Loan Loss Reserve Coverage, Unwrapped:
Enhancing Bank Risk Assessment and Market Discipline

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ABSTRACT

Using the data from a country where banks publicly report loan loss reserves (LLR) for both performing and nonperforming loans (NPL), we find that such a detailed breakdown increases transparency and improves assessments of bank financial health. Increases in uncovered NPL – delinquent loans for which a bank has not created LLR – are associated with a higher probability of bank failure. Higher reserve coverage of performing loans is also associated with a higher failure probability, likely due to a developing weakness in the loan portfolio. Interestingly, increases in NPL covered by reserves are not associated with a higher failure probability, suggesting that the timely creation of LLR signals the bank's ability to withstand losses even when NPL are high. Some uninsured depositors misread increases in covered NPL as negative signals and withdraw their funds. The detailed public disclosure of LLR coverage improves outsiders' ability to judge banks' financial health.

JEL Classifications: G14; G21; K23; M41; M48

Keywords: bank credit risk accounting; bank failure prediction; bank transparency; loan loss reserves; market discipline

1 INTRODUCTION

Banks are critical to economic development, financial stability, and the flow of credit. They are also inherently less transparent than most other businesses, mainly due to difficulties in assessing the quality of bank loan portfolios (Morgan, 2002). Bank transparency is, therefore, a hotly debated topic (Bushman, 2016). Banks' loan loss reserve (LLR) practices affect transparency (Bushman and Williams, 2012). No matter how prescriptive LLR-related accounting standards and financial regulations are, there is always room for managerial discretion. Banks may delay recognition of loan losses due to their reporting incentives rather than accounting constraints (Bischof et al., 2021). Even in forward-looking frameworks such as the Current Expected Credit Losses (CECL), managerial judgment plays a significant role in estimating such losses.[1]

The need to provision for loan losses depends on existing and expected nonperforming loans (NPL). Banks in most developed and many developing countries publicly report their LLR and NPL figures. The ratio of LLR to NPL is a common measure of bank credit risk and its overall health available to outsiders. This simple ratio is potentially misleading if a large portion of the numerator (LLR) is designated to cover performing loans (PL). NPL may appear to have adequate reserve coverage even though most of the LLR are intended for PL.

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[1] E.g., the European Banking Authority (2017) has the following statement in the executive summary of its *Final report on guidelines on credit institutions' credit risk management practices and accounting for expected credit losses*: "The EBA welcomes the move from an incurred loss model to an ECL model under IFRS 9. IFRS 9 is, overall, an improvement compared with IAS 39 in the accounting for financial instruments, and the changes to credit loss provisioning should contribute to addressing the G20's concerns about the issue of 'too little, too late' recognition of credit losses, and improve the accounting recognition of loan loss provisions by incorporating a broader range of credit information. IFRS 9 is therefore expected to address some prudential concerns and contribute to financial stability. However, the application of IFRS 9 also requires the use of judgement in the ECL assessment and measurement process, which could potentially affect the consistent application of IFRS 9 across credit institutions and the comparability of credit institutions' financial statements."

Figure 1 breaks down the loans-to-assets ratio by loan performance and LLR coverage into four components: uncovered performing loans to assets (*PLunc/A*), covered performing loans to assets (*PLcov/A*), covered nonperforming loans to assets (*NPLcov/A*), and uncovered nonperforming loans to assets (*NPLunc/A*). "Covered" ("uncovered") refers to loans for which LLR has (has not) been created. While banks in many countries report NPL and LLR, the i details of the loan coverage by LLR presented in the rightmost column of Figure 1 are usually not publicly released. We refer to this four-component breakdown as the *loan reserve coverage* (LRC).

We exploit the detailed monthly LRC decomposition from Russia during the 2008-2018 period, when banks publicly disclosed it, to investigate whether such unconventional transparency improves an outsider's ability to assess banks' financial health. Specifically, we focus on the most extreme outcome – bank failure. It is feasible as the sample period is characterized by numerous bank failures. We argue that using the LRC decomposition is useful in predicting less extreme outcomes such as bank distress.

The numbers in Figure 1 represent our sample means for each ratio. When we use the NPL-to-assets ratio in the regression framework, it is statistically insignificant in predicting bank failures. This ratio may not be very informative in the absence of loan coverage details. When we turn to the detailed LRC decomposition, however, bank failure prediction improves. A one-percentage-point (pp) increase in the ratio of uncovered NPL to assets, *NPLunc/A,* is associated with a 1 to 1.5 pp higher chance of bank failure in the following twelve months. Another ratio positively associated with bank failures is covered performing loans to assets, *PLcov/A*; its effect is 0.9 (0.3-0.4) pp in regressions with (without) bank fixed effects. An increase in this ratio may indicate a developing weakness in the portfolio of performing loans.

Notably, the ratio of covered NPL to assets, *NPLcov/A*, has an inverse relation with the probability of failure in the regressions without bank fixed effects, suggesting that banks that create LLR for NPL in a timely manner are less likely to fail even when NPL increase. Introducing bank fixed effects renders this variable insignificant. Either way, covered NPL is not positively correlated with bank failures. Interestingly, uninsured depositors react negatively to increases in both covered and uncovered NPL. Withdrawing uninsured deposits in response to an increase in covered NPL (which is *not* associated with increased chances of failure) can be viewed as misdirected market discipline. In sum, the detailed LRC breakdown is more informative about banks' ability to handle credit risk compared to traditional measures of credit risk such as NPL-to-assets.

While higher ratios of covered PL *(PLCov/A*) and uncovered NPL (*NPLUnc/A*) are associated with increased bank failure probabilities, these relationships are affected by regulatory stringency. Specifically, they weaken during a period of lax regulation in the wake of the global financial crisis between January 2009 and June 2010.

The study's contribution is in the use of unique data on the detailed loan reserve coverage to further the debate on bank disclosure and transparency. On one hand, greater disclosure may have many benefits such as enhanced market discipline, lower cost of capital for well-managed banks, improved bank governance, and potentially greater financial stability (Barth et al., 2004; Beatty and Liao, 2011; Bushman and Williams, 2015; Goldstein and Sapra, 2014; Nier and Baumann, 2006). On the other hand, (mostly) theoretical literature highlights potential undesirable side effects of maximum transparency, such as increased probability of bank runs, concerns about proprietary information, reduced risk-sharing, and heightened stock price volatility (Admati and Pfleiderer, 2000; Bushee and Noe, 2000; Chen and Hassan, 2006; Dang et al., 2017; Goldstein and Leitner, 2018).

The detailed LRC disclosure clearly increases bank transparency. The decomposition – an "intersection" of loan performance and LLR coverage – provides deeper insights into assessing banks' overall health and ability to handle credit risk than the less granular ratios of loans to assets or NPL to assets. The granular disclosure allows suppliers of uninsured funds to better discipline banks. A potential negative consequence of the increased transparency is uninsured depositors misinterpreting increases in the ratio of covered NPL to assets as a negative signal when it is not. However, the effect is economically small, and the benefits of the detailed LRC disclosure likely outweigh its drawbacks.

Regulators around the world have recently ramped up efforts to increase bank transparency and enhance credit risk management both prior to and in the aftermath of the global financial crisis and the European debt crisis. As a prominent example of such efforts, the European banking reform of 2019 focuses on improved credit risk management and better disclosure practices. The enhanced public disclosure relates to credit risk management, including expected current loss (ECL) estimates, but it does not provide for greater details of LLR coverage with respect to loan quality. [2]

Simple, easily understood measures of bank health are in short supply (Chernykh and Cole, 2015). Simplicity is an advantage of our study as it relies on accounting data. We believe that uninsured depositors, who collectively supply tens of trillions of dollars to the world economy through banking systems, and who individually have large amounts of money at stake,

[2] "Credit institutions should provide the disclosures needed to fairly depict a credit institution's exposure to credit risk, including its ECL estimates, and to provide relevant information on a credit institution's underwriting practices." (European Banking Authority [EBA], 2017)

deserve to know such details. The same is true for stock market investors, including existing and potential shareholders of publicly traded banks. Uninsured depositors' and investors' ability to make better decisions will improve market discipline. If public disclosure of the detailed LRC is mandated, it should be done with sufficient advance notice (e.g., three or five years) to avoid shocks.

Are our results generalizable to other countries? We believe the answer is yes. During our sample period, 2008-2018, Russia had a large economy (11th largest in the world in 2018, with a GDP of $1.64 trillion) and a developed banking system with total assets roughly equal to the GDP, similar to many OECD countries. Larger Russian banks were connected to the world banking centers. The Central Bank of Russia implemented Basel III regulations mostly in line with the global timeline, mirroring the regulatory environment in developed economies. While institutional and cultural differences exist, the fundamental mechanisms of credit risk assessment, loan loss provisioning, and their impact on bank stability are similar between Russia and most other economies. Therefore, given the size and complexity of the Russian banking system, coupled with its adherence to global regulatory standards, we believe our results offer valuable insights generalizable to other countries. Rich monthly bank-level financial reports make the Russian banking system an attractive setting for tackling research questions that are difficult to answer with less granular and less frequent data.[3]

[3] Recent studies that use the Russian banking system as a setting include Chernykh and Cole (2011), Karas et al. (2013), Chernykh and Mityakov (2017), Fungáčová et al. (2017), Brown et al. (2018), Chernykh and Kotomin (2022), and Chernykh et al. (2023).

2 LITERATURE REVIEW

2.1 Bank transparency and loan loss accounting

Banks are less transparent than nonfinancial firms (Morgan, 2002), mainly due to the difficulty of evaluating the quality of loan portfolios. Bushman (2016) defines bank transparency as *"the availability to outside stakeholders of relevant, reliable information about the periodic performance, financial position, business model, governance, and risks of banks."* A bank's approach to loan loss provisioning affects the degree of transparency. Banks replenish an accrual loan loss reserve (LLR) account through a periodic non-cash charge called the provision for loan losses (PLL). Loan charge-offs directly reduce the cumulative LLR account. PLL may be used to "manage" capital positions (Ahmed et al., 1999) or earnings (Kanagaretnam et al., 2004).[4, 5]

The complexity of loan portfolios may cause banks to delay the recognition of expected loan losses in their PLL, creating an overhang of unrecognized expected losses, which exacerbates the pro-cyclicality of bank capital positions, lending, and, by extension, the severity of recessions (Beatty and Liao, 2011; Bernanke et al., 1991; Bolton and Freixas, 2006; Bushman and Williams, 2012, 2015; Dugan, 2009; Laeven and Majnoni, 2003; Nichols et al., 2009; Peek and Rosengren, 1995; Van den Heuvel, 2002). Delayed loan loss recognition degrades transparency (Bushman and Williams, 2015; Ma and Song, 2016). In countercyclical provisioning systems, the timeliness of loss recognition is reduced (Illueca et al., 2022).

[4] Hasan and Wall (2004) find that LLR in different countries is sensitive to pre-provision income, suggesting possible earnings smoothing. Curcio and Hasan (2015) find that earnings management affects PLL in the Euro area.

[5] Because provisioning for losses reduces reported net income and, therefore, equity, much LLR-related research considers its effect on capital. Pre-Basel, a positive relationship existed between LLR and bank stock market values (Beaver et al.,1989; Elliott et al., 1991), consistent with banks signaling to the markets their ability and willingness to deal with bad loans (Elliott et al., 1991). Post-Basel, the relationship between discretionary PLL and stock returns became negative (Ahmed et al., 1999), implying that regulatory capital is a critical consideration when bank management exercises its discretion regarding PLL.

Bushman (2014, 2016) reviews the positive and negative effects of bank transparency. Increased transparency improves market efficiency because it allows outside parties to better discipline banks (e.g., Chen et al., 2022). Suppliers of uninsured funds discipline banks with a threat of withdrawal (Calomiris and Kahn,1991). Besides improved market discipline, transparency can reduce uncertainties about the solvency of individual banks in crises (Gorton and Huang, 2006; Ratnovski, 2013) and alleviate bank financing frictions under certain conditions (Beatty and Liao, 2011; Bushman and Williams, 2015). Greater transparency is also generally associated with lower banking industry concentration (Andrievskaya and Semenova, 2016).

Increased transparency also has potential downsides. It may trigger inefficient bank runs (Morris and Shin, 2002; Chen and Hassan, 2006), increase the risk of not rolling over uninsured short-term bank debt (Moreno and Takalo, 2016), create reputational contagion (Morrison and White, 2013), distort bank managers' incentives (Goldstein and Sapra, 2014), or undermine the role of banks as risk intermediaries keeping private information about their borrowers while providing liquidity to depositors (Dang et al., 2017). In practice, however, few bank failures occur due to bank runs (Correia et al., 2024)

No matter how prescriptive LLR regulations are, there is always room for managerial discretion. The introduction of IFRS 9 internationally and the CECL framework in the US pushed for more forward-looking estimates of credit losses, but it does not necessarily reduce the discretionary component of LLR. Researchers typically estimate discretionary PLL (and, therefore, LLR) by using regression residuals (e.g., Ahmed, et al., 1999). The data we use – the LLR reported separately for performing loans and NPL – provide an advantage over discretionary PLL charges. Having insufficient LLR to cover NPL is clearly a negative sign, and a more informative one, than either low or high estimated discretionary PLL.

2.2 Bank Failures

Bank failures can impose significant costs on taxpayers and suppliers of uninsured funds, while also causing broader disruptions to economies. To assess banks, regulators and researchers analyze fundamental factors such as capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market conditions—collectively known as the CAMELS framework. Although the specific components of regulatory CAMELS ratings are confidential and may vary across countries, researchers without access to nonpublic regulatory data often derive CAMELS-related variables from publicly available financial reports to evaluate bank health.

Early studies show that accounting-based approximations of CAMELS indicators do predict bank distress and failure (Sinkey, 1975; Thomson, 1992; Cole and Gunther, 1995; Wheelock and Wilson, 2000). More recent research focuses on detecting additional variables that improve the prediction of bank failure and distress. Such variables may include macroeconomic indicators (Arena, 2008; Cole and Wu, 2009), commercial real estate investments (Cole and White, 2012), income from nontraditional banking activities (DeYoung and Torna, 2013), auditor characteristics (Jin et al., 2011), bank internal control procedures (Jin et al., 2013), CEOs' risk-taking incentives (Boyallian and Ruiz-Verdú, 2018), or deposit rates (Poghosyan and Čihak, 2011; Chernykh and Kotomin, 2022).[6]

[6] Several papers, mainly based on the U. S. data, suggest that market-based indicators contain useful predictive information not contained in CAMELS. Discussing this literature is beyond the scope of our paper as we use only accounting data (the overwhelming majority of Russian banks are not publicly traded). A comprehensive survey is

Considering the reviewed research, we hypothesize that the use of the decomposed loan reserve coverage (LRC) improves the measurement of bank asset quality (A in the CAMELS framework), which in turn helps improve prediction of bank failures. Consistent with our hypothesis, we find that LRC improves bank failure prediction compared with using NPL alone. Two components of LRC, covered performing loans and uncovered NPL, are positively correlated with the probability of bank failure, while covered NPL are not. [7,8]

3 LOAN LOSS RESERVE ACCOUNTING AND DISCLOSURE IN RUSSIA

Regardless of the degree of managerial discretion, banks report to regulators general LLR, designated to cover potential future loan losses of the entire loan portfolio, and specific LLR earmarked against specific loans, usually nonperforming ones. Regulators may also advise or order banks to create additional LLR for performing loans with perceived weaknesses (i.e., loans that are likely to become nonperforming in the near future).

While the breakdown of LLR may be available to regulators, public disclosures are not required in most countries. The Russian Federation was a notable exception, as banks there publicly reported LLR separately for performing and nonperforming loans. The Central Bank of Russia (CBR) imposes extensive reporting requirements on banks, and monthly bank-level reports full of rich, high-quality data were available on the CBR website for our study period, 2008-2018. Banks classify loans into five credit risk categories as follows:

provided by Demyanyk and Hasan (2010), who review the empirical results of many economics, finance, and operations research papers that attempt to explain or predict financial crises or bank defaults.

[7] Recent attempts to improve the measurement of bank credit risk include addressing correlations between delinquencies of different loan types (Lee et al., 2024) and hand-collecting PLL by loan type (Bhat et al., 2021).

[8] Ng and Roychowdhury (2014) report a positive association of LLR creation with bank failure risk in the recent financial crisis. However, these authors do not consider the possibility of reverse causality that failing banks that recognize additional provisions (increase LLR) may undertake excessive risk if they gamble for resurrection.

Category	*Name*	*LLR, in % of loan balance*
I (highest quality)	Standard loans	0%
II	Substandard	1%-20%
III	Doubtful	21%-50%
IV	Problem	51%-100%
V (lowest quality)	Uncollectible	100%

Banks must regularly review loans and reclassify them due to changes in the borrowers' financial conditions or other circumstances. Strong collateral may reduce the required reserves by placing a loan into a higher-quality category. Banks may also create reserves for portfolios of homogenous loans based on expected default rates for a given loan type.

The reporting requirements for nonperforming loans (NPL) are rather strict in Russia. When a loan interest payment is not made on time (e.g., it is late even by a day), the bank should add the late interest amount to the NPL balance. It means that even strong loans (placed in Category I) may occasionally contribute to the NPL balances. However, late payments by strong borrowers are rare and randomly distributed (e.g., a borrower could not submit a payment due to an internet outage on a given day); thus, they should not drive or distort our results. Most NPL are loans 90 days or more past due. For such loans, both their balance and the missed interest payments are included in the NPL.

Bank managers may have an incentive to understate credit risk and place some loans into higher-quality categories than what an objective analysis would warrant. They may do so, e.g., by using optimistic expected loss assumptions or overstating collateral value. This is especially true for banks with relatively low levels of capital and ones operating at a loss, as increasing LLR directly reduces capital. If such behaviors prevail, our analyses will be less likely to generate significant results. Otherwise, separately reporting LLR for performing and nonperforming loans may help uncover developing loan portfolio challenges, improve prediction of failure or distress, and devise prompt corrective action (PCA) in a timely manner.

Compared to the United States, Russian regulations provided for more detailed and frequent public disclosures. In contrast, U. S. regulations emphasize a comprehensive and systematic approach to LLR estimation, importance of managerial judgment, strong internal controls, and documentation, but less detailed public disclosures.[9] Utilizing the detailed breakdown of LRC (as in Russia) helps improve predicting bank failures. While failure is an extreme outcome that is not common in most developed countries outside of crises, it is reasonable to assume that prediction of less extreme outcomes, such as bank distress, can also be improved with more detailed LLR data. Thus, granular disclosure of LLR coverage enhances transparency and, potentially, market discipline.

4 DATA AND METHODS

The data are monthly bank-level financial statement variables for Russian banks over the period 2008-2018, obtained from the Central Bank of Russia (CBR) website. The sample period starts one year after the completion of the country's transition to deposit insurance, whose introduction profoundly affected the banking system (Chernykh and Cole, 2011). In addition, significant changes in bank balance sheet reporting were introduced at the start of 2008. The end of the sample period coincides with another set of major changes in bank reporting, including changes to LLR reporting standards. We exclude a few banks that were not members of the deposit insurance system and banks with a loans-to-assets ratio below 10 percent.

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[9] See the Interagency Policy Statement on the Allowance for Loan and Lease Losses (Office of the Comptroller of the Currency [OCC], 2006).

There are three distinct groups of banks in Russia: state-controlled, foreign-owned, and domestic private banks. We focus on domestic private banks as this sample is cleaner and more similar to the banking systems of developed countries. State-controlled and foreign-owned banks are safer and much less prone to failure.[10] The number of banks declined from over 1,000 to 440 during the period, mostly due to domestic private bank failures. We plot the annual bank failures in Figure 2. A large number of failures makes a linear probability model (LPM) an econometrically feasible, parsimonious choice to study them.[11] Our LPM model is:

$$Fail12m_{it} = \alpha + \boldsymbol{\beta LRC_{it}} + \boldsymbol{\omega X_{it}} + \varepsilon_{it} \qquad (1)$$

where:

$Fail12m_{it}$ – an indicator equal to 1 if bank i fails in the twelve months following month t and 0 otherwise. We exclude banks closed solely for illegal activities, and count banks placed into receivership as failures. To avoid truncation bias, in the failure regressions we use monthly accounting data through December 2017 and track failures through December 2018 (twelve months after the end of the sample);

$\boldsymbol{\beta}$ is a vector of the loan reserve coverage (LRC) ratios, the variables of interest in our study. According to the loans-to-assets breakdown in Figure 1, these variables include the following metrics, all expressed in percent of assets:

(i) *PLunc* – uncovered performing loans, or performing loans for which the bank *has not* set aside loss reserves;

[10] We classify banks directly or indirectly controlled by federal or regional authorities, as well as by state-controlled banks or nonfinancial firms, as state banks. We classify banks controlled by Russian citizens, regardless of the headquarters' locations, as domestic, consistent with Bank of Russia's classification. Domestic private banks are the most numerous group, but they are, on average, much smaller than state-controlled banks.

[11] Cole and Wu (2009) show that a simple and parsimonious probit model estimated on the US data from the 1980s is highly accurate in predicting US bank failures occurring during 2009–2010. It provides support for the use of simple static binary choice models in detecting early-warning bank distress or failure signals. Accordingly, we use an even more parsimonious linear probability model.

(ii) *PLcov* – covered performing loans, or performing loans for which the bank *has* set aside loss reserves. While these are performing loans, they may be considered weak enough to prompt the creation of LLR to cover expected losses;

(iii) *NPLcov* – covered nonperforming loans, or past-due loans for which the bank *has* set aside loss reserves;

(iv) *NPLunc* – uncovered nonperforming loans, or past-due loans for which the bank *has not* set aside loss reserves. We also call this ratio the NPL coverage gap. A high NPL coverage gap may be a red flag suggesting a bank's inability to create sufficient loss reserves even for NPL;

X is a vector of bank-specific controls, which may include, depending on the specification, the following variables:

- *Eq/A* – equity to assets, a measure of capital,
- *L/A* – loans to assets, a rough measure of liquidity (sometimes also interpreted as a rough measure of credit risk),
- *PL/A* – performing loans to assets, a direct measure of asset quality,
- *NPL/A* – nonperforming loans to assets, an inverse measure of asset quality,
- *CorrCB/A* – balance on the correspondent account with the central bank to assets (this account is necessary for all ruble-denominated payment transfers). It is a stringent measure of liquidity that has a low correlation with the loans-to-assets ratio in our sample;
- *Ln(Size)* – natural logarithm of total assets, in thousands of rubles.[12]

[12] While we control for equity (capital) and liquidity (C and L in CAMELS), the use of monthly data prevents us from using the (annually reported) income statement data necessary to construct measures of earnings and management quality. In unreported annual-data regressions (the output is available upon request), we add ROA (E in CAMEL) and management quality, approximated by the ratio of regulatory fines to bank assets (M in CAMEL) to the measures of capital, asset quality, and liquidity. The results are similar to those of monthly regressions: when we use the (annual) breakdown of LRC, employing its four components in place of NPL to measure asset quality, the explanatory power of regressions improves, while *NPLunc/A* and *PLcov/A* (*NPLcov/A*) are positively (negatively or not) associated with the probability of failure.

We employ time fixed effects to absorb the influence of changing macroeconomic conditions. For robustness, we report estimations both with and without bank fixed effects. In the models with bank fixed effects, βs are interpreted as changes in a bank's probability of failure within twelve months when a given loan reserve coverage ratio of the bank changes by one percentage point (pp). Without bank fixed effects, βs are the differences in the probability of failure within twelve months for banks with a given LRC ratio differing by one pp.

In additional tests presented in Section 5.1.4, we examine the effect of past charged-off loans on bank failures. Such loans are kept in an off-balance sheet account for five years. We add one explanatory variable to Equation (1) to obtain the following LPM:

$$Fail12m_{it} = \alpha + \gamma OBSNPL_{it} + \boldsymbol{\beta LRC_{it}} + \boldsymbol{\omega X_{it}} + \varepsilon_{it} \qquad (2),$$

where *OBSNPL* are loans charged off in the last five years, in percent of assets.

We also study whether uninsured depositors discipline banks in response to changes in the various LRC ratios. For that analysis, we use an OLS regression of the following form:

$$(FTA/A)_{it+1} = \alpha + \boldsymbol{\beta LRC_{it}} + \boldsymbol{\omega X_{t}} + \varepsilon_{it} \qquad (3),$$

where $(FTA/A)_{it+1}$ is next month's ratio of private firms' transaction account balances to assets for bank i, in percent. Private firms' deposits were not insured during our sample period. The independent variables are the same as in Equation (1). We present the results of this analysis in Section 5.2.

Table 1 reports descriptive statistics. Panel A is for the entire sample (except for the indicator of bank failure within twelve months), while Panel B compares means for failed and survived banks during 2008-2017, with failures tracked through the end of 2018. The means for *NPLunc/A*, one of our variables of interest, differ by a factor of two for surviving and failed banks, 0.43 vs. 0.82 percentage points, respectively. The difference between the means of covered NPL, *NPLcov/A*, has an unexpected sign, with surviving banks carrying more covered NPL, and is economically small.

In Table 2, we break down three of the four LRC ratios – covered PL, covered NPL, and uncovered NPL to assets – into ranges and report numbers and percentages of bank-months with failures vs. survivals in the following twelve months. For the ratio of covered performing loans to assets, *PLcov/A*, we observe that the probability of failure increases with it. We cannot make the same conclusion for the ratio of covered NPL to assets, *NPLcov/A*: increases in it are not associated with higher chances of bank failure. In fact, the highest range of this ratio (over 4 percent) is associated only with a 3.73 percent probability of failure, below the probabilities for bank-months associated with lower ranges. Lastly, when the ratio of uncovered NPL to assets, *NPLunc/A*, or the NPL coverage gap, increases, so does the probability of failure. We use the same LRC buckets in the regression analysis presented in Section 5.1.3.

In Figure 3, we graph mean and median LRC component ratios – uncovered performing loans, covered performing loans, covered NPL, and uncovered NPL to assets – in four different plots (inevitably using different scales) for failed Russian banks starting twelve months prior to failure. Covered performing loans, covered NPL, and uncovered NPL all increase prior to failure. We now turn to multivariate analyses, which will allow us to make more accurate conclusions regarding the relationships of these ratios with the probability of a bank failure.

5 RESULTS

5.1 Loan reserve coverage and bank failures

5.1.1 Bank Failures

We present the output of various specifications of Equation (1) in Table 3. Regressions 1-4 (5-8) are without (with) bank fixed effects. We focus on the results that hold both without and with fixed effects, with an emphasis on the latter. When using the loans-to-assets ratio alone (regression 5), we find it is positively correlated with failures: a one-pp increase in it is associated with a 0.13-ppt increase in the probability of failure. This is expected: all else equal, an increase in lending should lead to an increase in loan losses and, thus, chances of failure.

When we split the loans-to-assets ratio into performing and nonperforming loans, *PL/A* and *NPL/A* (regression 6), the NPL-to-assets ratio has a greater effect on the probability of failure than *PL/A*, but it is only marginally significant. Without bank fixed effects (regression 2), *NPL/A* is not related to bank failures. It may appear counterintuitive at first. After all, why would an increase in performing loans be positively associated with the failure probability and an increase in NPL would not? The explanation may be two-fold. One, banks that make riskier loans may have higher capital and regularly provision for more losses to accommodate their business models. Two, stronger banks may be quick in recognizing and charging off NPL as they have little reason to delay.

The next breakdown of the loans-to-assets ratio is the most detailed and, we argue, the most informative one. It corresponds to the last column in Figure 1 and shows the effects of LLR coverage of both performing and nonperforming loans on bank failures. In regressions 7 and 8, the coefficients of covered performing loans, *PLcov/A*, are both statistically and economically significant. A one-pp increase in it is associated with a 0.85 or 0.87-pp increase in the probability of failure within twelve months. Creating additional LLR for performing loans suggests the quality of these loans have deteriorated and expected future losses on them increased. In an extreme case, a bank may not recognize NPL in a timely manner, continuing to report these loans as performing, but it may have already created LLR for some of them. Consistent with this conjecture, the changes in the ratio of covered NPL to assets, *NPLcov/A*, are not significant in the models with bank fixed effect (regressions 7 and 8) and are negatively associated with the probability of failure in the models without them (regressions 3 and 4). Thus, timely provisioning for NPL is either a positive or a neutral signal about the bank's chances of failure.

The NPL coverage gap, *NPLunc/A*, is positively correlated with bank failures: a one-pp increase in it is associated with a 0.95-pp higher chance of failure within a year (regression 7). Without bank fixed effects (regression 3), the effect is even stronger at 1.51 percentage points. The results are similar when we add controls for capital and liquidity (regressions 4 and 8). Not creating LLR for NPL is a sign of major weakness and may raise a red flag for regulators and suppliers of uninsured liabilities. The explanatory power of the models with the detailed LRC split (regressions 3, 4, 7, and 8) is higher than that of their counterparts without it (1, 2, 5, and 6). It suggests that reporting LLR separately for performing and nonperforming loans is more informative than simply reporting LLR and NPL.

5.1.2 Bank Failures under a Lax LLR Regulatory Regime

The results reported in Table 3 indicate that high ratios of LLR to performing loans and low ratios of LLR to NPL are both associated with higher bank failure probabilities. Does this relationship depend on regulatory stringency? After all, bank closure decisions rest with the regulator. We answer this question next. Between January 2009 and June 2010, the Central Bank of Russia relaxed loan loss provisioning rules for banks to help overcome the consequences of global financial crisis. Specifically, banks were allowed to classify some delinquent loans as performing, which reduced the need to create additional LLR. As a result, the relationship between LLR coverage and bank failures may have weakened. To test this hypothesis, we interact our loan reserve coverage variables with the dummy variable *Lax* turned on during the period of the less stringent regulations.

We report the estimation output in Table 4. Regressions 1-3 (4-6) are without (with) bank fixed effects. Adding controls for capital and liquidity (Regressions 2, 3, 5, and 6) does not change the main results. The relationship between LLR coverage of performing loans, *PLcov/A*, and bank failures indeed weakens: in regression 6, the coefficient of *PLcov/A* is 0.9 pp, but it is 0.31 pp lower during the period of lax regulation. Without bank fixed effects (regressions 1-3), the effect is practically erased under the lax regime. As to the NPL coverage gap, *NPLunc/A,* its relationship with bank failure is non-existent during the lax regulatory period and the twelve months following it in presence of bank fixed effects: the coefficients of *NPLunc/A* are fully offset by those of the interactions *Lax*(NPLunc/A)* in regressions 4-6. Without bank fixed effects (regressions 1-3), the effect remains present but becomes much weaker: a one-pp higher *NPLunc/A* is associated with a 0.4-0.5-pp higher probability of failure (the sum of the coefficients of *NPLunc/A* and *Lax*(NPLunc/A)*) during the lax regulatory regime and twelve months after it, compared to 1.8 pp in the rest of the sample period. Thus, the relationship between LLR coverage and bank failures depends on regulatory stringency.

5.1.3 Loan Reserve Coverage Ranges and Bank Failures

We have shown that the ratios of uncovered NPL to assets, *NPLunc/A*, and covered PL to assets, *PLcov/A*, are positively associated with the probability of bank failure, while the ratio of covered nonperforming loans to assets, *NPLcov/A*, is either negatively related or not related to bank failure (depending on the model specification). In this subsection, we analyze whether the initial levels of these ratios are related to the probability of failure. We split each of these three ratios (covered PL, uncovered PL, and uncovered NPL to assets) into five buckets – with the ratio falling into the range of up to 0.5 percent, 0.5 to 1 percent, 1 to 2 percent, 2 to 4 percent, and above 4 percent. We then create dummy variables for the last four (the range of up to 0.5 percent is the reference group for each ratio). While the split is somewhat arbitrary and the distributions differ somewhat across the three ratios, it ensures a sufficient number of observations in each bucket (see Table 2).

We report the output in Table 5. Regressions 1-4 (5-8) are estimated without (with) bank fixed effects. For comparison, we estimate regressions 1-3 and 5-7 with the range dummies for one ratio at a time, while employing the other three ratios as (continuous) control variables. Regressions 4 and 8 are the full models with all twelve range dummies (four buckets for each of the three ratios) and the continuous ratio of uncovered PL to assets as a control. Because the results are similar across specifications, we focus on regressions 4 and 8.

The ratio of covered performing loans to assets, *PLcov/A*, is associated with higher failure probabilities for the last three buckets in regression 8 (with bank fixed effects) and the highest range (over 4 percent) in regression 4 (without them). E.g., if a bank with an initial *PLcov/A* ratio in the 2-4 percent (over 4 percent) range experiences an additional one-percentage-point increase in it, its probability of failure within twelve months increases by 4.5 (9) pp. The next ratio, covered NPL to assets, *NPLcov/A*, is associated with a lower probability of failure – across all ranges in model without fixed effects (regression 4) but only for the highest bucket in the fixed effect model (regression 8).

Increases in the last ratio of interest, the NPL coverage gap, or *NPLunc/A*, are significantly correlated with the probability of failure both in the models with and without bank fixed effects, with the coefficients increasing from one range to the next. E.g., if a bank with the initial level of NPL coverage gap of over 4 percent experiences an additional one-pp increase in this ratio, its probability of failure within a year increases by 12.4 pp (regression 8).

5.1.4 Off-balance Sheet NPL and Bank Failures

In Russia, banks keep charged-off loans in an off-balance sheet account for five years. We denote the ratio of such loans to assets as *OBSNPL/A*. Holding assets constant, a monthly change in this ratio is the difference between charge-offs in the latest month and charge-offs sixty-one months ago (as month -61 falls out of the calculation). To test whether past charge-offs are related to bank failure probability, we estimate Equation (2).[13] We hypothesize that *OBSNPL/A* is not positively correlated with the probability of bank failure because timely provisions for and charge-offs of bad loans signal a bank's ability to deal with bad loans without jeopardizing its survival.

We report the output in Table 6. The results are consistent with our hypothesis. The ratio of historical charge-offs is negatively correlated with bank failure in the regressions without bank fixed effects (1-3) and uncorrelated with it in regressions without them. Thus, increasing charge-offs are not necessarily a sign of imminent failure.

[13] Charge-offs in a given month could be more informative than the historical charge-offs fully provisioned for, but the former are not reported on a monthly basis.

5.2 Loan reserve coverage decomposition and depositor discipline

Uninsured depositors have the incentive to monitor banks, and, if perceived bank risk increases to some critical level, they withdraw rather than demand higher rates (e.g., Baer and Brewer, 1986). Deposits of households became insured in Russia by the end of 2006. However, deposits of legal entities, including private firms, remained uninsured through 2018. We examine monthly balances of transaction deposits of private firms to reveal whether and how uninsured depositors react to changes in LLR coverage of performing and nonperforming loans.

We estimate Equation (3) and report the output in Table 7, without (bank fixed effects (columns 1-4) and with them (5-8). The dependent variable is the ratio of firms' transaction accounts to bank assets, *FTA/A*. Uninsured depositors react negatively to increases in the loans-to-assets ratio (regressions 1 and 5), especially to increases in NPL (regressions 2 and 6). Uninsured depositors also leave when the NPL coverage gap, *NPLunc/A*, increases: in regressions 7 and 8, a one-pp increase in the NPL coverage gap leads to roughly a 0.4-pp decline in the FTA-to-assets ratio. Interestingly, uninsured depositors' reaction to an increasing ratio of covered NPL to assets, *NPLcov/A*, is negative (regressions 3, 4, 7, and 8), even though this variable is not associated with a higher probability of failure. Such withdrawals can be viewed as misdirected discipline.

Without bank fixed effects (regressions 1-4), the negative response to increases in the NPL coverage gap is about twice the size of its covered NPL counterpart: in regression 4, the uninsured depositors' reactions to one-pp increases in covered and uncovered NPL are outflows of 0.47 and 1 percent of assets, respectively. Interestingly, in the regressions with bank fixed effects, the coefficient of *NPLunc/A* is close to that of *NPLcov/A*, -0.42 and -0.31 percentage points, respectively. Increases in capital (*Eq/A*) are associated with decreasing business transaction accounts as banks with higher capital may not need as much deposit funding. Increasing liquidity (*CorrCB/A*) is associated with increased uninsured transaction deposits as it may be viewed positively by suppliers of these funds.

In sum, uninsured depositors react negatively to increases in NPL, whether covered or uncovered by loss reserves. While we find that increases in covered NPL are not associated with a higher probability of failure, at least some uninsured depositors may not be aware of it and withdraw even when banks create reserves for NPL in a timely manner. These stakeholders may be paying attention to the reported NPL but not to provisioning for them.

6 CONCLUSION

Bank transparency is critical for outside stakeholders such as shareholders and uninsured depositors. They, as well as researchers, typically have to rely on ratios of loans to assets and nonperforming loans (NPL) to assets to measure bank asset quality. We show that a more detailed breakdown of the loans-to-assets ratio, which includes loan loss reserve (LLR) coverage of both performing and nonperforming loans, is more informative than using NPL and total LLR, as it increases bank transparency. Using monthly bank balance sheet data from Russia, where banks reported LLR coverage of both performing loans and NPL over a period characterized by numerous failures, we draw several new insights.

First, increasing LLR coverage of performing loans is associated with a higher probability of bank failure. If a bank must create additional provisions for performing loans, it likely indicates a developing weakness in the portfolio of loans that are still considered performing. Second, increases in the LLR coverage of NPL are not associated with higher failure probabilities, which may seem counterintuitive. However, timely provisioning for NPL is a sign of a bank's ability to deal with bad loans without jeopardizing its survival. Finally, an increasing gap in the LLR coverage of NPL is associated with higher chances of bank failure. While banks may have legitimate reasons for having less than full LLR coverage of NPL (e.g., by having pledged high-quality collateral against some NPL), our findings suggest that such a shortage is a red flag.

We argue that releasing the details of bank loan loss reserve coverage that we use in this one-country study should help bank investors and suppliers of uninsured funds in other countries make better decisions as increased transparency improves market efficiency. Regulators should weigh pros and cons of greater transparency, however, as it may lead to overreactions or misdirected discipline. Specifically, we find that uninsured depositors withdraw their funds in response to increases in covered NPL, despite the finding that such increases are not associated with higher failure probabilities.

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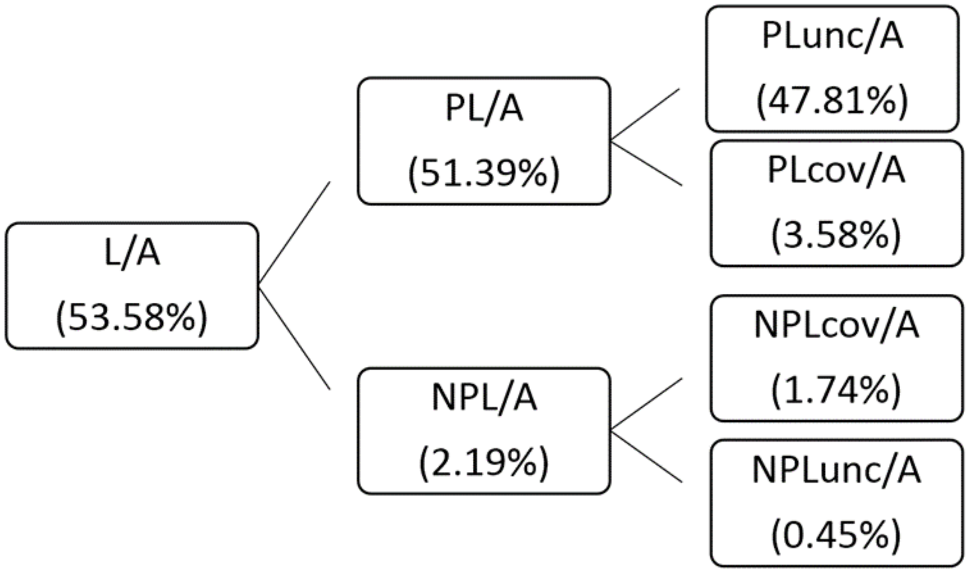
Figure 1

The loans-to-assets ratio breakdown by loan performance
and reserve coverage in Russia, 2008-2018



L/A is a bank's loans-to-assets ratio, PL/A is performing (not delinquent) loans to assets, NPL/A is nonperforming (delinquent, or past due) loans to assets. The extensions "cov" and "unc" stand for loans covered and uncovered by loan loss reserves (LLR), respectively. E.g., PLcov is the amount of LLR set aside to cover future expected losses on (currently) performing loans, while NPLuncov is the amount of nonperforming loans for which a bank has not set aside LLR. The means of the respective variables in our sample are in parentheses.

Figure 2

Bank failures in Russia, 2005-2018

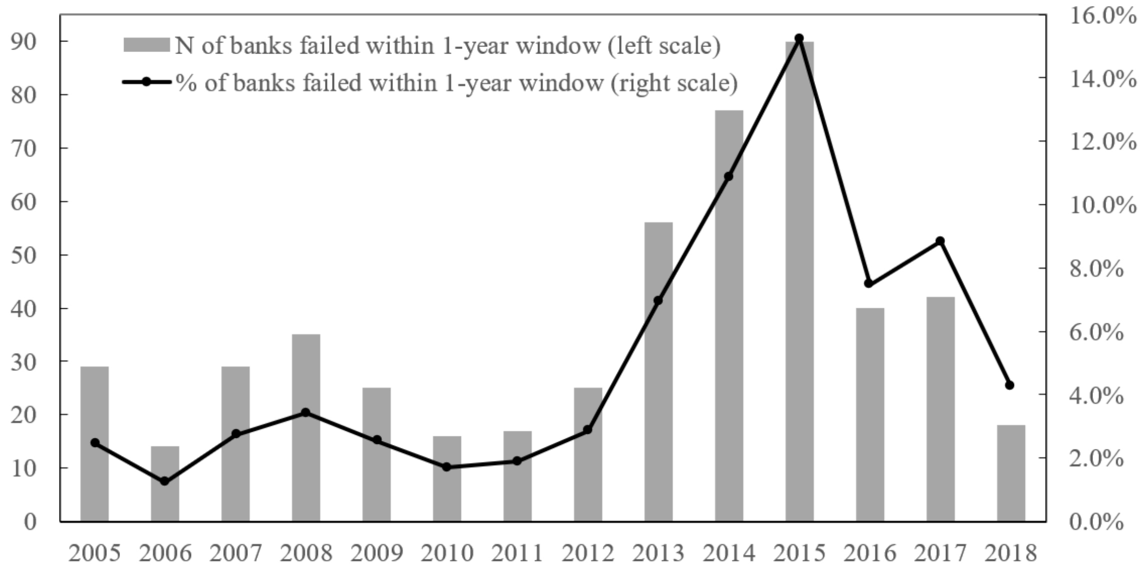


Figure 3

Loan reserve coverage components for Russian banks failed during 2008-2018

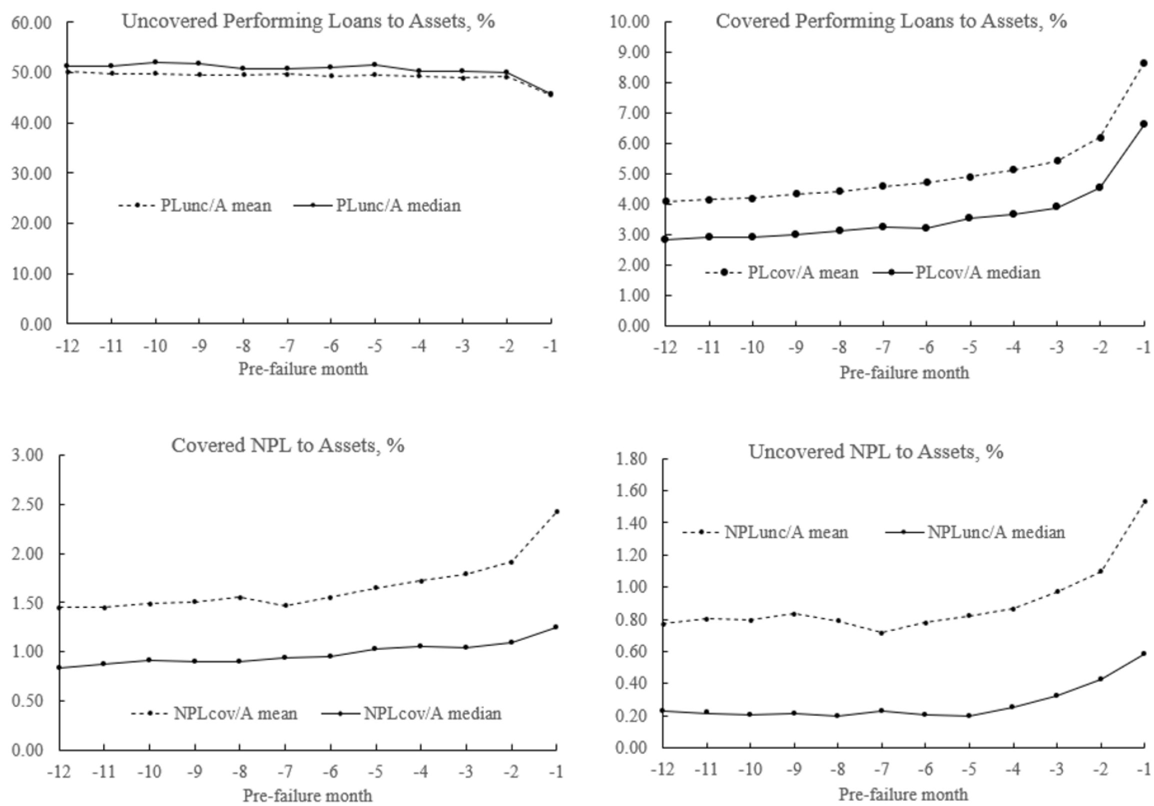


Table 1 Descriptive statistics

Panel A: Descriptive statistics, 2008-2018 (entire sample)

	mean	median	std.dev.	min	max	N, bank-months
Dependent variable (12-month window outcome):						
Fail_12m (0; 1)	0.0542			0	1	65,949
Loans-to-assets splits, %:						
L/A	53.58	55.59	17.65	10.00	98.52	69,714
PL/A	51.39	53.23	17.64	0.00	95.71	69,714
NPL/A	2.19	1.36	2.81	0.00	51.12	69,714
PLunc/A	47.81	49.51	17.15	0.00	93.16	69,714
PLcov/A	3.58	2.36	3.97	0.00	50.21	69,714
NPLcov/A	1.74	1.01	2.29	0.00	33.40	69,714
NPLunc/A	0.45	0.07	1.19	0.00	51.12	69,714
Control variables:						
Ln(Size)	15.21	15.02	1.62	9.27	21.97	69,714
Eq/A, %	19.21	15.09	13.00	0.00	98.01	69,714
CorrCB/A, %	5.76	2.94	7.78	0.00	85.80	69,714
Variables used in additional tests:						
FTA/A	16.80	13.71	13.30	0.00	89.67	69,714
OBSnpl	0.55	0.08	1.47	0.00	70.55	69,714

Panel B: Means and differences, 2008-2017 (bank failure sample)

	Fail = 0	Fail = 1	Diff (1 - 0)
Loans-to-assets splits, %:			
L/A	53.89	56.91	3.02***
PL/A	51.78	54.58	2.81***
NPL/A	2.11	2.32	0.21***
PLunc/A	48.35	49.88	1.53***
PLcov/A	3.43	4.71	1.27***
NPLcov/A	1.68	1.50	-0.18***
NPLunc/A	0.43	0.82	0.39***
Control variables:			
Ln(Size)	15.17	15.31	0.14***
Eq/A, %	19.37	16.59	-2.77***
CorrCB/A, %	6.07	3.82	-2.25***
Variables used in additional tests:			
FTA/A	17.35	12.09	-5.26***
OBSnpl/A	0.50	0.46	0.05***
N, bank-months	62,373	3,576	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table presents descriptive statistics for monthly bank-level variables. Fail_12m is 1 if the bank fails within 12 months of month t and 0 otherwise. The loans-to-assets ratio and its various splits are: L/A – loans to assets; PL/A – performing loans to assets, NPL/A – performing loans to assets; PLunc/A – performing loans not covered by loan loss reserves (LLR) to assets, PLcov/A – performing loans covered by LLR to assets, NPLcov/A – nonperforming loans covered by LLR, NPLunc – nonperforming loans not covered by LLR (we also refer to it as the NPL coverage gap). The remaining variables are: Ln(Size) – the natural log of assets, in thousands of rubles, Eq/A – the ratio of equity to assets, CorrCB/A – balances held with the central bank to assets; FTA/A – uninsured (private firms') transaction account balances to assets; OBSnpl are bad loans charged off during the most recent 5-year window to assets. All ratios are in percent.

Panel A is for the entire sample, 2008-2018, expect for the bank failure dummy (2008-2017, with failures tracked through December 2018 to allow for the twelve-month window). Panel B presents the means over 2008-2017 for banks that fail within twelve months vs. those that do not, with differences reported in the rightmost column.

Table 2 Loan reserve coverage ratio ranges and bank failure summary statistics

PLcov/A range	N	% of sample	Fail = 0	Fail = 1	% failed
Up to 0.5%	5,684	8.62	5,522	162	2.85
0.5 to 1%	8,454	12.82	8,170	284	3.36
1 to 2%	14,959	22.68	14,231	728	4.87
2 to 4%	18,080	27.42	17,201	879	4.86
4%+	18,772	28.46	17,249	1,523	8.11
NPLcov/A range	N	% of sample	Fail = 0	Fail = 1	% failed
Up to 0.5%	23,120	35.06	21,807	1,313	5.68
0.5 to 1%	10,365	15.72	9,796	569	5.49
1 to 2%	13,559	20.56	12,710	849	6.26
2 to 4%	12,234	18.55	11,638	596	4.87
4%+	6,671	10.12	6422	249	3.73
NPLunc/A range	N	% of sample	Fail = 0	Fail = 1	% failed
Up to 0.5%	51,031	77.38	48,755	2,276	4.46
0.5 to 1%	6,813	10.33	6,362	451	6.62
1 to 2%	4,741	7.19	4,312	429	9.05
2 to 4%	2,378	3.61	2,112	266	11.19
4%+	986	1.50	832	154	15.62
Total	65,949	100.00	62,373	3,576	5.42

This table presents numbers and percentages of bank-months with failures vs. survivals within the following twelve months for different ranges of the key loan reserve coverage ratios, PLcov/A, NPLcov/A, and NPLunc/A. PLcov/A is the ratio of performing loans covered by LLR to assets, NPLcov/A – nonperforming loans covered by LLR to assets, NPLunc – nonperforming loans not covered by LLR to assets (i.e., the NPL coverage gap): all in percent. For consistency, we use the same five percentage ranges for all three ratios: 0-0.5%, 0.5-1%, 1-2%, 2-4%, and above 4%.

Table 3 Loan reserve coverage and bank failures

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L/A	0.0007***				0.0013***			
	(0.000)				(0.000)			
PL/A		0.0007***				0.0012***		
		(0.000)				(0.000)		
NPL/A		-0.0003				0.0024*		
		(0.805)				(0.099)		
PLunc/A			0.0005***	0.0003			0.0007***	0.0008***
			(0.008)	(0.101)			(0.008)	(0.009)
PLcov/A			0.0034***	0.0038***			0.0085***	0.0087***
			(0.001)	(0.001)			(0.000)	(0.000)
NPLcov/A			-0.0070***	-0.0067***			-0.0027	-0.0027
			(0.000)	(0.000)			(0.156)	(0.168)
NPLunc/A			0.0151***	0.0146***			0.0095**	0.0095**
			(0.000)	(0.001)			(0.027)	(0.027)
Eq/A				-0.0013***				-0.0013***
				(0.000)				(0.004)
CorrCB/A				-0.0010***				-0.0001
				(0.000)				(0.827)
Ln(Size)	-0.0040**	-0.0038**	-0.0028	-0.0102***	0.0418***	0.0427***	0.0436***	0.0321***
	(0.024)	(0.031)	(0.111)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	no	no	no	no	yes	yes	yes	yes
N, bank-mn	65,949	65,949	65,949	65,949	65,949	65,949	65,949	65,949
N, banks	726	726	726	726	726	726	726	726
R^2	0.038	0.038	0.048	0.053	0.105	0.105	0.114	0.117

Robust p-values are in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table presents the output of the failure regressions for domestic private Russian banks over 2008-2018. The dependent variable is equal 1 if the bank fails within 12 months of month t and 0 otherwise. The key independent variables are: PLunc/A – performing loans not covered by LLR to assets, PLcov/A – performing loans covered by LLR to assets, NPLcov/A – nonperforming loans covered by LLR, NPLunc – nonperforming loans not covered by LLR (i.e., the NPL coverage gap): all in percent. The control variables are: Eq/A – the ratio of equity to assets, in percent; CorrCB/A – balances held with the central bank to assets, in percent; Ln(Size) – the natural log of assets, in thousands of rubles. Models 1-4 (5-8) are estimated without (with) bank fixed effects.

Table 4 Loan reserve coverage and bank failures during a lax regulatory period

Variables	(1)	(2)	(3)	(4)	(5)	(6)
PLunc/A	0.0006***	0.0005**	0.0004**	0.0008***	0.0009***	0.0009***
	(0.006)	(0.016)	(0.048)	(0.005)	(0.004)	(0.006)
Lax*(PLunc/A)	-0.0006**	-0.0006*	-0.0006**	-0.0003	-0.0003	-0.0003
	(0.050)	(0.055)	(0.031)	(0.221)	(0.253)	(0.246)
PLcov/A	0.0038***	0.0042***	0.0041***	0.0088***	0.0090***	0.0090***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Lax*(PLcov/A)	-0.0028*	-0.0028*	-0.0029*	-0.0032**	-0.0031**	-0.0031**
	(0.062)	(0.064)	(0.053)	(0.020)	(0.024)	(0.024)
NPLcov/A	-0.0076***	-0.0072***	-0.0074***	-0.0031	-0.0031	-0.0031
	(0.000)	(0.000)	(0.000)	(0.155)	(0.160)	(0.160)
Lax*(NPLcov/A)	0.0058***	0.0059***	0.0057***	0.0037*	0.0038*	0.0038*
	(0.003)	(0.003)	(0.004)	(0.087)	(0.076)	(0.076)
NPLunc/A	0.0181***	0.0178***	0.0175***	0.0128**	0.0127**	0.0127**
	(0.003)	(0.003)	(0.004)	(0.034)	(0.035)	(0.036)
Lax*(NPLunc/A)	-0.0136**	-0.0131**	-0.0133**	-0.0139**	-0.0135**	-0.0135**
	(0.033)	(0.036)	(0.033)	(0.017)	(0.021)	(0.021)
Eq/A		-0.0013***	-0.0013***		-0.0013***	-0.0013***
		(0.000)	(0.000)		(0.006)	(0.005)
CorrCB/A			-0.0011***			-0.0001
			(0.000)			(0.801)
Ln(Size)	-0.0027	-0.0083***	-0.0102***	0.0434***	0.0324***	0.0322***
	(0.128)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	yes	yes	yes	yes	yes	yes
Bank FE	no	no	no	yes	yes	yes
N, bank-mn	65,949	65,949	65,949	65,949	65,949	65,949
N, banks	726	726	726	726	726	726
R^2	0.049	0.053	0.054	0.116	0.118	0.118

Robust p-values are in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

This table presents the output of the failure regressions for domestic private Russian banks over 2008-2018, with interactions of the loan reserve coverage ratios with the lax regulatory regime dummy (turned on in January 2009 through June 2010). The dependent variable is equal 1 if the bank fails within 12 months of month t and 0 otherwise. The key independent variables pertain to reserve coverage of loans: PLunc/A – performing loans not covered by LLR to assets, PLcov/A – performing loans covered by LLR to assets, NPLcov/A – nonperforming loans covered by LLR, NPLunc – nonperforming loans not covered by LLR (i.e., the NPL coverage gap): all in percent. The control variables are: Eq/A – the ratio of equity to assets, in percent; CorrCB/A – balances held with the central bank to assets, in percent; Ln(Size) – the natural log of assets, in thousands of rubles. Models 1-3 (4-6) are estimated without (with) bank fixed effects.

Table 5 Loan reserve coverage buckets and bank failures

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0.5% < PLcov/A ≤ 1%	-0.0040			-0.0018	0.0090			0.0094
	(0.570)			(0.800)	(0.307)			(0.284)
1% < PLcov/A ≤ 2%	0.0085			0.0132*	0.0347***			0.0352***
	(0.266)			(0.087)	(0.002)			(0.001)
2% < PLcov/A ≤ 4%	0.0070			0.0136*	0.0446***			0.0451***
	(0.375)			(0.087)	(0.000)			(0.000)
PLcov/A > 4%	0.0398***			0.0480***	0.0888***			0.0902***
	(0.000)			(0.000)	(0.000)			(0.000)
0.5% < NPLcov/A ≤ 1%		-0.0153**		-0.0192***		-0.0034		-0.0063
		(0.023)		(0.004)		(0.649)		(0.386)
1% < NPLcov/A ≤ 2%		-0.0140**		-0.0210***		0.0014		-0.0033
		(0.046)		(0.002)		(0.865)		(0.680)
2% < NPLcov/A ≤ 4%		-0.0305***		-0.0401***		-0.0094		-0.0163*
		(0.000)		(0.000)		(0.339)		(0.087)
NPLcov/A > 4%		-0.0575***		-0.0711***		-0.0297**		-0.0395***
		(0.000)		(0.000)		(0.019)		(0.001)
0.5% < NPLunc/A ≤ 1%			0.0215***	0.0245***			0.0078	0.0082
			(0.001)	(0.000)			(0.249)	(0.219)
1% < NPLunc/A ≤ 2%			0.0490***	0.0524***			0.0305***	0.0318***
			(0.000)	(0.000)			(0.002)	(0.001)
2% < NPLunc/A ≤ 4%			0.0794***	0.0822***			0.0599***	0.0611***
			(0.000)	(0.000)			(0.000)	(0.000)
NPLunc/A > 4%			0.1316***	0.1320***			0.1168***	0.1241***
			(0.000)	(0.000)			(0.000)	(0.000)
PLcov/A		0.0039***	0.0042***			0.0087***	0.0089***	
		(0.000)	(0.000)			(0.000)	(0.000)	
NPLcov/A	-0.0071***		-0.0080***		-0.0029		-0.0037*	

	(0.000)		(0.000)		(0.118)		(0.053)	
NPLunc/A	0.0153***	0.0146***			0.0112***	0.0096**		
	(0.000)	(0.001)			(0.004)	(0.026)		
PLunc/A	0.0002	0.0003*	0.0002	0.0002	0.0006**	0.0008**	0.0007**	0.0006**
	(0.184)	(0.076)	(0.192)	(0.288)	(0.028)	(0.010)	(0.013)	(0.044)
Eq/A	-0.0013***	-0.0014***	-0.0013***	-0.0013***	-0.0013***	-0.0013***	-0.0013***	-0.0013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.004)	(0.005)	(0.005)
CorrCB/A	-0.0011***	-0.0011***	-0.0010***	-0.0011***	-0.0001	-0.0001	-0.0001	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.681)	(0.788)	(0.783)	(0.549)
Ln(Size)	-0.0102***	-0.0102***	-0.0105***	-0.0107***	0.0308***	0.0312***	0.0322***	0.0298***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	no	no	no	no	yes	yes	yes	yes
Observations	65,949	65,949	65,949	65,949	65,949	65,949	65,949	65,949
R-squared	0.054	0.054	0.057	0.060	0.116	0.117	0.120	0.120

Robust p-values are in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table presents the output of the failure regressions over 2008-2018 for domestic private Russian banks with dummy variables for different ranges of three of the four loan reserve coverage ratios, PLcov/A, NPLcov/A, and NPLunc/A, in place of continuous variables. The dependent variable is equal 1 if the bank fails within 12 months of month t and 0 otherwise. The four dummies are created for each of the ratios PLcov/A, NPLcov/A, and NPLunc/A falling between 0.5% and 1%, 1% and 2%, 2% and 4%, and above 4%, respectively; bank-months with the ratios between 0% and 0.5% are the reference groups. The remaining (control) variables are: Eq/A is the ratio of equity to assets, in percent; CorrCB/A is balances held with the central bank to assets, in percent; Ln(Size) – the natural log of assets, in thousands of rubles. Models 1-4 (5-8) are estimated without (with) bank fixed effects. Models 1-3 and 5-7 have the range dummies for one of the four loan coverage ratios, with the other three in the form of continuous variables. Models 4 and 8 have twelve dummy variables, one for each of the four ranges and each of the three ratios, PLcov/A, NPLcov/A, and NPLunc/A, with the continuous PLunc/A variable remaining as a control.

Table 6 Charged off loans and bank failures

Variables	(1)	(2)	(3)	(4)	(5)	(6)
OBSNPL/A	-0.0057***	-0.0036**	-0.0038**	-0.0034	-0.0018	-0.0016
	(0.001)	(0.039)	(0.035)	(0.147)	(0.467)	(0.503)
PLunc/A		0.0005***	0.0003		0.0007***	0.0008***
		(0.009)	(0.108)		(0.009)	(0.009)
PLcov/A		0.0034***	0.0038***		0.0085***	0.0087***
		(0.001)	(0.001)		(0.000)	(0.000)
NPLcov/A		-0.0064***	-0.0061***		-0.0027	-0.0026
		(0.000)	(0.000)		(0.159)	(0.172)
NPLunc/A		0.0150***	0.0145***		0.0094**	0.0094**
		(0.001)	(0.001)		(0.029)	(0.029)
Eq/A			-0.0013***			-0.0013***
			(0.000)			(0.005)
CorrCB/A			-0.0010***			-0.0001
			(0.000)			(0.845)
Ln(Size)	-0.0029*	-0.0027	-0.0102***	0.0419***	0.0428***	0.0314***
	(0.092)	(0.117)	(0.000)	(0.000)	(0.000)	(0.000)
Time FE	yes	yes	yes	yes	yes	yes
Bank FE	no	no	no	yes	yes	yes
Observations	65,949	65,949	65,949	65,949	65,949	65,949
R^2	0.037	0.048	0.053	0.101	0.115	0.117

Robust p-values are in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table presents the output of the failure regressions for domestic private Russian banks over 2008-2018. The dependent variable is equal 1 if the bank fails within 12 months of month t and 0 otherwise. The key independent variables are: OBSNPL/A – the ratio of loans charged off in the last five years to assets; PLunc/A – performing loans not covered by LLR to assets, PLcov/A – performing loans covered by LLR to assets, NPLcov/A – nonperforming loans covered by LLR, NPLunc – nonperforming loans not covered by LLR (i.e., the NPL coverage gap): all in percent. The control variables are: Eq/A – the ratio of equity to assets, in percent; CorrCB/A – balances held with the central bank to assets, in percent; Ln(Size) – the natural log of assets, in thousands of rubles. Models 1-4 (5-8) are estimated without (with) bank fixed effects.

Table 7 Loan reserve coverage and uninsured deposit flows

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L/A	-0.2029***				-0.1416***			
	(0.000)				(0.000)			
PL/A		-0.1921***				-0.1370***		
		(0.000)				(0.000)		
NPL/A		-0.7429***				-0.4010***		
		(0.000)				(0.000)		
PLunc/A			-0.1955***	-0.1733***			-0.1259***	-0.0951***
			(0.000)	(0.000)			(0.000)	(0.000)
PLcov/A			-0.1290*	-0.0347			-0.3074***	-0.2403***
			(0.076)	(0.594)			(0.000)	(0.000)
NPLcov/A			-0.6288***	-0.4716***			-0.3504***	-0.3129***
			(0.000)	(0.000)			(0.000)	(0.000)
NPLunc/A			-1.1025***	-0.9992***			-0.4236***	-0.3726***
			(0.000)	(0.000)			(0.000)	(0.000)
Eq/A				-0.1667***				-0.2109***
				(0.000)				(0.000)
CorrCB/A				0.4116***				0.1902***
				(0.000)				(0.000)
Ln(Size)	-1.5024***	-1.4193***	-1.4187***	-1.5283***	-0.1917	-0.3969	-0.4501	-2.1797***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.741)	(0.495)	(0.442)	(0.000)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank FE	no	no	no	no	yes	yes	yes	yes
N, bank-mn	69,036	69,036	69,036	69,036	69,036	69,036	69,036	69,036
N, banks	726	726	726	726	726	726	726	726
R^2	0.158	0.170	0.172	0.237	0.140	0.144	0.146	0.187

Robust p-values are in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

This table presents the output of monthly uninsured deposit flow regressions for domestic private Russian banks over 2008-2018. The dependent variable is the ratio of uninsured (private firms') transaction account balances to assets, FTA/A, in percent. The key independent variables are: PLunc/A – performing loans not covered by LLR to assets, PLcov/A – performing loans covered by LLR to assets, NPLcov/A – nonperforming loans covered by LLR, NPLunc – nonperforming loans not covered by LLR (i.e., the NPL coverage gap): all in percent. The control variables are: Eq/A – the ratio of equity to assets, in percent; CorrCB/A – balances held with the central bank to assets, in percent; Ln(Size) – the natural log of assets, in thousands of rubles. Models 1-4 (5-8) are estimated without (with) bank fixed effects.