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BAD MANAGEMENT, SKIMPING, OR BOTH? THE RELATIONSHIP BETWEEN COST EFFICIENCY AND LOAN QUALITY IN RUSSIAN BANKS

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This paper investigates the relationship between operating cost efficiency and the loan quality of Russian banks. It tries to answer the question whether it is always beneficial for banks to be highly cost efficient (the "bad management" hypothesis) or whether this higher cost efficiency could mean inadequate spending on borrower screening, which could subject banks to higher credit risk exposures in the future (the "skimping" hypothesis)? Our main result implies that, while the "bad management" hypothesis holds on average for the banking sector as a whole, the "skimping" hypothesis could be the case for those Russian banks that are not just highly cost efficient, as predicted by Berger and DeYoung (1997) for US banks, but that at the same time pursue aggressive strategies in the market for loans to households and non-financial firms, especially during the pre-crisis periods when banks are too optimistic to pay increased attention to the quality of borrowers in order to extract higher profits in the short run. Interestingly, we show that the "skimping" strategy is not the case for those Russian banks that demonstrate a lower equity-to-assets ratio and that are highly cost efficient at the same time because, as we believe, higher financial leverage forces these banks to filter out low quality borrowers to be able to repay borrowed funds. From perspective of regulatory policy, these conclusions provide clear arguments in favor of differential prudential regulation in Russia, which could, if being implemented, positively affect the loan quality of both banks that are skimpers (through restricting loans growth by higher capital adequacy requirements and/or increased payments to the Russian Deposit Insurance Agency) and banks that are not (through eliminating incentives to grow too fast), thus improving the stability of the banking sector as a whole.

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1. Introduction

The 2008-2009 crisis has revealed significant imbalances in the development of the Russian banking sector during the pre-crisis period, rising concerns monetary regulators and academics due to both "*a lack of efficient corporate governance and risk management, high risk concentrations, [and] poor transparency…*" (see Bank of Russia, 2010a), and the ability of banks to further expand credit to the economy given the persistent nature of accumulated bad debts (see Center for Macroeconomic Analysis and Short-term Forecasting, 2010). Before the crisis, the annual growth rate of banking loans to households and non-financial firms was permanently in 20-30% range in real terms from 2000 to 2008, reaching up to 40% in 2000 and 2007 and thus considerably outpacing the growth of the economy as a whole (four times in average). At the same time, the ratio of loans to deposits was attaining 1.3-1.5, thereby indicating a high dependency of bank assets on not just domestic liabilities, but on foreign liabilities as well[3]. Banks were aggressively expanding their businesses, exhibiting excessive risk appetites and paying much more attention to quick-and-easy profit extraction, rather than on adequate risk assessments given the high levels of return-on-equity ratios which, even after providing for loan losses, were in the 10-25% range during the same period (with the average of 16%). These large "appetites" resulted in an almost four-fold increase in the share of non-performing loans in the total loans (NPL) of Russian banks over just 2 years – from 2.5% at the beginning of 2008 to a peak of 9.6% at the beginning of 2010 (see Bank of Russia, 2010b; p.61).

Unfortunately, such a rapid growth of bad debts did not lead to an equally rapid decline. On the contrary, more than three years down the line, the NPL ratio decreased by just 3.4 percentage points and was 6.2% as of the end of the 1st quarter of 2013. This means that the process of "defusing" bad debts became rather protracted. The latter imposes serious restrictions on further business development because banks must keep higher provisions for loan loss instead of investing respective funds in new projects (granting new loans, developing branch networks, and many others). Moreover, banks suffer from lower capital adequacy ratios due to higher risk coefficients, which, in turn, imply further obstacles for banking activities.

So, we suggest that the recovery following increases of bad debts takes quite a long time in the Russian banking system and these bad debts tend to increasingly persist over time. In this situation, banks need to choose whether they want to earn short-term benefits from lower quality lending (being restricted by regulation in the future as a response to bad debts rising), or whether they

[3] All presented numbers are the author's calculations based on the Bank of Russia database on bank balance sheets (http://www.cbr.ru/credit/forms.asp) and the macroeconomic database of the Federal State Statistics Service (http://www.gks.ru/wps/wcm/connect/rosstat_main/rosstat/en/main/).

should trade these short-term benefits for stability in terms of credit risk over a longer horizon by paying more attention to borrower screening procedures.

In this respect, we believe that cost optimizing, if undertaken by bank managers, will help to improve the quality of a bank's loan portfolios much better (and for a longer time) than macroeconomic improvement would[4], as banks have absolute power over the former, but are virtually unable to influence the latter.

That, in turn, makes more urgent the need to analyze possible relationships between the quality of loan portfolios for Russian banks and their ability to manage expenses. Could banks benefit from higher cost efficiency in terms of lower credit risk exposures, or does higher cost efficiency imply insufficient spending on screening which leads to the deterioration of loan quality in the future? In terms of Berger and DeYoung (1997), who developed the efficiency-risk hypothesis[5], we ask whether Russian banks are "bad managers" or, alternatively, could they be "skimpers"? How robust is the identification of both "bad managers" and "skimpers" to different tests and specifications? These issues are essentially the subject of this study.

More specifically, we make an attempt to conduct a comprehensive study analyzing the relationships between bank efficiency and credit risk (loan quality), and pay special attention to the effects that come from efficiency to risk, such as a bank's ability to manage expenses and thereby improve their loan quality. We thus do not cover all possible types of bank risks (liquidity, interest rates, currency operations and others), but concentrate our efforts entirely on credit risk and its possible connections to efficiency[6]. For that reason, we propose utilizing the following two-step procedure.

In the first step, we test the efficiency-risk hypothesis of Berger and DeYoung (1997) and thus estimate the "pure" effect of efficiency on risk in the framework of a panel Granger causality test[7].

In the second step, we track changes in the efficiency of "pure" impact on credit risk when controlling for other micro- and macroeconomic determinants of risk in a single panel equation framework compared to estimation results obtained in the first step.

Through all of these steps, we perform estimations separately for those banks that could pursue a "skimping" strategy and those ones that do not. To identify skimpers we propose two new cri-

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[4] Actually, some banks may rely on macroeconomic improvement as it allows for recovering the creditworthiness of even those borrowers who are of a lower quality than the average borrower.

[5] Among these hypotheses are "bad luck", "bad management", and "skimping", see Section 2 for the details.

[6] In accordance with a study of the Bank of Russia called "The main results of the survey of credit institutions on stress testing in 2008", the majority of bank respondents assigned the first position in risk ranking to credit risk despite belonging to a particular region within the Russian Federation (135 out of 167 responding bankers), see Bank of Russia (2008). Undoubtedly, there is a need to study possible relationships between efficiency and other types of bank risks in future research.

[7] At this step, we also estimate the opposite effect, meaning the impact of risk on efficiency. We compare these two estimated effects in order to make a conclusion about the ability of the Russian banking system to control risk through efficiency.

teria, which could complement the high efficiency condition of Berger and DeYoung's study. The first one is *the extensive growth condition*, as those banks that grow too fast are more likely to weaken the lending standards that make them more efficient in the short run, but more exposed to credit risk in the long run. The second one is *the insufficient capital condition*, as those banks that suffer from lower capital buffers are restricted in their further business development, and that pushes them to cut expenses in order to increase and capitalize profits. It could be easier for bank managers to cut borrower screening expenses rather than personnel expenses (the well-known managerial power effect, see Hughes et al., 2003), which, similarly to the previous case, leads to short-term efficiency improvements and long-term deteriorations to loan quality.

Our main result implies that, while the "bad management" hypothesis holds on average for the banking sector as a whole, the "skimping" hypothesis could be relevant for those Russian banks that are not just highly cost efficient, as Berger and DeYoung (1997) predicted for US banks, but that at the same time pursue aggressive strategies on the market for loans to households and non-financial firms, especially during pre-crisis periods (when banks are too optimistic to pay increased attention to the quality of borrowers in order to extract higher profits in the short run). Interestingly, we show that the "skimping" strategy is not the case for those Russian banks that demonstrate a lower equity-to-assets ratio and that are highly cost efficient at the same time. A possible explanation for this phenomenon is that a higher level of financial leverage could force these banks to filter out low quality borrowers in order to be able to repay (expensively) borrowed funds.

We also show that, first, bank-specific characteristics play a different role in explaining the quality of loans from "skimpers" and "bad managers" and, second, that macroeconomic conditions have much stronger effects on the cost efficiency of the latter compared to the former. Essentially, skimpers continue to lend money to borrowers without regard to the state of the macroeconomic cycle – even during the periods of recessions.

We contribute to the literature in the following ways. First, we try to understand the motivations of bank managers that might stand behind the "skimping" strategy, and to test the relevance of such motivations for Russian banks. In that sense, we propose the extensive growth condition and the insufficient capital condition, which both compliment the high efficiency condition of Berger and DeYoung.

Second, we show that the "skimping" strategy could be characterized by *the speed-of-lending effect* and *the loans-pyramid effect*, which are both negatively related to banking stability. In that sense, we show that the real quality of loan portfolios can be hidden as skimpers lend funds too fast (the first effect) and offer to borrowers credit rollovers, debt refinancing programs, and so on (the second effect).

Third, we show differences in behavior between skimpers and other banks, which are reflected in business strategies and risk exposure. We claim that the Bank of Russia should take these differences into account by implementing some norms of differential prudential regulation. For example, skimpers could be subjected to higher capital adequacy requirements and/or increased payments to the Russian Deposit Insurance Agency to restrain their risk appetites.

Fourth, to the best of our knowledge, our study is the first to apply Berger and DeYoung's (1997) methodology to the Russian banking sector by testing the relationship between cost efficiency and credit risk.

The remainder of the paper is organized as follows. Section 2 presents a short overview of related literature. Section 3 reviews the methodology. Section 4 describes the data sources and descriptive statistics. The estimation results are presented and discussed in Section 5. Final comments and relevance of conclusions from policy perspectives are outlined in Section 6.

2. Literature review

The literature on banking and finance separately covers such problematic areas as identifying macro- and microeconomic determinants of bank loan portfolio quality (Berger et al., 2009; Jimenez and Saurina, 2005; and many others), on the one hand, and efficiency and its determinants (see, for example, Fernandez de Guevara and Maudos (2007) among others), on the other hand.

However, empirical studies analyze potential relationships between cost efficiency and credit risk to a lesser extent (Berger and DeYoung, 1997; Fiordelisi et al., 2011; and some others, see below). Moreover, none of these works try to identify those banks that could skimp on risk management using different identification criteria, comparing these banks with the other part of the banking system and explaining the possible motivation behind such skimping. In this sense, we try to fill this gap.

Berger and DeYoung's (1997) study is a fundamental work in the area of estimating the efficiency-risk relationship. The authors formulated the following hypotheses regarding possible relationships between loan quality and cost efficiency:

1. *Bad management*: A low level of a bank's cost efficiency is a signal of shortcomings in general managerial practices (moral hazard), which could also mean insufficient or inadequate efforts undertaken by bank management to analyze borrower quality, resulting in the deterioration of loan quality in the long run.
2. *Skimping*: In order to enhance cost efficiency in the short run, bank managers decide to reduce expenses devoted to screening borrowers, which leads to decreased loan quality in the long run via a possible adverse selection problem.

3. *Bad luck*: A worsening of macroeconomic conditions reduces the ability of both non-financial firms and households to repay debt, decreasing the quality of loans, which, in turn, causes banks to increase expenses devoted to monitoring borrower quality. As a result, cost efficiency reduces.

So, while the "bad management" and "bad luck" hypotheses could be considered as normal relationships between efficiency and risk, the "skimping" hypothesis represents an abnormal (positive) or, as we would say, distorted connection between the two. This abnormal reaction of risk on efficiency changes is fully dependent on the motivations of bank managers to skimp. Analyzing such motivations, we try to develop our own "skimping" identification criteria (see below), treating the Berger and DeYoung (1997) study as a foundation for our study.

In Berger and DeYoung's paper (1997), the authors conclude that the "bad luck" and "bad management" hypotheses are both relevant for the US banking sector as a whole, while the "skimping" hypothesis is relevant only for a subsample of highly efficient banks during the period of 1985–1994. Analyzing the Russian banking sector, we claim that this high efficiency condition is not enough to identify skimpers. In that sense, this condition is not universal and should be further complemented by other criteria.

In addition to Berger and DeYoung (1997), Kwan and Eisenbeis (1997) test the relationships between a bank's cost efficiency and its loan portfolio quality for US banks; Williams (2004), Altunbas et al. (2007), and Fiordelisi et al. (2011) do the same for European banks. While Williams (2004) comes to similar conclusions as do Berger and DeYoung and provides arguments in favor of the "bad management" hypothesis, Altunbas et al. (2007) come to the opposite conclusion and claim that the "skimping" hypothesis is more appropriate than the other ones.

On this background, Fiordelisi et al. (2011) try to shed more light on the contradictory findings of Williams (2004), on the one hand, and Altunbus et al. (2007), on the other hand, and conduct a comprehensive empirical analysis using both the non-performing loan ratio (NPL) and expected default frequencies (EDF, provided by Moody's KMV) as measures of risk and complement cost efficiency indicators with more generous profit efficiency scores. Their results provide strong evidence supporting the "bad management" hypothesis and rejecting the "skimping" concept for EU banking.

So, the experience of Fiordelisi et al. (2011) clearly shows us that the conclusion about whether the "skimping" exists or not depends firstly on how one identifies the criteria of the "skimping" existence and, secondly, on what country one chooses to identify skimping. That necessitates the use of country-specific empirical models for efficiency-risk relationships. To be sure that these models are robust to different possible specifications, one should show that these models provide qualitatively similar conclusions independently of adding some micro- and/or macroeconomic variables as controls to relationship estimation procedures.

For that reason, we also analyzed studies aimed at estimating the effects of efficiency on risk, controlling for both micro- and macroeconomic conditions. With this respect, we would like to refer first to the studies of Salas and Saurina (2002) and Louzis et al. (2011), which try to understand the macroeconomic and bank-specific determinants of NPLs in Spain and Greece, respectively. The authors use only cost-to-income ratio (CIR) as a measure of efficiency, instead of frontier estimates (such as Frontier Analysis) in empirical equations within a panel data framework. They lend additional support to the "bad management" hypothesis, though it is not their primary aim. The second paper by Quagliariello (2007), who performs basically the same analysis for Italian banks, comes to contradictory findings about the CIR influence on risk, as the contemporaneous effect was estimated to be positive while the one-year lagged effect of CIR was negative and both effects were significant.

Again, we see some contradictions in findings despite using the same proxies for credit risk and efficiency, such as the NPL ratio and CIR, respectively. Nevertheless, in our further empirical analysis we will use experience in modeling the NPL dynamics of Salas and Saurina (2002), Louzis et al. (2011), and Quagliariello (2007) in part of the authors' classification of credit risk determinants from both micro- and macroeconomic sides.

Studies based on Russian data are rather limited as well, but are more coordinated, at least as of yet. Mamonov (2012) and Pestova and Mamonov (2013), among other things, provide some evidence in favor of the "bad management" hypothesis using CIR and SFA scores, respectively. The authors did not test the other hypotheses from among those listed above.

Summarizing the findings of different authors regarding the efficiency-risk relationship, we state that, first, the nature of such a relationship is not universal across countries and implies some country-based specificities, which we would like to analyze using data on Russian banks. Second, the relevance of the "skimping" hypothesis is fully dependent on how one recognizes the essence of skimping. Moreover, it is hard to identify skimping using only one simple criterion like the high efficiency condition and so on. In that sense, we try to add to the literature by developing new criteria for identifying skimping.

3. Methodology

3.1. Indicators for bank cost efficiency

In order to test the validity of these hypotheses regarding the relationships between efficiency and risk in Russian banking, and to provide for the robustness of empirical conclusions, we use three different indicators for cost efficiency. The first two are obtained using a translog cost function within the stochastic frontier analysis (SFA) and the distribution free approach (DFA), respectively. The third one is the operating-cost-to-operating income ratio, which is less sophisticated than the first two, but more flexible. We do not exploit other possible measures of efficiency, including non-econometric approaches such as data envelopment analysis (DEA), which is more complicated in estimating the requiring linear programming technique, but which at the same time does not allow us to test different hypotheses regarding input/output influences on costs.

Following Berger and DeYoung (1997) and Fernandez de Guevara and Maudos (2007), we specify the following translog cost function:

$$\ln OC_{it} = \beta_0 + \sum_{j=1}^{3}\beta_j \cdot \ln Y_{j,it} + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3}\beta_{kl} \cdot \ln Y_{k,it} \cdot \ln Y_{l,it} + \sum_{m=1}^{3}\gamma_m \cdot \ln P_{m,it} +$$
$$+ \frac{1}{2}\sum_{r=1}^{3}\sum_{q=1}^{3}\gamma_{rq} \cdot \ln P_{r,it} \cdot \ln P_{q,it} + \sum_{s=1}^{3}\sum_{u=1}^{3}\delta_{su} \cdot \ln Y_{s,it} \cdot \ln P_{u,it} + \alpha_1 \cdot TREND + \alpha_2 \cdot TREND^2 +$$
$$+ \sum_{j=1}^{3}\varphi_j \cdot \ln Y_{j,it} \cdot TREND + \sum_{m=1}^{3}\psi_m \cdot \ln P_{p,it} \cdot TREND + v_{it} + u_{it} \qquad (1)$$

where

- OC_{it} represents operating costs for bank i at time t;
- $Y_{j,it}$ is the j-th output of bank i at time t ($j = 1 \ldots N$, $N = 3$): total loans (without taking into account loans granted to the state and to other banks), total accounts and deposits of households and non-financial firms, and fee and commission income (as a proxy for the scope of off-balance-sheet activities);
- $P_{m,it}$ – m-th input price of bank i at time t ($m = 1 \ldots N$, $N = 3$): price for borrowed funds (average funding rate), price for personnel expenses and price for other expenses not related to personnel or borrowed funds (as a proxy variable for the price for physical capital).
- TREND – time trend;
- β – parameters to be estimated;
- $\varepsilon_{it} = v_{it} + u_{it}$, where $v_{it} \sim i.i.d. N(0, \sigma_v^2)$ represents idiosyncratic shock and u_{it} represents the inefficiency term, $\sigma_\varepsilon^2 = \sigma_u^2 + \sigma_v^2$ (v_{it} and u_{it} are independent by assumption).

We claim that in estimating efficiency on the basis of a standard translog cost function, it is very important to exclude from the dependent variable (costs) not only (i) interest expenses, which reflect market power rather than efficiency (as actually done in Golovan et al., 2008; Peresetsky, 2010; and Kumbhakar and Peresetsky, 2013), but also (ii) revaluation of assets and liabilities denominated in foreign currency[8], which reflect a bank's involvement in the foreign exchange market, rather than bank efficiency, and (iii) expenses for loan loss provisioning, which reflect credit risk. Actually, Belousova (2009) and Aleskerov et al.

[8] Especially in the case of Russian banks whose incomes and costs are from $^1/_3$ to $^2/_3$ composed of foreign currency revaluation

(2010) do not consider elements (ii) and (iii) in their cost function and we are close to what they have already done, but they did not exclude element (i). Besides this, the authors use only one element in operating expenses – personnel expenses, but do not take into account such an important element as so-called other operating expenses[9] in terms of Russian accounting standards (RAS).

So, hereafter, operating costs are calculated as total cost minus the sum of interest expenses, expenses for loan loss provisions, and positive revaluation of assets and liabilities denominated in foreign currency[10]. Each of these three excluded components reflects market power, credit risk, and a bank's involvement in the foreign exchange market, rather than operating efficiency.

First, if we do not exclude interest expenses, our efficiency indices reflect both operating efficiency and market power due to distinctions in a bank's abilities to lower interest rates on deposits that have little relation to what we are estimating. Similar explanations could be found in Berger and DeYoung (1997) and Fernandez de Guevara and Maudos (2007).

Second, if we do not exclude expenses for loan loss provisions, the resulting efficiency indices will reflect more of a bank's aggressiveness in their lending strategies, rather than their operating efficiency. That also could lead to the endogenous relation between a credit risk proxy and cost efficiency indicator – by construction rather than by meaning – in respective equations of the Granger causality test[11].

Third, if we do not exclude a positive revaluation of assets and liabilities denominated in foreign currency, our efficiency indices will be strongly affected by the instability of the balance of payments in Russia and its large sensitivity to fluctuations in the official exchange rate, which are far from a bank's operating efficiency[12].

That is why we exclude all these three components from efficiency frontier estimations. In fact, this is the main distinction of our research from previous studies.

To the best of our knowledge, there are also no empirical works based on data for Russian banks that try to capture the effect coming from off-balance-sheet activities on the efficiency frontier. We fill this gap by controlling for commissions and fee-based income[13], treating it as a third

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[9] This element includes fines and penalties and some "strange" positions called "Other expenses attributable to other costs", which could be used by bank managers as a "black hole" to hide some important expenses or to falsify accounts.

[10] The latter is taken into account only when the positive revaluation is less than negative revaluation in order to account for the net importance of foreign currency operations of Russian banks

[11] Note that the expenses for loan loss provisions are much more economically important than personnel expenses (the base category of operating expenses), being equal to 11.8% and only 1.7% of total assets on average during the sample period.

[12] As in the previous case (see Footnote 10), a positive revaluation of assets and liabilities denominated in foreign currency are much more economically important than personnel expenses and amount to approximately 50% of total assets with a significant increase during the crisis (to almost 65%).

[13] We cannot omit this variable as it provides the second most important source of profit for Russian banks, after interest income, exceeding all the others sources of profit in magnitude. In that sense, as a percentage of total assets, net commission and fee-based

output in the translog cost function. Other researches use standard sets of outputs, including only assets, as in Fungachova and Weill (2011), or loans, deposits, and borrowings, as in Peresetsky (2010).

In order to ensure that the empirical conclusions are robust, several different interpretations of component u_{it} have been examined within the framework of stochastic frontier analysis (SFA):

– $u_{it} \sim i.i.d.N^{+}(0,\sigma_u^2)$ is a random variable with positive half-normal distribution with a mean of zero and dispersion σ_u^2;

– $u_{it} \sim i.i.d.N^{+}(\mu,\sigma_u^2)$ is a random variable with a positive normal distribution truncated at zero with mean μ and dispersion σ_u^2.

Another series of calculations of empirical cost function parameters was performed within the framework of a distribution free approach (DFA), assuming $u_{it} = u_i$ to be a fixed effect reflecting constant inefficiency of bank i throughout the defined period of time[14].

We perform our cost efficiency estimates in the STATA 11.2 econometric package, allowing us to exploit the maximum likelihood (ML) estimator within the SFA approach and the generalized least squares estimator (GLS) assuming fixed effects within the DFA approach.

SFA and DFA efficiency indices for each bank i at each time t were calculated using the resulting estimates of the cost inefficiency components $\hat{u}_{it}$:

$$SFA_{it} = e^{-\hat{u}_{it}} \in (0,\, 1) \tag{2}$$

$$DFA_{it} = \frac{\hat{u}_{\min,t}}{1+\left[\hat{u}_{\min,t};\hat{u}_{it}\right]} \in (0,\, 1] \tag{3}$$

where $\left[\hat{u}_{\min,t};\hat{u}_{it}\right]$ is the distance between the inefficiency component score of the most efficient bank at time t, and the similar component of bank i. When $\hat{u}_{\min,t} = \hat{u}_{it}$, the DFA index becomes equal to 1. This means that this approach allows a certain set of banks (the most efficient ones) to be directly located on the frontier while the SFA approach excludes that option.

In estimating the translog cost function, we put a standard set of restrictions on factor input prices, allowing for a constant return on scale, i.e.:

$$\sum_{m=1}^{3}\gamma_m = 1;\ \sum_{q=1}^{3}\gamma_{rq} = 0\ \forall r = 1...3; \sum_{u=1}^{3}\delta_{su} = 0\ \forall s = 1...3; \sum_{m=1}^{3}\psi_m = 0 \tag{4}$$

income equals 1.4% on average during the sample period, while net income from securities transactions and net income from foreign currency operations are only 0.9% and 0.2%, respectively (for comparison: net interest income is about 3.4%).

[14] Fixed effects u_i were estimated in a series of sequential panel regressions across four moving quarters in order to obtain DFA-estimations of efficiency at each time t, thus ensuring their comparability with SFA estimations. The estimated u_i components were assigned to the respective fourth quarter in each set of the four moving quarters.

In our further analysis, we also use a more simple balance-sheet-based indicator of bank cost efficiency, namely the "operating cost-to-operating income ratio" (CIR), to provide additional robustness to our conclusions[15].

3.2. The Granger causality test: an estimate of "pure" efficiency impact on loan quality

As a first step, we estimate the "pure" effect of cost efficiency indicators, described in the previous section, on a credit risk proxy. By saying the "pure" effect, we understand an estimated influence of efficiency on risk, obtained in a regression with no other micro- and macroeconomic control variables taken into account. In order to estimate this "pure" effect, we exploit the Granger causality test (Granger, 1969) in a panel application.

More specifically, we specify the following equations:

$$ODL_{i,t} = \sum_{k=1}^{4} \alpha_k^{(1)} \cdot ODL_{i,t-k} + \sum_{k=1}^{4} \beta_k^{(1)} \cdot EFF_{i,t-k} + \varepsilon_{i,t}^{(1)} \quad (5.1)$$

$$EFF_{i,t} = \sum_{k=1}^{4} \alpha_k^{(2)} \cdot ODL_{i,t-k} + \sum_{k=1}^{4} \beta_k^{(2)} \cdot EFF_{i,t-k} + \varepsilon_{i,t}^{(2)} \quad (5.2)$$

where

- ODL_{it} (Overdue loans ratio) is the share of overdue loans in the total loans of bank i at time t[16];
- EFF_{it} (Efficiency index) is an index for operating cost efficiency of bank i at time t, calculated using SFA methodology (base option), DFA methodology (first supplemental option), or as the ratio of operating costs to operating income (CIR, second supplemental option);
- $k = 1 \ldots 4$ is the lag structure of variables, which takes into account the quarterly format of the database being used (see description of the data below).

These specifications are very similar to those applied in the studies mentioned above (Berger and DeYoung, 1997; Fiordelisi et al., 2011; and others). We estimate specified equations using the

[15] The fundamental advantage of frontier efficiency indices (SFA and DFA scores) over simple balance sheet coefficients (like CIR) is as follows. In the former case, efficiency is understood as a bank's ability to possess lower costs – at given input prices and the predefined outputs – than its competitors, i.e. within market conditions which are external to a bank and its rivals, and the result of a bank's actions under these predefined conditions. The latter (CIR and its analogues) takes into account only the result – the resulting costs that guarantee the bank one ruble of income independent of the inputs prices. If a bank operates on competitive markets and cannot dictate prices to other rivals (i.e., is a price taker), then, all else being equal (including cases of unchanging demand for bank outputs), increasing the cost of production factors will lead to an increase in bank expenses, but will not change its income. In other words, there will be an increase in CIR, which is equivalent to reducing efficiency in this approach. However, there will be no efficiency reduction under both SFA and DFA approaches, guaranteed by the fact that the growth of input prices will be reflected in the growth of the modeled (meaning economically justified) value of the costs, while changes in the inefficiency component u_{it} will not occur.

[16] This measure is in accordance to Russian Accounting Standards (RAS). Unfortunately, Russian banks are not required to publish their non-performing loans ratios (NPLs). See Pestova and Mamonov (2013) for details.

two-step difference GMM procedure, designed by Arellano and Bond (1991), to account for persistency and endogeneity concerns in dynamic panel data models.

The "bad management" and "skimping" hypotheses are tested using the first of the two equations. Specifically, if:

– $\sum_{k=1}^{4} \hat{\beta}_k^{(1)} < 0$ holds on average for the whole sample of banks, then it would be an argument for the "bad management" hypothesis;

– $\sum_{k=1}^{4} \hat{\beta}_k^{(1)} > 0$ is true on average for the whole sample or some subsample of banks (e.g. with high operating cost efficiency), then the opposing "skimping" hypothesis is relevant.

The validity of the first hypothesis ("bad management") at the level of the whole sample of banks does not automatically mean that it is impossible to identify a subsample of banks for which the alternative concept ("skimping") would be valid. In order to determine the criteria for identifying banks of this type, we need to understand the motivation behind the respective behavior of credit organizations. So, in addition to the desire to be (or to seem to be) highly efficient (for example, to "embellish" results for shareholders), the following circumstances could also push bank managers to undertake these types of unjustified savings.

First is the *insufficiency of capital* needed to achieve strategic objectives that shareholders could set for managers. The objectives may be achieved by increasing a business' profitability (ROA) and, thus, profit charges, which is easier to perform by artificially "cutting" expenses and first screening expenses. The above will obviously result in the decline of portfolio quality, but it does help satisfy the hopes of shareholder in the short run.

Second is the *need to secure competitive positions* on the market (for example, in order to keep market shares during periods of growth in consumer optimism). This objective may be achieved by extensively expanding the credit portfolio – such as at rates exceeding the average for the system – by weakening lending standards. This results in increased cost efficiency in the short run, but is very likely to negatively affect the quality of loans in a longer horizon.

Thus, we consider *the high efficiency condition* as in Berger and DeYoung (1997), meaning that a bank's efficiency indices must be above the sample's median, and treat it as the basic filter aimed at defining skimpers. Next, we try to extend the Berger and DeYoung analysis and propose two additional filters to be applied to the whole sample of banks in order to identify skimpers. The first additional filter (*the insufficient capital condition*) is that the equity-to-assets ratio may not exceed the 50^{th} (25^{th}) percentile level. The second additional filter (*the extensive growth condition*) is that the annual loan growth rate in real terms must be above the sample's median. Then, we run a series of regressions using these filters, obtaining respective subsamples of banks within the framework of the Granger test.

The second Granger test equations (with the efficiency index as the dependent variable) is used to test the “bad luck” hypothesis. Specifically, if $\sum_{k=1}^{4}\hat{\alpha}_k^{(2)} < 0$, then this hypothesis is not rejected[17].

3.3. Micro- and macroeconomic controls: further estimates of the efficiency impact on loan quality

As a second step in our empirical analysis, we answer the question of how much the “pure” efficiency impact on loan quality, estimated in the first step (in the Granger framework), will change in response to adding micro- and macroeconomic control variables into the overdue loan equation (ODL).

Basically, we specify an empirical equation where ODL is the dependent variable and EFF (efficiency) is the key explanatory variable, alongside with other control variables reflecting bank-specific and macroeconomic conditions. In estimating such an equation, we track changes in the total EFF impact on the ODL ratio that occur, compared to the same effect revealed in the respective equation of the Granger test. In specifying such an equation, we follow Quagliariello (2007) and Louzis et al. (2011). This equation is as follows:

$$ODL_{i,t} = \alpha \cdot ODL_{i,t-1} + \beta \cdot EFF_{i,t-1} + \sum_{j=1}^{N_1}\rho_j \cdot BSF_{j,it-q} + \sum_{l=1}^{N_2}\rho_l \cdot MACRO_{l,t-k} + \varepsilon_{i,t} \tag{6}$$

where

- ODL_{it-1} (overdue loans ratio) is the overdue loans ratio of bank *i* at time (*t-1*) to account for credit risk persistency over time as pointed out in Salas and Saurina (2002)[18];
- EFF_{it} is one of the three estimated efficiency indicators of bank *i* at time *t*, namely the SFA score (under a half-normal case), the DFA score or the CIR;
- $BSF_{j,it}$ is the *j*-th microeconomic factor ($j = 1 \ldots N_1$), characterizing the parameters of the business strategy of bank *i* at time *t-q*, *q=0…4*;
- $MACRO_{l,t}$ is the *l*-th indicator from the group of macroeconomic factors ($l = 1 \ldots N_2$), characterizing the environment common for all banks at time *t-k*, *k=0…4*.

[17] Note that the opposite result, even if it is statistically significant, will not have a substantive explanation. A decline in portfolio quality cannot in and of itself improve bank efficiency without any additional conditions, which are not taken into account in the Granger test equations.
[18] Most of the empirical studies follow this rule. See, for example, Quagliariello (2007), Espinoza and Prasad (2010), Jimenez and Saurina (2005), Jimenez et al (2007), Fiordelisi et al (2011).

Tab. 1. Bank-specific (BSF) and macroeconomic (MACRO) determinants of bank credit risk in different studies

	BSF	MACRO
Salas and Saurina (2002)	Loan growth rate, Branch growth rate, Loans without collateral to total loans ratio, Bank size (in terms of assets), Net interest margin to assets ratio, Equity-to-assets ratio, Bank market share, Risk premium	GDP growth rate, Household debt to GDP ratio, Firm liabilities to firm market value ratio
Quagliariello (2007)	Loan growth rate, Loan loss provision to total loans ratio, Equity-to-assets ratio, ROA, Interest margin to assets ratio, Other (non-credit) income to total income ratio, Bank size (in terms of assets)	GDP growth rate, Stock exchange index growth rate, risk-free asset price, Spread between loan and deposit rates
Louzis et al. (2011)	ROE, Equity-to-assets ratio, Other (non-credit) income to total income ratio, Bank size (in terms of assets), Leverage, Ownership concentration	GDP growth rate, Unemployment rate, Real interest rate on commercial loans, Sovereign debt to GDP ratio

Note: Bank-cost inefficiency, proxied by the cost-to-income ratio, is used in all studies considered.

Sources: Salas and Saurina (2002), Quagliariello (2007), Louzis et al. (2011)

As was mentioned above in the literature review, in choosing particular bank-specific (BSF) and macroeconomic (MACRO) controls for our estimates of efficiency-risk relationship (Eq. 6), we follow, but are not constrained to, the experience of Salas and Saurina (2002), Quagliariello (2007), and Louzis et al. (2011), among others. We briefly summarize their views on credit risk determinants in Table 1.

More details in different authors' classifications of credit risk determinants and their review could be found in our recent paper (Pestova and Mamonov, 2013).

We stress that it is not of our primary concern to include as much micro- and macroeconomic variables into Eq. 6 as it is possible. We only need to incorporate some relevant set of these variables in our empirical equation to control for a particular pattern of the efficiency-risk relationship.

Aggregating the views of different authors on credit risk determinants, we firstly conclude that the BSF factors are those reflecting a bank's lending strategy and its riskiness (B1), its bank's concentration and ownership structure (B2), and a bank managers' risk tolerance (B3). Second, the MACRO factors are those standing for economic cyclicity and official exchange rate movements, and the economic conditions of firms and households (debt sustainability).

So, to match this aggregation, we choose the following set of BSF controls.

For the B1 subset:

— real interest rate charged on loans (positively affects the dependent variable, ODL, through the problem of adverse selection);

— loan-to-deposit ratio (positively affects ODL because of growing imbalance between allocated and attracted funds);

— loans to households as a share of the bank's total loans (positively affects ODL as retail lending is more risky compared to corporate lending and reflect a particular strategy to pursue, as chosen by managers);

— loans with maturities of three years or more as a share of a bank's total loans (can affect ODL either positively, through effects from an uncertainty of perspectives, or negatively, as such the long-term loans are supposed to be granted to higher quality borrowers)[19].

As the B2 subset:

— the bank's share in the total banking system loans and

— a bank's individual concentration index in domestic markets for banks liabilities[20] (as proxies for bank size and its market power in the market for loans, respectively. Both can affect ODL either negatively, through risk diversification or the "market power – stability" effect of Keeley (1990), or positively, through the too-big-to-fail problem or the "market power – fragility" effect of Boyd and De Nicolo (2005)).

For the B3 subset:

— equity-to-asset ratio (negatively affects ODL due to the "franchise value" effect of Keeley (1990), which is close to the "market power – stability" effect);

— liquidity-to-deposit ratio (negatively affects ODL in as much as the more funds are allocated to liquidity, the less the bank is able to lending).

As MACRO factors, we first consider the real GDP growth rate and the unemployment rate, which are counter- and pro-cyclical indicators for ODL, respectively. We also use here the standard deviation of the ruble-to-dollar exchange rate and the current account balance to GDP ratio to account for devaluation expectations and their negative effects on ODL, likely through a possible worsening of creditworthiness of those borrowers whose debt is denominated in foreign currency. Second, we employ two proxies for a household's economic condition – a household's real disposable income growth rate and consumer overheating, understood to be the annual growth of the ratio of consumer spending to disposable income, which can negatively and positively affect ODL. At last, we use one proxy for the debt sustainability of the non-financial sector – the profit to debt ratio.

[19] We thank Fuad Aleskerov for his suggestion to use this variable in our empirical analysis.
[20] We calculate this variable using the methodology of Berger and Hannan (1998).

4. Data

We use data from the monthly balance sheets of banks (Form 101) and quarterly profit and loss accounts (Form 102), published for open access on the Bank of Russia's website with the permission of banks (see Footnote 2). We use all available information that can be retrieved from this source, meaning for the period from the 1st quarter of 2004 to the 3rd quarter of 2012.

The descriptive statistics of variables reflecting the banks' operating costs, outputs, and input factor prices are presented in Table 2. We use these variables to estimate the efficiency frontier via the traslog cost function described in Section 3.1.

The descriptive statistics of the variables used to estimate the Granger test equations (see Section 3.2) and to estimate the impact of efficiency on the overdue loans ratio, controlling for other factors (see Section 3.3), are presented in Table 3. All data for macroeconomic variables were collected from the Federal State Statistics Service.

In order to eliminate the negative impact of outliers, we excluded from the sample all those observations for which:

- the real interest rate exceeded 200% annually (0.1% of the initial volume of data);
- the loans-to-deposits ratio was above 1000% (2% of the initial volume of data);
- the ratio of liquid assets to deposits exceeded 305% (1% of the initial volume of data).

Tab. 2. Descriptive statistics of variables used to estimate the parameters of the empirical cost function of Russian banks

	minimum	**average**	**maximum**	**standard deviation**	**percentile**		
					1	**50**	**99**
Operating costs	0.0	5.6	1769.7	42.2	0.0	0.2	104.7
Bank outputs (millions of rubles)							
Loans	0.0	16.2	8325.2	179.3	0.0	1.0	235.3
Deposits	0.0	14.8	7990.2	178.0	0.0	1.1	192.4
Fee and commission income	0.0	0.5	188.4	4.5	0.0	0.0	7.6
Input factors prices (as % of total assets)							
Borrowed funds	0.00	4.88	50.13	2.82	0.12	4.75	12.39
Personnel	0.10	4.03	75.76	3.07	0.53	3.35	14.29
Physical capital	0.13	32.29	496.59	36.08	3.04	21.72	181.82

Sources: Bank of Russia database, author's calculations

Tab. 3. Descriptive statistics of micro- and macroeconomic variables

	Minimum	Average	Maximum	Standard deviation	Percentile		
					1	50	99
Bank-specific factors (BSF)							
Overdue loans ratio, %	0.0	3.6	100.0	5.9	0.0	1.8	26.2
SFA cost efficiency index[1], %	7.0	62.9	96.5	10.3	32.0	64.0	83.6
DFA cost efficiency index[1], %	13.9	35.2	100.0	11.7	18.4	32.9	77.2
Operating costs to operating income ratio (CIR), %	12.4	72.1	376.5	17.7	30.0	73.6	104.3
Real interest rate charged on loans, %	-11.9	5.0	199.5	6.9	-5.0	4.3	23.9
Loan-to-deposit ratio, %	0.6	113.3	992.7	94.9	11.2	91.6	550.0
The bank's share in the total banking system loans, %	0.0	0.1	38.9	1.3	0.0	0.0	1.9
Liquid asset[2] to accounts and deposits ratio, %	0.1	30.7	304.7	30.3	3.0	20.9	153.0
Equity-to-asset ratio, %	-41.2	19.8	93.8	12.8	5.4	15.7	66.1
Bank's individual concentration index (in domestic markets for banks liabilities)[3]	365.7	1509.7	4014.6	509.6	608.8	1490.0	2850.4
The share of loans to households in total bank's loans, %	0.0	31.1	100.0	25.7	0.2	24.2	100.0
The share of loans with maturities of three or more years in total bank's loans, %	0.0	19.2	100.0	17.4	0.4	14.2	76.7
Macroeconomic factors (MACRO)							
Real GDP growth rate (annual), %	-11.2	4.4	8.6	4.9	-11.2	6.1	8.6
Unemployment rate, %	5.3	7.1	9.2	1.0	5.3	7.1	9.2
Standard deviation of the ruble-to-dollar exchange rate on the foreign exchange market	0.1	0.5	2.0	0.5	0.1	0.3	2.0
Household real disposable income growth rate (annual), %	-4.9	7.1	15.4	5.1	-4.9	7.5	15.4
The annual growth of the ratio of consumer spending to disposable income, perc. points	-7.5	0.7	5.6	3.1	-7.5	0.9	5.6
Profit-to-debt ratio for non-financial firms, %	-1.7	4.5	10.4	2.5	-1.7	4.7	10.4
Current account balance to GDP ratio, %	1.4	7.0	14.7	3.3	1.4	6.1	14.7

Notes:

[1] Cost efficiency indices are calculated on the basis of translog cost function (see Section 5.1 for details);

[2] The sum of bank funds in correspondent accounts and bank deposits at the Bank of Russia, and bank investments in Bank of Russia bonds

[3] Hereinafter, the indicator means the sum of the industry-level Herfindahl-Hirschman concentration indices at the various liabilities markets (retail deposits, non-financial corporation deposits, interbank deposits, loans by the Central Bank, issued securities), weighted by the shares of respective types of liabilities on total liabilities for each bank. The indicator reflects the level of involvement of each bank on the liabilities markets. This methodology proposed by Berger and Hannan (1998).

Sources: Bank of Russia database, Federal State Statistics Service, author's calculations

5. Estimation Results

5.1. Cost efficiency indicators of Russian banks

We now briefly discuss the behavior of different versions of SFA and DFA efficiency scores in order to understand the degree of their coherence. This is of vital importance for us as exactly these indicators will be used in the following sections to test the relationship between efficiency and credit risk proxy (i.e. the overdue loans ratio). We do not stop here in analyzing non-econometric efficiency measures, namely the operating-cost-to-operating income ratio (CIR). All necessary information about the later can be found in our recent research (Mamonov, 2013).

Our key results regarding the comparison of different efficiency indicators are as follows[21]. For the SFA approach, the average efficiency scores estimated under both the half-normal and the truncated normal cases turn out to be close over the sample period and are 62.5% and 66.7% from the frontier, respectively, which are about 10-20 percentage points less than those achieved in Belousova (2009) and Kumbhakar and Peresetsky (2013). This is explained by exclusion of the revaluation of assets and liabilities, denominated in foreign currency from the frontier analysis.

Some more detailed information about both the SFA and the DFA efficiency scores, including their pre- and post-crisis crisis development and distributions are presented in Appendix A.

Hereinafter, we treat the SFA scores under the half-normal case as the main efficiency indicators of Russian banks, while DFA and CIR are only considered as additional ones that are aimed at ensuring the robustness of our main results.

5.2 The Granger causality test

Now we present the Granger causality test results, first for the full sample of banks and second for the subsample of highly efficient banks, describing how we try to empirically identify banks that skimp on risk-management. These two sets of results allow us to obtain a range of "pure" efficiency impacts on loan quality (see Section 3.2).

The full sample (see Table 4). The basic results (Model M1) provide strong evidence in favor of the "bad management" hypothesis and some arguments supporting the "bad luck" hypothesis.

On the one hand, the overall impact of the preceding SFA values on the overdue loans ratio is negative at -0.056 (the estimate is significant on the 1% level)[22]. Thus, quarterly reductions in

[21] We do not provide estimation results for parameters from the translog cost function here in order to preserve space. All of them are available upon request.
[22] We highlight that the coefficient sign corresponds to the signs of pairwise correlations between the lagged SFA and ODL (Overdue loans ratio) value. See Table B1 of Appendix B.

efficiency by 1 standard deviation (10.3 percentage points, see Table 3) over four consecutive quarters leads to a future increase in the overdue loans ratio (ODL) by 0.58 percentage points on average (0.056×10.3), which corresponds to approximately 10% of the standard deviation of this credit risk indicator and is thus economically large.

On the other hand, the total impact of the preceding values of ODL on SFA is also negative at -0.047 (the estimate is significant only at the 10% level). This means that a quarterly increase of 1 standard deviation (5.9 percentage points, see Table 2) over four consecutive quarters can lead to a future increase in additional expenses related to managing overdue loans, which is equivalent to a decrease of SFA in the amount of 0.28 percentage points on average (0.047×5.9=0.28, approximately 5% of the standard deviation of SFA).

Consequently, the impact of loan portfolio quality deterioration on efficiency is approximately twice as weak as the impact of efficiency decreases on portfolio quality.

First, this means that controlling costs and ensuring their actual (not artificially inflated or falsified) efficiency – especially at the pre-crisis development stage – is an effective mechanism for ensuring a bank against the uncontrollable deterioration of loan portfolio quality during crisis periods (i.e. "bad luck")[23].

Second, it implies that the consecutive standardization and simplification of numerous reporting forms from banks (including daily ones) – if initiated by the Bank of Russia – would stimulate an increase in a bank's cost efficiency and loan quality improvement, as those funds that should have been spent by banks on the preparation of financial statements could instead be used to improve the monitoring of borrowers.

The M2 model where the DFA index was used as an efficiency indicator confirmed only the "bad luck" hypothesis, while the "bad management" hypothesis was rejected[24].

The M3 model using CIR as a measure of cost efficiency confirmed both hypotheses[25] like in the case of SFA.

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[23] Figuratively speaking, banks that improve cost efficiency during the pre-crisis period are on average half as susceptible to the "bad luck" effect during the crisis period as banks with an uncontrolled growth of expenses.

[24] The primary reason was that the lagged DFA values correlate with a loan risk indicator (ODL) that is 3 times smaller than the lagged SFA values (see Table B1 of the Appendix B).

[25] The impact of CIR increases in the amount of one standard deviation in preceding quarters on the current overdue loan ratio (ODL) is estimated to be 0.031×17.7=0.55 percentage points on average, which corresponds to a little less than 10% of a standard deviation of ODL. This means that the impact is similar to the SFA index, though it is somewhat less strong.

However, the growth of ODL of standard deviation in the preceding quarters can have more impact on the efficiency (CIR) than in case of SFA: 0.567×5.9=3.35 percentage points on average. The latter corresponds to approximately 19% of the standard deviation of the CIR indicator, which is 4 times greater than the corresponding impact of ODL on SFA.

But, as was noted above, one of the advantages of SFA over CIR is that the latter attributes efficiency decreases to banks much more often than the former, including cases where, among others, efficiency reductions do not actually happen. This phenomenon is indirectly proven by the higher volatility of the CIR as compared with the SFA (see their standard deviations in Table 2). That is why we shall consider conclusions related to CIR only in terms of quality and not in terms of quantity, meaning additional and as something that ensures the robustness of conclusions made on the basis of SFA.

Tab. 4. Results of the Granger causality test: the full sample of banks

Models	M1 "ODL vs SFA" (basic)		M2 "ODL vs DFA"		M3 "ODL vs CIR"	
Explanatory variables	**ODL**	**SFA**	**ODL**	**DFA**	**ODL**	**CIR**
Operating Cost Efficiency (SFA, DFA or CIR)						
lag = 1 quarter	–0.083*** (0.023)	0.820*** (0.025)	–0.012 (0.017)	0.561*** (0.021)	0.018 (0.019)	0.801*** (0.056)
lag = 2 quarters	0.015 (0.012)	0.034 (0.022)	0.009 (0.009)	0.151*** (0.019)	0.024 (0.032)	–0.063* (0.034)
lag = 3 quarters	–0.003 (0.010)	–0.065*** (0.015)	0.002 (0.013)	–0.221*** (0.020)	–0.007 (0.017)	0.051 (0.042)
lag = 4 quarters	0.016** (0.008)	–0.107*** (0.012)	0.011 (0.010)	0.092*** (0.014)	–0.003 (0.006)	–0.294*** (0.042)
Total effect	**–0.056*** (0.021)**		**0.010 (0.014)**		**0.031*** (0.012)**	
ODL						
lag = 1 quarter	0.812*** (0.058)	–0.052** (0.026)	0.803*** (0.057)	–0.169** (0.026)	0.813*** (0.052)	0.407*** (0.071)
lag = 2 quarters	0.019 (0.040)	0.022 (0.020)	0.021 (0.041)	–0.007 (0.014)	0.009 (0.037)	–0.010 (0.054)
lag = 3 quarters	0.014 (0.042)	–0.034 (0.023)	0.016 (0.043)	–0.006 (0.0163)	0.012 (0.043)	0.058 (0.045)
lag = 4 quarters	–0.045** (0.021)	0.018 (0.021)	–0.042* (0.022)	–0.077*** (0.014)	–0.064*** (0.022)	0.112** (0.052)
Total effect		**–0.047* (0.026)**		**–0.260*** (0.038)**		**0.567*** (0.117)**
Number of observations (banks)	16338 (950)	16385 (949)	16760 (952)	15411 (931)	16760 (952)	16882 (953)
Number of instruments	902	902	919	919	933	933
P–value, Hansen test	0.392	0.364	0.448	0.400	0.487	0.394
P–values, tests AR(1) / AR(2)	0.000 0.816	0.000 0.502	0.000 0.765	0.000 0.412	0.000 0.783	0.000 0.818

Notes: The M1-M3 models were estimated using the two-step difference GMM procedure proposed in Arellano and Bond (1991)

ODL (Overdue loans ratio) – overdue loans compared to a bank's total loans

SFA (Stochastic Frontier Analysis) – index of a bank's operating cost efficiency (under half-normal case)

DFA (Distribution Free Approach) – alternative index of a bank's operating cost efficiency

CIR – a bank's operating cost to operating income ratio

***, ** and * – a coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are provided in parentheses under the coefficients.

Sources: Bank of Russia database, author's calculations

Interestingly, our empirical results are more closer to those achieved by Fiordelisi et al. (2011), who analyze EU banking, compared to Berger and DeYoung (1997), who on the contrary study US banking, as we show that the estimated "bad management" effect is stronger than the "bad luck" one. This may possibly mean that the development of the banking business in Russia has more similar features with EU countries than with the USA.

The subsample of highly efficient banks (see Table 5). To test the “skimping” hypothesis, a number of conditions described above (see Section 3.2) were applied to the full sample of banks. Here we use only the SFA efficiency scores (under a half-normal case).[26]

Having a high efficiency is a filter condition that is common for all of the presented models (M4-M10): the SFA index must exceed the median value of the full sample of banks for a period of at least 4 quarters (M4), 8 quarters (M5), or 12 quarters (M6). The M7-M8 Models apply the insufficient capital condition, which is one of our two proposed conditions: the equity-to-assets ratio must not exceed the 50th percentile of the full sample (M7) or even be below the 25th percentile (M8) over at least 4 previous quarters. The M9-M10 Models replace insufficient capital conditions with the extensive growth condition, which is our second proposed condition: the real value of the annual lending growth rate must be higher (M9) than the median value of the full sample over a period of at least 4 quarters. To control for the robustness of the M9 Model, we also run the regression with the opposite condition (see M10), meaning that we set the loan growth rates below the median value of the full sample during this same period.

The results are as follows. The “skimping” hypothesis does not contradict the data in only one of the seven models, specifically in the M9 Model, which combines the high efficiency condition and the extensive growth condition. Using these two filters results in a subset of 1919 observations (394 banks during various quarters over the period of 2005-2012), which is approximately 8 times less than the original sample (see the M1 Model in Table 4). The total estimated impact of the preceding SFA values on the overdue loans ratio (ODL) of the banks in the defined subsample is positive and is 0.067 (significant at the 5% level)[27]. Thus, an increase in the SFA index of 1 standard deviation in this subsample of banks (5.2 percentage points) over the 4 previous quarters may result in growth of the ODL in the future by 0.067×5.2=0.35 percentage points (or approximately 8% of the ODL standard deviation in the given subsample).

The M10 Model was estimated as an alternative to the M9 Model in order to demonstrate the reverse effect: If we replace the extensive growth condition with its opposite, then the sign of correlation between the lagged values of SFA and ODL will switch from positive to negative again (see Table B2 of the Appendix B). Additionally, the total effect will also switch to the opposite sign (see Table 5), meaning that the “bad management” concept is again validated.

It is worth noting that in all the models, except M9, and despite applying the high efficiency condition and the insufficient capital condition, the total impact of efficiency on the overdue loans ratio (ODL) is not simply negative and statistically significant: it is 3-4 times stronger than

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[26] The estimation results for the other two efficiency measures are qualitatively the same and not presented here in order to save space.
[27] Again, as for the M1 model, the estimated coefficient sign coincides with the sign of pairwise correlation between the lagged SFA values and the ODL ratios for the corresponding subsample of banks (see Table B2 of the Appendix B)

Tab. 5. Results of the Granger causality test: the subsample of banks with above median cost efficiency levels

Models / Explanatory variables	M4	M5	M6	M7	M8	M9	M10
	Dependent variable – Overdue loans ratio						
Operating cost efficiency (SFA)							
lag = 1 quarter	–0.274***	–0.241***	–0.289***	–0.272***	–0.233***	0.021	–0.202**
	(0.049)	(0.054)	(0.067)	(0.044)	(0.063)	(0.037)	(0.080)
lag = 2 quarters	0.104**	0.115**	0.132**	0.060***	0.051**	0.046**	0.019
	(0.042)	(0.056)	(0.062)	(0.016)	(0.021)	(0.019)	(0.036)
lag = 3 quarters	–0.029	–0.046	–0.040	0.008	0.009	–0.008	–0.026**
	(0.024)	(0.034)	(0.036)	(0.016)	(0.022)	(0.016)	(0.041)
lag = 4 quarters	0.016	0.023	0.025	–0.002	–0.017	0.008	0.055
	(0.012)	(0.021)	(0.023)	(0.012)	(0.017)	(0.010)	(0.030)
Total effect	**–0.184*** **	**–0.150*** **	**–0.171*** **	**–0.206*** **	**–0.190*** **	**0.067** **	**–0.155** **
	(0.038)	**(0.045)**	**(0.055)**	**(0.041)**	**(0.053)**	**(0.033)**	**(0.066)**
Overdue loans ratio (ODL)							
lag = 1 quarter	0.443***	0.507***	0.483***	0.338***	0.257***	0.410***	0.320***
	(0.077)	(0.107)	(0.115)	(0.080)	(0.067)	(0.087)	(0.087)
lag = 2 quarters	0.076*	0.111**	0.107**	0.156***	0.188***	–0.023	0.015
	(0.045)	(0.048)	(0.049)	(0.043)	(0.056)	(0.059)	(0.068)
lag = 3 quarters	0.101**	0.063	0.062	0.139***	0.160***	–0.112*	0.132*
	(0.051)	(0.058)	(0.059)	(0.046)	(0.049)	(0.057)	(0.068)
lag = 4 quarters	–0.088***	–0.101**	–0.112**	–0.024	0.017	–0.063	–0.100*
	(0.031)	(0.040)	(0.045)	(0.024)	(0.076)	(0.060)	(0.057)
Number of observations	6344	4889	4207	3428	1308	1919	1479
(of banks)	(632)	(497)	(404)	(400)	(213)	(394)	(331)
Number of instruments	578	452	259	358	208	353	309
P–value, Hansen test	0.558	0.403	0.326	0.357	0.392	0.804	0.798
P–values, test AR(1) /	0.000	0.001	0.004	0.006	0.033	0.007	0.115
AR(2)	0.848	0.892	0.681	0.998	0.691	0.342	0.746

Notes: M4-M10 models were estimated using the two-step difference GMM procedure of Arellano and Bond (1991). The models were estimated using the following subsamples:

M4 – for banks that belonged to the group of high efficient banks (above the median) over at least the previous 4 quarters;

M5 – for banks that belonged to the group of high efficient banks (above the median) over at least the previous 8 quarters;

M6 – for banks that belonged to the group of high efficient banks (above the median) over at least the previous 12 quarters;

M7 – similar to the M4 Model, but with an additional requirement: the banks must also belong to the group with a low equity to assets ratio (below average) for the period of the same 4 previous quarters;

M8 – similar to the M4 Model, but with an additional requirement: the banks must also belong to the group with a very low equity to assets ratio (below the 25^{th} percentile level) for the period of the same 4 previous quarters;

M9 – similar to the M4 Model, but with an additional requirement: the banks must also belong to the group with high real loan growth rates (above average) for the period of the same 4 previous quarters;

M10 – similar to the M4 Model, but with an additional requirement: the banks must also belong to the group with low real loan growth rates (below the median) for the period of the same 4 previous quarters;

***, ** and * – a coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are provided in parentheses under the coefficients.

Sources: Bank of Russia database, author's calculations

the average effect for the full sample presented by the M1 Model (see Table 4). This means that the "bad management" concept is vastly more significant for this subsample of banks than in the original sample, and that the lack of capital may be compensated, at least partially, by the high efficiency of banks and does not mean a worse loan portfolio quality *a priori* [28].

So, we come to a similar conclusion as do Berger and DeYoung (1997) and Altunbus et al. (2007), who analyze US and EU banks, respectively, and we state that skimping does really exist in some Russian banks. But, unlike these two studies, we stress that skimping has a more complicated nature in Russia compared to both the EU and USA. As for its identification, it is not enough to just set one simple condition (for example, a high efficiency condition). The latter must be supplemented with one more thing – the extensive-growth condition – which is very important in the case of Russia, taking into account the developing nature of the Russian economy and its banking sector.

We also note that none of the other relevant studies (Fiordelisi et al., 2011; Salas and Saurina, 2002; Quagliariello, 2007; Louzis et al., 2011) found support for skimping as a possible bank strategy. This is not surprising because skimping is treated as something abnormal, as we previously stated in Section 2, and it is quite unrealistic to identify skimping at the level of the banking industry as a whole. It is possible only for some part of the banking industry, which requires criteria for its identification. But these authors did not look for such criteria.

From a technical standpoint, all models presented in Tables 4 and 5 satisfy the necessary conditions. First, the sets of instruments used by each of the M1-M10 Models are relevant according to the Hansen test results. Second, there is no second-order autocorrelation in the estimated regression errors, which is confirmed by the Arellano and Bond AR2-test. In the both cases the respective P-values exceed the 10% threshold.

5.3. The empirical equation of the overdue loans ratio: the joint estimation of efficiency and other controls

In this section, we present results for the estimation of Eq.6 (see Section 3.3), which describes how operating cost efficiency could affect the loan quality of Russian banks when controlling for other micro- and macroeconomic factors. The estimations were conducted in the following two steps[29]. We first perform regression analysis without the group of macroeconomic factors to account for the microeconomic effects only (see Table 6, models M11-M17). Second, we estimate the equation with both micro- and the macroeconomic factors to understand the role of the latter set

[28] The bank profile for the M4-M8 Models is as follows: These are banks with a high level of borrowed funds (leverage) that use these funds rather efficiently while paying due attention to risk management and screening procedures that allow them to control the quality of their loan portfolio. Indeed, the average overdue loan ratio in the subsample of such banks is just 2.9% on average for 2004-2012, which is 0.6 percentage points below the same indicator for the full sample.

[29] Again, we use here only the SFA scores (under the half-normal case) and do not present the results with the other two efficiency measures (the DFA and the CIR) in order to save space. The estimation results with the DFA and the CIR efficiency indicators are qualitatively the same and available upon request.

of variables in correcting the effects on the overdue loans ratio that come from the former set of variables (see Table 7, Models M18-M24).

Taking into account the empirically revealed phenomenon of “skimping” in a part of Russian banks (see Section 5.2), both Table 6 and Table 7 contain two panels, A and B, in which we present estimation results on the whole sample of banks and on the subsample of those banks that pursue a “skimping” strategy, respectively.

Then we compare the impact of cost efficiency on the loan quality estimated in Tables 6 and 7, with respective “pure” effects obtained under the Granger test and presented in Table 4 for the whole sample of banks (the M1 Model), and in Table 5 for the subsample of banks that are skimpers (the M9 Model).

5.3.1. Key findings

First, the “bad management” hypothesis and the “skimping” strategy still hold true for the full sample of banks and for the subsample of highly efficient fast growing banks, regardless as to whether only microeconomic controls were added or both micro- and the macroeconomic variables were added in the overdue loans ratio equation. In that sense, we confirm our previous results for the respective Granger causality tests, providing robustness to our main empirical findings.

Second, when we control for only microeconomic factors, the estimated effects of “bad management” and “skimping” become both stronger than those in the respective Granger causality tests. The first effect is -0.079 as an average of respective estimates in the M11-M14 Models, which is 1.4 times higher in absolute terms than the same effect in the M1 Model (see Table 4). The second effect is 0.109 as an average of respective estimates in the M15-M17 Models and that is 1.6 times higher in absolute terms than the same effect in the M9 Model (see Table 5).

But, when we add the macroeconomic variables to the respective regressions, we observe a substantial decrease in the average “bad management” effect (in absolute terms), while no significant changes occur with the “skimping” effect. Thus, the first effect becomes -0.035 (more than two times weaker compared to -0.079, see the M20-M21 Models) and the second effect becomes 0.125 (just a bit stronger compared to 0.109, see the M22-M24 Models). So, it clearly indicates that the macroeconomic conditions have much stronger effects on the cost efficiency of banks that do not pursue the “skimping” strategy compared to those banks that do pursue.

We additionally confirm this statement in Table C1 (see Appendix C), in which we simply regress the SFA cost efficiency indicator of respective subsamples for banks on the set of macroeconomic variables assuming fixed effects. We show from this table that the OLS-estimated coefficients of every macroeconomic variable imply stronger effects for the whole sample of banks compared to the subsample of skimpers. Thus, the smallest ratio of OLS-estimated coefficients

Tab. 6. Estimation results of the impact of bank cost efficiency on credit risk tolerance №1: Pure microeconomic effects

Models / Explanatory variables	Dependent variable – Overdue loans ratio						
	Panel A – “bad management”				Panel B – “skimping”		
	M11	M12	M13	M14	M15	M16	M17
Overdue loans ratio, lag = 1 quarter	0.767*** (0.040)	0.760*** (0.041)	0.700*** (0.060)	0.727*** (0.041)	0.402*** (0.092)	0.400*** (0.092)	0.379*** (0.080)
SFA Cost efficiency index, lag = 1 quarter	–0.060*** (0.017)	–0.075*** (0.018)	–0.111*** (0.016)	–0.068*** (0.019)	0.119** (0.056)	0.105** (0.052)	0.103** (0.050)
Real interest rate charged on loans, lag = 1 quarter	0.038*** (0.014)	0.031** (0.014)	0.028* (0.017)	0.027** (0.013)	–0.013 (0.012)	–0.016 (0.012)	–0.016 (0.013)
Loan to deposit ratio, lag = 1 quarter	0.003** (0.002)	0.005*** (0.002)	0.004** (0.002)	0.006*** (0.002)	0.003 (0.003)	0.002 (0.003)	0.002 (0.003)
The bank’s share in the total banking system loans, lag = 1 quarter	–0.445 (5.444)	1.329 (5.276)	4.164 (3.737)	5.002 (5.148)	0.387 (1.500)	0.651 (1.563)	–0.045 (1.330)
Equity to asset ratio, lag = 4 quarters	–0.059*** (0.018)					–0.041** (0.018)	–0.034* (0.018)
Liquid assets to accounts and deposits ratio, lag = 1 quarter		–0.017** (0.007)	0.004 (0.006)	–0.011* (0.007)	0.012* (0.006)	0.013** (0.006)	0.013** (0.006)
The share of loans to households in total bank’s loans, %		0.063*** (0.018)					
The share of loans with maturities of 3 and more years in total bank’s loans, %			0.065*** (0.011)				
Bank’s individual concentration index (in domestic markets for bank liabilities) / 10000, lag = 4 quarters				51.042*** (17.419)			–38.441** (16.321)
Bank’s individual concentration index (in domestic markets for bank liabilities) / 10000, squared, lag = 4 quarters				–0.018*** (0.005)			0.008** (0.004)
Number of observations (banks)	18983 (997)	18762 (970)	12237 (796)	18759 (970)	2342 (462)	2340 (461)	2340 (461)
Number of instruments	926	926	772	926	423	423	423
P–value, Hansen test	0.278	0.405	0.394	0.387	0.912	0.931	0.827
P–values, test: AR(1)	0.000	0.000	0.000	0.000	0.001	0.001	0.000
AR(2)	0.838	0.983	0.490	0.861	0.374	0.873	0.866
Maximum value for the concentration index variable (sample percentile)				1426 (50)			2285 (91)

Notes: M11-M17 models were estimated using the two-step difference GMM procedure proposed in Arellano and Bond (1991)

***, **, and * – a coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are provided in parentheses under the coefficients.

Sources: Bank of Russia database, author’s calculations

from the whole sample (“bad management”) to the subsample (“skimping”) is 1.14 (for the volatility of exchange rate variable), while the largest is 1.93 (for the real GDP growth variable). The key reason why this happens is that skimpers continue to lend money to borrowers regardless as to the state of the macroeconomic cycle – meaning even during periods of recession. This is additionally confirmed in Table 7 by the insignificant coefficient of real GDP growth

Tab. 7. Estimation results of the impact of bank cost efficiency on credit risk tolerance №2: controlling for both the micro- and the macroeconomic factors

Models	Dependent variable – overdue loans ratio						
	Panel A – "bad management"				Panel B – "skimping"		
Explanatory variables	**M18**	**M19**	**M20**	**M21**	**M22**	**M23**	**M24**
Bank-specific factors							
Overdue loans ratio,	0.718***	0.721***	0.721***	0.707***	0.400***	0.369***	0.364***
lag = 1 quarter	(0.041)	(0.041)	(0.045)	(0.042)	(0.086)	(0.079)	(0.078)
SFA Cost efficiency index,	0.023	–0.016	–0.035*	–0.035*	0.116**	0.129**	0.130**
lag = 1 quarter	(0.026)	(0.021)	(0.021)	(0.019)	(0.049)	(0.055)	(0.056)
Real interest rate charged on loans,	0.045***	0.029**	0.035**	0.038**	–0.012	–0.017	–0.008
lag = 1 quarter	(0.011)	(0.013)	(0.016)	(0.016)	(0.013)	(0.013)	(0.014)
Loan to deposit ratio,	0.003**	0.004***	0.004***	0.005***	0.002	0.000	0.000
lag = 1 quarter	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
The bank's share in the total banking sys-	2.433	3.602	4.410	4.250	0.094	1.173	0.263
tem loans, lag = 1 quarter	(5.059)	(4.863)	(4.917)	(4.917)	(1.330)	(1.644)	(1.444)
Liquid asset to accounts and deposits ra-	–0.008	–0.010	–0.007	–0.009	0.013**	0.017***	0.018***
tio, lag = 1 quarter	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Bank's individual concentration index (in	59.078***	53.245***	55.396***	62.465***	–41.193**	–37.708*	–35.887*
domestic markets for bank liabilities) /	(17.410)	(17.298)	(17.611)	(16.630)	(19.545)	(18.783)	(19.039)
10000, lag = 4 quarters							
Bank's individual concentration index (in	–0.018***	–0.019***	–0.017***	–0.018***	0.008*	0.008*	0.008*
domestic markets for bank liabilities) /	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
10000, squared, lag = 4 quarters							
Macroeconomic factors							
Real GDP growth rate (annual)	–0.061***				–0.021		
	(0.009)				(0.030)		
Unemployment rate		0.202***					
		(0.042)					
Households real disposable income			–0.022**	–0.019*		–0.017**	–0.019**
growth rate (annual)			(0.010)	(0.010)		(0.009)	(0.009)
The annual growth of the ratio of con-			0.023*			0.041***	
sumer spending to disposable income			(0.012)			(0.016)	
Profit to debt ratio for non-financial firms			–0.063***	–0.039**		–0.029*	–0.015
			(0.14)	(0.16)		(0.015)	(0.018)
Standard deviation of the ruble-to-dollar				0.218***			0.280***
exchange rate on the forex market				(0.070)			(0.094)
Current account balance to GDP ratio				–0.035***			0.009
				(0.010)			(0.011)
Number of observations	18759	18759	16537	16537	2340	2340	2340
(banks)	(970)	(970)	(960)	(960)	(461)	(461)	(461)
Number of instruments	927	927	929	930	427	427	427
P–value, Hansen test	0.340	0.334	0.332	0.400	0.914	0.882	0.848
P–values, tests AR(1)	0.000	0.000	0.000	0.000	0.001	0.000	0.000
AR(2)	0.826	0.894	0.835	0.779	0.764	0.808	0.451
Maximum value for the concentration index	1632	1387	1592	1765	2406	2414	2392
variable (sample percentile)	(63)	(47)	(60)	(71)	(94)	(94)	(94)

Note: The M18-M24 models were estimated using the two-step difference GMM procedure proposed in Arellano and Bond (1991)

***, **, and * – a coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are provided in parentheses under the coefficients.

Sources: Bank of Russia database, Federal State Statistics Service database, author's calculations variable for skimpers (see M22 Model) and, on the contrary, a highly significant coefficient of respective variable for other banks[30] (see M18 Model). We also note from Fig.D1 (see Appendix D) that the maximum increase of the overdue loans ratio of a median "skimper" during the crisis was only 2.5 times (from Q1 2008 to Q2 2009), while the maximum increase of a median "non-skimper" bank was about 4 times (from Q1 2008 to Q1 2010).

We next stress that, from a microeconomic point of view, not only the SFA index is mismatching variable for skimpers and for the other part of the Russian banking sector, but almost all other bank-specific characteristics as well. When we turn from the whole sample to the subsample of skimpers, we observe that these bank-specific characteristics either change the signs of their influence on the overdue loans ratio to the opposite (e.g. concentration variable) or even lose significance (e.g. real interest rate variable).

These are very interesting findings that suggest large differences between those banks that are skimpers and those that are not. That provides essentially the most important indication of the need for the Bank of Russia to implement some norms of differential prudential regulation to promote the stability improving of not only bad managers, but of skimpers as well.

So, the first two results clearly show us that the skimping existence is not spurious or random finding that could be due to functional misspecifications of the empirical model for the overdue loans ratio (ODL). Skimping does exist, as this is confirmed by three different versions of efficiency-risk estimates undertaken in our study (such as the Granger causality test, the ODL model with only bank-specific controls and with both bank-specific and macroeconomic ones). In this sense, we again stress that we confirm the findings of Berger and DeYoung (1997) and Altunbus et al. (2007) for US and EU banking, respectively.

Moreover, we claim that the findings of Williams (2004), Salas and Saurina (2002), Quagliariello (2007), Louzis et al. (2011), and Fiordelisi et al. (2011), which supported the "bad management" hypothesis and rejected the "skimping" hypothesis, are only relevant for an average bank at the level of respective banking sectors as a whole. These findings do not automatically reject the existence of skimping for some definite subsamples of banks, as we show in our study.

Third, despite the fact that both groups of banks are subjected to the inertia of their respective overdue loans ratios, the degree of such inertia is substantially (almost two times) higher for those banks that do not pursue a "skimping" strategy. Intuitively, this is explained by the speed-of-lending effect, as skimpers are those banks with higher-than-average yearly rates for loans growth

[30] Note also that when we add, such general macroeconomic factors as the real GDP growth rate or the unemployment rate, it results in a loss of significance for the bank cost efficiency indicator (SFA) for the full sample of banks (i.e. for "bad managers"), while the significance of respective variable for the subsample of skimpers is left unchanged (compare the M18-M19 Models with the M22 Model in Table 6). We interpret this finding for the full sample of banks as that even the most efficient banks experience deteriorations in loan quality during periods of recession, while the quality of loans improves even in inefficient banks during periods of expansion.

(as we discussed above), so that they issue new loans faster than the average competitor in the market for loans, which allows them to quickly renew their loan portfolios, thereby "hiding" the actual level of accumulated overdue loans. Actually, this speed-of-lending effect also explains why an average skimper demonstrates a lower overdue loans ratio compared to the average non-skimper bank (see Fig.D1 in Appendix D).

Summarizing our key findings, one could think that they indicate potential benefits of being skimpers, because such banks are less dependent on macroeconomic conditions and demonstrate both lesser levels and inertia for the overdue loans ratio, compared to other banks. But we claim that there are many negative effects hiding behind these positive features. In that sense, we remind that the efficiency of these banks is positively associated with overdue loans ratio (i.e. credit risk). In other words, these banks are very close or have even already achieved a sufficient efficiency frontier such that it is impossible for them to further increase efficiency without easing lending standards, which negatively affects the quality of new granted loans and thus a bank's overall stability. Moreover, despite the speed-of-lending effect, our calculations show that more than a quarter of all skimpers (i.e. above the 75th percentile) exhibit higher overdue loan ratios than the average bank from the full sample (see Fig. D1 in Appendix D)[31]. So, this is in fact the "price" paid by a large part of skimpers for higher efficiency and, additionally, is a source of destabilizing influence of one group of banks on the others (e.g. through inter-bank lending channels and/or panic-based deposit runs, which are to be analyzed deeper in future research). Besides, we question the validity of higher efficiency for skimpers, as we discussed above (se Section 3.2).

5.3.2. Additional findings.

First. We predict a significant and positive influence of both a bank's loan structure (proxied by the share of loans to households in total bank loans in the M12 Model) and the maturity composition of a bank's loan portfolio (proxied by the share of loans with maturities of 3 or more years in a bank's total loans in the M13 Model) on the overdue loans ratio. Both variables reflect higher risk. It is a well known fact that lending to households is riskier than lending to non-financial firms and thus when a bank switches from corporate to retail lending it becomes more exposed to credit risks. Similarly, the longer the lending horizon, the more the credit risk exposure thanks to uncertainty of perspectives for both banks and their clients, which makes it harder for borrowers to repay debts and may result in a higher overdue loans ratio for a bank.

But, when we additionally control for a bank's individual concentration index (in the domestic liabilities markets), both variables – a bank's loan structure and the maturity composition of a

[31] Note also that the 99th percentile of the overdue loans ratio for skimpers is at least 2 times higher compared to non-skimpers, with average excess equal to 8 times and maximum excess equal to more than 20 times.

bank's loan portfolio – lose their significance, which could be due to very high correlations between concentration and both variables.

Essentially, the influence of efficiency on loan quality does not change dramatically when we control for all of these three variables, whether jointly or separately. This is why we only use the concentration index in all of the following equations.

Second. Following the theoretical predictions of Martinez-Miera and Repullo (2010), we found strong evidence in favor of a non-linear relationship between bank concentrations and their credit risks in terms of the overdue loans ratio. However, results seem to be very different for the full sample of banks and for the subsample of skimpers (see the M14 and M17 Models in Table 6, respectively, and M18-M21 and M22-M24 Models in Table 7, respectively). While for the full sample of banks we found an inverse U-shaped impact of a bank's individual concentration indices on their overdue loans ratios as, which is considered by the literature to be a normal relationship (see, for example, Tabak et al., 2012), the opposite was true for the subsample of skimpers, which was somewhat surprising.

Thus, on the one hand, too much competition could be detrimental for the stability of skimpers. We explain this phenomenon by higher obstacles for skimpers to continue fast growth without easing lending standards when competition is high. But for the other banks, too much competition could lead to opposite effects due to the "competition-stability" phenomenon (see Boyd and De Nicolo, 2005), as it solves the adverse selection problem by setting minimal interest rates, which makes it easier for borrowers to repay debts and decrease their risk incentives, thereby positively affecting the quality of banking loans.

On the other hand, a lack of competition could lead to the lower stability of a skimper that wishes to enjoy its monopoly power through setting higher interest rates, when such higher interest rates in turn exacerbate the problem of adverse selection. Again, the opposite holds true for other banks in case of decreasing competition. In order to protect the growing charter value, if it is associated with higher concentration, or due to higher bargaining power, which results from lower competition, the other (non-skimpers) banks filter out lower quality borrowers, as proposed by Keeley (1990) to be the "market power-stability" effect (also known as the "franchise value" paradigm), which implies less exposures to bank risk.

For the full sample of banks, the estimated inflection points of respective quadratic functions are 1387-1765 points for a bank's individual concentration indices, depending on the specification (see the M14 Model in Table 6 and the M18-M21 Models in Table 7). That corresponds to the 47^{th}-71^{st} percentiles of data in the full sample, thus suggesting that from $^{1}/_{3}$ up to $^{1}/_{2}$ of all observations of banks with high market power are located within the conceptual area of "competition-fragility" (or the "market power-stability").

For the subsample of skimpers, the estimated inflection points turned out to be much higher than those compared to the full sample results – about 2285-2414 points for a bank's individual concentration indices, depending on the specification (see the M17 Model in Table 6 and the M22-M24 Models in Table 7). That is in about the 91^{th}-94^{th} percentiles of data, which implies that no more than 10% of all skimpers may enjoy the "competition-stability" effect.

We also note that previous studies on Russian banking, such as Fungáčová and Weill (2011) and Karminsky et al. (2012), did not find support for non-linearity in the competition-risk relationship.

Third. In line with the literature, we found that bank equity capital is inversely related to risk, as the equity-to-assets ratio has a negative effect on the overdue loans ratio, which is true for both skimpers and other banks in Russia. That essentially provides additional support to the "franchise value" paradigm of Keeley (1990), further developed by Allen and Gale (2004). The estimated effects seem to be much (at least 1.5 times) stronger for other banks, compared to skimpers (see the M11 Model and the M16-M17 Models, respectively, in Table 6). We suppose that fast growing loans require more borrowed funds than equity capital, especially if ROE grows slowly and, consequently, capitalization grows slower than needed to maintain higher paces of business development. That implies that skimpers could be more dependent on borrowed funds than on equity capital, compared to the average competitor in the market, at least while skimpers still satisfy the capital requirements of regulators.

Fourth. We found that the real interest rate charged on loans is positively associated with the overdue loans ratio for the full sample of banks, which is in line with our expectations and theoretical predictions, while no significant relationship was revealed for the subsample of skimpers, which is surprising, but robustly holds across all specifications presented in Tables 6 and 7. In general, higher real interest rates reflect higher risk premiums, but that is not the case for skimpers. There can be a couple of reasons why we observe this. On the one hand, if skimpers do artificially overvalue their cost efficiencies, as discussed above, they can do the same with their balance sheets and financial statements, which leads to the distortion of empirical relationships. On the other hand, when a bank decides to grow faster, it cannot set higher interest rates[32]. This implies that skimpers could substantially decrease risk premiums, which essentially eliminates the relationship between interest rates and credit risks.

Fifth. Liquidity seems to have no significant effect on the overdue loans ratio for the full sample of banks when we control for macroeconomic conditions, while a significant and positive effect was revealed for the subsample of skimpers. This is another interesting and important finding

[32] Indeed, the average real interest rate charged on loans by skimpers is 4.0%, which is 1.2 percentage points less than those charged by other banks.

for policy, which pushes us to the idea of a loans-pyramid effect, which could be the case of a "skimping" strategy and, consequently, that the real quality of skimper loans could be much worse than those that skimpers do actually report. As is well known, liquidity and lending are substitutive banking activities, and so if a skimper faces a higher liquidity normative and has to increase its liquidity ratios, then, as our estimations showed, for some reason this bank would be subjected to a higher overdue loans ratio. We claim that this is due to the need to slowdown lending activities resulting in the decreased abilities of borrowers to refinance their previously accumulated debts and that is actually the reason why the quality of loans worsens.

Conclusion

In this paper we study the relationships between cost efficiency and loan quality in Russian banks. Essentially, we try to answer the question of whether it is always beneficial – in terms of higher stability – for banks to be highly cost efficient (the "bad management" hypothesis) or if this higher cost efficiency could mean inadequate spending on borrower screening, which could subject banks to higher credit risk exposures in the future (the "skimping" hypothesis).

In that way, we test the "bad management" and the "skimping" hypotheses proposed by Berger and DeYoung (1997), who applied them to US banking. The essence is that these hypotheses are not mutually exclusive. Bad management can be relevant for the banking sector as a whole, while skimping can be relevent for some definite subsample of banks, which is not always taken into account by different authors. That is why they come to findings that could be either similar to or conflicting with Berger and DeYoung. The problem is that the conclusions about whether "skimping" is relevant or not are contradictory even for the same banking sectors. While Williams (2004) reports that European banks do not skimp on risk management, Altunbus et al. (2007) claim the opposite. It shows that conclusions are not robust to different estimation procedures, and necessitates our own analysis to be conducted for Russian banks.

We start this analysis by performing the panel version of the Granger causality test, applying the GMM estimator developed by Arellano and Bond (1991). Particularly, this empirical step allows us to obtain a range of "pure" estimated impacts, coming from efficiency on loan quality. In other words, "pure" in the sense that we do not control for other micro- and macroeconomic determinants of loan quality.

Second, we track changes in the impact of efficiency on loan quality compared to the previous step by specifying an equation in which we jointly estimate the influences of efficiency and other micro- and macroeconomic determinants of loan quality.

We obtain the following results.

First, we found strong empirical confirmation that both hypotheses – "bad management" and "skimping" – do really exist within the Russian banking sector. While the "bad management" holds on average for the banking sector as a whole, as in most relevant studies, (see, for example, Salas and Saurina, 2002; Williams, 2004; Quagliariello, 2007; Louzis et al., 2011; Fiordelisi et al., 2011), "skimping" could be the case for those Russian banks that are not just highly cost efficient, as predicted by Berger and DeYoung (1997) for US banks, but that simultaneously pursue aggressive strategies on the market for lending to households and non-financial firms, treating the latter as the extensive growth condition. As we suppose, this is especially true during pre-crisis periods, when banks are too optimistic to pay increased attention to the quality of borrowers in order to extract higher profits in the short run. This result holds across a wide range of empirical tests and specifications, for example either when we conduct a Granger test or when we specify the dynamic empirical equation of a bank's overdue loans ratio, controlling for other micro- and macroeconomic characteristics both jointly and separately.

Interestingly, we show that the "skimping" strategy is not the case for those Russian banks that demonstrate lower equity-to-assets ratio and that are highly cost efficient at the same time. A possible explanation for this phenomenon is that higher financial leverages force these banks to filter out low quality borrowers in order to be able to repay (expensively) borrowed funds. Thus, the insufficient capital condition does not lead us to identifying a "skimping" strategy as the extensive-growth condition does. This proved to be surprising, as initially we expected to see not only the latter, but also the former condition to be relevant in that sense, due to possible effects of moral hazard[33].

Second, we found clear indications that macroeconomic conditions have much stronger effects on the cost efficiency of "bad managers" compared to "skimpers". Initially, when we control only for microeconomic factors, the estimated effects of "bad management" and "skimping" on the overdue loans ratio become both stronger than those in respective Granger causality tests. But when we add the macroeconomic variables to respective regressions, we observe a substantial decrease in the average "bad management" effect (in absolute terms), while no significant changes occur with the "skimping" effect[34].

[33] In other words, our results imply that if a bank grows faster than the average competitor on the market for loans and demonstrates higher efficiency levels along the way, then it is more likely that this bank is a skimper and will be subjected to higher credit risk in the future (compared to the average competitor). Yet if a bank is highly efficient but suffers from lower capital buffers, it is less likely that this bank is a skimper. It is much more likely that this bank – albeit showing higher financial leverage – efficiently operates its funds by allocating them to projects with lesser credit risks.

[34] We also confirm this finding by two simple additional equations in which we regress the SFA cost efficiency indicator of respective subsamples of banks on a set of macroeconomic variables under the assumption of fixed effects. We show from these equations that the estimated coefficients of every macroeconomic variable imply stronger effects for the whole sample of banks compared to the subsample of skimpers. The key reason why this happens is that skimpers continue to lend money to borrowers irrespective to the state of the macroeconomic cycle – even during periods of recession. The latter is also confirmed by the insignificant coefficient of the real GDP growth variable for the subsample of skimpers in our main empirical equations and, on the contrary, a highly significant coefficient of respective variables for the full sample of banks.

Third, despite the fact that both groups of "skimpers" and "bad managers" are subjected to the inertia of their respective overdue loans ratios, the degree of such inertia is substantially (almost two times) higher for the latter when compared to the former. We explain this by the speed-of-lending effect, as "skimpers" are those banks with higher-than-average yearly rates of loan growth (as we discussed above), so that they issue new loans faster than the average competitor on the market for loans, which allows them to quickly renew their loan portfolios, thusly "hiding" the actual level of accumulated overdue loans. Actually, this speed-of-lending effect also explains why the average "skimper" demonstrates a smaller overdue loans ratio compared to the average "non-skimper" bank (as shown in Appendix D).

Fourth, the problem of "skimping" is of growing importance in the Russian banking system, as the share of "skimpers" on the market for loans increased from 1.6% at the beginning of 2010 to 16.4% as of the end of Q3 2012. Potentially, the Bank of Russia should subject these banks to higher capital adequacy requirements than other banks and, possibly, force them to pay extra funds to the Russian Deposit Insurance Agency in order to decrease the riskiness of such banks and promote the stability of the banking sector. This is a possible way to develop differential prudential regulation in the Russian banking system.

Fifth, our analysis revealed a large body of bank-specific differences between "skimpers" and "bad managers" in terms of concentrations, equity-to-assets ratios, real interest rates charged on loans, and liquidity ratios. More specifically, while for the full sample of banks we found an inverse U-shaped impact of individual concentration indices for banks on their overdue loans ratios, treated by the literature to be a normal relationship (see, for example, Tabak et al., 2012), the opposite was true for the subsample of skimpers, which was a little surprising. Next, the estimated effects of equity-to-assets ratio on the overdue loans ratio seem to be much stronger (at least 1.5 times) for "bad managers" compared to "skimpers"[35]. Next, the real interest rate charged on loans is positively associated with the overdue loans ratio for "bad managers", which is in line with our expectations and theoretical predictions, while no significant relationship was revealed for "skimpers", which is surprising[36]. And, finally, liquidity seems to have no significant effect on the overdue loans ratio for "bad managers", while a significant and positive effect was revealed for "skimpers"[37].

Sixth, we provide some empirical arguments supporting the "bad luck" hypothesis, when analyzing the full sample of Russian banks. The estimated impact of a decrease in loan quality on efficiency levels (the "bad luck" effect), is approximately two times smaller than the impact of an efficiency decrease on portfolio quality (the "bad management" effect). This implies that those banks

[35] As skimping requires more reliance on borrowed funds than on equity capital in order to continue fast growth.
[36] But the latter could be explained by minimizing risk premiums in order to attract more new borrowers and continue fast growth
[37] The latter is a possible indication of a loans-pyramid effect, when new loans are issued to repay previous debts, which works well until skimpers are forced to increase liquidity ratios and, consequently, slow down lending growth.

that are able to effectively control their own costs ensure themselves against an uncontrolled deterioration of loan portfolio quality in the future. From this ground, we suppose that Russian banks could benefit from the consecutive standardization and simplification of reporting forms (including daily ones) for all banks, which were implemented by the Bank of Russia over the past years. If such measures are realized, they would stimulate the cost efficiency of banks and can potentially improve loan quality, as those funds that should have been spent by banks on preparing financial statements could instead be used to enhance the screening procedures of borrowers.

From the perspective of regulatory policy, these conclusions provide clear arguments in favor of differential prudential regulation in Russia, which could, if implemented, positively affect the loan quality of both banks that are skimpers (by restricting a growth in loans by higher capital adequacy requirements and increased payments to the Russian Deposit Insurance Agency) and banks that are not (by eliminating incentives to grow too fast), thusly improving the stability of the banking sector as a whole.

We believe that such empirical analysis is very important for Russian banks, and the Central Bank of Russia as a regulator, because in an environment where bad loans rapidly increase, but decrease much more slowly (persistently), improving the quality a bank's loan portfolio may become an issue not so much of macroeconomic conditions, but of optimizing expenses and making them more efficient.

We suppose that future research in the area of relationships between cost efficiency and loan quality should try to understand whether there are any sources of heterogeneity in such relationships. If the latter holds, then is it possible to switch between the "bad management" and the "skimping" hypotheses? Analyzing these issues could help to more precisely localize banks that skimp on risk-management and further improve prudential regulation in the Russian banking system.

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Appendix A

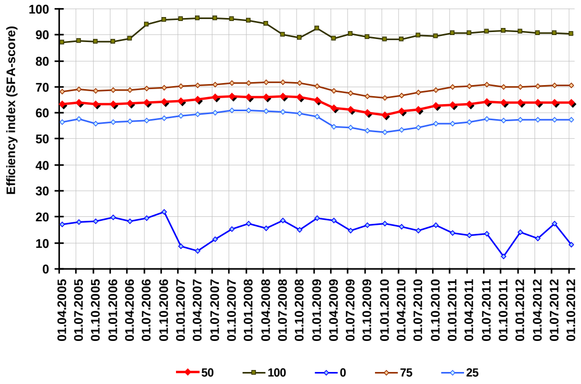
Here we present some more detailed information regarding the behavior of efficiency indicators in different percentiles of the full sample of Russian banks, as well as the distribution histograms of these indicators (see Figures 1 – 3). Such information allows us to understand, firstly, the processes of evolutionary development of efficiency in different groups of banks (low-, average-, and high-efficiency credit institutions) and, secondly, the impact of the 2008-2009 crisis on the ratio of efficient to inefficient banks.

The results of the SFA demonstrate the smooth growth of cost efficiency for the average bank in the sample through the end of 2008 – up until the beginning of the crisis. An efficiency reduction period followed, which switched to restoration of efficiency at the beginning of 2010, coinciding with the recovery of the credit market. Second, the pre-crisis maximum for the efficiency index was 66% (see Figure 1.a for the half-normal case), while 73% had not been reached even by the end of 2012 (see Figure 2.a for the truncated normal case).

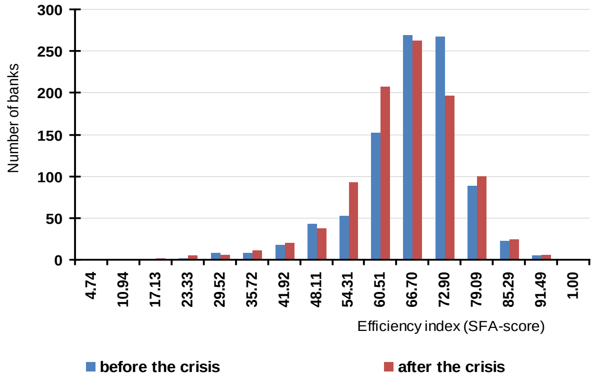
Note that in the group of low-efficiency banks (close to the sample's 25th percentile), efficiency started falling significantly earlier – as early as the Q1 2008. This proves the need to explore the state of these types of banks a year later – in 2009 – during the period of mass deterioration of the quality of loan portfolios for Russian banks. In other words, it is important to be able to answer the following question: How resistant are low-efficiency banks to the subsequent shocks of "bad debts"? If this type of resistance is significantly below average for the banking system, then the low values of the SFA index can be viewed as an early indicator for the future deterioration of loan-portfolio quality (the "bad management" concept).

Distribution histogram analysis shows that in both cases the SFA methodology predicts an increased number of high efficiency banks after the crisis – within the 55-65% interval (see Figure 1.b) and 50-75% (see Figure 2.b), with the averages of 67% and 75%, respectively.

The results of the DFA approach – as opposed to the SFA approach – assume that a stable efficiency trend was preserved from the beginning of the crisis through the endpoint of the observations in our sample (Q3 2012), which also looks less realistic if compared to the other approach (see Figure 3.a). At the same time, the density result of the low-efficiency bank group is the same (see Figure 3.b).

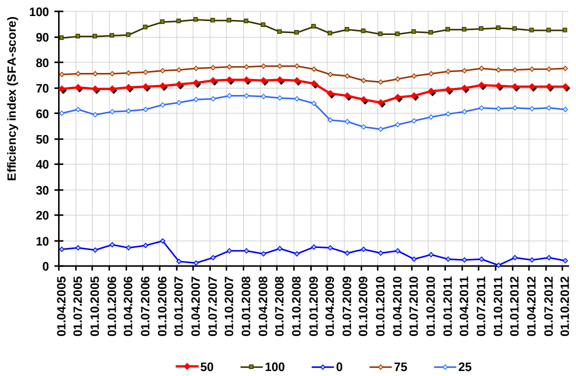


a) Dynamic of SFA index (half-normal case) at different percentiles of the bank sample

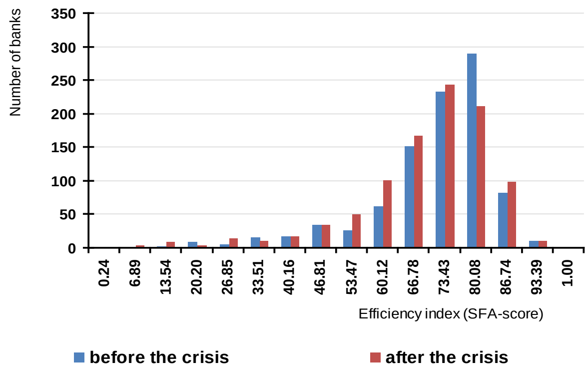


b) Histograms of the SFA index distribution before the crisis (until Q1 2008) and after the crisis (from Q2 2010)

Fig. 1. Dynamic and histograms of bank distribution according to the SFA index, assuming a half-normal distribution of bank inefficiency components

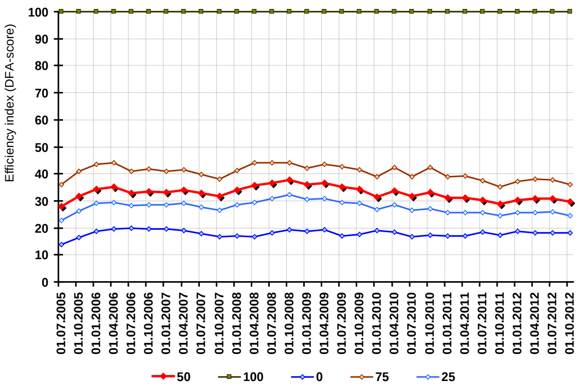


a) Dynamic of SFA index (truncated-at-zero normal case) at different percentiles of the bank sample

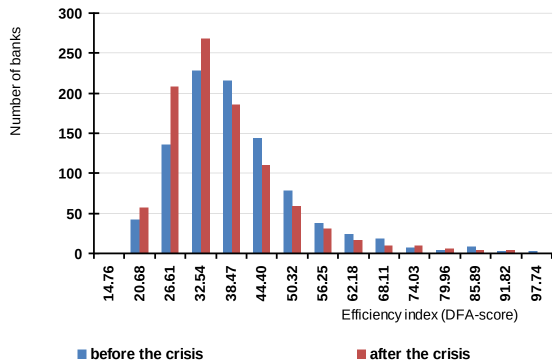


b) Histograms of the SFA index distribution before the crisis (until Q1 2008) and after the crisis (from Q2 2010)

Fig. 2. Dynamic and histograms of bank distribution according to the SFA index, assuming a zero-truncated normal distribution of bank inefficiency components



a) Dynamic of DFA index at different percentiles of the bank sample



b) Histograms of the DFA index distribution before the crisis (until Q1 2008) and after the crisis (from Q2 2010)

Fig. 3. Dynamic and histograms of bank distribution according to the DFA index

Appendix B

Tab. B1. Matrix of pairwise correlations for variables reflecting credit risk and operating cost efficiency: full sample of banks

	ODL	SFA (lag = 1 quarter)	SFA (lag = 2 quarters)	SFA (lag = 3 quarters)	SFA (lag = 4 quarters)	DFA (lag = 1 quarter)	DFA (lag = 2 quarters)	DFA (lag = 3 quarters)	DFA (lag = 4 quarters)	CIR (lag = 1 quarter)	CIR (lag = 2 quarters)	CIR (lag = 2 quarters)	CIR (lag = 4 quarters)
ODL	1.00												
SFA (lag = 1 quarter)	-0.13	1.00											
SFA (lag = 2 quarters)	-0.12	0.94	1.00										
SFA (lag = 3 quarters)	-0.10	0.87	0.94	1.00									
SFA (lag = 4 quarters)	-0.09	0.81	0.87	0.94	1.00								
DFA (lag = 1 quarter)	-0.04	0.49	0.50	0.50	0.50	1.00							
DFA (lag = 2 quarters)	-0.04	0.46	0.48	0.50	0.50	0.96	1.00						
DFA (lag = 3 quarters)	-0.03	0.43	0.45	0.48	0.50	0.92	0.96	1.00					
DFA (lag = 4 quarters)	-0.03	0.40	0.42	0.45	0.48	0.87	0.91	0.96	1.00				
CIR (lag = 1 quarter)	0.13	-0.46	-0.45	-0.42	-0.40	-0.40	-0.38	-0.36	-0.34	1.00			
CIR (lag = 2 quarters)	0.12	-0.46	-0.46	-0.45	-0.42	-0.41	-0.39	-0.38	-0.36	0.95	1.00		
CIR (lag = 3 quarters)	0.10	-0.45	-0.46	-0.46	-0.45	-0.41	-0.40	-0.39	-0.37	0.88	0.95	1.00	
CIR (lag = 4 quarters)	0.08	-0.43	-0.45	-0.46	-0.47	-0.42	-0.41	-0.40	-0.39	0.81	0.88	0.95	1.00

Notes:
ODL (Overdue loans ratio) – overdue loans to a bank's total loans.
SFA (Stochastic Frontier Analysis) – index of a bank's operating cost efficiency within the framework of the stochastic frontier analysis.
DFA (Distribution Free Approach) – index of a bank's operating cost efficiency within the framework of the distribution-free approach.
CIR (Cost-to-income ratio) – operating cost to a bank's total income ratio (minus transactions related to reserving funds for potential losses and depreciation).

Tab. B2. Pairwise correlations between the overdue loans ratio and operating cost efficiency: the subsample of highly efficient banks‡

Model	ODL	
	M9	**M10**
SFA (lag = 1 quarter)	0.037	-0.014
SFA (lag = 2 quarters)	0.062	-0.003
SFA (lag = 3 quarters)	0.068	-0.008
SFA (lag = 4 quarters)	0.075	-0.001

Notes:
‡ Above the respective subsample's average levels.
ODL (Overdue loans ratio) – overdue loans to a bank's total loans.
SFA (Stochastic Frontier Analysis) – index of a bank's operating cost efficiency within the framework of the stochastic frontier analysis.
Pairwise correlation coefficients were calculated for the following models (see Table 5):
M9 – the subsample of efficient banks with an additional restriction: the banks also belong to the group with a high annual real loan growth rate (above average) for four consecutive quarters (the extensive growth condition);
M10 – the subsample of efficient banks with the following restriction: the banks also belong to the group with a modest annual real loan growth rate (below average) for four consecutive quarters.

Sources: Bank of Russia database, author's calculations

APPENDIX C

Tab. C1. The estimated impacts of macroeconomic variables on a bank's cost efficiency: "bad management" vs. "skimping"

Models Explanatory variables	Dependent variable – SFA Cost efficiency index		The ratio of models coefficients of C1 to C2
	C1 **"bad management"**	**C2** **"skimping"**	**C1 / C2**
Real GDP growth rate (annual), %	0.313*** (0.017)	0.162*** (0.043)	1.93
Standard deviation of the ruble-to-dollar exchange rate on the Forex market	1.033*** (0.133)	0.699*** (0.223)	1.14
Households real disposable income growth rate (annual), %	–0.131*** (0.020)	–0.078*** (0.024)	1.67
Profit-to-debt ratio for non-financial firms, %	0.223*** (0.031)	0.120*** (0.037)	1.89
Current-account-balance to GDP ratio, %	-0.250*** (0.025)	–0.130*** (0.030)	1.92
Constant	60.947*** (0.187)	71.355*** (0.309)	
Number of observations (banks)	19994 (1043)	3466 (655)	
P-value, F-test for fixed effects	0.000	0.000	
R^2 (Least squares dummy variables)	0.645	0.642	

Notes: ***, **, and * – a coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are provided in parentheses under the coefficients.

Sources: Bank of Russia database, Federal State Statistics Service database, author's calculations

APPENDIX D

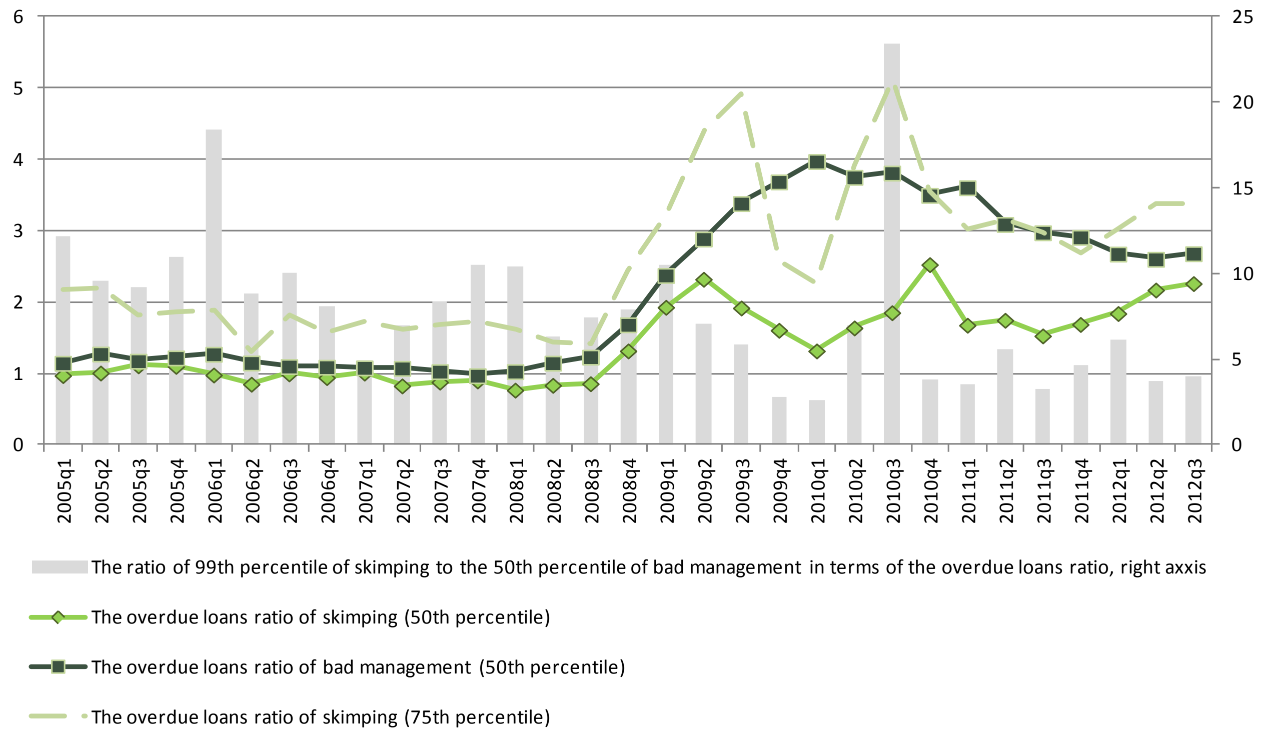


Fig. D1. Dynamics of the overdue loans ratios (average levels) of those banks that pursue a “skimping” strategy and those that are subjected to the effects of “bad management”

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