EFFICIENCY AND PRODUCTIVITY ANALYSIS OF INDONESIAN REGIONAL DEVELOPMENT BANKS: MULTI-STAGE DEA APPROACH AND MALMQUIST PRODUCTIVITY INDEX

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ABSTRACT

This research is intended to empirically examine the efficiency and productivity change of 26 regional development banks (BPDs) in Indonesia in 2011-2016 using a non-parametric approach of data envelopment analysis (DEA). This research was started by determining input and output variables based on three approaches, i.e., intermediation, operation, and the asset approach. The Multi-stage DEA was adopted to generate the efficiency score, and the input-orientated variable return to scale (VRS) assumption is specified in data analysis. The Malmquist Productivity Index (MPI) was used to measure the total factor productivity change indicating the improvement or deterioration of performance of BPDs over time. The multi-stage DEA result shows a significant difference in the number of efficient BPDs using the three approaches. MPI shows that the highest productivity increase was in the asset approach of 84.0%, supported by the increase in efficiency change and technological change. While in intermediation and operation approach, the increase was only 44.0% and 36.0%, depending on the increase in efficiency change and scale efficiency change. This research suggests that BPDs need to invest more in technology to increase firm efficiency.

Keywords: data envelopment analysis (DEA), efficiency, Indonesian regional development bank (IRDB), malmquist productivity index (MPI)

ANALISIS EFISIENSI DAN PRODUKTIVITAS BPD SE-INDONESIA: PENDEKATAN MULTI-STAGE DEA DAN MALMQUIST PRODUCTIVITY INDEX

ABSTRAK

Tujuan penelitian ini adalah untuk menguji secara empiris efisiensi dan perubahan produktivitas 26 Bank Pembangunan Daerah (BPD) di Indonesia selama periode 2011-2016 dengan pendekatan non parametrik Data Envelopment Analysis (DEA). Penelitian dimulai dengan menentukan variabel input dan output berdasarkan tiga pendekatan, yaitu intermediasi, operasi dan aset. Multi-stage DEA diadopsi untuk mengetahui nilai efisiensi BPD, asumsi Input-orientated variable return to scale (VRS) ditentukan dalam menganalisis data. Malmquist Productivity Index (MPI) digunakan untuk mengukur total factor productivity change yang menunjukkan peningkatan atau penurunan kinerja setiap tahunnya. Hasil Multi-stage DEA menunjukkan perbedaan yang signifikan pada jumlah BPD yang efisien dari ketiga pendekatan. MPI menunjukkan peningkatan produktivitas 84,0% BPD melalui pendekatan aset didukung dengan peningkatan efficiency change dan technological change, sementara peningkatan 44,0% dan 36,0% BPD dari pendekatan intermediasi dan operasi berturut-turut tergantung pada peningkatan efficiency change dan scale efficiency change. Penelitian ini memberi justifikasi kepada BPD untuk investasi pada teknologi untuk meningkatkan efisiensi perusahaan.

Kata-kata kunci: Efisiensi, Data envelopment analysis (DEA), Bank, Malmquist productivity index (MPI)

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INTRODUCTION

The Indonesian Regional Development Banks (IRDBs) play a strategic role in regional economic development. The ownership structure of the IRDBs is concentrated on the regional or local government in Indonesia. The IRDBs have a size and business scale, which may reduce poverty, increase access to the financing, and develop the real sector in the rural areas. According to the Indonesian Banking Statistics (2016), IRDBs were in the fifth position in terms of asset, third-party fund, and the credit provided – after Bank Rakyat Indonesia, Bank Mandiri, Bank Central Asia, and Bank Negara Indonesia. IRDBs are believed to be comparable with the large banks, and they can take part in the national development by developing the rural areas of Indonesia. The failure in IRDBs will have a systemic impact on the regional economy.

In 2016, there were only 26 BPDs throughout Indonesia. Currently, there are 27 IRDBs after the formation of Bank Banten in Banten province. The primary financial indicators of IRDB, namely, compound annual growth rate (CAGR) of asset, third-party fund, and the credit provided, generally had consistent growth in 2011-2016, as shown in table 1.

The improvement in primary financial indicators does not mean that the competitiveness of IRDBs also improves. Several studies show that the market share of IRDBs declined in each area. It shows that the competitiveness of IRDBs is assumed

to be low, so there is a chance to examine the efficiency and productivity of IRDBs to gain the empirical evidence and the steps needed to improve them. Low competitiveness is often associated with limited capital and weak corporate governance. The test of the efficiency of IRDBs using asset, operational, and intermediation approach was not commonly conducted in Indonesia (Wijatmoko, 2011). The previous research mainly focused on the financial ratios and financial conditions of IRDBs covering risk aspects, Good Corporate Governance (GCG), capital, and rentability. Bauer et al. (1998) stated that in measuring the company's performance, including banks, the efficiency analysis is much better than the financial ratio analysis such as using Return on Assets (ROA) or Operating Expense Ratio (OER).

This paper aims to empirically test the efficiency level and productivity change of IRDBs throughout Indonesia in 2011-2016 by using the non-parametric approach of Data Envelopment Analysis (DEA). Malmquist Productivity Index (MPI) was used to measure the source of a total change of productivity factor. The result of this study is expected to become useful input for IRDBs and regulators in transforming and developing the business of IRDBs.

Table 1. Total Assets, Third Party Funds, and Loans provided (in billion rupiahs)

	Dec-11	Dec-12	Dec-13	Dec-14	Dec-15	Dec-16	CAGR
Total Assets	307,80	371,81	390,17	451,86	486,35	529,19	
Growth	N/A	20,8%	4,9%	15,8%	7,6%	8,8%	11,6%
Third party funds	232,60	284,01	282,99	333,2	355,53	372,60	
Growth	N/A	22,1%	-0,4%	17,7%	6,7%	4,8%	10,2%
Loans provided	170,99	219,71	255,88	294,60	311,24	334,23	
Growth	N/A	28,5%	16,5%	15,1%	5,6%	7,4%	14,6%

Source: Bank Indonesia (2016)

LITERATURE REVIEW

The measurement of bank efficiency is practically measured by the ability of the bank to generate operational income by using operating expenses. This ratio is often called as Operating Expense Ratio or OER. The lower the OER is, the efficient a bank becomes, conversely. This idea is in line with Farrell (1957), stating that firm efficiency relates to how it can generate a maximum output using the input used. Efficiency is not always about minimizing the cost, but it can also mean the management of the input-output relationship. Farrell (1957) proposed that firm efficiency consists of two components, namely technical efficiency, and allocative efficiency. Technical efficiency reflects the ability of a company to gain maximum results by using particular input. While allocative efficiency reflects the ability of a company to use input in an optimum proportion by considering each input's price. These two measurements are used to measure total economic efficiency.

Farrell (1957) further illustrated his idea by using a simple example, as shown in figure 1. Figure 1 shows that a company uses two inputs (x_1 and x_2) to generate a single output (y), assuming a Constant Return to Scale (CRS). The knowledge about the isoquant unit of the fully efficient company is represented by SS' in figure 1, ensuring the measurement of technical efficiency. If a company uses particular input as determined by P point to generate an output of a certain unit, the technical inefficiency of this firm is represented by QP distance, i.e., the number which can be used by all inputs proportionally without reducing the output. It is usually stated in percentage using the ratio of QP/OP , representing the percentage where all input can be minimized. Technical Efficiency (TE) of a firm is often measured by the ratio of $TEI = OQ/OP$, which equals to $1 - QP/OP$. It can be shown by the value between zero and one, showing the indicator of firm technical efficiency level. The value of one shows that the firm is technically fully efficient. As

an example, the Q point is technically efficient because it is located on efficient isoquant.

Figure 1. Technical and Allocative Efficiency

Source: Farrell (1957)

If the ratio of input's price represented by the AA' line in figure 1 is known, the allocative efficiency can also be calculated. Allocative efficiency of a firm operating on P is defined as ratio $AEI = OR / OQ$ because the distance of RQ shows the reduction of production expense, which will happen if the production is on Q' point (efficient in terms of allocation and technical aspect). While if on Q point is technically efficient but inefficient in terms of allocation. The total economic efficiency (EE) is defined as the ratio of $EEI = OR/O$, where the distance of RP can also mean the reduction of cost. The technical and allocative efficiency contribute to the total economic efficiency as follows:

$$TEI \times AEI = (OQ / OP) \times (OR / OQ) = (OR / OP) = EEI.$$

The general measurement to measure the efficiency of financial institutions, including banks, consists of a parametric and non-parametric approach. According to Berger and Humphrey (1997), there are three methods that are commonly used in the parametric approach, namely, Stochastic Frontier Approach (SFA), Thick Frontier Approach (TFA), and Distribution-Free Approach (DFA). A stochastic frontier approach is an economical approach that defines the function of costs, profits, or production relationships among input, output, and environmental factors. Also, this approach enables the random error to presumably follow the standard symmetrical distribution. While TFA compares the average efficiency of a group of companies, and it does not predict the limitation aspect. DFA, on the other hand, uses the residual average of the functional cost estimation through panel data to determine measurement for frontier cost efficiency. This approach does not force a specific form of efficiency distribution but assumes that there is a core efficiency or average efficiency for a large company that is sustainable.

While in the non-parametric approach, there are two standard methods, namely Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH). Data envelopment analysis is a mathematical programming approach to test the efficiency of the Decision-Making Unit (DMU) responsible for utilizing certain inputs to generate certain output. FDH is a generalization of the DEA

model, which does not need frontier estimation. Frontier estimation approach is a mathematical technique to define a company with the best practices, meaning that the performing firm is defined as a frontier. Bauer et.al. (1998) stated that in testing the performance of a firm, the approach analyzing frontier is more advanced than the method using a traditional financial ratio such as ROA or OER.

The recent survey conducted by Emrouznejad and Yang (2017) showed that the implementation of DEA in banking study was one of the top five fields in the last four decades (1978-2016), where the most journal articles were published in 2015 and 2016. DEA is a non-parametric method using a mathematical technique called linear programming (LP), which relates to the allocation and utilization of limited resources. Charnes, Cooper, and Rhodes (1978) firstly introduced DEA to measure the efficiency based on the concept of efficiency measurement proposed by Farrell (1957). Charnes, Cooper, and Rhodes (1978) developed an input-orientated model by assuming a constant return to scale (CRS). This model is known as CCR model. Subsequently, Banker, Charnes, and Cooper (1984) proposed a model assuming a variable return to scale (VRS). This model is also known as the BCC model.

DEA is a performance measurement tool to evaluate the relative efficiency of production and business unit in an organization. This entity is known

as DMU in DEA. LP method solves a linear mathematical problem by resulting in an efficient virtual DMU and comparing it with the observed DMU in the analysis. The efficient virtual DMU is resulted from the best and most efficient DMU and becomes the standard for the observed DMU. From this analysis, the efficiency level of the observed DMU is known, and the slacks are identified and quantified. Slacks are the excess of input (or output), which can be reduced (or increased) to attain an efficient level after all inputs (or outputs) are reduced (or increased) proportionally to achieve the best practice. DEA identifies the “best practice” of DMU and gives a perfect score (fully efficient), and each variance of the “best practice” is considered inefficient. The inefficiency level depends on the score received by DMU. The efficiency score is based on several inputs and outputs as formulated as follows:

$$\text{Efficiency} = \frac{\text{Weighted sum of inputs}}{\text{Weighted sum of outputs}}$$

DMU with score one is considered efficient, and each score less than one is considered inefficient. According to Hadad et al. (2003), the DEA approach outperforms other methods because it does not need many data, so the needed data are fewer. Also, the assumption and sample size needed is fewer. However, the statistical conclusion cannot be drawn by using a non-parametric approach. The DEA approach is not included in random error, so the inefficiency score can only be used as a general inefficiency factor of DMU. The non-parametric

approach can be resulted to measure a general inefficiency level.

DEA has the advantage of being able to identify the unit, which will be used as a reference for helping to define the cause and solution of inefficiency, which is the primary thing in implementing managerial function. DEA uses many inputs and outputs with a few assumptions in the relationship between the input and output variables. Fetih and Pasiouras (2010) also stated that DEA does not require a complete specification in its function for showing the relationship between production and distribution under observation. Jemric and Vujcic (2002) stated that DEA has an advantage for not requiring early assumptions in the production function. Furthermore, DEA defines the best DMU practice by only using the observed data.

Meanwhile, the disadvantage of the DEA approach is the outlier, which affects the measurement of the total firm efficiency. Also, the frontier is highly sensitive in the extreme observation, and there is no random calculation. Thus, the frontier deviation is indicated as an inefficiency. Since DEA is a non-parametric approach, the test of the statistical hypothesis for DEA score is difficult, resulting in an inability to draw statistical decisions. DEA measures the relative efficiency between DMU under observation, not absolute efficiency.

As outlined previously, the CRS or CCR model was first introduced by Charnes, Cooper, and

Rhodes in 1978. The CRS model assumes that DMU will be compared with the entire sample of DMU in the research, where the internal and external conditions of DMU are assumed to be equal. CRS model was criticized because it is appropriate only for the condition where all DMUs are operated at an optimum scale. Even though DMU results in the same input as the output does, the internal and external conditions of DMU might be different so the DMU cannot be operated at an optimum scale.

According to Casu and Molyneux (2003), the CRS model is only appropriate to be used when all DMUs operate at an optimum scale. Several factors, such as imperfect competition and financial barriers result in DMU to operate less optimally. Thus, the CRS model implementation will result in inappropriate technical efficiency because it is not in line with the efficiency scale. The fundamental concept of this model is the constant result scale, meaning that adding one input to the operation will increase one output. If the input increases by x , the output will increase by x as well. The model of Charnes, Cooper, and Rhodes (1978) can determine technical efficiency as a whole or profit efficiency score for each DMU. Besides, Purwanto and Ferdinan (2006) also stated that CRS model is relatively more appropriate to be implemented in analyzing the performance of manufacturing companies.

Another model, called Variable Return to Scale (VRS) or BCC model, appeared as an

alternative to the CRS model. Banker, Charnier, and Cooper first introduced the VRS model in 1984. This model assumes that adding more input by x will not increase output by x . The output may be smaller or even larger. This model is used to test the efficiency of a service company, including a bank. According to Avkiran (1999), the VRS model is more appropriate for a large sample size. VRS portrays technical efficiency as a whole, consisting of pure technical efficiency and scale efficiency. Pure technical efficiency means the ability of the firm managers of DMU to maximize the available resources. Meanwhile, scale efficiency shows whether the DMU can operate at an appropriate production scale.

Wahidudin (2010) stated that the measurement of productivity change is a crucial aspect when considering the efficiency and performance of any financial institution. Banks and other financial institutions are expected to show productivity change as an innovation result of deregulation in the financial sector. Thus, technical efficiency and technological efficiency must be appropriately measured. Another aspect of DEA is Malmquist Productivity Index (MPI) mainly when focusing on the inefficiency aspect of a non-parametric method. Malmquist total factor productivity is based on the assumption of competitive behavior of the producer side regarding the input.

Total Factor Productivity (TFP) is the measurement of productivity involving production factors. Banks are said to be efficient if they are positioned as the frontiers. If they are found under the frontiers, they are technically inefficient. The shift in the production frontier is called technical change. TFP was initiated by Caves et al. (1982) who developed the Malmquist model from the scaling idea.

Nonetheless, Caves et al. (1982) did not calculate inefficiency. Fare (1992) tried to mix the ideas of Farrell (1957) in measuring efficiency and productivity. Subsequently, Caves et al. (1982) developed Malmquist Index of Productivity Change. The productivity of Malmquist measures productivity change of DMU. This research refers to the regional development banks in several periods. Some researchers defined MPI as a process where the production boundary shifts and the DMU are required to involve in productivity change (Caves et al., 1982). The important finding should cover two important aspects, namely, efficiency change and technological change. Therefore, TFP estimation must be obtained by explaining these two components.

Based on the DEA model, MPI is considered as the most popular index because it can handle much information related to the panel data and it has other useful features for researchers (Wahidudin, 2010). MPI appeared in the literature around 1980 as proposed by Nishimizu and Page (1982) in their

article regarding TFP growth. Their finding was based on the technological growth and technical change in Yugoslavia in 1965-1978. They explained productivity growth into two crucial elements by considering the change of time interval. For instance, technical change refers to the change of frontier level and efficiency change refers to the productivity change of individuals regarding the frontier. Also, MPI is based on the performance assumption that if the index is less than one, it worsens the condition. Moreover, if the index is more than one, it provides relevant improvement (Fare et al., 1994).

Chansarn (2008) utilized DEA by assuming a constant return to scale for analyzing the relative efficiency of commercial banks in Thailand in 2003 - 2006. The input and output variables were derived from the operation and the intermediation approach. Overall, the analysis showed that from the operation approach using the perspective of cost/revenue, the efficiency was stable and very high, or on average more than 90% per year. Nonetheless, from the intermediation approach, the efficiency was fair, and it fluctuated over the years or on average, 86% in 2003 and 2005 and 72% in 2004 and 2006.

Wijatmoko (2011) studied the efficiency of regional development banks in Indonesia in 2007-2009 using DEA approach. The intermediation approach was used to determine the input and output variables. Input variables consisted of general and administrative expenses, labor cost, and promotion expense, while output variables consisted of loan,

third-party fund, and net profit. The result of that research showed that in 2007, eight banks (30.77%) were fully efficient in their operations while the rest of 18 banks (69.23%) were not at maximum efficiency level. In 2008, nine banks (34.62%) were efficient in their operations, while the rest of 17 banks (65.38%) were not at maximum efficiency level. Subsequently, in 2009, five banks (19.23%) were fully efficient in their operations, while 21 of them (80.77%) were not at maximum efficiency level. The cause of the inefficiency was dominated by input variables, namely the general and administrative expenses, labor cost, as well as promotion expense. Nonetheless, the percentage decreased from 83.08% to 68.92%, and then to 63.64% (from 2007 to 2009).

In their study, Saeed et al. (2013) utilized a non-parametric DEA with two input and output orientations for calculating technical efficiency (TE), pure efficiency (PE), and scale efficiency (SE) of Islamic and conventional banks in Pakistan from 2007 to 2011. The results of their research showed that the TE of Islamic banks under the two measurements orienting to input and output was 83.9%, was better than the public sector and foreign banks, but was weaker than private sector banks. PE with measurements orienting to input in Islamic banks was 93.2%, which was better than public sector banks but worse than private and foreign banks. The measurement result orienting to the output of Islamic banks was 92.2%, better than the

public sector and foreign banks but the performance of private sector banks was much better than the performance of Islamic banks. SE of Islamic banks under the two measurements orienting to input and output was 88.7% and 89.5%. SE of Islamic banks with two measurements orienting to input and output was better than the public sector and foreign banks but worse than private sector banks in Pakistan.

Gunawan and Utiyati (2013) studied the efficiency of government-owned banks in Indonesia using the DEA approach. Input and output were defined using the intermediation approach consisting of the third-party fund, interest expense, and labor cost as the input and loan, interest income, and other operating income as the output. A variable return to scale (VRS) model with output orientation was used in his research. Gunawan and Utiyati (2013) found that four government-owned banks, namely BNI, BRI, BTN, and Bank Mandiri consistently reached the perfect efficiency score of 100%.

Firdaus and Hosen (2013) tested the efficiency of Islamic banks in Indonesia using two-stage DEA. Input and output variables were derived from the intermediation approach, namely third-party fund, total asset, and labor cost as the input, while loan and operating income as the output. The constant return to scale model was used in their study. The results of their study showed that the efficiency score of all Islamic banks from the second quarter of 2010 until the fourth quarter of 2012 fluctuated. None of the Islamic banks had a stable

efficiency score during their observation. The highest efficiency score was 91.89% in the fourth quarter of 2011, and the lowest score was 78.46% in the second quarter of 2011.

Several researchers have studied the Malmquist Productivity Index (MPI) to determine the productivity change in a particular period. In Europe, MPI was applied by Berger and Humphrey (1992) using Norwegian banks to evaluate the deregulation effect in the banking sector. Their finding empirically showed that productivity decreased before the deregulation had been implemented, and it increased after the deregulation was implemented. Using the same method, Sufian (2007) studied the difference of productivity index, technological change, efficiency change, as well as scale efficiency using intermediation variable approach. His research also tested whether domestic and foreign banks were formed by the same environment. The result of his research showed that the productivity of Islamic banks in Malaysia had U-shape behavior. Another finding showed that domestic banks had higher productivity than foreign banks did. Most of the middle-size Islamic banks in Malaysia had higher productivity because they utilized more advanced technology. The smaller Islamic banks in Malaysia had a lower productivity level because they were left behind in terms of technology.

Raphael (2013) investigated the productivity change of 21 commercial banks in Tanzania from

2005 to 2011 using the Malmquist Productivity Index (MPI) approach. In the intermediation variable approach, Raphael (2013) used panel data of 146 observations to be further analyzed. The result of his research showed that most of the commercial banks experienced an increase in their efficiency change by 67%, technological change by 83%, pure efficiency change by 67%, and scale efficiency change by 50%. Abbas et. al (2015) implemented the DEA method and Malmquist Index to evaluate the performance of Islamic and conventional banks in Pakistan for the period of 2005 to 2009. The result of their research showed that the productivity growth index of Islamic banks was higher than conventional banks in the years 2007 and 2008.

Nonetheless, in 2009, conventional banks had a higher productivity change. Malmquist TFP index showed that technological change index was the primary factor of productivity deterioration of Islamic banks. Thus, they were deemed as inefficient-scale banks.

Depren and Depren (2016) evaluated the efficiency of twenty deposit banks in Turkey from March 2014 to March 2015 using DEA and MPI. The input and output variables were prepared using intermediation and production approach. The result of their research showed that there were 11 and 14 efficient banks in 2014 and 2015. In the intermediation approach, sectoral efficiency decreased from 1.026 in 2014 to 1.018 in 2015. Besides, there were 12 efficient banks in terms of the

total productivity index of Malmquist. In the production approach, the efficiency score of the banking sector in Turkey increased from 0.916 in 2014 to 0.926 in 2015. However, the banking sector in Turkey was not efficient in terms of MPI.

This research differs from the previous research because the scope of this research is wider by preparing variables from three different approaches, namely, intermediation, operation, and the asset approach. Also, this research extends the observation period (from 2011 to 2016), allowing the comparison of the efficiency score of all DMUs (or IRDBs) in each approach and period. Also, panel data allows us to utilize Malmquist Productivity Index in determining the productivity change of each IRDB. So, it will help us draw a more complexed conclusion for resulting in better suggestions to support the improvement of IRDBs.

METHODS

The performance measurement using DEA starts by determining the input and output variable. According to Sealey and Lindley (1997), the primary approach to measure input and output variables of a bank is production and intermediation approach. Berger and Humphrey (1997) stated that the production approach is better for evaluating the efficiency of the branch of a financial institution. Initially, Berger and Humphrey (1997) commented the difficulty in selecting variables in bank performance using DEA because there is no a perfect approach in the explicit

definition and input as well as output measurement of a bank. Afsharian et al. (2016) proposed a solution to handle the issue of each input/output factor determination regarding the factor selection by developing Generalized DEA (GDEA).

Nonetheless, that approach requires us to explicitly determine the linear cost assumption and utility function. Besides, GDEA implementation is more recommended for benchmarking practice, and it is less practical to be implemented in this study. Therefore, this study uses three different approaches (as explained earlier) in the variable selection based on the list of input and output from the previous studies and the data availability. It is shown in Table 2 as follows.

Table 2. Variable of Input and Output

No	Approach of Variable Selection	Input	Output
1	Intermediation Approach (Depren and Depren, 2016)	Third-party funds	<i>Loans provided</i>
		Interest expense	Interest income
		Non-Interest Operating Expenses	Non-Interest income
2	Operational Approach (Chansarn, 2008)	Interest expense	Interest income
		Non-Interest Operating Expenses	Non-Interest income
3	Asset Approach (Altunbas et. al, 2001)	Labour Expenses	<i>Loans provided</i>
		<i>Cost of funds</i>	Investment / Placement
		Fixed Asset Expenses	

Coelli (1996) recommended the method of multi-stage DEA, instead of the other alternatives (one-stage and two-stage DEA). Multi-stage DEA

allows us to identify the efficient projection points, which have close input and output combinations, with the inefficient points and invariant for the measurement unit. The input-orientated measure shows the number of input, which can be proportionally reduced without having to change the number of the resulted output. Thus, input-orientated measure determines the input deduction needed to reach efficient performance in a similar output. Fethi and Pasiouras (2010) stated that banking industry using input-oriented measure assumes that bank managers have more control over the input variables (such as cost and employees) than the output variables (such as loan and income). Casy and Molyneux (2003) and most of the researchers tended to select input-orientated measures because the total input becomes the primary consideration in determining the variable, even though this reason may not be applied for all industries.

A high competition, financial barriers, and other factors may result in DMU to operate less optimally. Banker, Charnes, and Cooper (1998) suggested the extension of Variable Return to Scale, and this research uses this assumption because the condition of the banking industry in Indonesia is appropriate with that assumption. Besides, the VRS model is appropriate for a large sample size (Avkiran, 1999). Ferdian and Purwantoro (2006) generally measured the efficiency with the following formula:

$$\text{Efficiency} = \frac{\text{Input}}{\text{Output}}$$

Output

Nonetheless, that equation is no longer appropriate because of the large number of input and output. Thus, the efficiency score in this study uses the following equation:

$$\text{Efficiency} = \frac{\text{Weighted sum of inputs}}{\text{Weighted sum of outputs}}$$

$$e_i = \frac{\sum_{r=1}^n u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}}$$

with,

e_j = bank efficiency j

n = total bank output j

m = total bank input j

U_r = value of output r

y_{rj} = number of output r from bank j

v_i = input value i

x_{rj} = number of inputs r from banks j

Meanwhile, the manual equation to calculate efficiency using Variable Return to Scale with input-orientated measure according to Banker, Charnes, and Cooper (1998) is as follows:

$$\text{Efficiency Change} = \frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)}$$

$$\text{Technical Change} = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_{t+1}, y_{t+1})} \times \frac{d_o^t(x_t, y_t)}{d_o^{t+1}(x_t, y_t)} \right]^{1/2}$$

$$\begin{aligned} \min \quad & \theta \\ \text{Constraint; } \quad & \sum_{j=1}^n \lambda_j y_{rj} \geq y_{ro} \quad r=1,2,\dots,j \\ & \theta x_{io} - \sum_{j=1}^n \lambda_j x_{ij} \geq 0 \quad i=1,2,\dots,m \\ & \sum_{j=1}^n \lambda_j = 1 \\ & \lambda_j \geq 0 (j=1,2,\dots,N) \end{aligned}$$

with,

θ = technical efficiency bank

x_{ij} = number of inputs i bank j

y_{rj} = number of outputs r of bank j

1 {<1 inefficient; = 1 efficient}

Malmquist-DEA Analysis

The DEA approach with index number can be used as an alternative in measuring the change in productivity. Several researchers used the Fisher index, Tomqvist index, and Malmquist index. This study uses Malmquist, as has been used by several researchers studying bank efficiency because there is no need to do profit maximization or cost minimization. Besides, since the data used is panel data, this approach facilitates the decomposition of productivity change to be technical efficiency change or to chase the lag and technical change. This study adopts the model as initiated by Fare et al. (1994) as follows:

$$M_o(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d_o^t(x_{t+1}, y_{t+1})}{d_o^t(x_t, y_t)} \times \frac{d_o^{t+1}(x_{t+1}, y_{t+1})}{d_o^{t+1}(x_t, y_t)} \right]^{1/2}$$

The above equation represents the productivity of production point $(x_t + 1, y_t + 1)$, relative to the production point (x_t, y_t) . The value

larger than one shows the growth of total productivity of period t to the next period $(t+1)$, but the index is a mean geometric of two outputs based on the Malmquist index. The Malmquist productivity index based on the above output can be formulated as follows (Fare et al., 1992):

If there is no significant change between the time interval, which can be illustrated by $x_t = x_{t+1}$, and $y_t = y_{t+1}$, then MPI equals to 1. Therefore, productivity change is stated in the following indexes, namely $MPI = 1$ means steady, $MPI < 1$ means declining, and $MPI > 1$ means increasing.

According to Coelli (1996), VRS and CRS are assumed not to affect DEA Malmquist because both of them are used to measure the distance variation (or technical efficiency), which can be used to develop Malmquist index. Four distances were calculated for each company every year. It is relative to CRS DEA frontier of the previous period; CRS DEA frontier of the current period; CRS DEA frontier of the next period; and VRS frontier of the current period. Malmquist index has three advantages compared to other indexes, namely (Grifell-Tatje and Lovell, 1996): (1) It does not need the assumption of maximizing profit or minimizing cost; (2) It does not require input and output price; (3) Productivity change can be outlined to be technical efficiency change and pure technical change.

All Malmquist indexes are provided relative to the previous year. Thus, the input starts in the

second year. Five indexes are provided for each company every year (Fare et. al, 1994), namely (1) technical efficiency change (Effch); (2) technological change (Techch); (3) pure efficiency change (Pech); (4) scale efficiency change (Sech); and (5) total factor productivity change (Tfpch).

Malmquist index is the measurement of total factor productivity change (Tfpch) in a particular period. It portrays the performance of the entire company in a specific period. If the value is larger than one, the company has succeeded in increasing productivity. If the value is less than one, the company has declining productivity. Moreover, so for M. If M equals to one, the company has succeeded in maintaining the previous productivity level. This principle also applies to Effch and Techch, representing efficiency and technology improvement. Besides, it is crucial to clarify whether the change in technical efficiency is caused by pure technical efficiency or technological improvement. If Techch is larger than Pech, it can be said that the productivity change is not caused by better efficiency in the company, but by the technological improvement, conversely. Besides, if Pech is larger than Sech, then the change in efficiency is caused by the change in efficiency, not by the scale, conversely. Charnes et al. (1993) and Worthington (1999) provided a detailed explanation regarding this interpretation.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 4 describes the performance of input and output of all IRDBs throughout Indonesia in 2011-2016. Third-party funds of all IRDBs increased significantly during that period. The lowest value was in 2012 of 703,051 (in million rupiahs), and the highest value was in 2016 of 72,827,957 (in million rupiahs). Thus, the third-party fund increased by 60.19% in the last six years. Interest expense is the second input through the intermediation approach and the first input through the operation approach.

The average value of interest expense consistently increased from 2011 to 2015 and declined in 2016 by 5.2% as a result of the decrease in the reference interest rate. The maximum increase of non-interest expense was significant from 2011 to 2016 by 162.4%. The largest move was shown in 2015 by 3,730,665 (in million rupiahs) and 2016 by 5,316,500 (in million rupiahs). In other words, it increased by 42.5% from the previous period. It means that there was an increase in operational expenses such as general expense, labor expense, IT expense, and non-interest expense. The loan granted to the debtor in 2016 reached 81.1%. The interest income consistently grew from 2011 to 2015, meaning that the performance of IRDBs in providing loan got better. The labor expense also increased, reaching a maximum of 13.9% in 2016. The minimum value of the cost of the fund increased by 12.5% from 2011 to 2016. Besides, the cost of

physical capital substantially declined by 301% in terms of standard deviation and the securities increased by 142.1% from the previous six years. These results are shown in Table 3.

Table 3. Descriptive Statistics and Input-Output Variables

Tahun	Keterangan	N	Intermediation Approach Variable					Operation Approach Variable					Asset Approach Variable				
			Third party fund (x1)	Interest expense (x2)	Non interest expense (x3)	Loan granted (y1)	Interest income (y2)	Fee based income (y3)	Interest expense (x1)	Non interest expense (x2)	Interest income (y1)	Fee based income (y2)	Price of labor (x1)	Price of fund (x2)	Price of physical capital (x3)	Loan granted (y1)	Securities (y2)
2011	Minimum		732.337	32.690	91.944	565.842	124.865	3.625	32.690	91.944	124.865	3.625	0.012	0.016	0.747	565.842	38.726
	Maximum	25	37.008.489	2.812.721	2.026.483	34.863.841	5.722.361	303.498	2.812.721	2.026.483	5.722.361	303.498	0.036	0.060	17.523	34.863.841	3.972.149
	Mean		8.938.204	495.900	457.113	8.732.329	1.298.039	90.904	495.900	457.113	1.298.039	90.904	0.024	0.040	2.698	8.732.329	720.492
	Std. Deviation		8.430.472	569.533	425.910	8.879.361	1.179.064	83.298	569.533	425.910	1.179.064	83.298	0.007	0.012	3.208	8.879.361	1.076.229
	Minimum		703.051	41.301	91.216	754.178	137.154	12.943	41.301	91.216	137.154	12.943	0.013	0.016	0.276	754.178	47.777
2012	Maximum	25	52.375.515	2.986.156	2.566.496	35.054.040	6.430.688	768.000	2.986.156	2.566.496	6.430.688	768.000	0.035	0.059	12.215	35.054.040	4.142.992
	Mean		10.933.853	530.927	572.045	8.687.954	1.465.399	140.391	530.927	572.045	1.465.399	140.391	0.024	0.038	2.645	8.687.954	804.202
	Std. Deviation		11.374.855	599.743	554.489	9.148.400	1.323.074	166.962	599.743	554.489	1.323.074	166.962	0.006	0.011	2.480	9.148.400	945.678
	Minimum		910.747	170.758	92.924	1.169.712	172.724	10.126	170.758	92.924	172.724	10.126	0.014	0.015	0.317	1.169.712	71.990
	Maximum	25	46.762.799	2.936.780	3.487.470	44.989.950	7.563.097	926.000	2.936.780	3.487.470	7.563.097	926.000	0.038	0.095	9.450	44.989.950	10.291.810
2013	Mean		11.109.764	607.002	703.889	10.640.590	1.767.620	128.070	607.002	703.889	1.767.620	128.070	0.025	0.045	2.481	10.640.590	1.314.145
	Std. Deviation		10.616.146	630.305	752.383	11.710.145	1.562.659	200.761	630.305	752.383	1.562.659	200.761	0.006	0.018	1.851	11.710.145	2.259.513
	Minimum		1.692.565	82.764	111.006	2.038.574	317.827	16.278	82.764	111.006	317.827	16.278	0.012	0.023	0.297	2.038.574	166.516
	Maximum	25	57.741.031	4.430.222	3.627.016	54.017.114	8.791.820	1.251.000	4.430.222	3.627.016	8.791.820	1.251.000	0.037	0.083	11.229	54.017.114	7.125.371
	Mean		13.139.773	809.919	727.170	11.416.294	2.054.147	140.930	809.919	727.170	2.054.147	140.930	0.024	0.046	2.413	11.416.294	1.339.616
2014	Std. Deviation		12.762.571	904.264	780.611	11.424.371	1.798.583	266.905	904.264	780.611	1.798.583	266.905	0.006	0.016	2.214	11.424.371	1.776.332
	Minimum		3.251.207	116.837	170.418	2.258.233	440.151	21.849	116.837	170.418	440.151	21.849	0.016	0.020	0.253	2.258.233	100.000
	Maximum	25	62.749.458	4.441.211	3.730.665	55.311.067	9.188.175	1.881.000	4.441.211	3.730.665	9.188.175	1.881.000	0.036	0.113	8.022	55.311.067	12.838.700
	Mean		13.420.078	911.173	815.299	12.247.809	2.312.392	182.430	911.173	815.299	2.312.392	182.430	0.023	0.050	2.087	12.247.809	1.449.937
	Std. Deviation		13.374.574	937.911	856.974	11.767.914	1.936.177	377.013	937.911	856.974	1.936.177	377.013	0.005	0.022	1.703	11.767.914	2.621.406
2016	Minimum		2.870.480	109.201	187.506	2.638.283	495.974	31.674	109.201	187.506	495.974	31.674	0.017	0.018	0.382	2.638.283	93.767
	Maximum	25	72.827.957	3.935.029	5.316.500	63.143.595	9.839.617	1.609.000	3.935.029	5.316.500	9.839.617	1.609.000	0.041	0.109	4.250	63.143.595	9.206.598
	Mean		14.162.920	863.872	926.951	13.051.322	2.268.370	184.507	863.872	926.951	2.268.370	184.507	0.024	0.048	1.626	13.051.322	1.389.869
	Std. Deviation		15.025.077	806.888	1.117.905	12.884.467	2.029.404	335.406	806.888	1.117.905	2.029.404	335.406	0.006	0.021	0.961	12.884.467	1.811.194
	Minimum		15.025.077	806.888	1.117.905	12.884.467	2.029.404	335.406	806.888	1.117.905	2.029.404	335.406	0.006	0.021	0.961	12.884.467	1.811.194

Source: processed data

The efficiency of IRDBs throughout Indonesia: Intermediation Approach

The analysis result using multi-stage DEA using the intermediation variable in Table 4 shows that only 28.0% or 7 BPDs were consistently efficient from 2011 to 2016. The rest of 72.0% or 18 BPDs were not consistently efficient, having the lowest average

score of 0.760. The average efficiency score in six years was 0.936, showing that 40.0% or 10 BPDs had the efficiency score below the average. The best achievement was in 2014, where 72.8% or 18 BPDs ran intermediation function efficiently.

Table 4. Overall IRDBs Efficiency with Variable Intermediation Approach

No	IRDB	Year						Average
		2011	2012	2013	2014	2015	2016	
1	A01	1,000	1,000	1,000	1,000	1,000	1,000	1,000
2	A02	1,000	1,000	1,000	1,000	1,000	1,000	1,000
3	A06	1,000	1,000	1,000	1,000	1,000	1,000	1,000
4	A08	1,000	1,000	1,000	1,000	1,000	1,000	1,000
5	A23	1,000	1,000	1,000	1,000	1,000	1,000	1,000
6	A20	1,000	1,000	1,000	1,000	1,000	1,000	1,000
7	A18	1,000	1,000	1,000	1,000	1,000	1,000	1,000
8	A04	0,984	1,000	1,000	0,961	1,000	1,000	0,991
9	A24	1,000	1,000	0,925	1,000	1,000	0,976	0,984
10	A16	0,901	0,994	1,000	1,000	1,000	1,000	0,983
11	A19	1,000	0,893	1,000	1,000	1,000	1,000	0,982
12	A17	1,000	1,000	1,000	0,903	1,000	0,965	0,978
13	A11	1,000	1,000	0,938	1,000	0,900	1,000	0,973
14	A03	0,713	1,000	1,000	1,000	1,000	1,000	0,952
15	A14	1,000	0,906	0,885	0,945	0,954	0,982	0,945
16	A09	1,000	1,000	0,887	0,977	0,842	0,885	0,932
17	A22	1,000	0,779	1,000	1,000	0,877	0,875	0,922
18	A15	0,822	0,801	0,772	1,000	1,000	1,000	0,899
19	A25	0,534	0,857	1,000	1,000	1,000	1,000	0,899
20	A05	0,960	0,796	0,697	0,879	1,000	1,000	0,889
21	A07	0,652	0,791	0,795	1,000	1,000	1,000	0,873
22	A13	1,000	0,490	0,655	0,874	1,000	1,000	0,837
23	A21	0,554	0,633	1,000	0,904	0,964	0,905	0,827
24	A10	0,596	0,710	0,680	0,930	0,882	0,882	0,780
25	A12	0,455	0,884	0,724	0,794	0,902	0,802	0,760
Lowest		0,455	0,490	0,655	0,794	0,842	0,802	0,760
Highest		1,000	1,000	1,000	1,000	1,000	1,000	1,000
Average		0,887	0,901	0,918	0,967	0,973	0,971	0,936
Efficient IRDBs		15	13	15	16	18	17	7
Inefficient IRDBs		10	12	10	9	7	8	18

Source: processed data

Based on BUKU category or core capital size, IRDBs in BUKU 3 category had an average of 0.984. Meanwhile, in BUKU category 2 had an average of 0.912, and in BUKU category 1 had an average of 0.955. Although these numbers do not

differ significantly, it can be said that the IRDBs with the most considerable core capital had the highest efficiency.

Table 5. IRDBs Efficiency Based on BUKU Category with Variable Intermediation Approach

No	IRDBs	Year						Category
		2011	2012	2013	2014	2015	2016	
1	A01	1,000	1,000	1,000	1,000	1,000	1,000	BUKU 3
2	A02	1,000	1,000	1,000	1,000	1,000	1,000	
3	A03	0,713	1,000	1,000	1,000	1,000	1,000	
	Average	0,904	1,000	1,000	1,000	1,000	1,000	0,984
4	A04	0,984	1,000	1,000	0,961	1,000	1,000	BUKU 2
5	A05	0,960	0,796	0,697	0,879	1,000	1,000	
6	A06	1,000	1,000	1,000	1,000	1,000	1,000	
7	A07	0,652	0,791	0,795	1,000	1,000	1,000	
8	A08	1,000	1,000	1,000	1,000	1,000	1,000	
9	A09	1,000	1,000	0,887	0,977	0,842	0,885	
10	A10	0,596	0,710	0,680	0,930	0,882	0,882	
11	A11	1,000	1,000	0,938	1,000	0,900	1,000	
12	A12	0,455	0,884	0,724	0,794	0,902	0,802	
13	A13	1,000	0,490	0,655	0,874	1,000	1,000	
14	A14	1,000	0,906	0,885	0,945	0,954	0,982	
15	A15	0,822	0,801	0,772	1,000	1,000	1,000	
16	A16	0,901	0,994	1,000	1,000	1,000	1,000	
	Average	0,875	0,875	0,849	0,951	0,960	0,965	0,912
17	A17	1,000	1,000	1,000	0,903	1,000	0,965	BUKU 1
18	A18	1,000	1,000	1,000	1,000	1,000	1,000	
19	A19	1,000	0,893	1,000	1,000	1,000	1,000	
20	A20	1,000	1,000	1,000	1,000	1,000	1,000	
21	A21	0,554	0,633	1,000	0,904	0,964	0,905	
22	A22	1,000	0,779	1,000	1,000	0,877	0,875	
23	A23	1,000	1,000	1,000	1,000	1,000	1,000	
24	A24	1,000	1,000	0,925	1,000	1,000	0,976	
25	A25	0,534	0,857	1,000	1,000	1,000	1,000	
	Average	0,899	0,907	0,992	0,979	0,982	0,969	0,955

Source: processed data

Efficiency IRDBs throughout Indonesia: Operational Approach

Based on table 6, it is known that the mean or average efficiency score using the operation variable approach of IRDBs throughout Indonesia is 0.824 for the year 2011 to 2016. The number of efficient IRDBs was 24.0% or 6 IRDBs, while the rest of

76.0% was considered insufficient. We found that 13 IRDBs had a score lower than the average. In other words, 52.0% of the inefficient IRDBs operated below the performance of the IRDBs on average. The lowest efficiency score in that six-year-period was 0.515.

Table 6. Overall IRDBs Efficiency with Operation Variable Approach

No	IRDBs	Year						Average
		2011	2012	2013	2014	2015	2016	
1	A01	1,000	1,000	1,000	1,000	1,000	1,000	1,000
2	A02	1,000	1,000	1,000	1,000	1,000	1,000	1,000
3	A06	1,000	1,000	1,000	1,000	1,000	1,000	1,000
4	A08	1,000	1,000	1,000	1,000	1,000	1,000	1,000
5	A23	1,000	1,000	1,000	1,000	1,000	1,000	1,000
6	A20	1,000	1,000	1,000	1,000	1,000	1,000	1,000
7	A16	0,892	0,918	1,000	1,000	1,000	1,000	0,968
8	A03	0,697	1,000	1,000	1,000	1,000	1,000	0,950
9	A19	0,879	0,803	1,000	1,000	1,000	1,000	0,947
10	A17	1,000	1,000	0,928	0,724	0,925	0,930	0,918
11	A09	1,000	1,000	0,887	0,977	0,693	0,708	0,878
12	A24	1,000	1,000	0,804	0,801	0,735	0,701	0,840
13	A11	1,000	0,873	0,655	0,685	0,809	0,920	0,824
14	A04	0,781	0,884	0,681	0,775	0,776	1,000	0,816
15	A14	1,000	0,786	0,708	0,781	0,747	0,773	0,799
16	A22	0,647	0,572	1,000	0,870	0,781	0,875	0,791
17	A18	1,000	0,922	0,812	0,660	0,655	0,685	0,789
18	A25	0,495	0,531	1,000	0,777	0,759	0,797	0,727
19	A21	0,489	0,432	1,000	0,650	0,715	0,896	0,697
20	A15	0,803	0,481	0,471	0,590	0,904	0,806	0,676
21	A07	0,603	0,617	0,570	0,645	0,618	0,849	0,650
22	A05	0,960	0,792	0,407	0,550	0,505	0,632	0,641
23	A12	0,424	0,605	0,548	0,568	0,817	0,714	0,613
24	A10	0,547	0,543	0,501	0,524	0,557	0,665	0,556
25	A13	0,504	0,427	0,465	0,550	0,567	0,578	0,515
Lowest		0,424	0,427	0,407	0,524	0,505	0,578	0,515
Highest		1,000	1,000	1,000	1,000	1,000	1,000	1,000
Average		0,829	0,807	0,817	0,805	0,823	0,861	0,824
Efficient IRDBs		12	10	12	9	9	10	6
Inefficient IRDBs		13	15	13	16	16	15	19

Source: processed data

Also, as shown in table 7, in the operational variable approach, the IRDBs in BUKU 3 category had an efficiency score of 0.983. It indicates that there is a significant difference from IRDBs in BUKU category 2 and 1, which had an average

efficiency of 0.764 and 0.856. Therefore, the operation variable approach also supports the idea that IRDBs with a large core capital has the highest average efficiency score.

Table 7. IRDBs Efficiency Based on BUKU Category with Operational Variable Approach

No	IRDBs	Year						Category
		2011	2012	2013	2014	2015	2016	
1	A01	1,000	1,000	1,000	1,000	1,000	1,000	BUKU 3
2	A02	1,000	1,000	1,000	1,000	1,000	1,000	
3	A03	0,697	1,000	1,000	1,000	1,000	1,000	
	Average	0,899	1,000	1,000	1,000	1,000	1,000	0,983
4	A04	0,781	0,884	0,681	0,775	0,776	1,000	BUKU 2
5	A05	0,960	0,792	0,407	0,550	0,505	0,632	
6	A06	1,000	1,000	1,000	1,000	1,000	1,000	
7	A07	0,603	0,617	0,570	0,645	0,618	0,849	
8	A08	1,000	1,000	1,000	1,000	1,000	1,000	
9	A09	1,000	1,000	0,887	0,977	0,693	0,708	
10	A10	0,547	0,543	0,501	0,524	0,557	0,665	
11	A11	1,000	0,873	0,655	0,685	0,809	0,920	
12	A12	0,424	0,605	0,548	0,568	0,817	0,714	
13	A13	0,504	0,427	0,465	0,550	0,567	0,578	
14	A14	1,000	0,786	0,708	0,781	0,747	0,773	
15	A15	0,803	0,481	0,471	0,590	0,904	0,806	
16	A16	0,892	0,918	1,000	1,000	1,000	1,000	
	Average	0,809	0,764	0,684	0,742	0,769	0,819	0,764
17	A17	1,000	1,000	0,928	0,724	0,925	0,930	BUKU 1
18	A18	1,000	0,922	0,812	0,660	0,655	0,685	
19	A19	0,879	0,803	1,000	1,000	1,000	1,000	
20	A20	1,000	1,000	1,000	1,000	1,000	1,000	
21	A21	0,489	0,432	1,000	0,650	0,715	0,896	
22	A22	0,647	0,572	1,000	0,870	0,781	0,875	
23	A23	1,000	1,000	1,000	1,000	1,000	1,000	
24	A24	1,000	1,000	0,804	0,801	0,735	0,701	
25	A25	0,495	0,531	1,000	0,777	0,759	0,797	
	Average	0,834	0,807	0,949	0,831	0,841	0,876	0,856

Source: processed data

Efficiency IRDBs throughout Indonesia: Asset Approach

From 2011 until 2016, using asset variable approach, we found that only two IRDBs were efficient, as shown in Table 8. The rest of the 23 IRDBs were not efficient. The average efficiency score of IRDBs

0.836. The lowest score of the inefficient IRDBs was 0.515. Besides, of the 80.0% inefficient IRDBs, we found that 52.2% of them operated under the average performance.

Table 8. Overall IRDBs Efficiency with Asset Variable Approach

No	IRDBs	Year						Average
		2011	2012	2013	2014	2015	2016	
1	A01	1,000	1,000	1,000	1,000	1,000	1,000	1,000
2	A02	1,000	1,000	1,000	1,000	1,000	1,000	1,000
3	A05	1,000	1,000	1,000	1,000	1,000	0,968	0,995
4	A08	1,000	1,000	1,000	1,000	0,909	1,000	0,985
5	A09	1,000	0,861	1,000	1,000	1,000	0,984	0,974
6	A19	1,000	0,781	1,000	1,000	1,000	1,000	0,964
7	A13	1,000	0,981	1,000	1,000	0,842	0,909	0,955
8	A16	0,904	0,830	1,000	0,948	1,000	1,000	0,947
9	A20	0,920	1,000	1,000	1,000	0,805	0,932	0,943
10	A03	0,799	0,801	0,962	1,000	1,000	1,000	0,927
11	A04	0,977	0,933	1,000	0,817	0,785	1,000	0,919
12	A17	1,000	0,929	0,789	0,711	0,941	1,000	0,895
13	A14	0,861	0,843	0,925	0,997	0,749	0,916	0,882
14	A07	0,708	0,728	0,961	0,845	0,888	0,857	0,831
15	A10	0,645	0,852	1,000	0,860	0,766	0,782	0,818
16	A22	0,790	0,650	0,880	0,736	1,000	0,710	0,794
17	A12	0,677	0,700	0,968	0,801	0,762	0,770	0,780
18	A23	0,707	0,716	0,734	0,805	0,805	0,811	0,763
19	A06	0,702	0,631	0,897	0,759	0,726	0,722	0,740
20	A25	0,583	0,575	0,796	0,859	0,734	0,820	0,728
21	A11	0,601	0,569	0,718	0,724	0,606	0,898	0,686
22	A21	0,633	0,574	0,687	0,653	0,580	0,679	0,634
23	A15	0,665	0,625	0,639	0,532	0,711	0,543	0,619
24	A24	0,728	0,537	0,712	0,602	0,516	0,598	0,616
25	A18	0,459	0,466	0,560	0,580	0,546	0,478	0,515
Lowest		0,459	0,466	0,560	0,532	0,516	0,478	0,515
Highest		1,000	1,000	1,000	1,000	1,000	1,000	1,000
Average		0,814	0,783	0,889	0,849	0,827	0,855	0,836
Efficient IRDBs		8	5	11	9	8	8	2
Inefficient IRDBs		17	20	14	16	17	17	23

Source: processed data

Table 9 shows the average efficiency based on BUKU category of 25 IRDBs using asset variable approach. The IRDBs in BUKU 1 had an average efficiency of 0.761, while IRDBs in BUKU 2 and 3 had higher scores, namely 0.856 and 0.976.

Therefore, this approach also supports the results of the two previous approaches where the IRDBs with the large core capital had the highest efficiency score averagely.

Table 9. IRDBs Efficiency Based on BUKU Category with Asset Variable Approach

No	IRDB	Year						Category
		2011	2012	2013	2014	2015	2016	
1	A01	1,000	1,000	1,000	1,000	1,000	1,000	BUKU 3
2	A02	1,000	1,000	1,000	1,000	1,000	1,000	
3	A03	0,799	0,801	0,962	1,000	1,000	1,000	
	Average	0,933	0,934	0,987	1,000	1,000	1,000	0,976
4	A04	0,977	0,933	1,000	0,817	0,785	1,000	BUKU 2
5	A05	1,000	1,000	1,000	1,000	1,000	0,968	
6	A06	0,702	0,631	0,897	0,759	0,726	0,722	
7	A07	0,708	0,728	0,961	0,845	0,888	0,857	
8	A08	1,000	1,000	1,000	1,000	0,909	1,000	
9	A09	1,000	0,861	1,000	1,000	1,000	0,984	
10	A10	0,645	0,852	1,000	0,860	0,766	0,782	
11	A11	0,601	0,569	0,718	0,724	0,606	0,898	
12	A12	0,677	0,700	0,968	0,801	0,762	0,770	
13	A13	1,000	0,981	1,000	1,000	0,842	0,909	
14	A14	0,861	0,843	0,925	0,997	0,749	0,916	
15	A15	0,665	0,625	0,639	0,532	0,711	0,543	
16	A16	0,904	0,830	1,000	0,948	1,000	1,000	
	Average	0,826	0,812	0,931	0,868	0,826	0,873	0,856
17	A17	1,000	0,929	0,789	0,711	0,941	1,000	BUKU 1
18	A18	0,459	0,466	0,560	0,580	0,546	0,478	
19	A19	1,000	0,781	1,000	1,000	1,000	1,000	
20	A20	0,920	1,000	1,000	1,000	0,805	0,932	
21	A21	0,633	0,574	0,687	0,653	0,580	0,679	
22	A22	0,790	0,650	0,880	0,736	1,000	0,710	
23	A23	0,707	0,716	0,734	0,805	0,805	0,811	
24	A24	0,728	0,537	0,712	0,602	0,516	0,598	
25	A25	0,583	0,575	0,796	0,859	0,734	0,820	
	Average	0,758	0,692	0,795	0,772	0,770	0,781	0,761

Efficiency Changes of IRDBS

MPI of all IRDBs in 2011-2016 using intermediation variable approach shows that there are increases in efficiency change by 80.0%, technological change by 20.0%, pure technical change by 80.0%, and scale efficiency change by 80.0%. The declining tendency of efficiency change significantly happened in 2013 until 2015, increasing from 11.3% to 0.6%. Meanwhile, technological change declined by 7.4% on average. Other Malmquist indexes show increases in productivity change, namely, the technical efficiency changes by 4.7%, pure efficiency changes by 2.1%, and scale efficiency changes by 2.5%.

1.1% and 2014/2015 by 0.4%. While in other periods declined by 8.9% in 2011/2012, 9.1% in 2013/2014, and 0.6% in 2015/2016. Besides, the total factor productivity change of IRDBs declined by 3.4% during the observation period.

The fluctuation of total factor productivity, as shown in Figure 2, can be solved by sustainably increasing the indexes of technical efficiency change and technological change.

Table 10. Annual Average of Malmquist index using Intermediation Variable Approach

Period	<i>Effch</i>	<i>Techch</i>	<i>Pech</i>	<i>Sech</i>	<i>Tfpch</i>
2011/2012	1,089	0,836	1,018	1,070	0,911
2012/2013	1,026	0,986	1,012	1,013	1,011
2013/2014	1,113	0,817	1,077	1,034	0,909
2014/2015	0,994	1,010	1,001	0,993	1,004
2015/2016	1,012	0,982	0,998	1,014	0,994
Mean	1,047	0,926	1,021	1,025	0,966

Notes: *Technical efficiency change (effch), technological change (techch), pure efficiency change (pech), scale Efficiency change (sech), total factor productivity change (tfpch)*

The increase of total factor productivity change only happened in 2012/2013, increasing by

Figure 2. Total Factor Productivity Change with the Variable Intermediation Approach

Table 11 shows that most of the IRDBs increased their productivity in almost all Malmquist indices, except in technological change, declining by approximately 7.6%. Productivity changes in other indexes are; 60.0% of IRDBs increased their efficiency change, 16.0% IRDBs had declining

productivity, and 24.0% of them did not experience any productivity change. Around 44.0% of IRDBs had an increase in total factor productivity change, supported by the increase in index efficiency change and scale efficiency change.

Table 11. Average Malmquist Index IRDBs with Variable Intermediation Approach

No	IRDB	<i>Effch</i>	<i>Techch</i>	<i>Pech</i>	<i>Sech</i>	<i>Tfpch</i>
1	A25	1,220	0,868	1,219	1,001	1,060
2	A05	1,079	0,970	1,006	1,073	1,047
3	A14	1,162	0,900	0,997	1,166	1,045
4	A12	1,116	0,935	1,095	1,019	1,043
5	A03	1,137	0,916	1,041	1,093	1,041
6	A06	1,000	1,038	1,000	1,000	1,038
7	A16	1,022	0,999	1,021	1,000	1,021
8	A07	1,093	0,933	1,070	1,022	1,020
9	A09	1,021	0,995	0,980	1,041	1,016
10	A10	1,085	0,936	1,040	1,044	1,016
11	A01	1,071	0,947	1,000	1,071	1,015
12	A21	1,104	0,902	1,109	0,995	0,996
13	A20	1,000	0,980	1,000	1,000	0,980
14	A02	1,043	0,931	1,000	1,043	0,972
15	A08	1,000	0,971	1,000	1,000	0,971
16	A17	0,991	0,977	0,992	0,999	0,969
17	A11	1,041	0,927	1,000	1,041	0,965
18	A15	1,044	0,923	1,032	1,012	0,964
19	A24	0,988	0,947	0,995	0,993	0,936
20	A18	1,000	0,933	1,000	1,000	0,933

21	A04	1,058	0,878	1,001	1,057	0,929
22	A13	1,000	0,862	1,000	1,000	0,862
23	A19	1,000	0,862	1,000	1,000	0,862
24	A22	0,940	0,827	0,954	0,985	0,777
25	A23	0,973	0,754	1,000	0,973	0,734
Average		1,048	0,924	1,022	1,025	0,968

Notes: Technical efficiency change (effch), technological change (techch), pure efficiency change (pech), scale Efficiency change (sech), total factor productivity change (tfpch)

Table 12 shows the value of Malmquist indices using the operation variable approach, which is slightly lower than the intermediation variable approach. During the observation period from 2011 to 2016, the constant increase for all Malmquist indices was around 40.0%. The highest efficiency change was 13.1% in 2015/2016, but in this period,

technological change declined by 16.9%, resulting in a decrease in total factor productivity change by 6.0%. Meanwhile, the lowest efficiency change was 3.2% in 2012/2013. Overall, efficiency change grew by 1.8%, but technological change declined by 5.0% on average.

Table 12. Annual Malmquist Index Average with the Variable Operation Approach

Periode	<i>Effch</i>	<i>Techch</i>	<i>Pech</i>	<i>Sech</i>	<i>Tfpch</i>
2011/2012	0,976	1,043	0,980	0,996	1,018
2012/2013	0,966	0,953	0,976	0,989	0,921
2013/2014	1,047	0,870	1,042	1,005	0,912
2014/2015	0,972	1,055	0,979	0,993	1,026
2015/2016	1,131	0,831	1,063	1,064	0,940
Rata-rata	1,018	0,950	1,008	1,009	0,963

Notes: Technical efficiency change (effch), technological change (techch), pure efficiency change (pech), scale Efficiency change (sech), total factor productivity change (tfpch)

The fluctuation of total factor productivity change in Figure 3 shows that the increase only happened in 2011/2012 by 1.8% and in 2014/2015

by 2.6%. While in other periods, this value declined, i.e., 7.9% in 2012/2013, 8.8% in 2013/2014, and 6.0% in 2015/2016.

Figure 3. Total Factor Productivity Change with Operation Variable Approach

The average Malmquist index of IRDBs using the operation variable approach in table 13 shows that most IRDBs increased their productivity in almost all Malmquist indices, with the exception of the technological change and total factor productivity change index, decreasing by 5.3% and 3.5% respectively. Accordingly, 64.0% of IRDBs

succeeded in achieving an increase in efficiency change, 32.0% of IRDBs decreased, and 4.0% did not change in the efficiency change index. Also, the results of the analysis show that 36.0% of IRDBs that have achieved an increase in total factor change productivity is supported by an increase in the efficiency change and scale efficiency change index.

Table 13. Average Malmquist Index IRDBs with Operation Variable Approach

No	IRDB	<i>Effch</i>	<i>Techch</i>	<i>Pech</i>	<i>Sech</i>	<i>Tfpch</i>
1	A25	1,187	0,943	1,188	0,999	1,120
2	A03	1,151	0,931	1,044	1,103	1,072
3	A21	1,112	0,948	1,125	0,988	1,055
4	A06	1,000	1,045	1,000	1,000	1,045
5	A07	1,064	0,967	1,053	1,011	1,029
6	A13	1,030	0,997	1,025	1,005	1,026
7	A12	1,102	0,929	1,083	1,017	1,023
8	A04	1,053	0,959	1,033	1,019	1,010
9	A01	1,047	0,961	1,000	1,047	1,006
10	A10	1,040	0,959	1,000	1,040	0,998
11	A22	1,015	0,971	1,036	0,979	0,986
12	A16	1,017	0,968	1,023	0,994	0,984
13	A19	1,027	0,948	1,025	1,002	0,974
14	A14	1,109	0,869	0,954	1,163	0,964
15	A02	1,030	0,924	1,000	1,030	0,952
16	A09	0,977	0,967	0,941	1,039	0,945
17	A15	1,001	0,942	0,999	1,003	0,943
18	A11	1,044	0,902	0,985	1,060	0,942
19	A05	0,972	0,953	0,947	1,027	0,927

20	A08	0,970	0,941	1,000	0,970	0,913
21	A18	0,925	0,978	0,932	0,992	0,905
22	A20	0,901	0,987	1,000	0,901	0,889
23	A17	0,893	0,974	0,959	0,931	0,870
24	A24	0,877	0,937	0,878	0,998	0,821
25	A23	0,942	0,783	1,000	0,942	0,738
Average		1,019	0,947	1,009	1,010	0,965

Notes: Technical efficiency change (effch), technological change (techch), pure efficiency change (pech), scale Efficiency change (sech), total factor productivity change (tfpch)

Table 14 shows that the average annual Malmquist in 2011-2016 increases in terms of technological change and it has been the primary factor for supporting the productivity increase of IRDBs in utilizing their assets. During the

observation, the increase in technological change was 24.2%. The highest score was in 2014/2015, increasing by 35.8% after in the previous year (2013/2014) decreased by 5.4%.

Table 14. The annual average Malmquist Index with the Asset Variable Approach

Period	<i>Effch</i>	<i>Techch</i>	<i>Pech</i>	<i>Sech</i>	<i>Tfpch</i>
2011/2012	0,821	1,309	0,762	1,077	1,075
2012/2013	0,893	1,300	1,281	0,697	1,160
2013/2014	1,226	0,946	1,041	1,178	1,160
2014/2015	0,821	1,358	0,904	0,908	1,115
2015/2016	0,891	1,297	0,784	1,136	1,156
Average	0,930	1,242	0,954	0,999	1,133

Notes: Technical efficiency change (effch), technological change (techch), pure efficiency change (pech), scale Efficiency change (sech), total factor productivity change (tfpch)

Efficiency change declined over time, except in 2013/2014, increasing by 22.6%. Pure technical efficiency and scale efficiency decreased by averagely 4.6% and 0.1%. As a result of an increase in technological efficiency and efficiency change,

IRDBs were recorded to experience an increase in total factor productivity by averagely 13.3%. Besides, the highest increase was in 2012/2013 and 2013/2014, reaching 16.0%, followed by 15.6% in the last two years.

Figure 4. Total Factor Productivity Change with Asset Variable Approach

Table 15 shows that all IRDBs experienced an increase in the technological change index. Most of the IRDBs experiencing an increase in efficiency change and technological change were in the top position in terms of total factor productivity change, although they experienced a slight decrease in terms of scale efficiency. Around 84.0% of IRDBs successfully increased total factor productivity change in the six years of the observation period. Besides, the increase in total factor productivity change using asset variable approach, as revealed in Figure 4, shows that it has a better performance compared to the other two approaches in this research.

Table 15. Average Malmquist Index IRDB with Asset Variable Approach

No	IRDB	<i>Effch</i>	<i>Techch</i>	<i>Pech</i>	<i>Sech</i>	<i>Tfpch</i>
1	A03	1,131	1,279	1,149	0,984	1,446
2	A11	1,073	1,221	1,087	0,987	1,310
3	A20	1,009	1,292	0,913	1,105	1,304
4	A16	1,034	1,242	1,357	0,762	1,284
5	A17	1,182	1,085	1,000	1,182	1,283
6	A12	0,974	1,295	0,952	1,024	1,261
7	A10	0,987	1,275	0,990	0,997	1,259
8	A14	0,974	1,266	1,002	0,972	1,234
9	A25	0,946	1,302	0,952	0,993	1,231
10	A04	1,008	1,220	1,005	1,003	1,230
11	A01	1,000	1,021	1,000	1,000	1,201
12	A05	0,989	1,213	0,758	1,305	1,199
13	A18	0,948	1,234	1,039	0,912	1,169
14	A07	0,961	1,207	0,959	1,002	1,160
15	A06	0,945	1,213	0,945	1,001	1,147
16	A02	0,917	1,240	1,000	0,917	1,137
17	A24	0,890	1,275	0,927	0,960	1,135
18	A15	0,850	1,314	0,884	0,962	1,117
19	A21	0,859	1,215	0,841	1,022	1,044
20	A19	0,825	1,245	1,000	0,825	1,028
21	A23	0,835	1,204	0,884	0,999	1,006
22	A08	0,848	1,136	1,000	0,848	0,964
23	A09	0,794	1,199	0,809	0,981	0,952
24	A13	0,642	1,249	0,649	0,990	0,802
25	A22	0,606	1,199	0,641	0,946	0,726
Average		0,929	1,226	0,950	0,987	1,145

Notes: Technical efficiency change (effch), technological change (techch), pure efficiency change (pech), scale Efficiency change (sech), total factor productivity change (tfpch)

CONCLUSION

This research tests the efficiency and analyzes the productivity change of Indonesian Regional Development Banks (IRDBs) throughout Indonesia from 2011 until 2016, using a non-parametric approach of Data Envelopment Analysis (DEA). The analysis of the efficiency level of BPDs was conducted using three approaches, namely intermediation, operation, and the asset approach.

Multi-stage DEA was adopted to result in an efficiency score of each BPD. For data analysis, this research uses the assumption of an input-orientated variable return to scale (VRS). Malmquist Productivity Index (MPI) was utilized to measure the total factor productivity change (Tfpch), indicating the increase or decrease of performance of IRDBs from 2011-2016.

The analysis of Multi-stage DEA shows that; 28.0% of IRDBs were considered as the efficient frontier in the intermediation approach, 24.0% of IRDBs were considered efficient in operation approach, and only 8.0% of IRDBs were considered efficient in asset variable approach. These three approaches clarify that most of the IRDBs in Indonesia were not outstandingly efficient.

The analysis of Multi-stage DEA also shows that the IRDBs with the large core capital was consistently categorized as the BPDs with the highest average efficiency score (intermediation, operation, and asset approach). The results of this research support the idea that IRDBs should increase their capital for increasing firm efficiency.

The MPI analysis shows that the highest productivity increase was in the asset approach of 84.0%, supported by the increase in efficiency change and technological change. While in intermediation and operation approach, the increase was only 44.0% and 36.0%, depending on the increase in efficiency change and scale efficiency change.

MPI shows that the total factor productivity of the IRDBs with largest core capital consistently had the largest increase in the average score using the three approaches in this study. Thus, it is essential for the BPDs to have an effective capital strategy so they can improve themselves to be in BUKU 3 and BUKU 4.

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