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Повышение эффективности управления операционными рисками в российских банках

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Аннотация

В настоящем исследовании рассматривается эффективность управления операционными рисками 85 российских коммерческих банков за период 2008—2017 гг. В этом исследовании используется ориентированная на ввод модель анализа оболочки данных (DEA) с финансовыми коэффициентами для оценки эффективности управления операционным риском. В исследовании используется базовый подход к измерению операционных рисков. Кроме того, в исследовании используется чистая процентная маржа (NIM), доходность активов (ROA) и доходность собственного капитала (ROE) для измерения эффективности банков. Исследование показало, что малые банки наиболее эффективны в управлении операционным риском, в то время как крупные банки более эффективны, чем средние.

Ключевые слова: операционный риск, эффективность, анализ конвертов данных (DEA), производительность, российские банки.

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Assecs the Efficiency of Operational Risk Management in Russian Banks

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Annotation

This study examines the efficiency of operational risk management of 85 Russian commercial banks during the period 2008—2017. This study uses data envelopment analysis (DEA) with financial ratios to assess the efficiency of operational risk management. The study adopts the basic indicator approach (BIA) to measuring operational risk. Also, the study adopts net interest margin (NIM), return on assets (ROA), and return on equity (ROE) for measuring banks performance. The study found that the small banks were the most effective in managing operational risk, while large banks were more efficient than medium banks.

Keywords: operational Risk, Efficiency, Data Envelopment Analysis (DEA), Performance, Russian Banks.

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Содержание

Introduction

Banking performance is a wide concept that includes many issues, such as competition, concentration, efficiency, productivity and profitability (Bikker & Bos 2008, Heffernan 2005). There is a lot of studies that dealt with the subject of banking performance, but there is no approval among researchers on the most appropriate way to measure the efficiency and performance of banks. Most banking performance studies focus on performance and ignore the impact of risk. The study of bank performance and its relationship to risk is very important because of the long-term impact of risk factors. When looking at profitability, the risks associated with profitability indicators should also be analyzed. Research on the impact of risk on banks' performance is expanding rapidly because of its practical importance. The issue of banking risk assessment has become very important, so the study of risk preferences and their impact on bank efficiency is rapidly evolving and has become a magnet for researchers (Begumhan & Cenktan 2008).

The purpose of this study is to measure banks' performance with respect to operational risk preferences, and to assess whether operational risks are reasonably priced using the data envelopment analysis (DEA) approach which is a mathematical programming technique for measuring the performance of organizations in comparison with the boundaries in the sample. Comparing the efficiency of the Bank's operational risk management with its competitors may provide additional insights to regulatory and supervisory authorities as well as management of the Bank.

1. Literature Review

1.1. Overview of Operational Risk Concept

Operational risk is one of three major risks faced by banks, credit risk is believed to be the biggest risk to the bank, a senior risk officer in large German bank said: "more than 80% of our credit risk is really just operational risk" (a. s. khan, 2006: p. 7). ironically, over the last few years, the focus has been on developing models for measuring and managing credit risk and market risk, but most of the major losses in financial institutions were due to mismanagement of operational risks — more specifically, the behavior of individual individuals or small groups of individuals, operational risks have therefore gained more attention recently.

"Operational risk is the risk associated with business strategy, internal systems, processes, technology and mismanagement" (li sun, 2011, p. 55). in January 2001, the Basel committee on banking supervision (BCBS) convention defined operational risk as "the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events" (BCBS, 2001, p. 2). However, the committee believes that banks should not rely on this general definition, but each bank should have a unique definition of operational risk in accordance with the size, nature and complexity of its activities. Basel committee believes that shortage in understanding and managing operational risk — which almost exists in all bank activities and transactions — to a large extent might decrease the possibility of identifying and controlling some of the risks, thus, the operational loss mainly has three exposure classes namely: people, processes and systems:

1. People: people's risk determines the human error, lack of experience and fraud, including non-compliance with existing procedures and policies.

2. Processes: process risk scope includes insufficient procedures and controls for reporting, monitoring and decision-making, add also insufficient procedures for processing information, such as errors in booking transactions and failure to audit legal documents, organizational deficiencies risk surveillance and excess limits, management deficiencies in risk monitoring, such as not providing the right incentives to report risks, or not abiding by the procedures and policies in force and errors in the recording process of transactions.

3. Systems: technical: technical risks relate to model errors and implementation and lack of sufficient one's instruments for measuring of risk, information technology risks relate to deficiencies in the information system and system failure.

Operational risk management has become important for banks for the higher level of automation in rendering banking and financial services, and increase in global financial inter-linkages scope of operational risk is very wide, the most common operational risks are:

1. Transaction risk: risks arising from fraud, internal or external, failed business processes, inability to maintain business continuity, and information management.

2. Compliance risk: the risk of legal or regulatory sanction, financial loss or loss of reputation that the bank may suffer as a result of its failure to comply with any applicable laws, regulations, codes of conduct and standards of good practice, it is also called the risk of integrity because the bank's reputation is closely linked to its commitment to the principles of integrity and fair dealing.

Since operational risk is measured in terms of a total loss, there are two operational risk components: frequency and severity, effective operational risk management requires a framework designed to convert primary operational risk data into information that supports management decision making, this is much more difficult than market risk or credit risk.

1.2. Overview of Operational Risk Measurement Methods

1. The Basic Indicator Approach (BIA): the basic indicator approach (BIA) is the simplest method and can be applied by all banks. In the basic indicator approach (BIA), operating capital for operating risks is calculated as a fixed percentage of the annual positive gross income average of the financial institution for three years.

2. Standardized Approach (TSA) or Alternative Standardized Approach (ASA): In contrast to the basic indicator approach (BIA), a negative gross income can be used in a single line of action to offset the positive gross income in other lines, resulting in a lower total capital charge, however, the total cost of capital cannot be negative and therefore cannot be used as a deduction from the level of capital or market risk in the financial institution, a financial institution that uses standardized approach (TSA) must map its overall gross lines to eight business lines, which were previously determined by BCBS. for details, please refer to (BCBS, 2006).

The 2007 crisis highlighted shortcomings in the Basel II framework. The main concern was the simpler methods the basic indicator approach (BIA), standardized approach (TSA), alternative standardized approach (ASA), which reflecting lower operational risk exposure despite the highest observed losses during the crisis. These methods are based on the bank's total income as a medium for exposure to operational risk. These methods also assume the linear relationship between total income and exposure to risk, but this becomes more complex with increasing size in large organizations, making this relationship nonlinear.

3. Advanced Measurement Approach (AMA): This approach is based on the development of financial institutions for their own methodologies based on internal losses and risk measurement systems. According to BCBS (2001), the goal is to provide the opportunity for development and innovation, but this made comparisons between financial institutions difficult, and the problem of lack of transparency and lack of clarity emerged.

2011 Basel Committee revised its principles for the sound management of operational risks (BCBS-195) and issued supervisory guidelines for the AMA Approach (BCBS-196). However, in 2014, BCBS concluded that banks had made insufficient progress in applying the BCBS-292 principles, which meant that many organizations had not considered operational risks and dealt with them seriously despite losses since 2003.

4. The Operational Risk Capital-At-Risk Approach (OPCAR): This approach provides the foundation for the new approach, the standardized measurement approach (SMA), it only aims to replace the simpler approach (i.e., non-AMA).

5. The Standardized Measurement Approach (SMA): In 2016, the name SMA (BCBS-d355) appeared and the approach was expanded to replace the advanced measurement approach's (AMA). The calculation method is the same but the details have been reviewed. The new version was published by the Basel Committee as part of the final Basel III provisions in December 2017. Advanced flexible measurement method (AMA) and also the simple methods currently available Will be replaced to suit the new the standardized measurement approach (SMA) as of 2022.

2. Methodology [Data Envelopment Analysis (DEA) Application to Measure Banks Efficiency]

Researchers used different techniques to evaluate the efficiency of banks, three important surveys included bank efficiency studies:

1. The first (Berger and Humphrey 1997) in their review of 130 studies on the efficiency of banks found that 69 of them used data envelopment analysis (DEA).

2. The second (Fathi and Basoras 2010) in their review of 196 studies found that 151 of them used techniques similar to data envelopment analysis (DEA).

3. The third (Paradi and Zhu 2013) reported that there are 275 applications of Data Envelopment Analysis (DEA) in banking efficiency studies.

"Data envelopment analysis (DEA) is a mathematical programming technique for the development of production frontiers and the measurement of efficiency relative to these frontiers (Charnes et al, 1978). Data envelopment analysis (DEA), a non-parametric technique, for the estimation of production frontiers for given inputs and outputs of a set of decision-making units (DMUs). Introduced by Farrell (1957) and developed by Charnes, Cooper and Rhodes (1978), data envelopment analysis (DEA) assumes that if a unit can produce a certain level of output utilizing specific input levels, another unit of equal scale should be capable of doing the same. The most efficient producers can form a «composite producer», allowing the computation of an efficient solution for every level of input or output as a «Virtual producer» and to make comparisons." (Saha et al. 2015, p: 29). "The efficiency rate of a unit can be expressed as:

$$\frac{\text{Weighted sum of outputs}}{\text{Weighted sum of inputs}} = \frac{\sum_{i=1}^{s} u_i y_{iq}}{\sum_{j=1}^{m} v_j y_{jq}}, \quad (1)$$

$\mathbf{y_{iq}}$: is the quantity of output i produced by firm q.
$\mathbf{v_j}$: is the weight of input i.
$\mathbf{x_{jq}}$: is the quantity of input j consumed by firm q.
$\mathbf{u_i}$: is the weight of output i.
s: is the number of outputs.
m: is the number of inputs.
n: is the number of firms to be evaluated.

To estimate the efficiency rate in Formula (1) above, this is based on an estimate of the input and output weights. This requires specifying the weights Vj and Ui in advance, meaning that the decision maker must determine the relative importance of the inputs and outputs in the analysis, thus modules can be rated from worst to best performing. Data envelopment analysis (DEA) models derive input and output weights by optimizing. Accordingly, units can be classified as efficient and inefficient. The data envelopment analysis (DEA) analysis can determine the target values for inputs and outputs that may lead to efficiencies." (Kristína, 2005, p. 25)

"Data envelopment analysis (DEA) helps to identify efficient companies to build efficient production frontier. Data envelopment analysis (DEA) models measure the relative efficiency that is the efficiency of each company relative to similar companies in the sample, thus applying data envelopment analysis (DEA) in evaluating the performance of a set of companies, it is possible to form two groups: companies that comprise an efficient frontier and inefficient companies lying below the frontier. In applying the data envelopment analysis (DEA) model, the efficiency score is estimated as the ratio of weighted outputs to weighted inputs (Charnes et al.1978). Weights are selected for each variable of every analyzed unit in order to maximize its efficiency score. The efficiency rate for each unit of DMU is evaluated relative to the other set members (Charnes et al. 1978). The maximal efficiency score is equal to 1, and the lower values indicate relative inefficiency of the analyzed DMU." (Jelena et al. 2014, p. 742—743). "However, there are two conditions, the first is that the efficiency of any other units in the population should not be more than 1, the second condition is that weights of all inputs and outputs must be greater than zero. Such a model is defined as a linear divisive programming model:" (Kristína, 2005, p. 25).

$$\text{Maximize: } \frac{\sum_{i=1}^{s} u_i y_{iq}}{\sum_{j=1}^{m} v_j y_{jq}},$$

$$\text{Subject to: } \frac{\sum_{r=1}^{s} u_i y_{iq}}{\sum_{i=1}^{m} v_j x_{jq}}, \leq 1 \ k = 1, 2 \ldots, n \qquad (2)$$

where: $ui \geq \epsilon$ $i = 1, 2, \ldots, s$. $vj \leq \epsilon$ $i = 1, 2, \ldots, m$.

y_{iq}: is the quantity of output i produced by firm q.
v_j: is the weight of input i.
x_{jq}: is the quantity of input j consumed by firm q.
u_i: is the weight of output i.
s: is the number of outputs.
m:is the number of inputs.
n:is the number of firms to be evaluated.

"This model can be converted into a linear programming model1 and transformed into a matrix:

$$\text{Maximize: } z = u^T Y_q \qquad (3)$$
$$\text{Subject to: } v^T X_q = 1$$
$$u^T y - v^T X \quad \text{Where: } u \geq \epsilon, v \leq \epsilon.$$

Model (3) is often called the primary CCR (Charnes, Cooper, Rhodes) model. The dual model to this can be stated as follows:" (Kristína, 2005, p. 25).

$$\text{Maximize: } f = \theta - \epsilon\,(e^T s^+ + (e^T s^-) \qquad (4)$$
$$\text{Subject to: } Y\lambda - s^+ = Y_q$$
$$X\lambda + s^- = \theta Xq \quad \text{Where: } \lambda, s^+, s^- \geq 0.$$

$\lambda = (\lambda_1, \lambda_2, \lambda_n)$, $\lambda_1 \geq 0$, is a vector assigned to individual productive units.

s^+ and s^-, are vectors of addition input and output variables.

$e^T = (1, 1, \ldots, 1)$ and ϵ, is a constant1 greater than zero, which is normally pitched at 10^{-6} or 10^{-8}.

[1] The term linear programming consists of two words explaining the substance of this particular branch of operational research. Programming is a synonym for predicting future development. The word linear means that all equations and inequalities used in the model are linear (Jablonský, 2002. cited in Ing, 2005, p. 25)

"In evaluating the efficiency of unit DMU_q, model (4) seeks a virtual unit characterized by inputs $X\lambda$ and outputs $Y\lambda$, which are a linear combination of inputs and outputs of other units of the population and which are better that the inputs and outputs of unit DMU_q which is being evaluated. For inputs of the virtual unit $X\lambda < X_q$ and for outputs $Y\lambda > Y_q$. Unit DMUq is rated efficient if no virtual unit with requested traits exists or if the virtual unit is identical with the unit evaluated, i.e. $X\lambda = X_q$ and $Y\lambda = Y_q$. If unit DMU is CCR efficient, then:

- The value of variable θ is zero.
- The values of all additional variables s^+ and s^- equal zero." (Kristína, 2005, p. 25).

"Consequently, unit DMU_q is the primary CCR (Charnes, Cooper, Rhodes) model efficient if the optimum value of the model (4) objective function equals one. Otherwise, the unit is inefficient. The optimum value of the objective function/* marks the efficiency rate of the unit concerned. The lower the rate, the less efficient the unit is compared to the rest of the population. In inefficient units θ is less than one. This value shows the need for a proportional reduction of inputs for unit DMU q to become efficient. The advantage of the data envelopment analysis (DEA) model is that it advises how the unit evaluated should mend its behavior to reach efficiency. Models (3) and (4) are input-oriented — they try to find out how to improve the input characteristics of the unit concerned for it to become efficient" (Kristína, 2005, p. 25).

On the other hand, there are output-oriented models, but we will not address that because our study uses an input-oriented model. In data envelopment analysis (DEA) models, the input-oriented models are the most used to measure bank efficiency (Arshinova 2011; Asror 2010; Yang 2009; Zreika, Ekanj 2011). This is because bank managers have more control over inputs rather than outputs (Fethi,Pasiouras 2010).

"Later, the model was modified to the model Banker, Charnes, & Cooper (BCC) in 1984, which used the variable returns to scale technology (VRS) assumption. The variable returns to scale technology (VRS) assumption suggests that equiproportionate increases in factor inputs yield a greater (or less) than equiproportionate increase in output (Heffernan, S. 2005). Experts point to the fact that constant returns to scale (CRS) can only be applied for the companies which operate optimally (Coelli et al. 2005). However, in many industries (including banking sector) such factors, as imperfect competition or government regulations, may cause the deviation from an optimal scale (Coelli et al. 2005; Beccalli et al. 2006; Singh et al. 2008). In addition, the variable returns to scale technology (VRS) is considered to be a more appropriate assumption for measuring efficiency in developed banking sector (McAllister & McMaus 1993; Wheelock & Wilson 1995)." (Jelena et al, 2014, p. 743—744). So, our study will use variable returns to scale technology (The variable returns to scale technology (VRS) model).

3. Empirical Analysis

3.1. Data and Variables

This study aims to assess the operational risks efficiency and financial performance of Russian commercial banks according to the data envelopment analysis (DEA) relative efficiency measurement characteristic. This banks group should be as homogeneous as possible to be meaningful. Therefore, banks with the largest assets were selected. In this study, the data of the largest 85 Russian banks. The total assets of the largest 85 banks selected for the study constitute 87% of the total assets of the banking sector in Russia. We divided the banks into three equal groups based on the size of the assets. The first group consisted of 28 banks, it included the banks which have total assets between (270 billion Rubles to 23 trillion Rubles) were categorized as large banks, The second group consisted of 29 banks, and included the banks which have total assets of between (102—270 billion Rubles) were categorized as medium banks, and The third group consisted of 28 banks, and included the banks which have total assets of between(5 — 102 billion Rubles) were categorized as small banks. The sample panel data include the year-end data for the period 2008—2017. This study uses financial ratios, simple regression and data envelopment analysis (DEA) model to assess the efficiency of Russian banks in managing operational risks. All study data were obtained from the official website of the Bank of Russia. The study period includes 10 years (2008—2017). Table 1 defines the study variables, their abbreviations and the method of calculation.

Table 2 and Figure 1 shows the average of operational risks in Russian banks according to the size of the banks calculated on the basis of the basic indicator approach (BIA).

The next step is to find the appropriate variables to be included in the data envelopment analysis (DEA) model as inputs and outputs. The discriminatory power of the data envelopment analysis (DEA) will be reduced when there are a large number of variables. Therefore, until this problem is overcome, the variables must be minimized using appropriate scientific methods. This issue has been widely discussed and there are many ways to choose variables (Jenkins, Anderson, (2003); Fanchon, (2003); Ruggiero, (2005); Adler, Yazhemsky (2010); Luo, Liang (2012); Xie et al. (2014); Niranjan et al. (2011), Hiroshi Morita et.al., (2009); Subramanyam T (2016)). Here in our study, we will select the variables by analyzing the multiple regression of the variables to find the effect of dependent variables (inputs) on the independent variables (outputs) and then we will choose the variables with statistical significance.

3.2. The Simple-Regression Model

A general linear model of simple — regression is outlined in equation (5) where Y indicates the dependent variables (outputs), α is the constant, β is the regression coefficient, X is the independent factor (input) and finally, ε is a random factor.

$$Y = \alpha + \beta_1 X_1 + \varepsilon. \quad (5)$$

Table 1. Variables Definition and Measurement Units

Variables	Description	Abbreviation Variables	Proxy
Independent variables (Inputs)	Operational Risk	OPR	(Gross Income) / (Total Shareholder's Equity)
Dependent variables (Outputs)	Net Interest Income	NIM	(Net Interest Income) / (Total Assets)
	Return On Assets	ROA	(Income After Tax) / (Total Assets)
	Return On Equity	ROE	(Income After Tax) / (Total Shareholders' Equity)

Source: Author Design.

Table 2. The Average of Operational Risk in Russian Banks Based on The Basic Indicator Approach (BIA) (2008—2017)

Years	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
Large Banks	0.65	0.48	0.64	0.64	0.59	0.59	0.59	-0.58	0.31	0.45	**0.44**
Medium Banks	0.57	0.42	0.55	0.69	0.68	0.69	0.55	0.26	0.58	0.55	**0.55**
Small Banks	0.60	0.55	0.44	0.50	0.50	0.45	0.45	0.40	0.39	0.54	**0.48**
Mean	**0.61**	**0.49**	**0.54**	**0.61**	**0.59**	**0.58**	**0.53**	**0.03**	**0.43**	**0.51**	**1.47**

Source: Design and Calculation by Author Using (Excel). Data Source: Bank of Russia Website.

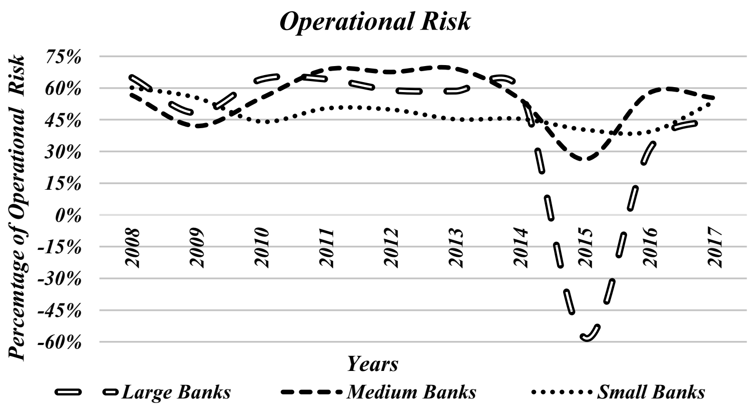

Figure 1. The Average of Operational Risk in Russian Banks Based on The Basic Indicator Approach (BIA) (2008—2017)
Source: Design and Calculation by Author Using (Excel And SPSS Software). Data Source: Bank of Russia Websit.

Net interest margin (MM), return on assets (ROA), and return on equity (ROE) are the factors of profitability and performance that are influenced by operational risks (OPR) factor. By putting the study variables in the above equation, three equations can be formed as follows:

$NIM = \alpha + \beta_1$ [*(Gross Income)/(Total Shareholder's Equity)*]. (6)
$ROA = \alpha + \beta_1$ [*(Gross Income)/(Total Shareholder's Equity)*]. (7)
$ROE = \alpha + \beta_1$ [*(Gross Income)/(Total Shareholder's Equity)*]. (8)

3.2.1. The Main Hypotheses

The main hypotheses can be formulated as follows:

H_o: Operational risks (OPR) don't affect financial performance (expressed by NIM, ROA and ROE) of the Russian commercial banks. H_1: Operational risks (OPR) affect financial performance (expressed by NIM, ROA, and ROE) in Russian commercial banks.

3.2.1.1. The Subset Hypothesis

1 — NIM Model:

H_o: Operational risks (OPR) doesn't affect MM in Russian banks. H_i: Operational risks (OPR) affect MM in Russian banks.

2 — ROA Model:

H_o: Operational risks (OPR) doesn't affect ROA in Russian banks. H_1: Operational risks (OPR) affect ROA in Russian banks.

3 — ROE Model:

H_o: Operational risks (OPR) doesn't affect ROE in Russian banks. H_1: Operational risks (OPR) affect ROE in Russian banks.

Based on the main and Subset hypotheses above, three sub-hypotheses will be tested for each year of study years which are MM model, ROA model and ROE model, because the study years are 10 years, therefore 30 models will be tested, 3 models for each year.

3.2.2. Testing(F) For the Suitability of The Research Models

To examine the suitability of the multiple regression models for analysis, by using the distribution (F-statistic) test, one of the following hypotheses will be rejected:

H_o: The model is unsuitable; when the independent variables don't affect the dependent variables.

H_1. The model is suitable; when the independent variables do affect the dependent variables. The decision rule as follows:

Accept H_o If p-value (Sig. F) > 0.05

Accept H_i vp-value (Sig. F) < 0.05

From the analysis output in Table 3, the results as follow: The Models (1), (2), (3), (4), (5), (6), (8), (9), (10), (11), (12), (13), (14), (15), (16) (17), (18), (19), (24), (25), (26), (27) and (28): values of p-value (Sig. F) < 0.05, So we shall refuse the null hypothesis H_o and accept the alternative hypothesis H_i, that means At the a = 0.05 level of significance, there is enough evidence to conclude that the predictor is useful for predicting the NIM or ROA or ROE ; therefore, the models are suitable.

The Models (7), (20), (21) ,(22), (23), (29) and (30): values of p-value (Sig. F) > 0.05 ,So we shall accept the null hypothesis Ho and refuse the alternative hypothesis Hi, that means At the a = 0.05 level of significance, there isn't enough evidence to conclude that the predictor is useful for predicting the MM or ROA or ROE ; therefore, the models are unsuitable (Table 3).

3.2.3. R-square for the Appropriate Models

Table 4 showing the variability percentage of independent variables. The (R square) demonstrates the relationship between dependent and independent variables whereas (R) represents the square root of (R). The value of (R) points out how independent variables are associated with MM, ROA and ROE.

Moreover, the (adjusted R square) mentions the statistical shrinkage of risks variables. Simply, (adjusted R square) refers to the compatibility of independent variables with dependent ones in order to validate the decisions based on the regression model (Table 4).

3.2.4. Testing (T) For the Appropriate Models

To examine the suitability of the multiple regression models for analysis, by using the distribution (T-statistic) test, one of the following hypotheses will be rejected:

H_o. The model is not suitable (when the independent variables don't affect the dependent variables).

Table 3. F-Test — ANOVA (2008—2017)

Years	Model Name	Model #	F-Statistic	Sig. F-Statistic	The Decision	Years	Model Name	Model #	F-Statistic	Sig. F-Statistic	The Decision
2008	NIM	Model (1)	4.328	.041[a]	Suitable	2013	NIM	Model (16)	67.162	.000[a]	Suitable
	ROA	Model (2)	8.523	.005[a]	Suitable		ROA	Model (17)	25.494	.000[a]	Suitable
	ROE	Model (3)	26.400	.000[a]	Suitable		ROE	Model (18)	50.934	.000[a]	Suitable
2009	NIM	Model (4)	6.077	.016[a]	Suitable	2014	NIM	Model (19)	22.077	.000[a]	Suitable
	ROA	Model (5)	31.714	.000[a]	Suitable		ROA	Model (20)	1.692	.197[a]	Unsuitable
	ROE	Model (6)	50.204	.000[a]	Suitable		ROE	Model (21)	.202	.654[a]	Unsuitable
2010	NIM	Model (7)	1.979	.163[a]	Unsuitable	2015	NIM	Model (22)	.327	.569[a]	Unsuitable
	ROA	Model (8)	5.498	.021[a]	Suitable		ROA	Model (23)	.145	.705[a]	Unsuitable
	ROE	Model (9)	19.559	.000[a]	Suitable		ROE	Model (24)	43.900	.000[a]	Suitable
2011	NIM	Model (10)	44.921	.000[a]	Suitable	2016	NIM	Model (25)	15.518	.000[a]	Suitable
	ROA	Model (11)	4.442	.038[a]	Suitable		ROA	Model (26)	28.063	.000[a]	Suitable
	ROE	Model (12)	31.693	.000[a]	Suitable		ROE	Model (27)	49.373	.000[a]	Suitable
2012	NIM	Model (13)	48.921	.000[a]	Suitable	2017	NIM	Model (28)	5.269	.024[a]	Suitable
	ROA	Model (14)	12.966	.001[a]	Suitable		ROA	Model (29)	.362	.549[a]	Unsuitable
	ROE	Model (15)	51.516	.000[a]	Suitable		ROE	Model (30)	2.721	.103[a]	Unsuitable

Source: Design and Calculation by Author Using (Excel And SPSS Software). Data Source: Bank of Russia Website.

Table 4. The Total Variation in The Dependent Variables (2008—2017)

Years	Model Name	Model #	R^2	Adjusted R^2	Sig. R	The Decision	Years	Model Name	Model #	R^2	Adjusted R^2	Sig. R	The Decision
2008	NIM	Model (1)	.050	.038	.223[a]	Suitable	2013	NIM	Model (16)	.447	.441	.669[a]	Suitable
	ROA	Model (2)	.093	.082	.305[a]	Suitable		ROA	Model (17)	.235	.226	.485[a]	Suitable
	ROE	Model (3)	.241	.232	.491[a]	Suitable		ROE	Model (18)	.380	.373	.617[a]	Suitable
2009	NIM	Model (4)	.068	.057	.261[a]	Suitable	2014	NIM	Model (19)	.210	.201	.458[a]	Suitable
	ROA	Model (5)	.276	.268	.526[a]	Suitable		ROA	Model (20)	*	*	*	Unsuitable
	ROE	Model (6)	.377	.369	.614[a]	Suitable		ROE	Model (21)	*	*	*	Unsuitable
2010	NIM	Model (7)	*	*	*	Unsuitable	2015	NIM	Model (22)	*	*	*	Unsuitable
	ROA	Model (8)	.062	.051	.249[a]	Suitable		ROA	Model (23)	*	*	*	Unsuitable
	ROE	Model (9)	.191	.181	.437[a]	Suitable		ROE	Model (24)	.346	.338	.588[a]	Suitable
2011	NIM	Model (10)	.351	.343	.593[a]	Suitable	2016	NIM	Model (25)	.158	.147	.397[a]	Suitable
	ROA	Model (11)	.051	.039	.225[a]	Suitable		ROA	Model (26)	.253	.244	.503[a]	Suitable
	ROE	Model (12)	.276	.268	.526[a]	Suitable		ROE	Model (27)	.373	.365	.611[a]	Suitable
2012	NIM	Model (13)	.371	.363	.609[a]	Suitable	2017	NIM	Model (28)	.060	.048	.244[a]	Suitable
	ROA	Model (14)	.135	.125	.368[a]	Suitable		ROA	Model (29)	*	*	*	Unsuitable
	ROE	Model (15)	.383	.376	.619[a]	Suitable		ROE	Model (30)	*	*	*	Unsuitable

* A Model Was Excluded Because It Failed to Pass An F-Test That Measures the Suitability of The Model for Prediction.
Source: Design and Calculation by Author Using (Excel and SPSS software). Data Source: Bank of Russia Website.

Table 5. T-Test (2008—2017)

Years	Outputs	Model #	Inputs	B	T Statistic	Sig. Statistic	The Decision	Years	Outputs	Model #	Inputs	B	T Statistic	Sig. Statistic	The Decision
2008	NIM	Model (1)	constant OPR	.048 .019	7.180 2.080	.000 .041	Suitable Suitable	2013	NIM	Model (16)	constant OPR	.012 .071	1.992 8.195	.050 .000	Suitable Suitable
	ROA	Model (2)	constant OPR	.000 .015	.054 2.919	.957 .005	Unsuitable Suitable		ROA	Model (17)	constant OPR	-.001 .024	-.161 5.049	.873 .000	Unsuitable Suitable
	ROE	Model (3)	constant OPR	-.254 .476	-3.700 5.138	.000 .000	Suitable Suitable		ROE	Model (18)	constant OPR	-.001 .189	-.067 7.137	.947 .000	Unsuitable Suitable
2009	NIM	Model (4)	constant OPR	.044 .032	5.471 2.465	.000 .016	Suitable Suitable	2014	NIM	Model (19)	constant OPR	.022 .054	2.966 4.699	.004 .000	Suitable Suitable
	ROA	Model (5)	constant OPR	-.023 .054	-3.784 5.632	.000 .000	Suitable Suitable		ROA	Model (20)	constant OPR	* *	* *	* *	Unsuitable Unsuitable
	ROE	Model (6)	constant OPR	-.151 .355	-4.832 7.086	.000 .000	Suitable Suitable		ROE	Model (21)	constant OPR	* *	* *	* *	Unsuitable Unsuitable
2010	NIM	Model (7)	constant OPR	* *	* *	* *	Unsuitable Unsuitable	2015	NIM	Model (22)	constant OPR	* *	* *	* *	Unsuitable Unsuitable
	ROA	Model (8)	constant OPR	.004 .013	.905 2.345	.368 .021	Unsuitable Suitable		ROA	Model (23)	constant OPR	* *	* *	* *	Unsuitable Unsuitable
	ROE	Model (9)	constant OPR	-.028 .166	-1.073 4.423	.286 .000	Unsuitable Suitable		ROE	Model (24)	constant OPR	-.334 .336	-2.090 6.626	.040 .000	Suitable Suitable
2011	NIM	Model (10)	constant OPR	.017 .058	2.711 6.702	.008 .000	Suitable Suitable	2016	NIM	Model (25)	constant OPR	.035 .026	7.675 3.939	.000 .000	Suitable Suitable
	ROA	Model (11)	constant OPR	-.002 .022	-.321 2.108	.749 .038	Unsuitable Suitable		ROA	Model (26)	constant OPR	-.014 .034	-3.179 5.297	.002 .000	Suitable Suitable
	ROE	Model (12)	constant OPR	-.016 .206	-.604 5.630	.548 .000	Unsuitable Suitable		ROE	Model (27)	constant OPR	-.173 .368	-4.896 7.027	.000 .000	Suitable Suitable
2012	NIM	Model (13)	constant OPR	.016 .055	2.962 6.994	.004 .000	Suitable Suitable	2017	NIM	Model (28)	constant OPR	.037 .017	7.126 2.295	.000 .024	Suitable Suitable
	ROA	Model (14)	constant OPR	-.004 .038	-.612 3.601	.542 .001	Unsuitable Suitable		ROA	Model (29)	constant OPR	* *	* *	* *	Unsuitable Unsuitable
	ROE	Model (15)	constant OPR	-.012 .226	-.573 7.177	.568 .000	Unsuitable Suitable		ROE	Model (30)	constant OPR	* *	* *	* *	Unsuitable Unsuitable

A model was excluded because it failed to pass an f-test that measures the suitability of the model for prediction.

Source: Design and Calculation by Author Using (Excel and SPSS software). Data Source: Bank of Russia Website.

H_1. The model is suitable (when the independent variables affect the dependent variables).

The decision rule as follows: Accept H_o If p-value (Sig. T) > 0.05, Accept H_1 If p-value (Sig. T) < 0.05 (Table 5).

From the T-test analysis in Table 5, the results as follow:

The Models (1), (3), (4), (5), (6), (10), (13), (16), (19), (24), (25), (26), (27) and (28): values of p-value (Sig. T) < 0.05 ,So we shall refuse the null hypothesis H_o and accept the alternative hypothesis H_1, that means At the $\alpha = 0.05$ level of significance, there exists enough evidence to conclude that the slope (B) of the variables mentioned above is not zero and, hence, that variables are useful for predicting MM, ROA and ROE in Russian banks; therefore, the models are suitable.

The Models (2), (8), (9), (11), (12), (14), (15), (17) and (18): values of p-value (Sig. T) < 0.05 for (OPR), but for (constant) (Sig. T) > 0.05, So we shall refuse the null hypothesis H_o and accept the alternative hypothesis H_1 with exclusion the constant of the regression equation , that means At the $\alpha = 0.05$ level of significance, there exists enough evidence to conclude that the slope (B) of the variable (OPR) is not zero Thus, this variable is useful for predicting MM, ROA and ROE in Russian banks with exclusion the constant, therefore, the models are suitable with exclusion the constant.

Table 6. Results of Multiple Regression Analysis of Study Models

Regression Analysis Results	Models #
Accepted Models	1, 3, 4, 5, 6, 10, 13, 16, 19, 24, 25, 26, 27, 28
Accepted Models Provided the Constant is Excluded	2, 8, 9, 11, 12, 14, 15, 17, 18
Rejected Models	7, 20, 21, 22, 23, 29, 30

Source: Design and Calculation by Author Using (Excel and SPSS software). Data Source: Bank of Russia Website.

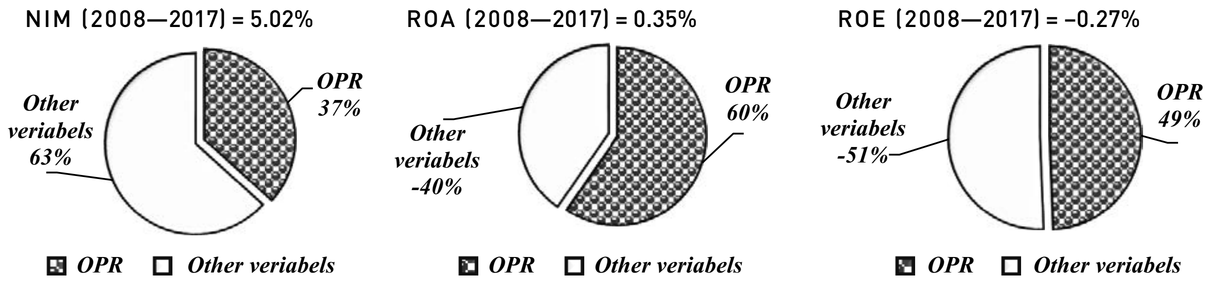

Figure 2. The Ratios of The Contribution of Operational Risk Indicators in the Formation of Performance Indicators (2008—2017)

OPR: Operational Risk. **NIM:** Net Interest Income. **ROA:** Return on Assets. **ROE:** Return on Equity.
Source: Design and Calculation by Author Using (Excel, Win4deap2 Software).
Data Source: Bank of Russia Website.

The Models (7), (20), (21) ,(22), (23), (29) and (30): values of p-value (Sig. F) > 0.05 ,So we shall accept the null hypothesis Ho and refuse the alternative hypothesis Hi, that means At the a = 0.05 level of significance, there isn't enough evidence to conclude that the variable is useful for predicting the MM or ROA or ROE ; therefore, the models are unsuitable. Table 6 below summarizes the results of multiple regression analysis (Table 6).

The value of slope B in the above Table 5 represents the ratio of effect and the type of relationship between the independent variables and the dependent variable. In order to know the importance of operational risk indicator and its impact on performance indicators, it is necessary to determine its real value compared to other variables. Therefore, we multiply the value B by the mean of the dependent variable (OPR), this makes us know the value of its effect as compared to other variables. Figure 2 shows the contribution of the operational risk index to the formation of performance indicators during the study period (2008-2017). Operational risk has contributed to the formation of NIM, ROA and ROE performance indicators at 37%, 60% and 49% respectively, reflecting the impact of operational risk on the performance of Russian banks (Figure 2).

Based on the above, inputs and outputs will be adopted in the data envelopment analysis (DEA) analysis as shown in Table 7.

3.3. The Efficiency of Operational Risk [Data Envelopment Analysis (DEA)]

Tables 8A and 8B present the results of Data Envelopment Analysis (DEA). We use an input-oriented model [data envelopment analysis (DEA) — the variable returns to scale technology (VRS)] to assess the technical efficiency of operational risk management. The results showed that no

Table 7. The Inputs and Outputs Which Will Use in Data Envelopment Analysis (DEA)

Year	Inputs	Outputs
2008	OPR	NIM,ROA,ROE
2009	OPR	NIM,ROA,ROE
2010	OPR	ROA,ROE
2011	OPR	NIM,ROA,ROE
2012	OPR	NIM,ROA,ROE
2013	OPR	NIM,ROA,ROE
2014	OPR	NIM
2015	OPR	ROE
2016	OPR	NIM,ROA,ROE
2017	OPR	NIM

OPR: Operational Risk. **NIM:** Net Interest Income. **ROA:** Return on Assets. **ROE:** Return on Equity.

Source: Author Design.

bank achieved full efficiency in operational risk management continuously in all ten years of study. In 2008 eight banks achieved the perfect efficiency score (1) namely, Banks # 32, 35, 42, 45, 49, 51, 71, and 76. while the worst bank in operational risk Management was namely, Bank # 24 with efficiency score 0.29.

In 2009 twenty-four banks achieved the perfect efficiency score (1) namely, Banks # 12, 24, 33, 39, 42, 46, 47, 48, 50, 51, 57, 59, 60, 61, 63, 64, 69, 70, 72, 73, 77, 78, 82 and 83. while the worst bank in operational risk Management was namely, Bank # 25 with efficiency score 0.12.

In 2010 three banks achieved the perfect efficiency score (1) namely, Banks # 35,41 and 69. while the worst banks in operational risk Management were namely, Banks #21 with efficiency score 0.29 (Table 8A).

In 2011 six banks achieved the perfect efficiency score 1.0, namely, Banks # 3, 12, 33, 39, 51 and 69. while the worst bank in operational risk Management was namely, Banks # 48 with efficiency score 0.42.

In 2012 three banks achieved the perfect efficiency score 1.0, namely, Banks # 23, 33 and 51. while the worst banks in operational risk Management were namely, Bank # 65 with efficiency score 0.07.

In 2013 three banks achieved the perfect efficiency score 1.0, namely, Banks # 29, 44 and 56. while the worst banks in operational risk Management were namely, Bank # 34 with efficiency score 0.29.

In 2014 nine banks achieved the perfect efficiency score 1.0, namely, Banks # 5, 21, 39, 44, 49, 61, 69, 73 and 80. while the worst banks in operational risk Management were namely, Bank # 77 with efficiency score 0.25.

In 2015 thirty two banks achieved the perfect efficiency score 1.0, namely, Banks 3, 4, 9, 11, 14, 18, 19, 20, 25, 28, 29, 31, 32, 37, 38, 40, 41, 43, 44, 45, 46, 49, 56, 59, 60, 62, 66, 79, 81, 82, 84 and 85. while the worst bank in operational risk Management was namely, Bank # 48 with efficiency score 0.01.

In 2016 eight banks achieved the perfect efficiency score 1.0, namely, Banks 3, 11, 14, 22, 36, 44, 64 and 66. while the worst bank in operational risk Management was namely, Bank # 48 with efficiency score 0.11.

In 2017 six banks achieved the perfect efficiency score 1.0, namely 22,23, 41, 44, 67 Banks and 83. while the worst bank in operational risk Management was namely, Bank #18 with efficiency score 0.08.

Table 8. The Technical Efficiency [(DEA) — Input Oriented — (VRS)] of Operational Risk Management in Russian banks (2008—2017)

Bank	Bank #	Years										Mean
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
Sberbank Of Russia	1	0.99	0.98	0.98	0.84	0.39	0.83	0.99	0.92	0.72	0.82	**0.85**
VTB Bank	2	0.81	0.96	0.84	0.78	0.52	1.00	0.33	0.99	0.97	0.90	**0.81**
Gazprombank	3	0.93	0.93	0.87	1	0.59	0.94	0.83	1	1	0.81	**0.89**
Rosselkhozbank	4	0.63	0.85	0.97	0.74	0.66	0.96	0.46	1	0.88	0.25	**0.74**
Alfa-Bank	5	0.97	0.86	0.90	0.96	0.36	0.84	1	0.85	0.99	0.95	**0.87**
Credit Bank Of Moscow	6	0.98	0.97	0.93	0.92	0.38	0.86	0.99	0.99	0.96	0.92	**0.89**
Bank Otkritie Financial Corporation	7	0.98	0.97	0.91	0.94	0.50	0.89	0.90	0.99	0.97	0.29	**0.83**
Unicredit Bank	8	0.95	0.99	0.94	0.99	0.57	0.88	0.87	0.99	0.99	0.97	**0.91**
B&N Bank	9	0.99	0.66	0.81	0.94	0.72	0.92	0.54	1	0.72	0.29	**0.76**
Promsvyazbank	10	0.64	0.68	0.91	0.97	0.43	0.82	0.49	0.91	0.98	0.40	**0.72**
Rosbank	11	0.94	0.74	0.89	0.98	0.59	0.91	0.95	1	1	0.51	**0.85**
Raiffeisenbank	12	0.88	1	0.95	1	0.46	0.82	0.99	0.93	0.69	0.85	**0.86**
Sovcombank	13	0.70	0.98	0.60	0.88	0.31	0.73	0.72	0.43	0.70	0.64	**0.67**
Bank Saint-Petersburg	14	0.99	0.97	0.84	0.95	0.70	0.87	0.95	1	1	0.93	**0.92**
Bank Uralsib	15	0.98	0.72	0.90	0.79	0.76	0.92	0.75	0.86	0.78	0.98	**0.84**
Bank RRDB	16	0.99	0.99	0.89	0.92	0.68	0.96	0.84	0.87	0.90	0.88	**0.89**

Bank	Bank #	Years										Mean
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
Citibank	17	0.54	0.96	0.81	0.99	0.48	0.82	0.98	0.57	0.71	0.71	**0.76**
Growth Bank	18	0.86	0.88	0.75	0.91	0.72	0.95	0.64	1	0.11	0.08	**0.69**
Ak Bars Bank	19	0.93	0.97	0.51	0.78	0.48	0.69	0.39	1	0.76	0.77	**0.73**
Bm-Bank	20	0.88	0.93	0.93	0.79	0.81	0.82	0.82	1	0.65	0.45	**0.81**
NB Trust	21	0.58	0.33	0.29	0.89	0.95	0.82	1	0.93	0.72	0.15	**0.66**
Mosobl bank	22	0.98	0.30	0.48	0.54	0.84	0.76	0.70	0.94	1	1	**0.75**
Smp Bank	23	0.97	0.96	0.56	0.90	1	0.89	0.95	0.98	0.80	1	**0.90**
Russian Standard Bank	24	0.29	1	0.56	0.71	0.41	0.87	0.65	0.37	0.86	0.78	**0.65**
Bank Dom.Rf	25	0.73	0.12	0.42	0.53	0.69	0.90	0.42	1	0.23	0.35	**0.54**
Novikom bank	26	0.76	0.97	0.97	0.97	0.72	0.88	0.96	0.90	0.88	0.89	**0.89**
The Ural Bank For Reconstruction And Development	27	0.88	0.42	0.87	0.68	0.90	0.81	0.96	0.91	0.93	0.25	**0.76**
Moscow Industrial Bank	28	0.98	0.99	0.85	0.75	0.96	0.95	0.82	1	0.49	0.25	**0.80**
Sviaz-Bank	29	0.44	0.66	0.83	0.99	0.83	1	0.76	1	0.66	0.88	**0.80**
HCF Bank	30	0.93	0.81	0.62	0.48	0.24	0.55	0.34	0.03	0.42	0.56	**0.50**
Absolut Bank	31	0.96	0.77	0.94	0.65	0.74	0.94	0.86	1	0.78	0.37	**0.80**
Vozrozhdenie Bank	32	1	0.98	0.82	0.97	0.68	0.83	0.97	1	0.94	0.94	**0.91**
Post Bank	33	0.99	1	1	1	1	0.55	0.49	0.29	0.66	0.77	**0.77**
Tinkoff Bank	34	0.57	0.31	0.53	0.43	0.18	0.29	0.33	0.09	0.29	0.44	**0.34**
Orient Express Bank	35	1	0.91	1	0.71	0.42	0.87	0.45	0.04	0.67	0.92	**0.70**
Surgutneftegas bank	36	0.72	0.42	0.63	0.94	0.61	0.85	0.99	0.95	1	0.98	**0.81**
Bank Zenit	37	0.98	0.99	0.83	0.90	0.98	0.94	0.80	1	0.37	0.31	**0.81**
Trans kapital bank	38	0.98	0.99	0.94	0.95	0.46	0.78	0.98	1	0.92	0.32	**0.83**
Rosevro bank	39	0.99	1	0.91	1	0.35	0.81	1	0.66	0.72	0.94	**0.84**
Nordea Bank	40	0.87	0.95	0.97	0.88	0.68	0.90	0.96	1	0.80	0.98	**0.90**
Cb Deltacredit	41	0.97	0.91	1	0.94	0.47	0.87	0.98	1	0.70	1	**0.88**
Ing Bank (Eurasia)	42	1	1	0.97	0.97	0.61	0.53	0.87	0.88	0.86	0.90	**0.86**
Mts Bank	43	0.70	0.50	0.49	0.46	0.76	0.90	0.84	1	0.98	0.97	**0.76**
Avers	44	0.93	0.96	0.86	0.83	0.92	1	1	1	1	1	**0.95**
Renaissance Credit	45	1	0.92	0.77	0.73	0.33	0.87	0.72	1	0.13	0.55	**0.70**
Invest trade bank	46	0.89	1	0.72	0.87	0.98	0.91	0.91	1	0.72	0.18	**0.82**
Cetelem Bank	47	0.68	1	0.88	1.00	0.45	0.89	0.98	0.31	0.92	0.78	**0.79**
Jsc "Otp Bank"	48	0.72	1	0.76	0.42	0.41	0.86	0.37	0.01	0.11	0.78	**0.54**
Joint Stock West Siberian Commercial Bank	49	1	0.97	0.84	0.99	0.40	0.75	1	1	0.97	0.98	**0.89**
Avangard Joint Stock Bank	50	0.99	1	0.85	0.93	0.57	0.75	0.98	0.81	0.79	0.91	**0.86**

Bank	Bank #	Years										Mean
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
Bank Finservice	51	1	1	0.95	1	1	0.93	0.93	0.77	0.81	0.77	**0.92**
Skb-Bank	52	0.98	0.97	0.86	0.83	0.40	0.82	0.62	0.81	0.72	0.98	**0.80**
Rgs Bank	53	0.84	0.89	0.87	0.94	0.78	0.86	0.95	0.99	0.93	0.31	**0.83**
Rusfinance Bank	54	0.99	0.92	0.71	0.60	0.49	0.85	0.70	0.17	0.59	0.77	**0.68**
Credit Europe Bank Ltd	55	0.72	0.98	0.98	0.86	0.50	0.83	0.79	0.27	0.69	0.99	**0.76**
Globexbank	56	0.69	0.99	0.79	0.88	0.74	1	0.33	1	0.35	0.83	**0.76**
Asian-Pacific Bank	57	0.92	1	0.72	0.84	0.34	0.64	0.88	0.99	0.80	0.64	**0.78**
Center-Invest Bank	58	0.97	0.95	0.91	1.00	0.45	0.82	0.99	0.93	0.94	0.93	**0.89**
Sme Bank	59	0.97	1	0.75	0.73	0.47	0.73	0.51	1	0.88	1.00	**0.80**
Eximbank Of Russia	60	0.83	1	1.00	0.82	0.76	0.94	0.38	1	0.81	0.64	**0.82**
Kuban Credit	61	0.78	1	0.93	0.98	0.71	0.83	1	0.95	0.88	0.96	**0.90**
Baltinvestbank	62	0.87	0.83	0.78	0.94	0.90	0.83	0.83	1	0.70	0.22	**0.79**
Locko-Bank	63	0.98	1	0.92	0.93	0.39	0.81	0.98	0.69	0.79	0.95	**0.84**
Hsbc Bank (Rr)	64	0.83	1	0.77	0.95	0.80	0.89	0.89	0.89	1	0.96	**0.90**
Rn Bank	65	0.75	0.87	0.90	0.94	0.07	0.89	0.65	0.78	0.68	0.71	**0.72**
Bank Soyuz	66	0.54	0.74	0.52	0.81	0.86	0.80	0.91	1	1	0.99	**0.82**
Deutsche Bank	67	0.95	0.92	0.91	0.63	0.41	0.89	0.94	0.89	0.89	1	**0.84**
Metallinvestbank	68	0.84	0.99	0.79	0.93	0.56	0.91	0.88	0.91	0.82	0.97	**0.86**
Centro Credit Bank	69	0.99	1	1	1	0.73	0.74	1	0.80	0.88	0.71	**0.88**
Expobank	70	0.65	1	0.83	0.77	0.79	0.76	0.98	0.60	0.75	0.99	**0.81**
Sdm-Bank	71	1	0.96	0.94	0.97	0.40	0.86	0.97	0.81	0.75	0.98	**0.86**
Bbr Bank	72	0.99	1	0.90	0.95	0.97	0.79	0.99	0.64	0.93	0.87	**0.90**
Toyota Bank	73	0.31	1	0.91	0.99	0.54	0.69	1	0.67	0.87	0.98	**0.80**
Banca Intesa	74	0.75	0.92	0.86	0.98	0.81	0.89	0.88	0.18	0.76	0.53	**0.76**
Primsotsbank	75	0.62	0.99	0.86	0.62	0.31	0.82	0.96	0.76	0.70	0.69	**0.73**
Bcs Bank	76	1	0.97	0.80	0.86	0.87	0.95	0.95	0.97	0.86	0.94	**0.92**
Bnp Paribas Bank	77	0.84	1	0.95	0.96	0.86	0.93	0.25	0.92	0.98	0.60	**0.83**
Levoberezhny	78	0.66	1	0.95	0.77	0.29	0.74	0.96	0.77	0.75	0.59	**0.75**
International Financial Club	79	0.95	0.70	0.77	0.95	0.97	0.83	0.55	1	0.91	0.67	**0.83**
Chelindbank	80	0.97	0.96	0.83	0.98	0.89	0.75	1	0.89	0.91	0.98	**0.92**
Credit Agricole Cib	81	0.80	0.99	0.76	0.93	0.92	0.93	0.85	1	0.86	0.51	**0.85**
Chelyabinvestbank	82	0.99	1	0.87	0.99	0.60	0.76	0.99	1	0.96	0.87	**0.90**
Commerzbank (Eurasija)	83	0.88	1	0.92	0.58	0.96	0.90	0.93	0.88	0.97	1	**0.90**
Sotsinvestbank	84	0.95	0.92	0.84	0.74	0.62	0.94	0.85	1	0.21	0.33	**0.74**
Mosuralbank	85	0.93	0.98	0.89	0.93	0.91	0.91	0.95	1	0.85	0.76	**0.91**
Mean		**0.86**	**0.89**	**0.83**	**0.85**	**0.63**	**0.84**	**0.81**	**0.83**	**0.78**	**0.73**	**0.80**

Source: Design and Calculation by Author Using (Excel, Win4deap2 Software).
Data Source: Bank of Russia Website.

The year 2009 was the best year in the efficiency of operational risk management during the study period, where the average efficiency of banks combined to score 89%, while in 2012 was the worst, the average efficiency of banks combined score was 63%. In 2008, 2010, 2011, 2013, 2014, 2015, 2016 and 2017 the measure of the efficiency of operational risk management for banks combined were score 86%, 83%, 85%, 84%, 81%, 83%, 78%, 73% respectively. The average operational risk efficiency of the combined banks from 2008-2017 indicates that Russian banks could have reduced their inputs (operational risk) by 14%, 11%, 17%, 15%, 37%, 16%, 19%, 17%, 23% and 27% % Respectively.

Efficiency of operational risk management also indicates that the profitability of banks is exactly in parallel with their operational risk — taking preferences in a bank for five years, three banks for four years, three banks for three years, twenty-one banks for two years and thirty four banks for a year. This means that these banks may have had good operational risk management in those years, It also means that these banks were working better than other banks in those years because their degrees of efficiency is equal to (1). On the other hand, there were twenty-three banks that have never achieved the full degree of efficiency (1) over the ten-year period. This means that the profitability of those banks did not reasonably match their operational risk levels as expected. Many banks could have achieved higher returns at the same operational risk levels or could have achieved the same returns at lower risk levels (Table 9).

Table 9 shows the average technical efficiency of operational risk management according to the size of the banks.

Table 9. The Average Technical Efficiency [(DEA) — Input Oriented — (VRS)] of operational Risk Management by Size of Russian Banks (2008 — 2017)

Years	Large banks	Medium banks	Small banks	Mean
2008	0.85	0.88	0.84	0.86
2009	0.82	0.89	0.95	0.89
2010	0.79	0.83	0.86	0.83
2011	0.86	0.83	0.88	0.85
2012	0.63	0.60	0.67	0.63
2013	0.87	0.81	0.84	0.84
2014	0.78	0.79	0.86	0.81
2015	0.90	0.73	0.85	0.83
2016	0.80	0.70	0.83	0.78
2017	0.64	0.75	0.80	0.73
Mean	0.79	0.78	0.84	0.80

Source: design and calculation by Author using (Excel, Win4deap2 Software). Data Source: Bank of Russia website.

During the ten years, the banks achieved average efficiency of operational risk management as follows: large banks (79%), medium banks (78%) and small banks (84%), In other words, small banks were the most effective in operational risk managing, while large banks were more Table 9 shows the average technical efficiency of operational risk management according to the size of the banks. During the ten years, the banks achieved average efficiency of operational risk management as follows: large banks (79%),

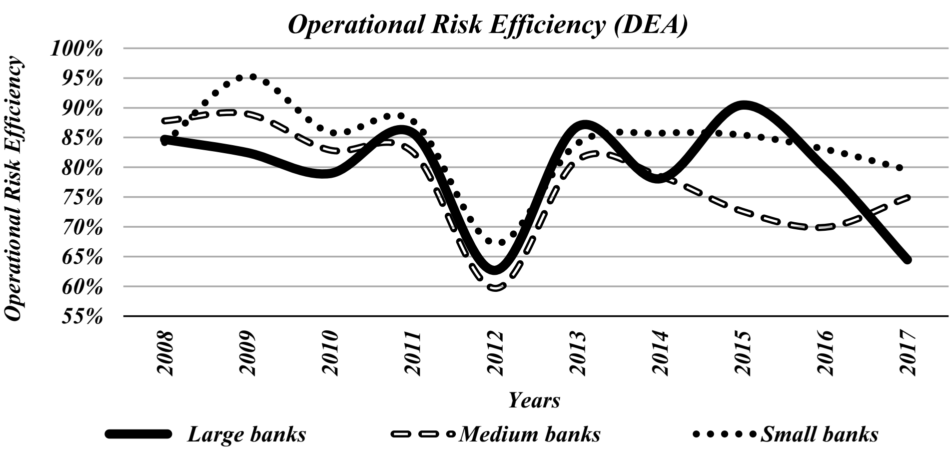

Figure 3. The Average Technical Efficiency [(DEA) — Input Oriented — (VRS)] of operational Risk Management by Size of Russian Banks (2008—2017)

Source: design and calculation by Author using (Excel, Win4deap2 Software). Data Source: Bank of Russia website.

Table 10. The Ratios of The Contribution of Operational Risk Indicators in The Formation of Performance Indicators, Comparison Between Real Ratios and Ideal Target Ratios (2008—2017)

The Variables	The Real Ratios			Mean	The Target Ratios			Mean
	Large Banks	Medium Banks	Small Banks		Large Banks	Medium Banks	Small Banks	
OPR	0.436	0.554	0.484	0.491	0.217	0.308	0.198	0.241
NIM	0.039	0.066	0.045	0.050	0.049	0.072	0.052	0.058
ROA	–0.004	0.011	0.004	0.003	0.021	0.026	0.023	0.023
ROE	–0.055	–0.001	0.048	–0.003	0.095	0.112	0.097	0.101

Source: Design and Calculation by Author Using (Excel, Win4deap2 Software).
Data Source: Bank of Russia Website.

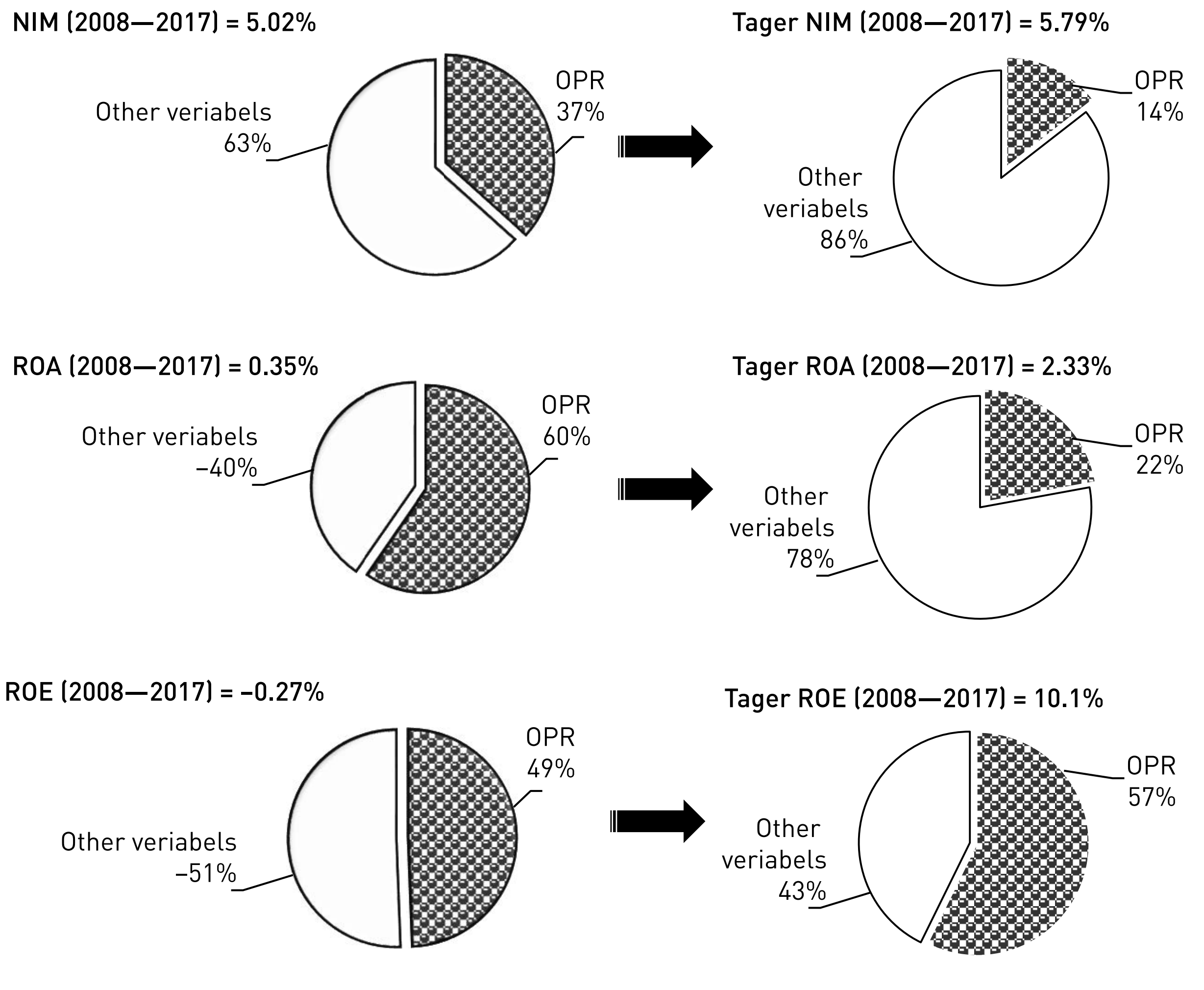

Figure 4. The Ratios of The Contribution of Operational Risk Indicators in The Formation of Performance Indicators, Comparison Between Real Ratios and Ideal Target Ratios (2008—2017)

OPR: Operational Risk., **NIM:** Net Interest Income. **ROA:** Return on Assets. **ROE:** Return on Equity.
Source: Design and Calculation by Author Using (Excel, Win4deap2 Software).

medium banks (78%) and small banks (84%), In other words, small banks were the most effective in operational risk managing, while large banks were more efficient than medium banks. The medium banks were the least efficient than other banks in efficiency of operational risk management. Figure 3 also shows that.

Conclusion

This study examines the efficiency of operational risk management of 85 Russian commercial banks During the period 2008—17. This study uses the input-oriented model [data envelopment analysis (DEA) — the variable returns to scale technology (VRS)] with financial ratios to assess the efficiency of operational risk management, also This study uses simple regression analysis to select variables that will enter as inputs and outputs in data envelopment analysis (DEA) approach. The study adopts the basic indicator approach (BIA) approach to measuring operational risk as this approach relies on gross income as an indicator of operational risk. Also, the study adopts net interest margin (MM), return on assets (ROA), and return on equity (ROE) to measuring banks performance. The study divided the banks into three equal major groups based on the size of the assets:

1. Large banks (L): consisted of 28 banks, it included the banks which have total assets between (270 billion rubles to 23 trillion rubles).

2. Medium banks (M): consisted of 29 banks, and included the banks which have total assets of between (102 — 270 billion rubles).

3. Small banks (S): consisted of 28 banks, and included the banks which have total assets of between (5 — 102 billion rubles).

The study found that:

• The impact of operational risk was positive on the performance of Russian banks in most years of study except for 2011, 2012, 2014 and 2017, as it had no effect on some performance indicators. Operational risk contributed to the formation of MM, ROA and ROE performance indicators at 37%, 60% and 49% respectively, reflecting the impact of operational risk on the performance of Russian banks.

• During the study period, 2009 was the best year in the efficiency of operational risk management in Russian banks, where the average efficiency of banks was 89%, While in 2012 was the worst, where the average efficiency of banks in operational risk management was 63%. In 2008,2010,2011,2013, 2014, 2015, 2016 and 2017, the efficiency of operational risk management in Russian banks was 86%, 83%, 85%, 84%, 81%, 83%, 78% and 73%, respectively. The average efficiency of operational risk management in Russian banks from 2008-2017 indicates that Russian banks could reduce their inputs (operational risk) by 14%, 11%, 17%, 15%, 37%, 16%, 19%, 17 23% and 27%, respectively.

• Operational risk efficiency indicates that banks' profitability is fully consistent with their operational risk preferences in one bank for five years, three banks for four years, three banks for three years and twenty one banks for two years and thirty four banks for one year, meaning that these banks may have risk management It also means that these banks have been working better than other banks in those years because their degree of efficiency is equal to (1). On the other hand, there were 23 banks that had never achieved full proficiency (1) over the study period. This means that the profitability of these banks did not reasonably match operational risk levels as expected. Many banks could have achieved higher returns at the same operational risk levels or could achieve the same returns at lower risk levels. The average technical efficiency of operational risk management by size of banks was as follows: Large banks (79%), medium banks (78%) and small banks (84%), the difference was clear between small banks and other banks. In other words, small banks were the most effective in managing operational risk, while large banks were more efficient than medium banks. Medium banks were less efficient than other banks in the efficiency of operational risk.

The study concluded that:

• Operational risk is an important risk affecting the performance of Russian banks.

• Russian banks could have reduced their inputs (operational risk) by 14%, 11%, 17%, 15%, 37%, 16%, 19%, 17%, 23% and 27% in 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016 and 2017 Respectively that means, Many Russian banks could have achieved higher returns at the same operational risk levels or could have achieved the same returns at lower operational risk levels.

• Small Russian banks were the most effective in operational risk managing, while large banks were more efficient than medium banks.

• The banks' performance is not necessarily parallel to their risk preferences, by comparing the Bank's risk effectiveness with its competitors, it is possible to determine whether the Bank's performance and profitability are reasonable compared to risk levels. Data envelopment analysis (DEA) is an effective measurement tool for such a comparison.

• These results may provide an alert for the inefficient banks to detect and verify their efficiency and compare it with their peers and delve deeper into this subject.

• The banks management should investigate in low profitability compared to other banks because in the long term this may not be sustainable or may result in loss of market shares and damage to the bank's financial health. A high-risk bank should continually review its position either to increase its profitability or to reduce its risk level.

• The risk management approach in standard banks can be seen as an exemplary approach.

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