Determinants of Bank Closures: Do Levels or Changes of CAMEL Variables Matter?

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This study examines the role of levels and changes in bank balance sheet variables in explaining bank closure. Using a unique set of monthly bank-level panel 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.

Keywords: *bank closure, bank failure, CAMEL indicators, Russia's banking sector*

JEL: G2, G21, G33

Citation: Makinen, M., Solanko, L. (2018). Determinants of Bank Closures: Do Levels or Changes of CAMEL Variables Matter? *Russian Journal of Money and Finance*, v. 77(2), pp. 3-21.

doi: 10.31477/rjmf.201802.03

1. Introduction

During the last ten years the Russian banking sector has faced two economic recessions. Central bank funding and government support loans, the dominant role of state-owned banks, and relatively low leverage ratios helped the sector through the recessions relatively untouched.¹ Significant changes in banking regulation, however, have swept through the Russian banking system and changed the sector thoroughly in recent years.

Since June 2013 the Central Bank of Russia (CBR) has become a single megaregulator, supervising both banks and other credit institutions. This has not

¹ See Fungacova and Solanko (2009) on the role of the state-owned banks before the crisis. For their role during the crisis, see Fungacova et al. (2013).

only improved overall supervision of financial markets but also 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. The large-scale cleaning up of the banking sector has not threatened systemic stability but undeniably has increased overall interest in assessing financial health of all operating banks in the market.²

In assessing the financial soundness of banks, the literature on the determinants of bank failures has focused on how levels in balance sheet indicators are associated with bank failure (see e.g. Demyanyk and Hasan, 2010; Mayes and Stremmel, 2014, for recent surveys). On broad terms, the literature suggests that higher levels of capital adequacy, earnings, liquidity as well as better asset quality are negatively associated with bank failure. More broadly, these studies support the validity of levels of CAMEL (capital, asset quality, management, earnings, and liquidity) indicators in explaining bank failure.

However, the literature is largely silent on whether changes of CAMEL-type indicators matter in explaining bank failure. 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. Similarly, financial analysts, in assessing company performance, often focus on changes in accounting indicators rather than absolute levels. What happens to bank capitalization or liquidity shortly before a bank failure? Should one be interested in levels of NPLs or rather in changes of NPLs if assessing short term viability of a bank? To the best of our knowledge, however, no study yet has systemically analyzed these questions.

We suspect that the most plausible reason for neglecting the changes in bank balance sheet information is the low frequency of available data. In most countries large banks typically release this information at quarterly intervals, but smaller banks may only publish annual reports. Annual changes in key accounting variables rarely convey surprising information. Russian banking sector data, however, offers access to exceptional information, as monthly balance sheet data on almost all credit institutions is regularly published by the CBR. This allows both the public and financial analysts to monitor changes in financial health of banks at monthly frequency.

Due to the large number of bank failures, Russian data is particularly well-suited for an analysis of determinants of bank failure. Most of the failed banks have been tiny, but a nontrivial number of top-100 banks have also lost their licenses. In four years since June 2013, the number of operating credit institutions decreased by almost 40%, standing at just 582 at the end of July 2017. In many instances, the cause for pulling of a bank's license has involved breaches of money-

² Due to the sudden change in banking supervision and the sheer amount of license withdrawals, the decisions often caught retail depositors by surprise. Smooth working of the Deposit Insurance Authority and the large share of state-controlled banks in the sector has helped to avoid any bank runs.

laundering regulations or other criminal activity rather than financial difficulties or excessive loan losses. Forensic audits of failed banks often reveal serious flaws in bank accounting information (see e.g. Mamonov, 2018).

In this study we take advantage of our unusual monthly data to analyse if changes in balance sheet information convey useful information on the determinants of bank failure. The interest is in short-term changes and therefore we focus on changes in balance sheet indicators up to 12 months prior to bank failure. To alleviate potential challenges in regressions caused by changes in bank regulation, we limit the analysis to the period after July 2013.

Our work contributes to bank failure literature in two ways. First, we confirm the key finding in the literature that banks with more capital, higher earnings, better asset quality and higher liquidity are less prone to fail in the subsequent month. Second, and novel to the literature, we consistently find that changes in capital, earnings, liquidity and asset quality are significantly associated with bank failure up to 12 months prior to failure. Further, the magnitudes of our changes estimates are economically significant.

Taken together, our results show that changes convey more significant information than mere levels of standard CAMEL-type bank balance sheet indicators. This finding complements and broadens earlier literature focusing only on liquidity creation and bank failure (Fungacova et al., 2015). Our finding on superiority of changes in balance sheet information in assessing determinants of bank failure may call for market participants to reassess standard approaches to analyzing banking market stability in the short run.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. The data and empirical methods are discussed in section 3. Section 4 reports our key findings. Section 5 concludes.

2. Literature review

This paper is linked to a broad empirical literature explaining determinants of bank failure using the various balance sheet indicators. Many previous studies in this literature focus on US banks' experience (e.g. Cole and Gunther, 1995; Wheelock and Wilson, 2000; Cole and White, 2012) or cross-country evidence (e.g. Männasoo and Mayes, 2009 for Eastern Europe and Poghosyan and Cihak, 2011 for Europe). At the risk of oversimplifying, these studies rather unanimously show that higher levels of lagged capital, earnings, and liquidity are negatively associated with bank failure in the subsequent period, while worse asset quality is positively associated (for a review, see e.g. Demyanyk and Hasan, 2010, and Mayes and Stremmel, 2014).

A related strand of the literature use CAMEL indicators as controls in analyzing the role of a specific question in bank failure. DeYoung and Torna (2013) examine whether nontraditional banking activities contributed to bank failure

during the 2008 crisis in the US. Bologna (2015) studies bank structural funding vis-à-vis bank failure. Pappas et al. (2017) analyze whether Islamic banks inherently are more stable than conventional banks. Similarly, there are studies that use CAMEL indicators (among other variables) in order to predict bank failure (e.g. Betz et al., 2014; Mare, 2015) or foresee bank crisis (for a review, see e.g. Kauko, 2014). Overall, these studies confirm the validity of CAMEL indicators in levels in explaining bank failure.

A number of scholars have analyzed bank closures in Russia, but most published works are based on data from the years before 2009. 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 2000Q1–2007Q1. They conclude that bank size and competition have a negative effect on failure probability. Fungacova et al. (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 failures in Russia. Lanine and Vander Venet (2006) reveal that most standard accounting variables have expected signs in explaining bank failures. Peresetsky et al. (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 failure. Notably, their sample was derived from the Bankscope database, which only includes annual data for Russia's largest commercial banks.

To the best of our knowledge, however, no studies to date have analyzed the role of changes of CAMEL indicators in explaining bank closure. Likewise, almost all existing studies rely on annual or quarterly accounting data in assessing determinants of bank failure, while we use monthly bank-level data. Also, compared to existing bank failure studies, our unique data include an exceptionally high number of failure events.

3. Data and empirical approach

3.1. Data

Our monthly bank-level panel data come from the Central Bank of Russia. Nearly all banks have consented to the CBR's release of this data with a one-month lag (e.g. data for June 2016 would become publicly available in July or early August 2016). The data contain detailed monthly balance sheet information, something quite exceptional in bank failure literature (see Karas and Schoors, 2010, for details). We combine this data with information on date and type of bank license withdrawals as reported by the CBR.

We construct our estimable sample as follows. First, we exclude the six largest state-controlled banks³ because the failure risk for them is likely to be marginal compared to the other banks in Russia. Similarly, we drop the largest foreign-owned banks.⁴ These banks differ in many respects from other private banks in Russia. Following Berger and Bouwman (2013), we require banks have customer loans and customer deposits outstanding (i.e. the ratio of customer total loans to total assets and the ratio of customer deposits to total assets is more than 1%). To mitigate the effects of extreme values in our covariates, we winsorize (replace) the balance sheet variables at the 1% and 99% levels. We also require at least five consecutive observations for any bank to be included in the sample.

As financial market supervision changed markedly after June 2013, we restrict our analysis to the period from July 2013 (2013M7) to July 2017 (2017M7). This allows us to disentangle the effects of a regime change in bank regulation and CAMEL indicators in assessing the determinants of bank failure. Compared to existing bank failure studies, our unique data include an extraordinary high number of bank closures. 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

On broad terms, a bank license can be withdrawn either due to a merger or due to failure to comply with banking regulations.⁵ We define bank failure as a bank closure following bank license revocation by the CBR, leaving out mergers due to financial difficulties as we are unable to distinguish between forced and unforced merger events. Hence, in our sample the cause for pulling a bank's license was breaches of banking regulations. Forensic audits of failed banks have often revealed serious flaws in accounting information leading to sizable estimates of hidden negative capital

³ These are Sberbank, VTB, VTB24, Gazprombank, Rosselkhozbank, and Bank of Moscow.

⁴ For the purpose of this study, the largest foreign-owned banks in Russia are Unicredit, Raiffeissen, Citi, Rosbank (Societe Generale) and Nordea.

⁵ In our full sample, about 15% of bank license withdrawals are M&A transactions.

(Mamonov, 2018). In many instances reasons for license withdrawals have also included serious evidence of money-laundering or other criminal activity. Our dependent variable for bank failure 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 established bank failure literature, our key explanatory variables are bank capital, asset quality, earnings, and liquidity. Unfortunately, our data do not contain information on management competence and expertise. We cannot use cost-to-income ratio, a common proxy for bank's management quality, as our monthly data does not include income statement data. Given the relatively short time-span of our sample, however, we assume that management quality remains time-invariant during the sample period. Thus, to control for bank's managerial quality and other characteristics that do not change during the sample period, bank fixed effects have to be controlled for in the estimations.

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 (%). Based on previous studies (e.g. Poghosyan and Cihak, 2011), we choose to use this simple (unweighted) capital ratio as our data set does not include information on risk-weighted assets.

Asset quality (or non-performing assets) is proxied by the ratio of total loan losses to total assets (%). A bank's total loan losses are 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 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 (%). 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 includes 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 (%).

We additionally control for bank size, share of lending and customer deposits in total assets and bank location.

Bank size may bear upon likelihood of failure. This would include such policy-design issues as the "too big to fail" problem, suggesting larger banks have a lower risk of failure. Consistent with previous studies on bank failure (e.g. Cole and White, 2012; Fungacova and Weill, 2013), we use the logarithm of total assets as a proxy for bank size.

We 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 could be positively or negatively related to bank failure. The importance of customer deposits in bank liabilities is captured by the ratio of a bank's customer total deposits to total assets (%). We take that as a proxy of sensitivity of bank's funding structure.

Finally, we include a dummy variable to control for the fact that about half of the banks in our sample are located in Moscow. This variable equals one if the bank's head office is located either in Moscow City or in the Moscow region (oblast), and zero otherwise.⁶ Until late 2017, banking supervision in Russia was conducted by regional offices of the CBR, what may have led to varying stringency of supervision between the capital region and the rest of the country. Similarly, banks in Moscow may have faced tighter supervision as those have been more closely followed by their HQ offices.

Tables 1a and 1b present descriptive statistics for the full sample, failed and non-failed banks, separately for levels and changes of explanatory variables. In both Tables sample mean of a bank failure is 0.008, what means that, on average, each month a bank has a 0.8% unconditional probability to fail. Table 1a shows that in levels, on average, there are significant differences between failed and non-failed banks. For example, failed banks have significantly lower earnings and liquidity ratios than non-failed banks. Somewhat counter-intuitively, 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 troubled banks typically had been remarkably slow to recognize their bad loans. Failed banks also have slightly lower capital ratios than non-failed banks (although the comparison of mean indicates the difference is statistically insignificant). Likewise, failed banks are somewhat smaller, have higher deposits ratios and lower loans ratios than non-failed banks. These ratios are all statistically significant. The median values of these ratios reveal a similar pattern as the mean values. The comparison of medians shows that now all the differences are significant at 1% level (also capital ratio). As the Shapiro-Wilk tests for normality and the kernel density estimates of individual ratios (not reported here but available upon request) suggest non-normality, skewness and fat tails, the comparison of medians is perhaps more revealing for the average differences between failed and non-failed banks. Summary statistics for changes are reported in Table 1b. In column (1), where we look at all banks, sample mean of a change (i.e. first difference) in capital to assets ratio is about 0.02, what means that, on average, capitalization

⁶ Even though variation is not very large, a nontrivial number of banks do change the location of their head office in the data.

Table 1a. Summary statistics: Levels

	(1)			(2)			(3)			(4)	(5)
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.		
Bank Failure (0/1)	0.008	0.000	0.091	–	–	–	–	–	–	–	–
CAPITAL (equity to total assets, %)	19.30	14.85	13.69	19.20	13.37	15.41	19.34	15.17	13.09	0.49	0.00***
ASSET QUALITY (total loan losses to total assets, %)	7.67	4.79	9.27	6.63	4.21	8.18	8.00	5.04	9.60	0.00***	0.00***
ROA (current profits to total assets, %)	0.04	0.06	0.75	-0.01	0.03	0.97	0.06	0.06	0.67	0.00***	0.00***
LIQUIDITY (liquid assets to total assets, %)	26.67	22.94	16.80	26.14	22.73	16.38	26.85	23.03	16.92	0.00***	0.00***
LOANS (customer loans to total assets, %)	63.97	66.57	17.39	63.39	65.26	17.58	64.16	66.97	17.32	0.00***	0.00***
DEPOSITS (customer deposits to total assets, %)	47.86	51.92	20.07	49.61	54.33	20.36	47.30	51.27	19.94	0.00***	0.00***
SIZE (log(total assets))	15.71	15.50	1.68	15.26	15.14	1.46	15.86	15.63	1.72	0.00***	0.00***
Moscow (0/1)	0.49	0	0.50	0.61	1	0.49	0.46	0	0.50	0.00***	0.00***
# Banks		818			290			528		–	–
# Observations		31,272			7,637			23,635		–	–

(1) – All banks; (2) – Failed banks; (3) – Non-failed banks; (4) – Failed vs. non-failed banks: Mean equality test (*t*-test, unequal variances, *p*-values); (5) – Failed vs. non-failed banks: Median equality test (Wilcoxon test, *p*-values).

Summary statistics are based on our baseline level model (i.e. Eq. (1) with one-month lagged levels of explanatory variables). Sample excludes large state-controlled banks and large foreign-owned banks.

Source: Bank of Russia; authors' calculations

of a bank increased by about 0.02 percentage points from *t*-1 to *t*-2. Further, sample mean of the change is positive (about 0.05) for non-failed banks and negative (about -0.07) for failed banks, and this difference is statistically significant. By and large, however, summary statistics for changes are qualitatively largely similar than those for levels in Table 1a.

Table 1b. Summary statistics: Changes

	(1)			(2)			(3)			(4)	(5)
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.		
Bank Failure (0/1)	0.008	0.000	0.091	–	–	–	–	–	–	–	–
ΔCAPITAL (change in equity to total assets, p.p.)	0.021	-0.004	2.73	-0.065	-0.040	3.19	0.048	0.000	2.56	0.00***	0.00***
ΔASSET QUALITY (change in total loan losses to total assets, p.p.)	0.157	0.030	2.12	0.199	0.035	2.46	0.143	0.029	1.99	0.07*	0.04**
ΔEARNINGS/ROA (change in current profits to total assets, p.p.)	-0.0083	-0.0007	1.06	-0.039	-0.002	1.31	0.001	-0.000	0.96	0.01***	0.20
ΔLIQUIDITY (change in liquid assets to total assets, p.p.)	-0.0981	-0.0469	5.76	-0.238	-0.142	6.06	-0.053	-0.023	5.65	0.02**	0.00***
ΔLOANS (change in customer loans to total assets, p.p.)	-0.0197	0.0000	5.82	0.015	0.000	6.02	-0.031	0.000	5.75	0.56	0.68
ΔDEPOSITS (change in customer deposits to total assets, p.p.)	0.0233	0.0000	3.90	0.080	0.037	4.14	0.005	0.000	3.82	0.16	0.04**
ΔSIZE (change in log(total assets))	0.0052	0.0035	0.09	0.006	0.006	0.10	0.005	0.004	0.09	0.59	0.01***
# Banks	818			290			528			–	–
# Observations	31,256			7,636			23,620			–	–

(1) – **All banks**; (2) – **Failed banks**; (3) – **Non-failed banks**; (4) – **Failed vs. non-failed banks**: Mean equality test (*t*-test, unequal variances, *p*-values); (5) – **Failed vs. non-failed banks**: Median equality test (Wilcoxon test, *p*-values).

Summary statistics are based on our baseline changes model (i.e. Eq. (2) and one month changes in explanatory variables). Sample excludes large state-controlled banks and large foreign-owned banks (*p.p.* = percentage point).

Source: Bank of Russia; authors' calculations

3.3. Empirical approach

As we have repeated observations of individual banks over several months, controlling for unobserved time-invariant bank heterogeneity is crucial. Further, controlling for bank-level fixed effects is essential as our data does not offer a direct proxy for bank management quality. As we focus on short-term developments only, bank management quality is assumed constant. We therefore opt to use the linear probability model with bank fixed effects (i.e. pooled least-square dummy variable approach)⁷.

Previous related Russian bank failure studies typically apply the random-effects panel logit estimator (e.g. Claeyns and Schoors, 2007; Lanine and Vander Vennet, 2006; Fungacova 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 explanatory variables on the conditional probability of bank failure.

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 explanatory variables both in levels and in changes.

We estimate two linear probability models. One with the levels of lagged explanatory variables:

⁷ A model with including $N-1$ dummy variables provides consistent parameter estimates for $\hat{\beta}_{FE}$ when time t is fixed and $N \rightarrow \infty$ (see e.g. Wooldridge, 2002, p. 273).

$$P(\text{FAILURE}_{i,t} = 1) = F(X, \beta) = \beta_0 + \beta_1 \text{CAPITAL}_{i,t-m} + \beta_2 \text{ASSETQUALITY}_{i,t-m} + \beta_3 \text{EARNINGS}_{i,t-m} + \beta_4 \text{LIQUIDITY}_{i,t-m} + \beta_5 \text{TOTLOANS}_{i,t-m} + \beta_6 \text{TOTDEPOSITS}_{i,t-m} + \beta_7 \log(\text{SIZE}_{i,t-m}) + \beta_8 \text{MOSCOW}_i + \beta_9 \text{MONTH}_{FE_t} + \beta_{10} \text{BANK}_{FE_i} + \varepsilon_{i,t} \quad (1)$$

where monthly lag $m = 1, 2, 3, 6, 9$, or 12 .⁸ This allows us to examine whether the information contained in the 1-, 2-, 3-, 6-, 9-, and 12-month lagged accounting information is useful in explaining the incidence of bank failure in subsequent period t .

In our second specification, we focus on the changes in accounting information prior to bank closure. We measure changes between a month prior to bank default event (i.e. $t-1$) and 2, 4, 7, 10, and 13 months before $t-1$:

$$P(\text{FAILURE}_{i,t} = 1) = F(\Delta X, \beta) = \beta_0 + \beta_1 \Delta \text{CAPITAL}_{i,(t-1)-(t-m)} + \beta_2 \Delta \text{ASSETQUALITY}_{i,(t-1)-(t-m)} + \beta_3 \Delta \text{EARNINGS}_{i,(t-1)-(t-m)} + \beta_4 \Delta \text{LIQUIDITY}_{i,(t-1)-(t-m)} + \beta_5 \Delta \text{TOTLOANS}_{i,(t-1)-(t-m)} + \beta_6 \Delta \text{TOTDEPOSITS}_{i,(t-1)-(t-m)} + \beta_7 \Delta \log(\text{SIZE}_{i,(t-1)-(t-m)}) + \beta_8 \text{MOSCOW}_i + \beta_9 \text{MONTH}_{FE_t} + \beta_{10} \text{BANK}_{FE_i} + \varepsilon_{i,t} \quad (2)$$

where monthly lag $m = 2, 4, 7, 10$, and 13 and $\Delta X_{(t-1)-(t-m)} = X_{t-1} - X_{t-m}$.

In both models Eq. (1) and Eq. (2) the definitions of the variables used are similar. The dependent variable $\text{FAILURE}_{i,t}$ takes a value of one if a bank fails in month t , and zero otherwise. $\text{CAPITAL}_{i,t-m}$ is the ratio of a bank's equity to total assets (%). $\text{ASSETQUALITY}_{i,t-m}$ is the ratio of a bank's total loan losses to total assets (%). $\text{EARNINGS}_{i,t-m}$ is a bank's return on assets (%; proxied by current profits). $\text{LIQUIDITY}_{i,t-m}$ is the ratio of a bank's liquid assets to total assets (%). $\text{TOTLOANS}_{i,t-m}$ is the ratio of a bank's customer total loans to total assets (%). $\text{TOTDEPOSITS}_{i,t-m}$ the ratio of a bank's customer total deposits to total assets (%). $\text{SIZE}_{i,t-m}$ is measured by the logarithm of a bank's total assets. The Moscow dummy variable equals one if the bank's head office is located in the Moscow region, and zero otherwise.

The period analysed includes both the remarkable changes in monetary policy at the end of 2014 and the recession of 2015-2016, which most likely affected all banks. We therefore include time (MONTH_{FE_t}) fixed effects to control for time-effects that are common to all banks. As discussed above, it is necessary to include bank fixed effects (BANK_{FE_i}) to control for unobserved time-invariant heterogeneity across banks (such as management quality). Subscript m always refers to a monthly lag.

⁸ The 3-, 6-, 9-, and 12-month lags reported roughly correspond to using quarterly balance sheet data.

4. Empirical findings

4.1. Baseline results

We first discuss the results based on levels of explanatory variables before moving to the discussion on changes in key explanatory variables. 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. Capital, earnings, and liquidity all are significant and negatively associated with bank failure in the subsequent month. Asset quality (as proxied by loan losses) is positively associated with probability of bank failure. These findings confirm the results from the number of previous studies using diverse data sets (e.g. Cole and White, 2012 for the US; Männasoo and Mayes, 2009 for Eastern Europe; Poghosyan and Cihak, 2011 for Europe; Fidrmuc and Suss, 2011 for Russia), implying that our monthly bank-specific balance sheet drivers of failure perform quite similarly compared to the prevailing literature. The estimated coefficient for capital is -0.001, which suggests that, on average, a 1 percentage point (p.p.) increase in capital ratio in $t-1$ is associated with a 0.001 decrease in the probability of bank closure in t , holding all other explanatory variables fixed. As the sample mean for bank failure is 0.008, this would suggest a 13 percent decrease in the probability of failure. Similarly, a 1 p.p. increase in liquidity in $t-1$ is estimated to decrease bank failure by about 0.001 in t . For asset quality, a 1 p.p. increase in bad loans is estimated to increase bank failure by about 0.0005 (or about 6 percent) in t . For earnings, as its sample mean is 0.04 percent, it makes more sense to look at the effect of a 0.1 p.p. increase rather than a 1 p.p. increase on the probability of bank failure: a 0.1 p.p. increase in $t-1$ is associated with 0.15 (or about 19 percent) decrease in the probability of bank closure in t .

For other covariates, column (1) suggests that bank size and share of loans in total assets (proxy for lending activity) are significantly negatively associated with bank closure. For bank size, this finding may indicate that larger banks tolerate financial troubles better than smaller banks. Alternatively, in an economy like Russia where banking supervision rests heavily on following formal rules, larger banks may have an advantage in risk management and accounting. The finding for lending activity is consistent with Männasoo and Mayes (2009), who find that the loans-to-assets ratio is negatively significant close to bank failure. The result supports a notion that banks that engage more in traditional financial intermediation (as opposed to e.g. money and forex market operations) have been better in fulfilling the regulatory requirements and weathering economic downturns.

The results using lags up to 12 months of explanatory variables are reported in columns (2) to (6). Unlike in column (1), we consistently find that capital and asset quality are insignificant. Importantly, we continue to find that liquidity is negatively significant, implying that in the short run only 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

Table 2a. Determinants of bank failure: Lagged levels

DV: Bank Failure _{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 Bank of Russia 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.

Source: Bank of Russia; authors' calculations

other covariates in columns (2) to (6), 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? 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 or relax this practice.

We next turn to the second specification to see if changes in CAMEL-type variables are any better than traditional levels in explaining bank failures in the short term. Table 2b represents the estimation results for Eq. (2), i.e. based on lagged changes in explanatory variables. Several important findings emerge. First, for CAMEL indicators in columns (1), we consistently find that signs and significance levels are similar to Table 2a. Also 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. Second, the magnitude of coefficients is larger than in the model based on levels of explanatory variables. For example, we see in column (1) that a 1 p.p. increase in $\Delta CAPITAL_{t-1,t-2}$ ($= CAPITAL_{t-1} - CAPITAL_{t-2}$) is expected to decrease bank closure by 0.004 (about 50 percent) in t , holding all other explanatory variables fixed. Similarly, a 1 p.p. increase in $\Delta LIQUIDITY_{t-1,t-2}$ is associated with a decrease of 0.001 (about 13 percent) in the probability of bank closure in t . For bad loans (i.e. $\Delta ASSET QUALITY_{t-1,t-2}$), a 1 p.p. increase is associated with 0.002 (about 26 percent) increase in the probability of bank closure in t . For $\Delta EARNINGS_{t-1,t-2}$, a 1 p.p. increase is estimated decrease the probability of bank failure by 0.03 (about 38 percent) in t . Third, also longer lags of changes in accounting variables are significant.

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 accounting data just prior to bank closure are more important than longer lags of changes in explaining bank closure. For other explanatory variables in columns (1) to (6), we note that changes in bank size are consistently negatively related to bank closure, while changes in 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).

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. Further, the signs of estimated coefficients are in line with previous studies using levels of explanatory variables.

Table 2b. Determinants of bank failure: Lagged changes

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						
$\Delta \text{CAPITAL}_{t-1,t-m}$	-0.0037*** (0.0008)	-0.0029*** (0.0006)	-0.0025*** (0.0005)	-0.0018*** (0.0004)	-0.0013*** (0.0003)	-0.0011*** (0.0002)
$\Delta \text{ASSET QUALITY}_{t-1,t-m}$	0.0021*** (0.0005)	0.0016*** (0.0004)	0.0015*** (0.0003)	0.0010*** (0.0003)	0.0005** (0.0002)	0.0004** (0.0002)
$\Delta \text{EARNINGS}_{t-1,t-m}$	-0.0028*** (0.0011)	-0.0053*** (0.0011)	-0.0060*** (0.0011)	-0.0085*** (0.0011)	-0.0090*** (0.0012)	-0.0087*** (0.0012)
$\Delta \text{LIQUIDITY}_{t-1,t-m}$	-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						
$\Delta \text{LOANS}_{t-1,t-m}$	-0.0007 (0.0006)	-0.0008* (0.0004)	-0.0006* (0.0004)	-0.0004 (0.0003)	-0.0006** (0.0002)	-0.0006*** (0.0002)
$\Delta \text{DEPOSITS}_{t-1,t-m}$	-0.0008*** (0.0002)	-0.0006*** (0.0002)	-0.0004** (0.0002)	-0.0002 (0.0001)	-0.0001 (0.0001)	0.0000 (0.0001)
$\Delta \log(\text{SIZE}_{t-1,t-m})$	-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 Bank of Russia 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.

Source: Bank of Russia; authors' calculations

4.2. Robustness checks

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

$$\begin{aligned}
 P(\text{FAILURE}_{it}=1) = & F(\partial X, \beta) = \beta_0 + \beta_1 \partial \text{CAPITAL}_{i(t-1)-(t-m)} + \\
 & \beta_2 \partial \text{ASSETSQUALITY}_{i(t-1)-(t-m)} + \beta_3 \partial \text{EARNINGS}_{i(t-1)-(t-m)} + \beta_4 \partial \text{LIQUIDITY}_{i(t-1)-(t-m)} + \\
 & \beta_5 \partial \text{TOTLOANS}_{i(t-1)-(t-m)} + \beta_6 \partial \text{TOTDEPOSITS}_{i(t-1)-(t-m)} + \beta_7 \Delta \log(\text{SIZE}_{i(t-1)-(t-m)}) + \\
 & \beta_8 \text{MOSCOW}_i + \beta_9 \text{MONTH}_{FE_t} + \beta_{10} \text{BANK}_{FE_i} + \varepsilon_{it} \quad (3)
 \end{aligned}$$

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

Table 3 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) if we substitute compound monthly growth rates for CAMEL indicators (except earnings still average growth rate) for average monthly growth rates.⁹

Table 3. Determinants of bank failure: Average growth of explanatory variables

	1 month (<i>m</i> =2) (1)	2 months (<i>m</i> =3) (2)	3 months (<i>m</i> =4) (3)	6 months (<i>m</i> =7) (4)	9 months (<i>m</i> =10) (5)	12 months (<i>m</i> =13) (6)
avegrowthCAR (<i>t</i> -1, <i>t</i> - <i>m</i>)	-0.289*** (0.0415)	-0.301*** (0.0449)	-0.337*** (0.0550)	-0.393*** (0.0632)	-0.413*** (0.0702)	-0.401*** (0.0776)
avegrowthCredQ3 (<i>t</i> -1, <i>t</i> - <i>m</i>)	0.0150*** (0.00439)	0.0154*** (0.00408)	0.0119*** (0.00372)	0.00384 (0.00296)	0.00372 (0.00233)	0.00389* (0.00228)
avegrowthROA (<i>t</i> -1, <i>t</i> - <i>m</i>)	0.000158 (0.000275)	0.000830** (0.000328)	-0.000412 (0.000523)	-0.00166** (0.000678)	-0.00169* (0.000963)	-0.00361*** (0.000984)
avegrowthLAR (<i>t</i> -1, <i>t</i> - <i>m</i>)	-0.0116 (0.0117)	-0.0184 (0.0136)	-0.0286 (0.0178)	-0.0615*** (0.0228)	-0.0842*** (0.0262)	-0.0800** (0.0323)
avegrowth- LoanAR (<i>t</i> -1, <i>t</i> - <i>m</i>)	-0.0179 (0.0244)	-0.0142 (0.0269)	0.0150 (0.0402)	0.0614 (0.0526)	-0.0927 (0.0621)	-0.0506 (0.0723)
avegrowthDe- poAR(<i>t</i> -1, <i>t</i> - <i>m</i>)	-0.0441*** (0.0114)	-0.0417*** (0.0139)	0.000419 (0.0227)	0.00205 (0.0263)	0.0199 (0.0298)	-0.00460 (0.0307)
avegrowthsize (<i>t</i> -1, <i>t</i> - <i>m</i>)	-6.007*** (0.767)	-6.548*** (0.816)	-7.408*** (1.007)	-8.020*** (1.187)	-8.193*** (1.336)	-7.502*** (1.467)
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)
Observations	30,589	30,567	30,494	30,416	30,322	30,222
R-squared	0.095	0.097	0.094	0.089	0.087	0.086

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

Source: Bank of Russia; authors' calculations

Second, 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. Finally, the key results are robust both to moving the time window in equations (2) and (3) backwards by one lag and to including the large state-owned banks in the sample.¹⁰

5. Conclusions

Data on Russian banking sector offers a unique possibility to examine determinants of bank failures. First, due to the exceptional period of intensified banking sector clean-up since mid-2013, bank closures are not a rare event. Second, availability of monthly bank-level balance sheet data enables us to analyse

⁹ Results are not reported here, but available on request.

¹⁰ Results are not reported here, but available on request.

determinants of bank closures very close to the actual event. While economic studies are often interested in how a change in a covariate is related to a change in an outcome variable, the prevailing bank failure literature has focused on how a level of a covariate is associated with bank failure. This approach may be justified when the aim is to arrive at a model that can correctly forecast bank distress several years in advance. On the contrary, the focus of this study is to use high-frequency bank-level data to explain conditional probabilities of bank failure during a fairly short time span.

The unique, monthly data allowed us to examine the role of both levels and changes in 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 strives to fill this gap by taking advantage of unusual bank-level panel data from the Russian banking sector from July 2013 to July 2017.

Our linear probability model allows us to compare explanatory power of levels and changes of balance sheet information in explaining bank failures. We find that the higher the levels of capital, earnings, and liquidity 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. Liquidity in levels, however, remains consistently highly significant up to 12 months prior to bank failure. These findings potentially have important implications for market analysts. First, they suggest that monthly accounting data may convey more useful information than lower-frequency accounting data. Second, liquidity may deserve special attention among policymakers and market participants assessing the conditional probabilities of bank closure.

Regarding changes in bank balance sheet 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 indicators in levels, however, longer lags of changes in these indicators remain consistently highly significant. Moreover, the size of these estimates are much larger than estimates in levels. Taken together, our findings imply that changes in accounting information are more important than levels when explaining bank failures. This key finding has clearly a policy implication. In assessing probabilities of bank failure policymakers and analysts should clearly pay more attention to changes than to levels of standard accounting variables.

Our analysis further shows that the magnitude of estimates decreases rather monotonically over time, suggesting that indicators just prior to closure are more important in explaining closure. In other words, accounting data just prior to bank closure contain more relevant information in addressing bank closure. This underlies the need for constant monitoring of potentially problematic banks. The results also suggest that changes in balance sheet variables could be included in future models striving to forecast bank distress or failure. More research on establishing optimal lag structures for changes in various variables is clearly warranted.

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