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Financial stability and public confidence in banks

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Contents

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Abstract

We use a novel, household opinions-based measure – Public Confidence in a Bank – to explore the role of bank-level and system-wide determinants of customers' trust in banks. Our study covers a panel of approximately 260 large Russian commercial banks publicly monitored during 2010–2017. We find that public confidence in a bank is highly sensitive to the industry-level financial stability indicators, but less sensitive to bank-level risk characteristics. This result reveals an important role of overall banking sector stability in determining public perception of the safety and soundness of individual banks.

JEL classification: G21; D14

Keywords: financial stability; public confidence; bank failures; customer opinions; online reviews

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1 Introduction

This study connects two important strands of literature – household sentiment and financial stability – by establishing a link between financial system health and the confidence of customers in their bank's soundness. Prior academic literature suggests that household confidence affects a range of conduct: savings behavior (Cull et al., 2012); participation in financial markets (Georgarakos and Pasini, 2011); investment behavior in the stock market (Guiso et al., 2008); investment portfolio composition (Delis and Mylonidis, 2015; El-Attar and Poschke, 2011); behavioral biases during a bank's distress episode (Boyle et al., 2015); as well as economic growth and development overall (Guiso et al., 2004; Knack and Keefer, 1997). Empirical evidence also shows that higher levels of public confidence in banks enhances financial inclusion (Allen et al., 2016), improves financial stability by stabilizing core deposit funding of banks (Han and Melecky, 2017) and reduces exposure to systemic risk (De Jonghe, 2010).

While the importance of trust in banks has always been recognized by policymakers, very little is known about the combinations of factors that affect trust. In this study, we attempt to bridge this gap with an empirical examination of bank- and industry-level determinants of public confidence in banks.

Our study setting is the vulnerable Russian banking sector during the 2010 to 2017 period. There are at least three notable characteristics of this banking market that allow powerful empirical tests of the relationship between financial stability and public trust in banks. First, this banking sector offers a novel and periodic measure of public confidence in a large sample of individual banks assembled by the banki.ru website since 2009. This measure builds on aggregated bank-level and time-specific (daily) reviews of individuals who are verified clients of rated banks. Second, the Russian banking sector faced an extremely high bank failure rate and sizable losses for a substantial number of depositors during the period of our analysis. Almost half of all Russian banks experienced forced license revocation and closure by the Central Bank of Russia (CBR). Third, the quality and the frequency of bank-level and industry-level data are exceptional for an emerging market setting and allow us to track detailed financial safety and soundness data on a monthly basis.

Using two alternative measures of public confidence in banks – a Public Confidence in Bank Rate (PCBR) and a Public Confidence in Bank Index (PCBI), both constructed by the aggregation of bank clients' opinions – we provide robust evidence that public confidence in individual banks is strongly associated with the overall financial health of the banking industry. We use three industry-level financial stability indicators that are well-observable on a monthly basis, relevant to household sentiments and easy to interpret: (1) the total number of banks that have failed during the previous six months; (2) the total number of retail depositors in failed banks; and (3) the total level of accumulated bad debt of households in the banking sector. Our results reveal that each of these closely correlated measures (used in our alternative prediction models) have a strong association with household sentiment about individual banks even after controlling for bank-level risk and business model characteristics such as capital and asset-quality risk, lending and deposit-taking services to households, bank size and bank ownership type.

In contrast, bank-level risk characteristics as defined above only play a marginal role in explaining the variation in public confidence in banks. We also find that public confidence measures are weak predictors of a bank's failure, as they provide no additional information beyond observable bank-level risk characteristics. At the same time, the reliance of households on industry-level financial stability indicators for assessing an individual bank's prospects seems rational as the health of the financial services industry strongly predicts the likelihood of a specific bank's failure. Collectively, these results support the significant role of the banking sector's stability in framing public perception of individual banks. These findings have important policy implications because they suggest that it may not be feasible to enhance public trust in a particular bank without first improving the financial stability of the banking sector as a whole.

It is well documented that economic downturns and bank runs go hand in hand with weak public confidence in banks (Owens, 2012; Stevenson and Wolfers, 2011). Moreover, confidence is fragile and hard to restore even in the presence of deposit insurance and bank capital buffers (Iyer and Puri, 2012). Through contagion, a single bank's distress may undermine public confidence in the entire banking sector. Indeed, theory suggests that a shift in public confidence in itself can lead to a full-blown financial crisis (Miao and Wang, 2015). As a result, finding ways to increase public confidence in financial institutions remains a primary concern of policymakers, especially since the recent global financial crisis. Particularly disconcerting is the recent decline in public confidence in banks (Sapienza and Zingales, 2012), despite the efforts of bank regulators to enhance the role of the liquidity and capital requirements in the micro- and macro-prudential regulation of banks.

One practical caveat in combating low trust in banks is associated with our limited empirical knowledge about the actual weights of determinants of public sentiment. Due to data availability limitations, the existing evidence must rely mostly on the socio-demographic determinants of individuals' trust in banks. For instance, Fungáčová et al. (2016) analyze data from 52 countries and document large differences in cross-country trust in banks. They find that trust is conditional on an individual's level of income, education, religious and political values, gender, age and access to media. Relevant to the content of our study, they point out that access to television is associated with higher trust in banks, while internet access is associated with lower trust in banks. Jansen et al.

(2015) study the decline in trust in Dutch banks and find that this decline is associated with negative news from the media and stock markets. They also find that public information about excessive executive compensation seems to have the most detrimental effect on the public's trust in banks.

Several studies compare the determinants of trust in banks around episodes of financial crisis. Knell and Stix (2015) for Austria and Afandi and Habibov (2017) for 29 transition economies find that sociodemographic factors, a country's economic situation, and previous experience of bank failures are significant determinants of public confidence in financial institutions. Osili and Paulson (2014) provide further evidence that confidence in banks by US immigrants is severely damaged if these individuals were previously exposed to a systemic banking crisis. A number of other country-specific studies confirm these findings (see e.g. Knell and Stix, 2015 for Austria; van der Cruijsen et al., 2016 for The Netherlands).

While the existing literature provides a number of interesting insights on the role of economic development and sociodemographic characteristics in public confidence in banks, none of the studies discussed above explore the role of bank-specific characteristics. An exception is a study by Carbo-Valverde et al. (2013), who examine the perception of aggregated bank-specific qualitative characteristics by Spanish households during the global financial crisis. They argue that these characteristics are the major determinants of public trust in financial institutions, while demographic and social factors do not play a significant role. In particular, Carbo-Valverde et al. (2013) document that bank attention to client problems has a positive effect on the level of trust. This result implies that confidence in a bank can be driven both by household characteristics and bank characteristics.

Another constraint is that the prior literature on determinants of public confidence and trust in banks relies exclusively on surveys and questionnaires. Most questions used in such surveys are general and impossible to attribute to a particular bank. For example, the World Values Survey (used in e.g. Fungáčová et al., 2016) asks: "How much confidence do you have in banks?" The Social Science Research Solutions survey (used in Sapienza and Zingales, 2012) relies on similar questions. Although generic survey data can be useful, it provides only an aggregated, macro-level view on the determinants of public confidence and emphasizes the sociodemographic characteristic of the respondents.

Our study offers a measure of public confidence in a bank that is extracted from customer online reviews. Online reviews have proven to be a valuable source of information on households as they are costless and relatively easy to access and interpret. Moreover, people increasingly rely on online information that allows them to browse reviews and ratings (Chevalier and Mayzlin, 2006). A large amount of interdisciplinary literature documents that online reviews help to reduce information asymmetry (Manes and Tchetchik, 2018), serve as a channel for public opinion generation (Dellarocas, 2003) and offers valuable information on the predictability of stock returns (Huang, 2018). Indeed, online reviews have the potential to replace survey data (Rese et al., 2014) due to fact that they accumulate opinions of much larger population groups than survey-generated data. Given these findings, we expect that aggregated opinions of bank clients extracted from online reviews contain valuable information on public confidence in the banking sector. Our measure allows us to generate a bank-specific scale of confidence, which is, to the best of our knowledge, the first cross-sectional measure of public confidence in banks.

The rest of the paper is organized as follows. In Section 2, we present our sample, describe how the two measures of public confidence in banks (rate and index) are constructed, and explain the bank-level and industry-level data used in this study. In Section 3, we detail the main empirical results on the determinants of public confidence in a bank. We also show how bank confidence measures are associated with the likelihood a bank will fail. Section 4 concludes.

2 Data

We draw our study sample from Russian commercial banks with at least five approved reviews in the previous twelve months. We exclude a small number of banks under regulator-assisted receivership program as these financial institutions are allowed to operate with unconventionally weak financial characteristics while undergoing the recovery and reorganization process. We further exclude banks that are not members of the Russian Deposits Insurance scheme, because these financial institutions are prohibited by law from retail deposit-taking. Finally, we exclude banks with total assets less than RUB 5 billion and banks with incomplete disclosures of their financial data.

The final sample is an unbalanced panel that consists of 9,408 bank-month observations for 263 unique banks from 1/1/2010 to 1/1/2017, i.e. the period after the global financial crisis. This is also a period when all covered banks accumulate at least twelve months of public confidence measure observations. Bank-level financial statement data are extracted from the CBR databank. Bank failure outcomes are tracked up to the end of 2017. Collectively, sample banks control at least 70% of the country's banking sector assets in each sample month.

In Table 1, we present summary statistics that describe the study sample. In the subsections below, we also explain the broad set of dependent, explanatory and control variables used in the study. Appendices 1 and 2 provide additional details on the construction and availability of the public confidence in Russian banks measure. In Appendix 3, we provide the definitions and data sources for the study variables.

Table 1 Bank-level summary statistics

	mean	p50	sd	min	max	N
Public Confidence:						
PCBR	2.67	2.56	0.66	1.00	4.83	9 408
PCBI	42.93	41.64	11.77	15.25	87.84	9 408
Capital and credit risk, %:						
E/A	11.09	9.81	5.53	0.00	91.27	9 408
NPA/A	7.04	5.86	5.11	0.07	44.89	9 408
Retail banking, %:						
HH Loans /A	20.72	12.04	21.84	0.00	95.53	9 408
HH Deposits /A	37.51	37.87	20.33	0.00	87.67	9 408
Bank size and ownership type:						
Bank size (Log of Assets)	17.87	17.86	1.75	13.70	23.93	9 408
State-controlled	0.091			0	1	9 408
Foreign-owned	0.167			0	1	9 408
Bank failures (tracked to 1/1/2018):						
Failed in 6m	0.097			0	1	9 408
Failed in 12m	0.154			0	1	9 408

The study sample covers 85 months (1/1/2010 to 1/1/2017) for 263 unique Russian banks. The total number of bank-month observations is 9,408. The definition of variables used in the study is provided in Appendix 3.

2.1 Public confidence measures

Our measures of public confidence in banks are based on feedback on bank products and services submitted by bank customers to the banki.ru website. Founded in 2005, the website rapidly gained popularity among households, media, analysts and banks. By 2016, the website was among the top three most-cited media sources in the financial industry. It now reaches an average monthly audience of more than 16 million unique viewers, making it the largest independent provider of information on Russian banks. Besides aggregating all bank news, analytical and financial data, and other information on all banks that operate in Russia, it includes a digest of products and services offered by each bank. Given the large number of commercial banks in Russia, this tool alleviates much of the challenge in cross-bank comparison and selection by bank customers.

A significant role in such interbank comparison is played by the "people's rating" of banks, essentially a bank-specific index of customers' assessment of bank products and services. The index builds on banki.ru user posts that describe their actual experience with a particular bank. In addition to textual comments, users have the opportunity to grade the bank, based on a five-step scale, with "1" meaning a poor experience and "5" an excellent one. These grades are used in calculations of a bank-specific rating, allowing us to objectively assess the aggregate of private opinions about the quality of bank products and services. The rules of the banki.ru rating system stipulate that individual reviews should be about personal experience with the bank, rather than the bank itself. Hence, the rating likely captures public perceptions of bank quality and trustworthiness, with trust being the expectation that a financial institution acts in (or at least not against) the interests of its customers.

While the rating system is fairly similar to ratings used by hotel and restaurant rating platforms, there are several important differences. First, in order to minimize conflicts of interest, all assessments and feedback are moderated by the website administrator to exclude PR-oriented posts and advertisements. To illustrate this process, consider a pleased bank client posting a positive review that praises the high-quality service and competence of the bank's personnel. To make sure the review is not part of the bank's marketing campaign, the moderator asks for additional verification such as names and positions of involved employees, branch address, date and time of contacting the bank. If the user specifies credible details, the grade is marked as "counted." The final rating of a bank only uses "counted" reviews that consist of complete information and are supported by the verification details. From the technical point of view, the system also excludes the possibility that the same person writes reviews under multiple user names. Each user is limited to one review of a particular bank every six months, unless an event occurs that causes the user to change their tone of assessment.

Second, banki.ru offers an interaction channel through which banks may impact their grades by responding to negative experiences described by users. Many banks closely follow public ratings on banki.ru, dedicating staff solely to the task of monitoring and responding to reviews with corrective measures. Consider, for example, an angry customer who posts a negative review about his or her frustrations with low-quality service or staff incompetence. If the bank is concerned about its customers and reputation, it will try to solve the issue by improving service and compensating customers for time wasted or expenses incurred. If the user is satisfied with the bank's response, he or she can return to the original review and check "problem solved." Such satisfactory remedial action automatically raises the customer's grade and ultimately the overall rating of the bank. These particular features of the rating system are intended to resolve self-selection bias documented in the previous literature (see e.g. Dellarocas and Wood, 2008; Hu et al., 2017) on specific type of users who only post reviews during a distinctly negative or positive bank experience.

In comparison with other problem-solving channels, such as a visit to a branch office or calling customer service, reviewers reporting their issues on banki.ru increase general awareness of such problems and can affect the reputational perception of the bank by other site visitors. To illustrate how such opinions might influence perception, consider a bank that fails to deliver adequate service to a particular customer, which results in a negative review. Other users see the feedback and react by commenting on the review. Most comments merely amplify the original reviewer's sentiment or report a similar experience with the same bank. For instance, a commenter might report that they "will never become a customer of this bank" or had "exactly the same problem," while others might sympathize merely by thanking fortune that they have managed to avoid the poorly reviewed bank. Extreme examples of public exposure include statements as: "I opened a deposit account in this bank today, but based on these reviews, plan to close my account tomorrow."

Finally, in contrast to hotel and restaurant recommendation platforms, where average scores may be driven by outdated reviews, the people's rating system allows for time decay by gradually diminishing the weights of older scores. A typical review loses approximately 35% of its weight in the total rating within a year and about 75% (90%) after three (five) years. Thus, ratings account for information obsolescence and make scoring reasonably representative of the current level of public confidence in a given bank.

Based on these online reviews, we introduce two new measures of public confidence in banks. Our "Public Confidence in Bank Index" (PCBI) is calculated as Bayesian weighted average and our "Public Confidence in Bank Rate" (PCBR) is calculated as a simple average of reviewers' grades. More detailed calculation techniques for both measures are described in Appendix A1.

To assure our measures relate to actual levels of confidence in banks, we compare them with the data obtained from traditional surveys. The National Agency of Financial Research (NAFR) is the only private independent source conducting surveys in a timely manner with sufficient frequency that focuses on trust in public institutions in Russia. These surveys, which began in 2012, typically poll around 1,600 people in 140 locations in 42 regions of Russia. The survey item of interest for us reads: "Please tell me how much confidence you have in the following financial institutions." The list includes banks, insurance companies, investment firms, microfinance companies and private pension funds. Allowable responses to each listing are "completely confident," "rather confident," "not very confident," and "no confidence at all". Consistent with our measures, the results of this survey indicate that the level of public confidence in banks has been declining in recent years. The fraction of completely and rather confident respondents dropped from 78% in 2013 to 60% in 2017 (Imaeva et al., 2017). Our average Public Confidence Index declined from 45.0 to 35.4 over the same sample period. Given the high correlation with survey results, we postulate that our measures correspond to the level of public confidence in banks.

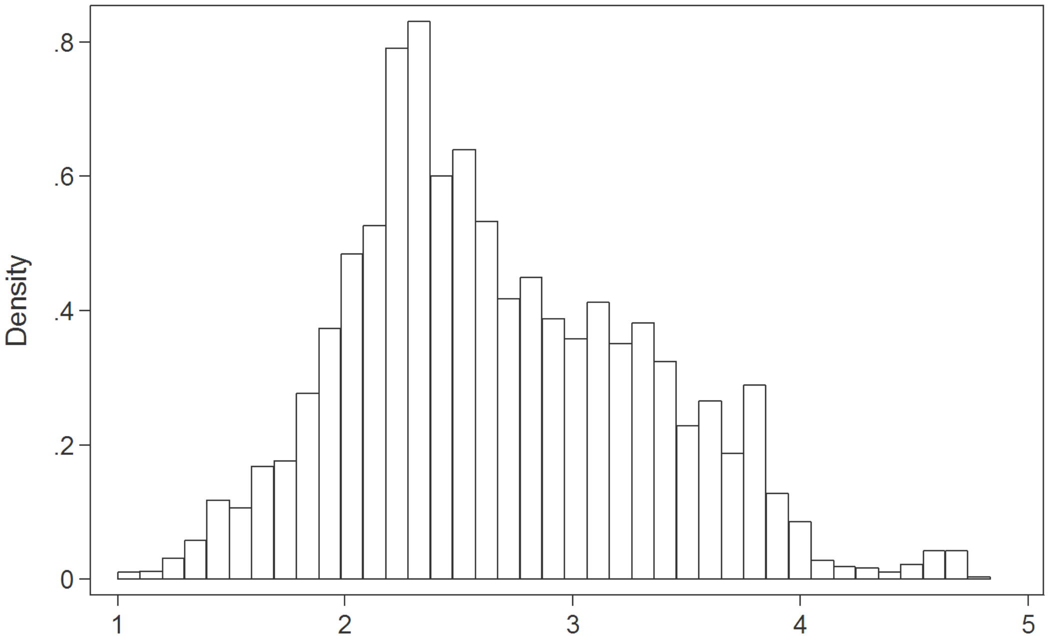
There are several advantages of our measures of public confidence. First, in contrast to prior studies that primarily use limited surveys to quantify public confidence, we rely on much larger population of private opinions on the quality of bank products and services. Our sample consists of

125,217 approved reviews of 263 individual banks. Moreover, reviews used in the index are related to the actual experience with a bank, which makes the assessment more attached to the actual attitude towards banks, rather than abstract understanding of questions used in surveys. Lastly, while previous studies examine confidence at the aggregate level, our measure is bank-specific, allowing extensive cross-sectional analysis of determinants of public confidence in banks. To the best of our knowledge, this paper is the first to examine this issue at the cross-sectional level.

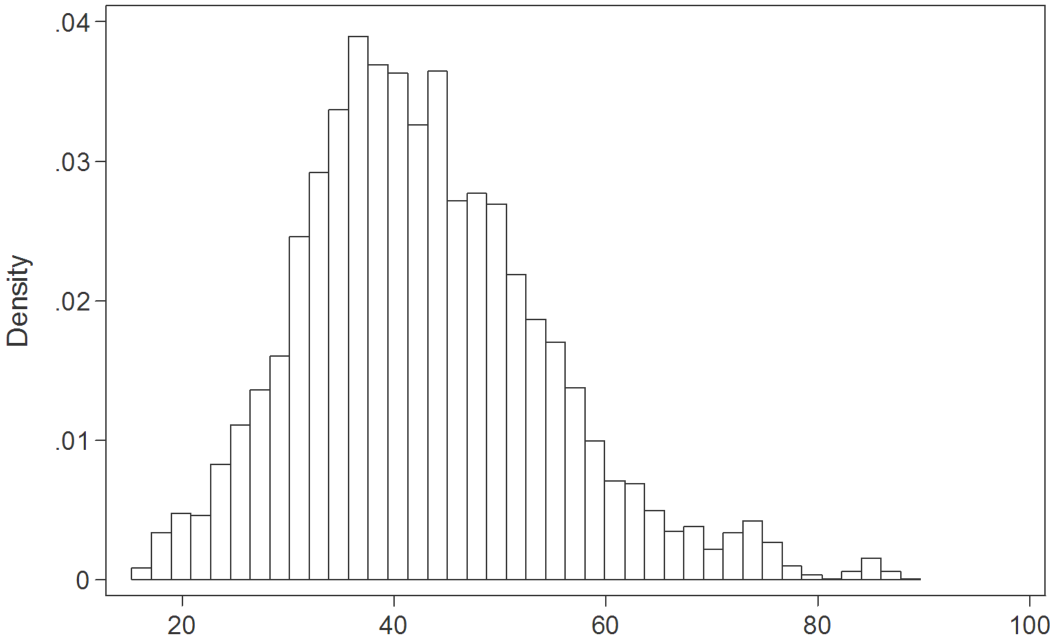
As seen in Table 1, both measures of public confidence vary widely in our sample. The PCB Rate (scale 1 to 5) ranges from 1.00 to 4.83 points with an average of 2.67 and the median of 2.56. The PCB Index (scale 1 to 100 and accounting for number of approved reviews) ranges from 15.25 to 87.84, with an average of 42.9 and the median of 41.6. Both measures are approximately normally distributed. Figures 1 and 2 detail distribution and correlation by showing the histogram for each rating and the scatterplot between the two. The correlation coefficient between the two measures is 0.896.

Figure 1 Distribution of public confidence measures in the study sample:
Public Confidence of Bank Rate (PCBR) and Public Confidence of Bank Index (PCBI)

Panel A: PCBR

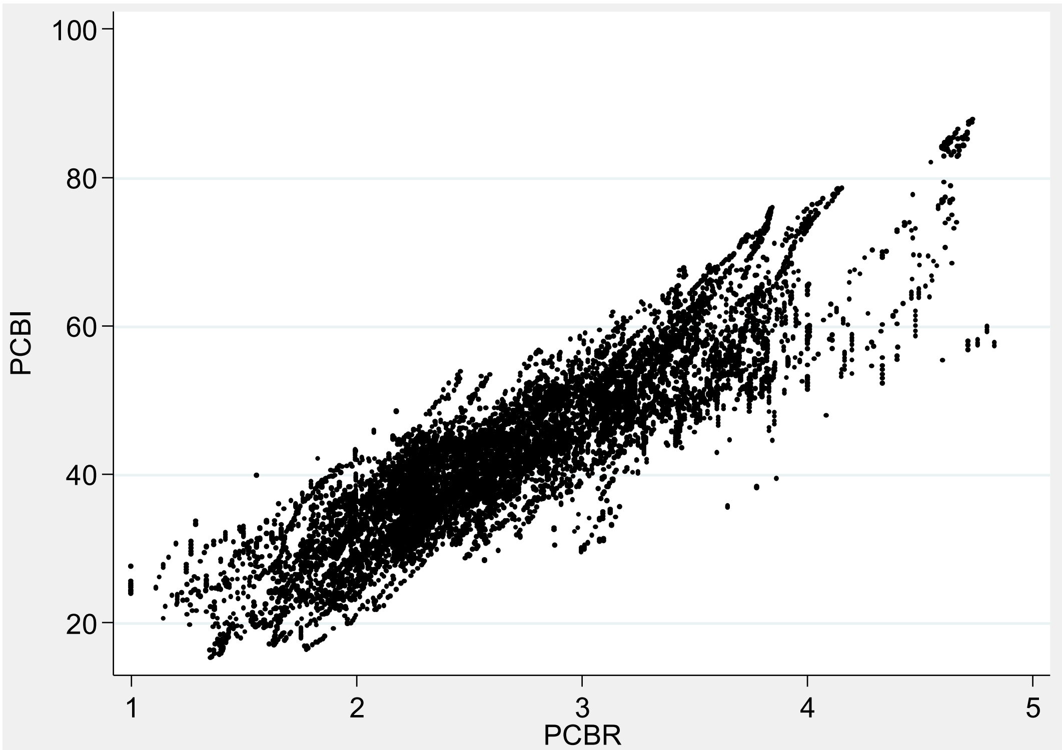


Panel B: PCBI



The total number of bank-month observations in the study sample is 9,408, for an unbalanced panel of 263 unique Russian banks over the 1/1/2010–1/1/2017 period. PCBR scale is from 1 to 5 (panel A); PCBI scale is from 1 to 100 (Panel B). We describe the construction of the two alternative measures of public confidence in a bank (as produced at banki.ru) in Section 2.1.

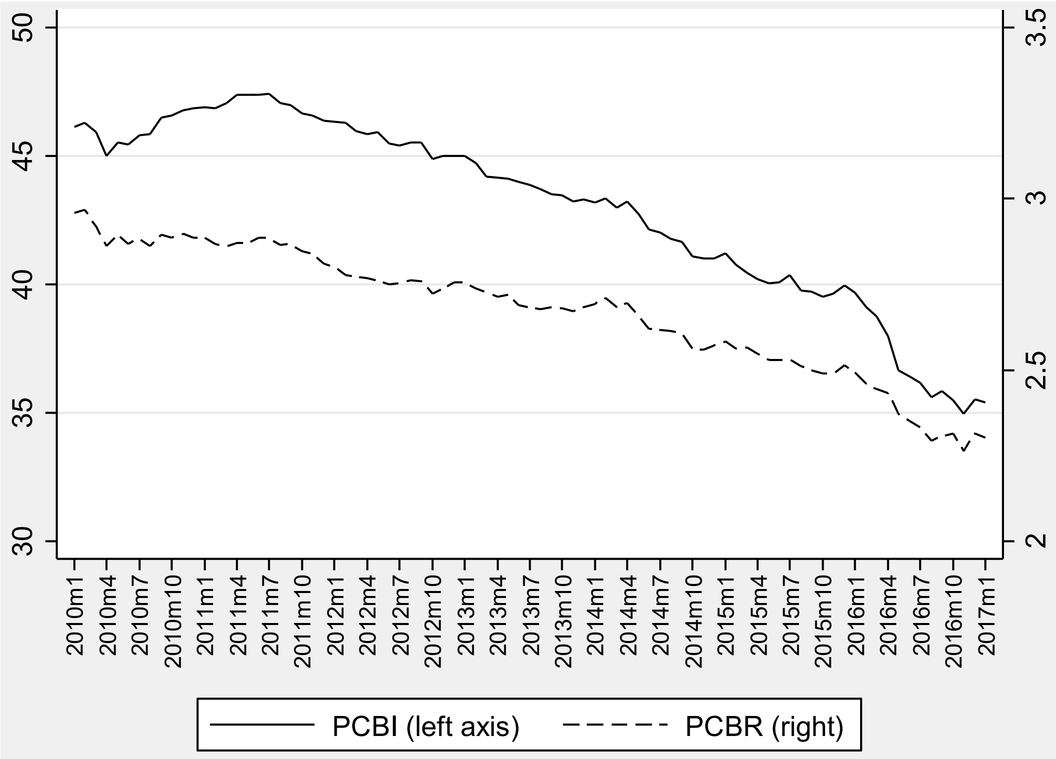
Figure 2 Scatterplot of public confidence measures: PCBR vs. PCBI



The total number of bank-month observations in the study sample is 9,408, for an unbalanced panel of 263 unique Russian banks over the 1/1/2010–1/1/2017 period. PCBR scale is from 1 to 5 (panel A); PCBI scale is from 1 to 100 (Panel B). We describe the construction of the two measures of public confidence in a bank (as produced at banki.ru) in Section 2.1.

In Figure 3, we show the evolution of the mean values of PCBR and PCBI. Both trends show a clear downward pattern suggesting a gradual decrease in the bank-level public confidence over the 2010–2016 period.

Figure 3 Evolution of public confidence measures over time: 1/1/2010–1/1/2017 (monthly data)



This graph reports mean values of the PCBR and PCBI for an unbalanced sample of 263 unique Russian banks over the 1/1/2010–1/1/2017 period. Both bank confidence measure exhibit a downward trend.

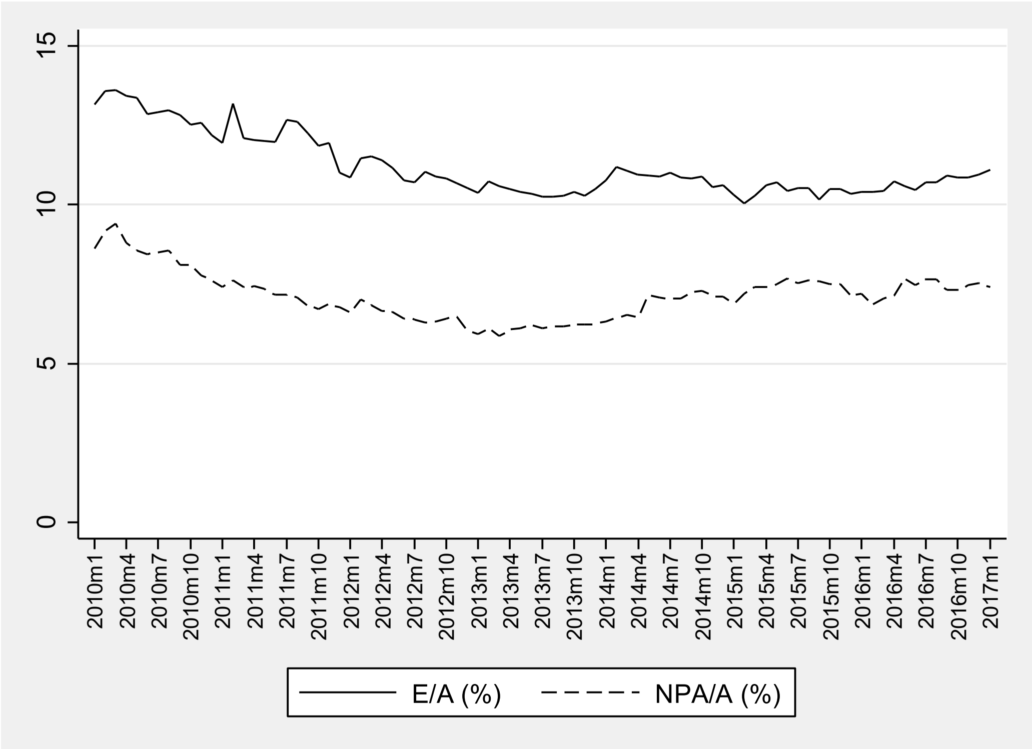
Table A2 in the Appendix illustrates a development of our measures of public confidence in greater detail. It depicts yearly development of the rating and rated banks (Panel A), as well as of the number of reviews for these banks (Panel B). While rated banks on average constitute about a sixth of all active banks in Russia, they correspond to 70–87% of total assets of the banking system. The average number of reviews per year per bank also gradually increases throughout the sample period, reflecting the growing popularity of the online assessment tool.

2.2 Bank risk and business model characteristics

We proxy bank risk characteristics with two fundamental measures – *capital risk* (book equity-to-assets ratio) and *asset-quality risk* (nonperforming assets-to-total assets ratio). We choose these variables as the most intuitive and simple measures that are likely to be understood by retail bank customers. As banki.ru provides periodic bank-level disclosure of these measures for portal users, we further assume that these accounting-based ratios are available for public monitoring.

Bank-level capital risk and asset-quality risk are expected to have robust effects on the likelihood of bank failure. As reported in Table 1, the mean (median) equity to assets ratio in the study sample is 11.09% (9.81%); the mean nonperforming assets ratio is 7.04% (5.86%). In Figure 4, we also illustrate the evolution of the two bank risk measures over time. Overall, they remain relatively stable with some seasonal fluctuations.

Figure 4 Evolution of bank risk measures over time



This graph reports mean values of the capital risk (E/A) and asset quality risk (NPA/A) measures for an unbalanced sample of 263 unique Russian banks over the 1/1/2010–1/1/2017 period.

We also control for bank orientation on retail customers as the public confidence measures are reported by retail customers. On the asset side, we capture bank retail operations with the loans to households to assets ratio. The average value of this indicator (20.72%) varies broadly from 0% to 95.53% of total assets. On the liabilities side, we control for household deposits to total assets ratio. The average bank in our sample finances 37.51% of its assets with this funding source.

Finally, we control for bank size and ownership type. We use monthly indicators of bank ownership that have been manually collected from public information sources. About 9% of the sample banks are state-controlled, and another 16% fully foreign-owned. The remaining 81% of observations in this sample are private and domestically-owned commercial banks.

2.3 Bank failures

We collect information on bank failures, our primary outcome variable of interest, from the CBR press-release database on bank closure (license revocation) announcements. We supplement this information with announcements of failed banks placed in receivership. Thus, if a bank fails, but is allowed to remain in the banking sector under the special, regulator-assisted rehabilitation and re-organization process, we treat such cases as bank failures (and exclude such banks from the sample for the post-failure period).

Bank failure outcomes are traced up to the end of 2017, which allows us to construct two alternative bank failure windows: bank that failed within the following six months (9.65% of bank-month observations) and banks that failed within the following twelve months (15.38% of observations). Although these failure rates outside of the global financial crisis period may seem unusually high, they are representative for the Russian banking sector during the period of our study. Overall, 49% of banks active at the end of 2009 ceased to exist or were no longer independent financial institutions at the end of 2017.

2.4 Industry-level characteristics for financial stability

In selected regression models, we control for three banking industry-level indicators of financial health and stability. All of these are observed over the 85 sample-months period, from 1/1/ 2010 to 1/1/2017. The first measure that we expect to be well-observable and understandable to retail bank customers is the aggregate nonperforming household loans ratio in the Russian banking sector. In a raw form, it ranges from RUB 243 billion to RUB 923 billion (Table 2). The second measure, the number of failed banks in the past six months, should also be well observable to unsophisticated retail monitors. This moving-average variable ranges from only 2 banks to 68 banks, with an average of 26. Our final measure, total number of retail depositors in failed banks eligible for a DIS repayment, should also be directly observable by retail customers. We also measure it as a six-month moving average. The total number of affected depositors of failed banks ranges from 6,000 to 1.3 million depositors, with an average of 426,000 depositors per bank.

Table 2 Industry-level summary statistics

Panel A: Summary statistics

	mean	p50	sd	min	max	N
NPL to HHs in (bill. RUB)	504	375	244	243	923	85
Failed banks (N in last 6m)	26	18	19	2	68	85
Depositors in failed banks (N in thousands in last 6m)	426	226	422	6	1 346	85
Log (NPL to HHs)	6.11	5.93	0.47	5.49	6.83	85
Log (N of failed banks)	2.91	2.89	0.88	0.69	4.22	85
Log (N of depositors in failed banks)	5.37	5.42	1.36	1.77	7.21	85

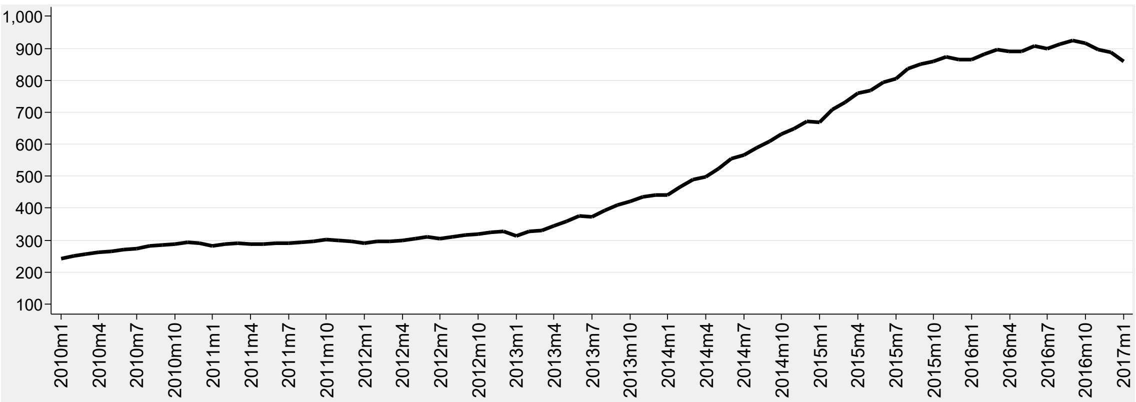
Panel B: Correlation matrix

	(1)	(2)	(3)
(1) Log (NPL to HHs)	1.00		
(2) Log (N of failed banks)	0.81	1.00	
(3) Log (N of depositors in failed banks)	0.78	0.85	1.00

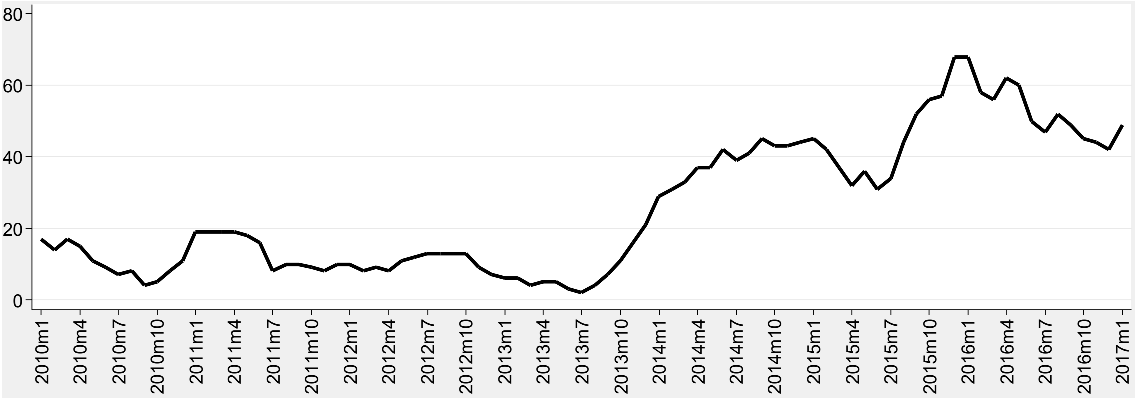
Notably, all three measures of the banking industry financial stability vary substantially over the study period. We report these trends in Panels A to C in Figure 5. In the regression analyses, we use log-transformed values of these industry-level explanatory variables. In Panel B of Table 2, we also show that all three measures are highly correlated.

Figure 5 Evolution of banking industry-level measures of risk and financial stability

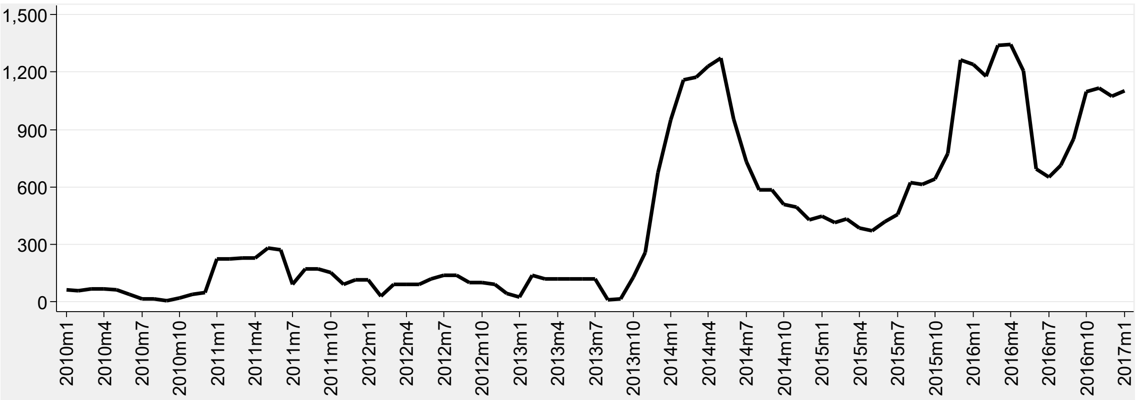
Panel A. Aggregate-level of nonperforming loans to Russian households (in RUB billion)



Panel B. Total number of Russian banks failed in the previous six months (in raw numbers)



Panel C. Total number of retail depositors in Russian banks that failed in the previous six months (in thousands of individuals)



This figure illustrates the development of three measures of financial stability in the Russian banking sector: Aggregated nonperforming loans to households (Panel A), total number of failed banks in the last six months (Panel B), and total number of retail depositors in banks that failed in the previous six months (Panel C). The raw data for these graphs are obtained from official periodic disclosures of the Central Bank of Russia and the Russian Deposit Insurance Agency and cover 85 months for the period 1/1/2010–1/1/2017.

3 Results

3.1 Descriptive evidence: Comparison of public confidence measures in failed and survived banks.

We start the empirical analysis from a series of simple comparison tests of PCBR and PCBI mean values in failed and survived banks. As described in the data section, bank failures are tracked for the six- and twelve-month forward-looking window for each bank-month observation. For completeness, we also compare bank risk, business model and industry-level financial stability characteristics between survived and failed banks in our sample.

As reported in Table 3, there is no evidence of lower public confidence in banks that will fail in subsequent six (or twelve) months. Contrary to expectations, the subsample of failed banks has a slightly higher average public confidence rate and index. In the case of bank-level financial variables, all comparison test results are consistent with the common expectations. Failed banks are characterized with significantly lower capital ratios, higher nonperforming assets ratios and smaller asset size. Failed banks are also less involved in retail lending and rely more on household deposits sources of financing (that tend to be relatively expensive in Russia). Ownership type matters; foreign banks are significantly less likely to fail, while state banks in our sample have a higher likelihood of failure. For industry-level variables, deterioration of financial stability conditions in the country's banking sector is associated with an increasing likelihood of failure.

Table 3 Means comparison of failed and survived banks over 6- and 12-month windows

	Failed in 6 months			Failed in 12 months		
	No (N=8,500)	Yes (N=408)	Diff (Yes - No)	No (N=7,168)	Yes (N=1,303)	Diff (Yes - No)
PCBR	2.66	2.74	0.08***	2.62	2.73	0.10***
PCBI	42.91	43.15	0.24	42.44	43.35	0.91**
E/A	11.23	9.74	–1.50***	11.13	9.54	–1.58***
NPA/A	6.94	7.93	0.99***	6.74	7.67	0.93***
HH Deposits /A	37.08	41.46	4.38***	37.00	45.40	8.41***
HH Loans /A	21.66	11.94	–9.72***	22.46	12.55	–9.91***
Bank size	17.92	17.44	–0.482***	18.00	17.28	–0.73***
State-controlled	0.087	0.189	0.102***	0.150	0.198	0.049***
Foreign-owned	0.113	0.013	–0.100***	0.178	0.023	–0.155***
Log (NPL to HHs)	6.11	6.37	0.26***	6.16	6.40	0.25***
Log (N of failed banks)	2.90	3.31	0.42***	2.96	3.31	0.35***
Log (N of depositors in failed banks)	5.41	6.01	0.60***	5.63	6.03	0.40***

This table provides the results of the mean comparison tests between bank-level and industry-level characteristics in failed and survived sample banks over the follow-up 6- and 12-month periods. The unbalanced panel consists of 9,408 bank-month observations over the 1/1/2010 to 1/1/2017 period for 263 unique Russian banks. The definition of the study variables is provided in Appendix 3. The difference in means is tested with T-test. ***, ** and * denotes significance at the 1%, 5% and 10% levels.

Overall, the descriptive evidence in Table 3, which is based on means comparison t-tests, supports the role of bank-level and industry-level characteristics. However, it also presents the puzzling finding of relatively high public confidence in banks falling into the failed banks subsample. We address this puzzle using the multivariate regression analyses framework.

3.2 Determinants of public confidence in banks: The role of bank-level risk

As the first step of our regression analysis, we explore which bank-level risk and business model characteristics drive public confidence in a bank. These results are reported in Table 4. We use two alternative dependent variables – PCB Rate (models 1 and 2 in Table 4) and PCB Index (models 3 and 4 in Table 4). Our main explanatory variables of interest are bank capital risk (measured with book equity-to-assets ratio) and bank asset-quality risk (measured with nonperforming assets ratio). We also control for retail-oriented business model (using loans to households ratio and households deposit ratio, each scaled to total assets). All regressions control for time fixed effects which absorb all macro- and industry-level factors over the 85 sample months. In models 1 and 3, we exploit cross-sectional variation and control for bank ownership type variables. In models 2 and 4, we exploit panel features of our dataset and control for bank fixed effects. All regressions in Table 4 also control for bank size. The standard errors are robust and clustered at bank level.

Table 4 Determinants of public confidence in banks: Bank-level risk

	Dependent variable			
	PCBR (scale 1 to 5)		PCBI (scale 1 to 100)	
Variables	(1)	(2)	(3)	(4)
E/A	-0.004	0.004	-0.056	0.192***
	(0.506)	(0.130)	(0.614)	(0.006)
NPA/A	-0.015**	-0.001	-0.366***	-0.068
	(0.046)	(0.837)	(0.009)	(0.389)
HH Loans /A	-0.006***	-0.002**	-0.072*	-0.048
	(0.003)	(0.037)	(0.097)	(0.290)
HH Deposits /A	0.001	0.003**	0.018	0.073**
	(0.600)	(0.045)	(0.713)	(0.011)
Bank size	-0.092***	0.035	-1.121**	2.071**
	(0.001)	(0.360)	(0.013)	(0.011)
State-controlled	-0.061		-3.003	
	(0.633)		(0.151)	
Foreign-owned	0.107		-0.039	
	(0.460)		(0.990)	
Time FE	yes	yes	yes	yes
Bank FE	no	yes	no	yes
Intercept	yes	yes	yes	yes
No. of Obs.	9,408	9,408	9,408	9,408
No. of Banks	263	263	263	263
R-squared	0.200	0.341	0.183	0.276

This table reports the estimated coefficients for the pooled (with time fixed effects – Models 1 and 3) and panel (with bank and time fixed effects – Models 2 and 4) regression estimations. The dependent variables are two alternative measures of public confidence in a bank: Public Confidence in a Bank Rating (PCBR) (Models 1 and 2) and Public Confidence in a Bank Index (PCBI) (Models 3 and 4). All explanatory variables in this set of regressions are at a bank-level. The definition of the study variables is provided in Appendix 3. Standard errors are robust and bank-clustered; *p*-values are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Overall, the results in Table 4 reveal only limited sensitivity of PCBR and PCBI measures to bank-level risk. Higher capital ratio seems to be positively and significantly associated with public confidence only when measured with the PCBI and only when controlling for bank fixed effects (model 4 in Table). The economic significance of this relationship is also weak. As the capital ratio increases by 1% (a substantial improvement), the PCBI (which ranges from 1 to 100) goes up by a modest 0.2%. A rise in the nonperforming assets ratio drives public confidence in a bank down. However, similar to the capital ratio, this relationship is not robust. It is significantly negative only in models 1 and 3 that do not control for bank fixed effects. Also, the magnitude of estimated coefficients is weak: a 1% increase in NPA ratio (sizeable asset quality deterioration) is associated with only 0.02 decline in PCBR points and 0.4% decrease in PCBI. Overall, neither capital nor credit bank-level risk appear to be strong and reliable predictors of public confidence in a bank.

For the business model proxies, we also find some plausible relations between bank-level characteristics and public confidence. Retail deposit-taking is generally positively associated with the level of confidence in a bank. In contrast, retail lending has a negative effect. These results are interesting, as it seems that earning interest (on household deposits) versus paying interest (on household loans) may potentially frame different public perceptions of a financial intermediary. Other bank characteristics, such as size and bank ownership are not robust across various model specifications. One notable result, however, is the sizeable (although not statistically significant at conventional levels) negative coefficient on a state-owned bank dummy in model 3 of Table 4, suggesting that state-owned banks demonstrate more than 3% lower PCBI. Collectively, the results in Table 4 suggest that bank-level risk characteristics have only a limited – i.e. not sizeable and not robust effect on public confidence measures.

3.3 Determinants of public confidence in banks: The role of industry-level risk

As the next step of our analysis, we introduce banking industry-level characteristics of financial stability to test their role in framing bank-level public confidence sentiments. Specifically, we release time fixed effects in the models described in Section 3.1 and substitute them with three alternative measures of the industry-level financial stability. As described in our data section, these measures are industry-level NPLs to households, number of banks that have failed in the past six months and the number of retail depositors of these banks. As all three measures of financial stability are strongly correlated (see Panel B of Table 2), we introduce them one-by-one in a series of separate regressions. To be conservative, we also control for bank fixed effects in all regression models and use robust standard errors. As before, we also control for bank risk, retail customers' operations and asset size. These results are reported in Table 5.

Table 5 Determinants of public confidence in banks: Industry-level risk

	Dependent variable					
	PCBR (scale 1 to 5)			PCBI (scale 1 to 100)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Industry-level financial stability:						
Log (NPL to HHs)	-0.318***			-7.353***		
	(0.000)			(0.000)		
Log (N of failed banks)		-0.058***			-1.436***	
		(0.000)			(0.000)	
Log (N of depositors in failed banks)			-0.040***			-0.835***
			(0.000)			(0.000)
Bank-level risk and business model:						
E/A	0.003	0.001	0.001	0.163**	0.112	0.115
	(0.295)	(0.815)	(0.752)	(0.023)	(0.138)	(0.127)
NPA/A	-0.000	-0.006	-0.007*	-0.072	-0.204**	-0.238***
	(0.941)	(0.109)	(0.056)	(0.362)	(0.021)	(0.006)
HH Loans /A	-0.003**	-0.002	-0.001	-0.047	-0.025	-0.014
	(0.032)	(0.187)	(0.289)	(0.274)	(0.546)	(0.713)
HH Deposits /A	0.002	-0.001	-0.001	0.052*	-0.017	-0.017
	(0.257)	(0.385)	(0.431)	(0.058)	(0.568)	(0.563)
Bank size	-0.020	-0.186***	-0.180***	1.305*	-2.454***	-2.538***
	(0.569)	(0.000)	(0.000)	(0.064)	(0.001)	(0.000)
Bank FE	yes	yes	yes	yes	yes	yes
Intercept	yes	yes	yes	yes	yes	yes
No. of Obs.	9,408	9,408	9,408	9,408	9,408	9,408
No. of Banks	263	263	263	263	263	263
R-squared	0.309	0.222	0.223	0.248	0.161	0.152

This table reports the estimated coefficients for the series of OLS panel regressions with bank fixed effects. The dependent variables are two alternative measures of public confidence in a bank: Public Confidence in a Bank Rating (PCBR) (Models 1-3) and Public Confidence in a Bank Index (PCBI) (Models 4-6). The explanatory variables of interest are industry-level indicators of financial stability. The definition of the study variables is provided in Appendix 3. Standard errors are robust and bank-clustered; *p*-values are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Similar to results in Table 4, we find only limited sensitivity of PCB measures to bank-level risk and business model in these estimation models. The estimation coefficients for capital ratio and nonperforming assets ratio provide no consistent evidence on their effect on public confidence measures, while bank business model characteristics exhibit even lower significance in public perception of a bank's trustworthiness.

On the other hand, the regression results for the role of the industry-level variables stand in sharp contrast with the results for the bank-level variables. All three industry-level determinants are sizeable and statistically significant suggesting that broader financial stability situation in a banking sector plays a strong defining role in the public confidence perception of individual banks even after controlling for the key bank-level risk characteristics.

3.4 Does public confidence reliably predict bank failure?

For completeness, we also look at the relationship between public confidence measures as explanatory variables and bank failure outcomes. In particular, we are interested in two broad research questions: (1) Does public confidence measure has any explanatory power of upcoming bank failure beyond observable bank risk fundamentals? (2) Do industry-wide financial stability characteristics play a defining role in the failure of an individual bank? The answer to the first question should help to explain if there is specific information content and, thus, market monitoring value in the PCB measures that are not captured by standard bank risk characteristics. The answer to the second question should help to understand if households behave rationally by framing their public confidence in a bank sentiment primarily based on the industry-wide financial stability measures instead of bank-level measures.

We start by addressing the first question. In Table 6, we report the results of the linear probability model estimation with bank and time fixed effects. The two alternative dependent variables are bank failure event in a six-month window (models 1 and 2) and a bank failure event in a twelve-month window (models 3 and 4). The primary variable of interest is public confidence in a bank, measured as PCBR (models 1 and 3) and as PCBI (models 2 and 4). Importantly, we control for bank capital and credit risk variables to see if PCB measures can contribute to the prediction of a bank failure event beyond the commonly used bank risk measures.

Our results provide no evidence of the ability of households to reliably predict a bank failure beyond traditional bank risk variables. In all regression models in Table 6, neither PCBR nor PCBI is significantly associated with higher likelihood of a bank failure. This (lack of) result holds for both bank failure windows. It is also consistent with the descriptive statistics and t-test results in Table 3.

Table 6 Public confidence in a bank and bank failure prediction

	Dependent variable			
	Failed in next 6 mo. (0; 1)		Failed in next 12 mo. (0; 1)	
Variables	(1)	(2)	(3)	(4)
PCBR	0.020 (0.246)		0.021 (0.318)	
PCBI		0.001 (0.345)		0.001 (0.265)
E/A	-0.005** (0.034)	-0.005** (0.033)	-0.007** (0.015)	-0.007** (0.015)
NPA/A	0.007* (0.052)	0.007** (0.048)	0.008** (0.048)	0.008** (0.041)
HH Loans /A	-0.002*** (0.001)	-0.002*** (0.001)	-0.003*** (0.000)	-0.003*** (0.000)
HH Deposits /A	-0.000 (0.652)	-0.000 (0.662)	0.001 (0.456)	0.001 (0.453)
Bank size	-0.033*** (0.000)	-0.034*** (0.000)	-0.046*** (0.000)	-0.046*** (0.000)
State-controlled	0.192* (0.080)	0.193* (0.079)	0.192* (0.086)	0.195* (0.083)
Foreign-owned	-0.000 (0.994)	0.002 (0.944)	0.005 (0.890)	0.007 (0.842)
Time FE	yes	yes	yes	yes
Intercept	yes	yes	yes	yes
No. of Obs.	9,408	9,408	8,471	8,471
No. of Banks	263	263	263	263
R-squared	0.109	0.109	0.148	0.148

This table reports the estimated coefficients for the series of LPM regressions with time fixed effects. The dependent variables are bank failure outcomes over a 6- and 12-month period. The explanatory variables of interest are two alternative measures of public confidence in a bank: Public Confidence in a Bank Rating (PCBR) and Public Confidence in a Bank Index (PCBI). The definition of the study variables is provided in Appendix 3. Standard errors are robust and bank-clustered; p-values are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

In contrast, bank-level risk variables play significant role in predicting bank failure outcomes. Higher capital risk (as revealed by lower capital ratio) and higher asset-quality risk (as revealed by higher NPA ratio) have significant effects on predicting a bank failure in the follow-up six- and twelve-month period. State-controlled banks also seem to have higher likelihood of failure.[1] Larger banks and banks that are more heavily involved in the retail lending activity have lower likelihood of failure. All there regression results are broadly consistent with a series of t-tests that compare failed and survived banks, reported in Table 3.

[1] As we explain in the data section, we classify both bank license revocations and the decision of the central bank to initiate regulatory-assisted receiverships of a troubled bank as failures.

For the final step of our analysis, we substitute time fixed effect with industry-wide financial stability indicators and test if these variables can reliably predict the failure of a specific bank. As reported in panels A and B of Table 7, we find strong and significant effects of the overall banking sector financial stability characteristics on the likelihood of future bank failures. In Panel A, we use the PCBR measure. In Panel B, we run the same specifications with the PCBI as the proxy for public confidence in a bank. In both cases, we observe that higher accumulated NPL in the banking sector, a larger number of recently failed banks and a larger number of retail depositors that were customers in these failed banks – are all associated with the higher likelihood of a bank failure, even after controlling for bank-level risk characteristics. Public confidence, in turn, is not significantly related to bank failure outcomes after we control for bank risk variables.[2] Thus, we provide a convincing result to the second question at the beginning of this section. Retail depositors seem to act rationally by relying on the overall financial stability situation in the country's banking sector by framing their trust to individual banks. This is because (as we show in Table 7) such industry-wide financial stability indicators act as reliable predictors of future bank failures.

Overall, the empirical results presented in Section 3 confirm the critical role of overall financial stability in the banking sector. It not only contributes to the likelihood of a bank failure, but also has an economically and statistically significant effect on households' trust and confidence in the financial stability of their individual banks. In other words, even if an individual bank's financial health does not seem to deteriorate, the poor financial health of the overall banking industry imposes downward pressure on public assessment of bank stability. Poor performance of a banking industry as whole undermines public trust in the performance of individual banks, even after controlling for the bank-specific risk characteristics.

[2] We also re-estimate all specifications in panels A and B of Table 7 with bank fixed effects and find virtually the same results for both measures of public confidence in a bank, as well as for all three financial stability proxies. We do not report these results for the sake of brevity, but they are available upon request.

Table 7 Public confidence, industry-level risk, and bank failure prediction

Panel A: Bank failures and PCB Rate

	Dependent variable					
	Fail in next 6 months			Fail in next 12 months		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PCBR	0.020	0.010	0.011	0.022	0.008	0.005
	(0.238)	(0.538)	(0.530)	(0.299)	(0.705)	(0.802)
Log (NPL to HHs)	0.125***			0.179***		
	(0.000)			(0.000)		
Log (N of failed banks)		0.047***			0.058***	
		(0.000)			(0.000)	
Log (N of depositors in failed banks			0.031***			0.038***
			(0.000)			(0.000)
E/A	-0.006**	-0.006**	-0.006**	-0.008**	-0.008***	-0.008***
	(0.029)	(0.022)	(0.024)	(0.010)	(0.007)	(0.007)
NPA/A	0.006*	0.006*	0.006*	0.008*	0.007*	0.008**
	(0.054)	(0.071)	(0.053)	(0.053)	(0.057)	(0.049)
HH Loans /A	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HH Deposits /A	-0.000	-0.000	-0.000	0.001	0.001	0.001
	(0.663)	(0.810)	(0.783)	(0.477)	(0.367)	(0.354)
Bank size	-0.034***	-0.033***	-0.033***	-0.047***	-0.046***	-0.045***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State-controlled	0.190*	0.187*	0.190*	0.189*	0.190*	0.191*
	(0.081)	(0.089)	(0.083)	(0.090)	(0.090)	(0.089)
Foreign-owned	-0.004	-0.008	-0.005	-0.000	-0.004	-0.004
	(0.898)	(0.761)	(0.849)	(0.998)	(0.905)	(0.912)
Intercept	yes	yes	yes	yes	yes	yes
No. of Obs.	9,408	9,408	9,408	8,471	8,471	8,471
No. of Banks	263	263	263	263	263	263
R-squared	0.099	0.086	0.085	0.136	0.113	0.108

Panel B: Bank failures and PCB Index

	Dependent variable					
	Fail in next 6 months			Fail in next 12 months		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PCBI	0.001	0.000	0.000	0.001	0.000	0.000
	(0.320)	(0.709)	(0.725)	(0.250)	(0.711)	(0.825)
Log (NPL to HHs)	0.125***			0.182***		
	(0.000)			(0.000)		
Log (N of failed banks)		0.046***			0.058***	
		(0.000)			(0.000)	
Log (N of depositors in failed banks)			0.031***			0.038***
			(0.000)			(0.000)
E/A	-0.006**	-0.006**	-0.006**	-0.008**	-0.008***	-0.008***
	(0.029)	(0.022)	(0.023)	(0.010)	(0.007)	(0.007)
NPA/A	0.006**	0.006*	0.006*	0.008**	0.007*	0.008**
	(0.050)	(0.069)	(0.051)	(0.046)	(0.053)	(0.046)
HH Loans /A	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
HH Deposits /A	-0.000	-0.000	-0.000	0.001	0.001	0.001
	(0.671)	(0.814)	(0.788)	(0.474)	(0.365)	(0.352)
Bank size	-0.035***	-0.033***	-0.033***	-0.048***	-0.046***	-0.045***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State-controlled	0.191*	0.187*	0.190*	0.192*	0.191*	0.191*
	(0.080)	(0.089)	(0.083)	(0.086)	(0.089)	(0.088)
Foreign-owned	-0.001	-0.007	-0.004	0.002	-0.003	-0.003
	(0.962)	(0.794)	(0.883)	(0.952)	(0.924)	(0.925)
Intercept	yes	yes	yes	yes	yes	yes
N of Obs.	9 408	9 408	9 408	8 471	8 471	8 471
N of Banks	263	263	263	263	263	263
R-squared	0.098	0.085	0.085	0.136	0.113	0.108

This table reports the estimated coefficients for the series of LPM regressions. The dependent variables are bank failure outcomes over 6- and 12-month periods. The explanatory variables of interest are two alternative measures of public confidence in a bank: Public Confidence in a Bank Rating (PCBR) in Panel A, and Public Confidence in a Bank Index (PCBI) in Panel B. The definition of the study variables is provided in Appendix 3. Standard errors are robust and bank-clustered; p-values are in parentheses; ***, ** and * indicate significance at the 1%, 5% and 10% levels.

4 Conclusions

This study is the first empirical attempt to connect public opinion-based measures of individual bank soundness and trustworthiness with underlying bank-level and industry-level measures of financial stability. We study these relationships in the Russian banking system, exploiting the recent massive wave of bank closures as an empirical laboratory for our analysis. Our key findings support the robust role of system-wide indicators of financial stability (such as cumulative number of failed banks, depositors affected by such failures and total bad debt in the sector) in framing the perceptions of retail customers about their own banks' soundness. Contrary to common belief, bank-level risk characteristics play only a marginal role in explaining public confidence in a bank. Collectively, these findings highlight the leading role of the overall financial sector's stability in framing public trust in banks. The policy implication is that it is not feasible to enhance public trust in a particular bank without first improving the financial stability of the whole banking sector.

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Appendices

Appendix 1 Computational approach of banki.ru in rating public confidence in a bank

The bank-specific rating of banki.ru is calculated as a Bayesian weighted average, an approach commonly applied in customer recommendation systems to increase the statistical precision of the mean estimate.[3] The Bayesian bank-specific rating is a weighted average of the raw bank rating and average bank rating, where the weight is a function of the number of reviews the bank has received and a minimum acceptable number of reviews:

$$Rating_{i,t} = \frac{R_{i,t} \times v_{i,t} + C_t \times m}{v_{i,t} + m} , \tag{1}$$

where v is the number of approved reviews, C is an average score across all banks, m is a scalar for statistical correction (this is usually set to 10, based on a 99% Bayesian credible interval for a 5-scale rating system), and R is the mean score adjusted for time effect, defined as:

$$R_{i,t} = \frac{\sum_{i=1}^{N} Y_i \times k_i^t(X_i)}{\sum_{i=1}^{N} k_i^t(X_i)} , \tag{2}$$

where Y is the score set by the user and k is an exponential decay function. The exponential decay incorporates the time interval since the score is given by placing more weight on recently set scores. The decay function thus explicitly accounts for the assumption that older scores convey less relevant information to current bank customers. Specifically, the decay function takes the form:

$$k_i^t(X_i) = \begin{cases} k_t = 1.106 \times e^{-.001697Xi}, \text{when } X_i > 90 \text{ days} \\ k_t = 1, \text{when } X_i \leq 90 \text{ days} \end{cases} , \tag{3}$$

where X_i is the number of days since the score was given and -.001697 is the rate of information decay. The decay function has a half-life measure of 1.28 years, which means that scores set more than (less than) 15 months ago receive less than (more than) 50% weight. The final value of the rating is linearly transferred into a 100-point scale and re-calculated every 24 hours. To be included in the rating, banks need to have at least one approved review within the past 365 days. Given that banki.ru maintains review records of all banks, including failed ones, the rating is also free of survivorship bias.

As can be noted from Equation 1, the index is corrected for the average score across all banks – *"C"*. This correction pulls down the rating of an individual bank with low number of reviews, meaning that a bank with 10 excellent grades would have a lower rating than a bank with 100 excellent grades, given that the population average is below the maximum grade. Although this correction improves the statistical precision of the rating estimate, it also links bank-specific reviews with industry average and yields in a sector-weighted index. In order to eliminate the industry average effects, we rely on a simpler measure based on simple average grades across all reviews for each bank. This measure ranges from one to five and does not take into account industry averages but accounts for time effects as in Equation (2). Therefore, we introduce two new measures of public confidence in banks: the "Public Confidence in Bank Index" (PCBI), calculated as Bayesian weighted average, and the "Public Confidence in Bank Rate" (PCBR), calculated as a simple average of reviewers' grades.

[3] The Bayesian average rating is used by e.g. Amazon, Internet Movie Database and Google in ranking products on the basis of customer reviews.

Appendix 2 Development of public confidence in banks measures over time

Panel A

Date	Mean PCBI	Mean PCBR	Number of banks with rating	Total number of banks in the system	% of banks with rating	% of banking assets with rating
1.1.2010	46.12	2.96	93	1 058	8.79 %	70.88 %
1.1.2011	46.92	2.89	110	1 012	10.87 %	72.71 %
1.1.2012	46.35	2.80	110	978	11.25 %	73.32 %
1.1.2013	44.99	2.75	126	956	13.18 %	75.20 %
1.1.2014	43.19	2.69	158	923	17.12 %	87.70 %
1.1.2015	41.21	2.58	137	834	16.43 %	87.39 %
1.1.2016	39.69	2.49	127	733	17.33 %	87.55 %
1.1.2017	35.41	2.30	110	623	17.66 %	86.54 %

Panel B

Date	Number of approved reviews per year			Cumulative number of approved reviews		
	Mean	Min	Max	Mean	Min	Max
1.1.2010	40.12	5	307	156.05	5	1 108
1.1.2011	53.71	5	728	184.56	5	1 660
1.1.2012	78.38	5	1629	258.60	5	3 286
1.1.2013	91.79	5	2 544	315.15	5	5 822
1.1.2014	103.63	5	3 802	353.89	5	9 642
1.1.2015	130.34	5	3 660	533.00	9	13 292
1.1.2016	138.09	5	3 756	680.87	5	17 095
1.1.2017	192.30	5	5 377	965.55	9	22 641

Appendix 3 Definition of variables

All data are monthly and cover 1/1/2010 to 1/1/2017 period.
Bank failure outcomes are traced to 1/1/2018.

Variable	Definition	Data source
Public confidence in a bank		
PCBI	Public Confidence of Bank Index (see Appendix 1 for details)	www.banki.ru
PCBR	Public Confidence of Bank Rate (see Appendix 1 for details)	
Other bank-level characteristics (bank risk and business model)		
Bank failed in 6 months (or in 12 months)	= 1 if a bank failed within the next 6 (or 12) months, zero otherwise Bank failure event defined as forced license revocation or putting bank into regulator-assisted receivership process	Central Bank of Russia periodic press-releases database
E/A	Book equity to total assets ratio, in %	Monthly financial statements (Form 101 reported by banks to the Central Bank of Russia)
NPA/A	Nonperforming assets to total assets ratio, in %	
HH Loans / A	Loans to households to total assets ratio, in %	
HH Dep. / A	Household deposits to total assets ratio, in % Household deposits partially insured in Russia	
Bank size	Ln (Total assets in ruble thousands)	
State-controlled	= 1 if majority of a bank is controlled by federal or local government authority, directly or indirectly, as of the end of each sample month, zero otherwise	Hand-collected
Foreign-controlled	= 1 if majority of a bank is controlled by a foreign entity, directly or indirectly, as of the end of each sample month, zero otherwise	
Industry-level financial stability		
Log (NPL to HHs)	Ln (Total Nonperforming Loans to Households in the Russian banking sector, as of the end of each month)	Central Bank of Russia monthly summary statistics on the financial sector stability
Log (N of failed banks)	Ln (Total number of failed banks in the most recent six months)	Calculated from the Central Bank of Russia press-releases on individual bank failure events
Log (N of depositors in failed banks)	Ln (Total number of retail depositors, in thousands, in banks that failed in the most recent six months)	Calculated from Russian Deposit Insurance Agency disclosures on insured cases of bank failures

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