Korea and the World Economy, Vol. 18, No. 3 (December 2017) 235-258

# The Comparative Study on Russian and Korean Commercial Banks Efficiency Based on the Measurement of Relative Efficiency Using the Data Envelopment Analysis*

Ho-Soo Nah** · Viacheslav Den***

Using data envelopment analysis, the study aims to measure the relative efficiencies of ten largest Russian and Korean commercial banks in 2010-2014. The results reveal that in 2010-2014 these banks operated at almost the same relative efficiency level while Korean banks were slightly more effective. Korean banks showed a decreasing overall technical efficiency trend in 2010-2014, their Russian counterparts showed an increasing trend after a substantial decline in 2011. Both Russian and Korean commercial banks from the sample tend to have a relatively effective management. Decreasing returns to scale trend is a predominant form of scale inefficiency in the sample.

JEL Classification: C14, G21

Keywords: commercial banks, technical efficiency, pure technical efficiency, scale efficiency, data envelopment analysis

* Received July 13, 2017. Revised October 9, 2017. Accepted November 6, 2017.

** Corresponding author, Professor, Division of International Trade and Economics, National Korea Maritime and Ocean University, Busan, Korea, E-mail: nhs1030@kmou.ac.kr

*** First author, Graduate school of National Korea Maritime and Ocean University, Busan, Korea, E-mail: v.a.den@mail.ru

## 1. INTRODUCTION

The significance of commercial banks cannot be underestimated. These institutions are both an indicator of country's economic potential and an economic growth catalyst. In order to stimulate economic growth, banks must grow themselves, which is impossible without efficient management. Kumar and Gulati (2008) stated that from the point of view of customers, only efficient banks can offer better services at reasonable prices and guarantee deposit safety. The point of stakeholders is that only efficient banks ensure reasonable returns. The perspective of bank managers is that in a dynamic and competitive market environment, only efficient banks will survive and maintain their market share, and inefficient ones will eventually be eliminated. The efficient banks are more competitive because of their lower operational costs; they can even steal business away from less efficient banks. This brings us to the importance of well-timed and reliable analysis of banks' economic values and indicators.

The data envelopment analysis (DEA) method may seem a bit outdated but is still very popular for analyzing economy branches, regions, major firms, banks, education institutions, hospitals etc.

Both Russia and South Korea have deep mutual economic interests. Even despite recent significant changes in South Korean government and military tensions in the region, we believe that Russian-Korean trade and investment partnership will keep being a top priority for both countries. In 2017, Korean investments in the Russian Far East reached 272 million $.[1] The accumulated amount of South Korean direct foreign investments in Russian economy reached 2.5 billion $. In 2016, trade turnover between two countries reached 13.5 billion $.[2]

In such conditions, banks serve as vital instruments for investment facilitation and business development financing. In addition, both countries' banking systems are relatively young, especially in comparison with European

[1] Ministry of the Far East Development of Russian Federation.
[2] Ministry of Economic Development of Russian Federation.

and American ones.

Considering first author's past career in Russia's largest commercial bank, the rarity of DEA in Russian economic literature and the fact that Russian versus Korean commercial banks' efficiency comparison was probably never conducted at all, this research may serve as a humble attempt to elaborate on the topic.

In order to get familiar with the practical side of banking efficiency analysis we looked into several previously conducted researches. Caner and Kontorovich (2004) studied the efficiency of Russian banks in comparison with European banks using a standard stochastic frontier model. The obtained results indicated that Russian banks in 1999-2003 were significantly less effective than European ones. Karas *et al.* (2010) tried to find out whether bank ownership type influences bank efficiency in Russia. They researched 747 banks before and 471 banks after the State Deposit Insurance System was introduced in 2004. It was discovered that foreign banks and Russian public banks were more efficient than Russian private banks in the researched periods. Lee and Ryu (2014) in their paper studied the efficiency of Korean commercial banks in 1991-2012 using DEA. They discovered that the efficiency of Korean commercial banks declined sharply during the financial crisis of 1997-1998, but improved in the subsequent restructuring period of 1998-2002, and continued to improve through 2007. In addition, they found that the efficiency of Korean banks had shown a downward trend since the world economic crisis of 2008.

## 2. DATA ENVELOPMENT ANALYSIS

### 2.1. The Concept of DEA

Data envelopment analysis (DEA) is a nonparametric mathematical programming technique for measuring the relative efficiency of a set of similar units, usually referred to as Decision Making Units (DMUs). DMUs are usually defined as entities responsible for turning input(s) into output(s), such as firms and production units.[3)]

The concept of DEA was pioneered by Michael J. Farrell in 1957 when he proposed his approach to frontier estimation. Unfortunately, it had not received much detailed empirical attention for about two decades, until 1978 when A. Charnes, William W. Cooper, and E. Rhodes published their paper, in which the term Data Envelopment Analysis was used for the first time. Since then there has been a large number of papers, which have applied and extended the methodology.[4)]

When studying commercial banks, it is usually impossible to determine the efficient output-to-input ratio. Consequently, we cannot determine whether a bank is absolutely efficient. We can, however, compare several banks' output-to-input ratios and determine that one bank is more or less efficient than another. The difference in efficiency will be due to the technology or production process used, how well that process is managed, and/or the scale or size of the unit.

For efficiency measuring purposes we can also use the more updated than DEA and equally popular stochastic frontier analysis (SFA) method. Usually most scientists agree that no method is relatively superior for the abovementioned purpose; moreover, DEA and SFA often give significantly inconsistent results on same data. Nevertheless, both methods are trusted and valid for measuring efficiency. However, for our research, SFA may not be the best choice, since it requires a specific pre-specified functional form of the modelled production or cost function, which may prove difficult with commercial banks, where inputs and outputs are multiple. In DEA, on the other hand, a production frontier is not determined by some specific functional form, but is generated from the actual data for the evaluated firms. The efficiency score for a specific DMU is defined not by an absolute standard, but

---

[3)] In the current study, DMUs refer to commercial banks. As the name indicates, a DMU must have at least some degree of freedom in setting behavioral goals and choosing how to achieve them.

[4)] For more detailed information on the DEA concept, please refer to the respective research papers.

relatively to the other DMUs in the specific data set under consideration. Also for the best SFA results, DMU quantity and time coverage should be much bigger than we can afford, since obtaining financial data from Russian and Korean banks is not easy, especially if we need data from past decades when the level of banking computerization and financial disclosure was very low in both countries. In general, we chose DEA for several reasons:

- It allows the estimation of overall technical efficiency (OTE) and decomposes it into two mutually exclusive and non-additive components — pure technical efficiency (PTE) and scale efficiency (SE). It identifies the DMUs that are operating under decreasing or increasing returns to scale;
- No need to select an a priori functional form relating to inputs and outputs like Cobb-Douglas and Translog production/cost functions;
- Easily accommodates multiple inputs and multiple outputs;
- It provides a scalar measure of relative efficiency, and the areas for potential addition in outputs and reduction in inputs;
- Not necessary to provide values for weights associated with input and output factors, although the user may exert influence in the selection of weight values;
- Works particularly well with small samples.

Unfortunately, DEA's major shortcoming is that data are expected to be free of measurement error. If the integrity of data is not assured, the obtained results may be unreliable.

## 2.2. DEA Model Input and Output Orientation

DEA models can be configured to measure efficiency in different ways. These configurations are usually being specified in either input-oriented or output-oriented models.

With input-oriented DEA, the model is configured to determine how much the input of a firm could be reduced if used efficiently in order to achieve the same output level (i.e., minimize the use of inputs to produce a given level of output).

In contrast, for output-oriented DEA, the model is configured to determine a firm's potential output given its inputs if it operated efficiently as firms along the best practice frontier (i.e., maximize the level of output given levels of the inputs).

Therefore, for the purposes of the current research and considering the specifics of our DMUs, the model was specified as input-oriented.

### 2.3. Constant Returns to Scale Model (CCR model)

In their original paper Charnes, Cooper, and Rhodes (1978) proposed a model that had an input orientation and assumed constant returns to scale (CRS). This model is also called the CCR model, after its developers. This model is an extension of the ratio technique used in traditional efficiency measurement approaches. The measure of efficiency of any DMU is obtained as the maximum of a ratio of weighted output to weighted input subject to the condition that similar ratios for every DMU be less than or equal to unity. The drawback with the CCR model is that it compares DMUs only based on overall efficiency assuming constant returns to scale. It ignores the fact that different DMUs could be operating at different scales.

### 2.4. Variable Returns to Scale Model (BCC model)

The CCR model is designed with the assumption of constant returns to scale. This means that there is no assumption that any positive or negative economies of scale exist. Under constant returns to scale it is assumed is that even a small commercial bank should be able to operate as efficiently as a large one. To overcome this drawback, Banker, Charnes, and Cooper (1984) developed the BCC model, which assumes variable returns to scale (VRS) and compares DMUs purely on the basis of technical efficiency.

### 2.5. Technical and Scale Efficiencies

The CRS assumption is only appropriate when all DMUs are operating at an optimal scale. However, factors like imperfect competition and constraints on finance may cause a DMU not to be operating at optimal scale. As a result, the use of the CRS specification when some DMUs are not operating at optimal scale will result in measures of technical efficiency (TE) which are confounded by scale efficiencies (SE).

Technical efficiency (TE) relates to the productivity of inputs. The technical efficiency of a firm is a comparative measure of how well it actually processes inputs to achieve its outputs, as compared to its maximum potential for doing so, as represented by its production possibility frontier. Thus, technical efficiency of a commercial bank is its ability to transform multiple resources into multiple financial services. A bank is said to be technically inefficient when it operates below the frontier.

A measure of technical efficiency under the assumption of constant returns to scale (CRS) is known as a measure of overall technical efficiency (OTE). The OTE measure helps to determine inefficiency due to the input/output configuration as well as the size of operations.[5)]

In DEA, the OTE measure has been decomposed into two mutually exclusive and non-additive components: pure technical efficiency (PTE) and scale efficiency (SE). This decomposition allows an insight into the source of inefficiencies.

The PTE measure is obtained by estimating the efficient frontier under the assumption of variable returns to scale (VRS). It is a measure of technical efficiency without scale efficiency and purely reflects the managerial performance to organize the inputs in the production process. Thus, PTE measure is used as an index to capture managerial performance.[6)]

The ratio of OTE to PTE provides SE measure (SE=OTE/PTE or

---

[5)] For the purposes of the current research, terms overall technical efficiency (OTE) and constant returns to scale technical efficiency (CRSTE) are interchangeable.

[6)] For the purposes of the current research, terms pure technical efficiency (PTE) and variable returns to scale technical efficiency (VRSTE) are interchangeable.

CRSTE/VRSTE). The measure of SE provides the ability of the management to choose the optimal size of resources, i.e., to decide on the bank's size or in other words, to choose the scale of production that will attain the expected production level.

Microeconomic theory of firms teaches that one of the basic objectives of firms is to operate at most productive scale size i.e., with constant returns to scale, in order to minimize costs and maximize revenue.

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-optimal 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-optimal scale size. Naturally, a bank is considered scale efficient if it operates at constant returns to scale (CRS).

In the short run, firms may operate in the zone of IRS or DRS, but in the long run they will move towards CRS by becoming larger or smaller to survive in the competitive market. The process might involve changes of a firms' operating strategy in terms of scaling up or scaling down in size.

### 2.6. Choosing Inputs and Outputs

Under the "production" approach, also called the service provision or value added approach, proposed by Benston (1965), financial institutions are considered as the producers of services for account holders — they perform transactions and process documents for customers. Thus, output is best measured by the number and type of transactions or documents processed over a given time period. Unfortunately, such detailed transaction flow data is typically proprietary and not generally available.

Under the alternative "intermediation" approach, proposed by Sealey and Lindley (1977), financial institutions are mainly considered as fund mediators between savers and investors. With this approach, the flows are typically assumed proportional to the stock of financial value in the accounts. Since the "intermediation" approach is more appropriate for evaluating entire financial institutions, for our model we have chosen inputs and outputs accordingly.

### 2.7. Sample Size

Since DEA results are influenced by the size of the sample, various empirical rules are available in DEA literature for choosing an adequate sample size. For example, Cooper *et al.* (2007) provides two such rules that can be generally expressed as:

$$n \geq \max\left\{m * s;\ 3\left(m+s\right)\right\}. \tag{1}$$

Where: $n$ - number of DMUs, $m$ - number of inputs and $s$ - number of outputs.

The first empirical rule states that sample size should be greater than or equal to product of inputs and outputs. While the second rule states that number of observation in the data set should be at least three times the sum of number of input and output variables. It should be mentioned that there are plenty of other empirical rules proposed in other DEA studies.

Given $m$=3 and $s$=2, the sample size ($n$=10), used in the current research, complies only with the first rule. Extension of the sample size would demand for additional data, which could be problematic, considering inconsistency and implicitness of some commercial banks' financial information.

## 3. DATA AND EMPIRICAL ANALYSIS

### 3.1. Data

For this research we chose five largest (by overall amount of total assets) commercial banks in Russia and Korea respectively. For the DEA model, three inputs and two outputs were assumed. Inputs: X1–Number of employees, X2–Fixed assets, and X3–Total equity. Outputs: Y1–Total loans

**Table 1 Inputs and Outputs. Russian DMUs in 2010-2014**

| Variable | Description | Units | Avg. | Min | Max | SD |
|---|---|---|---|---|---|---|
| Y1 | Total Loans | million $ | 125,899 | 24,334 | 467,648 | 124,756 |
| Y2 | Operating Revenue | million $ | 13,519 | 3,209 | 43,768 | 12,688 |
| X1 | Number of Employees | people | 81,062 | 9,000 | 275,723 | 89,797 |
| X2 | Fixed Assets | million $ | 4,240 | 329 | 14,710 | 4,772 |
| X3 | Total Equity | million $ | 18,499 | 2,910 | 59,126 | 17,560 |

**Table 2 Inputs and Outputs. Korean DMUs in 2010-2014**

| Variable | Description | Units | Avg. | Min | Max | SD |
|---|---|---|---|---|---|---|
| Y1 | Total Loans | million $ | 169,979 | 97,655 | 222,270 | 35,501 |
| Y2 | Operating Revenue | million $ | 2,701 | 219 | 6,564 | 1,751 |
| X1 | Number of Employees | people | 19,223 | 9,012 | 28,806 | 6,500 |
| X2 | Fixed Assets | million $ | 2,274 | 1,029 | 2,986 | 638 |
| X3 | Total Equity | million $ | 18,482 | 9,828 | 28,952 | 5,053 |

**Table 3 Combined Inputs and Outputs**

| Variable | Description | Units | Avg. | Min | Max | SD |
|---|---|---|---|---|---|---|
| Y1 | Total Loans | million $ | 147,939 | 24,334 | 467,648 | 93,467 |
| Y2 | Operating Revenue | million $ | 8,110 | 219 | 43,768 | 10,498 |
| X1 | Number of Employees | people | 50,143 | 9,000 | 275,723 | 70,326 |
| X2 | Fixed Assets | million $ | 3,257 | 329 | 14,710 | 3,513 |
| X3 | Total Equity | million $ | 18,491 | 2,910 | 59,126 | 12,788 |

and Y–Operating revenue. All money values were converted into USD using the respective average annual exchange rates (tables 1, 2, 3).

As we can see, in 2010-2014 five largest Korean banks attracted more loans at average than their Russian counterparts did. However, in terms of operating revenue, five largest Russian banks earned much more than Korean ones in the same period. Great disparity in employee numbers naturally occurs from Russia's vast territory and its major banks' necessity to have staffed subsidiaries in every region.

It is necessary to mention that Russian DMU 1 (Savings Bank of Russia or "Sberbank"), greatly surpasses other banks in the set by all economic parameters. Sberbank is the largest bank in Russia, 3rd largest bank in Europe and is ranked 69th in the World's Top 100 largest banks as of 2017. Russian VTB bank (DMU 2) is Russia's second largest bank and is ranked 116th in the world as of 2017.

Korean DMUs from the set are ranked in the World's largest banks list as following: DMU 8 — KB Financial Group (Kookmin Bank) - 75th, DMU 9 — Shinhan Financial Group (Shinhan Bank) - 80th, DMU 10 — Hana Financial Group (Hana Bank) - 91st, DMU 7 — Woori Bank - 97th, and DMU 6 — Industrial Bank of Korea - 109th as of 2017.

All the data were collected from respective banks' annual reports and financial statements. For calculations, we used the DEAP Version 2.1 computer software by Tim Coelli.[7)]

The period of 2010-2014 was chosen for the research purposes because of the relative availability of financial data for these years. In addition, this period lacks any critical global economic events, except for the negative post-effects of the Great recession.

---

[7)] This program is used to construct DEA frontiers for the calculation of technical and cost efficiencies and for the calculation of Malmquist TFP Indices (available at: http://www.uq.edu.au/economics/cepa/deap.php).

### 3.2. Results and Interpretations

Since our research DEA model was specified as input-oriented, it is necessary to mention that input-oriented efficiency measures address the question: “By how much can input quantities be proportionally reduced without altering the output quantities produced?”. Table 4 presents average efficiency scores of 10 DMUs in 2010-2014.

The average results indicate that in 2010-2014 largest Russian and Korean banks operated at almost the same efficiency level, though Korean banks were slightly more effective.

The average CRSTE of 10 DMUs, in percentage terms, ranges between 85.6% and 97%. The average CRSTE score for Russian banks in the research period is 0.907, for Korean banks –0.946. This suggests that, upon average, Russian and Korean banks, if producing their outputs on the efficient frontier instead of their current (virtual) location, would need only 90.7% and 94.6% of the inputs that are currently being used, respectively.

**Table 4 Russian and Korean Banks Average Efficiency in 2010-2014**

| Year | Country | CRSTE | VRSTE | SE |
|---|---|---|---|---|
| 2010 | RUS | 0.905 | 0.988 | 0.916 |
| | KOR | 0.970 | 0.982 | 0.987 |
| 2011 | RUS | 0.856 | 0.958 | 0.898 |
| | KOR | 0.956 | 0.999 | 0.958 |
| 2012 | RUS | 0.897 | 0.969 | 0.927 |
| | KOR | 0.945 | 0.958 | 0.985 |
| 2013 | RUS | 0.936 | 1.000 | 0.936 |
| | KOR | 0.929 | 1.000 | 0.929 |
| 2014 | RUS | 0.940 | 1.000 | 0.940 |
| | KOR | 0.928 | 0.995 | 0.933 |
| Average for 5 years | RUS | 0.907 | 0.983 | 0.923 |
| | KOR | 0.946 | 0.987 | 0.958 |

Notes: CRSTE - Constant Returns to Scale Technical Efficiency, VRSTE -Variable Returns to Scale Technical Efficiency, SE - Scale Efficiency, SE=CRSTE/VRSTE.

To visualize the “distance” from DMU’s current (virtual) location to the efficient frontier, some researchers use the technical inefficiency value (TIE), that can be obtained from TIE=1–TE. Thus, the average CRSTIE of Russian banks in the researched period is: 1–0.907=0.093 or 9.3%; for Korean banks: 1–0.946=0.054 or 5.4%. This means that, by adopting best practice technology, Russian and Korean DMUs can, on an average, reduce their inputs (number of employees, fixed assets and total equity) by at least 9.3 and 5.4%, respectively, and still produce the same level of outputs. Of course, the potential reduction in inputs from adopting best practices may vary from DMU to DMU.

If we construct a graphical plot of the average OTE results (figure 1), we can see that Korean banks showed a decreasing CRSTE trend in 2010-2014 period, while their Russian counterparts had shown an increasing CRSTE trend after a substantial decline in 2011.

The decreasing Korean banks’ OTE trend, discovered here, fits the results of another research by Lee and Ryu (2014), which discovered that Korean banks’ efficiency showed a downward trend since the beginning of the world economic crisis of 2008 and afterwards.

**Figure 1 Overall Technical Efficiency Trends of Russian and Korean Banks in 2010-2014**

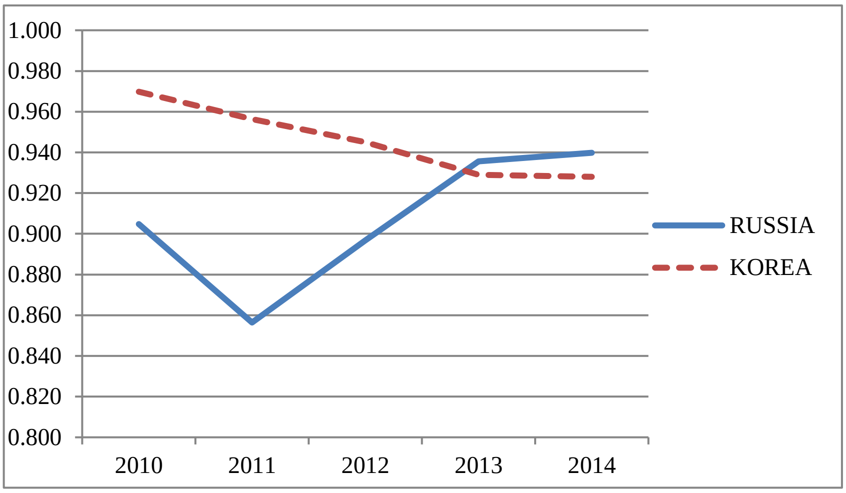


**Table 5 Efficiency Scores of Russian and Korean Banks in 2010-2014**

| DMU | | 2010 | 2011 | 2012 | 2013 | 2014 | Average |
|---|---|---|---|---|---|---|---|
| DMU 1 (SBB) | CRS | 0.732 | 0.626 | 0.723 | 0.780 | 0.839 | 0.740 |
| | VRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | SE | 0.732 | 0.626 | 0.723 | 0.780 | 0.839 | 0.740 |
| DMU 2 (VTB) | CRS | 0.908 | 0.866 | 0.921 | 0.898 | 0.860 | 0.891 |
| | VRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | SE | 0.908 | 0.866 | 0.921 | 0.898 | 0.860 | 0.891 |
| DMU 3 (V24) | CRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | VRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | SE | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| DMU 4 (GPB) | CRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | VRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | SE | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| DMU 5 (RSB) | CRS | 0.884 | 0.790 | 0.840 | 1.000 | 1.000 | 0.903 |
| | VRS | 0.941 | 0.791 | 0.847 | 1.000 | 1.000 | 0.916 |
| | SE | 0.939 | 0.999 | 0.991 | 1.000 | 1.000 | 0.986 |
| DMU 6 (IBK) | CRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | VRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | SE | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| DMU 7 (WB) | CRS | 1.000 | 1.000 | 1.000 | 0.900 | 1.000 | 0.980 |
| | VRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | SE | 1.000 | 1.000 | 1.000 | 0.900 | 1.000 | 0.980 |
| DMU 8 (KB) | CRS | 0.849 | 0.993 | 0.939 | 0.949 | 0.897 | 0.925 |
| | VRS | 0.910 | 0.994 | 0.943 | 1.000 | 0.974 | 0.964 |
| | SE | 0.933 | 0.999 | 0.996 | 0.949 | 0.921 | 0.960 |
| DMU 9 (SHB) | CRS | 1.000 | 0.789 | 0.786 | 0.796 | 0.743 | 0.823 |
| | VRS | 1.000 | 1.000 | 0.847 | 1.000 | 1.000 | 0.969 |
| | SE | 1.000 | 0.789 | 0.928 | 0.796 | 0.743 | 0.851 |
| DMU 10 (HNB) | CRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | VRS | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | SE | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

It is necessary to say that a bank with CRSTE score equal to one is considered the most efficient amongst the banks included in the analysis. A bank with CRSTE score of less than one is considered relatively inefficient.

Table 5 shows the efficiency scores, obtained through our DEA model (DMU-wise). Of the ten DMUs, four banks (VTB 24, Gazprombank, Industrial Bank of Korea, and Hana Bank) were found to be technically efficient, in the researched period, since they have CRSTE score of one.

These banks together define the best practice or efficient frontier and, thus, form the reference set for inefficient banks. The resource utilization process in these banks is functioning well. It means that the production process of these banks is fulfilled without any waste of inputs. In DEA terminology, these banks are called peers and set an example of good operating practices for inefficient banks to emulate.

The remaining six banks have CRSTE score of less than one, which means that they are technically inefficient. The results, thus, indicate a presence of marked deviations of these banks from the best practice frontier.

Interestingly enough that the Sberbank was found to be the least technically efficient bank in the data set in 2010-2014. Overall technical efficiency can be improved by reducing inputs. CRSTE scores among the inefficient banks range from 0.626 (Sberbank) in 2011 to 0.993 (Kookmin Bank) in 2011. This implies that Sberbank and Kookmin Bank in 2011 could potentially reduce their input levels by 37.4% and 0.7%, respectively, while leaving their output levels unchanged. This interpretation of OTE scores can be extended for other inefficient banks in the sample.

The DMU-wise presentation of Russian commercial banks' CRSTE trends on figure 2 shows us that only two out of five Russian banks in the sample may be considered relatively technically effective in the researched period. These effective banks are Gazprombank (GPB) and VTB 24 (V24). These banks showed a stable CRSTE score of one in the research period. This implies that these banks were relatively effective in utilizing their inputs.

The VTB bank showed a rather unstable effectiveness trend with a definite decrease in 2012-2014 period. Rosselkhozbank (RSB), on the other hand, has managed to overcome its ineffective input utilization and has become technically efficient by 2014. Sberbank (SBB) turned out to be the least technically effective DMU among all the commercial banks in the sample.

As for Korean banks, the situation was pretty much the same (figure 3). Industrial Bank of Korea (IBK) and Hana Bank (HNB) proved themselves

**Figure 2 Overall Technical Efficiency Trends of Russian Banks in 2010-2014**

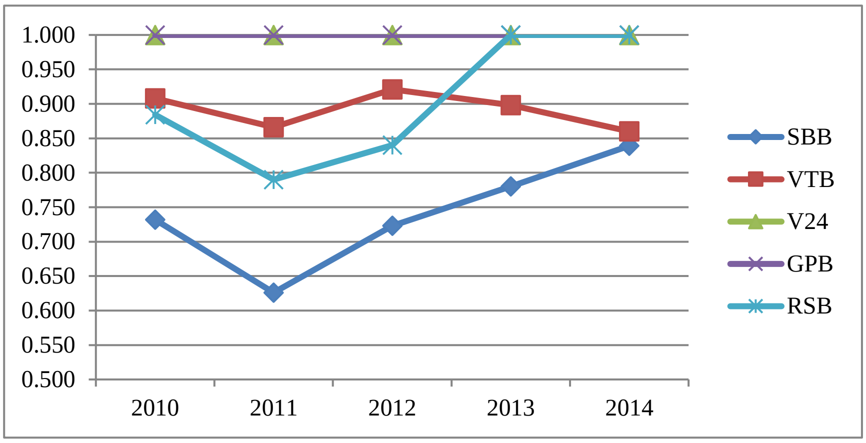
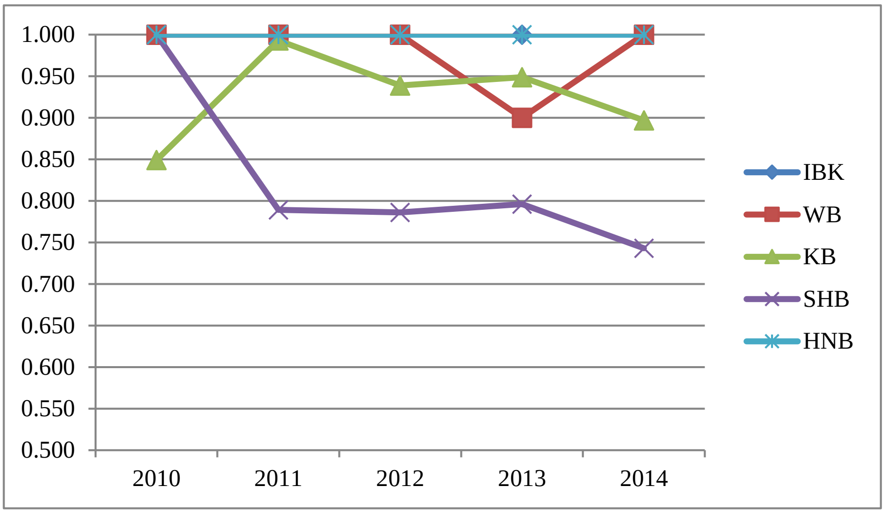



**Figure 3 Overall Technical Efficiency Trends of Korean Banks in 2010-2014**




relatively technically effective in the reviewed period. Woori Bank (WB) showed an interesting trend — while it was relatively efficient in 2010-2012, in showed a substantial decrease in effectiveness in 2013 and had managed to become effective again by 2014. Kookmin Bank (KB) showed an unstable technical efficiency trend during 2010-2014. After becoming effective in 2011, its efficiency began to decrease. Shinhan Bank (SHB) showed a negative efficiency trend after a critical drop in 2010-2011.

Once again, it should be noted that OTE measure helps to measure combined inefficiency that is due to both pure technical inefficiency (PTIE), i.e., inefficiency, caused by poor management performance and scale inefficiency (SIE), i.e., inefficiency, caused by inappropriate size of resources. However, the PTE measure derived from BCC model, under assumption of VRS, neglects the scale effects. Thus, the PTE scores provide that all the inefficiencies directly result from managerial underperformance (i.e., managerial inefficiency) in organizing the banks' inputs.

Tables 4 and 5 show us the PTE and SE scores obtained. It has been observed that seven banks (Sberbank, VTB, VTB 24, Gazprombank, IBK, Woori Bank, and Hana Bank) received the PTE score equal to one for the duration of the research period. This implies that these banks' management is relatively efficient.

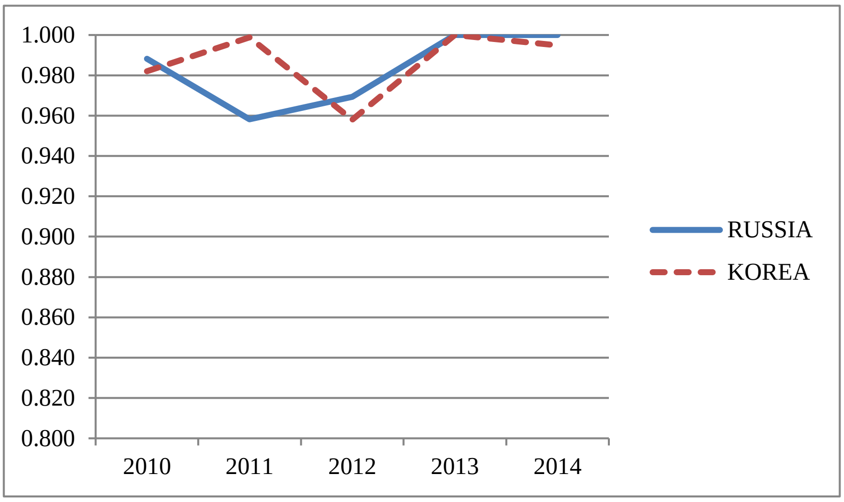
On the other hand, three banks (Rosselkhozbank, Kookmin Bank, and Shinhan Bank) showed PTE scores of less than one, this means that these banks had pure technical inefficiency, probably caused by relative managerial underperformance.

It is important to say that three out of seven banks that showed PTE score of one during the research period (Sberbank, VTB, and Woori Bank) at the same time showed OTE scores of less than one. This could mean that OTIE shown by these banks is not caused by poor input utilization (i.e., managerial inefficiency) but rather by the inappropriate scale size of bank operations.

Some DMUs (Rosselkhozbank, Kookmin Bank, Shinhan Bank) showed both OTE and PTE scores of less than one. Additionally, in some periods, Rosselkhozbank and Kookmin Bank had PTE scores, which were less than SE scores. This may indicate that the inefficiency in resource utilization (i.e., OTIE) in these banks is primarily attributed to the managerial inefficiency rather than to the scale inefficiency.

The DEA results (table 4) indicate that in 2010-2014 Russian banks had an

**Figure 4 Pure Technical Efficiency Trends of Russian and Korean Banks in 2010-2014**




average OTE score of 0.907, PTE score of 0.983. This may be interpreted as that only 1.7% (1–0.983) of 9.3% of OTIE (1–0.907) is caused by bank managers who are not following appropriate management practices and operate with incorrect input combinations. The rest of OTIE is caused by inappropriate scale of banking operations.

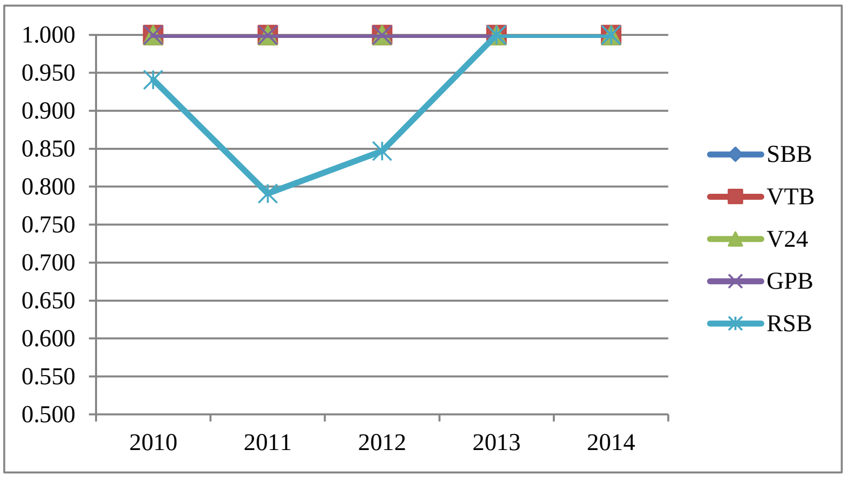
These calculations may be also applied to Korean banks. In 2010-2014, they showed an average OTE score of 0.946 and PTE score of 0.987. This means that only 1.3% of 5.4% of OTIE is caused by poor management, the rest goes to inadequate scale of operations.

Considering the results of the DEA model, we can state that both Russian and Korean DMUs tend to have a relatively effective management, while failure to operate at most productive scale size serves as the main reason of their overall technical inefficiency. On figure 4 we can see the average PTE trends of Russian and Korean banks in 2010-2014.

It may be noted that in the researched period Russian banks had managed to increase their relative PTE after a substantial drop in 2011.

Korean banks' trend, on the other hand, looks unstable throughout the

**Figure 5 Pure Technical Efficiency Trends of Russian Banks in 2010-2014**




research period with an improvement in 2013; however, in 2013-2014 there was a slight decrease.

Also in 2012 the average PTE of Korean banks showed a minimal value, which was probably due to overall slowdown in domestic economy and financial sector in that period, along with stabilization efforts of Bank of Korea that could cause a decline in managerial performance.

On figure 5 we can observe PTE trends for Russian Banks in the researched period. All banks showed effective managerial process in the researched period (i.e., earned PTE score of one; their trend lines look fused on the graph), except for Rosselkhozbank (RSB) that had managed to reach relative effectiveness only by 2013-2014.

On figure 6 we can observe PTE trends for Korean Banks in the researched period. Three banks showed an effective management (IBK, WB, and HNB — their trend lines look fused on the graph). Kookmin Bank's (KB) trend was unstable and multidirectional while Shinhan Bank (SHB) had only one serious effectiveness drop in 2012.

**Figure 6 Pure Technical Efficiency Trends of Korean Banks in 2010-2014**

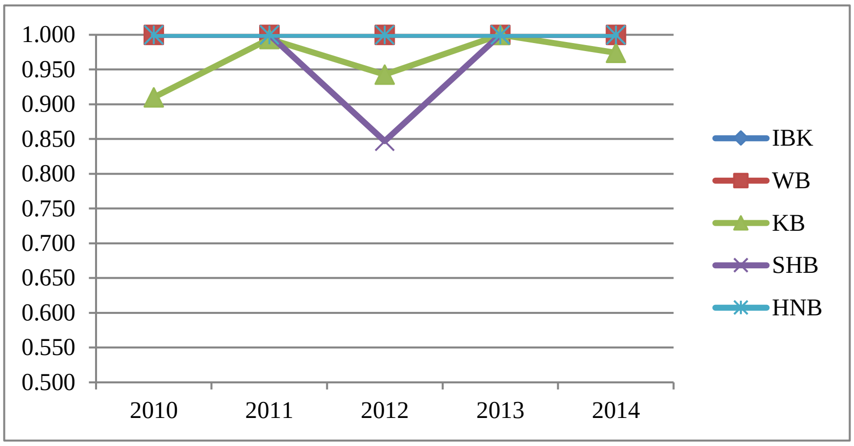



**Table 6 Model Returns to Scale Measurements**

| DMU | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|
| Sberbank | DRS | DRS | DRS | DRS | DRS |
| VTB | DRS | DRS | DRS | DRS | DRS |
| VTB 24 | CRS | CRS | CRS | CRS | CRS |
| Gazprombank | CRS | CRS | CRS | CRS | CRS |
| Rosselkhozbank | DRS | IRS | IRS | CRS | CRS |
| Industrial Bank of Korea | CRS | CRS | CRS | CRS | CRS |
| Woori Bank | CRS | CRS | CRS | DRS | CRS |
| Kookmin Bank | DRS | IRS | IRS | DRS | DRS |
| Shinhan Bank | CRS | DRS | DRS | DRS | DRS |
| Hana Bank | CRS | CRS | CRS | CRS | CRS |

Table 6 shows the returns to scale measurements of our DMUs. The results indicate that four banks (VTB 24, Gazprombank, Industrial Bank of Korea, Hana Bank) were operating at the most productive scale size and experienced constant returns to scale (CRS) in 2010-2014.

Three banks (Sberbank, VTB, Shinhan Bank) were operating at decreasing returns to scale (DRS), i.e., on supra-optimal scale size and, thus downscaling would be a suitable course of action, in order to achieve cost reduction.

None of the DMUs in our research showed a clear and constant increasing returns to scale (IRS) for the whole duration of the research period. For instance, Rosselkhozbank had an IRS period in 2011-2012, which indicates that the bank was operating at sub-optimal scale size and a size increase was advisable. That fact was apparently taken into consideration, because after 2012 Rosselkhozbank demonstrated a steady CRS. On the other hand, Kookmin bank showed IRS in 2011-2012, but in 2013-2014 scale of operations shifted to DRS, which was probably due to excessive expansion. In general, decreasing returns to scale seems to be the predominant form of scale inefficiency among the DMUs in the sample.

## 4. SUMMARY AND CONCLUSIONS

This paper endeavors to conduct a comparative study of 10 largest Russian and Korean commercial banks' efficiency in 2010-2014. In order to achieve the research objectives, an input-oriented DEA model was applied in which the estimates of overall technical, pure technical, and scale efficiencies for individual decision-making units were obtained through CCR and BCC models.

The results obtained indicate that in 2010-2014 ten largest Russian and Korean banks operated at almost the same relative efficiency level while Korean banks were slightly more effective.

Furthermore, Korean banks showed a decreasing overall technical efficiency trend in 2010-2014, while their Russian counterparts showed an increasing trend after a substantial decline in 2011.

VTB 24, Gazprombank, Industrial Bank of Korea, and Hana Bank were found to be technically efficient in the researched period, since they had an OTE score of one. These banks together defined the best practice or efficient frontier for the model's DMUs.

Notably that the Sberbank of Russia turned out to be the least technically efficient DMU among all the commercial banks in the sample. It had also showed a stable DRS trend through the research period. These factors indicate that the largest DMU in the set was definitely operating at supra optimal scale. It seems that the "large assets = large efficiency" proposition is not valid for our research.

Sberbank, VTB, VTB 24, Gazprombank, IBK, Woori Bank, and Hana Bank received the PTE score equal to one in the research period. This means that these banks' management was relatively efficient.

It is worth mentioning that Sberbank, VTB, and Woori Bank's overall technical inefficiency, revealed by our analysis, was not caused by poor input utilization (i.e., managerial inefficiency) but most likely by an inappropriate scale size of bank operations. In such case, adjusting the scale of banking operations would be an advisable course of action for these banks if they wish to increase their relative efficiency.

In order to decrease scale inefficiency, we can suggest several general optimization directions more or less viable for all the inefficient commercial banks in the sample:

- Administrative — decreasing the amount of smaller territorial subsidiaries by merging them into larger ones and redistributing control functions. Subsidiaries become more effective and easier to control. Administrative, inventory, salary and real estate expenditures are reduced;
- Technological — automatization and computerization of internal banking procedures allow reducing the required amount of employees significantly, especially in the back office activities (i.e., encashment, accounting, legal department, sales coordination, call center, paper document flow etc.). Laid off employees may be offered to move to front office jobs. Unification and consolidation of banking IT platforms reduces costs and boosts operational procedures;
- Human resources — most banks operating at supra optimal scale may benefit from general reduction of staff, especially in combination with

the abovementioned measures;

- External policy — banks that have foreign subsidiaries may consider selling or terminating some of them in order to relocate resources and concentrate business activities on more promising foreign markets.

We believe that many other measures may be applied to resolve the problem, considering all the conditions and specifics that may arise.

Generally, the study showed that both Russian and Korean commercial banks from the sample tend to have a relatively effective management. The main reason for their relative overall technical inefficiency is inability to operate at most productive scale size. Decreasing returns to scale was a predominant form of scale inefficiency in the researched sample.

It is possible to improve our DEA model if more decision-making units and/or inputs-outputs are included. Research period increase might be effective as well, however, involving earlier years in the research would make cross-sectional data gathering problematic. In addition, more complicated research techniques may be employed for determination of environmental factors (market share, asset quality, exposure to off-balance sheet activities, profitability, and size) and their impact on commercial banks' relative efficiency.

## REFERENCES

Banker, R. D., A. Charnes, and W. W. Cooper, "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis," *Management Science,* 30(9), 1984, pp. 1078-1092.

Benston, G. J., "Branch Banking and Economies of Scale," *Journal of Finance,* 20(2), 1965, pp. 312-331.

Berger, A. and D. Humphrey, "Efficiency of Financial Institutions: International Survey and Directions for Future Research," *European Journal of Operational Research,* 98(2), 1997, pp. 175-212.

Caner, S. and V. Kontorovich, "Efficiency of the Banking Sector in the Russian Federation with International Comparison," *High School of Economics' Economic Journal,* 8(3), 2004, pp. 357-376.

Charnes, A., W. W. Cooper, and E. Rhodes, "Measuring the Efficiency of Decision Making Units," *European Journal of Operational Research,* 2, 1978, pp. 419-444.

Cooper, W. W., L. M. Seiford, and K. Tone, *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, 2nd ed., New York: Springer Science + Business Media, 2007.

Farrell, M. J., "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society,* Series A, 120, III, 1957, pp. 253-281.

Forsund, F. and L. Hjalmarsson, "Generalized Farrell Measures of Efficiency: An application to milk processing in Swedish Dairy Plants," *Economic Journal,* 89, 1979, pp. 294-315.

Karas, A., K. Schoors, and L. Weill, "Are Private Banks More Efficient than Public Banks? Evidence from Russia," *Economics of Transition*, 18, 2010, pp. 209-244.

Kumar, S. and R. Gulati, "An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis," *Eurasian Journal of Business and Economics,* 1(2), 2008, pp. 33-69.

Lee, S. Y. and S. L. Ryu, "Efficiency of Korean Commercial Banks: An Exploratory Study," *Advanced Science and Technology Letters,* 47, 2014, pp. 97-100.

Ministry of the Economic Development of Russian Federation (available at: http://www.ved.gov.ru/exportcountries/kr/).

Ministry of the Far East Development of Russian Federation (available at: http://minvr.ru/press-center/new/7090/).

Sealey, Jr., C. W. and J. T. Lindley, "Inputs, Outputs, and a Theory of Production and Cost at Depository Financial Institutions," *The Journal of Finance*, 32(4), 1977, pp. 1251-1266.