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The Adoption of Digital Banking Technology and Bank Efficiency: Evidence in Indonesia

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This study investigates the impact of digital banking technology adoption (DBTA) to banks efficiency which has an important implication on banking industry performance. We use non-parametric DEA efficiency measure for bank intermediation, performance and market outreach efficiency and the ratio of IT-related cost to total bank operational cost as DBTA indicators. Our result confirms the non-linear effects of DBTA in the Indonesian banking sector to banks relative efficiency. We found a trade-off between bank performance efficiency and bank market outreach efficiency of DBTA effect. The less aggressive behavior of bank in DBTA results in lower market outreach, on the other hand too aggressive banks could face lower financial performance efficiency. These finding enacted issues on the optimal DBTA strategy for banks, since it could lower their competitiveness if they slowly adopt the digital banking technology and worsen their financial performance if they adopt aggressively. For all of the estimated models, we find the impact of digital banking technology adoption on banks scale efficiency is more robust compared to other types of bank efficiency.

JEL Codes: G21, L22, O33.
Keywords: efficiency, competition, digital banking, data envelopment analysis.

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INTRODUCTION

The advancement of digital technology in the banking and financial industries is currently a major strategic issue for the banking sector. Both in terms of opportunities for the development of bank businesses and in the aspects of threats to the bank's business existence issues (Dermine, 2016; Marinč, 2013). From the perspective of banking sector regulators and public policy, the penetration of digital banking technology can cause problems related to the impact on bank solvency, risks in the banking system and protection of customers. On the other hand, it has positives impact in the form of increased competition and expanding potential market which can ultimately boost bank’s efficiency and productivity in the financial industry. Lipton et al. (2016). Predict future shape and role of banks that adopt digital technology from the point of view of customers, investors and the bank itself. According to Lipton et al. (2016), in the future, there will be a banking system with digital technology that not only performs the basic functions of banks as financial intermediary institutions and financial service providers, but also beyond just as financial advisors to their customers and can interact real time through the mobile device used by its customers. Financial services that are integrated with sectors outside the financial sector can be a threat as well as an opportunity for the existence of the traditional banking business runs by banks. This future scenario condition certainly has broad implications for the architecture of the financial system in the economy.

According to McKinsey & Company research on digital banking in Asia (McKinsey & company, 2014), the full time equivalent (FTE) approach reveals that 30 top processes in banking use 50 percent of their cost, 20 percent of processes in banking services can be digitized and potentially can increase efficiency of 15-20 percent of the total banking costs. McKinsey (2016) also stated that consumer adoption for digital banking experienced a significant increase. AT Kearney's analysis of the Banking Transformation Roadmap (AT Kearney, Inc, 2014) survey revealed that by 2020, 80% of the market share will be dominated by smartphone users.

Furthermore, the Bank for International Settlements, predicts five scenarios that will be faced by banks related to the implementation of digital banking technology in the future. The first scenario is the emergence of a better bank, the incumbent bank is modernizing and digitizing. In this scenario, incumbent banks digitize and modernize themselves to maintain customer relationships and core banking services, utilizing technology that makes it possible to change their current business model. The second scenario is the emergence of new banks, the replacement of incumbents by challenging banks as a consequence of the emergence of new banks that have used digital technology. The third scenario is a fragmented financial industry between banks and financial service companies that utilize financial technology. The fourth scenario is that the role of banks is irrelevant because the role of banks as intermediary institutions has been completely replaced by technology. The latest scenario of incumbent banks being commodity service providers and submitting direct customer relations to other financial service providers, such as financial technology and big tech companies. (BIS Quarterly Review December, 2017) Financial Technology Company and big tech customers use front-end platform to offer a range of financial services from a diverse group of providers.

Apart from various future scenarios that will be faced by the banking industry, with the rapid penetration in the implementation of digital technology, economic theory explains that technological advances lead to increased productivity and drive the efficiency of the company. More efficient and productive a company will increase its capacity to compete and dominate the market. The empirical finding shows that most banks in Indonesia banking sector have made adoption of digital banking technology as a major strategy that is being implemented (Price Waterhouse and Coopers, 2018). Economic theory predicts banks need to keep their market share to compete in an oligopolistic market or industry. They should expand or at least maintain their market share to stay competitive in the market or lose their market power. This research investigates banks efficiency in Indonesia during the rapid implementation of digital banking technology and digital banking effect on banks efficiency.

The next part of this research will review the theoretical and empirical literature and develop hypothesis why banks should adopt the digital banking technology and elaborate the bank's efficiency indicators using data envelopment analysis (DEA) method. Part three we develop the empirical model and explains the empirical models and data used in this research, part four is the empirical finding of this research on banks efficiency and the impact of adoption of digital banking technology on bank efficiency in the Indonesian banking industry. The final part is the conclusions and the policy implications for banks regulator.

1. LITERATURE REVIEW

1.1 Bank Functions and Digital Banking Technology

In the simplest sense, a bank is an institution that in its operations aims to lend funds to borrowers and receive savings from the lenders in the economy (Freixas X. & Rochet, J. C, 2008). This definition describes the main activities of banks to pool funds from society and channeling them in the form of loans. According to Merton (1993), "A well-developed smoothly functioning financial system facilitates the efficient life-cycle allocation of household consumption and the efficient allocation of physical capital to its most productive use in the business sector." Bank function is not only as an intermediary institution between savers and borrowers but also have an important role in the allocation of capital in the economy.

As with companies in the analysis of economic theory, banks also optimize the use of inputs to produce output with the ultimate goal of maximizing profits. Base on the industrial organization theory, we can convey the theoretical implications of banking industry competition in Indonesia and the implications of the implementation of digital banking technology on bank efficiency in the banking industry.

Theoretical Model

The basic theoretical assumption is the Indonesian banking industry market structure is the oligopoly market with several dominant firms in the banking industry. This assumption is supported by the relatively concentrated Indonesian banking industry in several banks according to their business activities (GROUP). Based on Indonesian Financial Services Authority (OJK) data the GROUP 4 banks category consists of only 5 banks but controls 50.5 percent of the total banking industry assets in 2017. With the assumption that the market structure faced by each individual bank in the Indonesian banking industry is not a perfectly competitive, then the condition for banks profit maximization (MR = MC), optimal output of bank *i* (*qi*) in the industry (*Q*) is:

$$p(Q) + \frac{\Delta p}{\Delta Q} q_i = MC(q_i) \qquad (1)$$

Because *qi*/*Qi* is market share (s_i) for bank *i* in the market, then

$$p(Q)\left[1 - \frac{s_i}{|\varepsilon(Q)|}\right] = MC(q_i) \qquad (2)$$

With mathematical manipulation of equation (2) will be obtained

$$p(Q)\left[1 - \frac{1}{|\varepsilon(Q)/s_i|}\right] = MC(q_i) \qquad (3)$$

Equation (3) can be written in the form of price to cost margin ratio as follows:

$$\frac{p(Q) - MC(q_i)}{p(Q)} = \frac{1}{|\varepsilon(Q)/s_i|} \qquad (4)$$

Equation (4) is a standard form of the equation from Lerner's index of market power. But in this equation, there is a component of market share which is the denominator of the market demand elasticity faced by an individual bank in the industry. The implications of equation (1) to (4) in the analysis of banking industry competition are as follows. The more elastic the market demand faced by a bank, meaning the lower the market power of the bank. What distinguishes the ability of banks to determine their price to cost margin (left-hand side of equation 4), is the market share of each bank (s_i) since the elasticity of market demand is exogenous for each individual bank. The greater the market share of the bank, the more inelastic market demand faced by a bank relative to other banks in the industry, whereas the lower the market share of a bank, the more elastic the market demand faced by the bank and consequently the lower the bank's ability to compete.

In carrying out its functions, banks will face competition in various banking output markets, both in the provision of the payment system and liquidity services (funding) and borrower monitoring services (lending). All of bank operational activities lead to banking service function that generates fees based income, and intermediation services that generate interest income. In relation to the functions of the bank in its operations, the role of technology is important to accelerate and streamline the services provided by banks. According to Lipton et.al. (2016), banking activity is mostly technological and mathematical in nature. That means most of the operational functions in banks can be transformed into forms of technology-based digital services. The banking system from the front end to the back end of the process can be done by utilizing technology and replacing the role of labor. Consequently, the role of technological advances and the implementation of digital banking is an opportunity for banks to improve competitiveness in the banking industry through increasing bank operational efficiency.

In the Indonesian context, technological advances increase the number of digital devices users and changes in lifestyles leading to an increased market potential for digital banking and also the migration of conventional banking users to digital banking in Indonesia (Price Waterhouse and Coopers, 2018). Digital Banking product and services are one of the bank's strategies to increase and maintain its market share in the current era of digital competition. Based on digital banking surveys conducted by PWC in 2018, 66 percent of respondents stated that digital banking strategy is part of the company's strategy. Further still the same survey, only 12 percent of respondents said that digital banking is part of the company's information technology development strategy, and 16 percent as part of their product or customer strategy. The survey results indicate that digital banking in Indonesia has become a mainstream strategy and not a specific strategy in the field of information technology or in the field of banking service product development.

Hypothesis – The more aggressive a bank on digital banking technology implementation more efficient is that bank relative to other banks. Based on the explanations that have been conveyed, then in terms of digital banking implementation by individual banks in Indonesia, this can be presumed to be a bank strategy to maintain and expand their market share. Furthermore, the transmission of the impact of digital banking on the market share of an individual bank is through increasing the efficiency of a bank in carrying out business activities, both in collecting and managing public funds (liquidity and funding) and in channeling funds (lending).

1.2 Bank Efficiency

There are several literature reviews related to the efficiency of the banking and financial industry. Berger and Mester (2003) reviewed the literature on the efficiency of financial institutions and opportunities for improving efficiency. Berger et al. (1993) analyzed 130 studies related to the application of frontier analysis on the efficiency of financial institutions in 21 countries. Fethi, et al. (2010) conducted a survey of 196 studies related to operational research and artificial intelligence techniques used to evaluate bank performance.

Frontier approaches identify and assess the areas or examples of best performance or best practice within the sample, i.e. those located on the "frontier". These methods can be contrasted with regression techniques that seek to explain the average behavior within a sample. Frontier techniques can be divided into two types: parametric and non-parametric. Parametric techniques specify a frontier function to be fitted to the data, with or without accounting for noise in the data. The non-parametric approach means that no prior functional form is assumed for the frontier, outside of a simple assumption of piecewise linear connections of units on the frontier. This means that the analysis can proceed without knowing the production function, which is the way inputs are transformed into outputs. Non- parametric approaches can simultaneously handle multiple inputs and outputs, but do not account for noise in the data, treating all deviations from the frontier as inefficiencies (Cummins JD & HM Zi, 1998).

Data envelopment analysis (DEA) is a non-parametric approach in the frontier analysis (Paradi, 2018). Thanassoulis (1999) discusses DEA applications specifically for the banking industry. DEA was also applied to analyze individual banks not only at the bank level as DMU but also at the bank branch level as DMU. Paradi, and Zhu (2013) surveying 80 studies related to the DEA application to analyze bank efficiency at the branch level. Recent research, Kaffash et al. (2017) analyzed 620 publications in journals indexed in the web science database, from 1985 to April 2016, using the method of citations network analysis. The results of these studies indicate that the data envelopment analysis (DEA) method is the main method commonly used by researchers to analyze the level of bank efficiency, both from a bank's perspective with the aim of improving its performance, as well as from the perspective of the banking sector regulator.

A bank is an organization that has the resources (input) used to achieve certain goals (output). The level of efficiency of a bank can be seen from the bank's ability to use its inputs to produce the maximum possible output. DEA compared the bank's ability to produce output to the maximum possible extent by using existing resources as expected by each bank as a decision-making unit (DMU). This is the rationale of performance measurement using the Data Envelopment Analysis (DEA) method. According to Kaffash et al. (2017), DEA is a linear program introduced by Charnes, Cooper, and Rhodes in 1978 developed based on the study conducted by (Farrell,1957). DEA as an efficiency measurement method is widely used by academics and practitioners to measure banks efficiency at the level of the banking industry by using the bank as a DMU, or at the level of individual banks by using the branch offices or business units of the bank as a DMU. As a tool to measure and evaluate the efficiency of the DMU, especially for the banking sector, the DEA method is quite popular. According to Paradi et al. (2018), there are more than 15 thousand scientific articles that use DEA and are dominated by analysis in the banking and health sectors.

The different research analyzes different types of efficiency, not only differences in the objects analyzed, for example using the banking industry (bank efficiency) versus individual banks (branch office efficiency). Application of DEA analysis is also carried out using different performance indicators. In general, there are three main points of view in analyzing the efficiency of bank performance using the DEA method, namely the efficiency of banks as financial transaction service providers for their customers, the role of banks as financial intermediary institutions and bank efficiency to generate profits. Berger et al. (1993) suggested that the production point of view would be more appropriate to be used to analyze the efficiency level of bank branches, and intermediation efficiency is more suitable to be used to compare the efficiency level between banks. The results of a study conducted by Fethi et al. (2010) also support the findings expressed by Berger et al. (1993).

Analysis of bank efficiency using the DEA method is also combined with other methods. Alqahtani et al. (2017), analyzed the determinants of bank efficiency and used the results of the DEA score calculation for each bank in determining the difference in efficiency between conventional banks and Islamic banks in the period after the global financial crisis. Hen et al. (2018) combined the DEA method with discriminant analysis to classify banks in China in groups based on the results of their efficiency scores. Hu et al. (2009) combine DEA analysis with Principle Component Analysis, in the first stage they calculate the bank's efficiency score for 45 types of efficiency scores. At the next stage, using the results of the efficiency score calculation with the DEA so they can calculate the general efficiency level index of all efficiency indicators using the Principal Component Analysis method.

2. DATA AND EMPIRICAL METHODS

2.1 Data Envelopment Analysis Method

DEA identifies and determines operational units that have the best performance within samples being evaluated. The identification results generated by the DEA analysis does not mean giving theoretical conclusions to be the best units, but rather are operational units that have the best performance among the groups that are sampled to be evaluated (DMU). DEA is a non-parametric analysis that can be done without using the assumption of a specific production function and calculating simultaneously more than one input and output (Coelli, 1996). DEA analysis has the advantage of using the data used in accordance with the measurement units of each input and output used, so it does not have to convert to the same unit of measure or unit, for example by using monetary values.

The initial DEA model developed by Charnes et al. (1979) produces efficiency scores by contracting the excess input used (input oriented) and by maximizing the output obtained by using existing inputs. For models with *m* input variable, *s* output variables and *n* DMU, the mathematical form of the DEA model is as follows, (Charnes et al. 1979)

$$\min_{\theta,\lambda} \theta \tag{5}$$

$$s.t{:}\ \theta x_0 - \boldsymbol{X}\lambda \geq 0$$

$$\boldsymbol{Y}\lambda \geq y_0$$

$$\lambda \geq 0$$

Where, x_0 and y_0 are column vectors of input and output for DMU_0, **X** and **Y** are the matrices of each input vector and output vector for all DMUs. The λ is the intensity variable column vector to state the linear combination of all DMUs. Objective function θ is the contractive factor (weight) for input of DMU_0. Because DEA calculates and empirically measures the relative efficiency of the data used in the sample, using too little DMU as a sample will usually cause most of the sample to be categorized as efficient DMU. In general, Banker et.al (1989) provides advice to follow the following rules in determining the number of samples or DMU:

$$n \geq max\{m \times s, 3(m + s)\} \tag{6}$$

The model in equation (5) is input oriented efficiency, by determining the value of the overall proportion of inputs that can be reduced or used efficiently or in other words determine 1- θ at the given level of output. Optimization of the linear program in equation (5) is done for all DMUs used in the sample, the results will have values between 0 and 1. An efficient DMU with maximum DEA efficiency score (1 in this case) is a DMU that is relatively most efficient compared to other DMUs in the DEA sample. In its development, DEA has three main variants, namely the radial model, additives model, and slack base model [28]. The CCR DEA Model (1978) uses the constant return to scale (CRS DEA) assumption, which is only suitable for use if the DMU operates on its optimal scale. Banker, Charnes, Cooper (BCC) (1984) proposed using the assumption of the variable return to scale (VRS DEA) to overcome these problems. Using the CRS assumption causes the obtained technical efficiency score to contain the scale efficiency component. By using the BCC (1984) VRS DEA model, the calculation results are pure technical efficiency score, which is free from the scale efficiency component. According to Coelli (1996), the scale efficiency score can be calculated using the ratio of the technical efficiency (CRS DEA) to pure technical efficiency (VRS DEA).

One of the advantages of DEA analysis is that it can be used to analyze changes in efficiency scores from one period to another. Decomposition of changes in efficiency scores can provide information related to the source of efficiency changes. Rolf et al. (1983) use the Malmquist Total Factor Productivity Index (MTFPI) which explains the changes in the efficiency of each output and input in the production process. MTFPI formula to calculate changes in output oriented productivity can be written as follows:

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \left(\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)} \times \frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^{t+1}(x^t,y^t)}\right)^{1/2} \tag{7}$$

In equation (7) *M* is the productivity of production in period t + 1 compared to productivity in period t. All *D* notations are output distance functions in the DEA analysis. So if the value of *M* is greater than one, it shows the improvement in productivity from period t to period t + 1. MTFPI can be decomposed in two parts as follows (Fare, et.al, 1994):

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)} \times \left(\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^{t+1}(x^{t+1},y^{t+1})} \times \frac{D_0^t(x^t,y^t)}{D_0^{t+1}(x^t,y^t)} \right)^{\frac{1}{2}} \quad (8)$$

On the right-hand side of equation (8), the ratio outside parentheses is a measure of relative changes in efficiency, or changes in production efficiency to achieve optimal productivity (EFFCH). The part in the brackets on the right-hand side of equation (8) is the geometric mean of two ratios that indicate technological shifts from period t to period t + 1 (TECHCH). Furthermore, the EFFCH component in equation (8) can be decomposed again to pure technical efficiency change (PECH) and scale efficiency change (SECH) as follows [31] :

$$PECH = \frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)} \quad (9)$$

$$SECH = EFFCH/PECH \quad (10)$$

There is no difference in the formulation for calculating EFFCH and PECH, but the calculation of efficiency score (distance function, *D*) on both types of efficiency using different assumptions. EFFCH uses the assumption of CRS DEA while PECH uses the VRS DEA assumption. Using the results of the DEA decomposition, it can be known and analyzed the transmission of the impact of the implementation of digital banking technology on the changes in the efficiency of each bank and the average changes in the efficiency of the banking industry in Indonesia.

2.2 Data and Sample Selection

According to the Indonesian Banking Statistics in December 2017, there are 115 banks in Indonesia categorized based on their core capital, consist of GROUP 1 (18 banks), GROUP 2 (53 banks), GROUP 3 (26 banks), and GROUP 4 (5 banks), while the remaining 13 banks are Islamic banks. GROUP 4 banks are the least number of bank groups, but controls and manages 50.5 percent of total assets managed by the Indonesian banking industry.

The sample used in this study is all commercial banks, but not including Islamic commercial banks and rural credit banks (BPR). Furthermore, based on the availability of data needed to conduct DEA analysis, we used 95 banks as samples. The period of analysis for this study is from 2012 to 2017. The selection of this period is based on the rapid progress of digital banking technology adoption in Indonesia banking industry has only occurred in less than the last five years[1]. The data sources that we use in this study are commercial bank report data to OJK[2], and secondary data from the official publication such as the Indonesian Central Bank and Indonesian Central Agency on Statistics (BPS).

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[1] The focus group discussion with the Bank results (represented by the division that handles information technology or digital banking) in OJK on April 12, 2018 and May 14, 2018, the banking system stated that digital banking has only really developed in the last three years. The selection of the sample period of the last five years is quite reasonable.

[2] Some confidential data from individual banks reports to OJK was used in this study, with non-disclosure agreement between researchers and OJK.

2.3 Measuring Bank Efficiency

Based on the ability of the DEA method to generate efficiency score, bank efficiency in the banking industry can be analyzed from various perspectives, among others banks as financial intermediary institutions, banks as companies or production units and banks as individual actors in the banking industry. The intermediation model views banks as intermediaries that receive inputs in the form of deposits and investments to lend and output in the form of loans, mortgages, and investments. In 1997, Athanassopoulos (1997) published a DEA research that used an intermediation model to examine 68 bank branches in Greece using interest and non-interest expenses as inputs and non-interest income and total customers as output.

The production model commonly called the output approach considers the bank as the production units that convert inputs such as employees, resources, and capital into outputs, such as the amount of the deposit or loan amount. DEA researches that use the production model includes research by Soteriou and Stavrinides (1997); Sherman and Ladino (1995); Oral and Yolalan (1990). The profitability model which is also similar to the production model considers banks as production units that convert inputs into outputs. However, the type of input and output used is different from the production model. Oral and Yolalan (1990) conducted a study that measured the performance of 20 banks in Turkey with a profitability model. The input they use is operating expenses and interest expenses, while the output used is interest and non-interest income.

Merton (1993), perspective on financial services put forward bank function as the payment system provider and financial resources allocation in the economy. This perspective leads to bank market outreach approach, as a company in the banking industry, banks can also assess its output from the availability and their ability to provide services (market outreach) to customers. A bank in an oligopolistic market must be able to maintain and expand its market share so that the number of customer proxies by the number of banks accounts and the number of banking services can be used as an output indicator. In addition, the input indicators used in this market analysis are the service and bank operational infrastructures, such as the number of branch offices, information technology infrastructure, and banks marketing costs.

This research will focus on bank efficiency from the perspectives of the bank as financial intermediary institutions, as the profit-oriented institution as well as the payment services and resources allocation in the economy. Base on the focus of this research, the DMUs are at bank level as the object of this research, input and output variables used in the DEA analysis in this research for each category of bank efficiency are as follows:

Intermediation efficiency - Output variables are the number of credit accounts, the total value of outstanding credit and interest income from bank lending. On the input side, the following indicators are used: (i) Total number of total work force, (ii) Third party funds consist of total deposits, demand deposits, and savings. Total interest and non-interest expenses, (iii) Number of branch offices consist of, domestic branch offices, domestic auxiliary branch offices, functional offices, operational headquarters, and commercial bank regional offices.

Performance Efficiency - In calculating the efficiency of bank performance, this study uses total income as output indicators consisting of interest and non-interest income and current year profit. While the input variables used are the same as indicators in intermediation efficiency, but do not use the number of the branch office as input variables.

Market Outreach Efficiency – in term of bank capability to provide banking services within an economy, they should reach all segments of their customers. The function of banks in collecting public funds and managing liquidity is part of the bank's business that is suspected to be most exposed to technology and could be viewed as their ability to reach their market. The output used is bank third-party funds consisting of savings account and giro account but does not include time deposits. Whereas the inputs used are operating expenses related to the function of collecting public funds, consist of, interest expenses, number of employees and the number of branch offices.

Using the input and output variables as already defined, the DEA analysis in this study uses the period 2012 to 2017 dataset. The results of the calculation of efficiency scores for each year in this period of analysis will generate a panel data of the efficiency scores, annual changes in the efficiency score, and the decomposition of the efficiency changes. Calculation of DEA efficiency scores in this study using the assumption of the constant return to scale (CRS). The CRS DEA model is used because by using these assumptions, it becomes more possible to compare between companies of different sizes (Akhtar, 2010). The VRS DEA are calculated in order to decompose the CRS DEA efficiency score into pure technical efficiency and scale efficiency. At this stage, the results of the calculation of the efficiency score of each bank in the sample (DMU) will be obtained and also the calculation results for MTFPI along with the decomposition of the components.

2.4 The Digital Banking Technology Adoption Effect on Bank's Efficiency: Panel Data Regression Model

We develop a panel data regression model and uses banks efficiency scores and the Malmquist Index from the calculation result of DEA analysis as dependent variables. The time period is 2012-2017 with cross-section samples of all banks used in the DEA analysis. The general functional form of the panel data regression model is as follows:

$$EB_{i,t} = f\left(BC_{i,t}, Macro_{t}, DB_{i,t}\ \varepsilon_{i,t}\right) \quad (11)$$

Where *EB* is bank *i* efficiency score in year *t*, *ε* is error term, *BC* is a vector of variables, consist of characteristics of bank *i* in year *t*. Macro is a vector of macroeconomic condition variables which has an impact on the Indonesian banking industry. *DB* is a vector of variables that are used as proxies for banks digitization level indicators.

Bank characteristics variables and macroeconomic variables are vectors or groups of control variables which in the empirical studies of bank efficiency determinants have been known to have a significant effect. Following the previous empirical study these variables consisted of bank characteristics variables and external conditions of the bank (Repkova, 2015; Girardone et.al, 2004; Soteriou and Yiannos, 1997; Košak and Zajc, 2006) as follows:

a. ***Size***, Bank size, using the total assets of the bank as the indicator
b. ***LC***, level of capitalization, is the ratio of equity to total assets
c. ***ROA***, return on assets ratio is a proxy for bank profitability
d. ***RCr***, credit risk, uses the ratio of total credit to assets as an indicator.
e. ***RL***, liquidity risk, using the loan to deposit ratio as the indicator.
f. ***Int***, the interest rate, using the ratio of interest income to total credit as the indicator
g. ***NPL*** is a proxy for the overall risk of a bank's portfolio using the gross non-performing loan.
h. ***Branch***, Number of branch offices,
i. ***MP***, the monetary policy rate
j. ***GDP***, real Gross Domestic Product
k. ***DIG2***, is the ratio of information technology cost to total operational costs, developed from secondary data obtained from Indonesian bank supervision authority (OJK).

Equation (11) is the general form of our empirical model specification in order to investigate the effect of DBTA on each type of banks efficiency scores. As mentioned in Berger and Mester (2003) and Deyoung et al. (2003), technology adoption could reduce unit cost and some services of banks have evolved into low cost and high volume business dominated by high technology banks. The investment on the digital technology not only could raise bank's operational cost but also increase their revenue, the gap between increases in total revenue to rising total operational cost is positive. Their finding implies the non-linearity effect of technology adoption on bank scale efficiency. This study also estimates the quadratic specification in addition to the linear model specification to take into account the non-linear effect of DBTA on bank relative efficiency.

3. RESULTS

3.1 Stylized Facts

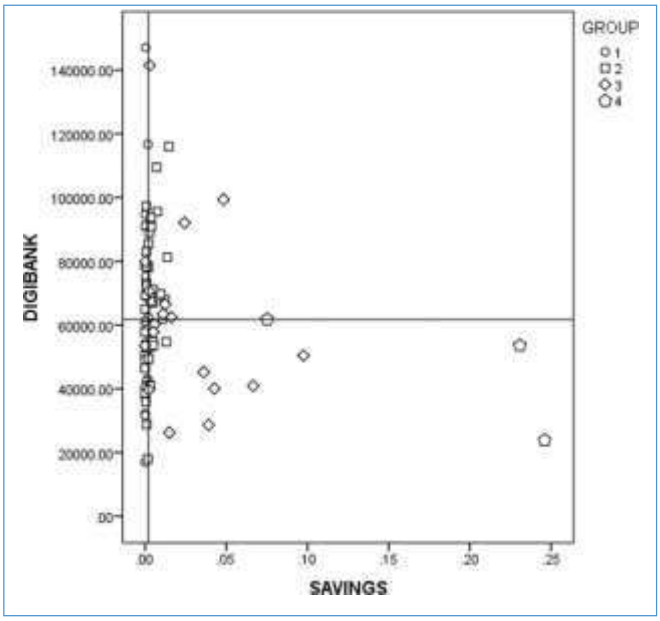

Figure 1.

Based on the quadrant, there are 24 banks in first quadrant,such as: 16 banks group two, 7 banks group three, and 1 bank group four. There are 20 banks In the second quadrant, such as: 8 banks group one, 11 banks group two, and 1 bank group three. There are 19 banks in the third quadrant, such as: 8 banks group two, 9 banks group three, and 2 banks group four. There are 23 banks in the fourth quadrant, such as: 9 banks group one, 13 banks group two, and 1 banks group three.

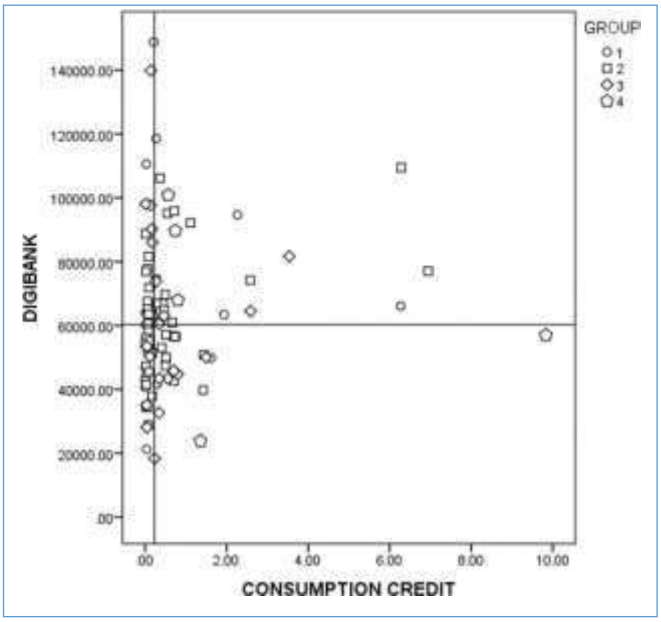

Figure 2.

Based on the Figure 2., there are 23 banks in the first quadrant, such as: 2 banks group one, 13 banks group two, 6 banks group three, and 2 banks group four. There are 19 banks in the second quadrant, such as: 5 banks group one, 11 banks group two, and 3 banks group three.

There are 21 banks in the third quadrant, such as: 1 bank group one, 9 banks group two, 8 banks group three, and 3 banks group four. There are 27 banks in the fourth quadrant, such as: 8 banks group one, 15 banks group two, and 4 banks group three.

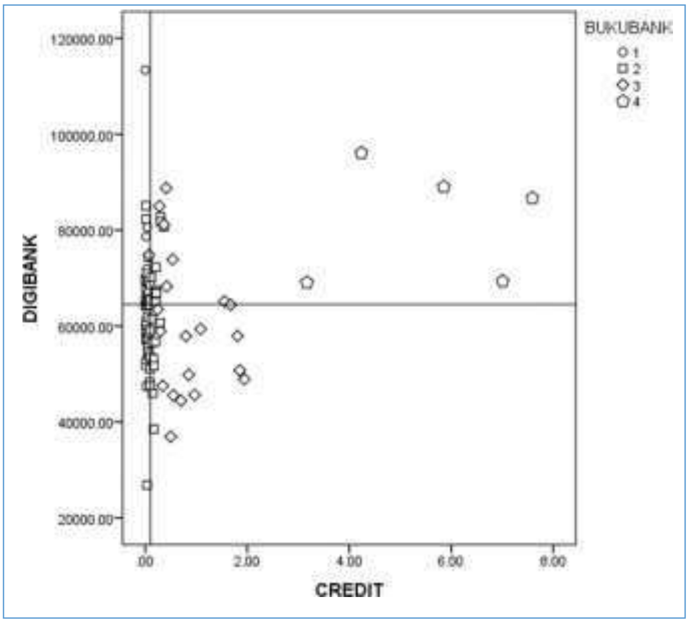

Figure 3.

Based on the Figure 3., there are 27 banks in the first quadrant, such as: 10 banks group two, 13 banks group three, 4 banks group 4. There are 29 banks in the second quandrant, such as: 13 banks group one and 16 banks group 2. There are 19 banks in the third quadrant, such as: 10 banks group two, 8 banks group three, and 1 bank group four. There are 17 banks in the fourth quadrant, such as: 4 banks group one and 14 banks group two.

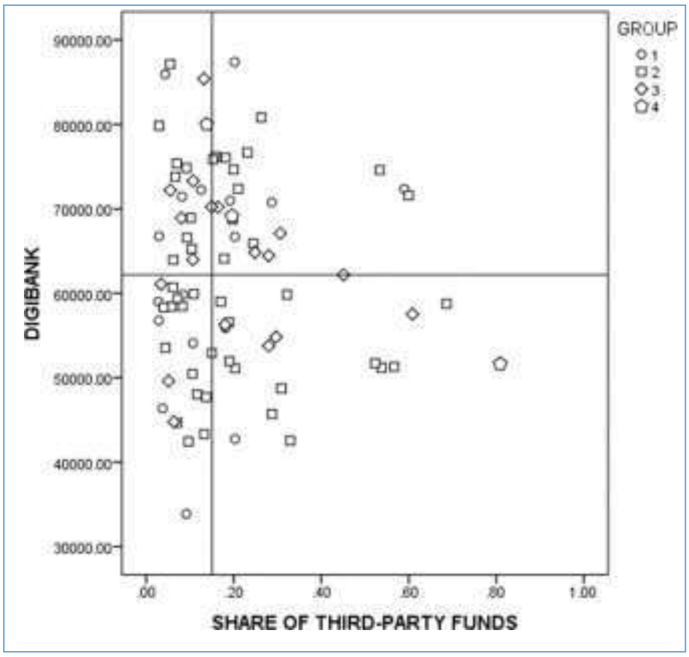

Figure 4.

Based on the Figure 4., the 18 banks in the first quadrant, such as: 3 banks group one, 8 banks group two, 5 banks group three, and 2 banks group four. There are 29 banks in the second quadrant, such as: 8 banks group one, 16 banks group two, 4 banks group three, and 1 bank group one. There are 16 banks in the third quadrant, such as: 11 banks group two and 5 banks group three. There are 23 banks in the fourth quadrant, such as: 6 banks group one, 12 banks group two, and 5 banks group three.

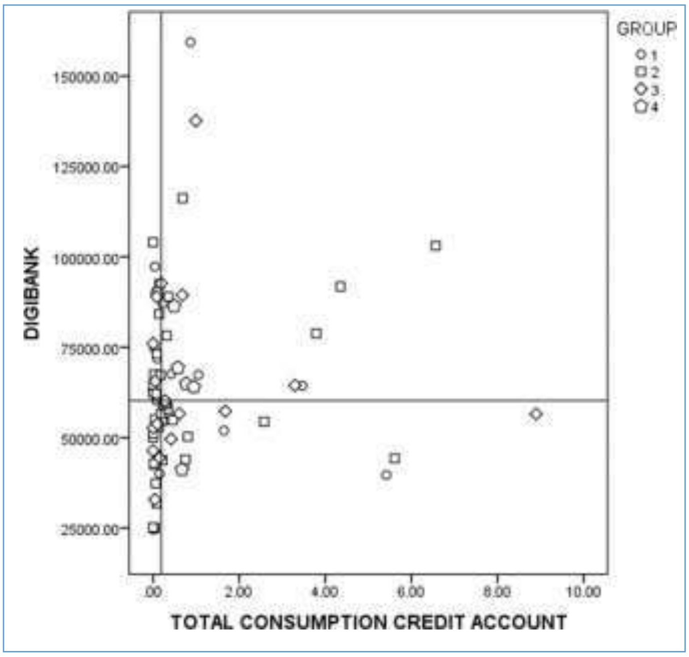

Figure 5.

Based on the Figure 5., there are 18 banks in the first quadrant, such as: 2 banks group one, 8 banks group two, 5 banks group three, and 3 banks group four. There are 18 banks in the second quadrant, such as: 4 banks group one, 11 banks group two, and 3 banks group three. There are 20 banks in the third quadrant, such as: 4 banks group one, 9 banks group two, 5 banks group three, and 2 banks group four. There are 21 banks in the fourth quadrant, such as: 4 banks group one, 12 banks group two, and 5 banks group three.

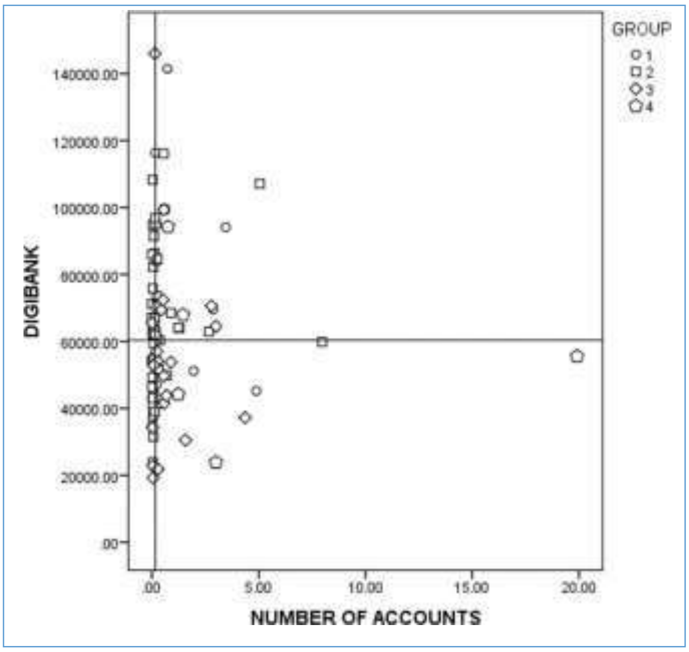

Figure 6.

Based on the Figure6., there are 18 banks in the first quadrant, such as: 2 banks group one, 8 banks group two, 5 banks group three, and 3 banks group four. There are 18 banks in the second quadrant, such as: 4 banks group one, 11 banks group two, and 3 banks group three. There are 20 banks in the third quadrant, such as: 4 banks group one, 9 banks group two, 5 banks group three, and 2 banks group four. There are 21 banks in the fourth quadrant, such as: 4 banks group one, 12 banks group two, and 5 banks group three.

3.2 Indonesian Banking Efficiency 2012-2017

We calculate efficiency score and changes in efficiency score from the three different efficiency perspectives as explained in the DEA input and output variables specification. To overcome the small sample problems of DMU or banks classifies in GROUP 4 by OJK, we calculate the DEA efficiency scores for two bank groups instead of four bank groups as already classifies by OJK. We gather bank in GROUP 1 and GROUP 2 as small banks group and banks in GROUP 3 and GROUP 4 as the large bank group. This grouping strategy makes the calculated efficiency score are the relative efficiency between the banks of their peers in term of banks business scale, the small bank's group and the larger bank group.

3.3 Intermediation efficiency

Based on **Table 1** and **Table 2**, the average level of banks efficiency in carrying out their intermediation function is higher in large banks group (GROUP 3 and GROUP 4) compared to banks in small banks group (GROUP 1 and GROUP 2). The average efficiency of bank intermediation functions in large banks group is 0.86, which means that this group can still improve its efficiency by another 14 percent, while for banks small bank group, on average they can improve their efficiency by 19 percent. Other findings from the calculation of the bank's efficiency score for their intermediation function were small banks group pure technical efficiency score was lower than their scale efficiency score. Indicating that the changes in the bank's business scale were more dominating compared to the bank's ability to streamline their operations in shaping their total efficiency scores. The opposite condition occurs in larger banks, which have a higher pure technical efficiency score compared to the scale efficiency score. The implication of these findings shows that their business expansion is the sources of small banks increasing level of efficiency, on the other hand for the larger banks technical and managerial advancement is the sources of the increase on their operational efficiency.

In GROUP 1 and 2 banks, the average annual minimum efficiency score (0.38) during the analysis period was much lower than the average efficiency score (0.81). This DEA efficiency score calculation indicates that this small bank group has banks that are relatively much less efficient in carrying out their intermediary function than the average level of efficiency of small banks group. For the larger banks group, the minimum efficiency score is 61 percent of the most efficient banks in the group, with average efficiency is 86 percent of the most efficient banks in the group.

Table 1.The Intermediation Efficiency of Small Banks Group (GROUP 1 and 2)

Efficiency Category		2012	2013	2014	2015	2016	2017	Average
Technical Efficiency	Mean	0.783	0.833	0.823	0.803	0.807	0.806	0.809
	Max	1	1	1	1	1	1	1
	Min	0.288	0.32	0.386	0.42	0.399	0.389	0.377
	SD	0.155	0.138	0.139	0.144	0.142	0.150	0.119
Pure Technical Efficiency	Mean	0.845	0.876	0.87	0.859	0.862	0.86	0.861
	Max	1	1	1	1	1	1	1
	Min	0.29	0.326	0.39	0.42	0.4	0.413	0.373
	SD	0.163	0.139	0.138	0.144	0.136	0.141	0.119
Scale Efficiency	Mean	0.926	0.950	0.945	0.934	0.936	0.937	0.938
	Max	1	1	1	1	1	1	1
	Min	0.659	0.689	0.731	0.626	0.627	0.681	0.703
	SD	0.084	0.070	0.071	0.090	0.087	0.082	0.068

Source: The results of the research team's calculations, using geometric averages.

Table 2. The Intermediation Efficiency of Large Banks Group (GROUP 3 and 4)

Efficiency Category		2012	2013	2014	2015	2016	2017	Average
Technical Efficiency	Mean	0.878	0.910	0.837	0.853	0.861	0.841	0.863
	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Min	0.642	0.718	0.487	0.610	0.634	0.599	0.611
	SD	0.121	0.089	0.138	0.122	0.120	0.130	0.119
Pure Technical Efficiency	Mean	0.972	0.986	0.965	0.958	0.955	0.932	0.961
	Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Min	0.672	0.780	0.616	0.612	0.651	0.638	0.659
	SD	0.071	0.045	0.089	0.086	0.089	0.106	0.078
Scale Efficiency	Mean	0.903	0.923	0.867	0.890	0.901	0.903	0.898
	Max	1	1	1	1	1	1	1
	Min	0.66	0.721	0.615	0.672	0.682	0.677	0.670
	SD	0.105	0.080	0.118	0.108	0.104	0.104	0.102

Source: The results of the research team's calculations, using geometric averages.

Table 3 and **Table 4** are the results for the Malmquist Total Factor Productivity Change (TFPCH) calculations and the decomposition of the TFPCH component, consist of efficiency change (EFFCH) and Technical Efficiency Change (TECHCH). Furthermore, EFFCH was decomposed into Pure Technical Efficiency Change (PECH) and Scale Efficiency Change (SECH). This efficiency changes scores calculation indicates that both small and large bank groups generally experienced an increase in their average efficiency levels during the analysis period. The TFPCH values were both higher than 1, but the increase in the intermediation function efficiency was only relatively small at 1.1 percent for small banks group and 1.7 percent for larger banks. In 2016 and 2017 the larger banks experienced a decline in their level of efficiency while the smaller banks experienced a declining efficiency in 2017. The progress of intermediation function efficiency of Indonesian banking sector during the rapid progress of digital banking technology adoption is relatively slow and decline at the end of the analysis period.

Table 3. ANNUAL AVERAGE OF MALMQUIST INDEX

The Small Bank Intermediation efficiency (GROUP 1 and 2)					
YEAR	**EFFCH**	**TECHCH**	**PECH**	**SECH**	**TFPCH**
2013	1.071	0.992	1.043	1.027	1.063
2014	0.988	1.024	0.994	0.994	1.011
2015	0.974	1.049	0.986	0.988	1.022
2016	1.006	1.008	1.007	0.999	1.014
2017	0.996	0.952	0.996	1.001	0.948
AVERAGE	1.006	1.004	1.005	1.002	1.011

Source: The results of the research team's calculations, using geometric averages.

Table 4. ANNUAL AVERAGE OF MALMQUIST INDEX

The Large Bank Intermediation efficiency (GROUP 3 and 4)					
YEAR	**EFFCH**	**TECHCH**	**PECH**	**SECH**	**TFPCH**
2013	1.041	1.013	1.017	1.024	1.055
2014	0.911	1.174	0.974	0.936	1.07
2015	1.023	1.028	0.994	1.03	1.052
2016	1.01	0.975	0.997	1.013	0.984
2017	0.976	0.954	0.974	1.002	0.931
AVERAGE	0.991	1.026	0.991	1.000	1.017

Source: The results of the research team's calculations, using geometric averages.

3.4 Performance Efficiency

Banks has the objective to optimize their profits earned, the bank's performance efficiency analyzes bank's ability to generate profits and income by using labor input and operational costs. In both bank groups used as samples in this study, it shows that the average technical efficiency is relatively very low. In small banks group, the average technical efficiency was only 47.28 percent compared to the most efficient banks in the sample. Furthermore, in large banks group, average efficiency level is only 66.08 percent compared to banks (DMU) that operate at their optimal efficiency level. These findings indicate the bank's performance efficiency score in the Indonesian banking industry has a high variation. This analysis is evidenced by the relatively high standard deviation of the level of efficiency of bank performance compared to the average value of the technical efficiency score.

Table 5. The Performance Efficiency of Small Bank (GROUP 1 and 2)

Efficiency Category		2012	2013	2014	2015	2016	2017	Average
Technical Efficiency	Mean	0.556	0.390	0.350	0.445	0.543	0.609	0.472
	Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	Min	0.235	0.145	0.116	0.190	0.165	0.223	0.173
	SD	0.214	0.188	0.188	0.213	0.221	0.233	0.209
Pure Technical Efficiency	Mean	0.692	0.598	0.580	0.608	0.667	0.683	0.636
	Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	Min	0.235	0.154	0.119	0.206	0.283	0.307	0.206
	SD	0.254	0.267	0.283	0.269	0.241	0.239	0.258
Scale Efficiency	Mean	0.803	0.652	0.603	0.731	0.814	0.891	0.742
	Max	1	1	1	1	1	1	1
	Min	0.471	0.281	0.321	0.384	0.440	0.616	0.405
	SD	0.164	0.194	0.204	0.193	0.172	0.103	0.168

Source: The results of the research team's calculations, using geometric averages.

Table 6. The Performance Efficiency Large Bank (GROUP 3 and 4)

Efficiency Category		2012	2013	2014	2015	2016	2017	Average
Technical Efficiency	**Mean**	0.682	0.654	0.660	0.679	0.557	0.748	0.660
	Max	1	1	1	1	1	1	1
	Min	0.215	0.299	0.299	0.323	0.294	0.322	0.289
	SD	0.253	0.236	0.222	0.249	0.219	0.219	0.232
Pure Technical Efficiency	**Mean**	0.834	0.801	0.817	0.818	0.729	0.834	0.804
	Max	1	1	1	1	1	1	1
	Min	0.274	0.359	0.403	0.492	0.339	0.362	0.365
	SD	0.204	0.214	0.183	0.180	0.238	0.192	0.201
Scale Efficiency	**Mean**	0.787	0.793	0.783	0.794	0.755	0.882	0.798
	Max	1	1	1	1	1	1	1
	Min	0.412	0.368	0.427	0.571	0.481	0.634	0.473
	SD	0.188	0.158	0.152	0.163	0.172	0.114	0.156

Source: The results of the research team's calculations, using geometric averages.

The dynamics of the efficiency score of Indonesian banking industry using the Malmquist Index technological change and its components can be seen in **Table 7** and **Table 8**. Improving performance efficiency in the large bank group is relatively better compared to small banks group. TFPCH of large banks group experienced an increase of 3 percent and for small banks group only increased by 0.3 percent. Overall, the bank's efficiency in using its inputs to obtain income and profit does not experience a significant increase but also does not experience a decline. An interesting finding in this section is the change in scale efficiency. All bank's groups experienced a relatively good increase. In 2017 the average banks in large banks group experienced improvements in scale efficiency reaching 16.8 percent. In 2015 small banks group experienced an increase in scale efficiency up to 19 percent compared to the previous year.

Table 7. The Malmquist Productivity Index for Performance Efficiency Small Banks Group

YEAR	Malmquist Index Indonesian Banking Industry				
	EFFCH	**TECHCH**	**PECH**	**SECH**	**TFPCH**
2012					
2013	0.682	1.508	0.833	0.819	1.028
2014	0.882	1.031	0.943	0.935	0.909
2015	1.291	0.77	1.085	1.19	0.994
2016	1.241	0.847	1.138	1.09	1.051
2017	1.129	0.921	1.029	1.097	1.039
AVERAGE	1.017	0.986	1.000	1.017	1.003

Source: The results of the research team's calculations, using geometric averages.

Table 8. The Malmquist Productivity Index for Performance Efficiency Large Banks Group

YEAR	Malmquist Index Indonesian Banking Industry				
	EFFCH	**TECHCH**	**PECH**	**SECH**	**TFPCH**
2012					
2013	0.966	1.114	0.96	1.007	1.077
2014	1.02	0.97	1.033	0.988	0.989
2015	1.018	1.012	1.003	1.014	1.029
2016	0.821	1.256	0.864	0.951	1.032
2017	1.371	0.749	1.174	1.168	1.027
AVERAGE	1.025	1.006	1.002	1.023	1.030

Source: The results of the research team's calculations, using geometric averages.

4.2.3. Market Outreach Efficiency

One of the bank activities that are highly affected by the implementation of digital banking technology is their activity in collecting public funds (funding) and providing payment system services (liquidity). Proxies for output indicators used for this efficiency is the total public funds in the bank in the form of savings account and current accounts. Both of this accounts type represents banks outreach to provide financial services to the society. Third party fund component in the form of time deposits are excluded because it is considered as the non-liquid saving account and relatively not affected by DBTA in terms of lowering unit cost. The DEA efficiency scores show that both of the bank groups have low average efficiency relative to the most efficient bank (frontier). In small banks group, the average technical efficiency score is only 59.4 percent compared to the most efficient bank. This result indicates that small banks group on average could increase their efficiency by up to 40 percent.

The relatively similar condition can also found in market outreach efficiency score calculation for large banks group. The average technical efficiency in these groups only slightly higher than the previous groups (61.1 percent). Compared to the most efficient bank in groups, on average less efficient banks within this groups could increase their efficiency score up to 39 percent. The differences between the two groups can be seen from the component of the DEA efficiency score. The efficiency score decomposition shows that the average scale efficiency score in small banks group is higher compared to the pure technical efficiency score. On the contrary, in the larger banks group, pure technical efficiency score is higher compared to their scale efficiency score. Implications from this findings are, small banks efficiency score changes are mainly from their expanding business scale instead of their operational technical improvement. On the contrary, bigger banks group efficiency score changes are from the improvement of their operational technical efficiency.

Table 9. The Market Outreach Efficiency for Small Bank Groups

Efficiency Category		2012	2013	2014	2015	2016	2017	AVERAGE
Technical Efficiency	Mean	0.577	0.568	0.575	0.601	0.625	0.622	0.594
	Max	1	1	1	1	1	1	1
	Min	0.21	0.151	0.137	0.081	0.147	0.103	0.132
	SD	0.223	0.248	0.231	0.270	0.271	0.260	0.250
Pure Technical Efficiency	Mean	0.649	0.629	0.635	0.709	0.716	0.718	0.674
	Max	1	1	1	1	1	1	1
	Min	0.25	0.168	0.144	0.252	0.209	0.171	0.194
	SD	0.236	0.263	0.241	0.252	0.250	0.244	0.248
Scale Efficiency	Mean	0.889	0.903	0.905	0.847	0.872	0.866	0.880
	Max	1	1	1	1	1	1	1
	Min	0.246	0.189	0.405	0.081	0.195	0.103	0.176
	SD	0.153	0.136	0.119	0.206	0.186	0.186	0.161

Source: Calculation results team researchers, using geometric averages.

Table 10. The Market Outreach Efficiency for Large Bank Groups

Efficiency Category		2012	2013	2014	2015	2016	2017	AVERAGE
Technical Efficiency	**Mean**	0.588	0.572	0.628	0.658	0.696	0.539	0.611
	Max	1	1	1	1	1	1	1
	Min	0.103	0.082	0.105	0.118	0.115	0.123	0.106
	SD	0.249	0.235	0.253	0.246	0.250	0.245	0.246
Pure Technical Efficiency	**Mean**	0.792	0.793	0.792	0.818	0.785	0.784	0.793
	Max	1	1	1	1	1	1	1
	Min	0.223	0.204	0.292	0.309	0.336	0.336	0.278
	SD	0.227	0.240	0.228	0.226	0.233	0.227	0.230
Scale Efficiency	**Mean**	0.742	0.721	0.792	0.804	0.886	0.687	0.769
	Max	1	1	1	1	1	1	1
	Min	0.308	0.283	0.359	0.381	0.342	0.226	0.312
	SD	0.175	0.181	0.177	0.158	0.155	0.203	0.174

Source: Calculation results team researchers, using geometric averages.

Based on results MTFPCH calculation in **Table 11** and **Table 12**, the dynamics of market outreach bank efficiency within the analysis period are declining for large bank group and only improved by 0.2 percent for the small bank group. Indonesian banking sector experience a decline in their capability to optimize their input in order to expand their market outreach. This finding indicates that in the large bank group, there are more banks with declining market outreach efficiency than banks with increasing market outreach efficiency. This condition leads to average market outreach efficiency decline in the banking industry in Indonesia during the analysis period.

Table 11. The Market Outreach Efficiency Change for Small Bank Groups

YEAR	Malmquist Index Indonesian Banking Industry				
	EFFCH	**TECHCH**	**PECH**	**SECH**	**TFPCH**
2012					
2013	0.956	1.027	0.941	1.016	0.982
2014	1.023	0.958	1.024	0.999	0.98
2015	1.012	0.96	1.129	0.896	0.972
2016	1.055	0.969	1.011	1.043	1.022
2017	0.998	1.057	1.001	0.997	1.055
AVERAGE	1.008	0.993	1.019	0.989	1.002

Source: Calculation results team researchers, using geometric averages.

Table 12. The Market Outreach Efficiency Change for Large Bank Groups

YEAR	Malmquist Index Indonesian Banking Industry				
	EFFCH	**TECHCH**	**PECH**	**SECH**	**TFPCH**
2012					
2013	0.974	0.957	0.992	0.981	0.932
2014	1.115	0.958	1.014	1.1	1.068
2015	1.059	0.89	1.038	1.02	0.942
2016	1.059	0.921	0.956	1.108	0.975
2017	0.759	1.312	1	0.759	0.996
AVERAGE	0.984	0.997	1.000	0.985	0.981

Source: Calculation results team researchers, using geometric averages.

In general, the average relative efficiency score of the banking industry in Indonesia is considerably low, both for small and bigger banks. This finding generates issues on the determinants of bank efficiency in order to identify the sources of this finding. In addition to the characteristics of a bank, DBTA is the potential factor to enhance banks efficiency.

3.5 Digital Banking Technology Adoption Impact on Banks Efficiency

Table 13 is the estimation results from the panel data regression model for analyzing the impact of digital banking technology adoption to banks relative efficiency score in Indonesia during the period of 2012 to 2017. All data already pass the unit root test using Levin, Lin, Chu Panel Unit Root Test method. Estimation method for the panel data model is the least square fixed effect panel data model with white robust standard error covariant. The robust standard error estimation ensures the efficiency of the regression coefficient variant resulted from model estimation. In relation to the possibility of non-linearity impact from the banking digital indicators, we also use quadratic model specifications. Based on the estimation results we can describe some main findings of this research on the impact of digital banking on banks relative efficiency in Indonesia.

DBTA statistically has a significant impact on Indonesia banks technical efficiency (CRS DEA). There are differences of the DBTA effects to each type of efficiency score used in the analysis, both in term of the direction of the DBTA effect and the level of statistical significance. For the bank's intermediation efficiency, the impact of digital banking is positive and significant, and this research finds there is no indication of the non-linear effect of digital banking technology adoption to banks intermediation efficiency. The bank's performance efficiency model shows a negative and statistically significant effect, our estimation results also show the impact of DBTA is non-linear and significant. The effect of DBTA on banks performance efficiency has the inverted U shape. This finding indicates that at the low ratio of information technology related cost to total operational cost will have a positive effect on banks performance, but this positive effect could turn to be negative when this ratio is too high. Banks that are too aggressive in implementing and adopting digital banking technology tend to have lower performance efficiency score during the analysis period.

For the banks market outreach efficiency, estimation results show a statistically significant and negative impact of digital banking technology adoption. Estimation results from the quadratic model specification for the market outreach efficiency also found to have a statistically significant effect with U shape relationship. This estimation result implies the effect of digital banking technology adoption proxies by the IT-related cost ratio to total operational cost have negative effect when this ratio is low and turn into positive at the higher level of this ratio, both of the estimation results are statistically significant.

The estimation of panel data model on banks efficiency has a linear effect on the intermediation efficiency and there is no indication of the non-linear effect of DBTA to this efficiency category. Furthermore, the effect of DBTA on the other two efficiency category has a contradictive finding. Banks faces trade-off between expanding their capacity and ability to improve their efficiency, too low investment in digital banking technology could cause lowering their funding and liquidity efficiency, otherwise when they invest too high in digital banking technology could harm their performance efficiency. From the banking regulator perspective the digital banking technology would improve banks intermediation function efficiency, but from individual bank perspectives, they have to balance the positive effect of digital banking technology adoption on their funding and liquidity efficiency versus the negative effect to bank financial performance efficiency.

Technical efficiency in DEA analysis can be decomposed to pure technical efficiency component (VRS DEA) and Scale Efficiency. The improvement of banks efficiency could be from their ability to improve their productivity and their business process or because of the economics of scale effect of their business expansion. The panel data regression estimation using pure technical efficiency score and scale efficiency score as the dependent variable for all efficiency score category reveals scale efficiency is more statistically significant than the pure technical efficiency.

For the intermediation efficiency, the impact of digital banking on pure technical efficiency score is not statistically significant, but it is statistically significant on the scale efficiency score. This explains that digital banking impact to bank intermediation efficiency is through the enhancement of bank's business scale. Digital banking technology does not affect the bank's intermediation efficiency through their operational improvement, but it is from more banks customer could be reached by banks as they adopt better digital banking technology. From the bank's performance efficiency perspectives, the impact of digital banking on banks performance efficiency score is negative for the pure-technical efficiency and positive for the scale efficiency. Both of these impacts are statistically significant. Bank performance efficiency is improved when it adopted the digital banking technology because of their business expansion effect, but when their IT-related cost ratio is too big could harmful for their financial efficiency. This decomposition of efficiency score estimation explains the inverted U curve impact of digital banking on bank performance efficiency.

Base on the estimation result from the decomposition of banks funding and liquidity efficiency, pure technical efficiency, and scale efficiency confirm significant non-linearity findings in the form of the U-curve shape of the impact of digital banking on bank's funding and liquidity efficiency score (CRS DEA).

Using the same empirical model and control variables, we also estimate the impact of digital banking on the bank's cost efficiency. We estimate a panel data regression model with the dependent variable the ratio of operational cost to operational income as the proxy for costs efficiency variable. The estimation result shows a significant and positive impact of digital banking on the bank's cost efficiency. Based on the quadratic model specification the impact of digital banking on the ratio of operational cost to operational income is non - linear and has inverted U-shaped, this finding is statistically significant. This result indicates banks operational cost will increase faster than the operating income at the low digital banking and vice versa.

Table 13. Results of Banking Digitalization Regression on Banking Efficiency (Model 1)

Variable	EFIN_CRS		EKIN_CRS		EFUN_CRS		EFFIN1_VRS		EKIN_VRS		EFUN_VRS	
	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)	Coefficient (std.error)
C	3.052.492 ***	3.056.572 ***	-3.620.186	-3.728.445	-0.248118	-0.378328	2.581.011 ***	2.605.685 ***	1.252.168	1.203.455	-3.587.849 **	-0.588122
	0.407702	0.436477	2.695.561	2.710.585	0.388051	0.48975	0.235451	0.240768	1.348.385	1.346.447	1.482.942	0.744701
DIG2	0.000148 ***	0.0000937	-0.000162 **	0.000646 **	-0.000171 ***	-0.000588 ***	0.00000199	-0.000101 *	-0.000379 ***	-0.0000151	-0.000186	-0.000536 ***
	0.0000503	0.000125	0.0000885	0.000314	0.0000601	0.000169	0.00000823	0.000056	0.0000888	0.00021	0.000125	0.000174
DIG2^2		0.000000379		-0.0000048 **		0.00000263 ***		0.00000068 *		-0.0000021 *		0.00000223 **
		0.000000895		0.00000203		0.000000946		0.000000371		0.00000125		0.000000981
LOG(SIZE)	0.081369 ***	0.08125 ***	-0.015071	-0.01687	-0.000565	-0.000351	0.064626 ***	0.06511 ***	0.026124	0.025314	0.040894	0.082011 ***
	0.022991	0.023122	0.026684	0.026292	0.002372	0.002267	0.005659	0.006043	0.017689	0.017916	0.04349	0.031669
LC	-0.028089	-0.028447	0.051483	0.050961	0.082797 ***	0.088066 ***	-0.011622	-0.013595	0.159897 **	0.159663 **	-0.034621	0.027526
	0.052659	0.052501	0.049025	0.050205	0.01145	0.012412	0.024713	0.024169	0.069953	0.069967	0.141526	0.034971
ROA	0.007755 **	0.007833 ***	0.014146 ***	0.013552 ***	-0.008186	-0.0106	0.000948	0.001089	0.01131 **	0.011043 **	0.010202 **	0.003441 *
	0.003045	0.00299	0.003942	0.003822	0.010359	0.011989	0.002109	0.002021	0.005609	0.005389	0.004809	0.002081
RCR	0.397922 ***	0.397587 ***	-0.296649 ***	-0.299457 ***	-0.022976	-0.019822	0.153017 ***	0.153929 ***	-0.0 454	-0.046664	-0.091648	0.060738 ***
	0.069153	0.068107	0.073845	0.075055	0.030388	0.036899	0.027567	0.028179	0.028107	0.029636	0.088902	0.015884
RL	0.000927 ***	0.000931 ***	0.000499	0.000449	-0.000712 ***	-0.000754 ***	0.000401 **	0.004855 ***	0.000313	0.007872 **	-0.024161 ***	-0.01332 ***
	0.000149	0.000157	0.000475	0.000504	0.000189	0.000226	0.000158	0.001092	0.000331	0.003092	0.005855	0.00322
INT	0.009069 ***	0.009181 ***	0.005677	0.005204	-0.004474 ***	-0.004641 ***	0.004779 ***	0.00042 **	0.008085 ***	0.000291	-0.001036 ***	-0.001016 ***
	0.002139	0.002185	0.004451	0.00465	0.001221	0.001307	0.001061	0.000166	0.003059	0.000337	0.000289	0.000221
NPL	0.003028 *	0.003081 *	0.001276	0.000911	-0.005406 **	-0.005453 *	0.000912	0.001062	0.003768	0.003603	-0.006412 **	-0.004571 ***
	0.001782	0.001871	0.003786	0.003638	0.002544	0.003087	0.000818	0.0009	0.006189	0.006072	0.002564	0.001051
LOG(BRANCH)	-0.01933	-0.019379	0.041361	0.042831	-0.076722	-0.0599	-0.024802 ***	-0.025549 ***	-0.010695	-0.010033	-0.018057	-0.002203
	0.016379	0.016691	0.048983	0.048039	0.072799	0.076674	0.004284	0.004579	0.06052	0.05967	0.036967	0.020125
MP	-0.002013	-0.001925	-0.075421 ***	-0.075285 ***	-0.003539	-0.003041	0.0000505	0.000124	-0.037699 ***	-0.037638 ***	-0.005206	-0.005221
	0.00294	0.002729	0.015205	0.015308	0.002508	0.002708	0.000784	0.000783	0.007088	0.007109	0.013144	0.004159
LOG(GDP)	-0.245511 ***	-0.245653 ***	0.301727	0.30904 *	0.107567 ***	0.128637 ***	-0.177288 ***	-0.179192 ***	-0.04982	-0.046529	0.256764 *	0.012143
	0.040853	0.043025	0.187089	0.187546	0.026851	0.021182	0.020361	0.021239	0.092867	0.092898	0.130872	0.072235
R-squared	0.940003	0.940812	0.838484	0.839605	0.984652	0.982394	0.932848	0.933477	0.870246	0.870452	0.819545	0.96641
Adjusted R-squared	0.926374	0.927204	0.80164	0.802562	0.981135	0.978309	0.917593	0.918182	0.840648	0.840534	5,4041667	0.958615
S.E. of regression	0.098913	0.099026	0.10935	0.109096	0.112236	0.112358	0.073962	0.073898	0.102817	0.102854	0.117425	0.112708
F-statistic	6.896.789 ***	6.913.714 ***	2.275.791 ***	2.266.586 ***	2.800.052 ***	2.404.544 ***	6.115.052 ***	6.103.388 ***	2.940.192 ***	2.909.398 ***	1.982.202 ***	123.98 ***

C	0.819498 ***	0.821392 ***	-5.673 ***	-5.719.841 ***	1.362.481 ***	1.390.745 ***	1.065.986 ***	1.079.631 ***
	0.256011	0.249622	1.882.157	1.914.481	0.094817	0.101015	2.592.489	2.521.519
DIG2	0.0000692 ***	0.000029	0.000259 ***	0.000608	0.0000058	-0.0000618 ***	0.002005 **	0.015567 ***
	0.0000138	0.0000806	0.0000624	0.000459	0.0000108	0.0000175	0.000868	0.004785
DIG2^2		0.000000253		-0.0000021		0.000000329 ***		-0.0000867 ***
		0.000000482		0.00000286		0.0000000722		0.000028
LOG (SIZE)	-0.011677 **	-0.011562 **	-0.070382 ***	-0.071161 ***	0.00338	0.003644	-1.338.616 ***	-1.545.301 ***
	0.005081	0.005084	0.026356	0.026561	0.003425	0.003183	0.324832	0.33804
LC	-0.006218	-0.006025	-0.126215 **	-0.126441 **	-0.042882 ***	-0.04077 ***	-1.820.402 ***	-1.687.295 ***
	0.023091	0.023581	0.049872	0.049519	0.013091	0.014844	0.490265	0.586337
ROA	0.002338 *	0.002459 *	0.00775 **	0.007493 **	-0.000858	-0.000857 *	-9.020.835 ***	-9.031.426 ***
	0.001321	0.001354	0.003343	0.003138	0.000521	0.000449	0.107549	0.118287
RCR	0.032005 *	0.032377 *	-0.366662 ***	-0.367877 ***	0.039432 ***	0.039002 ***	8.166.811 ***	6.728.846 ***
	0.016357	0.017032	0.10013	0.100557	0.014458	0.014128	1.229.834	1.318.174
RL	0.000265 **	0.000266 **	0.000364	0.000343	-0.0000832	-0.000089	-0.034994 ***	-0.035616 ***
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
INT	[illegible]	[illegible]	[illegible]	0.000332	[illegible]	[illegible]	[illegible]	[illegible] **
	0.001397	0.001383	0.003432	0.003672	0.000917	0.000887	0.094159	0.077492
NPL	[illegible]	[illegible]	-0.001238	-0.001396	-0.00051	-0.000548	0.21561 **	0.197943 ***
			0.002328	[illegible]	0.000445	0.000439	[illegible]	[illegible]
LOG (BRANCH)	**	**	0.051244 *	[illegible] **	0.015129 ***	0.014948 ***	***	***
			0.02608	[illegible]	0.002189	0.002649	[illegible]	0
[illegible]	[illegible]		-0.061172 ***	[illegible] ***	-0.00056	-0.000297	[illegible] ***	0 ***
			0.015472	[illegible]	0.000472	0.000357	[illegible]	0
[illegible]			0.501941 ***	[illegible] ***	-0.040666 ***	-0.042729 ***	[illegible]	0
			0.135059	[illegible]	0.008959	0.008962		
[illegible]			0.717362	[illegible]	0.88335	0.885942	[illegible]	0
Adjusted R-squared	0.913714	0.913371	0.652889	[illegible]	0.856623	0.859474		
S.E. of regression	[illegible]	[illegible]	[illegible]	4.820.738	0.082066	0.082338	3.322.389	3.335.495
F-statistic	5.820.318 ***	5.740.255 ***	111.266 ***	1.101.006 ***	3.305.141 ***	3.347.226 ***	5.439.915 ***	5.059.502 ***

5. CONCLUSIONS and POLICY IMPLICATIONS

The main purpose of the research is to investigate the impact of DBTA on banking industry efficiency and competition. This research found a significant impact of DBTA on banks efficiency, but the sign of the impact depends on the perspectives of bank efficiency. From the intermediation efficiency perspective, this research found a linear and positive significant impact of DBTA. Bank's performance efficiency and the bank's funding efficiency is non-linearly affected by DBTA, both are statistically significant. The impact on performance efficiency is following the inverted U-shape curve, on the contrary, the impact on the market outreach efficiency follows the U-shape curve. This finding implies the trade-off between the two efficiency perspectives of banks in the Indonesian banking industry. Banks decision to implement digital banking technology have to be aggressive enough in order to improve funding and liquidity efficiency, but on the other hand, too aggressive digital banking technology adoption could harm their performance efficiency.

Base on the efficiency score decomposition it is found that the scale efficiency is dominated the pure technological efficiency for positively affecting all category of banks efficiency score analyzed in this research. The positive effect of DBTA bank scale efficiency is robust for all efficiency category and all model specifications.

The implication of this finding for the banking industry regulator is, digital banking technology adoption by banks could enhance banking industry efficiency. The theoretical prediction of the impact of technology adoption affecting bank productivity is confirmed for bank intermediation efficiency. As long as the main concern of the banking industry regulator is related to the intermediation function of banks, promoting digital banking technology adoption is one of potential policy intervention.

A caveat for this policy implication is the negative effect of digital banking for too aggressive digital banking adoption on the banking performance efficiency. The negative effect of aggressive digital banking technology adoption on banks performance efficiency raise the issue of banking sector stability. For the further research, based on the trade-off faced by banks between performance and funding efficiency it is encouraging to empirically investigate the optimal level of digital banking technology adoption. The subject of this future research is both at the banking industry level as well as at the individual bank level. As a caveat of this research, we only use very simple digital banking indicator, measured by the ratio of the bank’s IT-related cost over their total operational cost. We also encourage future research to more precisely define the digital banking terminology and develop more precise measurements of a bank’s digital banking level indicators and comparable across countries.

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