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Measuring Fraud in Banking and its Impact on the Economy: A Quasi-Natural Experiment

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Measuring Fraud in Banking and its Impact on the Economy: A Quasi-Natural Experiment*

Mikhail Mamonov†

Abstract

This paper suggests 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] Before 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

[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 Nabiullina'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.

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 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

[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.

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 *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

[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.

[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.

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 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)—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*

[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).

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 2 presents the empirical design of the paper. In Section 3, I describe the bank-level data. Section 4 then presents the baseline estimation results. I perform sensitivity analysis in Section 5, 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 Empirical design and hypotheses

I first discuss how I suggest proxy the regulatory rule to inspect a suspicious bank with the Heckman selection approach. I then move to describe the construction of the treatment group, i.e., the banks that are suspected by the CBR of misreporting, and the control group. With these two groups, I further introduce the baseline difference-in-differences (DID) specification, in which I test the scale and composition effects of tightened regulation using an estimation window of ± 3 years around the regulatory change in mid-2013. I then introduce the channels of tightened regulation transmission to the bank balance sheets. Finally, I describe a VAR analysis suitable for uncovering the macroeconomic implications of tightened bank regulation.

2.1 Identifying fraudulent banks: the Heckman selection approach

I do not know the rule that the Central Bank of Russia (the CBR) uses to determine suspicious banks. However, I can assume that the CBR predicts the financial conditions of banks using certain econometric techniques and the banks' balance sheets. Since the CBR faces a large body of bank misreporting, in which the banks falsified the actual level of the funds they own (capital), I need to account for this phenomenon when attempting to mimic the CBR rule. Thus, as a baseline technique, I apply the Heckman selection model (Heckman, 1979), which allows me, all else being equal, to predict (i) whether a given bank is practicing misreporting (*extensive margin*) and (ii) the size of any hidden negative capital (HNC) conditional on misreporting (*intensive margin*). In the robustness checks, I switch to a simpler alternative and compute the rankings of bank soundness using the Z-score of banking stability, as in DeYoung and Torna (2013). Thus, my baseline specification is comprised of a selection equation, determining a bank's state (misreporting or not), and an outcome equation, defining the size of HNC conditional on the bank's state:

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

$$\mathrm{HNC}_{it} = a_2 + \sum_{j=1}^{5} c_{2,j}\mathrm{BSF}_{j,it-k} + \gamma\lambda\Big(a_1 + \sum_{j=1}^{M} c_{1,j}\mathrm{BSF}_{j,it-k} + \overline{\psi}\mathrm{Size}_{it-k}\Big) + \varepsilon_{2,it}. \tag{2}$$

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.

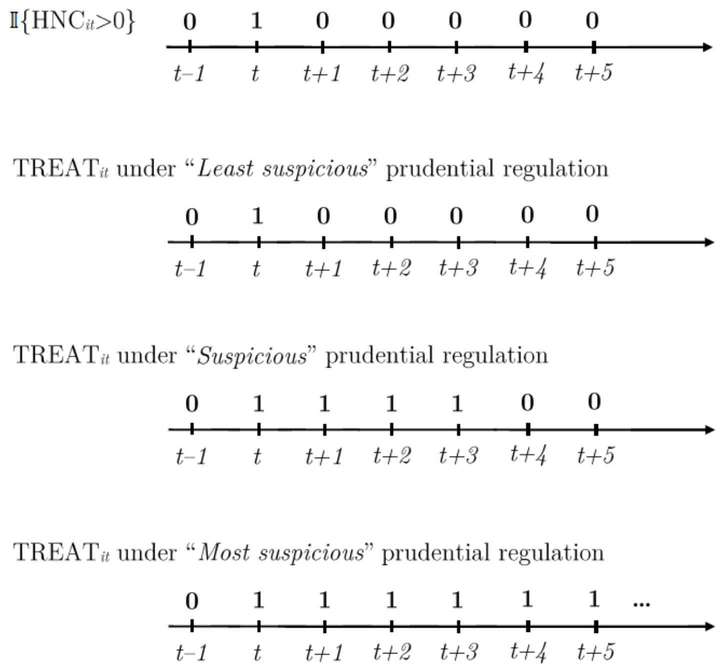
Regarding the choice of the variable identifying selection, I have several thoughts. First, the size variable is likely to pass from a statistical point of view, but could be confounded by the standard "too big to fail" mechanism. Below, I show statistically that the size is highly negatively correlated with the selection and exhibits no correlation with the *relative* HNC size (recall that I normalize HNC with bank total assets). However, this also implies that big banks are less likely to be selected than small banks, which is arguable. A more suitable alternative could be an indicator variable of whether a bank has a negative profit at date t. If the bank faces losses, it has to reclassify its assets and accrue additional loss reserves; however, the latter could threaten the bank by pulling its capital to risk-weighted assets below the regulatory threshold. If a bank expects that its continuation value *in* the banking sector will be larger than the *outside* option, the bank is likely to opt to misreport. Thus, to be in line with the literature, I follow the size variable in my baseline estimates and then, in robustness checks, switch to the indicator of negative profits.

I estimate equations (1)–(2) for each date $t = 1...T$ separately to account for changing the regulatory framework. I perform the estimates with Heckman's two-step efficient estimator. I next compute the fitted values of the two respective dependent variables at each date t and obtain their time-specific distributions across banks in the sample. The costly state verification problem (Townsend, 1979) applies to central banks, and it is unlikely that the CBR inspects all the banks in the system in every period. In the baseline estimates, I am agnostic about which part is inspected. Thus, for each t, I compute the median value of the fitted selection variable. I assume that this is the borderline $\hat{s}_t^*$, above which the CBR treats the banks as misreporting and applies tightened regulation. In robustness checks, I change the borderline from the median to the 25^{th} and then to the 75^{th} percentiles to check whether my results hold if I assume a *more tolerant* or *less tolerant* regulator. Regarding the HNC fitted values, I assume that, if $\hat{s}_{it} > \hat{s}_t^*$, $\widehat{HNC}_{it} > 0$ (*misreporting banks*); if else, then the CBR pays no attention to the estimated size of HNC (*non-misreporting bank*).

Overall, I approximate the regulatory rule of detecting misreporting banks with the Heckman selection model (1)–(2). I next make additional assumptions regarding the dynamic nature of how the CBR treats banks it has discovered to be misreporting.

2.2 Regulatory tightening and the operations of fraudulent banks: A difference-in-differences approach

I am agnostic about how the CBR treats detected banks and thus consider several options (Fig. 1). 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 $k = 1...T$.



Note: HNC is hidden negative capital. I assume three types of prudential regulation that the Central Bank of Russia (the CBR) could follow after the change of its head in mid-2013. Mid-2013 is a borderline that has marked a switch from an HNC-tolerant to an HNC-intolerant regime of prudential regulation. Fraudulent banks, when they are detected by the CBR, are subject to various forms of activity restrictions (e.g., a ban on attracting new deposits, a ban on granting new loans, etc.). The assumed three types of regulation deal with the time span of activity restrictions applied to fraudulent banks. First, by "*Least suspicious*" regulation I assume that the CBR allows fast recovery of fraudulent banks, i.e., that a bank detected by the CBR as fraudulent at t is able to fully recover at $t+1$ (able to switch from the treatment to control group). Second, by "*Suspicious*" regulation I assume that having detected a fraudulent bank at t, the CBR still believes the bank is misreporting until $t+4$ even if the rule $\mathbb{1}\{HNC_{it+1} > 0\}$ shows the bank has recovered from $t+1$ on. This partially accounts for the possibility of fraudulent banks' misreporting in the future. Third, by "*Most suspicious*" regulation I assume the CBR believes that a misreporting bank never recovers and, once detected, must always be treated (until the bank fails). This fully accounts for the possibility of continuing misreporting in the future.

Figure 1: Assumed types of differential prudential regulation

The first (baseline) option is that, having detected a fraudulent bank i at time t (by the rule $\hat{s}_{it} \geq \hat{s}^*_t$), the CBR tightens the regulation of all such banks by setting an appropriate range of activity restrictions at t and removing these restrictions as soon as the rule shows the banks are no longer misreporting. For instance, if, in the following period $t+1$ the bank i has improved its financial health—which is reflected in $\hat{s}_{it+1} < \hat{s}^*_{t+1}$—the CBR does not treat this bank as misreporting any longer. I refer to this scenario as "*the least suspicious*" regulation (the CBR fully trusts the rule). I can formalize the construction of the treatment group in this scenario as follows:

$$TREAT_{it}^{(1)} = \begin{cases} 1, & \text{if } \widehat{HNC}_{it} > 0 \\ 0, & \text{if } \widehat{HNC}_{it} = 0 \end{cases} \tag{3}$$

However, I cannot exclude that the CBR may continue to scrutinize banks that have been identified as misreporting at date t. The idea is that being detected as misreporting does not automatically entail license revocation, and the detected banks may either recover and stop misreporting, or continue misreporting in a different manner, pretending they have fully recovered.[12] The banks have incentives to mimic recovery to enjoy the removal of the CBR restrictions on their activities. To account for these features (i.e., expanding falsification practices by banks and the CBR attention to it), I introduce second and third options for the CBR regulation. The second option implies that the CBR remains suspicious and maintains restrictions on a bank's activities for at least one year after it detects misreporting. The third option implies that restrictions are maintained forever. I refer to these options as "*suspicious*" and "*most suspicious*" regulations. I check these two options in the robustness section. Formally, under these options, the treatment group is constructed as follows:

$$TREAT_{it}^{(j)} = \begin{cases} 1, & \text{if} \quad \widehat{HNC}_{it} > 0 \quad \text{or} \quad \widehat{HNC}_{it-1} > 0 \quad \ldots \quad \text{or} \quad \widehat{HNC}_{it-p} > 0 \\ 0, & \text{if} \quad \forall p = 0, 1 \ldots P \quad \widehat{HNC}_{it-p} = 0 \end{cases} \tag{4}$$

where I set $P = 4$ for the "suspicious" type ($j = 2$) and $P = \tilde{t}$ for the "most suspicious" type ($j = 3$), where $\tilde{t}$ is the first quarter in which the rule (1)–(2) detects misreporting by bank i.

I further define the indicator variable reflecting switching to the tightened regulation regime after the appointment of the new CBR head in mid-2013, which divides my sample period into two parts: before the change, when the enforcement was soft, and after the change, when the enforcement tightened. Formally, the indicator variable reads as:

$$REG.CHANGE_t = \begin{cases} 1, & \text{if } t \geq 2013Q2 \\ 0, & \text{if else} \end{cases} \tag{5}$$

Having defined the division of banks into treatment and control groups and given the time of regulatory change, I proceed to regression analysis. The concepts in this analysis appear in Fig. 2

[12]This is in line with a large body of anecdotal evidence that operating banks modify their falsification schemes as soon as the CBR reveals existing schemes and includes them in its current regulations, see, e.g., an analytical report in https://www.banki.ru/news/daytheme/?id=6609791.

below. The central bank sets regulation rules according to which it inspects banks each and every period but does not disclose the rules publicly. When inspecting banks, the central bank reveals a regulation type $j = 1, 2, 3$. The threshold between misreporting and non-misreporting banks is contingent and thus requires inspection. When it detects a misreporting bank, the central bank sets activity restrictions on the bank. Formally, I do not observe any connection between the CBR and a misreporting bank i until the CBR revokes its license and reports the reasons for doing so. However, I can observe that a fraudulent bank i, while still operating in the market, does or does not start to shrink its activities *more* than others after mid-2013 (within some specific window, during which one can be relatively certain that there were no other factors affecting the bank's decisions). If a shrinkage of the bank's i activities indeed takes place, it is likely to affect both sides of the bank's balance sheet and P&L accounts. Therefore, I expect that the bank i will (i) decrease its borrowed funds (relative to owned funds, or capital) and reduce its risk-bearing assets, e.g., loans to corporations and households (relative to total assets), *in absolute terms*, (ii) adapt the structure of its liabilities and assets *in relative terms*, and (iii) adapt expenses on its borrowed funds and face changing returns on its risk-bearing assets compared to other banks that have not been detected by the central bank.

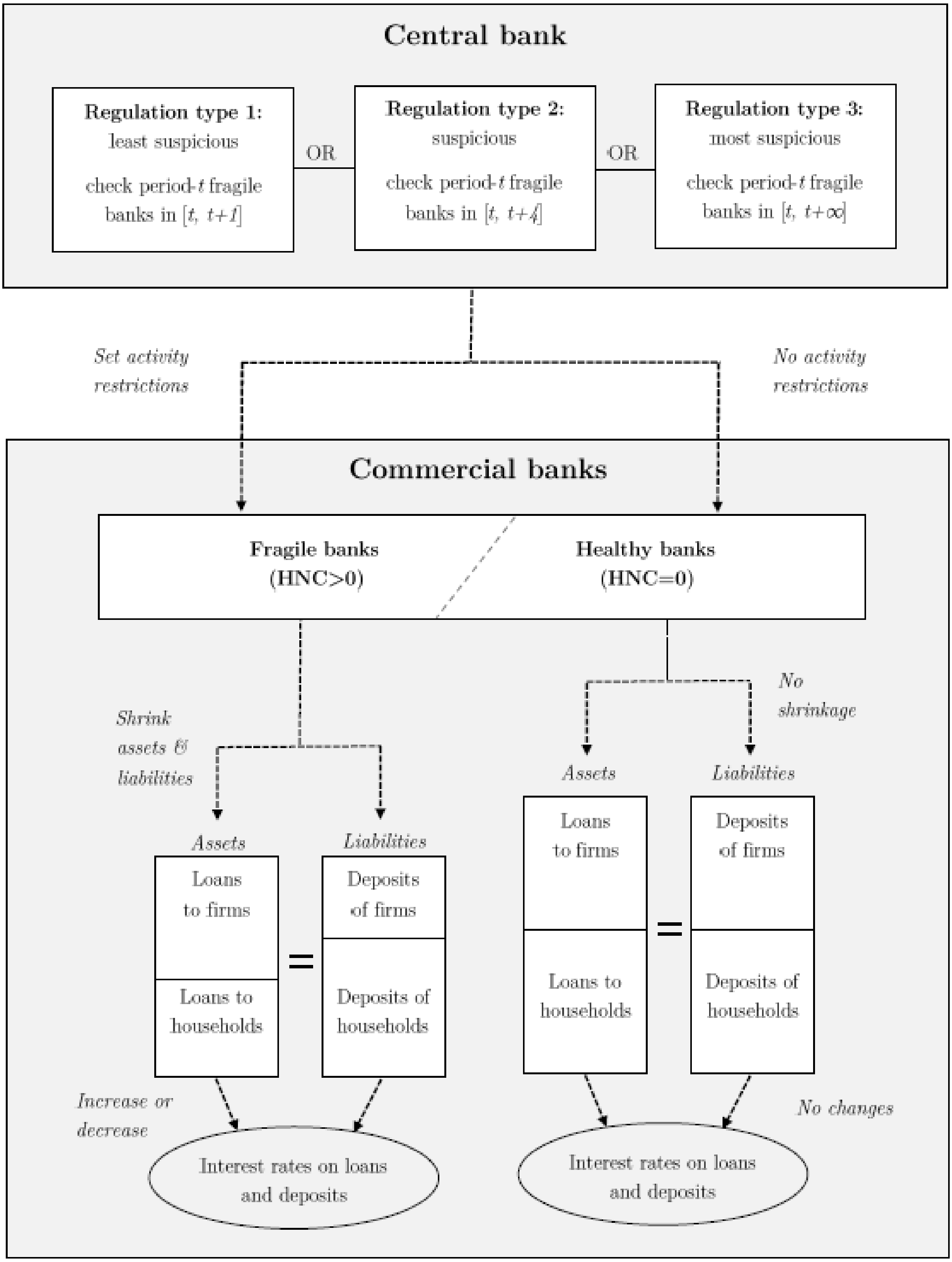
my treatment and control groups of banks are fuzzy by construction (de Chaisemartin and D'Haultfoeuille, 2017). The imposition of treatment varies over time, which requires one to control for time fixed effects to make the treatment effects comparable across times Goodman-Bacon (2021). I formalize these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

$$\begin{aligned} Y_{it}^{(n)} &= \beta_1 TREAT_{it}^{(j)} + \beta_2 REG.CHANGE_t + \beta_3 \Big(TREAT_{it}^{(j)} \times REG.CHANGE_t \Big) \\ &+ \sum_{m=1}^{M} \delta_m \mathrm{BSF}_{m,it} + \alpha_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{6}$$

where for bank i at time t $Y_{it}^{(n)}$ 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, $\mathrm{BSF}_{m,it}$ is m^{th} bank-specific control variable, as suggested by Gropp et al. (2018); α_i and γ_t represent bank and time fixed effects, and ε_{it} 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



Note: HNC is hidden negative capital. I assume three types of prudential regulation that the Central Bank of Russia (the CBR) could follow after mid-2013. Mid-2013 is a borderline that marked a switch from an HNC-tolerant to an HNC-intolerant regime of prudential regulation.

Figure 2: Differential prudential regulation and its effects on banks

significant, though its sign is ambiguous. The data show whether and how treated banks adjust the structure of their balance sheets.

I estimate regression (6) with a robust two-way fixed effects estimator. The estimation window for the baseline estimates is set to ±3 years around the regulatory change in mid-2013. In the robustness section, I check the sensitivity of my results to shrinking the length of the window. BSF, bank, and time fixed effects are aimed to capture observable differences across banks and in time. In the robustness section, I also reduce the sample size by applying the bias-adjusted matching estimator of Abadie and Imbens (2011) and re-running regression (6) on a matched sample.

2.3 Transmission channels

I further explore potential channels that can amplify the effects of tightened regulation on bank balance sheets. I consider a growing concentration in the banking system across the 2010s, deteriorating loan quality (rising NPLs), and declining equity capital to total assets ratios (rising leverage). To test these channels, I modify the DID regressions (6) from the previous section by including the respective transmission variable to the product of treatment and regulatory change binary indicators:

$$\begin{aligned} Y_{it}^{(n)} &= \beta_1 TREAT_{it}^{(j)} + \beta_2 REG.CHANGE_t + \beta_3 \Big(TREAT_{it}^{(j)} \times REG.CHANGE_t \Big) \\ &+ \beta_4 \Big(TREAT_{it}^{(j)} \times REG.CHANGE_t \times TRANSMIT_{it} \Big) \\ &+ \sum_{m=1}^{5} \delta_m \mathrm{BSF}_{m,it} + \alpha_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{7}$$

where $TRANSMIT_{it}$ is either banking sector concentration (as measured by the Herfindahl-Hirschman index, HHI) at t, bank i's NPLs at t, or bank i's equity capital to total assets ratio at t. All the rest is the same as before. All possible subproducts of the three variables entering the triple interaction are included but not fully reported to save space.

Banking sector concentration (HHI). On the one hand, the literature suggests that it may be easier for a central bank to monitor a banking system with fewer players and therefore less risk of financial contagion (Allen and Gale, 2000). In this case, I expect $\beta_4 < 0$. On the other hand, banks that survive in a more concentrated system could possess more bargaining power with the central bank and/or could have more scope for falsification practices. In this case $\beta_4 > 0$. The data show which force dominates.

Bank loan quality (NPLs). I expect that banks that report greater NPLs are more likely to be inspected by the central bank and, if misreporting is detected, to face larger activity restrictions, i.e., $\beta_4 < 0$.

Bank equity capital. Banks with lower reported equity capital to total assets ratios are also likely to be inspected and to face activity restrictions if misreporting is detected, i.e., $\beta_4 > 0$.

2.4 Macroeconomic implications of tightened regulation: A SVAR analysis

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 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 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.

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.[13] 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.[14] 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.[15] 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 groups in comparison.

3.2 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. E.I in Appendix E). 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.

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

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

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

4 Estimation results

4.1 Identification of treatment and control groups of banks

This section describes the construction of the treatment and control groups of banks using the Heckman selection model. I also provide a descriptive analysis of the two groups.

4.1.1 The Heckman selection model

As noted, data on bank closures due to detected misreporting started to appear publicly at the beginning of 2007. Because the subsequent DID analysis is based on six-year estimation window around mid-2013, it is enough to run the Heckman selection model starting from 2010. Hence, I estimate selection and outcome equations (1) and (2) quarter-by-quarter from 2010 Q1 till 2019 Q2. To account for the past experience of the CBR in detecting misreporting, when estimating the equations for a given quarter t, I include all banks that were closed for misreporting from 2007 till t ($s_{it} = 1$ in selection equation and $HNC_{it} > 0$ in outcome equation). To keep the sample balanced between closed and operating banks at each quarter t, when estimating the equations for the quarter t I include all operating banks active at this quarter ($s_{it} = 0$ in selection equation and $HNC_{it} = 0$ in outcome equation), not from 2007 till t as in the case of closed banks.

Table 1 below reports a snapshot of the estimation results for the key quarters in the sample: three years before, the time of, and three years after the Nabiullina's arrival to the CBR.[16] At these three points in time, the number of banks that were closed due to misreporting increased at least sevenfold.

Results from the Heckman selection estimates indicate that the CBR regulation rule could have been constantly updated since 2010. This comes from the fact that almost all of the estimated coefficients change considerably across time. Of course, some of these changes could be attributed to the fact that, from quarter to quarter, the size of the subsample of banks that were closed for misreporting is growing.

Nonetheless, *first*, I observe that, as time passes, the likelihood of being detected by the CBR becomes lower for banks with more equity capital and, if detected, the size of revealed HNC becomes smaller. This result is consistent with the literature on the losses associated with bank closures James (1991); Schaeck (2008); Kang et al. (2015); Cole and White (2017).

Second, NPLs seem not to be very important when the CBR decides whether to inspect a suspicious bank or not, which is indicated by mostly insignificant coefficients. This is likely to reflect the regulator's mistrust of the reported quality of the loans to the Russian economy.

[16] Full results are available upon request.

Table 1: Cross-sectional Heckman selection estimates:
±3 years around the regulatory tightening in mid-2013 [a]

	3 years before 2013Q2		2013Q2		3 years after 2013Q2	
	Out	Sel	Out	Sel	Out	Sel
	(1)	(2)	(3)	(4)	(5)	(6)
Equity capital / Total assets	–0.023	–0.009	–0.165	–0.018**	–0.829***	–0.036***
	(0.379)	(0.009)	(0.523)	(0.007)	(0.265)	(0.006)
NPLs on firm loans	0.128	–0.001	–1.117	–0.004	–0.007	–0.009*
	(0.499)	(0.010)	(1.026)	(0.010)	(0.286)	(0.005)
NPLs on household loans	–0.016	0.004	0.599	0.012**	0.006	0.001
	(0.218)	(0.006)	(0.476)	(0.005)	(0.193)	(0.004)
Liquid assets / Total assets	0.188	0.004	1.560***	0.013**	0.496**	–0.007*
	(0.231)	(0.007)	(0.502)	(0.006)	(0.220)	(0.004)
ROA (annualized)	–1.000	–0.067**	–2.116	–0.059***	1.310**	0.044***
	(1.300)	(0.030)	(1.711)	(0.019)	(0.538)	(0.013)
Growth of total assets	–0.020	–0.005**	0.102	0.001	0.064	0.002*
(annualized)	(0.120)	(0.003)	(0.079)	(0.001)	(0.040)	(0.001)
Net interbank loans	–0.066	–0.020*	0.865	–0.010	0.902***	–0.009*
/ Total assets	(0.541)	(0.010)	(0.651)	(0.008)	(0.257)	(0.005)
Household deposits	0.135	0.009**	0.098	0.007**	–0.018	0.003
/ Total assets	(0.210)	(0.004)	(0.267)	(0.003)	(0.132)	(0.003)
Loans to firms	0.323	0.014***	0.637*	0.009**	0.744***	0.016***
/ Total assets	(0.261)	(0.005)	(0.372)	(0.004)	(0.187)	(0.003)
Turnover of house.loans	–1.640	–0.014	8.050***	0.025	5.388***	0.036
/ Total assets	(1.026)	(0.031)	(1.793)	(0.024)	(1.145)	(0.023)
Turnover of firms.loans	0.303	0.016*	0.214	0.008	–0.214	–0.002
/ Total assets	(0.379)	(0.009)	(0.703)	(0.008)	(0.338)	(0.007)
log of total assets		–0.180**		–0.270***		–0.332***
		(0.075)		(0.065)		(0.045)
Constant	–11.792	–2.239***	–120.474*	–1.587***	–33.478*	0.174
	(53.505)	(0.474)	(61.923)	(0.353)	(19.666)	(0.295)
N obs.	886		899		852	
N censored / observed	844 / 42		814 / 85		567 / 285	
Wald χ^2	8.786		33.272***		47.555***	
ρ	0.350		0.834**		0.852***	

Note: The table reports efficient two-step estimates of the Heckman selection model for the three specific periods: 2013Q2, i.e., the time of regulatory change in the Central Bank of Russia, and three years before and after this date (recall that the estimation window in the baseline version of the difference-in-differences estimates equals ±3 years around mid-2013). Dependent variables are (i) an indicator variable of whether hidden negative capital, HNC, was detected by the CBR (columns "*Sel*") and (ii) the ratio of HNC to the equity capital reported one quarter before the closure (columns "*Out*"). *Sel* and *Out* are selection and outcome equations of the Heckman model. All explanatory variables are taken with a one-quarter lag. ρ is correlation between the regression errors of *Sel* and *Out*. *Wald* χ^2 is the Wald statistic that tests the null hypothesis that all coefficients equal zero simultaneously. N *censored* reflects all banks operating in the respective quarter for which the estimate is done. N *observed* accumulates all banks with HNC detected from the beginning of the sample, 2010Q2, to the respective quarter for which I perform an estimate.

[a] The rest of the estimates (i.e., for the other 44 quarters in the sample, 2010Q2 to 2019Q2) are not reported for the sake of space and are available upon request

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Robust standard errors appear in the brackets under the estimated coefficients.

Third, regarding the structure of assets, I observe that banks with more loans to firms are more likely to be inspected and, if misreporting is detected, to exhibit larger losses of closure. This is very much in line with the theory of Song and Thakor (2007). Further, holding more liquidity (in the form of cash and reserves) increases the size of losses, if a bank was inspected and misreporting was detected. The growth of total assets per se seems not to play a large role in the decision to inspect a suspicious bank. What could be important instead is how fast the loans—especially those to households—are turned over. The estimates suggest that faster turnovers, though not associated with a greater probability of being detected, are positively associated with losses in case of closure.[17] Finally, granting more loans in the inter-bank market is associated with larger losses, if a bank was detected for misreporting. This may indicate that either the bank attempted to withdraw funds in a coalition with other banks or that it lent to fraudulent banks.

Fourth, as for the liability structure, I observe that relying more on insured deposits (of households) is not a panacea per se and is unlikely to drive the CBR decision to inspect and the losses conditional on being audited.

Fifth, the profitability of bank assets (ROA) seems to play opposite roles before and after mid-2013. Before, as expected, a greater ROA reduced the likelihood of being audited, whereas after, less expectedly, the situation reverted and a higher ROA might have attracted the attention of the regulator. Though I regard this observation cautiously, it could reflect cyclical movements of profits and losses along with the business cycle phases.[18] Put differently, if a bank has a lower ROA during the positive phase of the business cycle, it is likely to induce the central banks to inspect it, and, conversely, if a bank reports profits when others tend to report losses, this could also raise suspicion.

Sixth, bank size is negatively related to the probability of the CBR inspection and is highly statistically significant in the selection equation, as expected. This could also reflect the "too big to fail" problem and as I discussed, I check the robustness of the findings by switching to an indicator of negative profits.

Finally, the estimated correlation between the errors from the selection and outcome equations is positive and rather large, exhibiting statistical significance at least from mid-2013. This indicates that selection issues are indeed present in the data.

Overall, the Heckman selection estimates deliver insight into what type of regulation rule a central bank may follow. In the robustness section, I turn to a very different approach to capturing such a

[17] Though indirectly, this conclusion is in line with the findings of Mian and Sufi (2009), which establish that a too-fast expansion of loans to households triggers financial crises in the future. Note that no such effects are observed in the estimates of the turnover of corporate loans, which is also in line with Mian et al. (2017).

[18] Mid-2013 witnessed a move of the economy towards another recession, while mid-2016 was a period of recovering from that recession.

rule, based on rankings by the Z-score of bank stability, as in DeYoung and Torna (2013).

I next predict the fitted values of both selection and outcome equations and report the results in Table 2 below. The table contains two groups of columns, one for banks closed for misreporting (1–5) and the other for the rest of the banks, which continued their operations and which could be misreporting but not yet detected by the CBR (6–10).

Table 2: In-sample predictions after the Heckman selection estimates: descriptive statistics, ±3 years around the regulatory tightening in mid-2013

	Banks failed with $HNC_{it} > 0$					Operating banks with $\widehat{HNC}_{it} > 0$				
	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HNC / Total assets (actual data)	371	35.7	36.8	0.6	413.9					
HNC / Total assets (predicted, baseline)	371	35.7	12.5	0.0	112.0	18,585	38.0	29.8	0.0	444.4
$Pr\left[\widehat{HNC}_{it} > 0\right]$ (predicted, baseline)	371	0.7	0.2	0.0	1.0	18,585	0.1	0.1	0.0	0.9

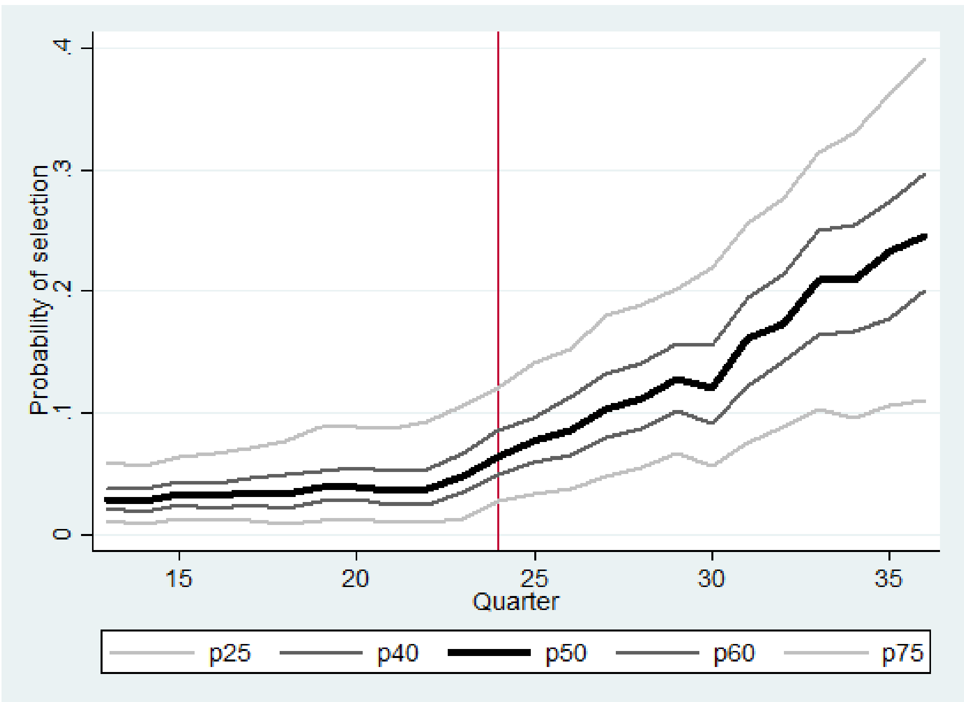
Note: The table reports descriptive statistics pooled across the periods from 2010 Q2 to 2016 Q2 for (i) banks closed for misreporting ($HNC_{it} > 0$) and (ii) the other operating banks with misreporting not-yet-detected ($\widehat{HNC}_{it} > 0$). Note that the Heckman selection model itself assigns a strictly positive probability of misreporting to all of them.

These pooled fitted values suggest that *first*, the model works well to capture the in-sample mean size of HNC but under-predicts (by about 4 times) the size of losses in the upper tail of the failed banks' distribution by HNC. Indeed, within the six years between 2010 Q2 and 2016 Q2, the final sample contains 371 banks closed for misreporting, with average losses (HNC) amounting to 36% of total assets reported on the eve of closure, and extreme losses largely exceeding assets.[19] The latter pertains to the cases in which banks were hiding illegal active operations from their balance sheets. *Second*, for operating banks, one can observe that the model predicts almost the same mean size of HNC as for the closed banks, i.e., slightly above one-third of their total assets. I note that these banks were still operating but not-yet-detected by the CBR within the period considered. It is even more notable that the model predicts huge losses in the upper tail, which more than four times exceed the assets (just as in the actual data of closed banks). The model's minimal fitted value is effectively zero. Thus, the model does work to distinguish between operating banks with potentially high and potentially low losses conditional on being detected. *Third*, regarding the probability of being detected itself, as expected, the model assigns a large mean value for closed banks and a small value for operating banks, with the difference amounting to a factor of 7. Note that the range of fitted probabilities is also wide, from almost zero to almost unity for both closed and operating banks.

[19]Notably, the mean losses are about 1.25 times larger than those reported by James (1991) for the US banking system when it suffered losses from the S&L crisis in the 1980s and approximately 1.5 times larger than the losses of US banks during and after the Great Recession, as reported by Cole and White (2017).

I next plot the time evolution of the probability s_{it} of being detected that I predict for operating banks. Fig. 3 below illustrates the results. The figure contains 25, 40, 50, 60, and 75th percentiles of the operating banks' distribution by $\hat{s}_{it}$ for each quarter t within ± 3 years around the mid-2013. Before Nabiullina's appointment at the CBR, the probability of being detected was rather stable, though it started to increase slightly two quarters prior to mid-2013. The median levels amounted to about 4-5% and the interquartile range was almost always below 10%. With Nabiullina's tightened regulation, the probability of being detected continued to grow along an almost linear trend so that, by mid-2016, the median probability increased to 25%, and the interquartile range was bounded between 11 and 40%.

As discussed in the previous section, in the baseline estimations below I am agnostic about which part of the banking system the CBR inspects each period and I set the threshold $\hat{s}^*_{it}$ to the median at each quarter. That is, I assume that every quarter the CBR audits each bank with $\hat{s}_{it}$ above the black solid line depicted in Fig. 3. I use θ to denote the regulation rule, with $\theta \in (0, 1)$, and thus refer to the baseline case as $\theta = 0.5$. In the robustness section, I recompute all results for the cases when the regulator is more concerned ($\theta = 0.25$, for concreteness) and less concerned ($\theta = 0.75$) about bank misreporting.



Note: The figure reports selection predictions after estimating the Heckman selection model. The predictions are performed at the bank-quarter level and then, for the sake of representation, averaged across the banks in the sample in each quarter. The vertical red line crosses the 24th quarter of the sample, which stands for 2013 Q2, i.e., the point at which the CBR shifted from soft to tight prudential regulation.

Figure 3: Predicted probability of fraud being detected at the bank-quarter level

4.1.2 Descriptive analysis of the treatment and control groups

Having defined the agnostic regulation rule ($\theta = 0.5$) in the previous section, I now analyze the descriptive statistics of resultant groups of banks in Table A.I (see Appendix A). In the table, columns 1 to 5 represent statistics for the control group, and columns 6 to 9 for the treatment group. As discussed above, in the baseline estimates, I use the time-varying median level of the fitted values of the probability of being detected, as implied by the selection equation (1). Thus, with $\hat{s}_t^*$ representing the time-varying medians, banks with $\hat{s}_{it} < \hat{s}_t^*$ are included in the control group and banks with $\hat{s}_{it} \geq \hat{s}_t^*$ in the treatment group. Panel 1 then reports the data for the dependent variables used in the family of equations (6) and (7) and Panel 2 contains the data on the explanatory variables for the same equations. All the data are computed for the six years horizon with the center in mid-2013, as in my DID regressions to follow. I drop observations below the 1st and above the 99th percentiles of the distribution by each explanatory variable (except the log of total assets) for both the control and treatment groups.

The descriptive statistics suggest that, first, even though I exclude SIFI, the six-year average size of total assets in the control group is 9 times larger than that in the treatment group, signaling that larger banks are still less likely to be inspected by the CBR. The same holds for all scale variables presented. Second, in relative terms, important differences arise in the structure of assets and liabilities between the groups. While banks in the control group have more or less similar weights on the funds attracted from households (insured) and non-financial firms (uninsured), banks in the treatment group are much more oriented toward insured funds.[20] Further, with these insured funds, treated banks are much more specialized in lending to corporations rather than households than are the control banks.[21] Third, with these differences in asset-liability structures, I observe further that treated banks pay more on both corporate and retail deposits and earn more interest on corporate loans than do the control banks. Fourth, treated banks are relatively less capitalized, report two times lower NPLs on corporate loans, hold more cash and reserves, provide fewer loans in the inter-bank market, have higher turnovers on corporate loans compared to the control banks, and exhibit lower returns on assets (ROA). Fifth, regarding the growth rate of total assets, both groups are more or less similar, except that treated banks are less volatile in this respect. Overall, the treatment group has a more risky profile compared to the control group.

[20]This recalls moral hazard issues going back (at least) to the theory of Keeley (1990) and cross-country empirical evidence by Demirguc-Kunt and Detragiache (2002).

[21]This indirectly speaks to the theory of Song and Thakor (2007), which shows negative consequences for the stability of banks that rely predominantly on informationally opaque corporate (relationship) loans funded with insured deposits, which are likely to be less monitored.

4.2 The effects of tightened regulation on not-yet-detected misreporting banks

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.

4.2.1 Scale effects

Table 3 below reports the results of estimating the DID regressions (6) with the set of scale-dependent variables under the regulation rule $\theta = 0.5$. The table contains two panels: one for the estimates at extensive margin ($TREAT_{it}$ is the binary indicator of bank misreporting) and the other for intensive margin ($TREAT_{it}$ equals the predicted value of losses in case of detection, i.e., $\widehat{HNC}_{it}$, if $\hat{s}_{it} \geq \hat{s}^*_{it}$, and zero, if-else). All regressions contain the full set of bank FEs, quarter FEs, and bank-specific control variables, which are not reported to preserve space.[22] In all regressions, I use the estimation window which is ± 3 years around the regulatory change in mid-2013.

Several outcomes emerge from the estimated scale effects.

First, in all six cases, the effects are negative and highly statistically significant on both the extensive and intensive margins, meaning that the tightened regulation after mid-2013 shrank the balance sheets of potentially misreporting banks, including the most important types of liabilities and assets, as compared to the other (non-misreporting / not inspected) banks.

Second, the estimated effects are economically very large, and in most cases exceed the average size of the respective operation in the treatment group, thus indicating high efficiency of the tightened regulation. For instance, the estimates suggest that, on the extensive margin, the average bank from the treatment group was forced to reduce its total assets by 18 billion rubles, which is 3.5 times more than the actual size of its total assets (Table A.I above). On the intensive margin, the average estimate decreases by two times but still exceeds the actual size.[23] Recall that the maximal value of total assets in the treatment group is 265 billion rubles. The estimated scale effects lie well between the mean and maximal values, which implies that the CBR tended to eventually close smaller banks detected in misreporting and to allow larger banks to continue their operations (possibly after requiring them to clean poor quality assets from their balance sheets).

Third, The treated banks were likely to reduce lending to both households and non-financial firms. This could have macroeconomic implications and I apply the estimated scale effects to trace this in Section 4.4.

One could argue that the chosen estimation window ± 3 years around the regulatory tightening in

[22] The full results are available upon request.

[23] The average predicted HNC is 38% of total assets (see Table 2), and the estimated respective scale effect is –0.303, which results in a decline of total assets by 11.5 billion rubles, more than 2 times larger than its actual size.

Table 3: Scale effects of declining regulatory forbearance:
±3 years around the regulatory tightening in mid-2013

Dependent variable	TA_{it}	EQ_{it}	$DEPf_{it}$	$DEPh_{it}$	$LNSf_{it}$	$LNSh_{it}$
$Y_{it}^{(n)}$ $(n = 1...6)$:	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: On extensive margin (the size of HNC does not matter)						
TREAT×REGIME	–18.521***	–1.176***	–3.278***	–5.032***	–3.001***	–3.922***
	(2.824)	(0.210)	(0.885)	(0.746)	(0.736)	(0.661)
TREAT	6.735***	0.405***	1.192***	2.089***	1.292***	1.694***
	(1.369)	(0.091)	(0.423)	(0.393)	(0.479)	(0.296)
REGIME	32.034***	1.573***	1.070	4.104***	0.569	1.887***
	(4.536)	(0.421)	(1.010)	(1.108)	(1.445)	(0.530)
N Obs.	17,696	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910	910
R^2_{within}	0.095	0.087	0.053	0.175	0.121	0.090
Panel 2: On intensive margin (the size of HNC may matter)						
TREAT×REGIME	–0.303***	–0.019***	–0.057***	–0.081***	–0.043***	–0.064***
	(0.053)	(0.004)	(0.017)	(0.015)	(0.015)	(0.012)
TREAT	0.078***	0.004***	0.011**	0.020***	0.012**	0.015***
	(0.019)	(0.001)	(0.005)	(0.005)	(0.005)	(0.004)
REGIME	27.465***	1.264***	0.263	2.750***	–0.329	0.862*
	(3.981)	(0.402)	(0.914)	(1.013)	(1.344)	(0.495)
N Obs.	17,696	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910	910
R^2_{within}	0.083	0.080	0.050	0.165	0.117	0.079

Note: The table contains difference-in-differences estimates of regression (6) with dependent variables $Y_{it}^{(j)}$ reflecting the size of total assets TA_{it} $(n = 1)$, equity capital EQ_{it} $(n = 2)$, deposits of non-financial firms $DEPf_{it}$ $(n = 3)$, deposits of households $DEPh_{it}$ $(n = 4)$, loans to non-financial firms $LNSf_{it}$ $(n = 5)$, loans to households $LNSh_{it}$ $(n = 6)$. All regressions include full sets of bank FE, quarter FE, and bank control variables, which are not reported for the sake of space and are available upon request. Mid-2013 marks the transition of the CBR to a new prudential regulation regime, in which the CBR is no longer tolerant of fraudulent banks. The treatment group consists of all banks which are likely to be treated as fraudulent by the CBR (the treatment rule is proxied with the Heckman selection model (1)–(2)). The composition of the treatment and control groups varies in time depending on the application of the treatment rule in each quarter (see Section 2.2 for details).

***, **, * 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.

mid-2013 is too wide and possibly includes other important events (sanctions, the crisis of 2014–2015), and thus relying on it could be misleading. Though I control for any macroeconomic shocks that could affect the results, by including quarter FEs, I re-estimated all the scale effects under narrower windows. The results of this exercise appear in Fig. B.I (see Appendix B). The figure enlarges all six regressions from Panel 1 of Table 3 by shifting to the following estimation windows centered at 2013 Q2: ±1 quarter, ±4 quarters, ±8 quarters, ±12 quarters (the baseline), and the full sample (for comparative reasons). Specifically, the figure reports only the estimated coefficient on $TREAT_{it} \times REG.CHANGE_t$

and its associated 95% confidence intervals in each of the six cases. It is clear from the figure that, qualitatively, the estimated scale effects are the same across the different estimation windows (perhaps, except ±1 quarter, which could be too narrow for the effect to materialize). As the window expands, each of the estimated effects tends to increase in magnitude, pointing to the persistency of the differences between treated and non-treated banks in time.[24] Notably, if I consider the ±4 quarters estimation window, I would obtain the scale effect on total assets equaled approximately –5 billion rubles (significant at 1%), i.e., exactly covering the sample mean.

Overall, the results indicate that, with the launching of tightened prudential regulation in mid-2013, banks engaging in misreporting were more likely to be inspected (and detected) by the CBR and to face substantial balance sheet shrinkage (Fig. 2 above).

4.2.2 Composition effects: asset and liability structure

Having established the existence and negativity of the scale effects of tightened prudential regulation, I now turn to the testing of its composition effects, i.e., whether the tightened regulation pushed fraudulent banks to adapt their liability and asset structures. I run the same DID regressions (6), as in the previous section, but now with dependent variables being scaled by total assets. The estimation results appear in Table 4 below.

The estimation results on the composition effects of tightened regulation suggest that, compared to non-inspected (control) banks, banks from the treated group in fact did significantly restructure their borrowed and owned funds and assets. In particular, they tended to decrease equity capital on the intensive margin, i.e., facing larger potential losses associated with being detected. This could be an unintended negative consequence of the tightened regulation because it implies that treated banks were more willing to withdraw their owned funds when facing the CBR inspection (and after) than to raise capital.[25] In addition, the estimates indicate that treated banks also tended to reduce their borrowing from non-financial firms (i.e., uninsured funds) on the intensive margin. Having reduced their owned funds and deposits from firms, the treated banks substituted them with household deposits (i.e., insured funds), on both the extensive and intensive margins.[26] With these new funds from

[24]Though I do not explore this directly, it is possible that the CBR may indeed be rather suspicious and scrutinized recovered banks in the future solely because they were engaged in misreporting in the past. An alternative explanation is that having been detected by the CBR for misreporting, a treated bank that continues its operations loses a part of its market share and never catches up with its rivals in the future. Though indirectly, this is also consistent with the findings of Berger and Bouwman (2013), who show that the inability of (some) US banks to raise their capital resulted in a partial waste of market shares during the Great Recession.

[25]Similar results appear in Gropp et al. (2018), who show in a quasi-natural experiment framework that after banking authorities in the EU differentially applied tighter capital regulation to targeted banks in 2011, the treated banks tended to decrease their capital rather than to reduce their risk-weighted assets.

[26]In Russia, a system of partial deposit insurance was established in 2004. In the 2010s, the deposit coverage amounted to 1.4 million rubles, which effectively encompasses as much as 99% of the quantity of all deposit accounts, which, however, cover only 55% of the total volume of individual deposits (data from the Deposit Insurance Agency of the

Table 4: The assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

Dependent variable $Y_{it}^{(n)}$ $(n = 1...5)$:	EQ_{it}/TA_{it} (1)	$DEPf_{it}/TA_{it}$ (2)	$DEPh_{it}/TA_{it}$ (3)	$LNSf_{it}/TA_{it}$ (4)	$LNSh_{it}/TA_{it}$ (5)
Panel 1: On extensive margin (the size of HNC does not matter)					
TREAT×REGIME	–0.467	–0.569	2.270***	2.250***	–0.500
	(0.309)	(0.463)	(0.463)	(0.471)	(0.371)
TREAT	–1.374***	–1.080***	1.871***	4.910***	0.499**
	(0.265)	(0.361)	(0.340)	(0.395)	(0.234)
REGIME	6.225***	–7.463***	5.584***	–4.699***	0.490
	(0.626)	(0.819)	(0.882)	(0.928)	(0.646)
N Obs.	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910
R^2_{within}	0.257	0.211	0.171	0.205	0.174
Panel 2: On intensive margin (the size of HNC may matter)					
TREAT×REGIME	–0.014**	–0.019**	0.053***	0.064***	–0.001
	(0.007)	(0.009)	(0.010)	(0.010)	(0.007)
TREAT	–0.011**	0.005	0.012*	0.054***	0.006
	(0.005)	(0.007)	(0.006)	(0.008)	(0.005)
REGIME	6.315***	–7.568***	5.909***	–4.743***	0.209
	(0.616)	(0.799)	(0.877)	(0.921)	(0.620)
N Obs.	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910
R^2_{within}	0.251	0.209	0.159	0.177	0.173

Note: The table contains difference-in-differences estimates of regression (6) with dependent variables $Y_{it}^{(n)}$ reflecting the composition of a bank i balance sheet from the liabilities and assets sides: the ratio of equity capital to total assets EQ_{it}/TA_{it} $(n = 1)$, deposits of non-financial firms to total assets $DEPf_{it}/TA_{it}$ $(n = 2)$, deposits of households to total assets $DEPh_{it}/TA_{it}$ $(n = 3)$, loans to non-financial firms to total assets $LNSf_{it}/TA_{it}$ $(n = 4)$, loans to households to total assets $LNSh_{it}/TA_{it}$ $(n = 5)$. All regressions include full sets of bank FE, quarter FE, and bank control variables, which are not reported to save space and are available upon request. Mid-2013 marks the transition of the CBR to a new prudential regulation regime in which the CBR was no longer tolerant of fraudulent banks. The treatment group consists of all banks which are likely to be treated as fraudulent by the CBR (the treatment rule is proxied with the Heckman selection model (1)–(2)). The composition of the treatment and control groups varies in time depending on the application of the treatment rule in each quarter (see Section 2.2 for details).

***, **, * 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.

households, the treated banks further expanded their lending to corporations, not to households, on both the extensive and intensive margins.[27] Notably, household deposits increased by the same 2.3 percentage points of the treated banks' total assets, as did loans to firms within the three years after mid-2013. Finally, loans to households remain unaffected by the composition effects. It seems that the risk profile of the treated banks indeed rose, as was previously suggested by the descriptive analysis

Russian Federation; see https://www.asv.org.ru/agency/annual/2018_full/report2018/ru/page2_1_6.html).

[27] As suggested by Song and Thakor (2007), this implies engaging more in the asset-liability mismatch in terms of added value.

(Section 4.1.2).

As in the previous section, I again address the concern regarding the chosen length of the estimation window. Fig. B.II in Appendix B presents the results obtained under different estimation windows (on extensive margins).[28] As can be inferred from the figure, my results are qualitatively robust to choosing different lengths of estimation windows. For the deposits of households, I observe that the effect becomes significant even within 1 quarter after the regulatory tightening, increases in magnitude during the next 11 quarters, and remains there till the end of the sample period in 2019 Q2. For loans to non-financial firms, the effect becomes significant starting 8 quarters after the tightening and reaches the peak under the baseline window.

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.

4.3 Channels of the effects of tightened regulation

I now investigate potential channels through which tightened bank regulation could have affected the scale and composition of bank balance sheets after mid-2013. As discussed in the methodology section, I consider three possible channels that were active in the 2010s in Russia: the increasing concentration of the banking system, measured by HHI (the industry level), and decreasing capitalization and increasing NPLs (the treated bank level); see Fig. C.I in Appendix C.[29] I run the DID regressions (7) in which I include all three possible channels simultaneously, first to test the scale effects and then the composition effects.

4.3.1 Channels of the scale effects

The estimation results on the channels of the scale effects appear in Table 5.

The results indeed suggest that all three channels could have transmitted the scale effects of tightened regulation after mid-2013. *First*, I still find that the mean scale effects remain negative and statistically significant (except for loans to firms), as before. *Second*, the coefficient on the triple interaction of the treatment indicator, regime indicator, and NPLs on household loans is negative and significant in three of six cases (columns 1, 4, and 6, that is, for regressions of total assets, deposits of and loans to households, respectively). This means that an increase in a treated bank's household

[28] The figure with the associated results on intensive margin is not reported to save space, and it is available upon request.

[29] Note that at the control bank level, the opposite trends were in play during the same time: increasing capitalization and decreasing NPLs.

Table 5: Channels of the scale effects of declining regulatory forbearance:
±3 years around the regulatory tightening in mid-2013

Dependent variable $Y_{it}^{(n)}$ ($n = 1...6$):	TA_{it} (1)	EQ_{it} (2)	$DEPf_{it}$ (3)	$DEPh_{it}$ (4)	$LNSf_{it}$ (5)	$LNSh_{it}$ (6)
TREAT×REGIME	–7.327***	–0.341**	–1.145**	–1.875***	–0.500	–0.660**
	(1.751)	(0.164)	(0.466)	(0.572)	(0.495)	(0.330)
TREAT×REGIME×NPLh	–0.553**	0.001	–0.008	–0.225**	0.008	–0.125**
	(0.258)	(0.021)	(0.046)	(0.097)	(0.045)	(0.059)
TREAT×REGIME×EQ	0.858***		0.177***	0.205***	0.123***	0.158***
	(0.158)		(0.053)	(0.038)	(0.043)	(0.028)
TREAT×REGIME×HHI	–723.931***	–2.559	–227.774**	–34.868	–68.483	268.387***
	(266.503)	(18.223)	(98.235)	(100.737)	(87.477)	(94.942)
N Obs.	17,696	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910	910
R^2_{within}	0.184	0.093	0.065	0.218	0.138	0.117

Note: The table contains difference-in-differences estimates of regression (6) with dependent variables $Y_{it}^{(n)}$ reflecting the size of total assets TA_{it} ($n = 1$), equity capital EQ_{it} ($n = 2$), deposits of non-financial firms $DEPf_{it}$ ($n = 3$), deposits of households $DEPh_{it}$ ($n = 4$), loans to non-financial firms $LNSf_{it}$ ($n = 5$), loans to households $LNSh_{it}$ ($n = 6$). All regressions include full sets of bank FE, quarter FE, bank control variables, and all possible combinations of $TREAT_{it}$, $REGIME_t$, and either of the three-channel variables considered, i.e., the ratio of non-performing loans in loans to households $NPLh_{it}$, equity capital to total assets ratio EQ_{it} (except column 2), or the banking systems concentration measured by the Herfindahl-Hirschman index HHI_t based on banks' total assets. All respective coefficients are not reported for the sake of space and are available upon request. Mid-2013 marks the transition of the CBR to a new prudential regulation regime in which the CBR was no longer tolerant of fraudulent banks. The treatment group consists of all banks which are likely to be treated as fraudulent by the CBR (the treatment rule is proxied with the Heckman selection model (1)–(2)). The composition of the treatment and control groups varies in time depending on the application of the treatment rule in each quarter (see Section 2.2 for details).

***, **, * 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.

NPL ratio further amplifies the negative scale effect of tightened regulation.[30] *Third*, the coefficient on the triple interaction of the main two binary indicators and bank equity capital is always positive and highly statistically significant (except for column 2 in which there is no such triple interaction because equity capital is the dependent variable). This implies that greater bank capital diminishes the negative mean scale effect of tightened regulation. *Fourth*, the HHI indicator delivers mixed predictions when interacting with the two main binary indicators. On the one hand, a denser concentration of the banking system amplifies the mean scale effect of tightened regulation on treated banks' total assets (column 1) and deposits of firms (column 3), which supports the idea that a regulator's ability to monitor a more concentrated banking system is higher than with a less concentrated one. However, this does not hold for regressions of equity capital, deposits of households, or loans to firms (columns 2, 4, and 5, respectively). Moreover, in the regression of household loans, the triple interaction with HHI switches the sign from negative to positive and appears to be highly significant (column 6). I

[30] The estimation results with firm NPL ratio reveal no significant triple effects.

thus treat the results associated with banking system concentration with caution.

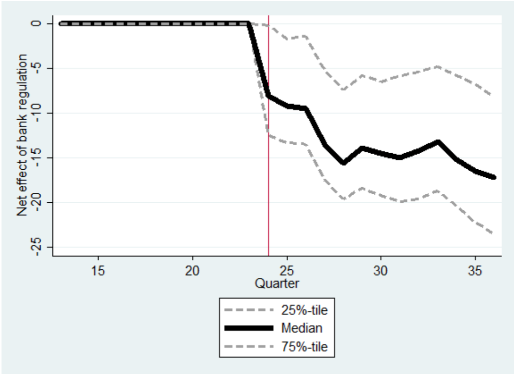
Because each of the three channels has time variation, the triple interactions also vary in time, thus allowing me to decompose the total effects and to rank the three channels by economic significance. I first plot the time evolution of the total effect of tightened regulation on the treated banks' total assets (Fig. 4.*a*), loans to non-financial firms (Fig. 4.*c*), and loans to households (Fig. 4.*e*). I then plot the time evolution of the respective total effect decomposed by the three channels (Fig. 4.*b*, Fig. 4.*d*, and Fig. 4.*f*). I choose these three variables, because, in the subsequent section, I focus on the macroeconomic implication of reductions in treated banks' credit to the economy. The results for the other three variables—equity capital, household deposits, and firm deposits—are presented in Fig. D.I in Appendix D.

Overall, the decomposition exercise indicates that the scale effects of tightened regulation reveal a large degree of heterogeneity across banks, and that bank capital plays the most prominent role in transmitting the effects on treated banks. First, I find that the effects on the treated banks' total assets and firm loans were rising in magnitude during the first year since mid-2013 and stabilized afterwards, remaining negative within the interquartile range (Fig. 4.*a* and Fig. 4.*c*); the effect on household loans was also large and negative during the first year, but then it soon diminished (Fig. 4.*e*). Second, in cases of total assets (Fig. 4a-b) and firm loans (Fig. 4c-d), I find that the decrease in treated banks' capital was the main factor pushing the effect downwards, i.e., to be more negative, and thus efficient from the standpoint of the CBR. Growing banking sector concentration was also efficient in helping the CBR shrink the activities of fraudulent banks, but less than the bank capital channel and can thus be ranked second. The growing NPLs of treated banks ranked third and thus were the least efficient. Finally, in the case of household loans (Fig. 4e-f), the bank capital channel is still the most efficient, but the near-zero role of NPLs and rising concentration made the overall effect low (recall a positive rather than negative sign of the coefficient on HHI in the respective regression).

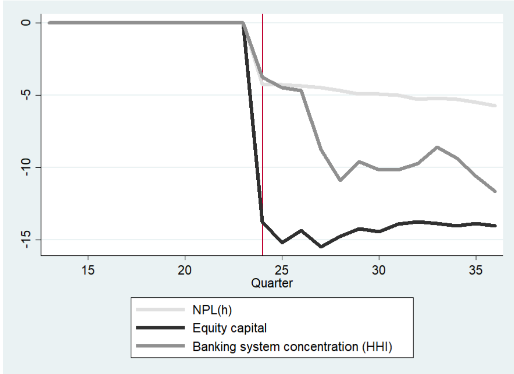
Quantitatively, the exercise shows that, during the three years after the regulatory change, the median effect on the total assets of treated banks could have doubled (from –9 to –17 billion rubles), the median effect on their firm loans could have also increased by roughly a factor of 2 (from –1 to –2 billion rubles), and the median effect on household loans diminished (from –2 billion rubles at the beginning to zero in the end).

4.3.2 Channels of the composition effects

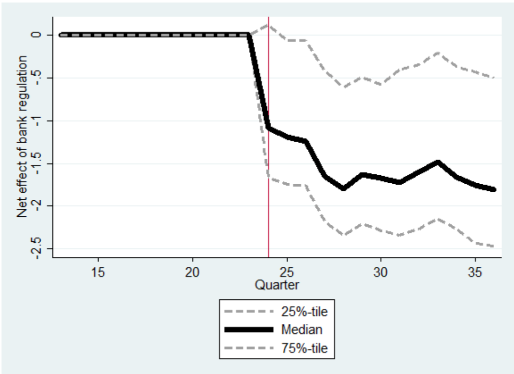
I now turn to the composition effects of tightened regulation and analyze the same three channels. Table 6 below reports the estimation results for the composition effects on the treated banks' structure



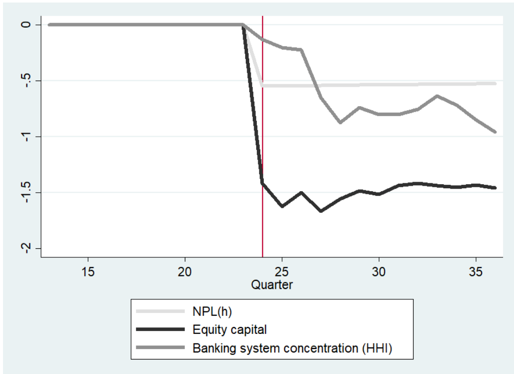
(a) Total assets (*aggregated effect*)



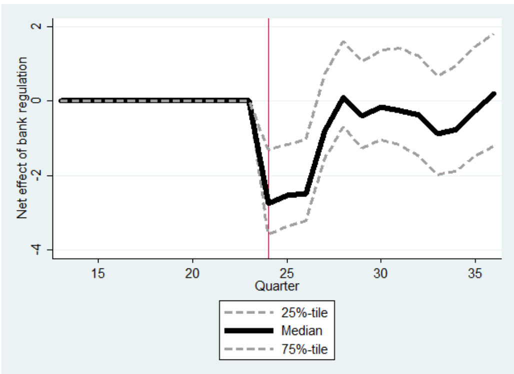
(b) Total assets (*disaggregated effects*)



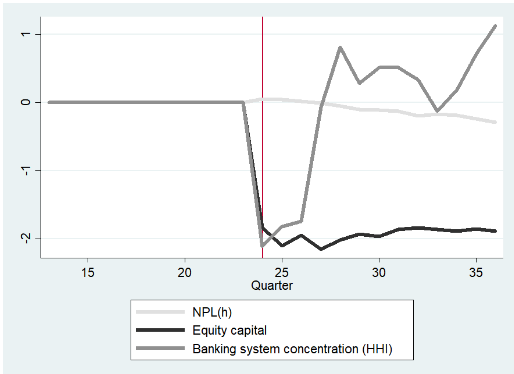
(c) Loans to firms (*aggregated effect*)



(d) Loans to firms (*disaggregated effects*)



(e) household loans (*aggregated effect*)



(f) household loans (*disaggregated effects*)

Figure 4: Time evolution of selected scale effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

of assets and liabilities.

Several outcomes emerge from the regression analysis. *First*, I obtain a negative and significant coefficient on the $TREAT_{it} \times REG.CHANGE_t$ variable in the case of firm deposits (column 2) and positive and significant coefficients in the cases of household deposits and loans to firms (columns 3 and 4). These estimates confirm my previous findings that the mean composition effects of tightened regulation were such that treated banks were reducing borrowed funds from corporations (uninsured) and increasing those from households (insured), and lending more to corporations than to households.

Table 6: Channels of the assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

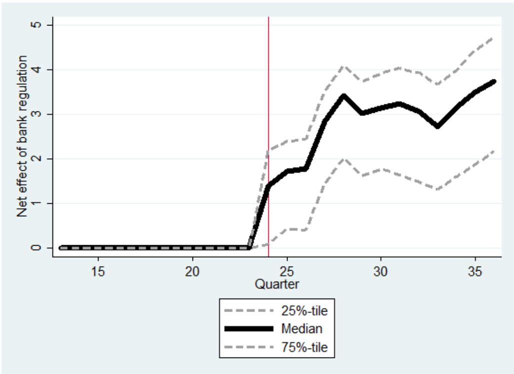
Dependent variable $Y_{it}^{(n)}$ ($n = 1...5$):	EQ_{it}/TA_{it} (1)	$DEPf_{it}/TA_{it}$ (2)	$DEPh_{it}/TA_{it}$ (3)	$LNSf_{it}/TA_{it}$ (4)	$LNSh_{it}/TA_{it}$ (5)
Panel 1: On extensive margin (the size of HNC does not matter)					
TREAT×REGIME	–0.254	–1.891***	1.864***	1.563**	0.392
	(0.347)	(0.546)	(0.474)	(0.613)	(0.383)
TREAT×REGIME×NPLh	0.007	0.003	0.062	0.073	–0.030
	(0.034)	(0.047)	(0.045)	(0.048)	(0.030)
TREAT×REGIME×EQ		0.033	–0.056*	–0.149***	0.069***
		(0.034)	(0.033)	(0.041)	(0.023)
TREAT×REGIME×HHI	14.830	–370.618***	203.627***	175.281**	109.689*
	(50.596)	(77.819)	(69.500)	(83.850)	(56.111)
N Obs.	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910
R^2_{within}	0.257	0.215	0.175	0.215	0.183

Note: The table contains difference-in-differences estimates of regression (6) with dependent variables $Y_{it}^{(n)}$ reflecting the composition of a bank i balance sheet from the liabilities and assets side: the ratio of equity capital to total assets EQ_{it}/TA_{it} ($n = 1$), deposits of non-financial firms to total assets $DEPf_{it}/TA_{it}$ ($n = 2$), deposits of households to total assets $DEPh_{it}/TA_{it}$ ($n = 3$), loans to non-financial firms to total assets $LNSf_{it}/TA_{it}$ ($n = 4$), loans to households to total assets $LNSh_{it}/TA_{it}$ ($n = 5$). All regressions include full sets of bank FE, quarter FE, bank control variables, and all possible combinations of $TREAT_{it}$, $REGIME_t$, and either of the three-channel variables considered, i.e., the ratio of non-performing loans in loans to households $NPLh_{it}$, equity capital to total assets ration EQ_{it} (except column 2), and the concentration of the banking system measured by the Herfindahl-Hirschman index HHI_t based on banks' total assets. All respective coefficients are not reported for the sake of space and are available upon request. Mid-2013 marks the transition of the CBR to a new prudential regulation regime in which the CBR was no longer tolerant of fraudulent banks. The treatment group consists of all banks which are likely to be treated as fraudulent by the CBR (the treatment rule is proxied with the Heckman selection model (1)–(2)). The composition of the treatment and control groups varies in time depending on the application of the treatment rule in each quarter (see Section 2.2 for details).

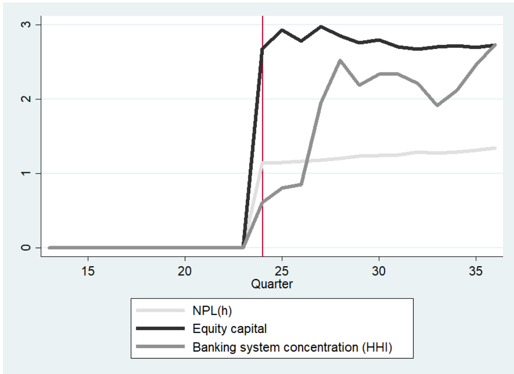
***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Standard errors are clustered at the bank level and appear in the brackets under the estimated coefficients.

Second, NPLs on household loans were unlikely to be a channel for those effects, because the respective coefficients on the $TREAT_{it} \times REG.CHANGE_t \times NPLh_{it}$ variable are never significant. In other words, although treated banks with relatively more NPLs were decreasing the absolute size of their operations more in response to the tightened regulation, greater NPLs *per se* were not pushing them to adjust the structure of these operations. *Third*, as opposed to NPLs, bank capital again plays a role in channeling the regulatory effect: treated banks with relatively less capital were raising their funding from uninsured sources by more than did relatively more capitalized treated banks. The same holds for lending to firms. The respective coefficients on the $TREAT_{it} \times REG.CHANGE_t \times EQ_{it}$ variable are negative and significant. Regarding household loans, I obtain the opposite result: treated banks with relatively less capital—while increasing loans to firms—were decreasing loans to households by more than did treated banks with relatively more capital. *Fourth*, regarding the banking system concentration, I again obtain mixed evidence, as in the previous section. However, now the sign of the coefficient on the $TREAT_{it} \times REG.CHANGE_t \times HHI_t$ variable coincides with the sign of respective mean effect, implying that the observed increase of the banking system concentration was amplifying the treated banks' reduction in firm deposits and expansion of household deposits and loans to firms.

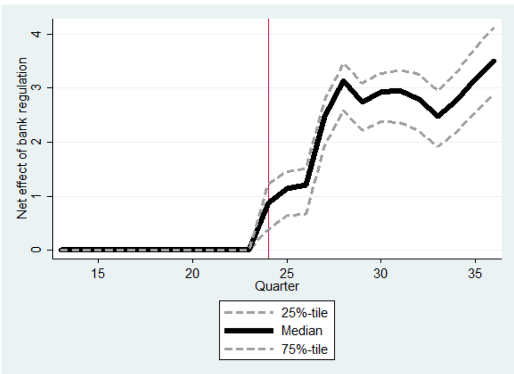
I plot the time evolution of the estimated composition effects and perform the decomposition exercise. The full results on the time evolution are reported in Appendix D (see Fig. D.II). Below, I analyze only the two most important effects—on treated banks' household deposits and firm loans (see Fig. 5).



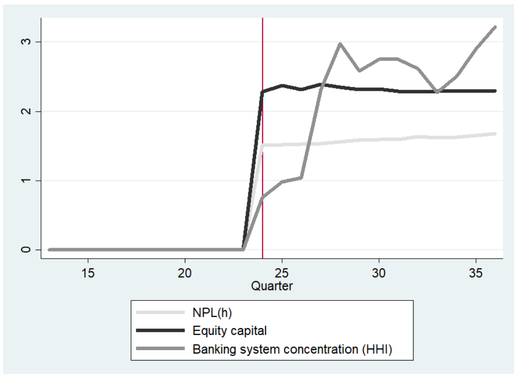
(a) Loans to non-financial firms / total assets (*aggregated effect*)



(b) Loans to non-financial firms / total assets (*disaggregated effects*)



(c) Deposits of households / total assets (*aggregated effect*)



(d) Deposits of households / total assets (*disaggregated effects*)

Figure 5: Time evolution of the assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

Overall, as in the previous section with channels of the scale effects, I again observe the same two results. First, the composition effects of tightened regulation on treated banks' household deposits and firm loans strengthened in time after mid-2013 (see Fig. 5a,c). Second, bank capital plays either the most important role in transmitting these effects (5b) or, at least, is as important as banking concentration (5d). Quantitatively, the exercise demonstrates that during the three years after the regulatory tightening, treated banks might have increased the share of firm loans in their total assets by as much as 4 percentage points, and increased the share of household deposits in their total liabilities by 3.5 percentage points (median estimates).

4.4 Macroeconomic implications of tightened bank regulation

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 F)—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 3 in Section 4.2.1). 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.[31] 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.

5 Sensitivity analysis

I run a battery of robustness checks, including a variation of the regulation rule applied ($\theta = 0.25$ and $\theta = 0.75$), changing the implied regulation type (degree of regulatory suspicion), matching treated banks with nearest neighbors within non-treated banks, simplifying the Heckman selection model to achieve greater generalizability, and finally switching from the Heckman model of the regulation rule to an alternative based on a popular statistical measure of bank soundness extensively used in banking literature (Z-score). In each case, I re-run all DID regressions and thus re-estimate every scale and

[31] 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).

composition effect of tightened regulation. Overall, the results survive.

5.1 Regulation rule

In the main text, I was agnostic regarding the fraction of banks the regulator audits each period, i.e., I set $\theta = 0.5$, meaning that banks with estimated probabilities of being audited above the median (across all banks in a given quarter) are treated as potentially misreporting by the regulator and are thus under threat of activity restrictions. In this section, I deviate from this rule by first decreasing the fraction of audited banks and then by increasing it. Because it is difficult to justify any particular number, I choose $\theta = 0.25$ in the first case and $\theta = 0.75$ in the second, which together embrace the standard interquartile range. When $\theta = 0.25$, it means that the regulator is more concerned with the state of misreporting in the system and audits a bank i if $\hat{s}_{it}$ is greater than the 25th percentile of the banks' distribution by $\hat{s}$ in a given quarter. $\theta = 0.75$ thus implies a less concerned regulator auditing a bank i if respective $\hat{s}_{it}$ is greater than the 75th percentile.

The estimation results on the scale effects of tightened regulation appear in Table G.I (see Appendix G). In this table, I report only the estimated coefficients on the $TREAT_{it} \times REG.CHANGE_t$ variable (the rest of the controls used are the same as in the main text, but are not reported to save space). The first three columns report the results with $\theta = 0.25$, $\theta = 0.50$, and $\theta = 0.75$ on the extensive margin, and the last three columns do the same on the intensive margin. By rows, the table contains six panels, one for each of the scale-dependent variables. Overall, the estimates suggest that my results are robust to varying regulations. All estimated DID coefficients remain negative, implying that tightened regulation forces treated banks to shrink their activities in absolute terms, and are highly statistically significant in almost all cases. Qualitatively, I obtain the result that the more concerned the regulator is (i.e., the lower the θ), the greater the shrinkage of the treated banks' balance sheets will be.

Table G.II reports the estimation results on the composition effects of tightened regulation on the asset and liability structure of the treated banks' balance sheets. I again observe that the effects concentrate in the panels with household deposits to total assets ratio and the firm loans to total assets ratio. Both ratios are rising, as in the main text, irrespective of the choice of θ. Again, the more concerned the regulator is, the stronger the composition effect will be.

5.2 Regulation type

In the main text, I assumed that when running its prudential regulation, the CBR is not suspicious (has no negative memory) in the sense that if the regulation rule applied in period $t + 1$ shows that a period-t misreporting bank is no longer identified as misreporting, the regulator has no reason to audit the bank. In this section, I deviate from this image of regulation to those implying more suspicion from the regulator's side. I assume that a period-t misreporting bank, despite no longer being identified by the formal rule as misreporting at period $t+1$ onwards, is still treated by the regulator as misreporting for at least four periods in the future (up to $t+4$, "suspicious regulation") or forever (to the end of the sample period, for concreteness; "most suspicious regulation"), and that all activity restrictions remain in place.

The re-estimated scale effects of tightened regulation appear in Table H.I (see Appendix H). The table has fully the same structure as in the previous section, except now I place the assumed regulatory suspicion by columns from least to most suspicious. The estimated DID coefficients are all negative, as in the main text, and statistically significant. Quantitatively, the more suspicious the regulator could be, the stronger the negative scale effect becomes. The results are robust to a particular assumption on the degree of regulatory's suspicion.

The re-estimated composition effects of tightened regulation are reported in Table H.II for the asset-liability structure of the treated banks' operations. Nothing new appears in these tables. Irrespective of the degree of assumed regulatory suspicion, the treated banks increase both their household deposits-to-assets ratios and firm loans-to-assets ratios, and decrease their firm deposits-to-assets ratios. The more suspicious the regulator is, the greater the effect.

5.3 Matching

In the main text, I run DID regressions on an unmatched sample of treated and control banks. Given the chosen baseline regulatory rule $\theta = 0.5$, this unmatched sample consists of almost the same quantity of treated and control banks. Though I control my regression estimates on a large set of bank-specific characteristics and bank and quarter FEs, some important differences could still exist. In this section, I apply the bias-adjusted matching estimator of Abadie and Imbens (2011), with which I construct 1-to-1 matched samples of banks. Because in the baseline estimates with $\theta = 0.5$ I have a slightly larger number of control banks, the first matched sample is constructed under the $\theta = 0.5$ rule. The second matched sample is then constructed under an assumption of a less concerned regulator, i.e., $\theta = 0.75$, which effectively shrinks the sample size in the DID regression by twofold. Matching under the third rule considered, i.e., $= 0.25$, is impossible for obvious reasons. I re-run all DID regressions on the two constructed matched samples.

The estimation results with the scale effects of tightened regulation appear in Table I.I (see Appendix I). The structure of the table is again the same as in the two previous sections, except that now

I locate unmatched regression results in the first column (for comparisons) and matched regression results under $\theta = 0.5$ and $\theta = 0.75$ in the second and third columns, respectively. The results clearly show that, again, nothing changes qualitatively. This is expected in the $\theta = 0.5$ case, but not that much under the $= 0.75$ case, due to a substantially smaller number of observations. I again find that the less concerned the regulator is, the less strong the scale effect becomes, in each of the six panels of the table, though it remains significant.

When I consider the composition effects of tightened regulation, I again find no qualitative changes—for the asset-liability structure of the treated banks' balance sheets (Table I.II).

Overall, the matching exercise confirms the results from the main text.

5.4 A more parsimonious Heckman selection model and a different identification of selection

In the main text, I specify an extended version of the Heckman selection model, i.e., I consider not only standard predictors of the bank in distress, such as capitalization, liquidity, profitability, etc. (in line with the CAMEL approach), but more specific characteristics of bank business profile (inter-bank market, rollovers of various types of loans, and so on). In this section, I step back to a more traditional set of determinants and re-estimate the Heckman selection model and all DID regressions covering the scale and composition effects of declining regulatory forbearance.

The estimation results on the more compact version of the Heckman selection model appear in Table J.I (see Appendix J). Qualitatively, I still observe that, across all periods of estimation, bank capital reduces both the probability of being audited and the size of losses, as measured by HNC, conditional on being detected. Other variables still deliver mixed effects, depending on the particular quarter of estimation. The bank size variable delivers a negative sign, statistically significant, across all periods, as in the main text. The estimated ρ coefficient, reflecting the correlation between the selection and outcome regressions' errors is positive and significant, but only after mid-2013, while in the main text, it was significant in mid-2013 as well.

With this re-estimated version of the Heckman selection model, I further report the re-estimated DID regressions, in which I assume the same structure of regulatory decision-making (i.e., $\theta = 0.5$ and no negative memory of the regulator), as in the main text. Table J.II in Appendix J reports the results on the scale effect of tightened regulation. The structure of the table is again the same as in the previous section, but now the columns compare the baseline estimates with those obtained here. For instance, the newly estimated coefficient on the $TREAT_{it} \times REG.CHANGE_t$ variable implies that treated banks could be forced to reduce their total assets by 21 billion rubles compared to non-treated banks on average within the three years after mid-2013 (significant at 1%). This is quantitatively similar to those obtained with the baseline specification. The same applies to the rest of the five scale variables in the table. Overall, the estimated scale effects are larger than those in the main text.

I next shift to the re-estimated composition effects on the asset and liability structure of the treated banks' balance sheets (see Table J.III in Appendix J), and find that all the results from the main text are still confirmed. Moreover, with the compact version of the Heckman model, I obtain significant effects on variables that were insignificant before. In particular, treated banks were likely to reduce their owned funds as a share of total assets both on extensive and intensive margins, which implies a negative consequence of tightened regulation. Further, unlike in the main text, treated banks could turn to decreasing the weights of firm deposits and household loans, again on extensive and intensive margins.

Finally, as discussed in the methodology section, the bank size variable was replaced with the binary indicator of whether a bank has losses in quarter t to identify selection. The estimated coefficient appears to be positive and highly statistically significant, implying that losses attract regulatory attention and thus the probability of being audited rises. The re-estimated DID regressions deliver no qualitative changes. The results are not reported to save space and are available upon request.

5.5 Why Heckman and not Z-score?

In the main text, I assume the regulator applies the Heckman selection model to detect misreporting banks. One could argue that there are more straightforward ways to meet this purpose. In particular, a very popular metric, the Z-score of bank soundness, could be applied to separate fraudulent from healthy banks, as is done in, e.g., DeYoung and Torna (2013). The Z-score is measured as a sum of the bank capital-to-assets ratio and monthly profit-to-assets ratio (ROA) divided by the standard deviation of ROA (three years moving average suggested by the literature). The Z-score is an upper-bound measure of a bank's overall stability that equals the number of deviations by which the bank's ROA should fall so that the resultant losses world fully destroy the bank's capital. The indicator stems from applying Chebyshev's inequality to measure the probability of a bank facing negative capital.

My essential reason for choosing Heckman's approach instead of the Z-score is that I can adjust it to account for the bank misreporting phenomenon so that I can trust a bank balance sheet's information only until the bank is not selected into the group of misreporting banks (the treatment group). In this respect, the Z-score could be less preferable simply because it does not contain any information on already revealed misreporting, only the information from (possibly falsified) balance sheets. Nevertheless, here I apply the Z-score metric and (i) compute an alternative to Heckman's approach bank treatment indicator based on the Z-score, (ii) show the relationships between both versions of the treatment indicator, and (iii) re-run DID regressions with the treatment indicator based on the Z-score.

Having computed the Z-scores for each bank and each quarter in my sample and, based on that, having ranked the banks by their Z-score at each quarter, I begin reporting comparative descriptive statistics in Table K.I (see Appendix K). By rows, in the first three panels of the table, I compare the treatment indicators based on the Z-score with those from the main text, i.e., based on the Heckman approach, for each of the three regulation rules considered ($\theta = [0.25, 0.50, 0.75]$). Here, I basically show that the number of treated banks is very much similar across the treatment indicators within each regulation rule.

Panel 4 presents the Z-score and size-adjusted Z-score for the full sample of banks.[32] I prefer the size-adjusted Z-score because the size and the Z-score are negatively associated, thus exhibiting the "too big to fail" phenomenon; because I aim to capture misreporting, which could be applied irrespective of bank size, I need to eliminate this concern. I find in this panel that, on average, a decline of monthly ROA by 50 standard deviations is able to fully deplete bank capital. Size adjustment renders the Z-score negative, and so I cannot interpret its levels in terms of standard deviations anymore, but I can still interpret its dynamics (the more the better). Finally, Panels 5 to 7 report the Z-scores themselves, the size-adjusted Z-scores, and (for subsequent comparisons) predicted losses, as measured with HNC, for treated banks across the three regulation rules. Across these three panels, the added value of adjusting Z-scores by bank size is clear: as θ grows, i.e., as the central bank checks banks with lower values of the Z-score, the mean value of size-adjusted Z-score declines from –3.2 in Panel 5 to –8.0 in Panel 7, whereas the mean value of the Z-score itself declines only marginally, if at all.

I further test the relationship between the size-adjusted Z-score and the baseline treatment indicator from the main text. The results appear in Table K.II (see Appendix K). This table contains two panels by rows, one with results on the extensive margin and the other with those on the intensive margin. In the first panel, I perform probit estimates with the baseline treatment indicator as the dependent variable. Columns (1)–(3) contain the marginal effects of the size-adjusted 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 a one standard deviation of the size-adjusted Z-score (36.95, in the full sample). As expected, banks with higher Z-scores are less likely to be treated under the baseline definition (significant at 1% for the $\theta = 0.50$ and $\theta = 0.75$ regulation rules). I further

[32] I run a regression of Z-scores on the bank size variables and bank FEs and quarter FEs and extract the estimated residuals. I find the coefficient on the size variable to be negative and highly significant.

transform the size-adjusted Z-score into a binary indicator that equals 0 for banks with the highest 25%, 50%, or 75% of all observable values of Z-scores in a given quarter and 1 for the rest of the banks, respectively. Columns (4)–(6) present the marginal effects of being treated under the Z-score definition on the probability of being treated under Heckman's (*baseline*) definition. In these columns, the banks that are likely to be treated under the Z-score definition are also more likely to be treated under Heckman. It is clear that the two approaches are consistent with each other in the full sample within the six years around the regulatory tightening. The results in the second panel of the table provide qualitatively the same conclusions.

Finally, I re-run the DID regressions, estimating the scale effects of regulatory tightening (see Table K.III in Appendix K) as well as the composition effects (Table K.IV). Overall, I still achieve the same outcomes as in the main text, with somewhat lower magnitudes of the scale effects than in the main text and sometimes lower or larger composition effects compared to the baseline. This exercise largely supports the use of the Heckman selection approach to determining misreporting banks.

6 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.

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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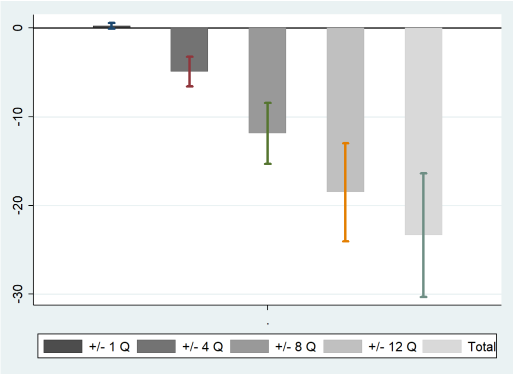
Appendix A Descriptive statistics at the bank level

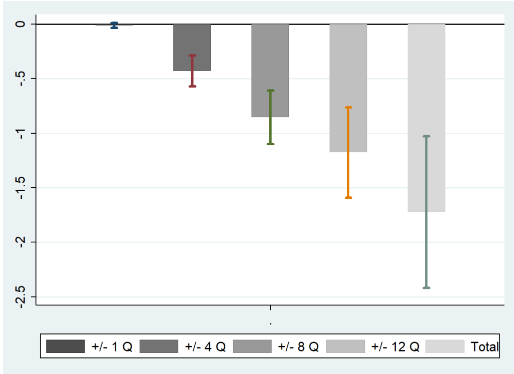
Table A.I: Descriptive statistics: ±3 years around the regulatory tightening in mid-2013

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

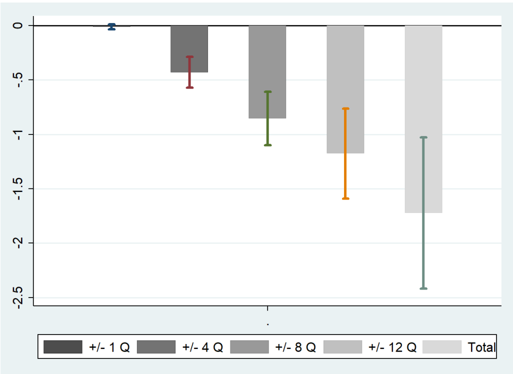
Appendix B Difference-in-differences estimates at different time windows



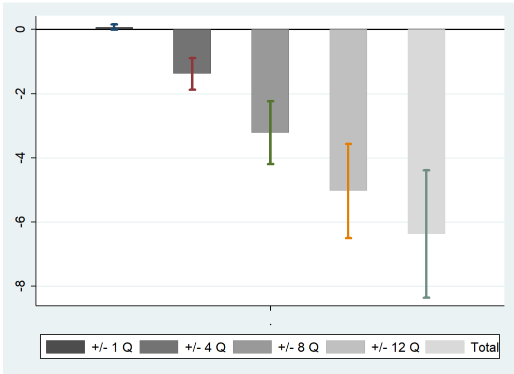
(a) Total assets TA_{it} $(n = 1)$



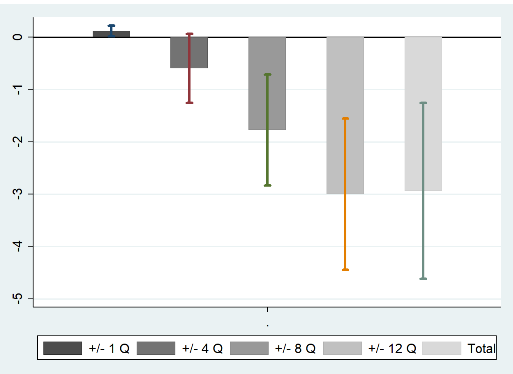
(b) Equity capital EQ_{it} $(n = 2)$



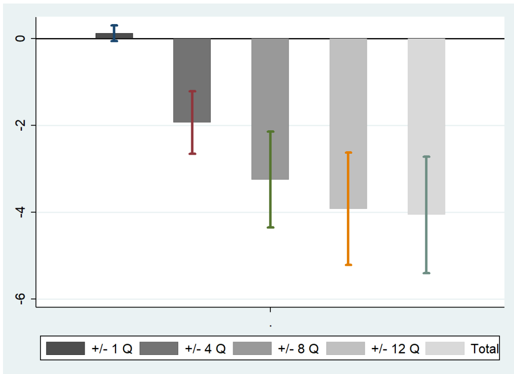
(c) Deposits of firms $DEPf_{it}$ $(n = 3)$



(d) Deposits of households $DEPh_{it}$ $(n = 4)$

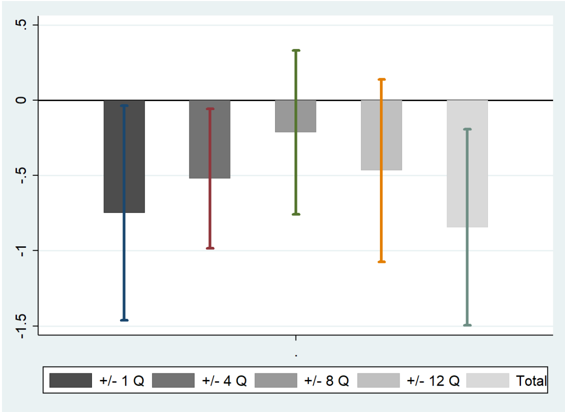


(e) Loans to firms $LNSf_{it}$ $(n = 5)$

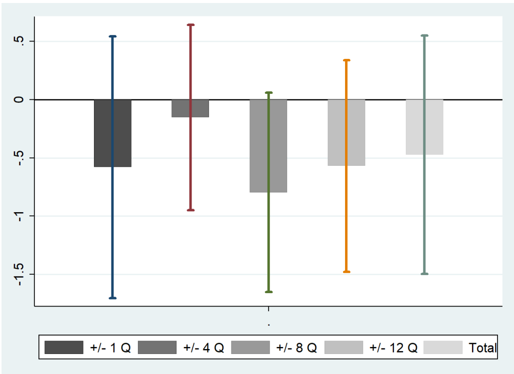


(f) Loans to households $LNSh_{it}$ $(n = 6)$

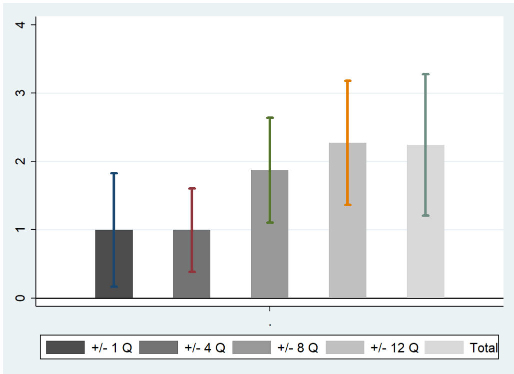
Figure B.I: The scale effects of tightened prudential regulation over different estimation windows in DID regressions



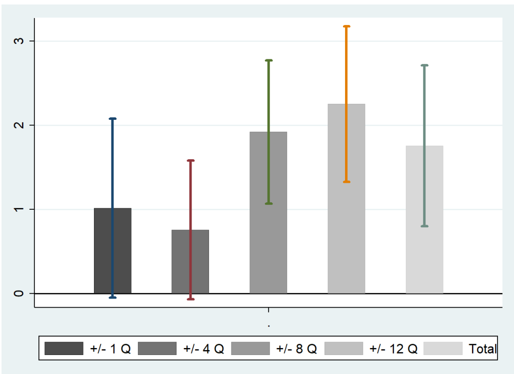
(a) Equity capital to total assets EQ_{it}/TA_{it} $(n = 1)$



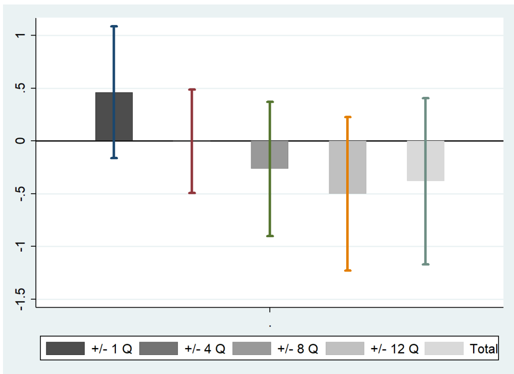
(b) Deposits of non-financial firms to total assets $DEPf_{it}/TA_{it}$ $(n = 2)$



(c) Deposits of households to total assets $DEPh_{it}/TA_{it}$ $(n = 3)$



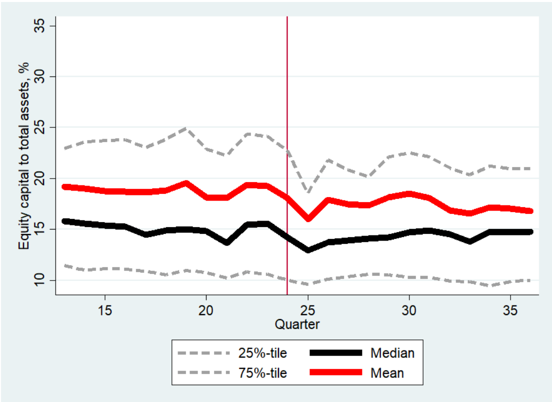
(d) Loans to non-financial firms to total assets $LNSf_{it}/TA_{it}$ $(n = 4)$



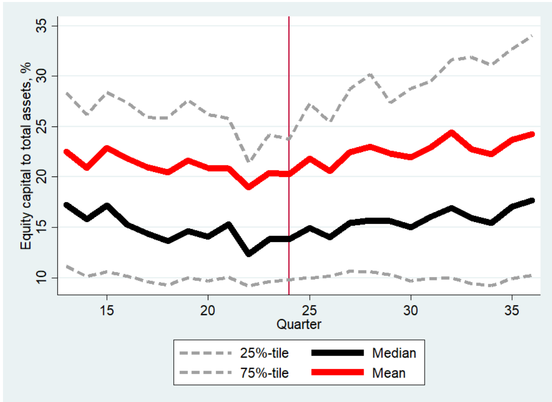
(e) Loans to households to total assets $LNSh_{it}/TA_{it}$ $(n = 5)$

Figure B.II: The assets and liability composition effects of tightened prudential regulation over different estimation windows in DID regressions

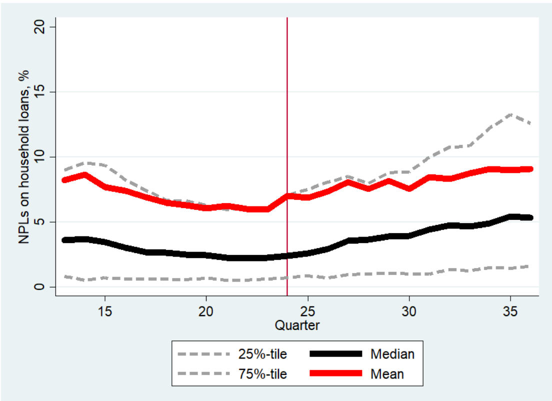
Appendix C Trends in the data on bank capital, NPLs, and banking system concentration



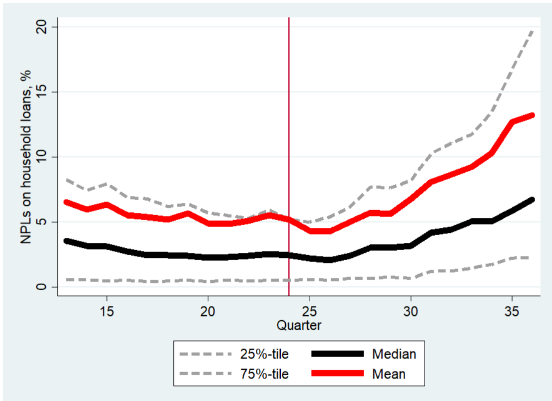
(a) Treated banks: Equity capital to total assets



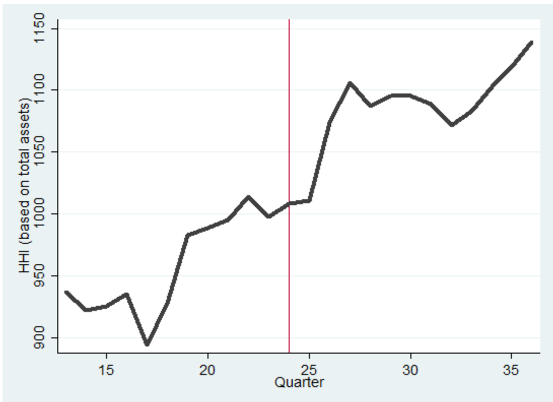
(b) Control banks: Equity capital to total assets



(c) Treated banks: NPLs on household loans



(d) Control banks: NPLs on household loans

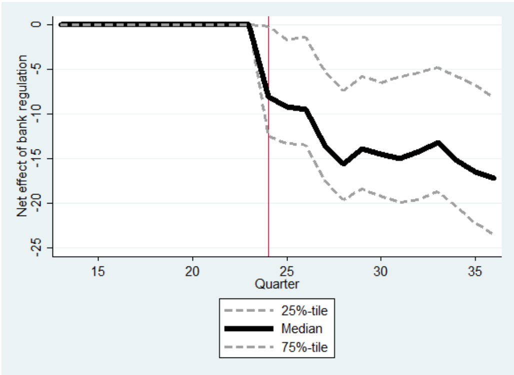


(e) Herfindahl-Hirschman index (HHI)

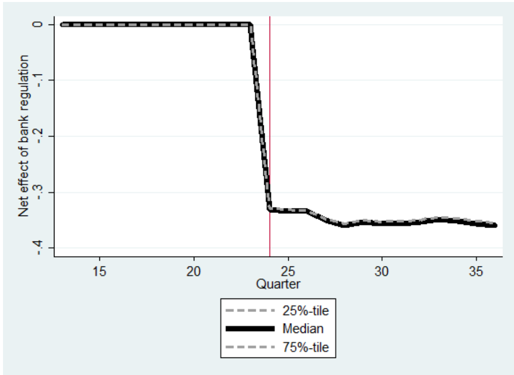
Note: The vertical red line crosses the 24th quarter of the sample, which stands for 2013 Q2, i.e., the beginning of Nabiullina's tightened prudential regulation.

Figure C.I: Equity capital to total assets ratio, NPLs on household loans, and banking system concentration (HHI) around the regulatory tightening in mid-2013

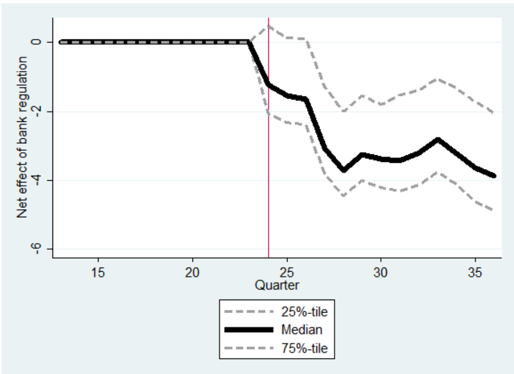
Appendix D Channels of the effects of tightened bank regulation



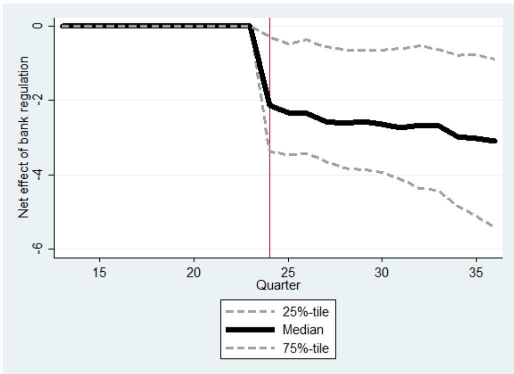
(a) Total assets TA_{it} $(n = 1)$



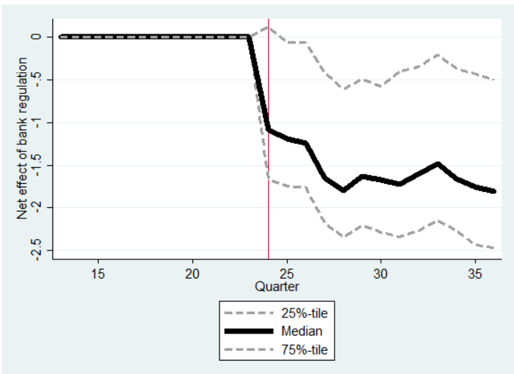
(b) Equity capital EQ_{it} $(n = 2)$



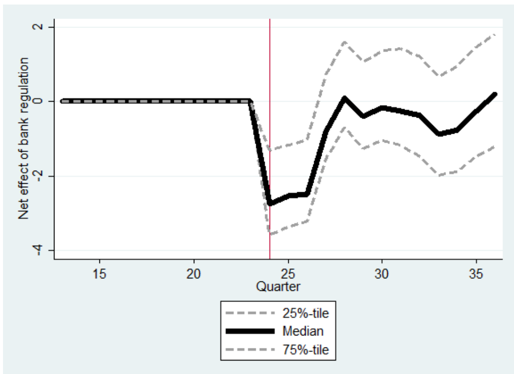
(c) Deposits of firms $DEPf_{it}$ $(n = 3)$



(d) Deposits of households $DEPh_{it}$ $(n = 4)$

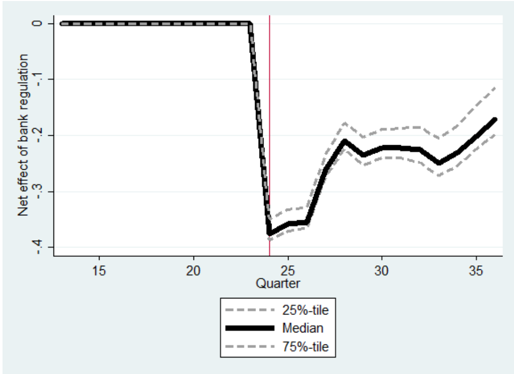


(e) Loans to firms $LNSf_{it}$ $(n = 5)$

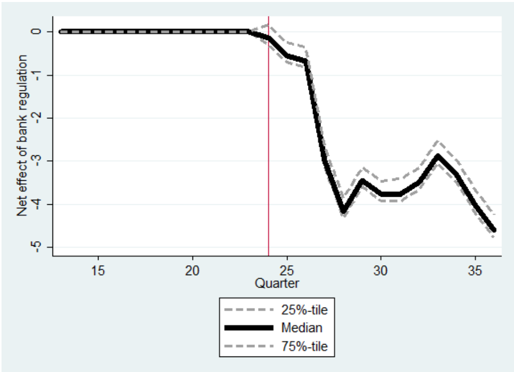


(f) Loans to households $LNSh_{it}$ $(n = 6)$

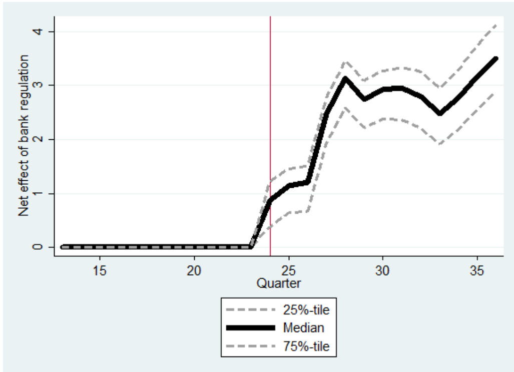
Figure D.I: Time evolution of the scale effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013



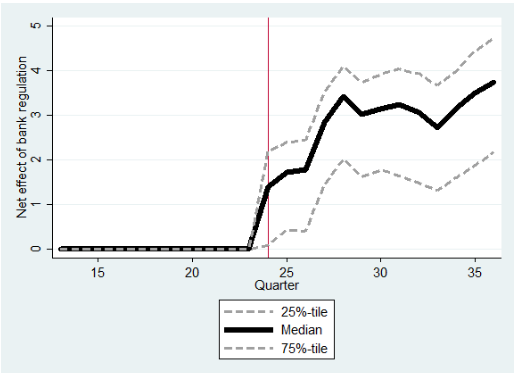
(a) Equity capital to total assets EQ_{it}/TA_{it} ($n = 1$)



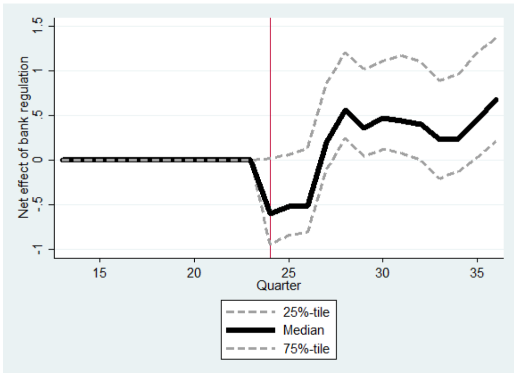
(b) Deposits of non-financial firms to total assets $DEPf_{it}/TA_{it}$ ($n = 2$)



(c) Deposits of households to total assets $DEPh_{it}/TA_{it}$ ($n = 3$)



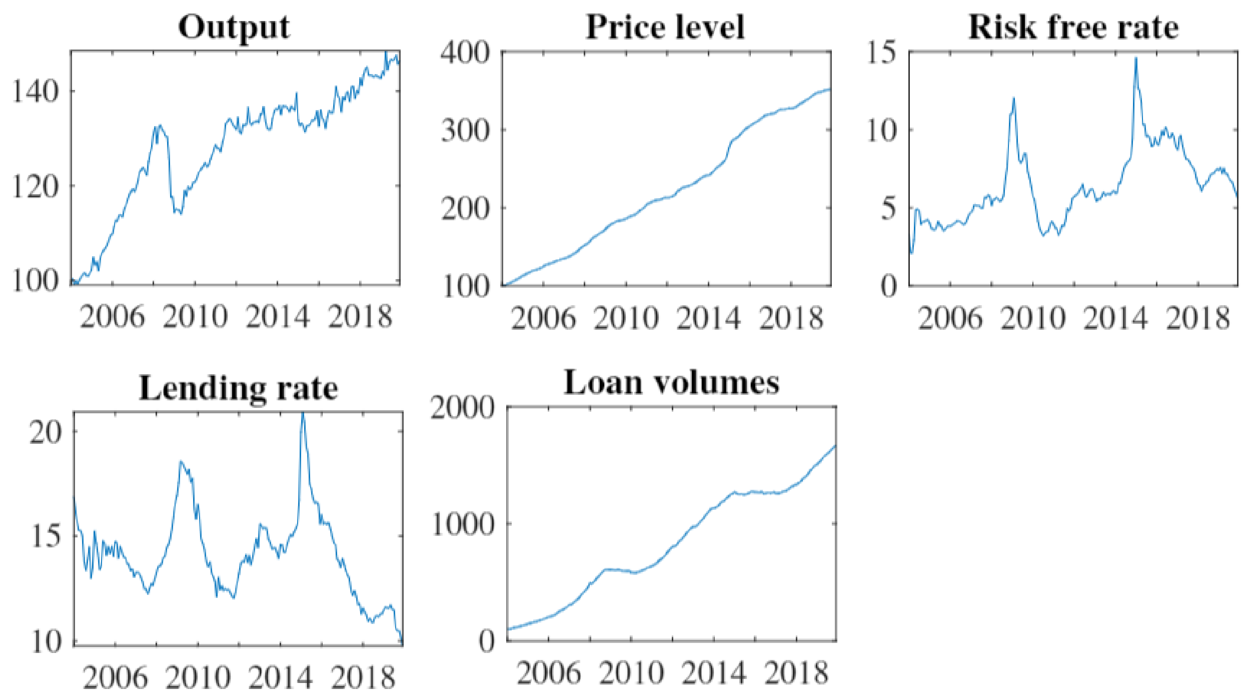
(d) Loans to non-financial firms to total assets $LNSf_{it}/TA_{it}$ ($n = 4$)



(e) Loans to households to total assets $LNSh_{it}/TA_{it}$ ($n = 5$)

Figure D.II: Time evolution of the assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

Appendix E 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.

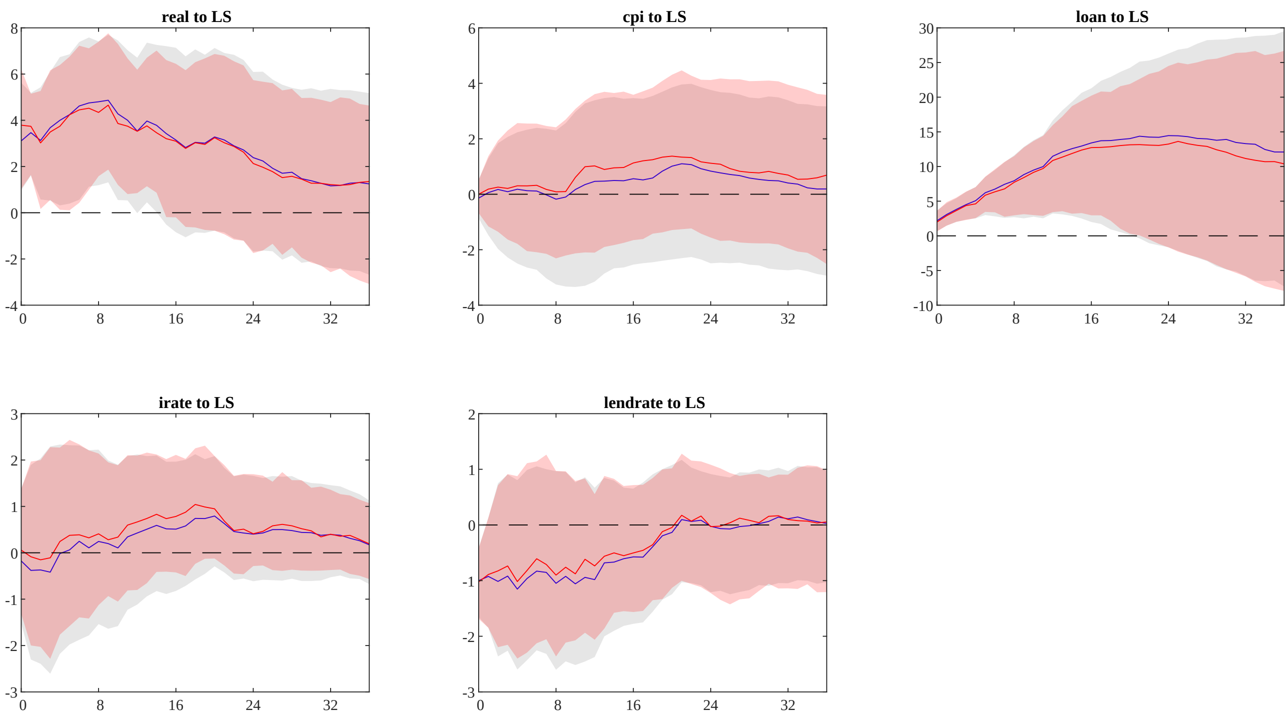
Sources: The Central Bank of Russia (the CBR, https://www.theCBR.ru/eng/key-indicators/), The Federal State Statistic Service (Rosstat, https://eng.gks.ru/folder/75924).

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

Appendix F 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. F.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 F.I: Impulse response functions to the identified credit supply shock (CS)

Appendix G Regulation rule

Table G.I: Scale effects of declining regulatory forbearance:
±3 years around the regulatory tightening in mid-2013

	Extensive margin			Intensive margin		
	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Dependent variable = the absolute size of a bank's total assets TA_{it}						
TREAT×REGIME	–28.601***	–18.521***	–13.674***	–0.278***	–0.303***	–0.261***
	(4.921)	(2.824)	(2.039)	(0.066)	(0.053)	(0.045)
R^2_{within}	0.116	0.095	0.080	0.082	0.083	0.076
Panel 2: Dependent variable = the absolute size of a bank's equity capital EQ_{it}						
TREAT×REGIME	–1.912***	–1.176***	–0.975***	–0.019***	–0.019***	–0.019***
	(0.356)	(0.210)	(0.166)	(0.005)	(0.004)	(0.004)
R^2_{within}	0.104	0.087	0.079	0.082	0.080	0.076
Panel 3: Dependent variable = the absolute size of a bank's deposits of non-financial firms $DEPf_{it}$						
TREAT×REGIME	–5.304***	–3.278***	–2.584***	–0.059***	–0.057***	–0.053***
	(1.632)	(0.885)	(0.666)	(0.022)	(0.017)	(0.015)
R^2_{within}	0.059	0.053	0.049	0.051	0.050	0.048
Panel 4: Dependent variable = the absolute size of a bank's deposits of households $DEPh_{it}$						
TREAT×REGIME	–7.313***	–5.032***	–4.175***	–0.067***	–0.081***	–0.080***
	(1.266)	(0.746)	(0.610)	(0.018)	(0.015)	(0.014)
R^2_{within}	0.189	0.175	0.164	0.162	0.165	0.160
Panel 5: Dependent variable = the absolute size of a bank's loans to non-financial firms $LNSf_{it}$						
TREAT×REGIME	–3.757***	–3.001***	–2.798***	–0.018	–0.043***	–0.050***
	(1.312)	(0.736)	(0.649)	(0.018)	(0.015)	(0.015)
R^2_{within}	0.123	0.121	0.118	0.114	0.117	0.116
Panel 6: Dependent variable = the absolute size of a bank's loans to households $LNSh_{it}$						
TREAT×REGIME	–6.613***	–3.922***	–2.908***	–0.072***	–0.064***	–0.057***
	(1.168)	(0.661)	(0.487)	(0.014)	(0.012)	(0.010)
R^2_{within}	0.117	0.090	0.076	0.085	0.079	0.073

Note: The table re-performs the estimations reported in Table 3 from the main text with the use of different regulation rules, as reflected in $\theta = [0.25, 0.5, 0.75]$. For example, $\theta = 0.25$ implies that the regulator applies the cut-off threshold equal to 25% for 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). All the notes from the reference table apply. In all regressions, N obs. = 17,696 and N banks = 910.

***, **, * 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.

Table G.II: The assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

	Extensive margin			Intensive margin		
	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Dependent variable = equity capital to total assets ratio EQ_{it}/TA_{it}						
TREAT×REGIME	–0.547	–0.467	–0.544*	–0.007	–0.014**	–0.020**
	(0.400)	(0.309)	(0.324)	(0.006)	(0.007)	(0.009)
R^2_{within}	0.116	0.095	0.080	0.082	0.083	0.076
Panel 2: Dependent variable = deposits of non-financial firms to total assets ratio $DEPf_{it}/TA_{it}$						
TREAT×REGIME	–1.188**	–0.573	0.288	–0.013	–0.018**	–0.003
	(0.532)	(0.463)	(0.519)	(0.009)	(0.009)	(0.012)
R^2_{within}	0.210	0.212	0.214	0.209	0.209	0.210
Panel 3: Dependent variable = deposits of households to total assets ratio $DEPh_{it}/TA_{it}$						
TREAT×REGIME	2.447***	2.280***	1.776***	0.034***	0.053***	0.051***
	(0.526)	(0.462)	(0.531)	(0.009)	(0.010)	(0.012)
R^2_{within}	0.161	0.173	0.169	0.153	0.161	0.160
Panel 4: Dependent variable = loans to non-financial firms to total assets ratio $LNSf_{it}/TA_{it}$						
TREAT×REGIME	2.830***	2.259***	2.440***	0.046***	0.063***	0.082***
	(0.498)	(0.470)	(0.546)	(0.009)	(0.010)	(0.015)
R^2_{within}	0.185	0.206	0.202	0.161	0.179	0.178
Panel 5: Dependent variable = loans to households to total assets ratio $LNSh_{it}/TA_{it}$						
TREAT×REGIME	–0.378	–0.494	–0.775**	0.001	–0.001	–0.011
	(0.441)	(0.372)	(0.388)	(0.007)	(0.007)	(0.010)
R^2_{within}	0.175	0.175	0.175	0.176	0.175	0.175

Note: The table re-performs the estimations reported in Table 4 from the main text with the use of different regulation rules, as reflected in $\theta = [0.25, 0.5, 0.75]$. For example, $\theta = 0.25$ implies that the regulator applies the cut-off threshold equal to 25% for 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). All the notes from the reference table apply. In all regressions reported, N obs. = 17,696 and N banks = 910.

***, **, * 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 H Regulation type

Table H.I: Scale effects of declining regulatory forbearance:
±3 years around the regulatory tightening in mid-2013

	Extensive margin			Intensive margin		
Regulator's suspicion within	$[t, t+1]$	$[t, t+4]$	$[t, t+\infty]$	$[t, t+1]$	$[t, t+4]$	$[t, t+\infty]$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Dependent variable = the absolute size of a bank's total assets TA_{it}						
TREAT×REGIME	–18.521***	–22.839***	–26.689***	–0.303***	–0.284***	0.021
	(2.824)	(3.455)	(5.617)	(0.053)	(0.052)	(0.098)
R^2_{within}	0.095	0.106	0.101	0.083	0.084	0.071
Panel 2: Dependent variable = the absolute size of a bank's equity capital EQ_{it}						
TREAT×REGIME	–1.176***	–1.498***	–1.661***	–0.019***	–0.020***	0.003
	(0.210)	(0.242)	(0.405)	(0.004)	(0.004)	(0.007)
R^2_{within}	0.087	0.096	0.093	0.080	0.083	0.072
Panel 3: Dependent variable = the absolute size of a bank's deposits of non-financial firms $DEPf_{it}$						
TREAT×REGIME	–3.278***	–3.915***	–3.814***	–0.057***	–0.052***	0.020
	(0.885)	(1.038)	(1.239)	(0.017)	(0.017)	(0.032)
R^2_{within}	0.053	0.055	0.051	0.050	0.050	0.047
Panel 4: Dependent variable = the absolute size of a bank's deposits of households $DEPh_{it}$						
TREAT×REGIME	–5.032***	–6.599***	–8.685***	–0.081***	–0.083***	–0.019
	(0.746)	(0.975)	(1.711)	(0.015)	(0.015)	(0.025)
R^2_{within}	0.175	0.187	0.191	0.165	0.168	0.154
Panel 5: Dependent variable = the absolute size of a bank's loans to non-financial firms $LNSf_{it}$						
TREAT×REGIME	–3.001***	–3.523***	–3.145**	–0.043***	–0.039***	0.028
	(0.736)	(0.881)	(1.423)	(0.015)	(0.014)	(0.024)
R^2_{within}	0.121	0.124	0.119	0.117	0.117	0.116
Panel 6: Dependent variable = the absolute size of a bank's loans to households $LNSh_{it}$						
TREAT×REGIME	–3.922***	–5.199***	–7.771***	–0.064***	–0.067***	–0.043**
	(0.661)	(0.903)	(1.647)	(0.012)	(0.012)	(0.018)
R^2_{within}	0.090	0.104	0.119	0.079	0.083	0.074

Note: The table re-performs the estimations reported in Table 3 from the main text with the use of different regulation types, as reflected in a horizon within which the regulator audits a fraudulent bank: $[t, t+1]$ (baseline, least suspicious regulation), $[t, t+4]$ (suspicious regulation) or $[t, t+\infty]$ (most suspicious regulation). All the notes from the reference table apply. In all regressions, N obs. = 17,696 and N banks = 910.

***, **, * 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.

Table H.II: The assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

	Extensive margin			Intensive margin		
Regulator's suspicion within	$[t, t+1]$	$[t, t+4]$	$[t, t+\infty]$	$[t, t+1]$	$[t, t+4]$	$[t, t+\infty]$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Dependent variable = equity capital to total assets ratio EQ_{it}/TA_{it}						
TREAT×REGIME	–0.467	0.099	0.870	–0.014**	0.000	0.023***
	(0.309)	(0.370)	(0.548)	(0.007)	(0.007)	(0.007)
R^2_{within}	0.257	0.258	0.253	0.251	0.248	0.250
Panel 2: Dependent variable = deposits of non-financial firms to total assets ratio $DEPf_{it}/TA_{it}$						
TREAT×REGIME	–0.569	–1.252**	–1.470*	–0.019**	–0.025***	0.002
	(0.463)	(0.546)	(0.808)	(0.009)	(0.009)	(0.011)
R^2_{within}	0.211	0.211	0.211	0.209	0.210	0.210
Panel 3: Dependent variable = deposits of households to total assets ratio $DEPh_{it}/TA_{it}$						
TREAT×REGIME	2.270***	2.353***	2.117***	0.053***	0.043***	0.013
	(0.463)	(0.531)	(0.793)	(0.010)	(0.009)	(0.010)
R^2_{within}	0.171	0.164	0.151	0.159	0.153	0.147
Panel 4: Dependent variable = loans to non-financial firms to total assets ratio $LNSf_{it}/TA_{it}$						
TREAT×REGIME	2.250***	2.296***	0.838	0.064***	0.055***	–0.004
	(0.471)	(0.523)	(0.710)	(0.010)	(0.010)	(0.010)
R^2_{within}	0.205	0.178	0.159	0.177	0.159	0.145
Panel 5: Dependent variable = loans to households to total assets ratio $LNSh_{it}/TA_{it}$						
TREAT×REGIME	–0.500	–0.345	–0.813	–0.001	0.001	0.008
	(0.371)	(0.436)	(0.631)	(0.007)	(0.007)	(0.009)
R^2_{within}	0.174	0.174	0.174	0.173	0.173	0.174

Note: The table re-performs the estimations reported in Table 4 from the main text with the use of different regulation types, as reflected in a horizon within which the regulator audits a fraudulent bank: $[t, t+1]$ (baseline, least suspicious regulation), $[t, t+4]$ (suspicious regulation) or $[t, t+\infty]$ (most suspicious regulation). All the notes from the reference table apply. In all regressions, N obs. = 17,696 and N banks = 910.

***, **, * 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 I Matching of treated and control banks

Table I.I: Scale effects of declining regulatory forbearance:
±3 years around the regulatory tightening in mid-2013

	Extensive margin			Intensive margin		
	Unmatched	Matched		Unmatched	Matched	
	$\theta = 0.5$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.5$	$\theta = 0.5$	$\theta = 0.75$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Dependent variable = the absolute size of a bank's total assets TA_{it}						
TREAT×REGIME	–18.521***	–17.091***	–12.393***	–0.303***	–0.269***	–0.200***
	(2.899)	(3.288)	(2.304)	(0.054)	(0.059)	(0.045)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.880	0.900	0.882	0.879	0.898	0.881
Panel 2: Dependent variable = the absolute size of a bank's equity capital EQ_{it}						
TREAT×REGIME	–1.176***	–1.322***	–0.972***	–0.019***	–0.022***	–0.017***
	(0.216)	(0.266)	(0.186)	(0.004)	(0.005)	(0.004)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	905	888	910	905	888
R^2_{LSDV}	0.914	0.951	0.946	0.913	0.950	0.946
Panel 3: Dependent variable = the absolute size of a bank's deposits of non-financial firms $DEPf_{it}$						
TREAT×REGIME	–3.278***	–4.089**	–2.620***	–0.057***	–0.069**	–0.047**
	(0.908)	(1.935)	(0.952)	(0.017)	(0.033)	(0.018)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.800	0.813	0.816	0.799	0.812	0.816
Panel 4: Dependent variable = the absolute size of a bank's deposits of households $DEPh_{it}$						
TREAT×REGIME	–5.032***	–4.489***	–3.506***	–0.081***	–0.071***	–0.056***
	(0.766)	(0.767)	(0.680)	(0.015)	(0.015)	(0.013)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.892	0.909	0.903	0.891	0.907	0.902
Panel 5: Dependent variable = the absolute size of a bank's loans to non-financial firms $LNSf_{it}$						
TREAT×REGIME	–3.001***	–3.774***	–2.972***	–0.043***	–0.054***	–0.043***
	(0.756)	(1.051)	(0.770)	(0.016)	(0.020)	(0.015)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.914	0.912	0.906	0.914	0.912	0.906
Panel 6: Dependent variable = the absolute size of a bank's loans to households $LNSh_{it}$						
TREAT×REGIME	–3.922***	–2.533***	–1.886***	–0.064***	–0.038***	–0.031***
	(0.678)	(0.467)	(0.436)	(0.012)	(0.008)	(0.007)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.898	0.933	0.913	0.897	0.932	0.913

Note: The table re-performs the estimations reported in Table 3 from the main text with the use of unmatched (baseline) and 1-to-1 matched samples of banks. Two matched samples are considered: one for the regulation rule $\theta = 0.5$ and the other for the rule $\theta = 0.75$. In the first case, half of all banks are in the treatment group, and I match each such bank with one counterpart from the control group. In the second case, only 25% of banks are treated (i.e., those with the probability of being selected above the 25%-tile of respective distribution), and I again find exactly one match from the control group. I perform matching using the Mahalanobis distance. I employ five bank-specific characteristics to match banks: (i) equity capital to total assets ratio (except Panel 2), (ii) NPLs ratio on loans to non-financial firms, (iii) NPLs ratio on loans to households, (iv) liquid assets to total assets ratio, and (v) ROA (annualized). In the rest, all the notes from the reference table apply.

***, **, * 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.

Table I.II: The assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

	Extensive margin			Intensive margin		
	Unmatched	Matched		Unmatched	Matched	
	$\theta = 0.5$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 0.5$	$\theta = 0.5$	$\theta = 0.75$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Dependent variable = equity capital to total assets ratio EQ_{it}/TA_{it}						
TREAT×REGIME	–0.467	–0.739**	–0.408	–0.014*	–0.019**	–0.017*
	(0.317)	(0.351)	(0.404)	(0.007)	(0.007)	(0.009)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	905	888	910	905	888
R^2_{LSDV}	0.873	0.884	0.879	0.872	0.883	0.878
Panel 2: Dependent variable = deposits of non-financial firms to total assets ratio $DEPf_{it}/TA_{it}$						
TREAT×REGIME	–0.573	0.114	0.630	–0.018*	–0.009	0.005
	(0.475)	(0.609)	(0.668)	(0.010)	(0.011)	(0.014)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.787	0.803	0.813	0.787	0.802	0.812
Panel 3: Dependent variable = deposits of households to total assets ratio $DEPh_{it}/TA_{it}$						
TREAT×REGIME	2.280***	1.323***	1.328**	0.053***	0.034***	0.034***
	(0.474)	(0.495)	(0.610)	(0.010)	(0.010)	(0.012)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.899	0.904	0.909	0.897	0.903	0.908
Panel 4: Dependent variable = loans to non-financial firms to total assets ratio $LNSf_{it}/TA_{it}$						
TREAT×REGIME	2.259***	2.288***	2.460***	0.063***	0.067***	0.067***
	(0.483)	(0.558)	(0.673)	(0.010)	(0.012)	(0.016)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.839	0.846	0.856	0.833	0.840	0.849
Panel 5: Dependent variable = loans to households to total assets ratio $LNSh_{it}/TA_{it}$						
TREAT×REGIME	–0.494	–1.030***	–0.722*	–0.001	–0.011	–0.005
	(0.382)	(0.367)	(0.406)	(0.007)	(0.007)	(0.010)
N obs	17,696	17,382	8,540	17,696	17,382	8,540
N banks	910	902	875	910	902	875
R^2_{LSDV}	0.882	0.892	0.891	0.882	0.892	0.891

Note: The table re-performs the estimations reported in Table 4 from the main text with the use of unmatched (baseline) and 1-to-1 matched samples of banks. Two matched samples are considered: one for the regulation rule $\theta = 0.5$ and the other for the rule $\theta = 0.75$. In the first case, half of all banks are in the treatment group, and I match each such bank with one counterpart from the control group. In the second case, only 25% of banks are treated (i.e., those with the probability of being selected above the 25%-tile of respective distribution), and I again find exactly one match from the control group. I perform matching using the Mahalanobis distance. I employ five bank-specific characteristics were used to match banks: (i) equity capital to total assets ratio (except Panel 2), (ii) NPLs ratio on loans to non-financial firms, (iii) NPLs ratio on loans to households, (iv) liquid assets to total assets ratio, and (v) ROA (annualized). In the rest, all the notes from the reference table apply.

***, **, * 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 J A more compact version of the Heckman selection model of bank misreporting

Table J.I: Cross-sectional Heckman selection estimates:
±3 years around the regulatory tightening in mid-2013 [a]

	3 years before 2013Q2		2013Q2		3 years after 2013Q2	
	Out	Sel	Out	Sel	Out	Sel
	(1)	(2)	(3)	(4)	(5)	(6)
Equity capital / Total assets	–0.045	–0.011*	–0.316	–0.019***	–0.623***	–0.037***
	(0.197)	(0.006)	(0.377)	(0.006)	(0.204)	(0.005)
NPLs on firm loans	–0.436	–0.010	–1.216	–0.006	–0.087	–0.015***
	(0.373)	(0.008)	(0.790)	(0.008)	(0.277)	(0.004)
NPLs on household loans	0.050	0.000	0.186	0.008*	–0.033	0.001
	(0.188)	(0.006)	(0.396)	(0.005)	(0.172)	(0.004)
Liquid assets / Total assets	–0.148	–0.013**	1.245***	0.002	0.291	–0.019***
	(0.197)	(0.006)	(0.327)	(0.005)	(0.196)	(0.004)
ROA (annualized)	–0.830	–0.033	–0.467	–0.046**	1.136**	0.040***
	(0.908)	(0.026)	(1.337)	(0.018)	(0.476)	(0.012)
Growth of total assets	–0.025	–0.007***	0.040	0.001	0.056	0.002*
	(0.113)	(0.002)	(0.068)	(0.001)	(0.036)	(0.001)
log of total assets		–0.175***		–0.255***		–0.354***
		(0.060)		(0.054)		(0.041)
Constant	8.789	–0.703***	–21.032	–0.599***	20.700***	1.215***
	(20.611)	(0.227)	(30.852)	(0.184)	(7.652)	(0.171)
N obs.	943		932		872	
N censored / observed	888 / 55		833 / 99		573 / 299	
Wald χ^2	3.160		17.455***		23.114***	
ρ	0.496		0.516		0.548***	

Note: The table reports efficient two-step estimates of the Heckman selection model for the three specific periods: 2013Q2, i.e., the time of regulatory change in the Central Bank of Russia, and three years before and after this date (recall that the estimation window in the baseline version of the difference-in-differences estimates equals ±3 years around mid-2013). Dependent variables are (i) an indicator variable of whether hidden negative capital, HNC, was detected by the CBR (columns "*Sel*") and (ii) the ratio of HNC to the equity capital reported one quarter before the closure (columns "*Out*"). *Sel* and *Out* are selection and outcome equations of the Heckman model. All explanatory variables are taken with a one-quarter lag. ρ is correlation between the regression errors of *Sel* and *Out*. *Wald* χ^2 is the Wald statistic that tests the null hypothesis that all coefficients equal zero simultaneously. N *censored* reflects all banks operating in the respective quarter for which the estimate is done. N *observed* accumulates all banks with HNC detected from the beginning of the sample, 2010Q2, to the respective quarter for which I perform an estimate.

[a] The rest of the estimates (i.e., for the other 44 quarters in the sample, 2010Q2 to 2019Q2) are not reported for the sake of brevity and are available upon request

***, **, * indicate that a coefficient is significant at the 1%, 5%, 10% level, respectively. Robust standard errors appear in the brackets under the estimated coefficients.

Table J.II: Scale effects of declining regulatory forbearance:
±3 years around the regulatory tightening in mid-2013

	Extensive margin		Intensive margin	
Heckman model:	Baseline	Additional	Baseline	Additional
	(1)	(2)	(3)	(4)
Panel 1: Dependent variable = the absolute size of a bank's total assets TA_{it}				
TREAT×REGIME	–18.521***	–20.846***	–0.303***	–0.520***
	(2.824)	(2.944)	(0.053)	(0.079)
R^2_{within}	0.095	0.102	0.083	0.095
Panel 2: Dependent variable = the absolute size of a bank's equity capital EQ_{it}				
TREAT×REGIME	–1.176***	–1.371***	–0.019***	–0.034***
	(0.210)	(0.211)	(0.004)	(0.006)
R^2_{within}	0.087	0.093	0.080	0.089
Panel 3: Dependent variable = the absolute size of a bank's deposits of non-financial firms $DEPf_{it}$				
TREAT×REGIME	–3.278***	–3.291***	–0.057***	–0.086***
	(0.885)	(0.844)	(0.017)	(0.024)
R^2_{within}	0.053	0.053	0.050	0.052
Panel 4: Dependent variable = the absolute size of a bank's deposits of households $DEPh_{it}$				
TREAT×REGIME	–5.032***	–5.873***	–0.081***	–0.149***
	(0.746)	(0.758)	(0.015)	(0.021)
R^2_{within}	0.175	0.183	0.165	0.177
Panel 5: Dependent variable = the absolute size of a bank's loans to non-financial firms $LNSf_{it}$				
TREAT×REGIME	–3.001***	–4.169***	–0.043***	–0.106***
	(0.736)	(0.754)	(0.015)	(0.021)
R^2_{within}	0.121	0.128	0.117	0.125
Panel 6: Dependent variable = the absolute size of a bank's loans to households $LNSh_{it}$				
TREAT×REGIME	–3.922***	–3.873***	–0.064***	–0.094***
	(0.661)	(0.644)	(0.012)	(0.016)
R^2_{within}	0.090	0.089	0.079	0.083

Note: The table compares the estimations reported in Table 3 from the main text (*Baseline*) with those obtained after switching to a more compact version of the Heckman selection model of bank misreporting (*Additional*). All the notes from the reference table apply. In all regressions, N obs. = 17,696 and N banks = 910.

***, **, * 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.

Table J.III: The assets and liabilities composition effects of declining regulatory forbearance: ± 3 years around the regulatory tightening in mid-2013

Heckman model:	Extensive margin		Intensive margin	
	Baseline	Additional	Baseline	Additional
	(1)	(2)	(3)	(4)
Panel 1: Dependent variable = equity capital to total assets ratio EQ_{it}/TA_{it}				
TREAT×REGIME	–0.467	–1.788***	–0.014**	–0.036***
	(0.309)	(0.312)	(0.007)	(0.009)
R^2_{within}	0.257	0.272	0.251	0.272
Panel 2: Dependent variable = deposits of non-financial firms to total assets ratio $DEPf_{it}/TA_{it}$				
TREAT×REGIME	–0.569	–0.800*	–0.019**	–0.029**
	(0.463)	(0.453)	(0.009)	(0.014)
R^2_{within}	0.211	0.209	0.209	0.209
Panel 3: Dependent variable = deposits of households to total assets ratio $DEPh_{it}/TA_{it}$				
TREAT×REGIME	2.280***	2.086***	0.053***	0.058***
	(0.462)	(0.486)	(0.010)	(0.013)
R^2_{within}	0.173	0.156	0.161	0.154
Panel 4: Dependent variable = loans to non-financial firms to total assets ratio $LNSf_{it}/TA_{it}$				
TREAT×REGIME	2.259***	0.995*	0.063***	0.022*
	(0.470)	(0.509)	(0.010)	(0.013)
R^2_{within}	0.206	0.151	0.179	0.147
Panel 5: Dependent variable = loans to households to total assets ratio $LNSh_{it}/TA_{it}$				
TREAT×REGIME	–0.494	–0.818**	–0.001	–0.021**
	(0.372)	(0.344)	(0.007)	(0.009)
R^2_{within}	0.175	0.177	0.175	0.175

Note: The table compares the estimations reported in Table 4 from the main text (*Baseline*) with those obtained after switching to a more compact version of the Heckman selection model of bank misreporting (*Additional*). All the notes from the reference table apply. In all regressions, N obs. = 17,696 and N banks = 910.

***, **, * 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 K Relationship with bank Z-scores

Table K.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), $HNC_{0,1}$	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)–(2), 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 K.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.

Table K.III: Scale effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

Dependent variable $Y_{it}^{(j)}$ $(j = 1...6)$:	TA_{it} (1)	EQ_{it} (2)	$DEPf_{it}$ (3)	$DEPh_{it}$ (4)	$LNSf_{it}$ (5)	$LNSh_{it}$ (6)
Panel 1: treatment based on Z-score (adjusted on bank size)						
TREAT×REGIME	–10.881***	–1.075***	–2.713***	–3.565***	–2.993***	–2.371***
	(2.821)	(0.218)	(1.005)	(0.780)	(0.806)	(0.599)
TREAT	1.960	0.245*	0.977*	1.283**	0.924*	1.221***
	(1.799)	(0.136)	(0.535)	(0.535)	(0.549)	(0.408)
REGIME	27.601***	1.421***	0.499	2.988***	0.303	0.800
	(4.268)	(0.459)	(1.046)	(1.101)	(1.492)	(0.584)
N Obs.	17,696	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910	910
R^2_{within}	0.079	0.085	0.050	0.164	0.121	0.075
Panel 2: treatment based on HNC (baseline, for comparison)						
TREAT×REGIME	–18.521***	–1.176***	–3.278***	–5.032***	–3.001***	–3.922***
	(2.824)	(0.210)	(0.885)	(0.746)	(0.736)	(0.661)
TREAT	6.735***	0.405***	1.192***	2.089***	1.292***	1.694***
	(1.369)	(0.091)	(0.423)	(0.393)	(0.479)	(0.296)
REGIME	32.034***	1.573***	1.070	4.104***	0.569	1.887***
	(4.536)	(0.421)	(1.010)	(1.108)	(1.445)	(0.530)
N Obs.	17,696	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910	910
R^2_{within}	0.095	0.087	0.053	0.175	0.121	0.090

Note: The table contains difference-in-differences estimates of regression (6) with dependent variables $Y_{it}^{(j)}$ reflecting the size of total assets TA_{it} $(j = 1)$, equity capital EQ_{it} $(j = 2)$, deposits of non-financial firms $DEPf_{it}$ $(j = 3)$, deposits of households $DEPh_{it}$ $(j = 4)$, loans to non-financial firms $LNSf_{it}$ $(j = 5)$, loans to households $LNSh_{it}$ $(j = 6)$. All regressions include full sets of bank FE, quarter FE, and bank control variables, which are not reported for the sake of space and are available upon request. Mid-2013 marks the transition of the CBR to a new prudential regulation regime in which the CBR was no longer tolerant of fraudulent banks. The treatment group consists of all banks which are likely to be treated as fraudulent by the CBR (the treatment rule is proxied with the Heckman selection model (1)–(2)). The composition of the treatment and control groups varies in time depending on the application of the treatment rule in each quarter (see Section 2.2 for details). All regressions reflect results on the extensive margin (the size of HNC does not matter).

***, **, * 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.

Table K.IV: The assets and liabilities composition effects of declining regulatory forbearance: ±3 years around the regulatory tightening in mid-2013

Dependent variable $Y_{it}^{(j)}$ $(j = 1...5)$:	EQ_{it}/TA_{it} (1)	$DEPf_{it}/TA_{it}$ (2)	$DEPh_{it}/TA_{it}$ (3)	$LNSf_{it}/TA_{it}$ (4)	$LNSh_{it}/TA_{it}$ (5)
Panel 1: treatment based on Z-score (adjusted on bank size)					
TREAT×REGIME	0.098	–1.825***	1.109**	1.402**	–0.553
	(0.158)	(0.539)	(0.535)	(0.580)	(0.385)
TREAT	–1.741***	1.439***	0.128	–1.117**	–0.624**
	(0.161)	(0.427)	(0.445)	(0.488)	(0.308)
REGIME	0.864***	–7.059***	6.123***	–3.931***	0.415
	(0.298)	(0.824)	(0.897)	(0.941)	(0.642)
N Obs.	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910
R^2_{within}	0.589	0.211	0.151	0.148	0.178
Panel 2: treatment based on HNC (baseline, for comparison)					
TREAT×REGIME	–0.467	–0.569	2.270***	2.250***	–0.500
	(0.309)	(0.463)	(0.463)	(0.471)	(0.371)
TREAT	–1.374***	–1.080***	1.871***	4.910***	0.499**
	(0.265)	(0.361)	(0.340)	(0.395)	(0.234)
REGIME	6.225***	–7.463***	5.584***	–4.699***	0.490
	(0.626)	(0.819)	(0.882)	(0.928)	(0.646)
N Obs.	17,696	17,696	17,696	17,696	17,696
N banks	910	910	910	910	910
R^2_{within}	0.257	0.211	0.171	0.205	0.174

Note: The table contains difference-in-differences estimates of regression (6) with dependent variables $Y_{it}^{(j)}$ reflecting the composition of a bank i balance sheet from the liabilities and assets side: the ratio of equity capital to total assets EQ_{it}/TA_{it} $(j = 1)$, deposits of non-financial firms to total assets $DEPf_{it}/TA_{it}$ $(j = 2)$, deposits of households to total assets $DEPh_{it}/TA_{it}$ $(j = 3)$, loans to non-financial firms to total assets $LNSf_{it}/TA_{it}$ $(j = 4)$, loans to households to total assets $LNSh_{it}/TA_{it}$ $(j = 5)$. All regressions include full sets of bank FE, quarter FE, and bank control variables, which are not reported for the sake of space and are available upon request. Mid-2013 marks the transition of the CBR to a new prudential regulation regime in which the CBR was no longer tolerant of fraudulent banks. The treatment group consists of all banks which are likely to be treated as fraudulent by the CBR (the treatment rule is proxied with the Heckman selection model (1)–(2)). The composition of the treatment and control groups varies in time depending on the application of the treatment rule in each quarter (see Section 2.2 for details). All regressions reflect results on the extensive margin (the size of HNC does not matter).

***, **, * 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.

Abstrakt

Tento článek navrhuje nový přístup ke měření podvodů v bankovnictví a k hodnocení jejich průřezových a agregátních dopadů. Prozkoumávám unikátní důkazy klesající regulatorní shovívavosti ze strany ruského bankovního systému v roce 2010, kdy centrální banka násilně uzavřela zhruba dvě třetiny všech operujících bank kvůli podvodným aktivitám. Nejprve představuji empirický model vysvětlující pravidlo pro regulační rozhodnutí, které určuje, zda je pravděpodobné, že regulátor v blízké budoucnosti provede neplánovanou kontrolu podezřelé banky. Model odhaduji pomocí unikátních dat o ztrátách aktiv skrytých komerčními bankami a objevených Centrální bankou Ruska při neplánovaných 'on-site' kontrolách v posledních dvou desetiletích. Zjišťuji, že průměrná velikost skrytých ztrát aktiv, zjištěných pravidlem, se rovná 38% celkových aktiv dosud neuzavřených podvodných bank, a že pravděpodobnost odhalení podvodů po roce 2013 stoupla pětkrát. Pomoci čtvrtletní predikce z odhadovaného pravidla, vytvářím „treatment" skupinu bank, které budou pravděpodobně kontrolovány, a poté odhaduji „fuzzy difference-in-difference" regresi (FDID), abych kvantifikoval účinky zpřísněné regulace. Výsledky FDID ukazují, že banky, u kterých je pravděpodobné, že budou kontrolovány, podstatně snížily úvěry domácnostem a firmám po zahájení politiky v roce 2013 ve srovnání s podobnými bankami kontrolní skupiny. Pomoci interpretace odhadů FDID o úvěrové kontrakci jako šoku do nabídky úvěrů a vyhodnocení makroekonomických důsledků tohoto šoku s využitím modelu VAR ruské ekonomiky zjišťuji, že ruský HDP by mohl být do konce roku 2016 kumulativně vyšší o 7,3 % bez implementace dané politiky. To je cena, kterou ekonomika platí za snížení podvodů v bankovním systému.

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