' of each bank [17].

[15]https://egrul.nalog.ru/index.html

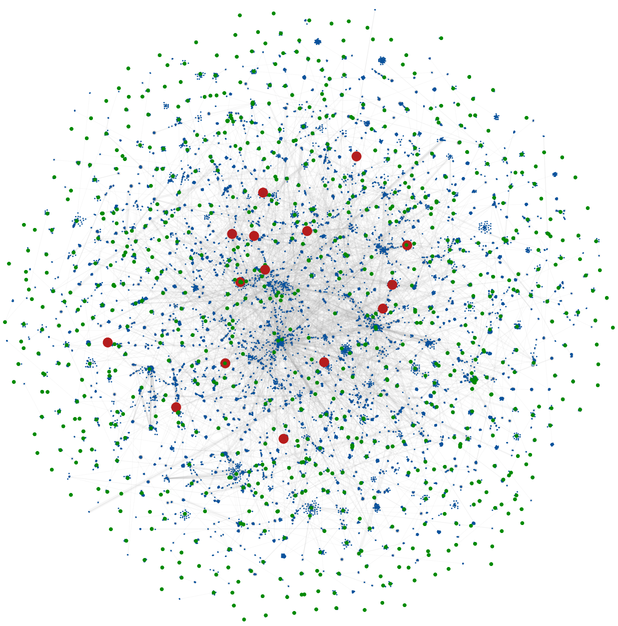
[16]All event dates in the raw registry are *floored* to the start of the calendar quarter to aggregate the daily data to the quarterly level.

[17]By the first 'handshake' network we imply the firms *directly* owned by or taking part in a given bank b. Second-level 'handshakes' are the direct counterparties of first-level 'handshakes' of bank b and so forth.

Figure 1. Firm networks



(a) Top-15 banks in terms of size ($N = 15$)



(b) All banks ($N = 1,150$)

Note: The figure illustrates ownership networks of Russian banking system one quarter before Nabiullina appointment by showing each bank's ego network up to the fourth degree depth (where first degree is represented by direct owners or firms owned by bank b, second - by owners and firms owned by the first degree counterparties and so forth). The figure 1 (a) focuses on the 15 largest Russian banks (as of 2013-Q1) illustrated as red dots with associated red labels. Blue dots represent all other firms in the network. Ownership links are plotted as gray arrows. The figure 1 (b) zooms-out to show *full* banking system with banks from figure 1 (a) plotted as red and all other banks - as green dots.

4 Empirical design and hypotheses

We begin with the prediction of already-weak but not-yet-inspected banks using panel logit models in the CAMELS manner. We then move to the fuzzy difference-in-differences regressions to evaluate the proactiveness of the bad bank closure policy and explore the role of firm networks in smoothing the anticipated effects of the policy. We finish with the back-of-the-envelope computations of the price the economy pays for hidden fraudulent banks using a structural VAR model.

4.1 The identification of already-weak but not-yet-inspected banks

The panel logit regression:

$$\mathrm{s}_{it} = \mathbb{1}\Bigg(\mathrm{HNC}_{it} = a_1 + \sum_{j=1}^{M} c_{1,j}\mathrm{BSF}_{j,it-k} + \overline{\psi}\mathrm{Size}_{it-k} + \varepsilon_{1,it} > 0\Bigg), \tag{1}$$

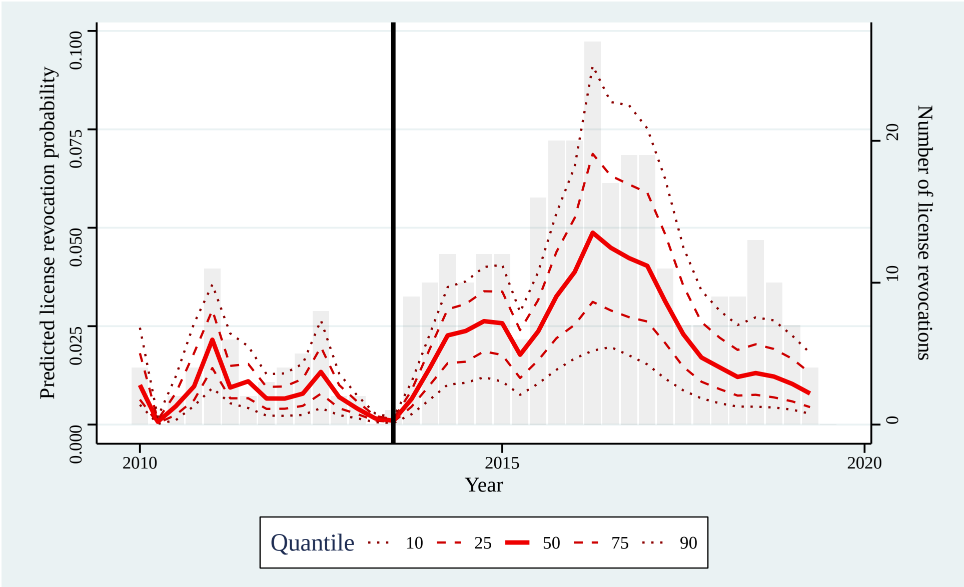
where s_{it} is a respective binary indicator and HNC_{it} is the conditional size of hidden negative capital (as % of bank total assets) of bank i at time t. $\mathrm{BSF}_{j,it-k}$ is a j^{th} bank-specific control variable ($j = 1...M$) stemming from the literature on bank failures and reflecting bank asset structure, liability structure, quality of assets, growth of assets, inter-bank linkages, etc. (see discussion of details in Section 3). I consider one-quarter lag $k = 1$ in my baseline estimations. Further, Size_{it-k} is the log of bank total assets. As is well-known, the selection equation must contain at least one variable identifying selection and not affecting the outcome. As shown by Lennox et al. (2012), empirical literature applying the Heckman selection approach most commonly uses the size variable for this purpose. Finally, $\lambda(\cdot)$ is the *Heckman's lambda* (the ratio of c.d.f. to p.d.f. at the respective point) aimed to capture the selection bias, and $\varepsilon_{1,it}$ and $\varepsilon_{2,it}$ are the selection and outcome regression errors.

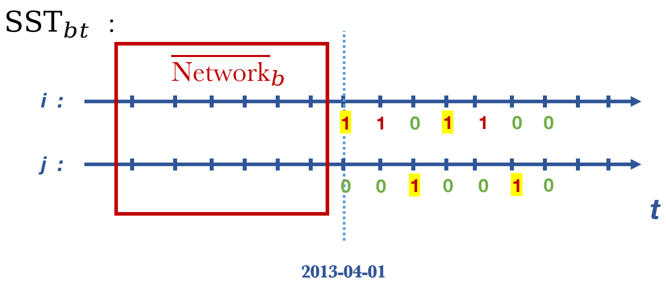
4.2 Supervisory tightening

I am agnostic about how the CBR treats detected banks and thus consider several options (Fig. ??). Suppose that a bank i was detected as misreporting at date t, i.e., $\mathbb{1}\big(\mathrm{HNC}_{it} > 0\big) = 1$, but the formal rule indicated that the bank had recovered in the subsequent periods, i.e., $\mathbb{1}\big(\mathrm{HNC}_{it+k} > 0\big) = 0$ for any $k = 1...T$.

	Full Sample						Control group		Treatment group		Comparison	
Variable	N	Mean	SD	Q1	Median	Q99	N (0)	Mean (0)	N (1)	Mean (1)	T-stat	ND
Predicted probabilities												
License Revocation, %	14065	2.2	1.9	0.0	1.7	9.0	8756	1.8	5309	2.8	1.01 ***	0.52 *
Dependent variables												
Total Assets	14076	64.8	254.9	0.1	7.2	1219.3	8764	97.1	5312	11.5	-85.64 ***	-0.38 *
Household Loans	14076	10.8	62.8	0.0	0.5	171.7	8764	16.7	5312	1.2	-15.52 ***	-0.28 *
Firm Loans	14076	16.5	73.1	0.0	1.7	296.1	8764	24.1	5312	4.2	-19.89 ***	-0.3 *
Non-Performing Loans	14076	6.3	44.8	0.0	0.2	117.8	8764	9.0	5312	1.8	-7.11 ***	-0.17
Total Equity	14076	5.6	28.0	-0.3	1.1	103.6	8764	8.6	5312	0.7	-7.91 ***	-0.32 *
Household Deposits	14076	17.7	84.1	0.0	1.7	248.9	8764	26.0	5312	4.0	-21.96 ***	-0.29 *
Firm Deposits	14076	10.7	44.3	0.0	0.9	204.8	8764	15.8	5312	2.3	-13.58 ***	-0.34 *
ln Total Assets	14076	2.1	2.0	-2.2	2.0	7.1	8764	2.5	5312	1.4	-1.12 ***	-0.63 *
ln Household Loans	14076	0.9	1.3	0.0	0.4	5.2	8764	1.2	5312	0.5	-0.68 ***	-0.61 *
ln Firm Loans	14076	1.4	1.3	0.0	1.0	5.7	8764	1.6	5312	1.0	-0.65 ***	-0.52 *
ln Non-Performing Loans	14076	0.7	1.1	0.0	0.2	4.8	8764	0.9	5312	0.3	-0.57 ***	-0.6 *
ln Total Equity	13903	0.3	1.6	-3.2	0.1	4.6	8695	0.7	5208	-0.4	-1.16 ***	-0.82 *
ln Household Deposits	14076	1.4	1.4	0.0	1.0	5.5	8764	1.6	5312	1.0	-0.65 ***	-0.49 *
ln Firm Deposits	14076	1.1	1.2	0.0	0.6	5.3	8764	1.3	5312	0.6	-0.7 ***	-0.62 *
Non-Performing Loans Share	14090	7.1	12.7	0.0	3.4	74.2	8771	7.7	5319	6.1	-1.67 ***	-0.14
Capitalization	14099	21.1	17.1	-0.7	15.3	82.2	8775	21.9	5324	19.8	-2.13 ***	-0.13
Control variables												
ROA	14056	0.3	2.2	-4.9	0.3	5.6	8748	0.4	5308	0.1	-0.29 ***	-0.13
Liquid Assets Share	14121	16.8	16.9	0.3	10.6	81.6	8789	17.3	5332	15.9	-1.37 ***	-0.08
Net Interbank Loans	14097	2.1	13.3	-43.1	0.0	47.6	8775	2.1	5322	2.1	-0.02	0
Total Assets Growth	14033	2.8	15.4	-33.5	1.5	63.0	8737	2.8	5296	2.8	-0.04	0
Network variables												
Degree (Out)	12311	3.7	4.7	0.0	2.0	23.0	7662	4.3	4649	2.7	-1.56 ***	-0.36 *
Strength (Out)	12311	1.4	2.3	0.0	0.6	11.1	7662	1.8	4649	0.9	-0.87 ***	-0.41 *
N. of Controlled Firms	12285	1.9	4.8	0.0	0.0	30.0	7636	2.5	4649	0.9	-1.56 ***	-0.36 *
1 / HHI (Out)	9836	3.0	3.0	1.0	2.0	15.8	6217	3.4	3619	2.4	-1.02 ***	-0.37 *

Figure 2. Predicted probabilities of fraud detection –





4.3 Empirical specification

...my treatment and control groups of banks are fuzzy by construction (de Chaisemartin and D'Haultfoeuille, 2017). The imposition of treatment varies over time, which requires one to control for time fixed effects to make the treatment effects comparable across times Goodman-Bacon (2021). I formalize these ideas in the following fuzzy time-varying difference-in-differences (DID) regression:

$$y_{bpt} = \alpha_b + \lambda_{pt} + \beta_1 SST_{bt} + \beta_2 SST_{bt} \times Network_{bt} + \gamma X_{bt-1} + \varepsilon_{bpt} \tag{2}$$

where b is bank, p is one of the eight possible profiles of banks, and t is quarter. ... $Y_{it}^{(n)}$ is n^{th} dependent variable from one of two categories: assets and liabilities in absolute terms, assets and liabilities in relative terms (see below). Further, $\text{BSF}_{m,it}$ is m^{th} bank-specific control variable, as suggested by Gropp et al. (2018); α_b and λ_{pt} represent bank and profile-time specific fixed effects, and ε_{bpt} is the regression error.

Regarding the choice of $Y_{it}^{(n)}$, the first of the two categories includes the sizes of assets, equity capital, deposits of households, deposits of non-financial firms, loans to households, and loans to non-financial firms. The null hypothesis reads as $\beta_3 < 0$ and is statistically significant. This would indicate declining regulatory forbearance, thus implying less CBR tolerance of misreporting banks after mid-2013.

The second category of dependent variables considers variables from the first category to be ratios to total assets (except the assets themselves). The null hypothesis implies that β_3 is statistically significant, though its sign is ambiguous. The data show whether and how treated banks adjust the structure of their balance sheets.

5 Estimation results

5.1 Fuzzy DID results

Having constructed and discussed the treatment and control groups of banks, I now present my baseline DID regression results on the scale and composition effects of declining regulatory forbearance.

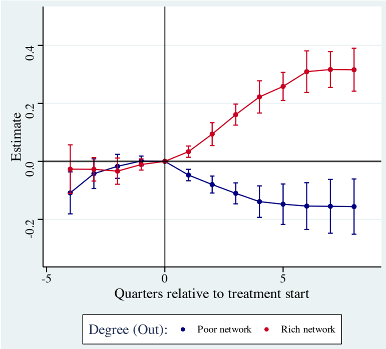
Overall, the results of this section indicate that the tightened prudential regulation launched in mid-2013 forced inspected banks to restructure their assets and liabilities. However, this restructuring was likely to increase the banks' risk exposure, because they tended to decrease owned funds, rely more on insured deposits of households, and provide relatively more loans to firms.

6 Aggregate implications of the supervisory tightening

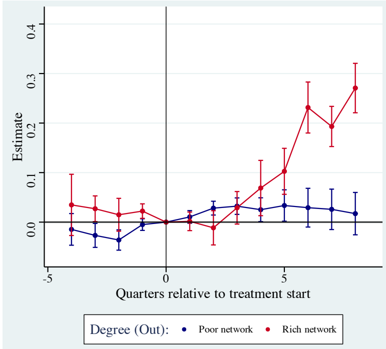
6.1 SVAR model of the Russian economy

In the absence of access to matched bank-borrower data of the CBR, I turn to alternative ways to evaluate the macroeconomic effects of tightened prudential regulation in the Russian economy. I aggregate the microeconomic estimates of credit reductions by misreporting banks to the macroeconomic level by applying a SVAR model with five endogenous variables, including

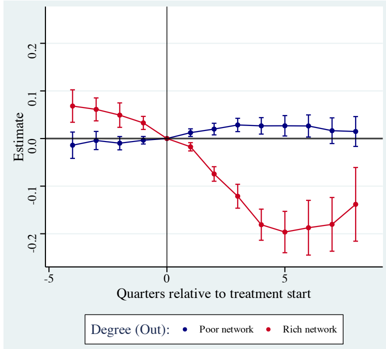
Figure 3. The effects on bank assets



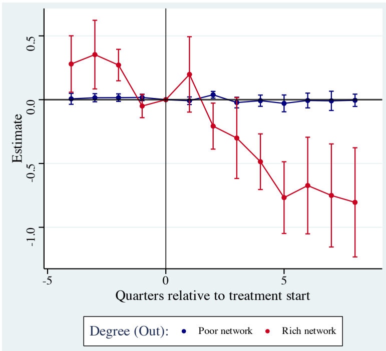
(a) Total assets



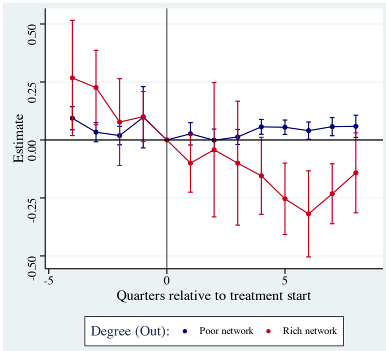
(b) Corporate loans



(c) Household loans

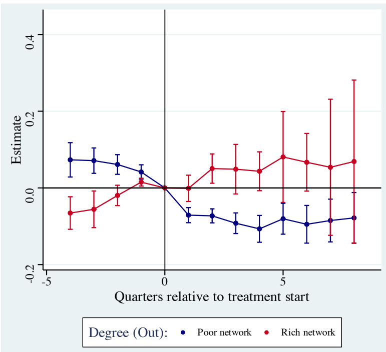


(d) Corporate bonds

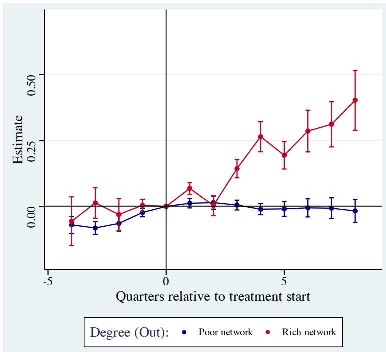


(e) Foreign assets

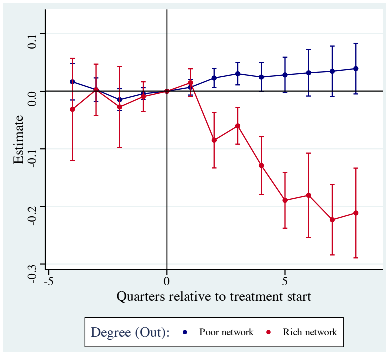
Figure 4. The effects on bank liabilities



(a) Total equity capital



(b) Corporate deposits



(c) Household deposits

Note: The figure shows ... based on the degree-out network measure

output, CPI inflation, risk-free interest rate, composite bank lending rate, and the volume of bank loans in the economy, following Gambetti and Musso (2017). I employ the authors' sign restriction approach and identify credit supply shock as a shock that simultaneously causes the lending rate to fall and loan volumes to rise (on-impact), and output, prices, and the risk-free rate to also rise (on-impact). I identify the other shocks—monetary, aggregate demand (AD), and aggregate supply (AS)—to separate them from the credit supply shock and avoid

Table 1. Supervisory tightening, firm networks, and bank outcomes: Baseline FDID estimates

	Assets			Liabilities			Risks	
	Total Assets	Household Loans	Corporate Loans	Equity Capital	Household Deposits	Corporate Deposits	NPL	CTA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Heterogeneous effects								
SST_{bt} × Poor network	-0.249***	0.032**	0.049	-0.164***	0.061**	-0.011	0.458	-0.841
	(0.065)	(0.016)	(0.030)	(0.046)	(0.030)	(0.034)	(1.052)	(0.600)
SST_{bt} × Rich network	0.557***	-0.207***	0.363***	0.179	-0.282***	0.652***	-3.654***	-2.362***
	(0.059)	(0.037)	(0.046)	(0.134)	(0.059)	(0.072)	(1.250)	(0.379)
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank profile × quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
N obs	8,921	8,905	8,905	8,737	8,905	8,905	8,905	8,905
Switchersin	3,260	3,257	3,257	3,211	3,257	3,257	3,257	3,257
Panel B: Average effects								
Susceptible (SST_{bt})	-0.246***	0.0131	0.0535**	-0.141***	0.049**	0.011	-0.125	-0.680
	(0.053)	(0.013)	(0.024)	(0.039)	(0.025)	(0.029)	(0.906)	(0.555)
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank profile × quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
N obs	10,789	10,745	10,745	10,745	10,745	10,745	10,745	10,745
Switchers-in	3,913	3,906	3,906	3,906	3,906	3,906	3,906	3,906

Note: The table contains estimates of regression (2) where treatment event is defined as getting susceptible to the central bank ($SST_{bt}^{0\to1}$) - thus, according to the (de Chaisemartin and D'Haultfoeuille, 2017) definition, we are using only 'switchers-in' banks in the treatment group. Bank profile × quarter fixed effects are included to allow for different dynamics for banks with different business models, which we capture by Bank profile bins being constructed as a combination of four dummies for: bank size and share of firm loans to assets (below or above median), and state and foreign bank dummies .

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

the "masquerading" of shocks (Wolf, 2020).

Following recent trends in the SVAR literature, I also apply the narrative sign restriction approach, suggested by Antolin-Diaz and Rubio-Ramirez (2018). I account for the fact that December 2014 is perceived as a time of dramatically restrictive monetary policy shock in Russia. That is, during the "Black Monday" of December 15, the CBR suddenly raised the key rate by 6.5 percentage points (from 10.5 to 17% per annum), which raised fears of further credit declines in the economy.

I then compute the impulse response functions of all endogenous variables to the identified credit supply shock and the implied elasticity of output with respect to credit at exactly the time a credit supply shock occurred. Tightened regulation has nothing to do with demand-side factors affecting the credit and thus can be understood as a force underlying negative credit supply shocks.

6.2 Macroeconomic data

For the SVAR analysis, I gather monthly data on output, CPI inflation, risk-free rate, composite lending rate, and the volume of loans to households and non-financial firms (see Fig. B.I in Appendix B). The data are collected from the official databases of the Federal State Statistic Service (Rosstat) and the CBR.

The data show that output grew 1.5 times over the period, exhibiting strong cyclical features (especially before the global financial crisis of 2007–2009) and clearly slowed after the recession of 2014–2015. Prices during the same period more than tripled. Loan volumes substantially outpaced the growth of output and prices, increasing approximately 17 times. This is a typical feature of emerging economies. Risk-free and lending rates vary considerably, between 5 to 15% and 10 to 20% per annum, respectively, also exhibiting strong pro-cyclical features.

6.3 Aggregate results: Back-of-the-envelope computations

Having established that tightened bank regulation had significant scale and composition effects at the treated (misreporting) bank level, I now evaluate the macroeconomic implications of these effects. The range of SVAR-estimated elasticities of output with respect to loan volumes—1.52 to 1.86 (see Appendix C)—provides a bridge between the micro part of the paper and evaluation of the macroeconomic implications of the tightened bank regulation. Recall from the estimated scale effects of the tightened regulation that the treated banks might have reduced their supply of loans to households by as much as 3.9 billion rubles and to firms by 3.0 billion rubles within the three years after mid-2013 (see Table **??** in Section **??**). Recall also that I applied an agnostic regulation rule ($\theta = 0.5$), according to which the CBR audits half of the banking system each quarter: the banks with estimated probabilities of being audited ($\hat{s}_{it}$) from selection equation (1 of the Heckman model) exceeding the median at each respective quarter. This results in 455 banks being audited each quarter.

To evaluate the macroeconomic effects of tightened bank regulation, I multiply the estimated elasticities by the average credit supply reductions and by the average number of banks to be audited, and obtain the following results. First, Russia's GDP might have contracted by 2.6–3.2% (or by 2,075–2,539 billion rubles) through the channel of *corporate* credit supply reduction by fraudulent banks.[18] Second, Russia's GDP might have contracted by another 3.2–4.1% (or by 2,697–3,301 billion rubles) through the channel of *household* credit supply decline by fraudulent banks. Needless to say, these are considerable numbers, reflecting the price of removing fraud from the banking system.

7 Conclusion

The results indicate that central banks can effectively detect banks engaged in misreporting their balance sheets and restrict their activities on both the extensive and intensive margins. Banks are likely to pursue a misreporting strategy when they are experiencing negative shocks, e.g., to the quality of their assets, that are sufficient to push their capital down to well below the minimum levels required by the central bank. The banks thus artificially increase the quality of their assets to avoid additional losses, and to continue to satisfy the capital regulation constraint. Of course, the banks pursue this strategy only if they evaluate their continuation value in the banking system as being greater than the outside option. Central banks understand this logic and may exercise forbearance of the losses of such banks in the future, in anticipation that the banks will experience positive shocks. This gives rise to a large degree of regulatory forbearance on the part of the central banks of advanced and emerging economies. This paper provides a unique example of an emerging economy (Russia), in which the central bank, after a decade of excessive forbearance, switched to a very tight regulation policy of detecting misreporting banks and revoking their licenses, thus cleaning the banking system. I also show that this policy had a meaningful macroeconomic effect: by forcing fraudulent banks to stop their lending to the economy, Russia's GDP might have lost roughly 7% in a three-year horizon. This is the price the economy has to pay for removing fraud.

[18] The average volume of nominal GDP in 2014–2016 equaled 80,180 billion rubles. This is equivalent to 1,618 billion US dollars (using the average dollar-to-ruble exchange course for the same period, 49.57).

These results can provide input for a new theory of bank regulation that would bring together the possibility of rapidly declining regulatory forbearance and the risk of the regulator's reputation declining. Kang et al. (2015) show that a central bank could force active license revocation if the incurred monetary (short-run) and non-monetary (long-run) losses associated with a bank's closure are small enough. On the other hand, Morrison and White (2013) suggest that it is important to take the reputation risk of the central bank itself into consideration, to prevent contagion caused by runs of distrustful bank creditors. Finding a bridge between the two studies and my work here could be an important avenue for future research.

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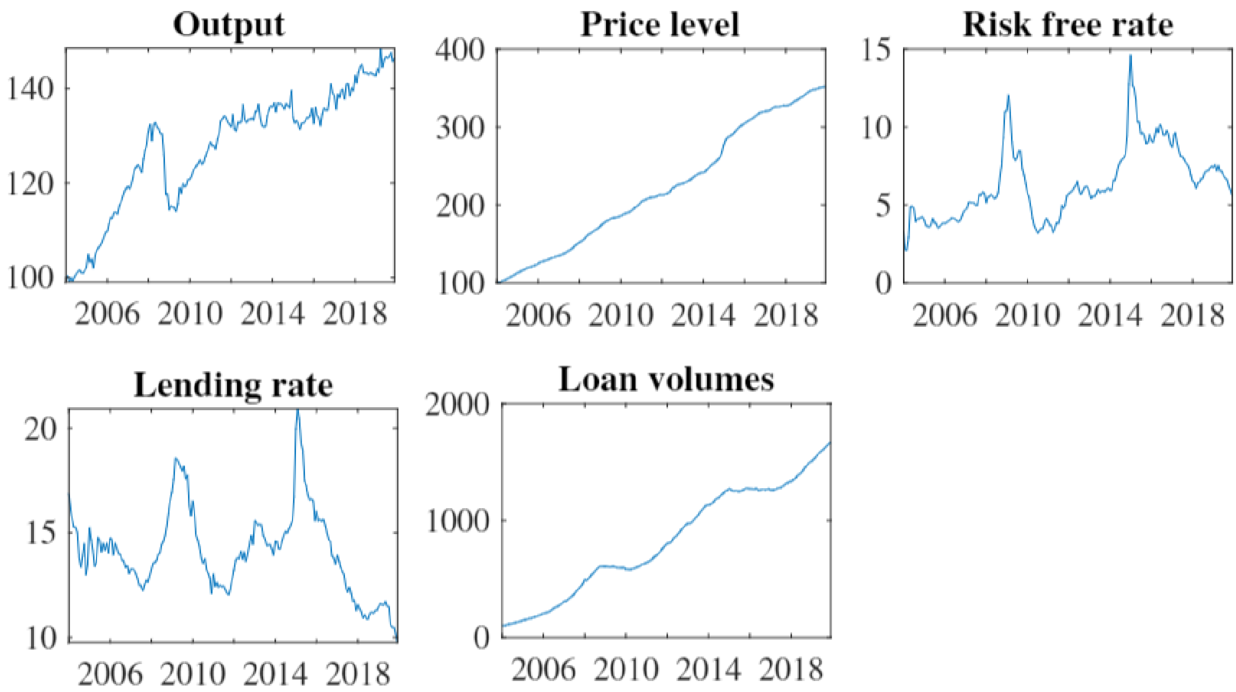
Appendix A Descriptive statistics at the bank level

Table A.I. Descriptive statistics: ±3 years around the regulatory tightening in mid-2013

Regulation type	Control group					Treatment group				
	N	Mean	SD	Min	Max	*N*	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel 1: The set of dependent variables										
Scale variables (billion rubles):										
Total assets	9,005	44.2	105.4	0.1	1415.5	8,691	5.5	10.1	0.1	264.5
Equity capital	9,005	4.6	10.2	–105.9	116.2	8,691	0.7	1.0	–1.1	31.4
firm deposits	9,005	9.9	29.2	0.0	622.1	8,691	1.2	2.8	0.0	120.5
Household deposits	9,005	12.7	31.0	0.0	364.6	8,691	2.3	4.2	0.0	69.0
Loans to firms	9,005	13.2	36.5	0.0	550.9	8,691	2.6	6.0	0.0	169.8
Loans to households	9,005	8.3	25.5	0.0	304.2	8,691	0.6	1.4	0.0	63.4
Composition variables (% of total assets):										
firm deposits	9,005	26.1	17.5	0.0	90.2	8,691	26.4	15.4	0.0	93.2
Household deposits	9,005	26.5	20.2	0.0	87.1	8,691	38.0	20.6	0.0	85.5
Loans to firms	9,005	27.6	17.4	0.0	92.7	8,691	42.1	18.5	0.0	96.2
Loans to households	9,005	16.6	17.2	0.0	94.8	8,691	15.2	12.7	0.0	87.8
% paid on firm deposits	7,692	6.5	2.9	0.1	19.7	7,660	7.0	3.0	0.1	19.7
% paid on household deposits	7,811	8.0	2.3	0.3	15.1	7,915	8.9	2.1	0.3	15.3
% received from loans to firms	8,799	13.5	3.8	2.6	32.9	8,669	14.9	2.9	2.9	32.6
% received from loans to households	8,865	15.8	5.0	3.5	43.6	8,625	15.6	4.0	3.2	43.7
Panel 2: The set of explanatory variables										
Equity capital / Total assets (%)	9,005	21.4	16.6	–19.0	97.6	8,691	18.1	11.4	–17.9	87.2
NPLs on firm loans (%)	9,005	6.9	14.3	0.0	100.0	8,691	3.1	5.5	0.0	100.0
NPLs on household loans (%)	9,005	6.0	9.7	0.0	100.0	8,691	7.0	11.7	0.0	100.0
Liquid assets / Total assets (%)	9,005	14.5	13.7	0.0	92.8	8,691	16.1	13.0	0.1	94.7
ROA (annualized, %)	9,005	1.8	2.9	–47.5	66.8	8,691	1.3	2.2	–16.2	26.7
Net interbank loans / Total assets (%)	9,005	2.8	12.2	–74.3	89.0	8,691	1.1	7.3	–71.6	62.2
Turnover of house.loans / Total assets (%)	9,005	2.1	3.2	0.0	61.8	8,691	2.0	2.6	0.0	52.7
Turnover of firms.loans / Total assets (%)	9,005	7.4	8.1	0.0	157.1	8,691	9.9	8.6	0.0	193.8
Growth of total assets (annualized, %)	9,005	24.6	54.7	–94.0	1540.5	8,691	22.9	40.7	–74.2	485.8
log of total assets	9,005	2.1	1.9	–2.5	7.3	8,691	1.0	1.1	–2.8	5.5

Appendix B Macroeconomic data for SVAR analysis



Note: The figures show the data inputs to the SVAR analysis, in levels. Base indices are normalized to 100 as of January 2004. Interest rates are in per cents. *Output* reflects the index of basic economic activities. *Price level* stands for the consumer price index. *Loan volumes* reflect the amount of bank loans outstanding. *Risk-free rate* is the short-term government bond yields, which proxies the policy rate. *Lending rate* is the weighted average of bank lending rates.

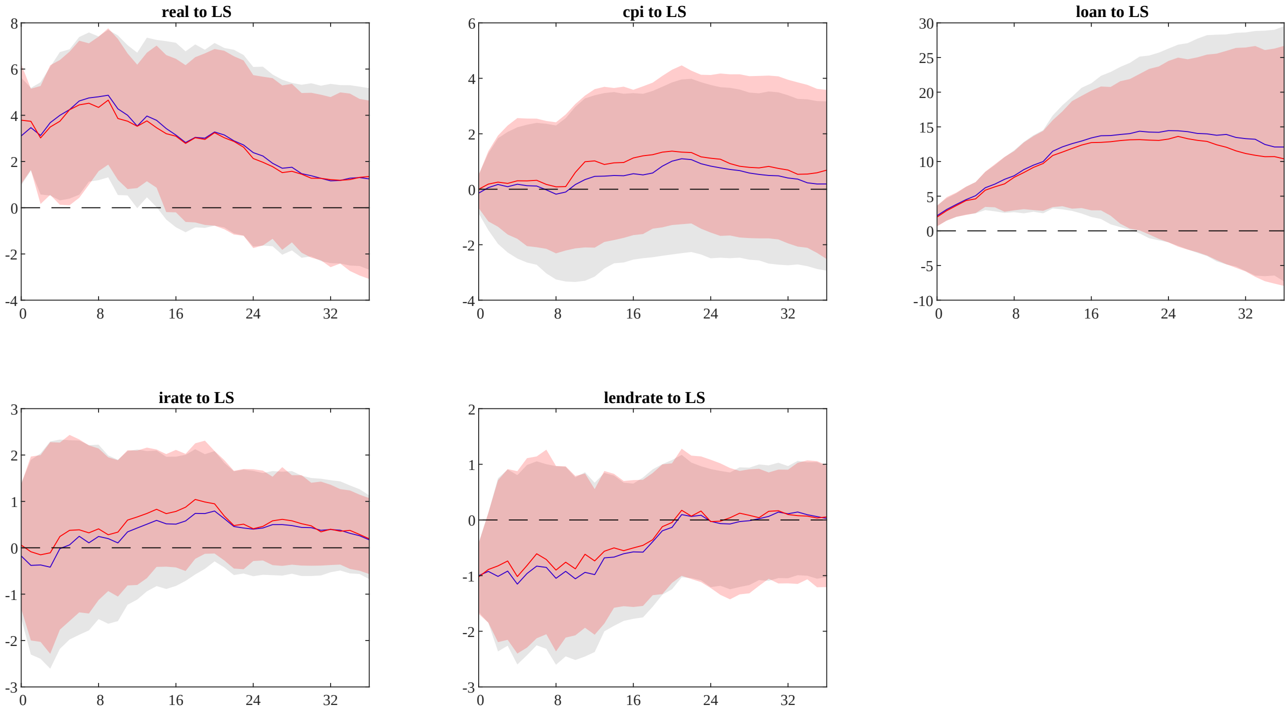
Sources: The Central Bank of Russia (the CBR, https://www.theCBR.ru/eng/key-indicators/), The Federal State Statistic Service (Rosstat, https://eng.gks.ru/folder/75924).

Figure B.I. Time evolution of selected real and financial characteristics of the Russian economy

Appendix C SVAR-estimates

I appeal to vector autoregressive models (VAR) with structural shocks identified through sign restrictions schemes. With such schemes, I can identify credit supply shocks (CSS) at the macro level and estimate the elasticity of GDP with respect to loan volumes caused by the credit supply shock. For this purpose, I borrow the CSS identification scheme from Gambetti and Musso (2017) and add the narrative component to the analysis, as recently suggested by Antolin-Diaz and Rubio-Ramirez (2018), to additionally account for the large negative interest rate shock of the "Black Monday" of December 15, 2014. I report the results obtained with only the first approach (GM, hereinafter) or both (GM+ADRR). I begin with a brief discussion of the estimated impulse responses in the VAR model and then demonstrate how I apply these to microeconomic estimates of the tightened regulation.

Impulse responses. Fig. C.I reports the estimated impulse responses to the positive credit supply shock, in which I normalize the lending rate reaction to –1 percentage points (per annum) on-impact. What can be observed from the figure is that output reacts positively (as I define through the sign restriction scheme) until at least the 15th month after the shock, with the on-impact response equal to +3.2 to +3.9 percentage points (under the "GM" and "GM+ADRR" schemes, respectively). Loan volumes also react positively until at least the 20th month after the shock, so that the on-impact response is +2.1 percentage points (under both schemes). I infer from these two last estimates that the implied on-impact elasticity of output with respect to loan volumes is bounded between 1.52 and 1.86, which is comparable, though somewhat larger, with those obtained in Gambetti and Musso (2017) for developed countries.



Note: The figures present the estimated impulse responses to identified credit supply (CS) shocks in the 5-variables SVAR with either one or two sign restriction schemes imposed. The first one (GM) follows the sign restriction scheme used to identify credit supply shocks in Gambetti and Musso (2017). The second one (GM+ADRR) adds narrative sign restrictions, as introduced by Antolin-Diaz and Rubio-Ramirez (2018). In the ADRR scheme, I consider December 2014 as a period of negative (restrictive) interest rate shock in the Russian economy. The blue line indicates the case in which only SR is considered. The red line represents the case in which both SR and NSR are in place. The confidence bands are defined as the range bounded by the 16^{th} and 84^{th} percentiles of distribution constructed from the successful draws from the posterior. X-axis shows months after the CS shock. IRFs are normalized so that the lending rate reacts by -1 percentage point on impact. Finally, the IRFs for output, CPI, and loan volumes are cumulative, i.e., they represent the effects of shocks on the sum of one-month log-differences from period -1 to t, i.e. $log(y_t) - log(y_{-1})$.

Figure C.I. Impulse response functions to the identified credit supply shock (CS)

Appendix D Machine learning results

Appendix E Relationship with bank Z-scores

Table E.I. Descriptive statistics of the treatment group:
±3 years around the regulatory tightening in mid-2013

	N obs	N banks	Mean	SD	Min	Max
Panel 1: Regulation rule: $\theta = 0.25$						
Heckman-based treatment indicator	16,845	906	0.24	0.43	0	1
Z-score-based treatment indicator	16,845	906	0.22	0.42	0	1
Panel 2: Regulation rule: $\theta = 0.5$						
Heckman-based treatment indicator (*baseline*)	16,845	906	0.49	0.50	0	1
Z-score-based treatment indicator	16,845	906	0.49	0.50	0	1
Panel 3: Regulation rule: $\theta = 0.75$						
Heckman-based treatment indicator	16,845	906	0.74	0.44	0	1
Z-score-based treatment indicator	16,845	906	0.75	0.43	0	1
Panel 4 (for comparisons): the sample of all banks (treated and control)						
Z-score	16,845	906	48.64	43.82	0.22	272.28
Z-score, adjusted to bank size	16,845	906	–1.01	36.95	–65.62	405.68
HNC to total assets (predicted), $\text{HNC}_{0,1}$	16,845	906	15.64	21.77	0.00	444.44
Panel 5 (for comparisons): the subsample of treated banks under regulation rule $\theta = 0.25$						
Z-score	12,467	837	50.21	44.84	0.22	272.28
Z-score, adjusted to bank size	12,467	837	–3.17	35.67	–65.62	372.16
HNC to total assets (predicted), HNC_1	12,467	837	33.98	22.67	0.02	444.44
Panel 6 (for comparisons): the subsample of treated banks under regulation rule $\theta = 0.5$						
Z-score	8,313	733	49.65	44.78	0.46	272.28
Z-score, adjusted to bank size	8,313	733	–5.42	35.08	–65.62	372.16
HNC to total assets (predicted), HNC_1	8,313	733	31.70	21.26	0.05	444.44
Panel 7 (for comparisons): the subsample of treated banks under regulation rule $\theta = 0.75$						
Z-score	4,075	543	48.14	44.70	0.46	272.28
Z-score, adjusted to bank size	4,075	543	–8.02	35.44	–65.62	282.16
HNC to total assets (predicted), HNC_1	4,075	543	30.41	21.26	0.05	444.44

Note: The table contains descriptive statistics of (i) various versions of a binary indicator of the treatment group of banks (Panels 1–3) and (ii) Z-scores, both commonly used and adjusted for bank size, and predicted values of HNC computed for the full sample of banks (Panel 4) and for the three subsamples of treated banks covered by the regulation rules considered in the main text: $\theta = [0.25, 0.5, 075]$ (Panels 5–7). The Heckman-based treatment indicator relies on the "*hidden negative capital*" (HNC) concept and follows the Heckman selection model (1)–(**??**), the baseline approach in the text. The Z-score-based treatment indicator is based on bank rankings on their respective Z-scores, as in DeYoung and Torna (2013), and additionally adjusted for bank size. The competing treatment indicators are reported for the three regulation rules. For example, for the Heckman-based treatment indicator, $\theta = 0.25$ implies that the regulator applies the cut-off threshold equaled 25% of the estimated probability of being selected into the group of misreporting banks: below the threshold, the banks are treated as healthy (non-misreporting), above it—as fraudulent (misreporting). For the Z-score-based treatment indicator, $\theta = 0.25$ means that, in a given quarter, all banks with the highest 25% of all values of Z-score are treated as healthy (non-misreporting) and the rest of banks—as fraudulent (misreporting).

Table E.II. Comparison of HNC and Z-scores: complements?
±3 years around the regulatory tightening in mid-2013

Panel 1: Extensive margin

Dependent variable:	TREAT (HNC, *baseline*)					
Key explanatory variable X_{it}:	Z-score			TREAT (Z-score)		
Regulation rule:	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$
	(1)	(2)	(3)	(4)	(5)	(6)
X_{it}	–0.010	–0.019***	–0.022***	0.032***	0.010	0.029***
	(0.007)	(0.008)	(0.007)	(0.012)	(0.013)	(0.011)
N Obs.	16,800	16,800	16,800	16,845	16,845	16,845
N banks	906	906	906	906	906	906
Wald χ^2	210.9***	286.6***	324.5***	215.4***	277.3***	315.6***
log Likelihood	–5,660.1	–7,207.0	–5,711.5	–5,682.4	–7,236.4	–5,733.5

Panel 2: Intensive margin

Dependent variable:	Full sample: $HNC_{0,1}$			Subsample of treated banks: HNC_1		
Key explanatory variable X_{it}:	Z-score			Z-score		
Regulation rule:	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$
	(1)	(2)	(3)	(4)	(5)	(6)
X_{it}	0.185	–0.074	–0.370	0.713*	0.912**	1.418*
	(0.443)	(0.406)	(0.333)	(0.428)	(0.421)	(0.744)
N Obs.	16,800	16,800	16,800	12,446	8,299	4,066
N banks	906	906	906	837	733	543
F-test	28.1***	12.3***	5.8***	53.1***	28.7***	9.9***
R^2_{within}	0.133	0.061	0.026	0.278	0.205	0.145

Note: The table contains regressions reflecting relationships between the Z-score adjusted for bank size and the estimated HNC at the bank level.

On the extensive margin (whether a bank is treated or not), in Panel 1 I perform probit estimates in columns (1)–(6). Columns (1)–(3) contain the marginal effects of the Z-score on the probability of being treated under the three regulation rules, $\theta = [0.25, 0.5, 075]$, respectively. Each of the three marginal effects is multiplied by the Z-score's one standard deviation (36.95, in the full sample). In columns (4)–(6), I further transform the Z-score into a binary indicator which equals 0 for the banks with the highest 25%, 50%, or 75% of all values of the Z-score in a given quarter and 1 for the respective rest of banks. I then present in columns (4)–(6) the marginal effects of being treated under the Z-score's definition of bank instability on the probability of being treated under the HNC (*baseline*) definition.

On the intensive margin (the size of HNC conditional on being treated), in Panel 2 I carry out two-way FE estimates in columns (1)–(6). Columns (1)–(3) show the relationship between the Z-score and the estimated HNC to total assets ratio in the full sample (all banks, i.e., treated and control), while columns (4)–(6) do the same for the subsample of treated banks only. The coefficients were multiplied by the Z-score's one standard deviation in the respective subsample.

All regressions include the full set of bank fixed effects (FE), quarter FE, and bank-specific characteristics.

***, **, * 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.