BOFIT Discussion Papers
16 • 2017

Mikko Mäkinen and Laura Solanko

Determinants of bank closures: Do changes of CAMEL variables matter?

THE BANK OF FINLAND INSTITUTE FOR ECONOMIES IN TRANSITION

BOFIT Discussion Papers
Editor-in-Chief Zuzana Fungáčová

BOFIT Discussion Papers 16/2017
30.10.2017

Mikko Mäkinen and Laura Solanko: Determinants of bank closures: Do changes of CAMEL variables matter?

ISBN 978-952-323-195-5, online
ISSN 1456-5889, online

Suomen Pankki
Helsinki 2017

Contents

Mikko Mäkinen and Laura Solanko

Determinants of bank closures: Do changes of CAMEL variables matter?

Abstract

This study examines whether changes in CAMEL variables matter in explaining bank closure. Using a unique set of monthly bank-specific balance sheet data from Russia, we estimate determinants of bank license withdrawals during 2013m7-2017m7. We make two key findings. First, changes in CAMEL indicators are always significantly correlated with probability of bank closure, and the magnitude of parameter estimates decreases with the lag length. Second, while the one-month lagged levels of capital, earnings, and liquidity are significantly associated with the probability of bank closure in the subsequent month, the level of liquidity is the only significant indicator for longer lags. Our key contribution that changes in CAMEL variables matter more than levels is robust to various robustness checks.

JEL Codes: G01, G21, G32, G34.
Keywords: bank closure, bank failure, Russia, CAMEL indicators.

Mikko Mäkinen, orcid.org/0000-0001-5898-5277. BOFIT, Bank of Finland, Helsinki, Finland.
E-mail: mikko.makinen@bof.fi.

Laura Solanko, orcid.org/0000-0002-7245-0217. BOFIT, Bank of Finland, Helsinki, Finland.
E-mail: laura.solanko@bof.fi.

Acknowledgements: The authors would like to thank Jeff Downing and the participants at research seminars at BOFIT and OeNB, the WGCE-2017, and 7th Annual CInSt Banking Workshop for useful comments.

1 Introduction

Assessments of the financial soundness of banks largely relies on publicly available accounting data. Large banks typically release their balance sheet information at quarterly intervals, but smaller banks may only publish annual reports. Relying on such data, the literature on bank failures tends to focus on how levels in the CAMEL indicators (i.e. capital adequacy, asset quality, management quality, earnings and liquidity) relate to bank failure probabilities.[1]

As the CAMEL system emerged from the US, early studies on individual bank failures focus primarily on the US experience (e.g. Cole and Gunther, 1995).[2] With increased adoption of CAMEL supervisory indicators, cross-country studies of the associations between a wide variety of bank accounting variables and indicators and bank default probabilities has emerged (see e.g. Arena (2008) for Latin America and Poghosyan and Cihak (2011) for Europe). The 2008 global financial crisis renewed interest in the drivers of bank failures, especially in the US (e.g. DeYoung and Torna, 2013; Mayes and Stremmel, 2014; Vazquez and Federico, 2015). At the risk of oversimplifying, these studies suggest that lagged levels of capital adequacy, earnings, and liquidity are negatively associated with bank failure, while asset quality is positively associated. More broadly, these studies support the validity of CAMEL indicators in levels in explaining bank failure.[3]

To the best of our knowledge, however, no study yet has systemically analyzed whether changes of CAMEL indicators matter in explaining bank closure. This is rather surprising as in the economic literature interest often focuses on how a change in a covariate is related to a change in an outcome variable.[4] Similarly, financial analysts, in assessing company performance, often focus on changes in accounting indicators rather than levels. This study aims to fill this gap in the literature on bank closures.[5]

A unique panel data set from Russia is particularly well-suited for an analysis of determinants of bank failure. First, we can rely on monthly balance sheet data on all credit institutions that

[1] Supervisors may possess confidential information on bank performance in advance of its closure, while other stakeholders have to rely on publicly available accounting information in forming their expectations of bank financial soundness.
[2] The CAMEL system evolved out of the US Federal Reserve's 1979 recommendation on adoption of a Uniform Financial Institutions Rating System. In the following decades, the CAMEL system gained global acceptance. The Fed added a sixth criterion, sensitivity to market risk, in 1995. Hence, the acronym CAMELS is also used.
[3] For a review, see Mayes and Stremmel (2014).
[4] For example, CEO compensation literature (e.g. Jensen and Murphy, 1990; Hall and Liebman, 1998; Mäkinen, 2008) studies how a change in CEO compensation is associated with a change in company performance. In public economics, a central tax policy parameter is the overall elasticity of taxable income (e.g. Gruber and Saez, 2002).
[5] We use the terms *bank closure* and *bank failure* interchangeably. Both refer to revocation of a bank's license by the Central Bank of Russia.

is regularly published by the Central Bank of Russia (CBR). More importantly, these monthly data, which cover almost the entire banking sector, allow us to examine month-on-month changes in CAMEL indicators as determinants of bank closure. Second, while the number of operating banks has gradually declined since late 1990s, the pace of bank closures has been stepped up significantly since the CBR's current governor, Elvira Nabiullina, took office in June 2013. During our sample period (July 2013–July 2017), the number of operating credit institutions decreased by almost 40 %, standing at just 582 at the end of July 2017.

Our work contributes to bank failure literature in two ways. First, quarterly accounting data, typically used in previous studies, may not accurately reflect a bank's financial problems prior to its closure. Monthly balance sheet information, however, allows us to examine deterioration in bank performance just prior to its closure. Second, monthly data allow us to compare the accuracy of levels of standard accounting measures and their changes in explaining bank closure. To the best of our knowledge, this question has not been analyzed previously in the bank failure literature.

Regarding *levels of CAMEL indicators*, we find that higher levels of capital, earnings, and liquidity one month prior to bank closure are associated with a lower the probability of bank failure in the subsequent month. Asset quality (as proxied by loan losses) is positively associated with probability of bank failure. For longer lags of capital, earnings and asset quality in levels, we find an insignificant association with bank closure. This implies that the levels of CAMEL indicators just prior to closure are more important than longer lags of levels in explaining closure. Liquidity in levels, however, remains consistently highly significant with longer lags. Although the magnitude of liquidity estimates decreases the longer the time lag, this finding suggests that liquidity has a relatively "long memory" in affecting bank closure.

Concerning *changes in CAMEL indicators*, we consistently find that changes in capital, earnings, and liquidity are negatively, while changes in asset quality are positively associated with bank failure and highly significant. In contrast to CAMEL indicators in levels, longer lags of changes are consistently highly significant, although the magnitude of the estimates decreases rather monotonically over time. As earlier, this indicates that changes in CAMEL indicators just prior to closure are more important than longer lags of changes in explaining closure. Overall, our findings are consistent with the view that changes in CAMEL indicators are more important drivers of bank closure than CAMEL indicators in levels.

The rest of the paper is organized as follows. Section 2 provides a brief description of the recent developments in the Russian banking sector and banking supervision in the 2010s. The data and empirical methods are discussed in section 3. Section 4 reports our key findings. Section 5 concludes.

2 Evolution of the Russian banking industry and bank supervision since 2010

The Russian banking sector experienced rapid growth in the early 2000s, supported in part by the introduction of a deposit insurance scheme in 2004 and subsequent increase in market discipline (Karas, Pyle, and Schoors, 2013). In contrast to most European transition economies, the Russian banking system evolved into a dual system consisting of a few large state-owned banks and initially thousands of small, private banks. This led to an extremely fragmented banking industry. Some tiny establishments survived largely on their contacts with a single enterprise and the relative opaqueness of banking supervision.

Notably, the Russian banking sector emerged from the global financial crisis largely untouched. Russian banks had very little exposure to subprime mortgages or troubled US and EU banks. The sudden drop in oil prices and the subsequent fall in stock prices and the ruble, however, increased the amount of non-performing loans and lowered bank profits. Central bank funding, the dominant role of state-owned banks, and relatively low leverage ratios helped the banking sector through the 2009–2010 economic recession.[6]

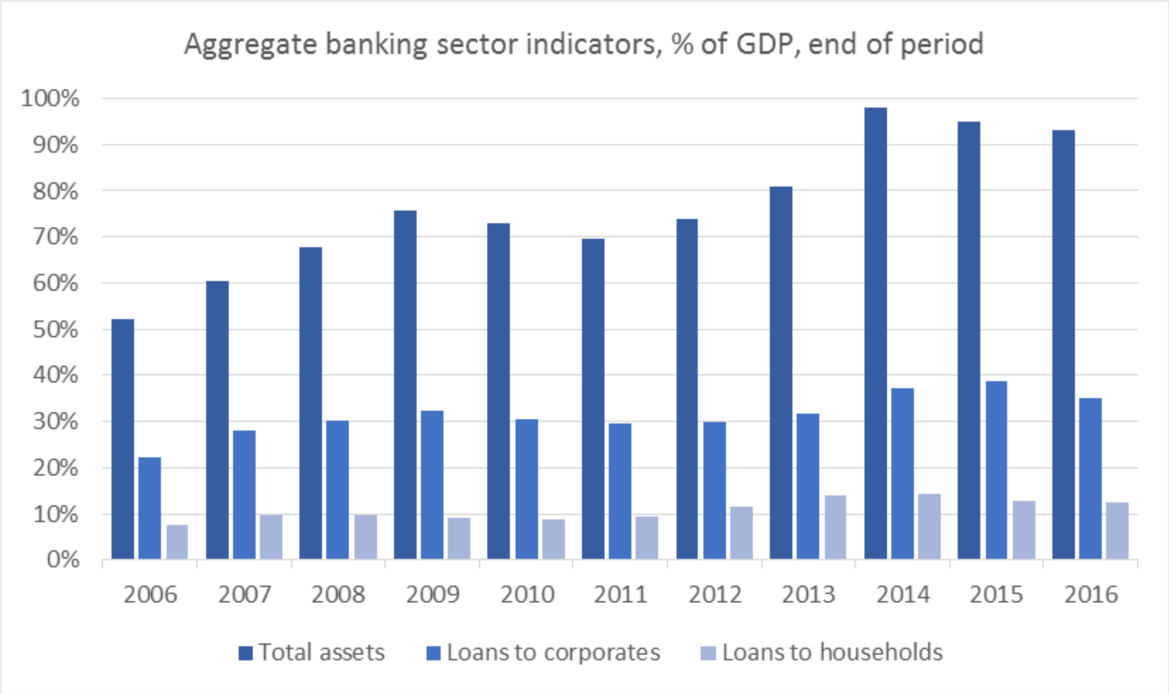
Positive economic growth resumed in 2011 and consumer lending boomed. Relative to GDP, banking sector assets surpassed the pre-crisis (2009) level already in 2013.

Significant changes have swept through the Russian banking industry more recently. Financial market supervision changed markedly after June 2013 when Elvira Nabiullina replaced long-serving Sergei Ignatiev as CBR governor. The CBR also became a single *megaregulator*, supervising banks and other credit institutions, as well as insurance companies, pension funds, stock market actors, microlenders, and even pawn shops. This has improved overall supervision and enabled the CBR to undertake a significant and determined policy of rooting out sketchier market participants. Over 300 credit institutions have lost their licenses and been forced to liquidate or restructure since summer 2013. Most of the failed banks have been tiny, but a nontrivial number of top-100 banks have also lost their licenses. In many instances, the cause for pulling of a bank's license

[6] See Fungacova and Solanko (2009) on the role of the state-owned banks before the crisis. For their role during the crisis, see Fungacova, Herrala, and Weill (2013).

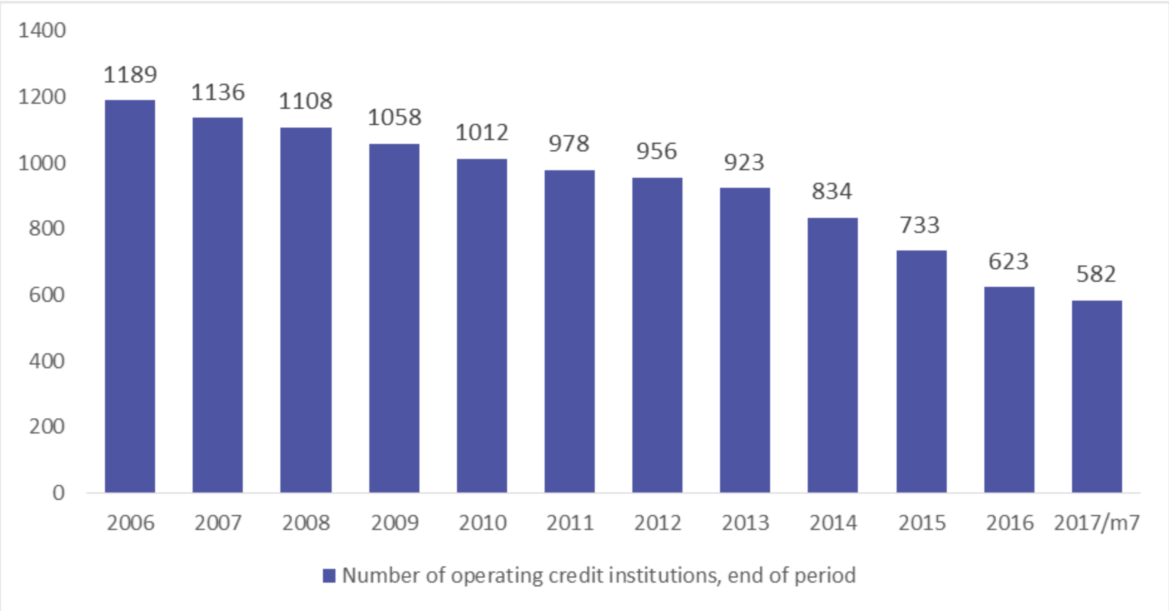
has involved breaches of money-laundering regulations or other criminal activity. Forensic audits of failed banks almost universally reveal serious flaws in bank accounting information (see e.g. Mamonov, 2017).

Figure 1 Russian banking sector: total assets and total loans in relation to GDP



Source: CBR and Rosstat via CEIC, calculations BOFIT.

Figure 2 Number of credit institutions operating in the Russian banking sector



Source: CBR and CEIC, calculations BOFIT.

A number of scholars have analyzed bank failures in Russia, but most published work is based on data from the years before 2009. For example, Fungacova and Weill (2013) study the effect of bank competition on probability of bank failure in Russia using quarterly data for the period of rapid economic growth of 1Q2000–1Q2007. They conclude that bank size and a bank-specific measure of competition (Lerner index) have a negative effect on failure probability. Funagcova, Turk, and Weill (2015) examine the effect of high liquidity creation on bank failures in Russia using quarterly data for 2000–2007. They find that excessive liquidity creation significantly increases failure probability, whereas bank size and ROA have expected negative signs. Clayes and Schoors (2007) document bank license withdrawals after Russia's 1998 financial crisis (1999–2002). They find that macro-prudential concerns are significant in banking supervision. Using monthly data from November 1995 to August 2003 to examine bank failure in Russia, Lanine and Vander Vennet (2006) reveal that most standard accounting variables have expected signs in explaining bank failures. Peresetsky, Karminsky, and Golovan (2011) use data for 1997–2003 to estimate binary choice models of bank defaults after 1998 financial crisis. Karminsky and Kostrov (2014) extend the analysis for 1998–2011.

The study of Fidrmuc and Suss (2011) is particularly relevant to the current study. Identifying 47 banks that failed in the immediate wake of the 2008 global financial crisis, they find that balance sheet information from as early as 2006 was informative in predicting bank failures. Notably, their sample was derived from the Bankscope database, which only includes annual data for Russia's largest commercial banks.

3 Data and empirical approach

3.1 Data

Our monthly bank-level panel data come from the Central Bank of Russia. Under Russian legislation, all operating credit institutions are required to submit their monthly balance sheet information to the bank supervision authority unit of the CBR. Nearly all banks have consented to the CBR's release of this data with a one-month lag (e.g. data for June 2017 would become publicly available in July or early August 2017). The data contain detailed monthly balance sheet information, something quite exceptional in bank failure literature.

We combine this data with information on exact date of bank license withdrawals. Compared to existing bank failure studies, our data include an extraordinary high number of bank closures. Due to a potential regime change in the CBR's bank license revocation policy in June 2013, we restrict our analysis to the period from July 2013 (2013m7) to July 2017 (2017m7).

We construct our estimable sample as follows. First, we exclude the six largest state-controlled banks[7] because the failure risk for them is likely to be marginal compared to other ownership forms of banks in Russia. Similarly, we drop the largest foreign-owned banks. These banks differ in many respects from other private banks in Russia.[8] To deal with potential extreme values in our covariates, we winsorize (replace) the continuous explanatory variables at the 1 % and 99 % levels. We also excluded observations for any bank where the ratio of customer total loans to total assets or the ratio of customer deposits to total assets was less than 1 %. We also require at least five consecutive observations for any bank to be included in the sample.

Our final sample consists of over 31,000 bank-month observations. This corresponds to 818 credit institutions, of which 290 (about 35 %) failed during our sample period.

3.2 Dependent and independent variables

Our dependent variable is a dummy variable (0/1), which equals one if the CBR revokes a bank's license in a given month, and zero otherwise. Following bank failure literature, we use the standard CAMEL indicators as explanatory variables: *capital*, *asset quality*, *earnings*, and *liquidity*.[9]

Capital denotes a bank's own equity, calculated as the sum of statutory capital, surplus capital, current and past retained earnings, and other capital. Our assumption is that higher capital reserves improve a bank's ability to tolerate financial losses. Thus, we expect capital ratio to be negatively related to the probability of bank failure. We measure capital as the ratio of capital to total assets (%).

Asset quality is proxied by the ratio of total loan losses to total assets (%). A bank's total loan losses is measured as the sum of credit losses and overdue loans in a given month. We include overdue loans to total loan losses because lax accounting standards or other reasons may allow

[7] These are Sberbank, VTB, VTB24, Gazprombank, Rosselkhozbank, and Bank Moskvi.
[8] For the purpose of this study, the largest foreign-owned banks in Russia are Unicredit, Reiffeissen, City, Rosbank and Nordea.
[9] Unfortunately, our data do not contain information on the M measure (management competence and expertise). As the monthly data does not include income statement data, cost-to-income ratios cannot be used as a proxy. Given the relatively short time-span of our sample, we argue that management quality remains time-invariant during the sample period.

financially troubled banks to delay reporting of losses from their overdue loans. We expect that higher total loan losses are positively related to bank failure.

Earnings is a bank's return on assets (%). It implies how well a bank's business model is working from a financial standpoint. We proxy earnings by a bank's current profits. Our assumption here is that a strong financial performance decreases probability of failure, and vice versa.

Liquidity include cash and other assets that the bank should be able to convert into cash quickly. These include e.g. investments in stocks, bonds, and promissory notes, as well as the accounts at the CBR and other banks. We assume that bank failure is negatively associated with liquidity. We measure the magnitude of liquidity by the ratio of liquid assets to total assets (%).

Consistent with previous studies on bank failure (e.g. Cole and White, 2012; Fungacova and Weill, 2013), we control for *bank size*. We also control for the degree by which a bank engages in traditional banking business by *lending activity* and *customer deposits*.

The magnitude of lending activity describes the importance of traditional lending businesses for the bank, captured by the ratio of total customer loans to total assets (%). Depending on the quality of borrowers in the bank's loan portfolio, lending activity can be positively or negatively related to bank failure. In the case of Russia, the sign of lending activity is somewhat ambiguous. A bank's total loans include government bonds that can be easily sold in a liquidity shortage. Moreover, because lending activity is rather underdeveloped in transition economies, the share of lending activities is marginal compared to other bank activities (Männasoo and Mayes, 2009).

The size of customer deposits is captured by the ratio of a bank's customer total deposits to total assets (%). It measures an importance of deposits in a bank's funding base.[10]

We also control for bank size, which may bear upon likelihood of failure. This would include such policy-design issues as the "too big to fail" problem. Bank size is measured as the logarithm of total assets.

Table 1a presents descriptive statistics for the full sample and Table 1b for failed and non-failed banks separately. Table 1b shows that, on average, there are significant differences between these two groups. Failed banks have significantly lower earnings and liquidity ratios than non-failed banks. Somewhat counter-intuitively, the failed banks on average had lower loan losses (i.e. better asset quality) than non-failed ones. This may be partly due to the fact that banks that run into troubles typically had been remarkably slow to recognize their bad loans. Failed banks also have slightly lower capital ratios than non-failed banks (although the difference is statistically insignificant).

[10] The deposit insurance system was established in Russia in 2004.

Likewise, failed banks are somewhat smaller, have higher deposits ratios and lower loans ratios than non-failed banks. These ratios are all statistically significant.

Finally, we include a dummy variable to control for the fact that about half of the banks in our sample are located in Moscow region. This variable equals one if the bank's head office is in the Moscow area, and zero otherwise. Table1b shows that the share of failed banks is significantly greater in the Moscow area.

Table 1a Summary statistics

	(1) Mean	(2) Standard deviation	(3) Min	(4) Max
Capital (equity to total assets, %)	19.30	13.69	3.77	89.71
Asset Quality (total loan losses to total assets, %)	7.67	9.27	0	59.83
Earnings/ROA (current profits total assets, %)	0.04	0.75	-3.31	3.34
Liquidity (liquid assets to total assets, %)	26.67	16.80	2.36	98.10
Loans (customer loans to total assets, %)	63.97	17.39	1.00	95.19
Deposits (customer deposits to total assets, %)	47.86	20.07	1.04	82.41
Size (*log*(total assets))	15.71	1.68	10.43	19.80
Moscow *(=1* if Moscow, 0 otherwise*)*	0.49	0.50	0	1

Source: CBR; authors' calculations. Sample excludes large state-controlled banks and large foreign-owned banks. Our sample contains a total of 818 banks and 31,272 bank-month observations.

Table 1b Summary statistics for failed and non-failed banks

	(1) Failed banks		(2) Non-failed banks		(3) Failed vs. non-failed banks: test on the equality of sample means (*p*-values) with unequal variances
	Mean	SD	Mean	SD	
Capital (equity to total assets, %)	19.20	15.41	19.34	13.09	0.49
Asset Quality (total loan losses to total assets, %)	6.63	8.16	8.00	9.57	0.00 ***
ROA (current profits total assets, %)	-0.01	0.97	0.06	0.67	0.00 ***
Liquidity (liquid assets to total assets, %)	26.14	16.38	26.85	16.92	0.00 ***
Loans (customer loans to total assets, %)	63.39	17.58	64.16	17.32	0.00 ***
Deposits (customer deposits to total assets, %)	49.61	20.36	47.30	19.94	0.00 ***
Size (*log*(total assets))	15.26	1.46	15.86	1.72	0.00 ***
Moscow (0/1)	0.61	0.49	0.46	0.50	0.00 ***
# Banks	290		528		
# Observations	7,637		23,635		

Source: The Bank of Russia; authors' calculations. Sample excludes large state-controlled banks and large foreign owned-banks. Significance levels: * 10 %; ** 5 %; *** 1 %, respectively.

3.3 Empirical approach

Previous related Russian bank failure studies typically apply the random-effects panel logit estimator (e.g. Claeys and Schoors, 2007; Lanine and Vander Vennet, 2006; Fungáčová and Weill, 2013). For our relatively short observation period, however, the linear probability model with bank fixed effects provides a more suitable modeling approach for bank failures.

First, as we have repeated observations of individual banks over several months, controlling for unobserved time-invariant bank heterogeneity is crucial. A random-effects panel logit model would assume that individual bank effects (c_i) are uncorrelated with included explanatory variables. In our view, this is a rather bold, unrealistic assumption.

Second, most banks in our sample do not fail in the period. Applying the pooled logit estimator, the estimator would drop all non-failed banks from the estimable sample, substantially reducing the number of observations and likely make our parameter estimates less reliable.

Third, an alternative to the panel logit estimator, the complementarity panel log-log estimator that is often used when one of the binary outcomes is rare relative to the other. Unfortunately, using the complementarity panel log-log estimator would again impose the random-effects assumption, which, as said earlier, appears implausible in our case. A further reason not to apply the complementarity panel log-log model is that we focus here on the *magnitude* of the marginal effects of CAMEL variables on the conditional probability of bank failure. In the complementarity panel log-log model, these average marginal effects are calculated based on the linear probability model without individual bank effects.

Fourth, we prefer the linear probability model over a pooled binary response model with fixed effects to avoid the incidental parameter problem as a result of including a large number of fixed effects. Hence, we model bank failure using the linear probability model with bank fixed effects (least-square dummy variable model), employing CAMEL explanatory variables both in levels and in changes.[11]

To deal with potential endogeneity concerns in our baseline models, we use one-month lagged explanatory variables. Because one-month lagged accounting variables are missing for some banks close to the time of their closure, we also apply the 2-, 3-, 6-, 9-, and 12-month lagged values of explanatory variables. This allows us to examine whether the information contained in the 2-, 3-, 6-, 9-, and 12-month lagged accounting information is useful in explaining the incidence of bank failure in subsequent period *t*.

We first estimate the following baseline linear probability model with the levels of lagged explanatory variables:

$$P(FAILURE_{i,t} = 1) = F(X,\beta) = \beta_0 + \beta_1 CAPITAL_{i,t-m} + \beta_2 ASSETQUALITY_{i,t-m} + \beta_3 EARNINGS_{i,t-m} + \beta_4 LIQUIDITY_{i,t-m} + +\beta_5 TOTLOANS_{i,t-m} + \beta_6 TOTDEPOSITS_{i,t-m} + \beta_7 \log\left(SIZE_{i,t-m}\right) + \beta_8 MOSCOW_i + \beta_9 MONTH_{FE_t} + \beta_{10} BANK_{FE_i} + \varepsilon_{i,t}, \quad (1)$$

where m = 1, 2, 3, 6, 9, or 12. In Eq. (1) the dependent variable $FAILURE_{i,t}$ takes a value of one if a bank fails in month t, and zero otherwise. $CAPITAL_{i,t-m}$ is the ratio of a bank's equity to total assets

[11] We recognize that the least-square dummy variable model imposes a linear link function. However, we are interested in the average marginal effects of the explanatory variables on the probability of bank failure, not in forecasting a bank failure in the subsequent month. Note that the linear probability model has been used in other fields in economics. For example, the study of Kugler and Pica (2008) uses the model for worker and job flows, Bernard and Jensen (2004) for firm entry into exporting, Friedman and Schady (2013) for infant mortality, and Frame (2017) for regulatory arbitrage.

(%), $ASSETQUALITY_{i,t\text{-}m}$ is the ratio of a bank's total loan losses to total assets (%).[12] $EARNINGS_{i,t\text{-}m}$ is a bank's return on assets (%; proxied by current profits). $LIQUIDITY_{i,t\text{-}m}$ is the ratio of a bank's liquid assets to total assets (%). $TOTLOANS_{i,t\text{-}m}$ is the ratio of a bank's customer total loans to total assets (%). $TOTDEPOSITS_{i,t\text{-}m}$ the ratio of a bank's customer total deposits to total assets (%). $SIZE_{i,t\text{-}m}$ is measured by the logarithm of a bank's total assets. We also include time (month) fixed effects into Eq. (1) to control for time-effects that are common to all banks. Likewise, we include bank fixed effects to control for unobserved time-invariant heterogeneity across banks (such as management quality). Subscript *m* refers to a monthly lag. The Moscow dummy variable equals one if the bank's head office is located in the Moscow region, and zero otherwise[13]. We estimate Eq. (1) using 1-, 2-, 3-, 6-, 9- and 12-month lagged levels of accounting information.

In our second baseline linear probability model specification, we focus on the changes in accounting information prior to bank closure. As earlier, we use lagged changes of explanatory variables. Further, we measure changes between a month prior to bank default event (i.e. *t*-1) and 2, 4, 7, 10, and 13 months before *t*-1:

$$
\begin{aligned}
&P(FAILURE_{i,t} = 1) = F(\Delta X, \beta) = \beta_0 + \beta_1 \Delta CAPITAL_{i,(t-1)-(t-m)} + \\
&\beta_2 \Delta ASSETQUALITY_{i,(t-1)-(t-m)} + \ \beta_3 \Delta EARNINGS_{i,(t-1)-(t-m)} + \\
&\beta_4 \Delta LIQUIDITY_{i,(t-1)-(t-m)} + + \beta_5 \Delta TOTLOANS_{i,(t-1)-(t-m)} + \\
&\beta_6 \Delta TOTDEPOSITS_{i,(t-1)-(t-m)} + \beta_7 \Delta \log\left(SIZE_{i,(t-1)-(t-m)}\right) + \beta_8 MOSCOW_i + \\
&\beta_9 MONTH_{FE_t} + \ \beta_{10} BANK_{FE_i} + \ \varepsilon_{i,t}, \qquad (2)
\end{aligned}
$$

where m = 2, 4, 7, 10, and 13. The definitions of the variables used are similar to those used in Eq. (1).

4 Empirical results

4.1 Baseline results

Table 2a reports the estimates for the determinants of bank closure using Eq. (1), i.e. lagged levels of explanatory variables. In column (1) we use the one-month lagged explanatory variables prior to bank closure. Concerning CAMEL indicators, capital, earnings, and liquidity all are significant and

[12] A bank's total loan losses is measured as the sum of credit losses and overdue loans in *t* – *m*.
[13] Even though variation is not very large, there is a nontrivial number of banks that do change the location of their head office in the data.

negatively associated with bank failure in the subsequent month. Asset quality (as proxied by loan losses) is positively associated with probability of bank failure. The parameter estimate for capital is -0.001, which suggests that a 1 percentage point (pp) increase in capital ratio in *t*-1 is associated with a roughly 0.1 pp decrease in probability of bank closure in *t*. Similarly, a 1 pp increase in liquidity in *t*-1 is associated with about 0.5 pp decrease in bank closure in *t*. For earnings, a 1 pp increase in *t*-1 is associated with about 1.5 pp decrease in bank closure in *t*. For other covariates, column (1) suggests that bank size and total loans (proxy for lending activity) are significantly negatively associated with bank closure. For bank size, this finding indicates that larger banks tolerate financial troubles better than smaller banks. The finding total loans may reflect the fact that bank total loans portfolio also include government bonds that can be easily sold in a liquidity shortage.

We use longer lags of CAMEL variables in columns (2) to (6). Unlike in column (1), we consistently find that capital and asset quality are insignificant. In column (2) earnings is significant (-0.005) at 1% level, but thereafter clearly insignificant. Importantly, we continue to find that *liquidity is negatively significant*, implying liquidity has a relatively "long memory" in affecting the probability of bank closure. However, the magnitudes of estimates for liquidity decreases the longer the time lag. For example, the estimate for the 12-month lagged value of liquidity (-0.0004) is about one-third of the size of the 1-month lagged liquidity estimate (-0.0011). Concerning other covariates in columns (2) to (12), the lagged values of total loans are negatively related to bank closure up to the 9-month lag. For bank size, the 6-, 9-, and 12-month lagged size is positively associated with bank closure.

The finding that *only* one-month lagged levels are significant is interesting in its own right. Balance sheet data are published with a lag of one month, so if a bank loses its license in, say, June, its May data would become available in late June when market participants already know the bank has failed. Why then is the last-published data only significant in levels? Unfortunately, our data does not allow us to draw any definite answers. It could be in that many failed banks earlier inflated their assets to appear in better shape, but, as closure becomes increasingly evident, bank management and owners abandon this practice.

Table 2a Determinants of bank failure: the lagged levels of explanatory variables

DV: *Bank Faiure$_t$=1*	Monthly lag					
	1 month (m=1) (1)	2 months (m=2) (2)	3 months (m=3) (3)	6 months (m=6) (4)	9 months (m=9) (5)	12 months (m=12) (6)
CAMEL indicators						
Capital$_{t-m}$	–0.0010 *** (0.0003)	–0.0004 (0.0002)	–0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0002 (0.0002)
Asset Quality$_{t-m}$	0.0005 *** (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)	–0.0001 (0.0001)	0.0002 (0.0002)	0.0000 (0.0001)
Earnings$_{t-m}$	–0.0150 *** (0.0018)	–0.0050 *** (0.0014)	–0.0012 (0.0013)	–0.0008 (0.0011)	–0.0001 (0.0001)	0.0012 (0.0010)
Liquidity$_{t-m}$	–0.0011 *** (0.0003)	–0.0010 *** (0.0002)	–0.0009 *** (0.0002)	–0.0008 *** (0.0002)	–0.0005 ** (0.0002)	–0.0004 ** (0.0002)
Other variables						
Loans$_{t-m}$	–0.0007 ** (0.0003)	–0.0007 *** (0.0002)	–0.0006 *** (0.0002)	–0.0006 *** (0.0002)	–0.0003 * (0.0002)	–0.0003 (0.0002)
Deposits$_{t-m}$	0.0001 (0.0001)	0.0002 ** (0.0001)	0.0003 ** (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
log(Size$_{t-m}$)	–0.0161 *** (0.0056)	–0.0045 (0.0044)	0.0004 (0.0040)	0.0090 ** (0.0041)	0.0109 *** (0.0038)	0.0085 ** (0.0034)
Moscow dummy (0/1)	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Banks	818	818	818	814	812	811
# Observations	31,272	31,259	31,243	31,193	31,145	31,098
R-squared	0.102	0.084	0.084	0.080	0.079	0.079

Notes: The dependent dummy variable equals one if the bank has its license revoked by the CBR in month t, and zero otherwise. Standard errors in parentheses are adjusted for clustering at bank level. Significance levels: * 10 %; ** 5 %; *** 1 %, respectively. The models also include a constant term, bank fixed effects and time (month) fixed effects. At least five consecutive observations are required for a bank to be included in the sample. Definitions of variables are reported in Table 1.

Table 2b represents the estimation results for Eq. (2), i.e. lagged changes in explanatory variables). For CAMEL indicators in columns (1) to (6), we consistently find that changes in capital, earnings, and liquidity are negatively associated with bank failure, while changes in asset quality (bad loans) are positively associated and highly significant. For example, we see in in column (1) that a 1 pp increase in $\Delta\text{capital}_{t\text{-}1,t\text{-}2}$ (= $\text{capital}_{t\text{-}1}$ - $\text{capital}_{t\text{-}2}$) is associated with a roughly 0.4 pp decrease in bank closure in *t*. Similarly, a 1 pp increase in $\Delta\text{liquidity}_{t\text{-}1,t\text{-}2}$ is associated with 0.1 pp decrease in closure, while a 1 pp increase in $\Delta\text{asset quality}_{t\text{-}1,t\text{-}2}$ is associated with a 0.2 pp increase in closure in *t*. The estimate of $\Delta\text{earnings}_{t\text{-}1,t\text{-}2}$ is -0.0028, implying a 1 pp increase in Δearnings is associated with a decrease of about 0.3 pp in closure. In columns (2) to (6), when the lag length increases from *t*-1, the magnitude of the parameter estimates of CAMEL indicators decreases rather monotonically. This suggests that changes in CAMEL indicators just prior to bank closure are more important than longer lags of changes in explaining bank closure. More importantly, compared to Table 2a, changes in CAMEL indicators seem to be much more central than the levels of these indicators in explaining bank closure. For other explanatory variables in columns (1) to (6), we shortly note that changes in bank size are consistently negatively related to bank closure, while deposits are negatively significant up to the 3-month lag (column 3). The estimates of loans are consistently negative but significant in columns (2), (3), (5), and (6).

Table 2b Determinants of bank failure: the lagged changes of explanatory variables

DV: *Bank Failure*$_t$*=1*	Monthly lag					
	1 month (m=2) (1)	2 months (m=3) (2)	3 months (m=4) (3)	6 months (m=7) (4)	9 months (m=10) (5)	12 months (m=13) (6)
CAMEL indicators						
$\Delta Capital_{t-1,t-m}$	–0.0037 *** (0.0008)	–0.0029 *** (0.0006)	–0.0025 *** (0.0005)	–0.0018 *** (0.0004)	–0.0013 *** (0.0003)	–0.0011 *** (0.0002)
$\Delta Asset\ Quality_{t-1,t-m}$	0.0021 *** (0.0005)	0.0016 *** (0.0004)	0.0015 *** (0.0003)	0.0010 *** (0.0003)	0.0005 ** (0.0002)	0.0004 ** (0.0002)
$\Delta Earnings_{t-1,t-m}$	–0.0028 *** (0.0011)	–0.0053 *** (0.0011)	–0.0060 *** (0.0011)	–0.0085 *** (0.0011)	–0.0090 *** (0.0012)	–0.0087 *** (0.0012)
$\Delta Liquidity_{t-1,t-m}$	–0.0011 * (0.0006)	–0.0010 ** (0.0004)	–0.0008 ** (0.0004)	–0.0007 *** (0.0003)	–0.0008 *** (0.0003)	–0.0008 *** (0.0002)
Other variables						
$\Delta Loans_{t-1,t-m}$	–0.0007 (0.0006)	–0.0008 * (0.0004)	–0.0006 * (0.0004)	–0.0004 (0.0003)	–0.0006 ** (0.0002)	–0.0006 *** (0.0002)
$\Delta Deposits_{t-1,t-m}$	–0.0008 *** (0.0002)	–0.0006 *** (0.0002)	–0.0004 ** (0.0002)	–0.0002 (0.0001)	–0.0001 (0.0001)	0.0000 (0.0001)
$\Delta log(Size_{t-1,t-m})$	–0.1108 *** (0.0225)	–0.0837 *** (0.0161)	–0.0695 *** (0.0126)	–0.0472 *** (0.0089)	–0.0340 *** (0.0067)	–0.0265 *** (0.0056)
Moscow dummy (0/1)	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
# Banks	818	818	817	814	812	811
# Observations	31,256	31,240	31,223	31,175	31,127	31,080
R-squared	0.096	0.102	0.099	0.097	0.088	0.088

Notes: The dependent dummy variable equals one if the bank has its license revoked by the CBR in month t, and zero otherwise. Standard errors in parentheses are adjusted for clustering at the bank level. Significance levels: * 10 %; ** 5 %; *** 1 %, respectively. The models also include a constant term, bank fixed effects and time (month) fixed effects. At least five consecutive observations are required for a bank to be included in the sample. Definitions of variables are reported in Table 1.

4.2 Robustness checks

As most failed banks in our sample are small (even if a number of top-100 banks also lose their licenses in the observation period), we split our sample in small and large banks using median size (*log*(total assets)), as a cutoff. This is done to determine whether allowing the signs of CAMEL estimates to differ between small and large banks affect our key finding (i.e. changes of CAMEL variables are more important than levels), not to test whether the estimated parameters of CAMEL indicators differ between small and large banks. Table 3a displays our findings for Eq. (1) for small and large banks separately. For CAMEL indicators, we find that liquidity remains consistently negatively significant up to the 6-month lag for both large and small banks, and thereafter for large banks only. For small banks, we find that the 1-, 2-, 3-, and 9-month lagged asset quality is positively significant. Earnings is negatively significant up to the 2-month lag for small banks and up to the 3-month lag for large banks.

Table 3b represents our estimation results for changes in explanatory variables in Eq. (2) for large and small banks separately. Column (1) uses the one-month lagged covariates (i.e. x_{t-1} - x_{t-2}) and columns (2) to (4) the 3-, 6-, and 9-month lagged changes in covariates, respectively. By and large, these results confirm our baseline result that changes in CAMEL variables are more important that levels in explaining bank failure.

In our second robustness check, we consider whether the initial levels of CAMEL variables matter for our results by examining growth rather than change in our explanatory variables. The equation (2) is modified as follows:

$$P(FAILURE_{i,t} = 1) = F(\partial X, \beta) = \beta_0 + \beta_1 \partial CAPITAL_{i,(t-1)-(t-m)} + \beta_2 \partial ASSETSQUALITY_{i,(t-1)-(t-m)} + \beta_3 \partial EARNINGS_{i,(t-1)-(t-m)} + \beta_4 \partial LIQUIDITY_{i,(t-1)-(t-m)} + +\beta_5 \partial TOTLOANS_{i,(t-1)-(t-m)} + \beta_6 \partial TOTDEPOSITS_{i,(t-1)-(t-m)} + \beta_7 \Delta \log\left(SIZE_{i,(t-1)-(t-m)}\right) + \beta_8 MOSCOW_i + \beta_9 MONTH\_FE_t + \beta_{10} BANK\_FE_i + \varepsilon_{i,t}, \quad (3)$$

where m = 2, 4, 7, 10, 13, and 19 and ∂ = average monthly growth.

Table 3a The determinants of bank failure using the lagged levels of explanatory variables: small and large banks

DV: *Bank Failure$_t$=1*	Monthly lag											
	1 month (*m*=1)		2 months (*m*=2)		3 months (*m*=3)		6 months (*m*=6)		9 months (*m*=9)		12 months (*m*=12)	
	Small banks (1)	Large banks (2)	Small banks (3)	Large banks (4)	Small banks (5)	Large banks (6)	Small banks (7)	Large banks (8)	Small banks (9)	Large banks (10)	Small banks (11)	Large banks (12)
CAMEL indicators												
Capital$_{t-m}$	-0.0013 *** (0.0005)	-0.0007 * (0.0004)	-0.0004 (0.0004)	-0.0001 (0.0003)	-0.0004 (0.0003)	0.0002 (0.0003)	-0.0000 (0.0003)	0.0004 (0.0003)	-0.0001 (0.0002)	0.0006 ** (0.0003)	0.0000 (0.0002)	0.0005 ** (0.0002)
Asset Quality$_{t-m}$	0.0011 *** (0.0004)	0.0002 (0.0002)	0.0008 ** (0.0004)	0.0000 (0.0001)	0.0007 * (0.0004)	-0.0001 (0.0001)	0.0002 (0.0003)	-0.0002 * (0.0001)	0.0011 *** (0.0004)	-0.0001 (0.0002)	0.0001 (0.0002)	-0.0000 (0.0001)
Earnings$_{t-m}$	-0.0121 *** (0.0021)	-0.0195 *** (0.0035)	-0.0048 *** (0.0017)	-0.0052 ** (0.0026)	-0.0032 * (0.0017)	0.0033 (0.0022)	-0.0001 (0.0014)	0.0020 (0.0015)	-0.0019 (0.0014)	0.0002 (0.0014)	0.0012 (0.0014)	0.0017 (0.0015)
Liquidity$_{t-m}$	-0.0012 ** (0.0005)	-0.0011 *** (0.0003)	-0.0007 ** (0.0003)	-0.0012 *** (0.0003)	-0.0006 ** (0.0003)	-0.0012 *** (0.0003)	-0.0007 ** (0.0003)	-0.0009 *** (0.0003)	-0.0001 (0.0003)	-0.0008 *** (0.0003)	-0.0003 (0.0003)	-0.0006 ** (0.0003)
Other variables												
Loans$_{t-m}$	-0.0007 * (0.0004)	-0.0006 ** (0.0003)	-0.0005 * (0.0003)	-0.0008 *** (0.0003)	-0.0003 (0.0003)	-0.0007 *** (0.0003)	-0.0005 * (0.0003)	-0.0007 *** (0.0003)	-0.0001 (0.0003)	-0.0005 ** (0.0002)	-0.0003 (0.0003)	-0.0002 (0.0002)
Deposits$_{t-m}$	0.0003 (0.0002)	-0.0002 (0.0002)	0.0004 ** (0.0002)	0.0001 (0.0002)	0.0004 ** (0.0002)	0.0002 (0.0001)	0.0001 (0.0002)	0.0002 * (0.0001)	0.0001 (0.0002)	0.0002 * (0.0001)	0.0001 (0.0002)	0.0002 ** (0.0001)
log(Size$_{t-m}$)	-0.0291 ** (0.0138)	-0.0119 ** (0.0049)	-0.0061 (0.0096)	-0.0042 (0.0046)	0.0061 (0.0084)	-0.0024 (0.0045)	0.0152 * (0.0086)	0.0069 * (0.0042)	0.0160 ** (0.0077)	0.0109 *** (0.0041)	0.0108 (0.0068)	0.0108 *** (0.0037)
Moscow dummy (0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Banks	489	455	589	455	489	455	485	455	483	455	481	455
# Observations	15,634	15,6382	15,622	15,637	15,609	15,634	15,569	15,624	15,744	15,614	15,496	15,602

Notes: The dependent dummy variable equals one if the bank the bank has its license revoked by the CBR in month t, and zero otherwise. Standard errors in parentheses are adjusted for clustering at the bank level. Significance levels: * 10 %; ** 5 %; *** 1 %, respectively. The models also include a constant term, bank fixed effects and time (month) fixed effects. At least five consecutive observations are required for a bank to be included in the sample. Definitions of variables are reported in Table 1.

Table 3b The determinants of bank failure using the lagged changes of explanatory variables: small and large banks

DV: *Bank Failure$_t$=1*	Monthly lag											
	1 month (*m*=1)		2 months (*m*=2)		3 months (*m*=3)		6 months (*m*=6)		9 months (*m*=9)		12 months (*m*=12)	
	Small banks (1)	Large banks (2)	Small banks (3)	Large banks (4)	Small banks (5)	Large banks (6)	Small banks (7)	Large banks (8)	Small banks (9)	Large banks (10)	Small banks (11)	Large banks (12)
<u>CAMEL indicators</u>												
ΔCapital$_{t-1,t-m}$	-0.0042 *** (0.0011)	-0.0036 *** (0.0012)	-0.0033 *** (0.0008)	-0.0026 *** (0.0009)	-0.0026 *** (0.0006)	-0.0025 *** (0.0007)	-0.0019 *** (0.0005)	-0.0018 *** (0.0005)	-0.0014 *** (0.0004)	-0.0013 *** (0.0004)	-0.0011 *** (0.0003)	-0.0012 *** (0.0003)
ΔAsset Quality$_{t-1,t-m}$	0.0026 *** (0.0008)	0.0015 ** (0.0007)	0.0020 *** (0.0005)	0.0011 ** (0.0005)	0.0022 *** (0.0005)	0.0078 ** (0.0004)	0.0014 *** (0.0005)	0.0006 ** (0.0003)	0.0009 *** (0.0003)	0.0002 (0.0002)	0.0009 *** (0.0003)	0.0001 (0.0002)
ΔEarnings$_{t-1,t-m}$	-0.0010 (0.0013)	-0.0057 *** (0.0020)	-0.0026 ** (0.0012)	-0.0101 *** (0.0020)	-0.0048 *** (0.0013)	-0.0078 *** (0.0020)	-0.0075 *** (0.0013)	-0.0100 *** (0.0020)	-0.0072 *** (0.0013)	-0.0118 *** (0.0022)	-0.0072 *** (0.0013)	-0.0113 *** (0.0023)
ΔLiquidity$_{t-1,t-m}$	-0.0017 * (0.0009)	-0.0001 (0.0005)	-0.0014 ** (0.0007)	-0.0002 (0.0004)	-0.0011 ** (0.0006)	-0.0002 (0.0004)	-0.0009 * (0.0005)	-0.0004 (0.0003)	-0.0009 ** (0.0004)	-0.0005 * (0.0003)	-0.0009 ** (0.0004)	-0.0006 ** (0.0002)
<u>Other variables</u>												
ΔLoans$_{t-1,t-m}$	-0.0012 (0.0009)	0.0001 (0.0005)	-0.0013 * (0.0007)	-0.0001 (0.0004)	-0.0009 (0.0006)	-0.0001 (0.0003)	-0.0006 (0.0005)	-0.0001 (0.0003)	-0.0007 * (0.0004)	-0.0004 (0.0002)	-0.0007 * (0.0004)	-0.0005 ** (0.0002)
ΔDeposits$_{t-1,t-m}$	-0.0010 *** (0.0003)	-0.0007 *** (0.0003)	-0.0006 ** (0.0002)	-0.0007 *** (0.0002)	0.0004 * (0.0002)	-0.0005 *** (0.0002)	-0.0001 (0.0002)	-0.0003 ** (0.0002)	0.0000 (0.0002)	0.0002 (0.0001)	0.0001 (0.0002)	-0.0002 * (0.0001)
Δlog(Size$_{t-1,t-m}$)	-0.1384 *** (0.0334)	-0.0898 *** (0.0241)	-0.1106 *** (0.0235)	-0.0618 *** (0.0155)	-0.0852 *** (0.0181)	-0.0563 *** (0.0125)	-0.0575 *** (0.0141)	0.0419 *** (0.0087)	0.0412 *** (0.0114)	0.0329 *** (0.0070)	-0.0309 (0.0099)	0.0289 *** (0.0061)
Moscow dummy (0/1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Banks	489	455	589	455	488	455	485	455	482	455	481	455
# Observations	15,622	15,634	15,622	15,631	15,595	15,628	15,557	15,618	15,520	15,607	15,485	15,595

Notes: The dependent dummy variable equals one if the bank has its license revoked by the CBR in month t, and zero otherwise. Standard errors in parentheses are adjusted for clustering at the bank level. Significance levels: * 10 %; ** 5 %; *** 1 %, respectively. The models also include a constant term, bank fixed effects and time (month) fixed effects. At least five consecutive observations are required for a bank to be included in the sample. Definitions of explanatory variables are reported in Table 1.

Table 4 describes our estimation results using growth in explanatory variables instead of changes. Comparing these results with our baseline results in Tables 2a and 2b reveals that the results are quantitatively similar. Levels of standard accounting variables perform worse than changes or growth in these variables in explaining bank failure within the 12-month period. Our findings remain qualitatively intact in Eq. (3) we substitute compound monthly growth rates for CAMEL indicators (except earnings still average growth rate) for average monthly growth rates.[14]

Table 4 Determinants of bank failure: average growth of explanatory variables

	(1) 1 month (*m*=2)	(2) 2 months (*m*=3)	(3) 3 months (*m*=4)	(4) 6 months (*m*=7)	(5) 9 months (*m*=10)	(6) 12 months (*m*=13)	(7) 18 months (*m*=19)
avegrowthCAR (t-1,t-m)	**–0.289***** (0.0415)	**–0.301***** (0.0449)	**–0.337***** (0.0550)	**–0.393***** (0.0632)	**–0.413***** (0.0702)	**–0.401***** (0.0776)	**–0.406***** (0.0823)
avegrowthCredQ3 (t-1,t-m)	**0.0150***** (0.00439)	**0.0154***** (0.00408)	**0.0119***** (0.00372)	0.00384 (0.00296)	0.00372 (0.00233)	**0.00389*** (0.00228)	**0.00486**** (0.00214)
avegrowthROA (t-1,t-m)	0.000158 (0.000275)	**0.000830**** (0.000328)	–0.000412 (0.000523)	**–0.00166**** (0.000678)	**–0.00169*** (0.000963)	**–0.00361***** (0.000984)	–0.00197 (0.00133)
avegrowthLAR (t-1,t-m)	–0.0116 (0.0117)	–0.0184 (0.0136)	–0.0286 (0.0178)	**–0.0615***** (0.0228)	**–0.0842***** (0.0262)	**–0.0800**** (0.0323)	**–0.122***** (0.0366)
avegrowthLoanAR (t-1,t-m)	–0.0179 (0.0244)	–0.0142 (0.0269)	0.0150 (0.0402)	–0.0614 (0.0526)	–0.0927 (0.0621)	–0.0506 (0.0723)	–0.122 (0.0828)
avegrowthDepoAR (t-1,t-m)	**–0.0441***** (0.0114)	**–0.0417***** (0.0139)	0.000419 (0.0227)	0.00205 (0.0263)	0.0199 (0.0298)	–0.00460 (0.0307)	–0.00888 (0.0338)
avegrowthsize (t-1,t-m)	**–6.007***** (0.767)	**–6.548***** (0.816)	**–7.408***** (1.007)	**–8.020***** (1.187)	**–8.193***** (1.336)	**–7.502***** (1.467)	**–7.280***** (1.599)
Constant	–0.0185*** (0.00191)	–0.0184*** (0.00191)	–0.0198*** (0.00199)	–0.0183*** (0.00213)	–0.0168*** (0.00206)	–0.0166*** (0.00211)	–0.0167*** (0.00206)
Observations	30,589	30,567	30,494	30,416	30,322	30,222	30,127
R-squared	0.095	0.097	0.094	0.089	0.087	0.086	0.085

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Third, to facilitate comparisons of our results with earlier literature, we estimate equations (1) and (2) with a panel logit RE model. Our main results of the superiority of changes in explaining bank failure remain intact. The results are summarized in Tables 5a and 5b (we report estimated coefficients in order to assess the signs and significance levels).

[14] Results not reported here, but are available on request.

Table 5a Determinants of bank failure: Panel RE logit in levels

	Monthly lag				
	1 month	3 months	6 months	9 months	12 months
$Capital_{t-1,t-m}$	–0.056 *** (0.011)	–0.037 *** (0.011)	–0.033 *** (0.009)	–0.030 *** (0.010)	–0.025 *** (0.009)
$Asset\ Quality_{t-1,t-m}$	0.003 (0.007)	0.001 (0.009)	–0.012 (0.009)	0.001 (0.008)	–0.006 (0.009)
$Earnings_{t-1,t-m}$	–0.921 *** (0.072)	–0.063 (0.107)	–0.061 (0.105)	–0.102 (0.101)	0.096 (0.096)
$Liquidity_{t-1,t-m}$	–0.063 *** (0.013)	–0.071 *** (0.014)	–0.059 *** (0.011)	–0.046 *** (0.009)	–0.045 *** (0.009)
$Loans_{t-1,t-m}$	–0.041 *** (0.010)	–0.051 *** (0.012)	–0.047 *** (0.010)	–0.038 *** (0.009)	–0.038 *** (0.009)
$Deposits_{t-1,t-m}$	–0.007 (0.005)	0.018 *** (0.006)	0.014 *** (0.005)	0.012 *** (0.005)	0.014 *** (0.004)
$\log(Size_{t-1,t-m})$	–0.495 *** (0.077)	–0.567 *** (0.115)	–0.464 *** (0.071)	–0.438 *** (0.065)	–0.431 *** (0.063)
Moscow dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank fixed effects	*No*	*No*	*No*	*No*	*No*
Month fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
# Banks	*818*	*818*	*814*	*812*	*811*
# Observations	*30,809*	*30,780*	*30,731*	*30,684*	*30,637*

Notes: Table 5a reports estimated coefficients of random-effects panel logit model. Bank-level clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Table 5b Determinants of bank failure: Panel RE logit in changes

	Monthly lag				
	1 month	3 months	6 months	9 months	12 months
$DCapital_{t-1,t-m}$	–0.157 *** (0.036)	–0.121 *** (0.021)	–0.091 *** (0.017)	–0.071 *** (0.014)	–0.057 *** (0.012)
$DAsset\ Quality_{t-1,t-m}$	0.098 *** (0.020)	0.060 *** (0.014)	0.036 *** (0.012)	0.021 ** (0.010)	0.021 ** (0.010)
$DEarnings_{t-1,t-m}$	–0.299 *** (0.091)	–0.449 *** (0.062)	–0.610 *** (0.055)	–0.664 *** (0.056)	–0.634 *** (0.061)
$DLiquidity_{t-1,t-m}$	–0.070 ** (0.031)	–0.063 *** (0.019)	–0.072 *** (0.016)	–0.068 *** (0.012)	–0.068 *** (0.013)
$DLoans_{t-1,t-m}$	–0.045 (0.031)	–0.048 ** (0.019)	–0.044 *** (0.016)	–0.042 *** (0.013)	–0.044 *** (0.012)
$DDeposits_{t-1,t-m}$	–0.046 * (0.024)	–0.012 (0.014)	0.006 (0.010)	0.012 (0.009)	0.011 (0.008)
$D\log(Size_{t-1,t-m})$	–5.711 *** (1.271)	–4.339 *** (0.738)	–3.058 *** (0.449)	–2.058 *** (0.336)	–1.517 *** (0.305)
Moscow dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Bank fixed effects	*No*	*No*	*No*	*No*	*No*
Month fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
# Banks	*818*	*817*	*814*	*812*	*811*
# Observations	*30,793*	*30,760*	*30,713*	*30,666*	*30,620*

Notes: Table 5a reports estimated coefficients of random-effects panel logit model. Bank-level clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1.

Finally, the results are robust both to moving the time window in equations (2) and (3) backwards by one lag and to including Russia large state-owned banks in the sample.[15]

5 Conclusions

The economic literature is often interested in how a change in a covariate is related to a change in an outcome variable. It is surprising that the prevailing bank failure literature has largely focused on how a level of a covariate is related to bank failure. In this study, we investigated the role of both levels and changes in CAMEL accounting indicators in explaining bank closure. To the best of our knowledge, no study to date has addressed the role of changes in CAMEL variables. This paper aims to fill this gap in the bank failure literature by taking advantage of monthly individual bank-level panel data from the Russian banking sector from July 2013 to July 2017.

For CAMEL indicators in levels, we find that the higher the levels of capital, earnings, and liquidity one month prior to closure the lower the probability of bank failure the next month. For longer lags of capital and earnings in levels, we find an insignificant association with bank closure. This finding has important policy implications. First, it suggests that the lags of longer than one month for the indicators capital and earnings may fail to flag bank financial distress. Second, it implies that that monthly accounting data may be more useful than quarterly accounting data when the issue is bank failure. Liquidity in levels, however, remains consistently highly significant with longer lags, even though the magnitude of liquidity estimates decreases the longer the time lag. This finding suggests that liquidity has a relatively "long memory" in affecting bank closure. For policy-makers assessing the conditional probability of bank closure, liquidity in levels deserves special attention.

Regarding changes in CAMEL indicators, we consistently find that changes in capital, earnings, and liquidity are negatively associated with bank failure, while changes in asset quality are positively associated and highly significant. Unlike CAMEL indicators in levels, however, longer lags of changes in these indicators remain consistently highly significant. Moreover, the size of these changes estimates are much larger the estimates in levels. As earlier, the magnitude of estimates decreases rather monotonically over time, suggesting that changes in CAMEL indicators just prior to closure are more important than longer lag of changes in explaining closure. In other words, accounting data just prior to bank closure contain more relevant information in addressing bank closure. From a policy perspective, our findings are consistent with the view that changes in CAMEL indicators may be more important drivers of bank closure than CAMEL indicators in levels.

[15] Results not reported here, but are available on request.

References

Arena, Marco (2008). "Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data." *Journal of Banking and Finance*, 32, 299–310.

Berglof, Erik, and Alexander Lehmann (2009). "Sustaining Russia's growth: The role of financial reform." *Journal of Comparative Economics*, 37(2), 198–206, June.

Bernard, Andrew B., and J. Bradford Jensen (2004). "Why some firms export." *Review of Economics and Statistics*, 86(2), 561–569.

Chernykh, Lucy, and Alexandra K. Theonossiou (2015). "Determinants of Bank Long-Term Lending Behavior: Evidence from Russia." *Multinational Finance Journal*, 15(3/4), 193–216.

Claeys, S., and K. Schoors (2007). "Bank supervision Russian style: Evidence of conflicts between micro- and macro-prudential concerns." *Journal of Comparative Economics*, 35, 630–657.

Cole, R. A., and J. W. Gunther (1995). "Separating the likelihood and timing of bank failure." *Journal of Banking and Finance*, 19, 1–15.

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

Fidrmuc, Jarko, and Philipp Suss (2011). "The Outbreak of the Russian Banking Crisis." *Czech Economic Review,* 5(1), 46–63.

Friedman, Jed, and Norbert Schady (2013). "How many infants likely died in Africa as a result of the 2008–2009 Global Financial Crisis." *Health Economics*, 22(5), 611–622.

Frame, W. Scott, Atanas Mihov, and Leandro Sanz (2017). "Foreign Investment, Regulatory Arbitrage, and the Risk of U.S. Banking Organizations." Federal Reserve Bank of Atlanta, Working Paper 2017–2.

Fungacova, Z., R. Herrala, and L. Weill (2013). "The influence of bank ownership on credit supply: Evidence from the recent financial crisis." *Emerging Markets Review*, 15, June 2013, 136–147.

Fungacova, Z. and L. Weill (2013). "Does competition influence bank failures?" *Economics of Transition*, 21, 301–322.

Fungacova, Z, Rima Turk, and L. Weill (2015). "High Liquidity Creation and Bank Failures." IMF Working Paper WP/15/103.

Fungacova Z. and L. Solanko (2009). "Risk-taking by Russian banks: Do location, ownership and size matter?" *Higher School of Economics Economic Journal*, 13(1), 101–129.

Gruber Jon and Emmanuel Saez (2002). "The elasticity of taxable income: evidence and implications." *Journal of Public Economics*, 84(1), 1–32.

Hall Brian J. and Jeffrey B. Liebman (1998). "Are CEOS Really Paid Like Bureaucrats?", *Quarterly Journal of Economics*, 113(3), 653–691.

Jensen Michael C. and Kevin J. Murphy (1990). "Performance Pay and Top-Management Incentives." *Journal of Political Economy*, 98(2), 225–264.

Karas, A., W. Pyle, and K. Schoors (2013). "Deposit Insurance, Banking Crises, and Market Discipline: Evidence from a Natural Experiment on Deposit Flows and Rates." *Journal of Money, Credit and Banking*, 45, 179–200.

Karminsky, A. M., and A. Kostrov (2014). "The probability of default in Russian banking." *Eurasian Economic Review*, 4(1), 81–98.

Kauko, Karlo (2014). "How to foresee banking crises? A survey of the empirical literature." *Economic Systems*, 38, 289–308.

Kugler, Adriana and Giovanni Pica (2008). "Effects of employment protection on worker and job flows: Evidence from the 1990 Italian reform." *Labour Economics*, 15, 78–95.

Lanine, G., and R. Vander Vennet (2006). "Failure prediction in the Russian banking sector." *Expert Systems and Applications*, 30, 463–478.

Mamonov, Mikhail (2017). "Holes in the Capital of Failed Russian Banks: Old Indicators and New Hypotheses" (in Russian), *Ekonomitcheskaya Politika*, 12(1), 166–199. DOI: 10.18288/1994-5124-2017-1-07.

Mayes, D. G., and Hanno Stremmel (2014). "The effectiveness of capital adequacy measures in predicting bank distress." SUERF Studies 2014/1. Vienna.

Mäkinen, Mikko (2008). "CEO compensation, firm size and firm performance: Evidence from Finland", in L. Oxelheim and C. Wihlborg (Eds), Markets and compensation for executives in Europe, International Business and Management, vol. 24, 315–348. Emerald Group Publishing Limited.

Männasoo, K., and D. G. Mayes (2009). "Explaining bank distress in eastern European transition economies." *Journal of Banking and Finance*, 33(2), 244–253.

Peresetsky, A. A., A. A. Karminsky, and S. V. Golovan (2011). "Probability of default models of Russian banks." *Economic Change and Restructuring*, 44(4), 297–334.

Poghosyan, Tigran, and Martin Cihak (2011). "Determinants of bank distress in Europe: Evidence from a new data set." *Journal of Financial Services Research*, 40, 163–184.

Schoors, Koen, Maria Semenova, and Andrey Zubanov (2017). "Depositor discipline in Russian regions: Flight to familiarity or trust in local authorities?" BOFIT Discussion Papers 1/2017, Bank of Finland, Institute for Economies in Transition.

Vazquez, Francisco, and Pablo Federico (2015). "Bank funding structures and risk: Evidence from the global financial crisis." *Journal of Banking and Finance*, 61, 1–14.

BOFIT Discussion Papers

A series devoted to academic studies by BOFIT economists and guest researchers. The focus is on works relevant for economic policy and economic developments in transition / emerging economies.

2016	No 1	Guonan Ma and Wang Yao: Can the Chinese bond market facilitate a globalizing renminbi?
	No 2	Iikka Korhonen and Riikka Nuutilainen: A monetary policy rule for Russia, or is it rules?
	No 3	Hüseyin Şen and Ayşe Kaya: Are the twin or triple deficits hypotheses applicable to post-communist countries?
	No 4	Alexey Ponomarenko: A note on money creation in emerging market economies
	No 5	Bing Xu, Honglin Wang and Adrian van Rixtel: Do banks extract informational rents through collateral?
	No 6	Zuzana Fungáčová, Anastasiya Shamshur and Laurent Weill: Does bank competition reduce cost of credit? Cross-country evidence from Europe
	No 7	Zuzana Fungáčová, Iftekhar Hasan and Laurent Weill: Trust in banks
	No 8	Diana Ayala, Milan Nedeljkovic and Christian Saborowski: What slice of the pie? The corporate bond market boom in emerging economies
	No 9	Timothy Frye and Ekaterina Borisova: Elections, protest and trust in government: A natural experiment from Russia
	No 10	Sanna Kurronen: Natural resources and capital structure
	No 11	Hongyi Chen, Michael Funke and Andrew Tsang: The diffusion and dynamics of producer prices, deflationary pressure across Asian countries, and the role of China
	No 12	Ivan Lyubimov: Corrupt bureaucrats, bad managers, and the slow race between education and technology
	No 13	Tri Vi Dang and Qing He: Bureaucrats as successor CEOs
	No 14	Oleksandr Faryna: Exchange rate pass-through and cross-country spillovers: Some evidence from Ukraine and Russia
	No 15	Paul D. McNelis: Optimal policy rules at home, crisis and quantitative easing abroad
	No 16	Mariarosaria Comunale and Heli Simola: The pass-through to consumer prices in CIS economies: The role of exchange rates, commodities and other common factors
	No 17	Paul Castañeda Dower and William Pyle: Land rights, rental markets and the post-socialist cityscape
	No 18	Zuzana Fungáčová, Ilari Määttä and Laurent Weill: What shapes social attitudes toward corruption in China? Micro-level evidence
	No 19	Qing He, Jiyuan Huang, Dongxu Li and Liping Lu: Banks as corporate monitors: Evidence from CEO turnovers in China
	No 20	Vladimir Sokolov and Laura Solanko: Political influence, firm performance and survival
2017	No 1	Koen Schoors, Maria Semenova and Andrey Zubanov: Depositor discipline in Russian regions: Flight to familiarity or trust in local authorities?
	No 2	Edward J. Balistreri, Zoryana Olekseyuk and David G. Tarr: Privatization and the unusual case of Belarusian accession to the WTO
	No 3	Hongyi Chen, Michael Funke, Ivan Lozev and Andrew Tsang: To guide or not to guide? Quantitative monetary policy tools and macroeconomic dynamics in China
	No 4	Soyoung Kim and Aaron Mehrotra: Effects of monetary and macroprudential policies – evidence from inflation targeting economies in the Asia-Pacific region and potential implications for China
	No 5	Denis Davydov, Zuzana Fungáčová and Laurent Weill: Cyclicality of bank liquidity creation
	No 6	Ravi Kanbur, Yue Wang and Xiaobo Zhang: The great Chinese inequality turnaround
	No 7	Yin-Wong Cheung, Cho-Hoi Hui and Andrew Tsang: The Renminbi central parity: An empirical investigation
	No 8	Chunyang Wang: Crony banking and local growth in China
	No 9	Zuzana Fungáčová and Laurent Weill: Trusting banks in China
	No 10	Daniela Marconi: Currency co-movements in Asia-Pacific: The regional role of the Renminbi
	No 11	Felix Noth and Matias Ossandon Busch: Banking globalization, local lending, and labor market effects: Micro-level evidence from Brazil
	No 12	Roman Horvath, Eva Horvatova and Maria Siranova: Financial development, rule of law and wealth inequality: Bayesian model averaging evidence
	No 13	Meng Miao, Guanjie Niu and Thomas Noe: Lending without creditor rights, collateral, or reputation – The “trusted-assistant” loan in 19th century China
	No 14	Qing He, Iikka Korhonen and Zongxin Qian: Monetary policy transmission with two exchange rates and a single currency: The Chinese experience
	No 15	Michael Funke, Julius Loermann and Andrew Tsang: The information content in the offshore Renminbi foreign-exchange option market: Analytics and implied USD/CNH densities
	No 16	Mikko Mäkinen and Laura Solanko: Determinants of bank closures: Do changes of CAMEL variables matter?

BOFIT Discussion Papers
http://www.bofit.fi/en • email: bofit@bof.fi
ISSN 1456-4564 (print) // ISSN 1456-5889 (online)