St. Petersburg University

Graduate School of Management

Master in Management Program

BENCHMARKING THE OPERATIONAL PERFORMANCE OF RUSSIAN BANKS IN 2013-2017: FINDING BEST PRACTICES AND SOURCES OF IMPROVEMENT

Master's Thesis by the 2nd year student

Concentration — General Track

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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

Я, Тюнин Дмитрий Маркович, студент второго курса магистратуры направления «Менеджмент», заявляю, что в моей магистерской диссертации на тему «Бенчмаркинг операционной эффективности российских банков в 2013-2017: определение лучших практик и источников повышения эффективности», представленной в службу обеспечения программ магистратуры для последующей передачи в государственную аттестационную комиссию для публичной защиты, не содержится элементов плагиата.

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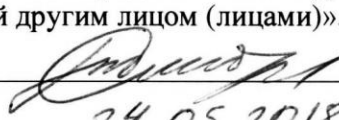

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I, Dmitry Tyunin, second year master student, program «Management», state that my master thesis on the topic « Benchmarking the Operational Performance of Russian Banks in 2013-2017: Finding Best Practices and Sources of Improvement », which is presented to the Master Office to be submitted to the Official Defense Committee for the public defense, does not contain any elements of plagiarism.

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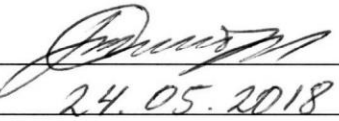

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24.05.2018

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АННОТАЦИЯ

Автор	Тюнин Дмитрий Маркович
Название магистерской диссертации	Бенчмаркинг операционной эффективности российских банков в 2013-2017: определение лучших практик и источников повышения эффективности
Факультет	Высшая Школа Менеджмента
Специальность	Менеджмент
Год	2018
Научный руководитель	Федотов Юрий Васильевич, доцент кафедры операционного менеджмента
Описание цели, задач и основных результатов	Цель: провести бенчмаркинг операционной деятельности банков России и выявить лучшие практики и дать направление по улучшению текущей эффективности для неэффективных банков Задачи: 1) Изучение существующей литературы по анализу эффективности и DEA в частности; 2) Выявление ключевых ограничений существующей литературы по данной теме; 3) Выбор модели измерения и определение списка входов (inputs) и выходов (outputs); 4) Сбор и структурирование соответствующих эмпирических данных из открытых источников; 5) Применение моделей DEA с учетом различной структуры входов и выходов, а также с учетом нежелательных выходов (undesirable outputs); 6) Сравнение результатов различных моделей, оценивающих разные типы технической эффективности; 7) Выявление лучших практик для всей группы из 200 банков; 8) Выявление лучших практик для подгрупп, сформированных сообразно размерам банков (очень большие, большие, средние, маленькие). 9) Предоставление выводов из полученных результатов. Результаты: Разработан метод многоуровневого бенчмаркинга на основании анализа свертки данных. Оценена эффективность 200 банков РФ в период 2013-2017 по трём BCC-I DEA моделям, измеряющим разные типы эффективности: общую техническую эффективность деятельности банка, эффективность банка в качестве финансового посредника и эффективность того, как хорошо банк работает с привлеченными средствами. Банки России довольно эффективны согласно первым двум моделям (средний уровень технической эффективности 87,46%), но демонстрируют низкую техническую эффективность согласно третьей модели (32,01%). Очень большие банки более эффективны, чем большие, которые в свою очередь превосходят средние банки, которые демонстрируют более высокий уровень эффективности, чем маленькие банки. Иностранные банки, в среднем, имеют более высокий уровень технической эффективности, чем частные российский банки, которые, в свою очередь, более эффективны, чем российские банки, находящиеся под прямым или косвенным контролем Центрального Банка России или Правительства России. Также, были выявлены образцовые банки, принадлежащие выборке из 200 банков: Сбербанк, КБ Дельтакредит и Danske Bank. Кроме того, была отдельно оценена техническая эффективность каждого банка, входящего в подвыборки, сгруппированные согласно размеру банков, и были выявлены образцовые банки для подвыборок средних (Citibank и КБ Дельтакредит) и малых (Cetelem Bank and Danske Bank) банков.
Ключевые слова	Бенчмаркинг, банки, Анализ Свертки Данных, Россия, эффективность

ABSTRACT

Master Student's Name	Dmitry Tyunin
Master Thesis Title	Benchmarking the Operational Performance of Russian Banks in 2013-2017: Finding Best Practices and Sources of Improvement
Faculty	Graduate School of Management
Major Subject	Management
Year	2018
Academic Advisor's Name	Yury V. Fedotov, Associate Professor
Description of the goal, tasks and main results	Goal: to benchmark Russian banks with regard to their operational efficiency for identification of the best-practice units in observed period and evaluation of the potential for improvement of inefficient banks. Tasks: 1) Study existing literature on efficiency analysis and DEA in particular; 2) Identify key limitations of current existing literature on the topic; 3) Select the measurement model and identify the list of Inputs and Outputs; 4) Collect and structure relevant empirical data from open public sources; 5) Apply DEA models, accounting for: a. different structure of Inputs and Outputs; b. undesirable output (NPLs); 6) Compare the results of different models; 7) Find out best practices in general sample; 8) Find out best-practices in subsamples; 9) Make managerial implications from the obtained results. Results: The present study developed a multilevel benchmarking method on the basis of Data Envelopment Analysis. The study assessed the technical efficiency of 200 commercial banks which operate in Russia between 2013 and 2017 with the help of three different BCC-I DEA models, tailored to gauge different types of efficiency: overall efficiency of a bank, efficiency of the bank as financial intermediary and efficiency of how well the bank utilizes attracted funds. Russian banks are rather efficient according to the first two models (average technical efficiency 87.46%) but demonstrate low technical efficiency scores according to the third model (32.01%). Very big banks are more efficient than big banks, which dominate medium banks that outperform small banks. Foreign banks have, on average, higher technical efficiency scores than Russian private banks, which in turn are more efficient than Russian banks that are directly or indirectly controlled by the Central Banks of Russia or Russian government. Also, the study has identified best-practice banks, pertaining to the general sample: Sberbank, KB Deltakredit and Danske Bank. Finally, the present paper has separately gauged the efficiency of each subsample (composed according to the size of banks) and has identified the following best-practice banks: Citibank and KB Deltakredit (for medium banks) and Cetelem Bank and Danske Bank (for small banks).
Keywords	Benchmarking, Banking, DEA, Russia, Efficiency, Bank performance

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INTRODUCTION

The financial services sector plays crucial role in the economic development of any country in the world. The banking industry in turn has always played a very important role within financial sector, being the most important financial intermediaries and acting as the primary source of financing of an economy. Banks not only facilitate economic growth and prosperity by channeling funds from savers to investors, playing as intermediaries between the capital demand and supply, but also undertake the responsibility of adjusting the capital flow among industries, promote capital formation, and activate commercial and industrial developments. The commercial bank is a type of financial intermediary that plays the role of provider of liquidity insurance, monitoring services and producers of information. Therefore, the sound performance of banking sector is of utmost importance to economic development. As a result, the soundness and efficiency of the banking system and the financial environment have a profound and significant impact on economic development.

The concept of banking operational performance and efficiency is not entirely new, but it is still as relevant as it was at the time of its emergence, because financial services are developing and so are the banks, providing them. In general, methodology for estimating banking efficiency is rather wide and complex. However, not all countries have been studied in the light of the banking efficiency concept, for example, Russia is seriously understudied in this sense from the scientific point of view. Meanwhile, banking industry might be interesting in the sense that in the current conditions of Russian banking business (sanctions and severe policy of the bank of Russia) it is very important for the banks' managers to understand how effective and efficient their business relatively to their peers.

This study is relevant because during the period of time this thesis is being written monumental changes are taking place and the shape of the banking system is changing dramatically due to two factors:

1. CBR policy aimed at the removal of ineffective banks that do not comply with the requirements produced by controlling authorities – see figure 1 for the graph showing the quantity of banks which licenses were withdrawn by the Bank of Russia.
2. External factors (e.g. sanctions) influence on Russia's banking system (banks have restriction on financing from abroad).

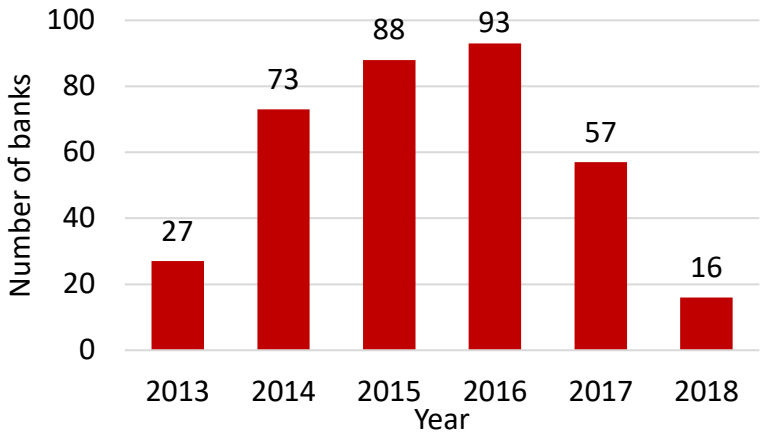

Figure 1 Quantity of credit organizations which licenses was revoked in a certain year during the period of 2013-2016

It is important to note, that there are different operational performance models that assess different things:

1. Operational performance reference model that assesses the bank's compliance with legal standards and indicators.
2. Productivity model that concentrates on the Productivity of the bank's performance through output-input ratios, e.g. ROE, ROA, Income/Cost etc.
3. Technical Efficiency Model (Farrell Model) that assesses the actual position of the bank (combination of inputs and outputs) against the empirical production frontier, constructed for chosen sample of units.

This paper will concentrate on the technical efficiency model, because it is a leading, not a lagging measure of organizational performance. This means that if the bank has problems with technical efficiency, it will suffer from the decrease in productivity, i.e. its financial ratios (ROE, ROA etc.) will decrease and if the bank does nothing, then it will encounter with the inability to comply with regulatory requirements, posed by the Bank of Russia or other regulators and, as a result, its license may be revoked. Therefore, the clear connection between the current CBR's policy, aimed at the removal of inefficient banks, and technical efficiency is established. This proves the relevance of the research for the bank managers and for the theoretic, interested in performance assessment and benchmarking.

Furthermore, according to the Russian Ranking Agency (ACRA, 2018), profit and returns in banking industry are going to decline from 4.0% in 2017 to 3.1% in 2022. This means that banks need to understand how to manage their inputs (costs) to improve their operational efficiency and

technical efficiency provides useful information on the possible ways to improve bank's operational performance, not to mention it gives management a clear picture of where their bank stands relatively to the other banks in the general sample of 200. This is the second point that proves the relevance of the present research.

To summarize, this research is relevant because:

- Bank management gets useful decision-support information from the estimates of their bank's operational efficiency, i.e.:
  - Technical efficiency scores that can help managers to better control productivity and as a result better maintain compliance with the legal requirements, posed by the Bank of Russia.
  - The position of a bank against its peers
  - Information on the possible ways to improve bank's operational performance
- Controlling authorities may find in this paper the promising technique for enhancement of supervision of the sector through getting deeper insights on the banks' performance by benchmarking their operational efficiency.
- Multidimensional efficiency DEA rankings, calculated in this work, help investors and market analysts to decide upon investments.

Research gap which this paper tries to cover lies in the fact that usually banks are compared with the help of one-dimensional productive measures, e.g. ratios, like ROE, ROA, ROC etc. Ratio analysis is a quick and easy to master concept that has its disadvantages, namely it does not account for output mix, it uses highly aggregated measures, it is partial measure of productivity and not of efficiency, it has a very limited capability to give a signal for improvement. DEA analysis on the contrary overcomes all the weak sides of ratio analysis and, what is more important, is used as a great tool for benchmarking. To put it simply, most of the researches use ratio analysis to assess the efficiency and to assign criteria for the choice of best-practice units, while this study uses a superior method that was not applied to the Russian banking sector in the recent 8 years.

Theoretical contribution of this research is that it employs performance measure applicable for multi-inputs, multi-outputs technology and indicating areas of potential improvement (Frontier Analysis) to construct a multilevel benchmarking method on the basis of DEA models. This study also utilizes undesirable output in DEA model (Non-Performing Loans), as well as variables with negative values (i.e. Profit). This is an enhancement of the DEA in Russian context in which

negative values and undesirable variables are omitted. Finally, the present research extends the current study pool on frontier analysis of Russian banking and particularly on cost-efficiency measures.

The main aim of this paper is to benchmark Russian banks with regard to their operational efficiency for identification of the best-practice units in observed period and evaluation of the potential for improvement of inefficient banks.

This paper aims to accomplish the following research objectives to reach the abovementioned goal:

1. What is an operational efficiency for the bank? (construct the performance measure)
2. What is the best-practice bank? ~ specification of the attributes (define selection criteria)
3. Does the size matter for a bank's operational efficiency?
4. Does the size matter for identification of a bank as a best-practice?
5. Are state-owned banks perform better than private and foreign ones?
6. Identification of the sources and evaluation of potential improvement for inefficient banks in the subgroups

In more details, the research objectives include review of the history of the development of the banking system in the light of its effectiveness (inefficiency) and the allocation on its basis of the main trends and characteristics of the banking sector. This is impossible without the specification of an extremely versatile concept of efficiency, so the next task is to review the existing concepts and identify the one that best meets the requirements of the research. But in order to apply this concept in practice, it is necessary to understand how it is possible to measure effectiveness, what methods and concepts exist for this, so the next task is to give a brief overview of the methods used to calculate the efficiency index. Then, a thorough review of the literature and managerial theory that were relevant and necessary for understanding and interpreting the results of this study is done. Afterwards, the main goal is the substantiation of the methodology for calculating the efficiency index used in this study and the subsequent justification of the reasons for choosing a certain time interval and a relatively heterogeneous sample of the surveyed credit institutions. The next task is to introduce and justify the selection of certain parameters, which, in accordance with the previously chosen methodology of calculation, can be considered as inputs and outputs. The subsequent objective is to calculate efficiency score for the whole sample of 200 banks, identify best-practices and examine how ownership and size of a bank is connected with the efficiency scores or banks of

best-practices. The final objective is to find best-practice banks, pertaining to each of the subsamples.

The research method applied in this paper is quantitative empirical study. The method includes an extensive literature analysis and formulation of a clear research gap. The present paper will utilize the secondary data of 200 Russian banks that operate during 2013-2017. The data will be gathered from reliable data aggregators (Thompson Reuters, SPARK-Interfax, CBR.ru). The formation of the subsamples will be done in accordance with the lists, released by the Bank of Russia. This research will consider Capital, Fixed Assets and Deposits as input variables and Loans, Non-Performing Loans and Profit as output variables. The study assesses the technical efficiency of 200 banks in general sample and in subsamples with the help of three different BCC-I DEA models, tailored to gauge different types of efficiency: overall efficiency of a bank, efficiency of a banks as financial intermediary and efficiency of how well the bank utilizes attracted funds. The efficiency will be gauged with the help of an add-in plugin for Excel, called DEA-Solver. Finally, the research clearly defines selection criteria for the best-practice banks and reveals exemplar banks for the general sample and for subsamples.

This study consists of multiple consecutive stages, each of which follows logically from the previous one. So, the first stage was the outlook for the banking sector, i.e. how it developed in the last five year and what trends are present or just emerging on the market. Then, based on the market analysis, the managerial theory that will be the most useful in reaching the research goal is chosen and discussed in detail. Afterwards, the existing concepts of efficiency and different approaches to its measurement are revealed, as well as scientific literature review is conducted on the basis of which the research gap is identified. The next stage of the research includes thorough description of the methodology and justification of the choice of Data Envelopment Analysis as the main tool. Finally, the raw results of the analysis are discussed, and best-practice banks are identified for the whole sample of 200 banks and for subsamples of banks, clustered by size.

1. MARKET DESCRIPTION AND LITERATURE REVIEW

1.1 Overview of Russian banking sector

The banking sector in Russia is quite young in comparison, for example, with similar sectors in the US or England, but it is also promising and developing. In just 28 years, the system has undergone an amazing path from extensive development to the need for intensive, qualitative growth and has faced a multitude of crisis phenomena that emphasized the inefficiency of its components. For an objective analysis of the efficiency of the banking system, one should consider the history of development and formation of this sector. That is why the following part of this study will be devoted to revealing how certain phenomena that took place in 1990-2018 influenced a banking system. The above-mentioned time interval can be divided into 3 main stages in the development of the Russian banking system:

1. 1990-1999 – Emergence and formation stage
    - 1992-1997 - rapid growth in the number of banks
    - September 1993 - crisis of the cash union
    - October 11, 1994 - Black Tuesday
    - August 22, 1995 - Black Thursday
    - 1998 - banking crisis, default
2. 2000-2011 - Stage of qualitative transformations
    - 2002 - creation of a deposit insurance system
    - 2004 - a crisis of confidence
    - September 2008 - the global financial (banking) crisis
3. 2012-2018 – External pressure and sanitation stage
    - 2013 – start of the clearing of the banking sector by Bank of Russia
    - 2014 – sanctions on banking sector due to Ukrainian crisis

Let’s consider the current stage which starts from 2012 – a year when repercussions of the global financial crisis although were present, were considerably less threatening than a couple of years before. In the year 2012 retail lending literally "blew up" the banking sector. As predicted by Expert RA[1], by the beginning of 2013 the portfolio of loans to individuals reached 7.7 trillion RUB, showing growth rate of almost 40% – a record since 2008. This is more than twice the results of

[1] https://raexpert.ru/press/articles/bank_sector-2012

other segments – SME lending (+17%) and large businesses (+12%). However, the segment of unsecured consumer lending showed even higher dynamics – its growth rate was about 55-60%. This implies that credit institutions were willing to take more risks, which in turn may pose a threat to the long-term stability of the sector. That is why Central Bank of Russia increased provisions for unsecured loans to individuals and announced the transition to the calculation of capital according to Basel III. According to Russian rating agency ExpertRa one of the main trends in 2012 is the increasing specialization of banks, which was expressed in the desire of a number of credit institutions to move away from the principle of universalization and to focus on certain areas. This is due to the desire of banks to reduce costs and maximize profits.

A year after, in 2013, Bank of Russia (CBR) decided to start the policy of sanitation of Russian banking sector in order to enhance and strengthen it. All banks became subjects of strengthened control and checks for non-compliance with such regulatory requirement imposed by Bank of Russia as standards of capital adequacy and liquidity. Moreover, CBR payed special attention to the detection of banks that participated in money laundering, provided false reports or did not create reserves that meet the high-risk credit policy of the Bank of Russia. As a result of such policy more than 228 licenses were revoked from the beginning of 2013 till 2018 – more than was revoked from the establishment of CBR. Today, the number of credit institutions continues to decline steadily due to inefficiency of the banks, fraud and their failure to comply with the requirements set by the regulator. The abovementioned trend is clearly visible on the graph, presented below.

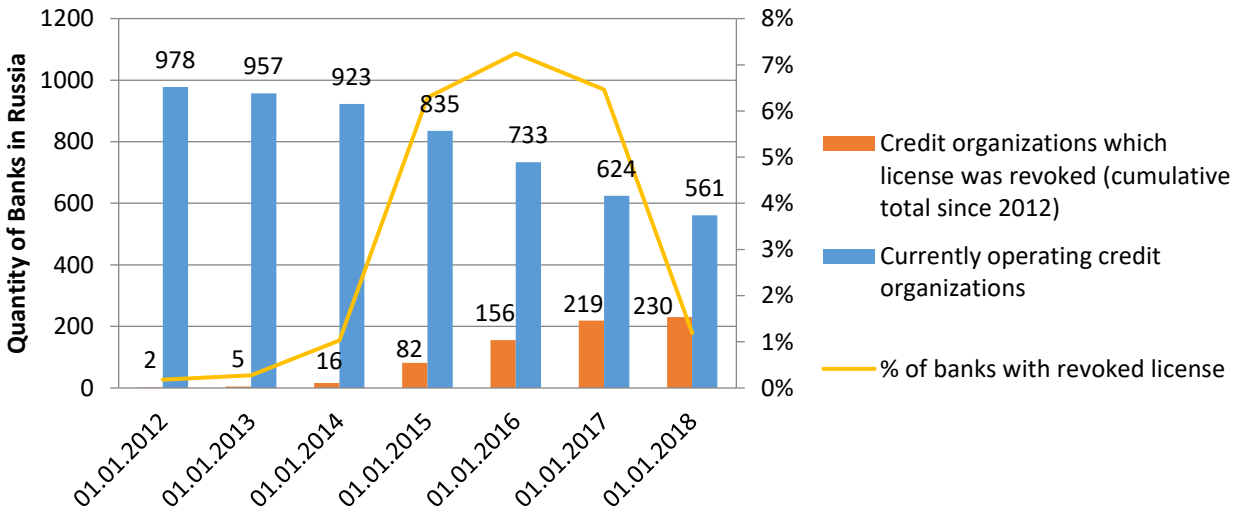

Figure 2 Total quantity of banks and number of banks with revoked licenses

As of now (01.01.2018) there are 561 operating credit organizations in Russia, which means that the number of banks declined by 41.4% in 6 years - a little bit less than a half. At the same time, it is clear that percentage of banks with revoked licenses peaked in 2015 and reached 7.2% from all credit organizations that were registered in the country. However, it should be noted that not all banks that have problems are subjects to the revoke of the license. Some of such banks are given to other, healthier, banks for sanitation or transferred to the Banking System Consolidation Fund (BSCF) – a special investment fund, created by Bank of Russia (CBR) in 2017 for financial rehabilitation of the insolvent banks. So, CBR can impose its administration in the problematic bank, improve it financial state and sell it (not necessarily with profit). As of now, there are four banks in the fund which were selected according to their importance to the stability of the banking sector of Russia; the banks that are “too big to fail”:

1. Bank Otkritie Financial Corporation
2. B&N Bank
3. Promsvyazbank
4. Bank Sovietskiy

However, it cannot be said that tightening of the regulations by Bank of Russia was an absolutely unexpected decision, because couple of years ago in the article of Kolosova (2011) and in the analytical bulletin "The Banking System of Russia: Trends and Forecasts", presented by "RIA-Analytics", it was noted that as a result of the financial crisis of 2008 there is a need for a toughening of control over the banking sector by the national regulator in order to further stabilize and strengthen the banking system. Therefore, the most likely scenario for the further development of the banking industry is the change in the structure, which will be expressed in the reduction of the number of banks and increase of the size of the remaining banks. As it can be seen now, the scholar and experts of RIA-Analytics were right in their expectations and Bank of Russia started the policy aimed at the reduction of the inefficient and fraudulent credit organizations.

A logical consequence from such policy is the increase of concentration in banking sector. The concentration can be measured via Herfindahl-Hirschman index (HHI) and the results can be analyzed according to the next criteria: <1000 means low concentration; 1000-1800 means moderate concentration; 1800-10000 means high concentration. The table below demonstrates the distribution of credit institutions ranked by assets in descending order and reveals HHI for the six consecutive years.

Table 1 Concentration of assets in Russian banking sector, %

	01.01.2013	01.01.2014	01.01.2015	01.01.2016	01.01.2017	01.01.2018
Share in assets of top 5 banks	50,3	52,7	53,6	54,1	55,3	55,8
Share in assets of top 20 banks	69,8	71,7	71,7	75,1	78,1	79,3
Share in assets of top 50 banks	81,4	82,8	85,7	87	88,7	90,1
The index HHI (assets)	1104	1153	1156	1162	1221	1227

Source: Bank of Russia

It is clear that top-5 banks continue to increase their share in the total assets of banking system (they hold 55,8% of all assets as of 01.01.2018) with Sberbank maintaining the largest share, which according to different estimates is between 23% to 47% (Stazhkova et al., 2017). Also, HHI show constant growth which implies a trend for an increase in concentration. According to the index, the concentration on the market can be concluded to be of a medium level.

The increase in concentration within banking sector may be considered as a negative factor, because it implies low levels of competition and higher prices (higher interest rates). These two factors combined may result in lower efficiency in terms of quality of services provided to clients, because they simply don't have a choice, because there are few players on the market. Moreover, lower cost efficiency may emerge, because banks will be less concentrated on cutting costs and enhancement of the internal business processes because of the increased revenues (higher process and less competition). Increase in concentration also exerts pressure on small banks that have to follow tightening regulations of the regulator and at the same time stay competitive with the large players. Furthermore, the tendency to revoke licenses from small and medium banks pushes consumers and organizations to move their assets to more reliable large banks, preferably with a large share, pertaining to the government. On the other hand, higher concentration implies higher stability of the sector and makes it easier for the regulator to better control all players in the industry. Moreover, large banks tend to diversify, and this allows them to decrease their susceptibility to risk, namely: when one sector is not profitable, the bank can mitigate this with the help of another, healthier, sector, while a bank, concentrating on one sector is vulnerable to the fluctuation within the sector. Finally, due to the increase in interest rates and fees, banks will have higher profits which may serve as a safety cushion from economic shocks. So, it is clear that increased concentration has its own advantages and disadvantages and as of now there is no unanimous opinion among scholars

about whether it is positive or negative phenomenon. Some arguing that traditional measures of concentration only reflect the structure of the market and do not have a clear connection with the competition (Beck, 2008). For example, an increase in the concentration of the banking sector may occur simultaneously with an increase in competition in the consolidation of the banking sector (Beck, 2008) which calls into question the connection between two phenomena.

If one is to analyze the structure of incomes and expenses of Russian banking sector for the period of 2012-2015 he could notice a sharp increase in share of incomes and expenses, connected with foreign currency (see Appendix 2). This may occur because of the steep decrease in the ruble exchange rate, which began in the second half of 2014. Incomes and expenses from foreign currencies comprised more than 82% of total incomes and expenses of banking sector for more than 4 years, starting from 2014. However, despite the fact that this share is huge, one can notice that it was rather big before, for instance, it was 57.5% and 57.5% of total income in 2012 and 2013 respectively.

In general, for the period from 2012 to 2017 income from legal entities rose by 71%, while income from physical entities rose two-times slower, only by 36%. Commission income grew gradually and for six years increased by 71%. Similarly, the structure of expenses demonstrates a growth of expenses on legal entities of 156% and two-times slower growth of expenses on physical entities (71%). Interestingly, the second biggest line of income and expense for Russian banks is reserves. It is perfectly clear from the figures, presented below. Both graphs are cleared from the income and expenses on foreign currencies to facilitate understandability and make presented

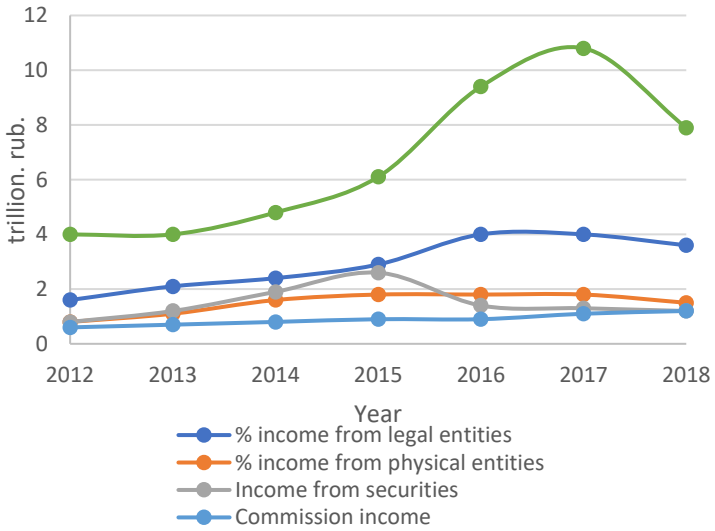

Figure 3 Structure of income of Russian banks, trillion. rub.

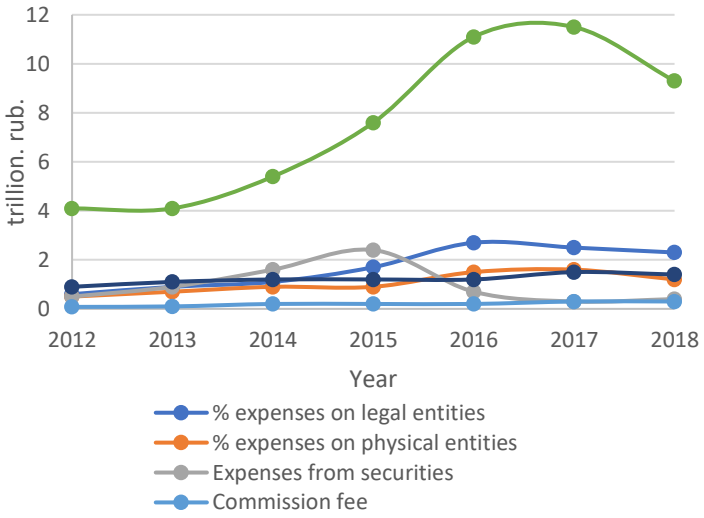

Figure 4 Structure of expenses of Russian banks, trillion. rub.

information clearer. One can see that after 2013-2014 allocations to reserves were increasing sharply probably as a result of strengthening of the policy of Bank of Russia and due to a significant decline in the quality of banks' loan portfolio in the light of the current financial crisis. The standard for accrual (allocation) of reserves for possible loan losses depends on both the quality of debt servicing and the financial condition of the borrower, which, over the past two years, has significantly deteriorated for most companies. Quality of debt servicing declined especially sharply for the companies that took loans in foreign currency, but which operations are ran in local currency (rubles). Besides, interest income on funds provided to legal entities was increasing in absolute values for almost 5 years and then started to decline. Similar situation occurred with interest income on loans granted to individuals, although the growth war much slower. However, the increase in incomes came with increase in respective expenses, for instance, allocations to reserves grew faster than recovery of reserves; in relative terms, as it was mentioned before, expenses demonstrate higher growth rate than income for the period of 6 years. Probably, this may mean that banks were not cost-efficient and were not able to grant more loans and deliver more services without increasing costs.

To further deepen the understanding of banking sector, let's consider its structure (see Appendix 3 for a full table). Total banks' assets increased from 49 510 bln RUB in 2012 to 85 192 in 2016 – an increase of 72% – while total credit to the economy (loans to legal entities and individuals) increased from 27 709 in 2012 to 42 366 in 2016 – an increase of almost 53%. The key drivers of these dynamics were loans to individuals and unsecured consumer loans. The former increased by 3,8% during 2016-2017 partially supported by government led programs in the mortgage and car loan sectors. One can notice general positive trends on all indicators, presented in absolute values in Appendix 3, during the period of 2012-2018.

From the graph below, it is clear that the most profitable year during the period under review is 2012 – banks got 1 trillion rubles in profits. After, the profits started to decline and jeopardized almost twofold in 2014, a year when foreign sanctions on banking sector were implemented. The lowest profit banks generated in 2015 – only 192 bln RUB. Probably in 2014-2015 banks were trying to recover from sanctions and find another way of generating revenues and taking credits. In 2016 the sector was able to generate 930 bln RUB – almost as much as in 2013. However, 2017 was not as profitable for the sector, probably because of the losses, generated by one of the biggest Russian bank, Promsviazbank, that was taken for sanitation by Banking System Consolidation Fund

(BSCF). Also, smaller profit in the year 2017 may be explained by the fact that Bank Otkritie FC and B&N Bank were showing disappointing financial results and were sent to BSCF for recovery.

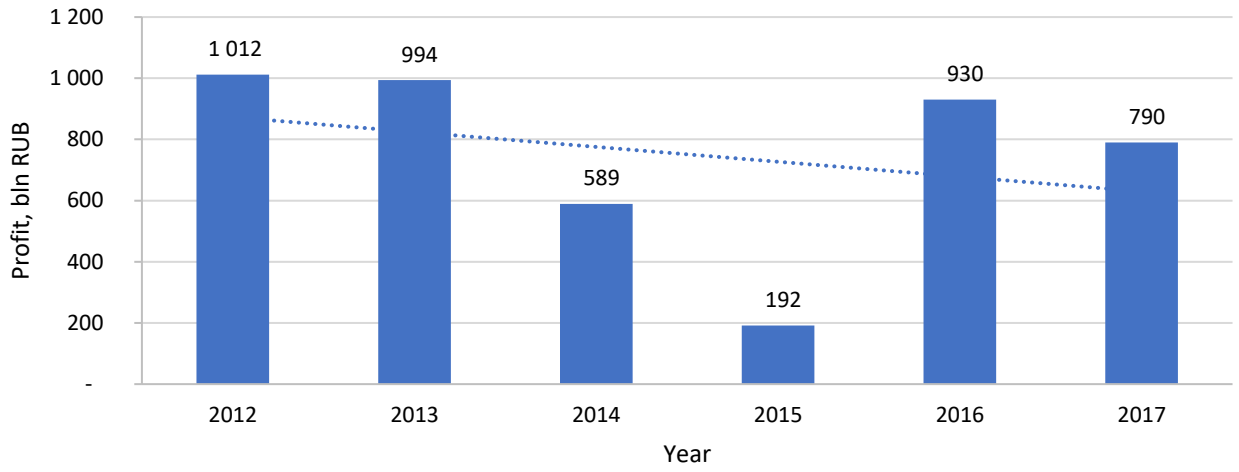

Figure 5 Profit of Russian banking system per year, bln RUB
Source: Bank of Russia

Another interesting fact is that biggest part of the profit was created by the biggest Russian bank Sberbank. According to the ExpertRA rating agency it generated 37% of total profit of the banking system in 2017, while 28% of the banks remained loss-generating entities.[2] This is a clear disproportion that may pose a threat to the stability of the banking system in the future. This shows that almost quarter of banks are not efficient in terms of generating profits or being cost-efficient.

At the same time, banking sector has been increasing allocations to reserves for possible losses during the period of 2012-2014, which indicates that banks were trying to create a safety-cushion to mitigate possible geopolitical and financial risks. In the year when sanctions against banking sector were implemented (2014) reserves rose by almost 40% to 7 569 bln RUB and in 2015 they increase once more by 46% to 11 081 bln RUB. Although in 2017 reserves decreased and amounted to 9 328 bln RUB.

On the graph below, one can see Bank of Russia's interest rate (this base rate is a monetary tool used by the Russian central bank which can influence the interbank interest rates and the interest rates for loans, mortgages and savings) change throughout the period of 2014-2018 which clearly indicates the response of the regulator to the external challenges, e.g. sanctions against banking sector in 2014. This decision (rise of the interest rate) led to an even greater reduction in ruble liquidity in the banking system in the face of a significant outflow of capital. As a result,

[2] https://www.raexpert.eu/files/Industry_annual_report_Banks_06.09.2017.pdf

Russian banks found themselves between the "hammer and anvil", forced to repay their debts and operate without having access to cheap loans in the foreign currency market and on the domestic ruble market. Also, obviously, the increase in interest rate to 17% led to the increase in the cost of credit resources, which accordingly reduced the demand of potential borrowers. The decline in the volume and pace of lending is very negative for the effective economic development and stability of the banking system, since the revival of economic activity will depend on the saturation of the economy with monetary resources.

As of 2017 Bank of Russia decreased the rate 6 times in a row, but this process is far from over and in case of favorable inflation in 2018 CBR will continue this policy. More accurately, in 2018, the Central Bank of the Russian Federation, according to RIA Rating analysts (“Banking sector of Russia”, 2017), will reduce the key rate within 1.5-2 percentage points, and under favorable conditions, the rate may fall even below 6%.

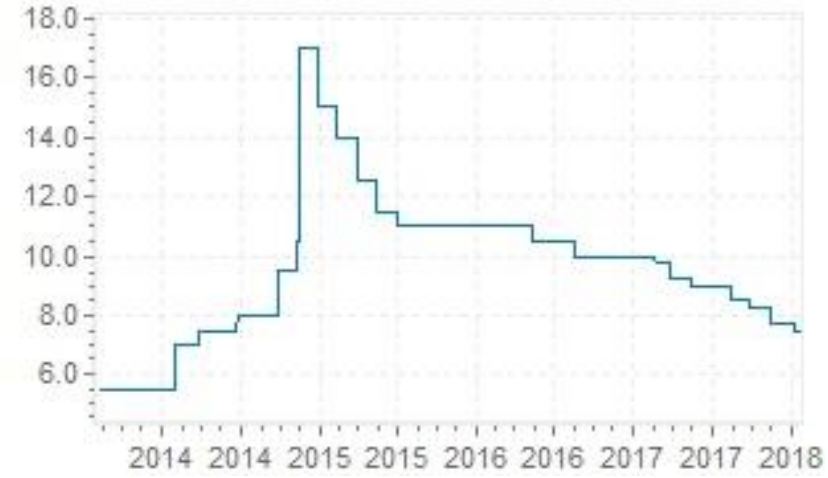

Figure 6 CBR interest rate change 2014-2018

Source: (Global Rates, 2018)

Now we shall single out the basic administrative and external economic factors, which are connected with the efficiency of the banking sector. Precisely, managerial factors as triggers of inefficiency and crisis.

There are several main factors that may contribute to a decrease in the efficiency of banking management and, as a result, to a decrease in the competitiveness of the banking organization and its inability to withstand crisis phenomena based on the history of the Russian banking sector:

Concentration of power in the hands of one person and the absence of a system of multifaceted internal control. Obviously, one person cannot account for everything and as a result the mistakes in governance affecting banking effectiveness are unavoidable.

Significant relationship of many banks with political organizations. This gave many banks the feeling that they will certainly be provided with financial support from the state in case of difficulties. As a result, some banks became less risk-averse and were involved in risky deals, because they counted on a solid financial backup from the government or structures and people which are closely affiliated with it.

Investments in long-term and expensive projects that are not an absolute necessity. Some managers are trying to "build an empire" and start spending bank's money on useless purchases and questionable investments that may not be beneficial to the stakeholders.

Close ties of banks with large enterprises. An extremely dangerous phenomenon, as the bank can be liquidated in order to save a more profitable business for no apparent reason. The point is particularly bright in the case of MENATEP and YUKOS.

And, finally, lack of competent integration of the risk control system.

1.2 Main trends and features of the banking sector

Finally, analyzing the development of Russian banking system, we can identify several trends that either started earlier and continue to exist in the banking sector, or are new trends in the development of the system.

The main trend is the sanitation of the sector which will for sure continue in the future. Interesting fact is that notwithstanding the possible decrease in the number of the revoked licenses the banks that a sanitized may be rather big and important to the sector, as it was the case with banks given to the BSCF. That means that not only the number of the revoked licenses should be taken into account, but also the size of the bank and its importance to the sector.

Governmentalization of the banking sector is partially a consequence of the first trend, because the licenses were revoked mainly from the private banks. Only two banks in top-10 (by assets) are still private and one of the two has close relations with state owned company. As of the start of 2018 only three of the largest twenty banks can be called fully independent from the state, which means that the state now directly and indirectly controls about three-quarters of the assets of

the Russian banking sector. Needless to say, that too big involvement of the government in the sector can lead to the decrease in efficiency in terms of costs and profits.

Concentration is rather important trend too. The main assets of the banking sector are concentrated, as already mentioned in the hands of a very small number of players. Thus, the 5 largest players own 55.8% of the assets of the banking sector.

Another trend that began in 2016 is the exposure of banks to cyberattacks. The level of cyberattacks on the banking sector last year was rather threatening. In 2017 cyberattacks that have disrupted a number of businesses including banks. For instance, a significant damage was caused by the virus-cryptographer WannaCry, and then encoder Petya for a few days stopped the work of a number of banks. This happened despite the increase in banks' spending for cyber defense in Russia and around the world. Taking into account that the last large-scale attacks affected many countries at once, it is possible to compare how much Russian banks were ready to defend in comparison with foreign competitors. In this regard, the comparison is quite in favor of Russian financial institutions. In most of banks, the damage was avoided, and the affected banks were able to restore their performance relatively quickly. All in all, the trend on the increase in spending on cybersecurity will continue in the future.

One more trend is high degree of dependence of the banking sector on the national economy, political trends and the current phase of economic development. Therefore, worsening of international relations, which could lead to undesirable restrictions imposed on the banking sector of the Russian Federation by foreign countries. For example, the USA continued the policy aimed at toughening sanctions against Russia, its sectors of economy and individuals. Further strengthening of the sanctions may be painful to the Russian banking and financial sectors. Consequences of the sanctions can be twofold: either only the strongest and most effective banks will survive or the banks that have connections with government. Realization of the latter option will lead to the deterioration of financial stability of the sector and economy as a whole.

Finally, the development of banking sector was marked by the emergence of new financial technologies on a global scale. And if the blockchain, despite all its popularity, is still only among the promising innovations, the remote service has become a real mainstream. A great impetus was given to the development of chatbots, as well as the automation of banking in both front and back office. One of the pioneers in implementation of such strategy in Russia is Tinkoff Bank that completely abandoned offices and that effectively uses strategy of remote service. Nowadays, this

strategy is being used by other players on the market and as a result the number of offices is shrinking. For example, in Russia at the beginning of the year 2016 there were almost 40 thousand and then, a year after, there are about 33 thousand (Banking Sector, 2016). One of the major drivers of this trend is Sberbank that in 2017 reduced the number of offices that were unprofitable and continued an active development of remote services. This trend sets the ground for the competition in the future between banks that develop online-services and IT-giants that develop their payment systems (Apple, Google, Samsung and others).

Now we turn to the theoretical part in which the main managerial theory on which this thesis is built upon will be revealed. Also, the outlook of the most commonly used methods for conducting competitor analysis will be discussed and the choice of the benchmarking will be highlighted.

1.3 Applied managerial theory

In this section the managerial theories that lay behind the present research will be revealed. This paper is based on the strategic management theory of competitive analysis. Strategic management allows a company to employ much more proactive stance towards its own future and give it a chance to start initiatives that will influence its destiny. However, before going deeper into the concepts, utilized within abovementioned managerial theory, the necessary definitions should be given.

The first definition is the one of competitive analysis. It is the process with the help of which the firm is trying to better understand its industry, identify its competitors and find out their strengths and weaknesses to better anticipate their future moves (Porter, 1980).

The second one is competitor analysis, which is the process of assessment of current and potential rivals to provide formulation, implementation, monitoring and adjustment steps of the strategy with the useful decision-support information.

In fact, competitor analysis is a part of competitive analysis, while the latter serves as a basis for a strategy formulation. The company has to consider both internal and external environments to conduct a strategic analysis. In the previous sections the market analysis was conducted in order to give an understanding of what is going on and what trends take place in the Russian banking industry, i.e. to give a reader an outlook of the external environment in which all analyzed sample of 200 banks are operating. Competitive analysis deals with the external environment of the organization.

Although definitionally grounded in the positioning school of prescriptive strategy making common competitor analysis techniques are used in a variety of settings to support varied approaches to strategy making. Firms may use competitor analysis as part of an annual strategic planning process or may perform competitor analysis during preparation for submission of a competitive proposal to a specific client (Fleisher & Bensoussan, 2007). Competitor analysis is included in strategic planning process models and strategic thinking process models, and is cited as useful for strategy formulation, implementation, monitoring and adjustment

Porter (1980) proposed to build a portrait of a competitor with the help of twofold framework: first, to analyze what drives the competitor and, second, what a competitor is doing and can do. The former comprised of future goals and assumptions the competitor holds about itself and the industry. The latter consists of the understanding of how the competitor is currently competing and the strengths and weaknesses that comprise the competitor's capabilities (Fleisher & Bonsoussan, 2007). Poorly accomplished competitor analyses have resulted in firms being surprised by, overtaken, and faring poorly against competitors (Porter, 1980; Tovstiga, 2010).

Critiques of competitor analysis.

Researchers note that few firms undertake competitor analysis seriously, because they find most approaches suspect, too complicated or time-consuming (Coyne & Horn, 2009). Indeed competitive and competitor analysis are comprehensive and require significant organizational resources. This difficulty may lead to poor analysis that results in ineffective strategy. Zahra and Chaples (1993) discovered six potential pitfalls in competitive analysis:

1) misjudging industry boundaries,
2) poor identification of the competition,
3) overemphasis on competitors' visible competence,
4) overemphasis on where, not how, rivals will compete,
5) faulty assumptions about the competition, and
6) paralysis by analysis.

Also, they found that companies usually pay attention to a very limited set of a well-established, familiar competitors and tend to overemphasize their own beliefs about the behavior of this competitors.

Another point of critique is that managers tend to request more information than needed, excusing it by "the more, the better" thinking. This results in the information overdose and in the obfuscation of the analysis. To put it simply, there is usually a mismatch between the type of information a manager wants and needs and what is typically provided by activities such as competitor analysis. As a result of such requests managers receive a huge pile of raw data that lacks what is truly needed for a high-quality competitor analysis.

One more point of critique is that the literature on competitor analysis is overly focused on methodologies and specific techniques (Ghoshal & Westney, 1991) without enough consideration given to context and human interaction. Most of the competitor analysis activities are done in the "top-down" manner and, therefore, lack the necessary alignment among different levels of organization.

Finally, competitor analysis frequently is performed too late to make a difference in operational decision making and firms failing to link their strategy and operational decision-making processes with their competitive analysis efforts.

Techniques of competitor analysis.

This subsection will discuss some of the most frequently used tools and techniques to conduct a competitor analysis with the bigger emphasis on such technique as benchmarking its types, advantages and disadvantages, as it is the key technique used within this research.

Industry Forces Model (5 Forces)

Porter's (1979) Five Forces Model is a technique used to analyze a firm's operating environment. This model is based on the observation that a strategy is formed in reaction to the firm's environment. The five forces of the model include: a) the bargaining power of buyers and customers, b) the bargaining power of suppliers, c) competition among existing companies in the industry, d) the possibility of competitive forces exerted by potential new entrants to the industry, and e) the threat of substitutes.

Five forces analysis offers a qualitative evaluation of the strategic position and organizational capacity of an industry for sustaining its competitive advantage and enhancing external competitiveness. Hence, five forces analysis is more suitable for examining industries with steady performance and desire for expansion

The Five Forces model can be utilized in three steps: 1) collect information to identify each force, 2) determine the relative strength of each force and 3) assess and evaluate the forces in light of the firm conducting the analysis's competitive ability.

In short, this technique identifies the profit potential of an industry and provides a foundation for bridging the strategic gap between a firm's external environment and its resources

SWOT-analysis

According to Porter (1980) analysis should be conducted in reference to a firm's competitors and its strengths and weaknesses should be identified and evaluated in comparison to competition, while opportunities and threats are derived from changes in the environment. Compared with other approaches, SWOT emphasizes an extensive analysis of the external environment as a prerequisite for strategy formulation, and due consideration given to internal resources and capabilities.

SWOT is well-known for its wide applicability and ease of use in dealing with complex scenarios in limited amounts of time. However, the drawbacks of SWOT analysis include that it is overly simplistic and is used just to make list of factors with which managers have little understanding how to work with. Also, this analysis is purely descriptive and does not offer strategic recommendations. Therefore, it leads to the implementation of reactive strategies and can be easily distorted by the improper or overly subjective definitions of strengths and weaknesses or by giving some factors too much emphasis, or too little emphasis, or equal importance. On the other hand, thanks to its advantages, SWOT is used more frequently than other competitor analysis techniques because it is very straightforward and requires little preparation.

In short, this technique identifies own firm's distinctive competencies Identifies opportunities own firm is not currently able to take advantage of.

BCG Growth/Share Portfolio Matrix

This technique was presented by the consulting firm BCG in 1960s and it was designed to help people, working in multi-product, multi-market and multi-national organizations, in the development of corporate-level strategies. In this technique the business is viewed as a portfolio of businesses. BCG matrix plots market attractiveness and competitive position to compare the situation of different products or business units. Industry's growth rate is a proxy for market attractiveness, while business unit's market share is a proxy for competitive position.

The main advantage of the method is that it gives a very good picture of the organization's business portfolio is its main strength. The major disadvantage is too simplistic analysis and too big number of assumptions, underlying the application of the matrix.

GE Business Screen Matrix

The present technique combines the internal analysis of business strength with external industry analysis to describe the competitive situation of different business units and to guide resource allocation across these units.

Factors that are not controllable by the organization's management (external factors) include market size, market growth rate, barriers to entry, social issues and technology. On the contrary, internal factors, that management can control include market share, R&D, sales, financial resources, marketing and managerial competence.

The advantage of a method in comparison with the previous one is that it includes multiple factors and, thus, allows to increase the accuracy of the analysis. However, the multidimensional indicator requires managers to give each factor a weight. This may entail biased estimates and as a result imprecise analysis and, ultimately, biased recommendations and flawed strategy formulations.

Strategic Group Analysis

This technique concentrates on the examination of different groups of rival companies that are grouped together according to their similarities in strategic position or competitive approach. As a result of this technique, management gets a strategic group map that demonstrates different competitive positions of the rivals within the industry. This technique is helpful in determination of

- the competitive position that a company stands in,
- the intensity of a rivalry within and between industry groups,
- the profit potential of various groups in the industry.

One of the main strengths of this technique is that a lot of variables can be included in the analysis. This allows to scrutinize multiple layers of factors and at the same time to look at a lot of finer details. Another advantage is the positive effect of a strong group identity. If organizations within a group work well together, they can enjoy a synergetic effect in terms of their increased positive perception by the consumer.

As for the disadvantages of the technique is that it gives a lot of insights to the analysts but does not give any guidance on the possible ways for implementation of these ideas. Therefore, group analysis should be used together with other techniques, especially with those that have a stronger emphasis on the implementation.

All the above-mentioned techniques are the most frequently used in conducting the analysis, however, there are numerous other techniques that can be applied together with the previously mentioned ones by the management to get a synergetic effect. One of such techniques is benchmarking that can be used to analyze competitors and find out best-practices to look forward to. This paper will discuss benchmarking in greater details as it is the core concepts applied in the present research.

Benchmarking

Benchmarking provides a set of specific measures comparing the firm with its competitors on a set of key variables, such as capital investment, productivity, quality, and so on. Another definition is given by Camp (1989) and it considers benchmarking as a process that gives company an opportunity to enhance its performance by the mean of comparing its products and services with others that are recognized references (benchmarks). Tu put it simply, benchmarking is a tool for improving performance.

Watson (1993) has identified five generations of benchmarking practices that have emerged in history: reverse engineering, competitive benchmarking, process benchmarking, strategic benchmarking and global benchmarking.

There are two concepts of benchmarking that can be applied by the company (Camp, 1989):

1. according to the first, the company continuously compares its own products and processes against the best-performing company in the industry;
2. according to the second, the company permanently thoroughly scrutinizing for significantly superior practices that may lead to an enhanced competitive performance.

The present technique has its own advantages and disadvantages. The advantages include:

- After a good benchmarking an entity will know where it stays relative to its peers and how to improve its processes to become more efficient.

- A good benchmarking leads to a prioritization of employed resources and their enhance usage.
- In order to reap the benefit of benchmarking companies have to undergo a thorough self-analysis to ensure a clear understanding of its own business-processes. This process of self-knowledge may provide a company with very valuable insight about the nature of its operations; these insights may be more valuable than the benchmarking itself (Epper, 1999).

The possible pitfalls of benchmarking include:

- Benchmarking can be overly expensive and too broad in scope. To mitigate this risk, management should organize participative training and awareness for all staff involved.
- Some researchers, like Hammer and Champy (1993, cited in Meade, 1998), argue that benchmarking can stifle innovations in the company because of its focus on the processes and practices that are already occurring in another companies.
- It is hard to choose the right reference company to benchmark. The wrong choice of a best-practice may lead to inefficient strategy formulation and flawed processes. It may be impossible to know which potential partner organization is the best in any specific area is until data has been gathered and comparisons made.
- Likewise, if the company is the best in the industry it may be impossible to find a benchmark to look forward to.
- Data among different companies may be non-comparable due to the different reporting standards or other reasons, thus, making the benchmarking unreliable.

Benchmarking can be classified according to its concentration on product (compares products and services), process (focuses on discrete work processes and operating practices), best-practice (finds out exemplar companies with superior products or processes) or strategy (examines how companies compete).

Also, benchmarking can be of different types, depending on the type of partner to benchmark with (Meade, 1998): internal (compares different divisions within the company), direct competitor (comparisons are made against direct competitors), related industry/functional benchmarking (the

benchmarking partner is not a direct competitor but does share the same industry) or unrelated industry/generic benchmarking (compares processes and practices regardless of the industry).

Finally, one can conduct a standards-based benchmarking analysis in two ways:

- Criterion reference benchmarking – manager states the attributes of a good practice in a pre-defined are and then assesses whether that criteria has been achieved. If the benchmarking process concludes that the entity meets the criterion then the company meets that benchmark.
- Quantitative benchmarking – manager sets some normative or commonly used levels for each of the metrics that are used in the analysis and searches for companies, demonstrating superior level of a pre-defined metric.

An important concept used in benchmarking is best-practice unit. An early definition of best practice associates it with "superior performance within an activity, regardless of industry, leadership, management, or operational approaches, or methods that lead to exceptional performance" (Lema and Price, 1995, p. 30). This study will use this concept a lot as it is easy to comprehend and at the same time comprehensive definition, perfectly applicable for a banking institution.

There are multiple ways on how one can conduct a benchmarking, i.e. by setting up a set of criteria, by doing a qualitative assessment, through expert judgement based on empirical evidence etc. This study will utilize Data Envelopment Analysis (DEA) method within Frontier Analysis Approach to assess the efficiency of all banks in the sample and then, on the basis of these marks find out best-practices and identify possible ways of improvement. The best-practice benchmarking utilized in this paper will be quantitative and focused on the direct and functional competitors.

DEA method is a superior method to a simple ratios or one-dimensional criteria comparison, because it is a mathematical programming-based approach for measuring the relative efficiency of decision-making units (DMUs) that have multiple inputs and outputs (Charnes et al., 1978). DEA is mainly concerned with the estimation of efficiency of the DMUs, applying input-output weights that maximize the efficiency score of the evaluated units, while the benchmarks provided by the DEA can be seen as a side product of the envelopment problem. In the circumstance of benchmarking, the efficient DMUs may not be necessarily a "production frontier", but rather a "best-practice" frontier.

As DEA is primarily concerned with efficiency of DMUs, the next section will reveal in detail what definitions of efficiency exist and how they are different from each other, as well as the major concepts of efficiency and performance will be revealed.

1.4 Review of existing concepts of efficiency

One of the main goals of this paper is to calculate and analyze efficiency scores of Russian banks. In order to correctly fulfill this goal and resolve possible ambiguity, the clear set of definitions relating to the topic should be given. The terms and definitions discussed in this section lay the ground for a firm understanding of the topic and form a part of a theoretical base for the reader.

Interestingly, nowadays, regarding the banking environment there is no generally accepted and established concept of efficiency. On the one hand, this complicates the work of the researcher, but, on another hand, it gives some flexibility in the formulation of the definition that in his or her opinion will be the most appropriate. However, before defining efficiency, it is better to clarify the terminology by giving similar terms that are frequently used interchangeably with the efficiency, but in fact differ from it, i.e. effectiveness and efficacy.

A company is said to be effective if it achieves planned outcomes or goals as a result of a strategy or activity under ordinary circumstances (not in the controlled environment).[3] In other words, effective means being adequate to accomplish a purpose; producing the intended or expected result. In business effectiveness is equivalent to “doing the right things”, meaning that a company or a person is efficient if it achieves the intended outcome.

Efficacy is a much narrower term than efficiency and it means the ability to produce a desired result under ideal conditions (controlled environment, lab circumstances).[4] A good example is a vaccine that might have efficacy under lab conditions but be ineffective in uncontrolled environment. In business this term is used to evaluate plans and test strategies before executing them.

An organization is said to be efficient when it performs in the best possible manner (maximizes outputs) with the least waste of resources (minimizes inputs). In business effectiveness

[3] http://www.businessdictionary.com/definition/effectiveness.html
[4] http://www.hayajneh.org/healthcare_glossary/efficacy/

is equivalent to “doing the things right”, meaning that a company or a person is effective if it achieves the goal with minimum waste.

There are two approaches by which you can measure efficiency (Cooper, 2006):

- Output-oriented approach (maximization of output with the given resources);
- Input-oriented approach (efficient use of resources) - linking the performance of the bank with total costs and the ability to have lower costs, all other things held equal.

The most common option is input-oriented approach, because when measuring this efficiency, managers receive data based on which they can directly influence certain inputs of the company in order to increase the efficiency of the organization entrusted to them. In contrast, while measuring the effectiveness of output, managers have fewer levers of influence that decreases practical utility of conducted research. In addition, when deciding between two options it is worth taking into account that the organization, for example, can have extremely high profit margins, but extremely inefficient, irrational resource costs.

The vivid difference between efficiency and effectiveness is presented in the Figure 6 (see the Figure below).

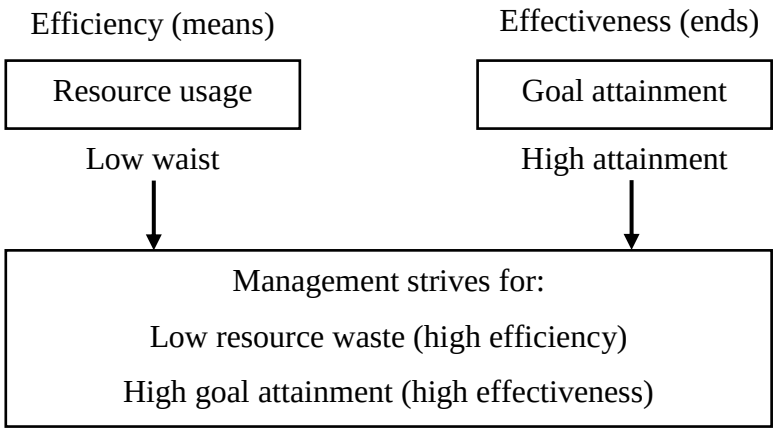

Figure 7 Effectiveness and efficiency in management

Source: author

One more definition that should be given to clarify the terminology is productivity which often used interchangeably with efficiency. Indeed, the difference is subtle: productivity of a firm is simply the ratio of outputs to inputs, while efficiency has to do with the relative productivity over time (Abdul-Wahab et al., 2017). Unfortunately, it might be difficult to use productivity indicator if

a company employs multiple inputs to get numerous outputs (which is usually the case), because in this instance components of numerator and denominator must be aggregated in some economically sensible fashion, so that productivity remains the ratio of two scalars.

Delving into more specific definitions of efficiency, one should pay attention to economic or overall efficiency (EE). According to Farrell (1957) economic efficiency is a situation in which every resource is optimally allocated to serve each company or individual in the best way while minimizing waste at the same time. Overall efficiency is the product of two components: allocative efficiency and technical efficiency. For the entity to be economically efficient (i.e. EE=1) it should be simultaneously technically and allocatively efficient (i.e. TE=AE=1).

Allocative efficiency (AE; efficiency of distribution) is the ability of a firm to use resources (inputs) in the optimal proportion (proportion that minimize production costs) at their given prices. The allocative efficiency reflects the ability of a commercial bank to optimally use a combination of resources, in terms of both the cost of attracting banking resources and the prices of products and services produced by the bank. A firm is said to be allocatively efficient if it selects an input mix that minimizes the cost of producing the given set of outputs.

Technical efficiency (TE), formalized in 1951 by T. Koopmans (1951), sounds like this: an economic unit with a production configuration (X *, Y *) belonging to the set T will be effective, if there does not exists another vector (X, Y) different from (X *, Y *) and belonging to T, such that X ≤ X *, Y ≥Y *. In other words, technical effectiveness reflects the firm's ability to achieve the maximum possible output (products, services) with the given set of resources (output-oriented TE) or the company's ability to use the minimum amount of resources to produce a given output volume (input-oriented TE).

In general, there are many concepts of efficiency and some of them are summarized in Table 2 with a brief description.

Table 2 Types of efficiency

Type of efficiency	**Description**
Technical efficiency	The ability to use the minimum amount of resources to produce a given volume of goods and services. The efficiency boundary is the production function, the isoquant or the production capacity curve.

Table 2 Types of efficiency (continued)

Type of efficiency	Description
Allocative (structural) efficiency	The bank's ability to use the optimal combination of resources with the available technology and the corresponding prices for factors of production.
X-efficiency	The degree of efficiency maintained by individuals and firms under conditions of imperfect competition. The bank is X-effective if it produces maximum possible output from the given set of inputs and with the best possible technology. X-inefficiency is the difference between efficient behavior of banks assumed or implied by economic theory and their observed behavior in practice. X-inefficiency doesn't consider whether the inputs are the best ones to be used, or whether the outputs are the best ones to be produced (Leibenstein, 1966).
Boundary efficiency (efficient frontier)	Was first introduced by Harry Markowitz and is wildly applied in portfolio theory. Efficient frontier shows the boundary of the set of portfolios that have the maximum return for a given level of risk. Portfolios laying below the frontier are dominated by Markowitz efficient portfolios (Markowitz, 1952). In DEA method which will be discussed in detail further, the border is formed by the so-called best-practice units (i.e. by efficient (non-dominated) banks) (Coelli, 2005).

Source: author

1.5 Parametric and Non-Parametric approaches to measure efficiency

In order to determine economic efficiency, it is necessary to measure it, therefore, the definition of measurement is needed. Measurements are accurate, pre-prepared observations of the real world made to describe objects and phenomena in terms of their inherent properties with variable values (Babbie, 1998). Also, the concept of measurement can be interpreted as a process or a result of determining the value of quantities (e.g. profit) in relation to a unit of measure (e.g. the ruble, the US dollar or the euro).

Also, in order to correctly choose the variable for the analysis one has to understand what properties it must fulfill to be clearly and similarly perceived by all interested parties. The variable must be: (a) reliable, (b) accurate, (c) invariant among observers, (d) different from other variables, (e) stable in time (Fedotov, 2014). However, in reality, compliance with all five conditions is relatively rare, and therefore the assumption is made that the data provided by the companies are

accurate and reliable. However, measures to reduce the risk of inclusion of incorrect variables in the analysis are also introduced. For example, it is believed that Russian banks often distort the balance sheet profit (Belousova, 2009) in order to optimize the tax burden, which leads to erroneous, incorrect estimates of the bank's performance and reduces the overall quality of the conducted study. That is why this indicator frequently excluded from the analysis of banks' effectiveness when DEA method is used.

After conducting the measurement, the researcher gets at his disposal the so-called metrics – the quantitative values of some characteristics of the object (quality, properties) – that can be used for comparison purposes of the study. The calculation of the metric in absolute units of measurement is not necessary, because the use of a metric for comparison allows the usage of the relative (normalized) values. In this case, a specific metrics can be used for comparison (Fedotov, 2014):

- with their values fixed in time (the dynamics of the change in the indicator),
- with its own values for sampling objects (spatial comparison)
- with the established target value of the characteristic or its evaluation (comparison with the normative value of the characteristic).

In general, performance indicators can be of three types, depending on the ratio of "inputs" and "outputs" used. These types of performance indicators are presented in Table 3. In this study, a general performance indicator will be used, since it allows to consider all input factors and all bank's products (outputs) simultaneously which is a great advantage of the DEA method over other methods of efficiency estimation (e.g. ratio comparison).

Table 3 Types of indicators

Private	Multifactorial	General
The ratio of "output" and one particular resource at the "input"	The ratio of the output and any group of resources at the "input"	The ratio of the total "output" and the total "inputs"

Source: author

To gauge efficiency, researchers use a lot of different methods, ranging from simple ratio comparison to advanced statistical techniques and neuro-modelling. As part of this paper, two approaches to build the efficiency frontier of commercial banks – parametric and nonparametric –

will be discussed in detail. The main difference between these two methods is the different definition of the efficiency frontier. However, before proceeding with the description of these two approaches, the reasons why ratio analysis will not be used will be listed.

Ratio analysis approach will not be used in this paper, even though this approach is rather popular and simple. Historically, ratio analysis (output-input ratios) has been the regular method used by regulators, market analysts, as well as managers to measuring productivity in the banking industry. However, this approach does not offer independent ways to detect unproductive components and necessitates a partial split-up of the unproductive and productive levels. Similarly, financial ratios do not control for product mix and thus they are misleading measures of efficiency. Also, financial ratios assume that the cost of production is the same for all assets and that the cost of doing business is the same for all locations based on the "cost to asset" ratio. Ratio analysis is therefore insufficient for efficiency assessments due to its inability to explain complex input and output procedures in addition to its failure to identify the best performers in any identical set (Berger et al., 1993; Paradi et al., 2011).

In general, measurement of productivity can be done in two ways, taking into account the level and trend of productivity. The productivity ratio represents a level at a given moment, expressed as relation between a produced output and a combination of utilized inputs. For the examination of change in dynamics of productivity over time indices have been used, while the analysis of variations of productivity in the function of time comes down to the research of development tendencies models.

The ratio analysis provides a relatively insignificant amount of information when considering the effects of economies of scale and evaluating overall measures of a bank's performance. The ratios are used to identify trends over time for one bank or to compare two or more banks at one point in time (Knežević et al., 2011). As an alternative to traditional bank tools for the bank management of bank efficiency, the frontier DEA analysis was used that enables management to objectively identify the best practices in the dynamic environment in which banks operate (Yang, 2009). DEA provides a comprehensive analysis of the relative efficiencies for defined inputs and outputs (Banker et al., 1984).

The parametric approach evaluates the parametric function (for example, the cost function) on the basis of statistical data, and the residuals reflect the measure of organization inefficiency

(Resti, 1997). SFA is based on the assumption that empirical data cannot lie above the optimal production function (or cost function). In other words, the very parametric approach involves proposing assumptions about the exact form of production functions, more precisely, it involves obtaining an econometric estimate of the functional form of the production function. However, it is worth noting that the efficiency boundary that the parametric approach allows to build is a theoretical ideal and the deviations from this boundary can be interpreted by the researcher, both as a result of inefficiency of the object and as a result of a random error (Berger, Humphrey, 1997).

A nonparametric approach does not imply creation of assumptions about the form of the production function. The efficiency boundary in the case of non-parametric approach is based on the best Decision-Making Units (DMUs). The approach itself suggests considering each bank as a microeconomic firm that uses resources ("inputs") to create a release ("outputs") with the help of some production function. The main disadvantage of this approach is that it is non-statistical, and, therefore, there are difficulties in trying to test hypotheses about the significance of the results obtained. This disadvantage is almost leveled by using the bootstrapping method, which assumes that the true distribution of data can be approximated empirically. This approach gives the researcher an opportunity to construct a piecewise-linear bound of efficiency, as a certain "shell" of actual observations available to the researcher. Deviations from the efficiency boundary are interpreted in this case, as a result of inefficiency of the object (Coelli, 1996). This is also an omission of the model, since there is no random error.

In the work (Alekseev, Martynov 2008), the authors state that the estimates obtained with the use of the two approaches can differ significantly, not only in absolute value, but also in ranking banks by the level of efficiency. However, it is also noted that when distinguishing homogeneous groups, these differences become insignificant. In order to facilitate the perception, Table 4 provides a brief description of the parametric and non-parametric approaches, as well as examples of methods that represent one or another approach. But anyway, no consensus exists as to which method is most appropriate to determine the efficiency. SFA is the most popular technique for parametric methods while DEA still the most used technique for nonparametric methods.

Table 4 Approaches to assess the level of boundary efficiency

	Estimation of the level of boundary efficiency	
	Parametric approach	Nonparametric approach
Basis	Econometric evaluation of the	Estimation of the line of the efficiency

Table 4 Approaches to assess the level of boundary efficiency (continued)

	Parametric approach	Nonparametric approach
	exact functional form of the production function (functions of costs, revenues or profits). Estimation of unknown parameters by the methods of econometrics.	boundary through the construction of enveloping data values (the approach does not assume a specification of the exact functional dependence). Estimation of unknown parameters by methods of mathematical programming.
Examples of methods	• Stochastic frontier approach (SFA) • A thick frontier approach (TFA) • A method without a distribution specification (DFA).	• Data envelopment analysis (DEA) • The free-hull method (FHM) - a special case of the DEA.

Source: author

Also, it is very important to understand that when analyzing banks via DEA approach, the selection of "input" and "output" variables is of utmost importance. There are three ways of how one can set choose the variables, and each allows you to position the bank in a certain way, to emphasize its functions. The description of each method is given in Table 5. It should be noted that the production and intermediation approaches are particular cases of a modified one. In general, the results obtained using the three approaches, according to (Golovan, 2006), do not differ, but the author notes that the modified approach remains the most preferable, since it allows to treat deposits in a more general form.

Table 5 Interpretation of deposits depending on the positioning of the bank

	Production approach	Intermediation approach	Modified production approach
The role of deposits	The bank is a producer of financial services, including deposits.	Deposits are the source of the formation of the bank's resource base and, accordingly, are accounted for in the resources of a commercial bank.	Deposits are included in the analysis simultaneously both as products, and as resources of a commercial bank

Source: author

This section introduced necessary concepts of efficiency and gave an understanding of the basic terms, as well as revealed important concepts and peculiarities that should be taken into account while conducting research. The idea of the section is summarized in a clear and concise manner in the conceptual table, presented in Appendix 4. In the next section, various studies about the efficiency of banking sector in Russia and other countries will be discussed.

1.6 Analysis of existing DEA banking studies

At the moment, there is a sufficient amount of work devoted to the study of the banks efficiency in various countries. Although, as noted by many scholars, banking systems of developed countries are more studied than the systems of the developing ones. Furthermore, despite the fact that papers, using DEA to gauge efficiency in developing countries, are growing in number, the last study of banking efficiency in Russia was conducted in 2009. Clearly, the fact that the topic of banking efficiency in Russia is still underdeveloped forms a scientific gap that this paper is trying to bridge. The summary of this section can be found in the Appendix 5, where all mentioned studies are presented together with the types of DEA models used and with the specification of inputs and outputs.

In the studies of Russian and foreign scientists, the methods of SFA and DEA are frequently used, as the most developed and effective. In the work (Aleskerov, Belousova, 2007) it is stated that for the evaluation of the efficiency commercial banks, the most common approach is the Data Envelopment Analysis. Although, simple quantitative indicators are used too: the number of open accounts for the period, the revenues received, the amount of loans issued, etc. Sometimes, especially within the US banking system, the aggregated rating of the bank's performance is used, for example, CAMEL (Capital adequacy, Assets, Management Capability, Earnings, Liquidity, Sensitivity) (Vishnyakov, 2001). These methods attract scientists by simplicity, but they represent a one-sided cutoff of the current situation and do not give a complete picture of the current situation in comparison with DEA.

The notion of technical efficiency was first formulated and introduced in the work of (Koopmans, 1951). Then, in 1957 Farrel undertook an attempt to empirically measure the efficiency of agricultural sectors of different countries, using linear programming tools. Farrel also developed the TE concept by introducing various returns to scale that may influence the quantitative estimate of the level of efficiency.

Then, 20 years later, the works of Meeusen, van den Broeck (1977) and Aigner, Lovell, Schmidt (1977) gave rise to the concept of a stochastic frontier approach (SFA). A little later, Forsund, Lovell and Schmidt (1980) and Greene (1993) proposed various assumptions about the types of distribution functions, more general statements of problems, and so on.

The DEA method was introduced by Charnes, Cooper and Rhodes (1978), (CCR), and assumed constant return to scale (CRS), i.e. that there is no significant relationship between the scale of operations and efficiency, together with input orientation. The usage of the model might be not feasible when not all DMUs are operating at an optimal scale. To overcome this limitation the second modification, called BCC (Banker, Charnes, Cooper, 1984) was introduced and it was based on the assumption of a variable return to scale (VRS).

1.6.1 Assessment of operational banking efficiency around the world

This subsection will present in chronological order different papers that gauge efficiency of banking sector in various countries with the usage of many approaches, based on DEA. The following literature review is rather comprehensive and aims to demonstrate the variety of approaches to the efficiency measurement with the help of DEA.

Firdaus and Hosen (2013) gauged the efficiency of ten Islamic banks in Indonesia via two-stage CRS DEA method from the second quarter of 2010 until the fourth quarter of 2012. Also, the paper proposes a modification of wildly applied bank soundness model, called CAMELS, with the help of DEA method. The results indicate that the efficiency of Indonesian banks lays in the range between 72.12% and 93.82%, indicating that there is still a room for improvement in terms of efficiency. According to a Tobit regression, number of bank branches, non-performing financing, and the capital adequacy ratio have statistically significant negative effect on DEA scores; while assets, ROA and ROE have statistically significant positive impact. Finally, the authors tested several ways of how DEA can be incorporated into CAELS (Managerial factors were excluded because they are too subjective and of a qualitative nature) methodology and concluded that DEA scores can replace ROA, because the latter is only a simplification of the measurement of the efficiency of a bank. The work is interesting because of the combination of the traditional methodology (CAMELS) with the DEA approach.

Zeitun and Benjelloun (2013) examined relative efficiency of 12 Jordanian banks over the period 2005-2010, that is the period after bank deregulation. The authors used both CRS and VRS DEA models and within each tested three combinations of inputs and outputs to find out how the

mix will influence the efficiency scores. To delve deeper into the sources of inefficiencies, technical efficiency was decomposed into pure technical efficiency and scale efficiency. The paper concludes that most of the Jordanian banks were inefficient in managing their inputs (the average cost efficiency demonstrated a declining trend during the period under consideration) and that global financial crisis affected the efficiency of the banking sector. Also, the paper proves that different specifications of inputs and outputs exert influence on the obtained efficiency scores. The paper is interesting because it assesses the efficiency of a highly concentrated banking sector, where three largest banks represent 66.5% of the total assets of the banking system out of which Arab Bank holds 48%. The situation slightly resembles one in Russia that was described earlier, therefore the work possess value for the research.

Hosen and Muhari (2014) used DEA with the operational approach to assess the efficiency of 73 Sharia Rural Banks (SRB) in Indonesia during the period of June 2011 to March 2013. The results showed that the average efficiency score for Indonesian banks during this period was 65.23%. Such result indicates that if the mean DMU produced its output on the efficiency frontier, then it would have needed only 65.23% of the inputs currently being used. Also, the authors compared the results of DEA with those of CAEL (minus management assessment) with the help of spearman correlation and found a weak correlation. This indicates that the CAEL analysis of a soundness of a bank has not reflected the efficiency levels of DMUs. As a suggestion based on the results of the research the authors propose to replace CAMEL's efficiency measure (a simple ratio of operating expense to operating income) with a more advanced one, namely DEA or SFA.

Mustafa and Behmood (2015) analyzed technical efficiency of Pakistan banks and were trying to find out if the adoption of information and communication technology (ICT) exerted any influence on the efficiency or productivity scores. The authors examined 11 commercial banks for the period of 1998 to 2012 via VRS and CRS DEA (to get efficiency scores) and via Malmquist productivity index (MPI) (to get productivity scores). Interestingly, in order to track more precisely whether the digitalization have had an impact over efficiency or productivity, the researchers divided the period under investigation in two parts: pre-digital reforms (1998-2005) and post-digital reforms (2006-2012) period. Results of the study demonstrated that the efficiency of the sector was constantly increasing in the post-digital period (15% growth in technical efficiency), while the average score was 94.2% under CRS assumption and 97% under VRS assumption, which is a good result. Another outcome is that technical restructuring of the sector helped banks to be more scale efficient, because the majority of them demonstrated CRS and IRS (increasing return to scale),

while only the minority were experiencing decreasing return to scale. As for the MPI, it showed total factor productivity change (TFP) of 1.156, which indicated a 15.6% growth in a post-restructuring period. Probably, the paper could be improved by the usage of the super-efficiency concept that allows researchers to rank and differentiate among DMUs that were estimated to be efficient. I.e. this concept does not influence the estimation of the inefficient DMUs but allows to prescribe efficiency scores greater than 1 to the efficient DMUs. This allows to get a more complete picture of the efficiency in the banking sector and to differentiate among non-dominated banks.

Marković et al. (2015), similarly to the previously mentioned study, assessed the efficiency and productivity of 33 Serbian banks for the period of 2007-2010 via input-oriented CRS DEA model and MPI. According to the former, there was no significant efficiency change in the sector; the mean efficiency score was equal to 72%. According to the latter, productivity of the Serbian banks was decreasing for the whole period under consideration and this result was due to the lack of the technological advances, rather than due to the technical inefficiency. Probably the paper could be improved by taking a longer period for the analysis and by a more specific formulation of research aim and objectives. Furthermore, the authors could use regression analysis to find out the triggers of efficiency scores. This would lead to a deeper analysis and much more precise conclusions.

Shyu et al. (2015) conducted an extensive study about the influence of the environment on the efficiency of 56 banks in Taiwan, Hong Kong, and Mainland China throughout post-financial reform period (2004-2009). The authors used a comprehensive three-stage DEA model that allows to account for environmental effects and statistical noise before conducting DEA. This is especially important for cross-country analysis and leads to a less biased estimates of the banking efficiency. In comparison, usual DEA model assumes that the differences in efficiencies among banks, located in different countries, are attributable to managerial decisions within banks and not to the country-specific conditions. Another important feature of the research is the usage of "slacks" concept[5], i.e. the authors could quantify by how many percent the input variables should be adjusted for the banking sector to become efficient. This leads to more precise recommendations to the authorities and management and allows to get more insights about how to manage efficiency. As a part of a three-stage procedure the authors ran an SFA regression to find out how environmental variables can influence input slack variables. It turned out that banks with higher capital adequacy ratio, more

[5] Slacks are abundant inputs or insufficient products. By using more inputs than necessary or generating fewer products than expected, DMUs with slacks are considered inefficient.

economic freedom, and longer years of service tend to have higher slack of waste in deposits, fixed assets, and number of employees. On the contrary, banks with higher total population (means registered population in each area), higher economic growth rate, and belonging to financial holding companies or conglomerates tend to have less slack of waste in deposits, fixed assets, and number of employees. The paper is relevant because it presents unconventional three-stage approach that mixes DEA and SFA, reveals how environmental factors influence the efficiency and demonstrates a technique for a more precise estimation of banking efficiency across different countries.

Jingyi (2016) review 20 research articles on Chinese bank efficiency and summarized their results, methodologies and approaches within one paper. The author discussed different estimation methods, used by others and came to a conclusion that SFA approach is the most popular among the studies articles. However, this article is useful for this research because it summarizes determinants of banking efficiency, found by different scholars, i.e. the author categorizes triggers of efficiency in three big groups: banks ownership, bank specific factors and environmental factors. First group usually includes hypotheses like "state banks are more efficient than private ones because government can support the former with funds" or "foreign banks are more efficient thanks to the faster adoption of modern technologies, than domestic ones". Second group includes such variables as bank size, loan loss reserves (LLR) as a proxy for credit risk, loan to deposits ratio as a proxy for liquidity risk, equity to total assets as a measure of capital risk and ROA volatility and stock return volatility to proxy for accounting operational risk. Third group involves GDP growth, interest rate, exchange rate, regional economic development, global financial crisis, and time trend variables. So this paper is relevant as it presents a general outlook on possible banking efficiency determinants, checked by numerous scientists.

Soba et al. (2016) assessed the influence of corporate governance on the efficiency of 10 listed Turkish banks during 2005-2015, via DEA and panel regression analysis. Routinely for DEA researches, efficiency scores are regressed on such variables as board size, board independence, institutional ownership, major shareholder, number of committees held during financial year (NoC), free float rate. The control variables were bank size, leverage (total assets to total equity), CAR. The results indicate that board size, major shareholder and NoC variables have a positive impact on bank efficiency. The study contributes to the DEA literature by researching the connection between corporate governance practices and banking efficiency.

1.6.2 Global DEA studies on bank size and efficiency

Sufian and Majid (2007) examined the efficiency of Singaporean banks and how it is related to stock returns in the 10 years period of 1993-2003, using DEA and panel regression. In other words, they examined the influence of X-efficiencies derived from the DEA window analysis technique on the share prices of listed Singapore commercial banks. The study found that the average efficiency level of banks under examination was quite high (95.4%); that small banks are more efficient than the large ones and that the stocks of cost efficient banks to some extend outperform cost inefficient banks. Researchers used a three-year window to investigate efficiency and to obtain a higher degree of freedom, because DEA window analysis considers DMU as different entity in each year. Therefore, a three-year window with six DMUs is equivalent to 18 DMUs and 9 such windows will result in a sample of 162 DMUs, leading to a greater degree of freedom. After obtaining the results via DEA, combined with window analysis, Sufian and Mijid built a panel regressions model where the moving average of bank j's daily share returns in window t was regressed on bank j's mean annual percentage change in X-efficiency in window t. The results appeared to be statistically significant, implying that cost-efficiency explains share prices performance of Singapore banks in the long-term.

Seelanatha (2012) in a study on the efficiency of Sri Lanka's banks, reached the following conclusions: there is no evidence of a relationship between the size of the bank and its technical efficiency. While there is one between form of ownership of banks (private or public) and technical efficiency, that is, private banks have proved to be more efficient than state ones. Also, banks with extensive experience on average proved to be more efficient than new banks.

Wanke and Barros (2014) assessed the efficiency of Brazilian banks via two-stage DEA model. The authors built two DEA models: first assessed cost efficiency and second gauged productive efficiency. The main trick of the paper is that the outputs of the former model are at the same time inputs for the latter one and both models should be optimized simultaneously. I.e. the first model states that the number of branches and employees are used to attain a certain level of administrative and personnel expenses per year, which in turn are used as inputs to produce such outputs as equity and permanent assets. The paper not only builds a connection between two types of efficiencies, but also uses truncated regression combined with bootstrapping to explain differences in the efficiency level of both stages. DEA scores are regressed on contextual variables, such as whether the bank is public, private or foreign, recent M&A activity and bank size. As for results, Brazilian banks were less cost efficient (average score is 43%) than productive efficient

(average score is 86%) and M&A activity together with the size exert statistically significant positive influence on the cost efficiency levels, while private ownership has statistically significant positive influence on the productive efficiency. The work is relevant because it demonstrates a comprehensive approach that allows to measure two types of bank efficiency simultaneously which in turn leads to more reliable estimates.

Kutlar et al. (2015) gauged technical and allocative efficiencies of 23 Turkish commercial banks (11 private, 9 foreign and 3 public banks), using input-oriented CRS and VRS DEA models, combined with DEA Window Analysis and MPI. The study uses uncommonly big number of input and output variables, 7 and 5 respectively, in the attempt to have more inclusive efficiency estimates. This approach distinguishes the paper from others on the similar topic. Also, this study is representative because banks under examination account for 99% of the total trading volume of all banks. The authors employ Window analysis to capture the fluctuations of mean efficiency score of the same DMU over time and MPI to obtain total factor productivity change scores. The results indicate that efficiency under CRS assumption tends to be lower than under VRS; that DEA window analysis indicates that public banks with high amount of deposits tend to have higher efficiency scores while private banks have lower efficiency scores; that according to VRS assumption, all banks were efficient in 2008 (although showed a decrease in efficiency afterwards as a result of global financial crisis) and that small-scale banks are less-efficient than big ones. The study is relevant because it demonstrates an interesting and valuable combination of three abovementioned techniques for efficiency measurement and analysis. Furthermore, this paper generates insights on how to analyses banking efficiency from different theoretical perspectives and, therefore, is rather useful.

Cava et al. (2016) assessed efficiency of 110 Brazilian banks in 2013 via CRS output-oriented BCC DEA model. The authors decided to augment the DEA with the analysis of the sample in order to get a better understanding of such banks' characteristics as size and capital of origin. Results of the study indicated that 26 banks are efficient (non-dominated) and that the mean efficiency score is 49% which is rather small. The curious aspect of this paper is that authors, after obtaining efficiency scores, decided to group the banks in multiple sets, rank them within sets and analyze the subsegments taking into consideration the mean DEA efficiency score, calculated for each segment. For example, they analyzed banks by size and for that they united banks in four groups (micro, small, medium and large) and calculated the average efficiency score for each group. Similar aggregation of banks was done by capital of origin and by business segment. This allowed

the authors to get insights about the structure of the banking segment and broaden the explanation of various DEA efficiency scores. One of the insights is that federal public banks had the highest mean efficiency score, while another one is that banks rated AAA had higher mean efficiency scores, which suggests that banks with better services have more solid results and better risk classification. Also, the results of the study indicate that efficient banks lend less, are more profitable, and receive fewer complaints from clients. This study is relevant as it introduces a simple and useful approach to delve deeper in the structure of the bank industry and to understand how efficiency scores relate to different banking characteristics, such as size of the banks, the business segments in which banks operate etc.

Tran Thi Thu and Bhaiyat (2016) gauged the efficiency of 31 Vietnamese commercial banks during 2011-2014 via DEA conducted under CRS and VRS assumptions. The mean technical efficiency score is equal to 87%, indicating that Vietnamese banks were operating at 13% waste of banking resources. Interestingly, instead of running a regression to determine how certain variables influence the efficiency, the authors decided to group banks according to the following criteria – whether the bank is listed or not; size of the bank (small, medium, large, very large); whether the bank is state-owned or not – and to calculate the average efficiency score within each group. This approach is similar to the one, presented in (Cava et al., 2016). The authors conclude that state-owned and listed banks had higher efficiency levels than non-state-owned and not listed ones. Another finding of the paper is that very large and large banks obtained higher efficiency scores that small and medium banks. The paper could be improved with the usage of Tobit regression model to identify the triggers of efficiency of Vietnamese banks.

1.6.3 Global DEA studies on ownership and efficiency

The literature on international business and management argues that foreign firms experience additional costs due to unfamiliarity with the foreign environment, what is known as ‘the liability of foreignness’ (Hymer, 1960). However, to overcome the liability of foreignness and compete successfully against local firms, multinational firms may direct resources to their overseas units providing them with a competitive advantage in the form of organizational or managerial capabilities.

Berger et al. (1999) assessed cost and profit efficiency of American banks and demonstrated that liability of foreignness relates to the differences in the operational efficiency scores. On the

basis of their calculations they created two hypotheses to explain the possible differences in the efficiencies of foreign and domestic banks.

The first one is called *the home field advantage hypothesis* and it states that domestic banks are generally more efficient than foreign banks. According to Berger et al. (1999): 'The home field advantage may be manifested as disadvantages to foreign banks in terms of higher costs of providing the same financial services or lower revenues from problems in providing the same quality and variety of services as domestic institutions' (p. 3). In the study it is stated that the major factors underlying this disadvantage are organizational diseconomies from operating or monitoring an institution from a distance. Moreover, differences in currency, culture, language, regulations and many other country-specific factors may contribute to the potential disadvantage. Also, in the country it can be a bias against foreign institutions or other explicit or implicit barriers are highlighted as potential determinants of the home field advantage.

Tu put it simply, *the home-field advantage hypothesis* states that domestic banks will be more efficient than foreign ones because they can avoid certain implicit and explicit barriers: cultural clashes and language differences, management and monitoring challenges etc.

The second one is called *the global advantage hypothesis* and it states that some foreign banks can overcome the cross-border drawbacks and work even more efficiently than their domestic peer. According to Berger et al. (1999) some banks may have higher operational efficiency when operating in other countries because they can:

- disseminate their superior managerial skills or best-practice policies and know-hows to the available resources and thus decreasing costs;
- increase revenues via superior risk management skills or via obtaining diversification of risks that allows them to undertake higher risk/higher expected return investments or they can afford products and services of a superior quality or variety to those of the domestic competitors.

Also, the work (Berger et al., 1999) argues that the global advantage hypothesis can be formulated in two ways:

1. The general form: foreign banks that are efficiently managed and are presented in many countries are able to overcome any cross-border disadvantages and conduct operations with a higher efficiency than domestic credit institutions in other nations;

2. The limited form: only efficiently managed foreign banks headquartered in nations with specific favorable conditions in their home countries can overcome cross-border disadvantages and operate with a higher efficiency than the domestic banks.

In short, the global advantage hypothesis assumes the higher operational efficiency of foreign banks due to superior managerial skills, corporate policies and surpassing risk and investment management skills. These factors reduce costs, increase profitability, and diversify the risks of foreign banks.

Now, let's proceed to the description of the various DEA studies that examined how ownership is connected with the operational efficiency. The following literature review provide a reader with a broad and clear picture of how the two abovementioned hypotheses are proved or not in different countries, in various specifications of DEA models and under different assumptions.

In the study of Indian banking environment (Sanjeev, 2006) the data of 94 banks, operating in India during the period of 1997-2001 were analyzed. The study included three types of banks: 27 public sector banks, 33 private banks and 38 foreign owned banks. There were two main objectives of the paper: to analyze the efficiency of different banks in the post-reform era and to see if any relationship between the efficiency score and the percentage of non-performing assets can be established. To fulfill the objectives, researchers tested 4 hypotheses with the help of DEA: the efficiency of the banks has become better in the post-reform era; public banks are less efficient than private and foreign; the competition in the sector has increased due to liberalization and deregulation; efficiency estimate have a negative relationship with the percentage of non-performing loans. All 4 hypotheses were confirmed, and the results gave scholars the ground to formulate recommendations to the Indian authorities and banks. Although some recommendations may be considered as too general, e.g. "the regulators should observe and review the performance of banks for whom the performance is deteriorating, and suitable corrective measures be taken", they are based on the solid empirical research and can be incredibly helpful in the decision-making process of Indian banking regulator.

Mostafa (2009) in his work employs DEA and probabilistic neural-networks approaches to assess the efficiency of top-85 Arab banks in 2005. The DEA was conducted in two forms, CCR and BCC, that gave different results: according to the former, the average efficiency score is 31%, while, according to the latter, the mean score is 43%. Although, the author used Spearman's rank-order correlation coefficient, that turned to be equal to 0.98, to find out that the choice of methodology has

no apparent impact on the estimated average efficient scores. Similar conclusion was reached in the work of Koshelyuk (2008) who investigated the efficiency of Russian banks. Also, Mostafa substantiated other empirical results that stated that banks in developing countries have lower efficiency scores in comparison with banks from developed ones.

Gaganis and Pasiouras (2009) estimated the efficiency of 39 Greek bank (18 foreign and 21 domestic) during 1999-2004. To select inputs and outputs for the input-oriented DEA BCC model authors used profit-oriented approach (also called operating or income-based approach) that considers costs to be inputs and revenues to be outputs. The results indicate that the average pure technical efficiency score for the period under consideration was 73.25%, while scale efficiency amounted to 68.30%. Interestingly, the finding that, according to DEA, domestic banks were more technically efficient, while foreign ones were more scale efficient was proved to be invalid with the help of Kruskal-Wallis (K-W) non-parametric test and with the help of Tobit regression model, where pure technical efficiency was regressed on ownership, while controlling for size and time. This study shows the importance of the additional inspection to the result of DEA.

Luo and Yao (2010) assessed the efficiency of a panel of 14 listed Chinese commercial banks with 139 observations during 1999 to 2008. The main idea of the article is to find out whether IPO is effective in enhancing bank performance. Also, Luo and Yao tried to know how efficient Chinese listed banks are; what are the key determinants of bank efficiency in China and how performance of State-Owned Banks (SOBs) is different from that of Joint Equity Banks (JEBs). The authors used input-oriented DEA CCR model with intermediation approach to the choice of inputs and outputs. Furthermore, in addition to DEA, other performance indicators, i.e. ROA, LLR/TL (Loan Loss Reserve to Total Loans) and Equity to Total Assets (E/A), were used to track the change in performance throughout the stated time-interval. The average efficiency score of the Chinese commercial banks is about 0.86 that means that there is still a room for improvement. Within the sample JEBs were more efficient (mean score is 0.89) than SOBs (mean score is 0.79), however, the gap between the former and the latter is narrowing. Results of the study show that on average, bank efficiency increased by almost 5% after listing, but a year after IPO the scores tend to decrease. Authors note that this may be due to operational and managerial weakness that may be covered up before the IPO to create favorable financial reports in order to be listed on the stock market or due to the deteriorating macroeconomic environment: banks were listed in 2007 and a year after they were badly hit by the global financial crisis. After obtaining DEA scores (dependent variable), Luo and Yao used Tobit regression model in order to identify determinants of bank efficiency. Seven

independent variables were used: two dummy variables, ownership structure and stock listing indictor (IPO), return on asset (ROA), time trend (t), GDP growth and two risk indictors, ratio of LLR to TLs (control for credit risk) and E/A (to control for capital risk). GDP, ROA and LLR/TLs variables proved to be not statistically significant, while other variables have significant influence on the efficiency of the Chinese banks, ceteris paribus.

Ke et al. (2014) uses 2-stage VRS additive DEA model to assess the efficiencies of 16 major commercial banks during the third round of the Chinese banking reform period (2003–2011). This comprehensive scientific paper shows that the entire operational process of banking system can be divided into two sub-processes – deposit producing and profit earning – that can shed light on the sources of inefficiency. The additive approach implies that the overall efficiency of the whole process is a weighted average of its sub-stages efficiencies rather than a product of them. So, the researcher has to assign weights to both stages in order to signify their respective importance (e.g., if the stages are of equal importance, then each of the two weights is 0.5). Thanks to two-stage process the authors identified that the inefficiency of the Chinese banks was primarily driven by the inefficiency of their deposit-producing sub-process. Furthermore, by complicating initial DEA model with some mathematical advancement the authors treated non-performing loans (NPLs) as undesirable outcomes. This means that despite the fact that this outcome will grow, the efficiency scores will not rise but vice versa will decline. The paper concludes that the overall efficiency of Chinese banking sector has increased over the study period; that state-owned banks (SOBs) are more overall efficient than joint-stock commercial banks and that the increase in efficiency among Chinese banks can be explained by the decrease in the number of NPLs. This paper is relevant for this research because it demonstrates additive DEA approach and presents an in-depth analysis of the banking system.

Henni and Chachoua (2016) analyzed and compared the efficiency scores of 7 foreign and 2 domestic banks in Algeria from 2009 to 2013 via CRS DEA. The authors checked two hypotheses: whether the efficiency of the sector has increased over the period under investigation and that foreign banks are more efficient than domestic ones. The former hypothesis was confirmed while the latter was rejected. Authors assumed that they failed to accept the second hypothesis because of the government intervention that helped domestic banks to improve efficiency via NPLs repurchases. Although this research is rather straightforward it can assist in generating insights about hypothesis formulation and about how to compare banks of a different ownership. This paper could be further improved by the inclusion of a wider time-interval and by use of truncated

regression model which would assist in identifying the determinants of efficiency of the Algerian banking sector.

Ramakrishna et al. (2016) evaluated the performance of 48 Indian commercial banks during the post-liberalization period (2002-2013) via output-oriented VRS DEA and MPI of total factor productivity (TFP). The banks were divided in three groups for further comparison: nationalized banks, State Bank of India & Associates and private sector banks. However, before conducting DEA, the authors analyzed the sector with the help of descriptive statistics to get a broader understanding of its trends and current state. They analyzed deposits and advances, credit deposit ratio, total income and total expenses, profitability, asset quality and key ratios (% of NPAs, ROA, CAR, Net Interest Margin). Afterwards, they did DEA and found out that the mean efficient score for all the three groups was 73% which means that on average banks can increase their performance by 27% without increasing inputs. Another finding is that all banks (except private ones) have shown an increase in the efficiency. According to MPI there was a minimal increase in total factor productivity as the mean growth was 2%, largely driven by changes in technical efficiency. The paper is relevant because it demonstrates the combination of descriptive statistics, ratio analysis, DEA and MPI. Some of the ratios, addressed in the study, may be considered as efficiency drivers.

Ab-Rahim and Chiang (2016) analyzed the relationship between market structure and bank performance via DEA, regression and ratio analyses. The study included 19 Malaysian banks, divided in two groups: domestic and foreign, and covered the period 2000-2011. The authors used concentration ratio (CR) and Hirschman-Herfindahl (HHI) index to measure market concentration and ROA, ROE and NIMTA (the difference between interest income and interest expense to total assets) to measure performance. Unusual part is that the authors, put three performance measurements to the dependent variables of the regression model and put efficiency scores, concentration ratio and market share of an individual bank to the independent variables. Also, several control variables were used: ratio of operating expenditures to total assets (measures the ability of a bank to operate a lower costs), ratio of total loans to total assets (proxy for a credit risk) and logarithm of total assets (to control for costs, varying with the bank size). The paper concludes that market concentration positively affects the financial performance of Malaysian banks and that larger banks are more likely to perform better than smaller banks, because the former are more professionally managed with better diversified asset portfolios. Also, the study found that the technical efficiency scores are rather low with the mean being equal to 40%. This study is relevant as it introduces unusual look at how to conduct regression analysis with the help of DEA scores.

1.6.4 DEA efficiency estimation in Russia

This subsection presents scientific papers aimed at the efficiency estimation of the Russian banking sector from various perspectives. The subsection is rather short because of the lack of literature on the topic within Russian context, which forms a research gap that this research aims to bridge.

The effectiveness of banks was evaluated in some works of other Russian scientists. For example, in (Golovan, Nazin, Peresetsky, 2009), the technical efficiency of Russian banks was assessed using the DEA CCR model for the period 01.03.2002-01.03.2006 (quarterly data). At the same time, the authors broke the initial sample of approximately 275 banks into subsamples based on the location of the bank (Moscow or other city), whether non-residents are present in the authorized capital of the bank, whether the bank in question belongs to the group of the largest. As a result, banks with non-residents turned out to be more efficient than Russian banks, it turned out that asset growth reduces bank efficiency, and the differences between Moscow and regional banks turned out to be statistically insignificant. The results obtained using the DEA method were close to the results according to the SFA method. Fries & Taci (2005), Golovan et al. (2008) also received confirmation that foreign banks are more efficient than Russian banks. According to Aleskerov et al. (2009) this is the case because foreign banks are more technologically advanced and, according to (Karas et.al., 2008) this is so because they employ more stringent corporate governance standards.

The negative influence of the size of the bank on its effectiveness was also confirmed in (Golovan, Karminsky, Peresetsky, 2008). However, in this paper, Moscow banks were more efficient than regional banks, and foreign banks were less efficient than Russian banks. This difference in estimates may perhaps be explained by the use of the Cobb-Douglas production function in this study to evaluate the effectiveness, rather than nonparametric methods.

In work (Koshelyuk, 2008) the efficiency of 100 largest banks of the Russian Federation for the period 2004-2005 was investigated. using a Data Envelopment Analysis. The author repeatedly noted the difficulty and subjectivity inherent to the process of selecting adequate indicators of "inputs" and "outputs" and applied an approach that assumed the separation of various indicators by their belonging to the passive or active side of the balance sheet. In accordance with the obtained results, the author came to the following conclusion: large banks are more efficient. Also, a group of effective banks (only banks with an efficiency index of one, that is, lying on the efficiency border) corresponds to the generally accepted ideas about the leaders of the banking sector (Gazprombank,

Bank of Moscow, Citibank). Interestingly, the transition from the CRS (constant return to scale) model to VRS (variable return to scale) did not change the results.

In the work of Nikishin (2007), the relationship between the bank's share of liabilities and its effectiveness was negative, it was also shown that in 2006-2007 banks with a developed branch network (big sized) had a higher efficiency index than banks with a small network (small sized). Finally, banks with the presence of non-resident investments in the authorized capital proved to be more effective than banks with exclusively domestic investments.

In the work Aleskerov et al. (2008) 800 Russian banks were assessed on the basis of their cost-efficiency during the period 2006-2008. Interesting thing here is that the authors classified DMUs not according to their size or ownership, but according to their regions of registration and to the respective number of branches that banks have. They found out that banks with big branch network were more efficient on average, than other banks in the sample. Also, banks from Moscow and Saint Petersburg were deemed more efficient than DMUs, registered in other cities.

Interestingly, according to the work (Karas et. al. 2008) Russian state-owned banks proved to be more effective than national private banks. This may be due to the fact that state banks have profitable access to physical capital, as well as labor.

In general, the stochastic frontier approach was used to analyze the effectiveness of banking organizations in the following works of Russian scientists: Styrin, 2005; Caner, Kontorovich, 2004; Golovan, Karminsky, 2008; Belousova, 2009.

The DEA method was also used to obtain estimates of the effectiveness of banks in the following papers: Grigorian, Manole, 2002; Konstandina N., 2006; Aleskerov, Belousova, 2007; Koshelyuk, 2007; Golovan, Nazin, Peresetsky, 2009

As it is clear, no papers in Russia use DEA as a benchmarking tool that can provide management with certain recommendations on how to improve efficiency. Also, very few papers consider cost-efficiency and mainly concentrate on the profit. Finally, existing Russian literature on the topic does not demonstrate the utilization of undesirable outputs, e.g. Non-Performing Loans. These are the identified gaps in the existing studies on the efficiency of Russian banking sector. The present paper will try to bridge these gaps via the usage of DEA method with inclusion of undesirables for benchmarking of cost-side of Russian banks.

Conclusion

In order to grasp the current state of affair in the Russian banking sector and find out possible similarities in its behavior in comparison with the past events, the general description of the market is conducted. It helps to get an understanding of practical issues which banks are facing now as well as contributes to the understanding of what is considered to be efficient bank. On the basis of the abovementioned analysis five managerial factors that contribute to inefficiency are inferred. Also, after the analysis of the sector five main trends of its future development are revealed. Then, the existing concepts of efficiency and models of its assessment are analyzed in detail to reveal the variety of methods and models used to define and assess efficiency. Further, with the help of the scientific literature some vivid examples on the topic of banking efficiency are demonstrated.

This part acts as a main theoretical block of the paper and will be followed by the methodological part, where the choice of the special model for the efficiency assessment will be justified and where the specification of the time-interval will take place. Also, the following chapter will look in greater detail at the sample and its content as well as at the choice of the variables and fine specifications of the chosen model.

2. METHODOLOGY OF THE RESEARCH

The present paper is done in a style of descriptive research, because the main idea is to describe quantitatively the phenomenon of banking (in)efficiency in Russia during the last five years. The goal is to find the best practices among Russian banks and calculate what they can do in order to improve their operational efficiency. The following paragraphs will describe in greater details what timeframe was chosen and why it is worth analyzing. Then, the specification of data, necessary for the analysis will be stated, after which the justification of the choice of the model together with the specifics of the model will be revealed.

2.1 Definition and justification of the choice of time interval for analysis

It was decided to take the data for the period of 01.01.2013-01.01.2018 for the study. This time interval can be defined as the period after the implementation of the sanctions against Russia and Russian banking sector in particular. For instance, during the third round of sanctions (starts approximately in July 2014) the United States extended its transactions ban to two major Russian energy firms, Rosneft and Novatek, and to two banks, Gazprombank and Vnesheconombank. United States also urged EU leaders to join the third wave of sanctions leading EU to start drafting European Sanctions a day after. On 25 July, the EU officially expanded its sanctions to an additional fifteen individuals and eighteen entities, followed by an additional eight individuals and three entities on 30 July. On 31 July 2014 the EU introduced the third round of sanctions which included an embargo on arms and related material, and embargo on dual-use goods and technology intended for military use or a military end user, a ban on imports of arms and related material, controls on export of equipment for the oil industry, and a restriction on the issuance of and trade in certain bonds, equity or similar financial instruments on a maturity greater than 90 days (the latter was stiffen on September 2014, decreasing the maturity to 30 days). As one can see, sanctions definitely influenced the whole economy of Russia and, as a consequence, they influenced banking sectors, because a bank is basically a mediator between two different entities: one has an extensive amount of money and another one has few, so bank helps them to invest and borrow money respectively. Under sanctions economic activity is decreasing and so there is less ‘free’ money and it is harder for a bank to perform its duties. The latter restriction greatly reduces the capabilities of Russian banks to get financing abroad to which they used to, so it may affect their performance.

In a nutshell, three main negative consequences of imposed sanctions that affect Russian banking sector are:

1. Reduction in access to cheap long-term credit resources;
2. Deterioration of indicators of the monetary and credit system;
3. Decline in investment.

During this time period it is especially important for the banks to stay operationally efficient and in order to do so, they can refer to the banks of best practices to get an outlook of what helps them to stay highly competitive.

Therefore, it is quite interesting to look at the different efficiency measures of Russian banks to better understand their performance during such a tough time for the economy in general and banking sector in particular. The banks, according to multiple sources, have already started to adapt to the new economic reality, so this time period is although non-calm for the sector, is not incredibly unusual, thus there should be no extremely unconventional patterns in the data. Hence, the data, gathered during this period can serve as a base for this study.

2.2 Specification of data and sample for analysis

To conduct the study, it was decided to collect secondary yearly data from 2013 to 2017 reflected in the accounts of 200 largest Russian banks. The list of banks was taken from SPARK database (a system of professional analysis of markets and companies), provided by Interfax news agency. The banks were sorted according to their Assets in a same way that Central Bank of the Russian Federation does to compile the summary statistical information about the largest banks, which is presented in Appendix 1 and compiled as of January 1, 2018. The choice of this set of credit institutions makes it possible to ensure the representativeness of the sample and will allow to get an understanding about how efficient Russian banking system is. However, it is extremely important to state that DEA is totally sample specific which means that the results obtained for the chosen sample cannot be generalized for the entire population. Furthermore, it produces relative efficiency scores and not absolute ones which entails that the best-performing DMU from the chosen sample will be considered as 100% efficient, while the rest of the DMUs will be benchmarked against this one. Nonetheless, the description of the chosen set will give a good illustration of the state of affairs of banking in Russia, because Assets of this set of banks in the assets of the Russian banking system as a whole are 97.20%. Also, such sample will allow to examine differences in various groups within 200 banks, i.e. how banks of different size diverge in operational efficiency and whether foreign, governmental or private ownership coincides with operational efficiency scores.

2.3 Selection of research methods and specification of data sources

The main concentration of this paper will be on quantitative analysis as it allows making conclusions with the usage of complex mathematical and statistical modeling, measurement, and research. In order to quantify operational efficiency levels, pertaining to a bank, the linear programming technique (DEA) should be used, therefore, quantitative research is a feasible choice.

Quantitative type of analysis allows employing rather simple and cost-effective data collection format. Also, it allows to provision for replicated and generalized data. This gives the researcher an opportunity to conduct a broader study with rather low time-costs and with a greater number of subjects. Quantitative research can allow for greater subjectivity and accuracy of results. Another benefit of quantitative research is that it can be verified in a fast and convenient manner. Finally, personal bias can be avoided by researchers keeping a 'distance' from participating subjects and employing subjects unknown to them.

Disadvantages of quantitative research are that one has monitor model performance in order to verify continuous compliance with the original hypothesis. This activity can be rather time consuming. Also, quantitative research can lead a researcher to erroneous conclusions due to the usage of improper data in the model. This is especially true if researcher uses a secondary data from the unreliable source. Therefore, while working with this type of a study, one has to be sure that the source of data is verified. That is why in this paper all raw data for the analysis were taken from the credible sources, namely, CBR and SPARK. Another drawback of such type of a study, especially if compared with qualitative research is that it frequently fails to reveal the full complexity of the situation under investigation, because any model, even the best one, is just an approximate reflection of a reality. Quantitative studies are less useful in revelation of the complexity of human experience and perceptions. In other words, this type of a study is good at description of the events in terms of what happened and to what extent some factors might influence another ones, but it is not fully able to explore why it is happened or how.

Quantitative part will contribute to the determination of the efficient and non-efficient banks according to a DEA. Main banking indicators are considered to be quantitative information, e.g. profit, equity, operating assets, deposits of individuals, deposits of enterprises and deposits of banks etc. The choice of the indicators will be revealed and substantiated in the subsequent paragraphs. The main source of such data is the site of the Central Bank of Russian Federation (CBRF) and

SPARK database as a big aggregator of the banking data. Both sites provide both quantitative and qualitative information about Russian banks, their financial indicators, balance shits etc.

Quantitative data will be analyzed with the help of DEA and basic statistics. It will be visualized via graphs, tables and diagrams to ensure an easy comprehension of the research outcomes.

2.4 What banking data will be collected and why

As it was mentioned earlier, the choice of the parameters of "input" and "output" is a complex and subjective process, in which the author of the study independently selects the indicators that, in his opinion, are most consistent with the objectives of the study (Kolosova, 2011). DEA is highly sensitive to the number of variables: with the increase in the quantity of variables, the ability to differentiate between DMUs decreases. The more variables are added the greater becomes the chance that some inefficient unit dominates in the added dimension and becomes efficient (Mostafa, 2009). Therefore, the number of inputs and outputs should be limited relative to the sample size in order to retain the discriminatory power of DEA. Unfortunately, unlike statistics, there is no test exists that would allow to check for model misspecification. However, usually the rule of thumb is applied: the minimum number of DMUs is greater than three (or even eight) times the number of inputs plus outputs. This rule was used in the studies of Asmild et al. (2004), Sufian and Majid (2007), Umoren et al. (2012), Foowei et al. (2017), Kong et al. (2017) etc. The present study will have 3 inputs and three outputs, therefore the minimum of 18 or even 48 data points are needed. This requirement is completely fulfilled as we examine 200 banks.

Since this paper will concentrate on a sample of Russian banks and will not compare them with banks located in other countries, country factors (aspects that cannot be controlled by the management of the organization: GDP per capita, the level of competition in the industry, interest rates, etc.) will not be used. Instead, this paper will utilize more specific, banking factors that can be regulated by the management. This will increase the practical applicability of current study. As an example of specific factors, one can think of the volume of deposits and loans, investments in securities, the balance sheet profit, the amount of net assets and so on.

One of the most common approaches to the choice of inputs and outputs for the DEA model is based on the structure of a balance sheet. The resources related to the passive part of the balance sheet are treated as "inputs" and the resources related to the active part (assets) are treated as “outputs”. This approach for building the specification of the DEA model is reasonable, since the

very structure of the organization's balance assumes that the funds related to the passive part will be used to produce any "output" variables, which in turn are written to the active (asset) side of the balance sheet. For example, such approach was successfully implemented in the paper of (Koshelyuk, 2008), described in the literature review section. With this approach it is possible to test how efficiently the bank uses its available resources in comparison with other similar banks from the sample. However, strict adherence to the balance sheet may not be feasible since a bank may, for example, use its fixed assets to give more loans that will provide it with interest-income. Therefore, this common approach will be used only as a general frame for the specification of inputs and outputs that will be chosen based on the financial logic of how bank is functioning.

The first input is Capital of a bank which consists of initial and additional paid-in capital, shareholders equity, retained earnings, cash, securities and disclosed reserves. Basically, it reflects the net worth of the bank to its investors. The issue is that the asset side of Capital also includes loans which will be used as outputs. Therefore, to account for this, Loans were excluded from the Capital. This indicator can be considered as input, because the bank uses it to grant outputs that will be revealed later. This input was also used in the studies of Kosheluk (2008), Savio et al. (2012), Ab-Rahim and Chiang (2016) and (Lee, 2017).

Another input is Total Deposits that consists of households, firms and interbank deposits. This indicator is in the passive side of the balance sheet, i.e. in liabilities section and in accordance with the intermediary function performed by the bank, it uses the liabilities (deposits) to issue loans, i.e. uses this indicator as a resource ("input"). According to the literature review section this is one of the most frequently used indicators in the analysis of the banking technical efficiency, see for example, Aleskerov et al. (2009), Ramakrishna et al. (2016), Soba et al. (2016) and Foowei (2017).[6]

The last input is Fixed Assets that the bank employs. This type of assets cannot be easily converted into cash and is also called property, plant and equipment (PP&E). This choice of input variable violates the idea that one should choose inputs according to the balance sheet structure, but it goes well with the logic of DEA according to which the bank uses its fixed assets to produce more loans and get more profit. In fact, it is logical that the more offices the bank has, the more it will be presented in the country and the more loans it will be able to grant. Thus, the choice of this input is sensible and contributes to the model’s descriptive power. It was used in international studies of

[6] Please, refer to Appendix 5 for a complete list of papers, using this variable

Tran Thi Thu and Bhaiyat (2016), Cava et al. (2016) and Shyu et al (2015), but was not used in Russian studies.

The first output is Total Loans that consists of households, firms and interbank loans. This indicator was chosen as an output in accordance with the bank's intermediary function, i.e. bank uses attracted funds (e.g. deposits) to issue loans.

The second output is Net Profit of a bank which includes net interest and non-interest incomes. This is a classical output of a bank's total activity. Net interest of a banks is the difference between interest earned on loans, bonds and promissory notes and expenses on loans, deposits and issued bonds and promissory notes. Net non-interest (operating) income is the difference between operating income and operating expenses. The former include income from operations with securities, income from participation in capital of other organizations, positive revaluation of securities, funds in foreign currency, precious metals, commission fees, rental income from the transfer of assets in trust management, from the restoration of provisions for possible losses on loans and some other income of the Bank. The latter include expenses on operations with the acquired securities, negative revaluation of securities, means in foreign currency, precious metals, commission fees, expenses from transfer of assets in trust management, deductions in reserves on possible losses, expenses on the maintenance of the personnel, depreciation of property, organizational and administrative expenses (in particular, on advertising, security, communication services, official business trips, audit, training). In Russia, this indicator is reported in the statements 101 and 102, published by the Central Bank.

The usage of Net Profit as an output distinguishes this paper from others in a way that this study proposes a new technique to account for the negative data in the sample. Initially, DEA cannot account for negative values and researchers usually just replace negative data points with very small numbers, close to the zero (e.g. 0.000123). This, although an applicable solution, is distorting the data and leads to biased efficiency estimates. The solution proposed by this work is a normalization technique. The idea is that for DEA it is not important in which form the specific output of many DMUs is present until the order of the values is saved. In other words, if one sorts the dataset according to the profit from largest to smallest, for DEA it will not make difference whether the largest profit is 1 million rubles or just 1 ruble until the order is maintained. So, normalization allows to put all the values in the range from 0 to 1 and maintain the relativeness of the output among different DMUs, i.e. if DMU1 had bigger profit than DMU2 and DMU3 had negative profit,

then after normalization this relation will be sustained, but the third DMU will have positive value of profit that will allow to account it in DEA estimation.

From the mathematical perspective is a simple and easy-to-use technique: it requires the calculation of maximum and minimum values of output among all DMUs, contained in the dataset. In terms of formulae it looks in the following way:

$$Normalized(X_i) = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

According to this formula if Xi = Xmin, then $\widetilde{X_i}$= 0 and if Xi = Xmax, then $\widetilde{X_i}$= 1. So, basically this allows to use a unified scale from 0 to 1 to transpose the order of initial values and account for negative value which increases the validity of the results, produced by the model.

The last output is the amount of Non-Performing Loans that is the sum of borrowed money upon which the debtor has not made his scheduled payments for at least 90 days. A nonperforming loan is either in default or close to being in default. This indicator is taken as a proxy for the risk that a bank faces, while grants loans. The usage of this output also distinguishes this study from multiple others, because it is not common to use this indicator as the DEA model considers the growth in outputs as a positive sign and, therefore, it assigns a higher efficiency score to a bank. This is completely wrong from the financial point of view. Another scientific contribution of this paper is the introduction of normalization technique relating to the undesirable output. The main difference from the previous output is that the more NPLs a bank has, the worse its efficiency score is (an inverse relationship), while with the profit the relationship with efficiency is direct. To account for undesirable outputs the following formula is used:

$$Normalized(X_i) = \frac{X_{max} - X_i}{X_{max} - X_{min}}$$

The formula states that the bigger the value of a variable X, the lower (worse) its value will be in the unified scale from 0 to 1. So, the bank with the biggest amount of NPLs will have the value of 0 in the output, meaning the worst performance in the sample.

In order to check how efficiency scores will react to the inclusion or exclusion of inputs or outputs three models were built. Table 6 presents these models with their respective and nonoverlapping inputs and outputs.

Table 6 The specification of three models

	Model 1	**Model 2**	**Model 3**
Inputs	Capital Fixed Assets Total Deposits	Capital Fixed Assets Total Deposits	Fixed Assets Total Deposits
Outputs	Total Loans Profit NPLs	Total Loans NPLs	Total Loans Profit NPLs

Source: author

2.5 Justification of the choice of DEA method to analyze the data.

This research employs DEA method for data analysis, since the sample is homogeneous and there will be no enormous difference in the indicators after correction for the outliers in case of necessity. The opposite situation would signal for the need to select the SFA method (Styrin, 2005). The main reason for choosing this method was the fact that in this case there is no need to specify the production function (for example, linear, Cobb-Douglas or Fourier) and to specify the additional prerequisites about the distribution of random errors in the model. In addition, when using DEA, it is possible to work with multidimensional output vectors, while when selecting the SFA model only with one-dimensional ones. The ease of using DEA in combination with the availability of the data also played in its favor. Finally, in case of DEA the efficiency boundary is built on the best DMU of the sample, and is not an unattainable ideal, thus making it much more practical.

The drawbacks of the method include the absence of random errors and the instability of estimates and the fact that it is non-statistical. Any deviation from the efficiency boundary in the DEA is treated as inefficiency.

In general, the analysis carried out in (Resti, 1997) did not reveal any significant differences between the results obtained via the methods of the stochastic frontier and the data envelopment analysis, thus making the choice of the easier model more evident.

Specification of the type and orientation of the model

For the DEA analysis, a modification of the CCR model, called BCC, was chosen as the most appropriate for the purposes of this study. It allows to consider only technical effectiveness (inefficiency) of the organization, without taking into account economic inefficiency, but more

importantly, this model takes into account the return on scale, which is especially important in considering organizations which assets together constitute almost 98% of the total assets of the entire banking system. In addition, the BCC model allows the researcher to identify the so-called slacks. As the direction of the model, the resource-orientation (BCC-Input) was chosen, because in this case, according to the analysis of the results of this research, it will be possible to talk about what inputs should be changed to increase the efficiency score. Also, this orientation is favorable because it is much easier for the management of the organization to influence the costs (or inputs) rather than the final product (output). Furthermore, such orientation can give information about how efficiently management had used the available resources (Koshelyuk, 2008). However, it should also be noted that in some papers, for example (Coelli, 1996), it is empirically proven that the choice of the directionality of the model in the vast majority of cases has little effect on the results obtained, and the list of effective DMUs between the models is not significantly different.

2.6 Plan of empirical research

The research will consist of multiple stages and will be conducted in the manner described further. First, the research problem will be stated to make it clear what this paper intends to check. Second, all the necessary data mentioned before will be gathered – this is the most time-consuming thing of this research. Then this data will be used in the calculation of the efficiency indicators of each bank with the help of the DEA model, specified in a way stated above. Efficiency indicators will have a range from 0 to 1, where 1 is efficient bank and 0 is totally inefficient bank. The research will continue with the formation of set of efficient banks for each year for each of three models. Then, the sets of truly efficient banks, i.e. banks with no slacks, will be formed. After, the banks that were truly efficient during all 5 years will be united in tables and they will represent the sustainable efficiency practice banks.

The next stage will reveal how banks were clustered by size and how efficiency scores differ with respect to this parameter. The division into clusters will be done according to a methodology of Central Bank of Russia, applied in its reports to analyze the concentration in the sector (CBR, 2018).

Also, the set of banks will be divided into three groups representing different ownership to answer the question of which banks are more efficient. The list of foreign banks will be compiled according to the “List of operating credit institutions with non-resident interest in the paid-in authorized capital of the credit institution 100% as of March 1, 2018”, published by Central Bank. The list of banks that are directly or indirectly controlled by the Russian Federation or Central Bank

of Russia will be retrieved from “The list of credit institutions entitled to open accounts and Bank Deposit (Deposit) agreements with the companies of strategic importance for the military-industrial complex and the security of the Russian Federation as of March 1, 2018”.

Finally, the efficiency will be assessed within the subsamples, created according to the sizes of the banks (very big, big, medium, small). And best-practices for subsamples will be revealed.

All abovementioned divisions would allow to examine efficiency from different perspectives and will ensure a deeper level of analysis. Finally, the findings of the paper will be described and analyzed in great detail. In the end, conclusions and managerial applications with the further research areas will be revealed.

Conclusion

In this chapter all the factors necessary to run a DEA were described in details and their choice was justified. At the start, the choice of time interval was justified with the help of literature and some analysis of why this time-frame may be of a great interest for the research. Afterwards, the choice of data which comprises the sample is substantiated, and it is explained why exactly 200 banks will be analyses in this paper. Then, quantitative method is described thoroughly, with the revelation of where the data will be taken from and in which form it will be presented. After, specific banking indicators which will be used as inputs and outputs for the model are exposed and selection of each is backed up not only by critical thinking and logic, but also by scientific literature. Finally, it is explained why DEA method is the most suitable for the assessment of effectiveness of retail banks in Russia and more precise specification of the model is uncovered.

At this point understanding of the existing concepts and frameworks, related to the topic of this article should be clear as well as theoretical backing and DEA model that will be used for a future analysis. In the next chapter analysis of the gathered data will be performed, firstly, with the help of DEA model. Next chapter will concentrate on the presentation of the obtained results.

3. FINDINGS

This chapter will reveal the findings, obtained throughout the research and will describe some interesting patterns that are evident from the outcomes of the calculations. It will start from the very general description of a sample and will narrow the narrative in a funnel way to ease the comprehension and ensure the proper description of the data in the tables and graphs.

3.1 Operational efficiency of the 200 banks

The results obtained with the help of the first model are presented in the Table 7. Overall, the technical efficiency of all 200 Russian banks was the lowest in 2013, then it demonstrated a considerable rise in 2014 and a slight decrease in two subsequent years before rising again to its maximum in 2017. From the table, it is indicated that during the study period, Russian banks have demonstrated an overall average technical efficiency of 88.5%. This suggests that by implementing best management practices, the Russian banks, on average could reduce their inputs by at least 12.5% and yet volume of outputs produced would remain unchanged. That is, the Russian banks could produce identical volume of outputs by using only 88.5% of the amount of inputs. It is important to note however, that the potential reduction in inputs from implementing best management practices varies from bank to bank

Table 7 The results of the first model

	2013	2014	2015	2016	2017	All years
Mean	0,7146	0,9282	0,9181	0,8913	0,9742	0,8853
Max	1	1	1	1	1	1
Min	0,1881	0,4696	0,3747	0,2099	0,7251	0,1881
St Dev	0,1965	0,1024	0,1188	0,1639	0,0455	0,1254

Source: author

The efficiency scores obtained via the second model are close to the ones of the first model with the minimum score in 2013 and the maximum score in 2017. The exclusion of Profit from the input-oriented model has had little impact over the efficiency scores and it just slightly increased the standard deviation within the sample.

Table 8 The results of the second model

	2013	2014	2015	2016	2017	All years
Mean	0,6922	0,9059	0,881	0,8839	0,9578	0,8642
Max	1	1	1	1	1	1
Min	0,1532	0,4007	0,2072	0,2099	0,2991	0,1532
St Dev	0,1949	0,1234	0,1773	0,1651	0,0893	0,150

Source: author

The third model shows rather different results, presented in Table 9, however, the pattern of the changes in the figures resembles the one from the first model. The mean efficiency estimates are more than two times smaller than according to the first model, with the lowest point in 2015 (30.62%) and the highest one in 2017 (36.16%). Also, the standard deviation of the obtained scores greatly increased, mainly due to the tenfold smaller estimates of minimum efficiency scores. In 5 years' time the model assessed the average efficiency for a banking sector about 32.01%, which is more than two times smaller than in the previous model.

Table 9 The results of the third model

	2013	2014	2015	2016	2017	All years
Mean	0,3084	0,3173	0,3062	0,307	0,3616	0,3201
Max	1	1	1	1	1	1
Min	0,0143	0,0146	0,0193	0,0205	0,0214	0,0143
St Dev	0,3432	0,3544	0,3221	0,3313	0,3356	0,3373

Source: author

Another interesting and important outcome, that is presented in Table 10, is the number of efficient DMUs in each model. The results divided in two subgroups for each model: first subgroup counts DMU as efficient even if it has some slacks (falsely efficient DMU), while the second considers DMU as efficient only if it has zero slacks (truly efficient DMU), i.e. if it has combination of inputs and outputs optimal for the chosen set. In the first subgroup, similar to the efficiency scores, presented above, the first model reveals the biggest number of efficient DMUs (31), while the third model states that only 18 DMUs are efficient, with the second model being in between the two with 21 efficient DMUs. The results of the second subgroup are expectedly smaller with the

first model providing the biggest number of truly efficient DMUs (19) and with the third model assigning the efficiency score of 1 to only 11 DMUs, the smallest number.

Table 10 The number of efficient DMUs according to 3 models

		2013	2014	2015	2016	2017	All years average
M1	Slacks	27	33	33	27	37	31
	No slacks	20	28	13	18	16	19
M2	Slacks	19	24	20	16	26	21
	No slacks	16	17	13	12	13	14
M3	Slacks	21	18	18	19	16	18
	No slacks	15	13	12	7	10	11

Source: author

Inappropriate size of a bank (too large or too small) may sometimes be a cause of technical inefficiency. This is referred as scale inefficiency and takes two forms: decreasing returns-to scale (DRS) and increasing returns-to-scale (IRS). Decreasing returns-to-scale (also known as diseconomies of scale) implies that a bank is too large to take full advantage of scale and has supra-optimum scale size. In contrast, a bank experiencing increasing returns-to-scale (also known as economies of scale) is too small for its scale of operations and, thus, operates at sub-optimum scale size. A bank is scale efficient if it operates at constant returns-to-scale (CRS). Table 11 demonstrates the distribution of DMUs according to their return to scale. It is clear that the vast majority of banks operate at DRS according to all three models, thus implying that they are too big for the scale of their operations. Interestingly, the third model demonstrates the biggest number of the banks, operating at CRS, in other words it reveals the biggest number of scale-efficient banks despite the fact that it assigns the smallest efficiency scores in comparison with other two models.

Table 11 Number of DMUs with different RTS

	RTS	2013	2014	2015	2016	2017
M1	I	5	14	3	1	0
	C	37	62	36	29	14
	D	158	124	161	170	186
M2	I	62	8	2	0	1
	C	66	59	23	26	13
	D	72	133	175	174	186
M3	I	0	0	0	18	22
	C	15	12	28	48	17
	D	185	188	172	134	161

Source: author

3.2 Finding the best-practice banks in general sample

The results of three models allowed to identify specific sets of banks that were sustainably efficient during the whole period under investigation. These banks are presented in the Table 12 and marked if they have slacks, i.e. if they are not truly efficient. The first model marks 8 banks as efficient, second model marks 7 and third one considers only 3 banks as technically efficient. All three models identify Sberbank, KB Deltakredit and Danske bank as truly sustainably efficient DMUs.

Table 12 Sustainably efficient banks[7]

Model 1		**Model 2**		**Model 3**	
Name	**Slacks?**	**Name**	**Slacks?**	**Name**	**Slacks?**
SBERBANK	No	SBERBANK	No	SBERBANK	No
BANK VTB	Yes	BANK VTB	Yes	KB DELTAKREDIT	No
BANK GPB	Yes	BANK GPB	Yes	DANSKE BANK	No
KB DELTAKREDIT	No	MOSKOVSKI KREDITNY BANK	Yes	-	-
DANSKE BANK	No	KB DELTAKREDIT	No	-	-
FINANS BIZNES BANK	Yes	DANSKE BANK	No	-	-
KIVI BANK	Yes	GARANT-INVEST	Yes	-	-
GARANT-INVEST	Yes	-	No	-	-

Source: author

Mostafa (2009) states that DEA technique is an adequate tool for benchmarking, since it allows the identification of a group of efficient firms for each non-efficient one. This identified group may be used in the definition of operational goals for their non-efficient counterpart, considering its various input and output variables. Table 13 provides the reference set of banks on the efficiency frontier closest to a particular bank. The reference set is also referred to in the literature as the peer group or the linear combination for this bank and indicates to which of the efficient banks an inefficient bank is closest in its combination of inputs and outputs. A bank, which appears frequently in the reference set is likely to be a bank which is efficient with respect to a large number of factors and is probably a good example of an exemplary operating performer. Efficient banks that appear seldom in the reference set of other banks are likely to possess a very uncommon input/output mix and are thus not suitable examples for other inefficient banks. For examples of reference sets for the first 10 banks and for the banks 52-74, one can refer to Appendix 9 and 10.

[7] Please, note that all names of the banks from this point and further in the text are written according the their writing in the SPARK and CBR databases, so they may differ

In order to form a table in an easy-to-read manner out of the efficiency set of each year three banks that most frequently appeared in the reference sets of other DMUs were shown. This does not decrease the reliability of the results because as it was mentioned earlier, the most frequently appearing DMU is probably the one with the most efficient combination of resources. As one can see, URI bank appears in the reference sets of other banks most frequently, according to all three models in 2013. The year after, Mosoblbank is the top according to the first and second models, while according to the third one KB Deltakredit is the leader. Interestingly, KB Deltakredit is the most frequently appearing bank throughout the whole period under consideration and it is number one in terms of frequency of appearance in reference sets of other banks, according to the third model during 2014, 2015 and 2017. In 2015 Baltinvestbank and Rost Bank were the examplars according to the first and third models respectively. A year after Rost Bank reinforced its position as the bank of reference number one according to the 1st and 2nd models. In 2017 Finans Biznes Bank, a part of MSP Bank group, was the exemplar bank according to the same models as in the previous case. MSP Bank itself also was twice considered as an exemplar bank, both times according to the third model.

Table 13 Comparison of the top-3 most frequent peer group banks

	Model 1	**Model 2**			**Model 3**	
Year	**Name**	**Reference set frequency**	**Name**	**Reference set frequency**	**Name**	**Reference set frequency**
2013	URI BANK	120	URI BANK	129	URI BANK	120
	BANK MBA-MOSKVA	100	BANK MBA-MOSKVA	107	NORDEA BANK	96
	NORDEA BANK	95	NORDEA BANK	107	POCHTA BANK	31
2014	MOSOBLBANK	139	MOSOBLBANK	138	DELTAKREDIT	125
	DELTAKREDIT	113	DELTAKREDIT	104	MSP BANK	73
	KIVI BANK	107	BANK VORONEZH	83	TSENTROKREDIT	19
2015	BALTINVESTBANK	105	ROST BANK	127	DELTAKREDIT	97
	ROST BANK	90	DELTAKREDIT	89	BANK NFK	90
	DELTAKREDIT	86	GARANT-INVEST	13	MSP BANK	69
2016	ROST BANK	119	ROST BANK	127	BANK NFK	135
	FINANS BIZNES BANK	93	FINANS BIZNES BANK	97	DELTAKREDIT	125
	DELTAKREDIT	60	DELTAKREDIT	63	DANSKE BANK	146
2017	FINANS BIZNES BANK	97	FINANS BIZNES BANK	92	DELTAKREDIT	121
	DELTAKREDIT	66	DELTAKREDIT	91	RFK-BANK	88
	RFK-BANK	58	ROST BANK	48	EKSPRESS-VOLGA	66

Source: author

3.3 Banks' size and efficiency

In order to deepen and broaden the understanding of efficiency within the Russian banking sector, the present paragraph describes 4 clusters of banks, compiled in accordance with the division, applied by the Central Bank of Russia in "Review of the Banking Sector of the Russian Federation". As Table 14 demonstrates, very large banks (5 biggest banks in Russia if sorted by Total Assets) are the most sustainably efficient, i.e. their mean efficiency scores for 5 years according to all 3 models are greater than 90% which signifies that on average the waste of input was only 10%. This indicates that the biggest Russian banks as a whole could produce identical volume of outputs by using only 90% of the amount of inputs employed. The greatest decrease in efficiency levels is seen in the third model, where large banks are just 53% efficient, while medium and small banks are only 29% efficient in their usage of inputs. Interestingly, according to the first and second models, small banks are just a little bit less efficient than the very large ones, 91% and 90% efficient respectively.

Table 14 Average efficiency scores for 5 years for banks of different sizes

	Very Big (1-5)	**Big (6-20)**	**Medium (21-50)**	**Small (51-200)**
M1	0,94	0,81	0,77	0,72
M2	0,91	0,76	0,73	0,71
M3	0,92	0,53	0,29	0,27

Source: author

The Figure 9 allows to distinguish in greater details how the efficiency of banks of different sizes changed over the 5 years period. The first model signalyses that very big banks are loosing their operational efficiency over time: it decreased from 96.6% in 2013 to 83.4%. it is clear that very big banks are the most efficient ones according to the second model, although a starting trend on diminishin efficiency is clear. The opposite trend is with the Big banks which efficiency showed a constant increase since 2014. Medium and Small banks are quite similar in their efficiency scores with medium banks being more efficient in 2013 and 2017.

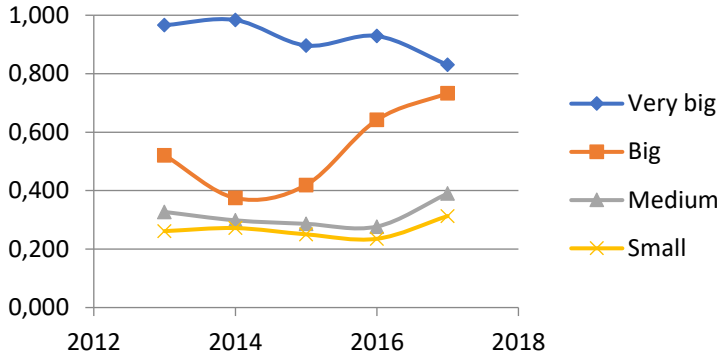

Figure 9 Efficiency scores for banks of different sizes by the third model

Figure 11 demonstrates the change in the number of truly efficient banks throughout the 5 years period under consideration according to the first model. One can note a rather uniform distribution of banks if small banks are ignored. In each of the years there is one truly efficient vry large bank, which is Sberbank. Some Big banks are: Rostbank, Mosoblbank and Rosbank. Another banks that is truly efficient and represents medium banks is KB Deltakredit: it is considered as efficient during all five years. Also, Citibank and Nordea were included and exluded from the list rather frequently. As for the small banks, one can note that there is a lot of them, but their number

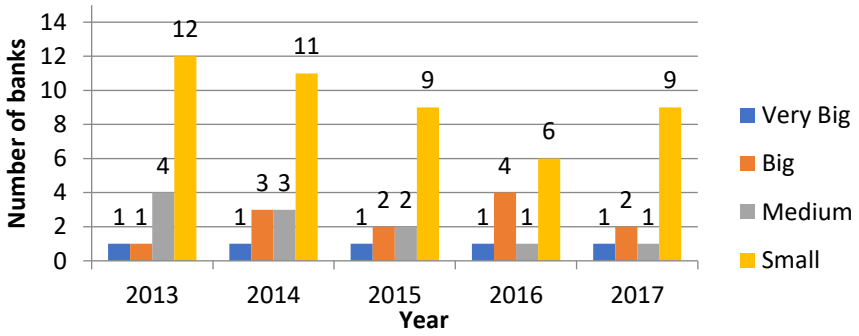

Figure 11 Number of truly efficient banks according to the 1st model

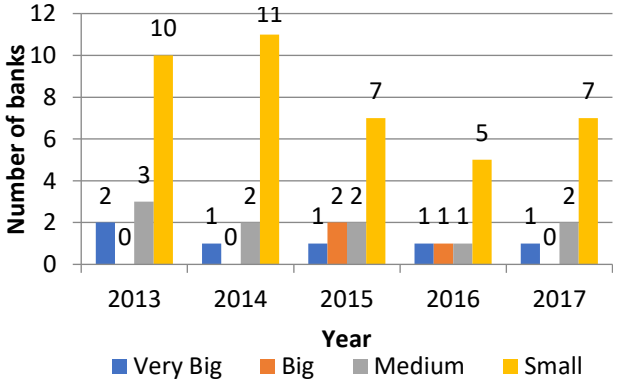

Figure 10 Number of truly efficient banks according to the 3rd model

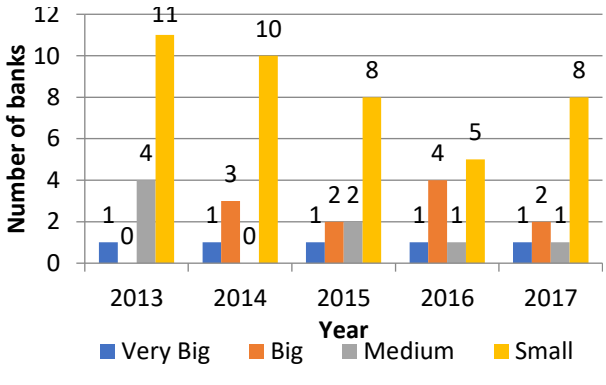

Figure 8 Efficiency scores for banks of different sizes by the 2nd model

has a tendency to decrease in all years under consideration except the last one. However, despite the fact that there are plenty of truly efficient small banks, there is only one sustainably efficient bank that made it through all 5 years – Danske Bank.

Figures 8 and 10 show similar pattern to that of Figure 11: small banks are the biggest in number and banks of other sizes are distributed rather uniformly. Interestingly in the third model one very big banks was evaluated as sustainably efficient: Alfa bank.

3.4 Banks' ownership and efficiency

To examine how banks with different ownership differ in efficiency, the previously assessed set of banks was divided into three groups, according to the type of ownrship of the bank: direct or indirect control of the Russian Federation or Central Bank of Russia; 100% foreign control and private banks. The list of banks that were included in each cluster are presented in Appendices 6 and 7; all banks that do not appear in any of these two lists are considered to be private Russian banks.

As one can see from the Figures 12 and 13 (1st and 2rd models provided very close results) banks with 100% foreign control were the most efficient in the sample, reaching the efficiency score of 98.17%. At the same time, banks that are under control of Central bank or Government (for ease, State Controlled Banks – SCBs) are the least efficient in all years except 2013. Also, SCBs demonstrate the most fluctuating results within the sample as can be concluded from the graph.

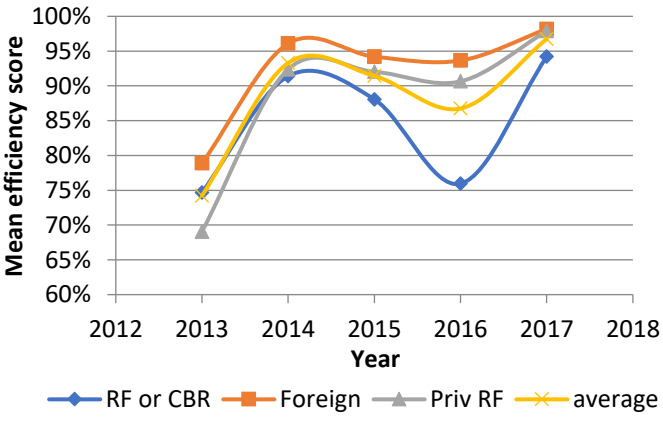

Figure 13 Efficiency of banks with different controlling shareholders (2nd model)

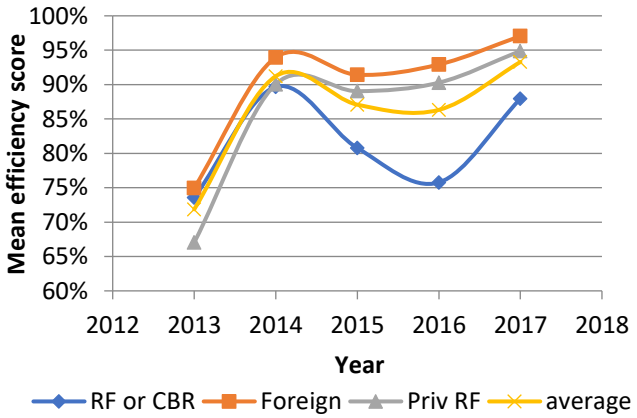

Figure 12 Efficiency of banks with different controlling shareholders (1st model)

The third model demonstrated even more vivid results and much lower efficiency scores for all types of ownership. However, it also maintained the proportion according to which foreign banks

are more efficient than Russian private bank that in turn are dominating SCBs in efficiency during the whole period under investigation.

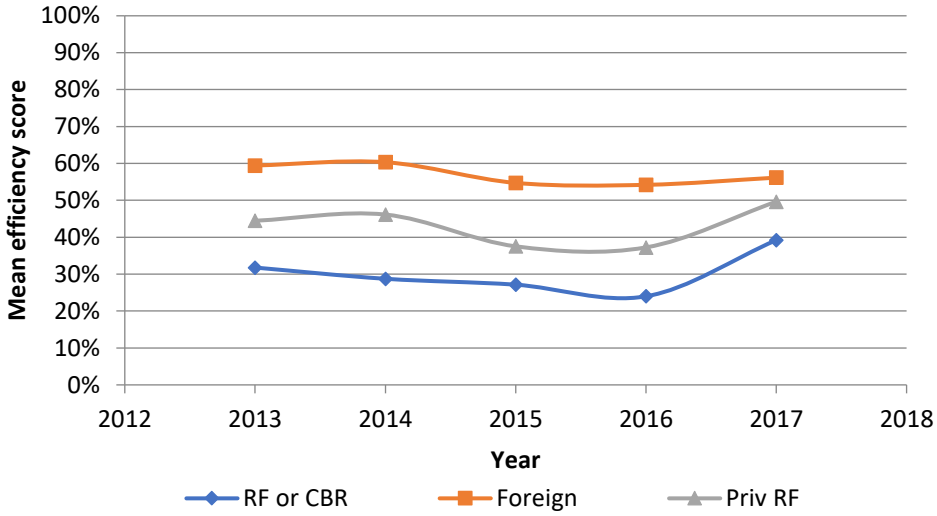

Figure 14 Efficiency of banks with different controlling shareholders (3rd model)

3.5 Finding best-practice banks in subsamples

The next step of the research included the identification of best-practices within the subsamples. Subsamples were created according to the size of the banks, namely very big, big, medium, small. The major difference with the division of banks in the section 3.3 is that here the efficiency for each subsample is assessed separately, while in section 3.3 the efficiency scores were assessed only once and for the whole sample of 200 banks and then, the assessed DMUs were marked as very big, big, medium and small.

Before conducting the analysis, the Kendall's W (also known as Kendall's coefficient of concordance), a non-parametric statistic that shows the coincidence of the rank order between two models, was calculated for each of the three models and the results are the following:

Model 1 and 2 have Kendall's W equal to 0.976

Model 2 and 3 have Kendall's W equal to 0.495

Model 1 and 3 have Kendall's W equal to 0.498

So, it was decided that for identification of best-practices in subsamples only two models will be used: the model that assesses the overall technical efficiency of a bank (first model) and the model that assesses how well the banks utilizes the attracted funds (third model).

First gauged subsample was comprised of only 5 very big banks and it was, therefore, impossible to assess efficiency of the group as it is. To mitigate this problem the panel was created, i.e. each bank out of the 5 very big ones was compared not only to other banks from the subsample, but also to its own performance in the past. Nonetheless, the subsample size still was not sufficient to get meaningful findings. No best-practice banks were identified in this subsample, however, Gazprombank was very close to the being the banks of best practice.

Second subsample was prone to the similar problems, notwithstanding its panel comprised of 75 DMUs. No best-practice banks were identified in this subsample and no bank was even close to be an exemplar for others.

Third subsample consisted of 30 DMUs, but it was possible to find out two banks that fulfilled the stated criteria for being a bank of best-practice for subsample. These banks are KB Deltakredit (average frequency of occurrence in reference sets of other banks in the subsample by two models is 41.33%) and Citibank (average frequency of occurrence in reference sets of other banks in the subsample by two models is 12.5%). The average statistic for the subsample, according to two models, is presented in the Table 14. It is clear that average efficiency scores are higher according to the first model. A stark contrast can be seen in the assessments of minimum efficiency scores between two models. If minimum efficiency score for all five years as stated by the first model is 31.36%, then according to the third one it is just 2.36%. Likewise, a clear difference in standard deviations is easily noticed.

Table 14 Average statistics for the subsample of medium banks

	Characteristic	**2013**	**2014**	**2015**	**2016**	**2017**
Model 1	**Average**	0,8023	0,9389	0,9026	0,8939	0,9727
	Max	1	1	1	1	1
	Min	0,5026	0,7901	0,7456	0,3136	0,8726
	St Dev	0,1618	0,0571	0,0808	0,1416	0,0338
	# of efficient	5	8	5	7	9
Model 3	**Average**	0,4523	0,3538	0,3668	0,4258	0,4884
	Max	1	1	1	1	1
	Min	0,0405	0,0472	0,0358	0,0236	0,027
	St Dev	0,3751	0,3727	0,3777	0,3589	0,3964
	# of efficient	3	4	2	2	4

Source: author

The fourth subsample consisted of 150 small banks and two banks were identified as best-practice banks: Cetelem bank (average frequency of occurrence in reference sets of other banks in the subsample by two models is 24.33%) and Danske bank (average frequency of occurrence in reference sets of other banks in the subsample by two models is 6.78%). The differences in efficiency scores between two models are the almost the same as in the case of medium banks, discussed in detail above. However, the number of efficient DMUs is bigger than in the case of a medium banks.

Table 15 Average statistics for the subsample of medium banks

	Characteristic	2013	2014	2015	2016	2017
Model 1	**Average**	0,7195	0,9856	0,9744	0,9715	0,9899
	Max	1	1	1	1	1
	Min	0,2213	0,8928	0,8172	0,8076	0,9096
	St Dev	0,2013	0,019	0,0311	0,0358	0,0148
	# of efficient	14	33	29	27	22
Model 3	**Average**	0,2863	0,3388	0,3364	0,3326	0,3832
	Max	1	1	1	1	1
	Min	0,021	0,0161	0,0194	0,0264	0,0285
	St Dev	0,3336	0,3631	0,3349	0,3498	0,3422
	# of efficient	13	9	10	10	13

Source: author

Conclusion

This chapter presented all the main findings of the research in a structured and easy-to-comprehend manner. First, The general description of a sample was given with the results of all three models about how efficient the sector is. Then, truly efficient banks were identified and were analyzed according their return to scale. It was concluded that the majority of banks has a decreasing return to scale, thus, impliying inefficient size of operations. Afterwards, sustainably efficient banks, those that were efficient during all five years under investigation, were identified and listed. Then the comparison of the top-3 most frequent peer group banks was done in a table and KB Deltakredit Banks was found to be the most frequently mentioned in the reference set of other banks. The second part of findings concentrated on the review of how efficient banks of different sizes are relatively to each other and found that big banks are dominating small ones. Also, this part of the chapter told about how banks, controlled by different parties (foreign, government, private), vary in efficiency. It was revealed that banks with 100% foreign ownership have better technical efficiency

scores that those with governmental or private control. Finally, this chapter discovered the best-practice banks for subsamples of bank that was created based on the sizes of the banks. The subsamples of very big and big banks failed to reveal the best-practice banks due to the various reasons, but medium and small banks revealed 4 banks in total (2 for each group): KB Deltakredit and Citibank for medium subsample and Cetelem Bank and Danske Bank for the small subsample.

4. DISCUSSION

4.1 Summary of findings

The present paper aims to benchmark the performance the Russian banks on the basis of technical efficiency, get into the picture of what is going on in the sector with regard to the size of the banks and their ownership and subsequently to identify the banks that can be considered as best-practices in operational efficiency in their respective samples.

The study revealed that the average technical efficiency of 200 banks in Russia demonstrated positive dynamics from its lowest point in 2013 to its maximum point in 2017 according to all models. An improving performance of banks' management might be the reason for such result. Technical efficiency can be effectively controlled by banks management and that is why this type of efficiency was chosen for the analysis. However, the annual average efficiency estimates for the original sample of 200 banks still revealing inefficiencies of 12.5% and 37.99% according to the first and third models respectively. The difference in the results of two models is due to the exclusion of the Capital variable from the list of inputs of the third model. It resulted in substantial reduction of efficiency scores in all years, making many banks inefficient, and highly increased the standard deviation of scores. From the technical point of view this is an obvious outcome for an input-oriented DEA model because an exclusion of one input from the list of compared variables generally reduces the number of non-dominated DMUs in the sample (Coelli, 2005). Despite partial attributing of the harsh differences provided by the first and the second models to the technical peculiarities of the DEA model, it should be noted that such a drastic reduction of the scores witnesses about the banks poor management of fixed assets and deposits.

In order to verify the differences between the three models, Kendall's coefficient of concordance (also known as Kendall's W), a non-parametric statistic that shows the coincidence of the rank order between two models, was calculated. Kendall's W for the first and second models was very close to 1, it was 0.976, which signalizes that the ranking according the two models will be almost identical. This is an interesting finding of research, because it shows that if a bank will be in the top-rank according to the overall efficiency model (first one), then it probably will be in the top-rank according to the model that demonstrates efficiency of a bank as an intermediary (second model). Surprisingly, totally different results were obtained for the third model (assesses the efficiency of utilization of attracted funds): Kendall's W for it and the first model and for it and the second model were 0.498 and 0.495 respectively. This signals that rank order assigned by the

models is rather different and that if a bank is good as an intermediary, he might not be as efficient in the utilization of attracted funds.

For instance, the excessive amount of fixed assets can be interpreted as a reason for a low score and this is substantiated by the fact that the vast majority of banks in the sample have decreasing returns to scale which means that they are too big for the scale of their operations. For the simplicity of further analysis, the first model will be chosen as the most comprehensive one in attributes, taken into account that capital is an integral part of a bank as a financial institution and its wise management as input variable should be considered in the analysis.

So, technical inefficiency of 12.5% witnesses about the high potential to increase efficiency among the initial sample of banks by either reducing the costs or increasing the outputs. Critically, despite the satisfactory performance of Russian banking sector as shown in Chapter 1, this study empirically demonstrates that Russian banking sector had a potential for higher operational efficiency. Therefore, there is still a room for further improvement in the management performance via proper planning and control (Abdul-Wahab, 2016).

After the calculation of the efficiency score and identification of banks with technical efficiency score of 1 for each of the 5 years according to all models, the banks with slacks were excluded from the list of efficient banks, because they can be considered as falsely efficient. Truly efficient DMUs has no slacks as their combination of inputs and outputs is an optimal one for the chosen set of companies. As this study aims to reveal true best practices, only the zero-slack DMUs was considered.

Estimation of the banking technical efficiency under different models in each year of the observed period (2013-2017) allowed for identification of the best-practice banks in Russian banking sector. The best-practice bank is the bank was efficient in all years of observation in every model. These banks are:

1. Sberbank;
2. KB Deltakredit;
3. Danske bank.

Noteworthy that these banks represent different groups of banks: Sberbank would be the 1st, KB Deltakredit would be 44th and Danske Bank would be 106th by the number of total assets. This means that these three banks uniformly represent three out of the four groups, namely: very big (1-5

banks, sorted by total assets), medium (21-50) and small banks (51-200). Unfortunately, no banks from the "big banks" (6-20) group were deemed truly sustainably efficient and, therefore this group lack a best-practice bank of its exact size. These findings suggest that a bank can be efficient no matter of what size it is. In this case, only three banks occurred operationally efficient during the whole period under consideration.

In the first group the banks are almost always demonstrate high level of operational performance, being very close to efficient (approximately, 98%) from year to year, however it appears that this result is achieved to their exceptional size, because they are rarely found in the reference set of other banks with the exception of Sberbank and Gazprombank. In the table 15 one can find how many times each of the best-practice banks appeared in reference sets of other banks. For example, Rosselkhozbank, as one of the very big banks was never in a reference set of any other bank. This probably could be explained by the uniqueness of its combination of inputs and outputs in terms of size and proportions. In fact, because there are very few of very big banks and each of them is adept at something they represent a set of pareto-optimal units. Therefore, it is not surprising that they have such a big operational efficiency scores and never appear in the reference set of the banks from other groups. In general, that mean that such big banks are vital for the banking system of Russia, according to the chosen set of operational inputs and outputs.

Table 15 How many times best-practice bank occurs in the reference set of banks of different sizes

Year	**2013**			**2014**			**2015**			**2016**			**2017**		
Name	**S**	**KB**	**D**	**S**	**KB**	**D**	**S**	**KB**	**D**	**S**	**KB**	**D**	**S**	**KB**	**D**
Appearances in reference sets of other banks	2	26	2	0	114	4	0	86	0	3	61	1	1	67	0
Very Big	-	-	-	-	-	-	-	-	-	-	-	-	2	-	-
Big	2	-	1	-	2	-	-	2	-	3	4	-	-	4	-
Medium	-	-	1	-	14	-	-	37	-	-	20	-	-	23	-
Small	-	-	24	-	98	4	-	72	-	-	37	1	-	40	-

Source: author's calculations

The group of medium banks is represented by KB Deltakredit, which is on the contrary to Sberbank, is the most frequently seen in the reference set of almost every bank (see Table 15), thus implying that it has the most typical structure of inputs and outputs for the sample. Around 10% of

banks of medium size are truly efficient which means that the vast majority of credit institutions has a room for improvement.

It is highly remarkable that the Danske bank, representing the group of small banks, is also among best practice banks in the observed period. This bank is a small one, but just as Sberbank it rarely appears in the reference sets of other credit institutions. This may be explained by some unique practices or combinations of resources.

The third section of a findings chapter empirically proved that foreign banks have higher operational efficiency scores throughout the whole period under consideration. Therefore, the infrequency of appearance of Danske banks may be explained by the foreign ownership and transfer of foreign best-practices. Similar ideas were also demonstrated in Golovan et al. (2009), Aleskerov et al (2009), (Wanke et al., 2016) and (Mu-Jen, 2015). This group as the most numerous in the current study has the smallest percentage of truly efficient banks – an average for 5 years is only 5.33%.

Basically, the analysis of the groups, presented above, leads to a conclusion that the smaller the size of a bank, the bigger the chance that it will not be technically (operationally) efficient.

The fact that size may be a factor that contributes to the increase in bank's efficiency goes in accordance with the evidence found in the studies of Kosheluk (2008), Wolters et al. (2014) and Cava et al (2016), yet it goes in the opposite direction of the results obtained by Golovan et al. (2008), Macedo and Barbosa (2009) and Staub et al. (2010), which did not identify the influence of size on efficiency. The justification for the contribution of size to efficiency is the possibility of economies of scale in banking activities. Also, frequently researchers propose that the efficiency of large companies comes from their ability to coordinate their resources better and use specialized inputs (Alvarez & Crespi, 2003).

Due to the extreme heterogeneity of a sample it was divided into subsamples according to the sizes of banks, applied previously – Very Big, Big, Medium, Small – to get more homogeneous sample and to see whether subsample will reveal different set of best-practice banks. However, the subsample of very big banks consisted of only 5 banks – this posed some difficulties to the analysis due to the lack of point upon which a production frontier could be constructed. The same situation happened with the subsample of Big banks, where there are 15 banks. The problem is that according to the rule of thumb, discussed in the second chapter of the paper, the number of DMUs should be

not less than the sum of inputs and outputs, multiplied by 8. To overcome this problem the panel was done, i.e. the data for each big bank in each of the years was listed in the following way: Sberbank 2013, Sberbank 2014, Sberbank 2015, Sberbank 2016, Sberbank 2017, VTB 2013, VTB 2014, VTB 2015, VTB 2016 etc. This allowed to increase the subsample size, although the number of point in the sample of Very Big banks was still too little, thus, making the results inconclusive. Although the number of points in the case of big banks was big enough (75 DMUs) the results have proven inconclusive and according to the chosen set of criteria for determination of the best-practice this group failed to demonstrate any. This may be explained by the fact that in the panel each bank in each year is treated as a different entity, so if a bank showed an extremely good performance in one out of the five years of observations, it will probably dominate itself in other years, thus, making it impossible to find best-practice banks according to the chosen set of criteria.

A different case occurred with subsamples for Small and Medium banks. There were enough observations in each of them, making it possible to apply the developed benchmarking methodology with no restrictions. As a result, four banks were identified as sub-sample best-practice banks:

1) Small banks
    - Cetelem Bank (57th by TA)
    - Danske Bank (106th by TA)
2) Medium banks
    - Citibank (21th by TA)
    - KB Deltakredit (44th by TA)

Interestingly, the two banks that were considered as best-practice for the whole general sample were considered best-practice for their respective subsamples. This proves that the previously identified banks (Danske and Deltakredit) are truly exemplar.

Another interesting result is the appearance of Cetelem bank and Citibank in the list of best-practices for the small and medium banks' groups respectively. These banks, unlike Danske and Deltakredit are exemplar for their respective size-group only.

Subsample analysis also demonstrates that exemplar banks are close to the extremes of subsamples in terms of the total assets, i.e. medium banks are the banks from 21st to 50th and as it is clear from the results, Citibank is on the 21st position and KB Deltakredit is on the 44th which is very close to the other extreme. This leads to the one more proof of the previous statement (made while

analyzing general sample) that within subsample size of the bank does not matter. Similar case occurred with the small banks subsample, although less vivid, because the subsample is rather big and Danske banks is 106th out of 200 banks. Nonetheless the distribution of the banks is similar to the one in medium banks subsample.

Finally, it is interesting to note that Citibank is a foreign bank, according to a classification, discussed in the chapter two, and therefore some transfer of knowledge and know-hows may have played a role in establishing this bank as a bank of a best practice for a respective subsample. This may also be the explanation with the Cetelem bank which is owned by Sberbank and BNP Paribas Personal Finance. Sberbank is an exemplar bank according to the present research and is a very big bank, while BNP is a foreign bank. Both may have transferred resources and knowledge into Cetelem, thus, making it a bank of a best-practice for a respective subsample.

As for the sources of improvement for inefficient banks, DEA method allows to calculate so-called projections, i.e. quantified measures of how inefficient DMU should change its inputs in order to relocate itself to efficient or, in this case, best-practice frontier. One can refer to Appendices 10-12 for projections made for the first 100 banks according to the first model for the year 2017. The first model was chosen as it measures the overall technical efficiency of a bank and provides management with a comprehensive picture of what it should do with the input variables. The absolute values of the variable "Capital" were excluded from the Appendices 10-12 to save space and increase readability of the tables. It was decided to leave only the percentage by which, according to the constructed model, the banks should change their respective capitals (if they should do anything with it at all) in order to improve their stance in terms of technical efficiency. Also, because this variable was normalized, its absolute values (projections) are too difficult to comprehend, while the percentage by which capital should be changed is not only easily understandable, but also demonstrative. As one can see from the Appendix 10, for example, bank Promsvyazbank should decrease its capital by 2% to become more efficient, as well as decrease its fixed assets and deposits by 85% and 33%. Alfa-Bank, in its turn, should decrease all three input variables by 21% to move to the efficient frontier.

At this point it is necessary to notice that sources of improvement (projections), proposed by BCC-I DEA with the chosen set of inputs and outputs are prone to exaggeration due to the specifics of the DEA method and should be taken into consideration by bank's management with caution. Precisely, one should read tables in Appendices 10-12, considering the percentage figures as clues

about where to find sources of to become more technically efficient. These tables should serve as a decision-support information for management of the bank but should not be considered in direct manner.

Taking into consideration what was mentioned above, if one is to increase the technical efficiency of the bank Peresvet (see Appendix 11), he/she should not momentarily decrease the capital by 27%, fixed assets by 38% and deposits by 27%, instead, he/she should probably look closer into these three variables and especially into fixed assets as they may need some extra attention from the management, because they may be too big for the bank to be technically efficient according to the chosen model and in the chosen sample. If the management is to improve efficiency of a bank Ekspobank, then it should look thoroughly first at the deposits, because they may prevent the bank from being an exemplar bank, ceteris paribus.

4.2 Theoretical contribution

One theoretical contribution is the development of a multilevel benchmarking method on the basis of DEA models. This study goes further than just determining performance scores and ranking banks, it clearly objectifies the notion of best-practice banks and on a basis of it builds benchmarking method.

The present paper attempts to cover the gap, clearly outlined in the literature review section. As it was stated, there are extremely few modern researches that would employ multidimensional criteria, i.e. DEA, to assess efficiency of Russian banking sector. Usually and most frequently simple ratio analysis is applied for the analysis of a single bank or the banking sector. However, ratio analysis has its downfalls, e.g. weak signals for areas for improvement and not accounting for output mix. All the drawbacks of it do not allow to use it as a reliable benchmarking tool. Therefore, this research contributes to the theory by introducing a complex method that allows to identify the best-practice banks within the given sample according to the pre-defined set of operational inputs and outputs with the usage of BCC-I DEA technique.

Also, the current study enhances the methodology of DEA by introducing the normalization technique. As it was stated in the methodology section of the research, DEA cannot process negative data which is frequently a case while considering profit or revenue as outputs of the bank's activity. Normalization does not require vast mathematical background and will not affect the results of the calculations, while giving an opportunity not to worry about the negative data, because norming

saves the order of initial values of variables and this is the most important for the DEA to produce credible results.

Another benefit of normalization is that with a slight change in the formula it allows the researches to solve a second problem: treatment of the undesirable outcomes. For example, in the current study such an outcome is the indicator of Non-Performing Loans (NPLs). Normalization technique in this case will not only normalize value proportionally in the interval from zero to one, but also will reverse the numbers in a way that the more outcome is, the worse efficiency score will be.

Finally, this research contributes to the theory by extending the current study pool on frontier analysis of Russian banking, particularly cost-efficient measures. Also, the paper summarizes recent studies on DEA in the world and in Russia with the indication of inputs and outputs. The table is compiled by the author and provides an easy guide for the interested party with the clear specification of the authors, methods, approaches and, most valuable, inputs and outputs. The table covers the period from 2005 to 2016 and can be used as a helper in the choice of inputs and outputs.

4.3 Managerial implication

Systematic benchmarking through efficiency measurement is one method managers can use to benchmark the efficiency of their banks. Benchmarking via DEA can be applied by an inefficient bank to find out the best banking practices within the relevant peer group in order to adopt effective operating procedures and winning strategies that can enhance its state of affairs, e.g. increase the efficiency via cost improvements. The major difference of DEA in comparison with the standard piecemeal examination of every single performance indicators is that DEA technique can offer Russian bank managers a rounded assessment of their banks' performance. They can use the results of DEA to support other objectives, such as allocation of finance or identifying the priorities for inspection and improvement of performance. So, Bank management gets useful decision-support information from the estimates of their bank's operational efficiency:

1) Technical efficiency estimates itself are useful as a leading indicator of the bank's performance;
2) The position of a bank against its peers;
3) Information on the possible ways to improve bank's operational performance.

Performance measurement in the banking industry can be beneficial not only to management but can also be very helpful to the regulator that monitors financial stability while attempting to detect distress, i.e. Bank of Russia. The information obtained with the help of DEA can be useful in deciding on whether to close a bank or not. The policy makers can examine how the public-sector banks are performing relative to their private sector and foreign counterparts (this is done within this study). Finally, investors and market analysts, interested in Russian Banking sector, will be interested in comprehensive assessment of financial institutions and banks for inclusion in their investment portfolios.

4.4 Limitations and direction for further research

Notwithstanding this paper has carefully considered and selected the most appropriate research approach, it is not free of the limitations which suggest directions for further research.

The first limitation is that rather general variables were chosen for the inputs and outputs, i.e. each of the inputs and outputs except NPLs can be divided further into more specific categories and, thus, lead to a more specific conclusions. This limitation is caused by the availability of banking data.

The second limitation is that the banks are compared with each other based on only 3 inputs and 3 outputs which is rather narrow comparison. This limitation is conditioned by the sample size: to include more variables, the sample size should be bigger, otherwise there would be too many non-dominated banks which would decrease the ability to make sound conclusions.

The third limitation is that this study measures only technical efficiency, without considering scale efficiency (which, for example, can be calculated with the help of CCR DEA model). The usage of latter may provide insights about the impact of scale size on the productivity of a bank.

Future researchers may consider more specific inputs and outputs or apply both, CSR and BCC, models to find out best-practice banks. In order to deepen the understanding of the sources of efficiency future studies could use Malmquist total factor productivity (TFP) index.

In addition, future researchers may extend the time-period under investigation and use even larger data sample, together with the inclusion of the Tobit-regression in the second stage to test the relationship between the efficiency scores and bank-specific (e.g. liquidity risk, capital risk etc.) and environmental characteristics (GDP growth, interest rate etc.).

Even though this study is subject to some limitation, their presence does not diminish the reliability of results and conducted research. Conclusions presented in this paper can be used by various stakeholders of a bank who need to understand the current state of affairs in the sector, search for examples of best practices in the Russian banking sector or conduct benchmarking.

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APPENDICES

Appendix 1 Statistical information on the largest banks of the RF

№№ п/п	Наименование банка	Субъект Российской Федерации	Номер лицензии
1	ПАО "АК БАРС" БАНК	Республика Татарстан	2590
2	АО "АЛЬФА-БАНК"	г.Москва	1326
3	АО "Банк Русский Стандарт"	г.Москва	2289
4	ПАО "Банк "Санкт-Петербург"	г.Санкт-Петербург	436
5	ПАО "БАНК УРАЛСИБ"	г.Москва	30
6	ПАО "БИНБАНК"	г.Москва	323
7	Банк "ВБРР" (АО)	г.Москва	3287
8	Банк "Возрождение" (ПАО)	г.Москва	1439
9	ПАО КБ "Восточный"	Амурская область	1460
10	Банк ВТБ (ПАО)	г.Санкт-Петербург	1000
11	Банк ГПБ (АО)	г.Москва	354
12	ПАО "МИнБанк"	г.Москва	912
13	ПАО "МОСКОВСКИЙ КРЕДИТНЫЙ БАНК"	г.Москва	1978
14	ПАО "Почта Банк"	г.Москва	650
15	ПАО "Промсвязьбанк"	г.Москва	3251
16	АО "Райффайзенбанк"	г.Москва	3292
17	ПАО РОСБАНК	г.Москва	2272
18	АО "Россельхозбанк"	г.Москва	3349
19	АКБ "РОССИЙСКИЙ КАПИТАЛ" (ПАО)	г.Москва	2312
20	АО "АБ "РОССИЯ"	г.Санкт-Петербург	328
21	ПАО Сбербанк	г.Москва	1481
22	ПАО АКБ "Связь-Банк"	г.Москва	1470
23	АО КБ "Ситибанк"	г.Москва	2557
24	АО "СМП Банк"	г.Москва	3368
25	ПАО "Совкомбанк"	Костромская область	963
26	АО "Тинькофф Банк"	г.Москва	2673
27	ПАО КБ "УБРиР"	Свердловская область	429
28	ПАО Банк "ФК Открытие"	г.Москва	2209
29	ООО "ХКФ Банк"	г.Москва	316
30	АО ЮниКредит Банк	г.Москва	1

*Banks are in alphabetic order

Source: Central Bank of Russian Federation

Appendix 2 Structure of income and expenses of operating credit institutions

	01.01.2013		01.01.2014		01.01.2015		01.01.2016		01.01.2017		01.01.2018	
	trillion. rub.	as % of total income / expenses	trillion. rub.	as % of total income / expenses	trillion. rub.	as % of total income / expenses	trillion. rub.	as % of total income / expenses	trillion. rub.	as % of total income / expenses	trillion. rub.	as % of total income / expenses
1. Income - total	31,9		31	100	110	100	192	100	183		105	
% income from legal entities	2,1	7,7	2,4	7,7	2,9	2,7	4	2,1	4	2,2	3,6	3,4
% income from physical entities	1,1	4,0	1,6	5,1	1,8	1,7	1,8	0,9	1,8	1,0	1,5	1,4
Income from securities	1,2	4,4	1,9	6,1	2,6	2,4	1,4	0,7	1,3	0,7	1,2	1,1
Income on foreign currency	21,1	77,0	17,9	57,5	91,2	82,6	169	88,1	162	88,5	87,9	83,7
Commission income	0,7	2,6	0,8	2,6	0,9	0,8	0,9	0,5	1,1	0,6	1,2	1,1
Recovery of reserves	4	14,6	4,8	15,6	6,1	5,5	9,4	4,9	10,8	5,9	7,9	7,5
2. Expenses - total	30,9	112,8	30	100	110	100	192	100	182		104	
% expenses on legal entities	0,9	3,3	1,1	3,8	1,7	1,6	2,7	1,4	2,5	1,4	2,3	2,2
% expenses on physical entities	0,7	2,6	0,9	2,9	0,9	0,8	1,5	0,8	1,6	0,9	1,2	1,1
Expenses from securities	0,9	3,3	1,6	5,2	2,4	2,2	0,7	0,4	0,3	0,2	0,4	0,4
Expenses on foreign currency	21,1	77,0	17,7	59,1	90,8	82,7	168,6	87,9	162	88,5	87,8	83,6
Commission fee	0,1	0,4	0,2	0,5	0,2	0,2	0,2	0,1	0,3	0,2	0,3	0,3
Allocations to reserves	4,1	15,0	5,4	18,1	7,6	6,9	11,1	5,8	11,5	6,3	9,3	8,9
General and administrative expenses	1,1	4,0	1,2	3,9	1,2	1,1	1,2	0,6	1,5	0,8	1,4	1,3

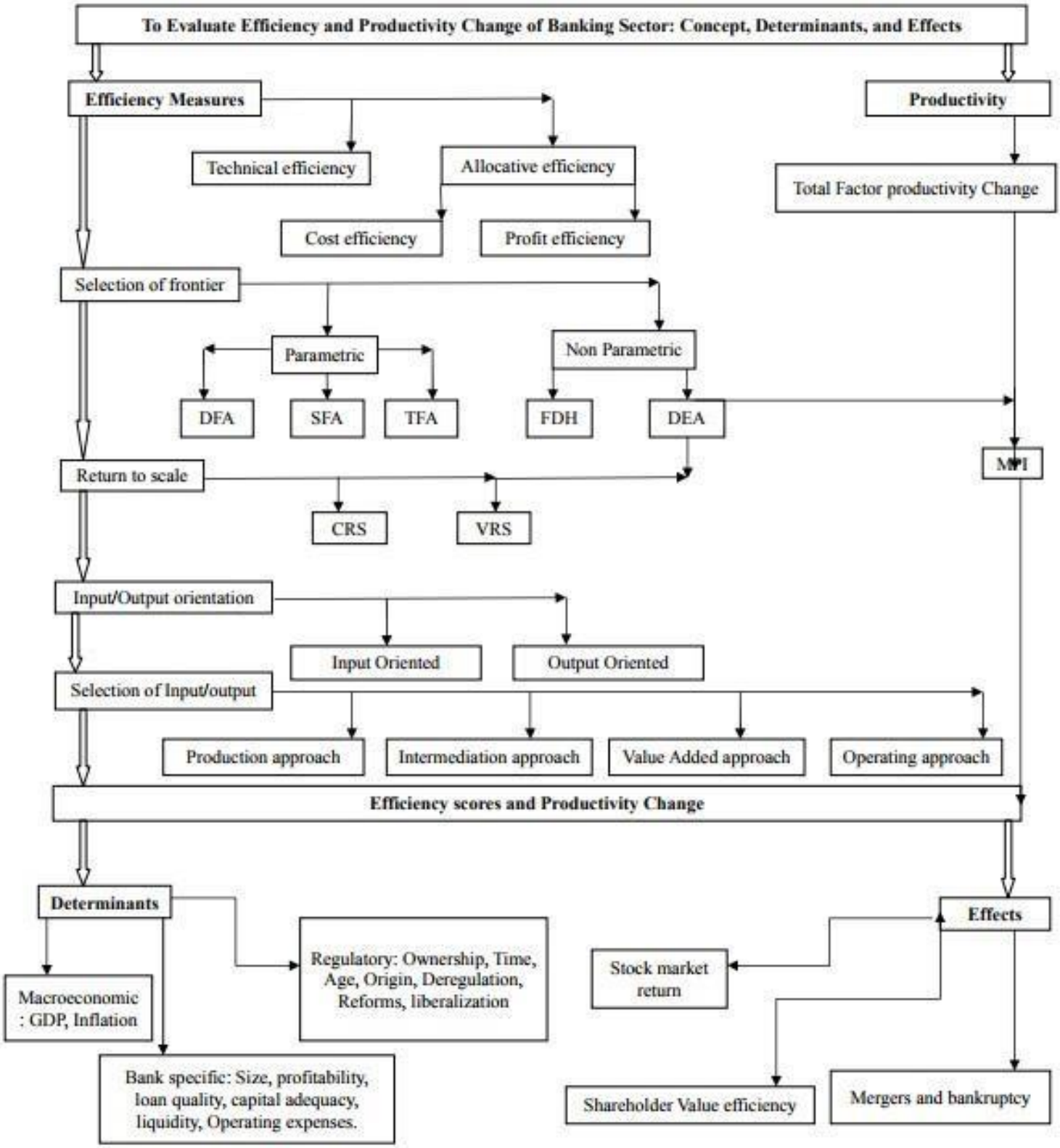
Source: Bank of Russia

Appendix 3 Macroeconomic indicators of Russian banking Sector

Indicator	2012	2013	2014	2015	2016	2017
Banking sector assets, total (billion rubles)	49 510	57 423	77 653	83 000	80 063	85 192
Banking sector own funds (capital) (billion rubles)	6 113	7 064	7 928	9 009	9 387	9 397
Loans and other claims on non-financial organizations and individuals, including overdue claims (billion rubles)	27 709	32 456	40 866	43 985	40 939	42 366
Individual deposits (billion rubles)	14 251	16 958	18 553	23 219	24 200	25 987
Deposits and funds on accounts of non-financial and financial organizations (except credit institutions) (billion rubles)	14 565	16 901	23 419	27 064	24 322	24 843

Source: Bank of Russia

Appendix 4 Conceptual framework of banking efficiency measurement



Appendix 5 DEA literature review summary: papers, methods, specifications

Author	Method	Approach	Inputs	Outputs
DEA efficiency estimation of banks around the world				
Sanjeev (2006)	1-stage DEA	Intermediation	Interest Expenses Non-interest expenses	Interest income and fees Commission and brokerage
Sufian and Majid (2007)	2-stage DEA	Intermediation	Total Deposits (deposits from customers and other banks) Interest Expenses	Total Loans (loans to customers and other banks) Interest Income Non-Interest Income (as a proxy to non-traditional activities as output)
Laurenceson and Yong (2008)	1-stage DEA	Intermediation	Deposits, Number of Employees Fixed Assets Value	Loans (net) and other earning assets Loans plus deposits
Mostafa (2009)	DEA + PNN	Profitability	Assets Equity	Net Profit ROA ROE
Gaganis and Pasiouras (2009)	1-stage DEA	Profitability	Staff expenses Other administrative expenses	Net interest income Net commission income plus other operating income
Luo and Yao (2010)	2-stage DEA (Tobit regression)	Intermediation	Number of employees, Fixed assets Deposits	Total Loans Other Earning Assets (including short-term investments, long-term investments, deposits with central banks, other investments, etc.).
Dİler (2011)	2-stage DEA	Mixed approach	Securities/Total Assets	Return on Average Assets (ROA): Net

	(FEM regression model)		Deposits/Total Assets Non-Performing Loans (Gross) / Total (Cash) Loans Total Loans / Total Assets Non-Interest Expense / Total (Average) Assets	Profit (Loss) / Total (Average) Assets Return on Average Equity (ROE): Net Profit (Loss) / Total (Average) Equity Net Interest Income / Total Income
Savió et al. (2012)	1-stage DEA (profit-oriented and operational models)	Intermediation	Interest expenses Non-interest expenses	Interest income Non-interest income
			Number of employees Fixed assets and intangible investments Capital Deposits	Granted loans and Deposits Non-interest income
Firdaus and Hosen (2013)	2-stage DEA (Tobit regression)	Intermediation	Third Party Funds (DPK) Assets Cost of Labor	Financing Income Operating Income
Zeitun and Benjelloun (2013)	1-stage DEA	Intermediation	Deposits Equity Other Assets	Net Income Before Tax
			Deposits Equity Fixed Assets	Net Income Total Loans
			Deposits Equity Other Assets Fixed Assets	Net interest Other earning assets

Wanke and Barros (2014)	2-stage DEA (Truncated regression combined with bootstrapping)	Intermediation	Number of branches Number of employees	Administrative expenses (BRL) Personnel expenses (BRL)
			Administrative expenses (BRL) Personnel expenses (BRL)	Equity (BRL) Permanent assets (BRL)
Ke et al. (2014)	2-stage VRS additive DEA	Intermediation	Fixed assets Labor	Deposits
			Deposits	Interest income Non-Interest income Bad Loans
Hosen and Muhari (2014)	1-stage DEA and CAMEL	Operational (Jemric and Vujci, 2002)	Employment expense Operating expense Other expense Amortization	Operating income Other income
Sok-Gee and Karim (2015)	1-stage DEA (Tobit regression)	Value-added approach	Personnel costs (price of labor) Capital cost (price of capital) Cost of loanable funds	Loans Investments Deposits
Mustafa and Behmood (2015)	1-stage DEA and MPI	Intermediation	Deposits Total Operating Expenses	Total Income (Interest on (Loans + Securities Portfolio + Deposits in other Banks + Interbank Funds Sold) + Other Interest Income) Advances (Loans and advances for all time periods, customer loans)
Marković et al.	CRS DEA and MPI	Mixed	Assets	Total revenue

(2015)			The number of employees Equity	Earnings before taxes
Shyu et al. (2015)	3st DEA, including SFA as a stage	Intermediation	Deposits Fixed Assets Number of employees	Loans Long-term investments Non-Interest Income
Kutlar et al. (2015)	CRS/VRS DEA and MPI and Windows Productivity Analysis	Mixed	Net Assets Deposits Interest Expenses Paid Fees & Commissions Other Operations Expenses Salaries # of Personnel	Credits & Lending Operational Income Interest Income Received Fees & Commissions Other Operational Income
Henni and Chachoua (2016)	1-stage CRS DEA	Intermediation	Deposits Fixed assets General Operating Expenses	Net Loans Other operating assets Non-interest income
Cava et al. (2016)	1-stage VRS DEA	Production	Number of staff Operating expenses (excluding interest) Fixed Assets	Total deposits Revenue not related to interest
Ramakrishna et al. (2016)	1-stage VRS DEA and MPI and ratio analysis	Intermediation	Deposits Number of employees	Loans and advances Interest income Total investments
Ab-Rahim and Chiang (2016)	1-stage CRS and VRS DEA (regression)	Intermediation	Personnel expenses Capital (book value of premises and fixed assets)	Total loans Other earning assets

			Deposits and short-term funding	
Soba et al. (2016)	2-stage CRS DEA (fixed-effects regression model)	Intermediation	Total deposits Interest expenses Personnel expenses	Total loans Interest income
Tran Thi Thu and Bhaiyat (2016)	1-stage CRS and VRS DEA	Intermediation	Fixed Assets Deposits Staff Expenses	Loans Securities Investments Non-interest income
DEA efficiency estimation of Russian banks				
Styrin (2005)	SFA	Intermediation	Labor Deposits bank capital (fixed input) Purchased funds	Loans Securities
			The variable input prices are wage rate, interest rates on deposits and purchased funds.	
Nikishin (2007)	CRS and VRS DEA and MPI	Production	Fixed assets Personnel expenses Interest expenses	Deposits The size of the loan portfolio The amount of attracted funds of the population
Golovan, Nazin, Peresetsky (2008)	CRS and VRS DEA and SFA	Intermediation	Personnel expenses Loan loss reserves Other expenses	Net Interest Income Net Non-Interest Income
Golovan, Karminsky, Peresetsky (2008)	DEA and SFA		Total Deposits Interest expenses Received interbank loans	Total Loans

			Issued securities Equity	
Koshelyuk (2008)	1-stage CRS DEA	Intermediation	Capital Deposits Received Interbank Loans	Operating Assets Net Profit
Karas et. al. (2008)	VRS DEA and Tobit regression and SFA	Production	Personnel expenses Other operating expenses	Total Loans Total Deposits
Aleskerov et al. (2009)	CRS DEA and SFA	Intermediation	Equity Deposits Other Liabilities	Operating Assets Profit
Golovan et al. (2010)	DEA and SFA	Profit	Personnel expenditures Provision for possible losses Other expenditures	Net interest expenditures Net other operational income

Source: author

Appendix 6 Lists of banks under control Russia or CBR

#	# by Assets	Name
1	1	SBERBANK, PAO
2	2	BANK VTB (PAO)
3	3	BANK GPB (AO)
4	4	ROSSELKHOZBANK, AO
5	6	FK OTKRYTIE, PAO BANK
6	16	BM-BANK, AO
7	17	TRAST (PAO), BANK
8	22	VBRR (AO), BANK
9	25	ROSSISKI KAPITAL (PAO), AKB
10	27	NOVIKOMBANK, AO AKB
11	32	SVYAZ-BANK, PAO AKB
12	33	PERESVET (AO), AKB
13	34	POCHTA BANK, PAO
14	47	RNKB BANK (PAO)
15	52	GLOBEKSBANK, AO
16	53	RGS BANK, PAO
17	57	SETELEM BANK OOO
18	63	FONDSERVISBANK, AO
19	64	MSP BANK, AO
20	67	ROSEKSIMBANK, AO
21	81	SOTSINVESTBANK, AO
22	83	KRAIINVESTBANK, PAO
23	88	EVROFINANS MOSNARBANK, AO AKB
24	114	KUB (AO), BANK
25	129	GENBANK, AO
26	162	DENIZBANK MOSKVA, AO
27	168	RFK-BANK, AO

Source: Central Bank of Russia

Appendix 7 Lists of banks with 100% foreign control

#	# by Assets	Name
1	10	YUNIKREDIT BANK, AO
2	11	RAIFFAIZENBANK, AO
3	15	SOVKOMBANK, PAO
4	21	SITIBANK, AO KB
5	31	TINKOFF BANK, AO
6	40	ING BANK (EVRAZIYA) AO
7	55	KREDIT EVROPA BANK, AO
8	73	RN BANK, AO
9	75	EICH-ES-BI-SI BANK (RR), OOO
10	76	BANK KREDIT SVISS (MOSKVA), AO
11	79	DOICHE BANK, OOO
12	86	BANK INTEZA, AO
13	89	TOIOTA BANK, AO
14	90	BNP PARIBA BANK AO
15	100	KOMMERTSBANK (EVRAZIYA), AO
16	101	AISIBISI BANK (AO)
17	106	DANSKE BANK, AO
18	108	KREDI AGRIKOL KIB AO
19	112	BENK OF CHAINA (AO), AKB
20	113	SEB BANK, AO
21	122	FOLKSVAGEN BANK RUS, OOO
22	124	BMV BANK OOO
23	133	CHAINA KONSTRAKSHN BANK, OOO
24	134	MOSKOMMERTSBANK (AO), KB
25	139	MERSEDES-BENTS BANK RUS OOO
26	149	DZHEI END TI BANK (AO)
27	153	NATIKSIS BANK AO
28	154	BANK MBA-MOSKVA OOO
29	157	ALEF-BANK, AO AKB
30	162	DENIZBANK MOSKVA, AO
31	180	ISHBANK, AO
32	192	MS BANK RUS, AO
33	195	URI BANK, AO

Source: Central Bank of Russia

Appendix 8 Reference set for the first 10 banks

No.	DMU	Score	Rank	Reference set			
1	SBERBANK, PAO	1		1	SBERBANK, PAO		
2	BANK VTB (PAO)	1		1	BANK VTB (PAO)		
3	BANK GPB (AO)	1		1	BANK GPB (AO)		
4	ROSSELKHOZBANK, AO	0,886		147	BANK GPB (AO)	FK OTKRYTIE, PAO BANK	MOSKOVSKI KREDITNY BANK, PAO
5	ALFA-BANK, AO	0,7611		170	FK OTKRYTIE, PAO BANK	MOSKOVSKI KREDITNY BANK, PAO	ROST BANK, AO
6	FK OTKRYTIE, PAO BANK	1		1	FK OTKRYTIE, PAO BANK		
7	MOSKOVSKI KREDITNY BANK, PAO	1		1	MOSKOVSKI KREDITNY BANK, PAO		
8	PROMSVYAZBANK, PAO	0,5318		189	BANK VTB (PAO)	FK OTKRYTIE, PAO BANK	ROST BANK, AO
9	BINBANK, PAO	0,6944		178	SBERBANK, PAO	BANK VTB (PAO)	FK OTKRYTIE, PAO BANK
10	YUNIKREDIT BANK, AO	0,855		155	SBERBANK, PAO	MOSKOVSKI KREDITNY BANK, PAO	ROST BANK, AO

Source: author

Appendix 9 Reference set for the banks 52-74

No.	DMU	Score	Rank	Reference set		
52	GLOBEKSBANK, AO	0,3334	197	ROST BANK, AO	RFK-BANK, AO	
53	RGS BANK, PAO	0,6993	177	ROST BANK, AO	SOTSINVESTBANK, AO	
54	BANK AVB, AO	0,997	44	KB DELTAKREDIT, AO	BKS BANK, AO	KS BANK (PAO), AKKSB
55	KREDIT EVROPA BANK, AO	0,7221	176	ROST BANK, AO	KB DELTAKREDIT, AO	BKS BANK, AO
56	AVERS, OOO BANK	0,9954	46	SITIBANK, AO KB	AVERS, OOO BANK	SEB BANK, AO
57	SETELEM BANK OOO	0,9176	134	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB	BANK NFK (AO)
58	AZIATSKO-TIKHOOKEANSKI BANK (PAO)	0,8185	162	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
59	SKB-BANK, PAO	0,8042	164	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
60	ZAPSIBKOMBANK, PAO	0,918	133	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
61	BANK FINSERVIS, AO	0,9698	85	ROST BANK, AO	KB DELTAKREDIT, AO	BKS BANK, AO
62	RUSFINANS BANK, OOO	0,7972	165	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
63	FONDSERVISBANK, AO	0,3565	196	ROST BANK, AO	RFK-BANK, AO	
64	MSP BANK, AO	0,8588	153	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
65	TAVRICHESKI (PAO), BANK	0,4207	193	ROST BANK, AO	RFK-BANK, AO	
66	TSENTR-INVEST, PAO KB	0,9163	135	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
67	ROSEKSIMBANK, AO	0,783	167	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
68	BALTINVESTBANK, PAO	0,7556	171	ROST BANK, AO	SOTSINVESTBANK, AO	
69	KUBAN KREDIT OOO, KB	0,9384	119	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
70	BANK SOYUZ (AO)	0,8933	146	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
71	TSENTROKREDIT, AO AKB	0,833	159	ROST BANK, AO	KB DELTAKREDIT, AO	FINANS BIZNES BANK, OOO KB
72	LOKO-BANK (AO), KB	1	1	LOKO-BANK (AO), KB		
73	RN BANK, AO	0,978	73	KB DELTAKREDIT, AO	BKS BANK, AO	FINANS BIZNES BANK, OOO KB
74	METALLINVESTBANK, PAO AKB	0,9062	140	ROST BANK, AO	FINANS BIZNES BANK, OOO KB	BANK MBA-MOSKVA OOO

Source: author

Appendix 10 Projections for the first 20 banks (1st model)

				Capital	Fixed Assets			Deposits		
No.	DMU	Score	Rank	Diff.(%)	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
1	SBERBANK, PAO	1	1	-	465 560 698 000	465 560 643 772	-	17 207 680 691 000	17 207 678 686 663	-
2	BANK VTB (PAO)	1	1	-	317 186 738 000	317 186 601 583	-	5 692 437 584 000	5 692 436 124 355	-
3	BANK GPB (AO)	1	1	-	24 281 782 000	24 281 771 171	-	3 809 099 319 000	3 809 097 040 755	-
4	ROSSELKHOZBANK, AO	0,886	147	24	19 959 626 000	17 684 729 303	- 11	2 080 202 761 000	1 843 111 826 058	- 11
5	ALFA-BANK, AO	0,7611	170	21	26 197 270 000	19 938 147 379	- 24	1 592 553 240 000	1 212 056 111 523	- 24
6	FK OTKRYTIE, PAO BANK	1	1	16	24 324 339 000	24 324 316 984	-	1 437 737 633 000	1 437 736 331 694	-
7	MOSKOVSKI KREDITNY BANK, PAO	1	1	-	6 530 160 000	6 530 148 162	-	799 819 634 000	799 818 184 040	-
8	PROMSVYAZBANK, PAO	0,5318	189	2	24 566 614 000	13 063 977 307	- 47	986 607 151 000	524 655 674 234	- 47
9	BINBANK, PAO	0,6944	178	-	17 047 321 000	11 837 246 801	- 31	746 136 286 000	518 098 964 923	- 31
10	YUNIKREDIT BANK, AO	0,855	155	16	14 736 964 000	12 600 544 458	- 14	749 750 243 000	641 058 855 070	- 14
11	RAIFFAIZENBANK, AO	0,8791	148	3	13 173 141 000	9 285 405 463	- 30	552 999 650 000	486 125 715 158	- 12
12	ROSBANK, PAO	0,5343	188	13	25 793 802 000	2 067 231 399	- 92	459 005 023 000	245 230 114 191	- 47
13	AB ROSSIYA, AO	0,8642	152	7	8 170 461 000	1 957 233 139	- 76	654 579 708 000	227 474 958 025	- 65
14	ROST BANK, AO	1	1	-	390 461 000	390 461 000	-	39 073 515 000	39 073 515 000	-
15	SOVKOMBANK, PAO	1	1	0	1 747 006 000	1 746 983 957	- 0	282 728 772 000	282 722 950 501	- 0
16	BM-BANK, AO	0,7955	166	18	567 797 000	451 691 576	- 20	300 740 224 000	48 735 411 240	- 84
17	TRAST (PAO), BANK	0,473	191	19	5 740 177 000	1 308 572 916	- 77	259 898 969 000	122 938 446 945	- 53
18	BANK SANKT-PETERBURG, PAO	0,7505	172	7	13 099 528 000	1 518 108 406	- 88	355 240 341 000	173 801 904 843	- 51
19	BANK URALSIB, PAO	0,5437	187	12	15 244 041 000	390 096 966	- 97	300 699 574 000	34 626 562 360	- 88
20	MOSOBLBANK, PAO	1	1	-	3 054 844 000	3 054 844 000	-	282 451 676 000	282 451 676 000	-

Source: author

Appendix 11 Projections for the banks 21-50 (1st model)

				Capital	Fixed Assets			Deposits		
No.	DMU	Score	Rank	Diff.(%)	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
21	SITIBANK, AO KB	1	1	-	1 423 332 000	1 423 332 000	-	418 166 212 000	418 166 212 000	0
22	VBRR (AO), BANK	0,9994	48	- 0	1 838 815 000	1 836 209 382	0	382 873 384 000	382 625 291 257	0
23	AK BARS BANK, PAO	0,8516	192	- 15	3 876 084 000	1 651 977 944	57	348 049 509 000	63 144 835 628	82
24	BANK RUSSKI STANDART, AO	0,7894	198	- 21	6 765 241 000	3 301 412 685	51	205 017 052 000	140 829 984 551	31
25	ROSSISKI KAPITAL (PAO), AKB	0,9156	184	- 8	3 889 204 000	2 968 178 178	24	207 270 716 000	173 957 094 781	16
26	SMP BANK, AO	0,9882	117	- 1	5 458 700 000	797 429 945	85	205 024 489 000	76 267 533 078	63
27	NOVIKOMBANK, AO AKB	0,9895	108	- 1	8 676 364 000	1 314 868 406	85	251 244 350 000	194 900 180 809	22
28	UBRIR, PAO KB	0,9681	160	- 3	10 787 134 000	256 445 385	98	215 215 534 000	12 705 079 227	94
29	VOSTOCHNY, PAO KB	0,8623	190	- 14	23 032 398 000	3 200 907 686	86	176 815 745 000	152 468 858 930	14
30	MINBANK, PAO	0,9742	156	- 3	11 897 486 000	670 786 822	94	241 199 982 000	31 034 753 736	87
31	TINKOFF BANK, AO	0,9812	138	- 2	6 913 193 000	3 033 743 332	56	202 501 870 000	198 695 288 565	2
32	SVYAZ-BANK, PAO	0,9137	185	- 9	3 471 062 000	1 885 353 057	46	174 215 397 000	65 565 347 565	62
33	PERESVET (AO), AKB	0,7251	200	- 27	3 201 675 000	1 995 140 774	38	109 851 695 000	79 657 747 664	27
34	POCHTA BANK, PAO	0,9769	148	- 2	5 713 553 000	1 958 966 573	66	177 850 728 000	167 923 327 212	6
35	ABSOLYUT BANK (PAO), AKB	0,9442	173	- 6	3 515 841 000	1 108 614 147	68	168 353 056 000	34 402 770 908	80
36	KHKF BANK, OOO	0,9356	176	- 6	4 419 271 000	788 084 097	82	203 941 414 000	69 249 450 109	66
37	VOZROZHDENIE (PAO), BANK	0,9337	177	- 7	10 177 266 000	1 539 737 145	85	201 372 151 000	51 656 328 964	74
38	SNGB, AO BANK	0,9915	95	- 1	2 455 941 000	214 217 737	91	217 427 787 000	14 731 599 782	93
39	BANK ZENIT, PAO	0,9499	169	- 5	1 334 646 000	716 542 340	46	118 696 309 000	52 116 232 249	56
40	ING BANK (EVRAZIYA) AO	0,9275	179	- 7	345 515 000	320 450 049	7	117 534 756 000	18 793 129 868	84
41	TKB BANK PAO	0,9373	175	- 6	1 687 352 000	1 438 136 402	15	107 284 938 000	41 360 166 629	61
42	ROSEVROBANK (AO)	0,9646	162	- 4	3 363 294 000	665 224 980	80	150 733 370 000	78 643 502 433	48
43	EKSPRESS-VOLGA,	1	1	-	157 218 000	157 218 000	-	3 643 974 000	3 643 974 000	-

Appendix 11 (continuation)

					Fixed Assets			Deposits		
No.	**DMU**	**Score**	**Rank**		**Data**	**Projection**	**Diff.(%)**	**Data**	**Projection**	**Diff.(%)**
44	KB DELTAKREDIT, AO	1	1	-	223 821 000	223 821 000	-	6 101 955 000	6 101 955 000	-
45	MTS-BANK, PAO	0,9109	186	- 9	3 432 154 000	2 221 265 627	35	113 524 284 000	103 413 086 913	9
46	NORDEA BANK, AO	0,9998	40	- 1	238 803 000	238 751 780	0	51 349 794 000	51 255 980 293	0
47	RNKB BANK (PAO)	0,9998	40	- 2	3 508 518 000	3 497 248 868	0	81 938 512 000	81 925 468 169	0
48	INVESTTORGBANK (PAO), AKB	0,9237	181	- 8	3 902 972 000	2 139 162 022	45	105 333 910 000	97 295 826 748	8
49	OTP BANK, AO	0,9224	182	- 8	2 581 146 000	1 609 940 948	38	85 223 830 000	66 504 017 921	22
50	AVANGARD, PAO AKB	0,944	174	- 6	2 215 083 000	902 454 539	59	89 118 914 000	20 327 609 003	77

Source: author

Appendix 12 Projections for the banks 51-100 (1st model)

				Capital	Fixed Assets			Deposits		
No.	DMU	Score	Rank	Diff.(%)	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
51	RENESSANS KREDIT (OOO), KB	0,9962	71	- 0	1 064 138 000	936 758 083	- 12	100 959 238 000	78 534 051 067	- 22
52	GLOBEKSBANK, AO	0,9018	187	- 10	4 838 862 000	1 982 157 501	- 59	81 260 913 000	44 740 328 239	- 45
53	RGS BANK, PAO	0,9209	183	- 8	2 551 675 000	1 324 449 584	- 48	84 599 027 000	33 123 555 573	- 61
54	BANK AVB, AO	1	1	-	1 258 578 000	1 258 578 000	-	368 588 000	368 588 000	-
55	KREDIT EVROPA BANK, AO	0,948	171	- 5	386 601 000	366 509 581	- 5	76 336 038 000	45 329 829 423	- 41
56	AVERS, OOO BANK	0,9987	53	- 0	335 539 000	335 095 608	- 0	107 162 881 000	106 128 221 323	- 1
57	SETELEM BANK OOO	0,9827	135	- 2	791 694 000	319 707 070	- 60	4 707 352 000	4 626 049 704	- 2
58	AZIATSKO-TIKHOOKEANSKI BANK (PAO)	0,9485	170	- 5	6 847 275 000	1 239 027 385	- 82	80 892 268 000	32 705 602 870	- 60
59	SKB-BANK, PAO	0,9583	165	- 4	6 422 585 000	1 174 369 080	- 82	85 289 742 000	33 105 720 940	- 61
60	ZAPSIBKOMBANK, PAO	0,9771	147	- 2	2 677 649 000	602 044 318	- 78	100 002 016 000	8 972 184 007	- 91
61	BANK FINSERVIS, AO	0,9909	99	- 1	168 826 000	167 287 891	- 1	83 787 122 000	14 133 801 792	- 83
62	RUSFINANS BANK, OOO	0,97	158	- 3	608 216 000	589 977 743	- 3	12 964 659 000	12 575 894 500	- 3
63	FONDSERVISBANK, AO	0,8488	193	- 15	1 202 749 000	1 020 843 545	- 15	95 975 813 000	81 460 295 682	- 15
64	MSP BANK, AO	0,9601	164	- 4	284 392 000	273 045 908	- 4	5 491 111 000	5 272 037 848	- 4
65	TAVRICHESKI (PAO), BANK	0,8601	191	- 14	1 674 487 000	1 440 276 121	- 14	73 876 881 000	63 543 704 790	- 14
66	TSENTR-INVEST, PAO KB	0,9857	125	- 1	3 353 692 000	752 883 177	- 78	85 412 937 000	18 847 818 618	- 78
67	ROSEKSIMBANK, AO	0,9579	167	- 4	275 108 000	263 530 406	- 4	42 072 015 000	40 301 464 135	- 4
68	BALTINVESTBANK, PAO	0,9776	146	- 2	10 481 646 000	1 344 661 308	- 87	33 213 503 000	32 469 492 983	- 2
69	KUBAN KREDIT OOO, KB	0,9919	92	- 1	5 490 843 000	488 753 082	- 91	72 724 941 000	7 573 903 090	- 90
70	BANK SOYUZ (AO)	0,9744	154	- 3	1 081 035 000	555 313 930	- 49	68 247 137 000	14 566 599 497	- 79
71	TSENTROKREDIT, AO AKB	1	1	- 0	1 193 016 000	1 192 745 237	- 0	17 093 473 000	17 093 049 860	- 0
72	LOKO-BANK (AO), KB	0,9745	153	- 3	182 986 000	178 322 431	- 3	59 739 975 000	27 461 506 578	- 54
73	RN BANK, AO	0,9999	38	- 0	309 873 000	309 843 017	- 0	13 217 495 000	13 216 216 087	- 0
74	METALLINVESTBANK, PAO AKB	0,9849	128	- 2	1 798 485 000	809 545 376	- 55	49 104 086 000	26 545 077 791	- 46
75	EICH-ES-BI-SI BANK (RR),	0,9846	130	- 2	143 520 000	141 313 529	- 2	41 809 142 000	11 446 259 990	- 73

Appendix 12 (continuation)

				Capital	Fixed Assets			Deposits		
No.	DMU	Score	Rank	Diff.(%)	Data	Projection	Diff.(%)	Data	Projection	Diff.(%)
76	BANK KREDIT SVISS (MOSKVA), AO	0,9989	51	- 0	209 863 000	203 828 154	- 3	2 801 793 000	2 798 620 444	- 0
77	BALTISKI BANK, PAO	1	1	- 0	2 618 793 000	2 618 747 134	- 0	56 911 746 000	56 911 409 100	- 0
78	METKOMBANK, PAO	0,9578	168	- 4	181 518 000	173 855 933	- 4	33 085 036 000	15 031 572 712	- 55
79	DOICHE BANK, OOO	0,9697	159	- 3	293 239 000	284 346 209	- 3	45 322 732 000	12 782 492 128	- 72
80	OFK BANK, PAO	0,9928	89	- 1	436 753 000	433 606 036	- 1	27 935 206 000	8 949 108 339	- 68
81	SOTSINVESTBANK, AO	1	1	- 0	2 638 099 000	2 637 912 879	- 0	23 220 087 000	23 219 933 069	- 0
82	EKSPOBANK, OOO	0,9787	145	- 2	1 927 560 000	774 906 349	- 60	42 154 146 000	5 358 517 068	- 87
83	KRAIINVESTBANK, PAO	0,9611	163	- 4	1 131 475 000	1 087 435 175	- 4	53 822 766 000	48 011 971 619	- 11
84	BBR BANK (AO)	0,9938	87	- 1	1 116 783 000	718 339 691	- 36	44 586 180 000	21 874 848 598	- 51
85	SDM-BANK (PAO)	0,9851	127	- 1	1 388 531 000	771 125 672	- 44	48 493 707 000	3 787 967 769	- 92
86	BANK INTEZA, AO	0,9583	165	- 4	1 685 467 000	1 076 413 772	- 36	30 523 202 000	14 376 447 694	- 53
87	BANK SGB, PAO	0,9887	114	- 1	1 906 620 000	706 007 231	- 63	49 012 462 000	9 888 074 141	- 80
88	EVROFINANS MOSNARBANK, AO AKB	0,9763	150	- 2	2 566 036 000	773 842 911	- 70	22 688 281 000	6 274 435 636	- 72
89	TOIOTA BANK, AO	0,987	122	- 1	212 343 000	209 582 579	- 1	16 493 358 000	12 416 580 757	- 25
90	BNP PARIBA BANK AO	0,9743	155	- 3	70 657 000	68 841 895	- 3	20 039 057 000	11 379 915 335	- 43
91	SMBSR BANK, AO	0,9746	152	- 3	97 603 000	95 122 084	- 3	30 224 169 000	12 065 737 392	- 60
92	PRIMSOTSBANK, PAO SKB PRIMORYA	0,9896	107	- 1	1 024 019 000	795 246 232	- 22	41 762 294 000	12 450 452 126	- 70
93	BKS BANK, AO	0,9913	96	- 1	163 489 000	162 067 870	- 1	46 285 581 000	16 535 327 013	- 64
94	CHELYABINVESTBANK,	0,9802	141	- 2	2 401 397 000	753 137 553	- 69	37 419 522 000	13 288 201 190	- 64
95	LEVOBEREZHNY BANK	0,9898	103	- 1	1 582 905 000	779 143 583	- 51	39 002 563 000	14 983 008 476	- 62
96	CHELINDBANK, PAO	0,9827	135	- 2	2 284 291 000	760 453 334	- 67	37 945 595 000	5 231 512 377	- 86
97	FORA-BANK (AO), AKB	0,9849	128	- 2	1 086 522 000	836 562 060	- 23	39 165 967 000	5 704 380 553	- 85
98	MEZHDUNARODNY FINANSOVY KLUB, AO AKB	0,9843	131	- 2	63 319 000	62 327 555	- 2	33 528 696 000	23 188 226 964	- 31
99	VUZ-BANK, AO	1	1	- 0	148 369 000	148 368 003	- 0	22 391 013 000	22 389 738 546	- 0
100	KOMMERTSBANK (EVRAZIYA), AO	0,9752	151	- 2	65 843 000	64 213 078	- 2	24 290 218 000	9 612 897 343	- 60

Source: author