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RISK-ADJUSTED EFFICIENCY AND BANK SIZE IN A DEVELOPING ECONOMY: AN ANALYSIS OF VIETNAMESE BANKS

***Abstract:** The literature has abundant empirical evidence showing that larger banks are more efficient than smaller banks in developed countries. However, little empirical literature focusses on small developing economies such as Vietnam where bank size is associated with increased risk, especially credit risk. This paper provides empirical evidence to fill in this gap. We employ a slack-based directional distance function using the intermediation approach in measuring the inefficiency of banks in Vietnam during 2006-2015. Non-performing loans are used as an undesirable output to capture credit risk. Results show that small banks are more efficient than large banks at the mean level and across the entire distributions of inefficiency of the two groups. Input waste, output shortage and risk surplus of big banks are nearly three times higher than those of small banks. Results are robust under constant and variable returns to scale for production technologies. Our empirical results contribute to the ongoing debate on the merits of enlarging bank size in a small transitional economy and suggest that policy makers should pay attention to the risk and inefficiency of large banks in order to enhance the performance of Vietnam's banking system as a whole.*

Keywords: risk-adjusted efficiency, Vietnamese banking industry, slack-based directional distance function.

1. Introduction

Economic theories postulate that large banks could gain economies of scale and economies of scope; hence larger banks can generate more revenue, operate at lower costs or both. The Structure-Conduct-Performance (SCP) hypothesis also suggests that large banks are more likely to show collusive behaviors that increase profitability (Bain, 1951). The efficient structure (ES) hypothesis predicts that efficient banks defeat their inefficient competitors and hence become larger (Demsetz, 1973; Peltzman, 1977). However, large banks may cause concerns for at least two reasons. First, the moral hazard hypothesis outlines that the entire banking system becomes riskier when a large percentage of total assets is concentrated in a small number of banks (Boyd and De Nicolo, 2005; Jiménez et al., 2013). This hypothesis implies that concentration in the loan market could increase lending rates, raising default probabilities of borrowers and their incentive to engage in riskier investments. In addition, higher concentration implies the existence of “too-big-to-fail” banks, which may follow excessive risk-taking strategies and create a greater risk to public finance (Bertay et al., 2013). Moreover, interconnectedness is common in the banking sector. Hence, distress of large banks can impose greater externalities to the financial instability (Laeven et al., 2016). Second, large banks are more likely to shift away from traditional lending activities towards non-banking ones (DeYoung and Torna, 2013). These non-banking activities are also considered to be riskier than lending ones (De Jonghe et al., 2015). These studies indicate that ignoring risk in assessing bank performance is incomplete.

Literature has produced strong empirical evidence supporting the SCP and ES hypotheses in developed economies (Kovner et al., 2014; Wheelock and Wilson, 2012). While many empirical studies about how efficiency and risk-adjusted efficiency vary in accordance with bank size have focussed on more developed countries, little is known about the relationship in a transitional economy like Vietnam. As the business environment in the transitional economies is not be as

apparent as in developed economies, the relationship between size and risk-adjusted efficiency may be not in line with the prediction of the SCP and ES hypotheses. This motivates us to answer the question that whether there is a difference in risk-adjusted efficiency conditional on size in Vietnam.

To answer the question, this paper employs the non-radial slack-based directional technology distance function developed by (Färe and Grosskopf, 2010) to estimate the efficiency of banks using the data envelopment analysis (DEA) technique. The advantage of the function is that it allows us to incorporate risk into measures of efficiency (so-called risk-adjusted efficiency). Then we conduct the Li-test (Simar and Zelenyuk, 2006) to compare efficiency scores between banks classified into large and small groups.

The banking system in emerging transitional economies often experiences a sharp expansion in relation to the scale of the national economy. For example, in term of size, the credit to GDP ratio of banks in Vietnam has doubled in recent years - from 65 percent of GDP in 2006 to 124 percent in 2010. More importantly, the recent growth of Vietnam's banking sector has been concentrated in a small number of banks. A group of 12 big banks dominates the banking sector with a 75 percent market share and the four largest banks account for around 50 percent of the market.

We collected data from FitchConnect. Our sample data includes 28 Vietnamese banks from 2006 to 2015. These banks represent the banking sector in Vietnam as they account for more than 86 percent of total deposits and 80 percent of total loans in the entire banking system as in 2015. To estimate bank efficiency, we employ the slack-based directional distance function. The advantage of this function is that it allows us to estimate efficiency with the presence of credit risk which is often considered as undesirable outputs. We take non-performing loans (NPLs) as a proxy for credit risk for two reasons. The first reason is that NPLs are one of most used indicators for risk in

the banking industry and have been widely used in the empirical literature (Barros et al., 2011; Chiu and Chen, 2008). The second reason is that the use of NPLs is particularly suited to Vietnam where the industry literature documents a continuing increase in their incidence. As noted, a growing level of NPLs is one of the best direct indicators of increasing risk in the banking system (Berger and De Young, 1997; Fiordelisi et al., 2011).

Then based on the median of total assets, we classify banks into two groups, small and large, for each year. We compare the mean of the risk-adjusted efficiency for each bank group annually. To check for statistical significance of the mean difference, we use the Li-test (Simar and Zelenyuk, 2006) to test the equality of distributions of efficiency scores. The test shows that small banks are more efficient than big banks. This finding is opposite to the SCP and ES hypotheses.

The paper makes several important contributions to the empirical literature. First, this paper extends the extant literature by examining whether efficiency is associated with size in a typical transitional developing economy. Our empirical results show that size enlargement is not positively associated with risk-adjusted efficiency, and therefore at variance with the established literature focussing on developed countries. Second, our empirical findings should be of interest to decision-makers in Vietnam for two important reasons. On the one hand, as larger banks have higher levels of inefficiency, more attention should be given to improving their performance. On the other hand, empirical analysis decomposes total inefficiency into a variety of input waste and output shortage variables - information which can help decision-makers identify areas for improvement for both small and large banks.

This paper is organized as follows. We review bank efficiency literature in Section 2. Section 3 provides the background to the Vietnamese banking sector. Section 4 introduces the methodology

used and Section 5 discusses the data and input/output selection. Section 6 presents the empirical results. The conclusion is given in Section 7.

2. Related literature review

The classic Cournot model in Bikker and Bos (2008) postulates that the profit level of a bank depends on its own behavior and its rivals in the oligopoly market. This model shows that profit increases when the size of the bank in terms of an increase in its market share increases, price elasticity decreases, conjectural variation¹ increases and price increases. Consequently, banks enlarge its size to achieve greater profitability.

Two well-established hypotheses also support a positive correlation between size and efficiency in the banking industry, namely the Structure-Conduct-Performance (SCP) and the Efficiency Structure (ES). The SCP hypothesis depicts the influence of a market's structure on the conduct of banks (pricing of inputs and outputs) and on the performance of banks in the market. It asserts that larger banks in an oligopoly competition can extract monopolistic rents (captured by profits) because they are able to mobilize deposits (and other borrowings) less costly but charge higher interest rates on the loans they grant. Also, the ES hypothesis states that banks become larger because they have a higher efficiency level. Under this hypothesis, efficiency is captured by either higher profits or lower costs achieved through superior management (Goldberg and Rai, 1996).

Consistent with these theoretical backgrounds, empirical research on bank efficiency in developed markets suggests that bank size is a key determinant of efficiency (Berger, 2003; Mester, 2005; Wheelock and Wilson, 2012). Highlighted is that banks grow larger to exploit technologically - driven scale economies to produce services at a lower cost. This finding reflects modern

¹ Conjectural variation captures the expectation of a bank about the reactions of its rivals output conditional on a change of bank i 's output

intermediation theory which states that bigger banks can contract with more customers for both fund mobilization and loan provision. That is, rising numbers of borrowers and lenders are assumed to result in more efficient diversification delivering a higher return for the same level of risk. In addition, larger numbers of customers result in lower contracting costs (e.g. cost of verification) and permit banks to allocate their funds to more highly profitable investments. Such synergy helps to explain the process by which banks become larger due to a mutual relationship between size advantage and higher efficiency. Similarly, Hu and Fang (2010) apply two-stage least squares procedure² and find that size (captured by market share) and efficiency mutually benefit each other for 266 securities firms in Taiwan from 2001 to 2005.

However, there exist hypothesis and empirical studies that show a negative relationship between size and bank efficiency. The quiet life hypothesis proposes that large banks with greater market power operate less efficiently than small banks because they do not target to reap all potential rent (Koetter et al., 2012). In competitive markets, bank managers have a strong incentive to give their best effort for profit maximization. But in oligopolistic markets, large managers may not be motivated by profit maximization and may choose to enjoy the “quiet life.” The norm “quiet life” refers to a situation when managers of larger banks avoid making hard decisions or taking on difficult tasks.

Empirically, Srairi (2010) finds that size is negatively related to cost inefficiency scores in the banking industry of Gulf Cooperation Council countries over the period 1999-2007. The result is in line with Koutsomanoli-Filippaki et al. (2012), who, using a non-parametric directional technology distance function approach, observe a negative relationship between size and efficiency for the European Union banking industry over the period 1998-2008. The superior

² The authors estimate the predicted market share, which will be a regressor to explain efficiency level.

performance of small banks is due to their operating mostly in local (niche) markets, having access to ‘soft’ information about local conditions, engaging in relationship banking and exercising some monopoly power, all of which allows them to operate more profitably. On the other hand, Staub et al. (2010) report no empirical support for differences in cost efficiency due to bank size by using a two-stage analysis of the Brazilian banking system from 2000 to 2007.

There are several studies examining Vietnamese bank efficiency. However, they only consider bank size as a control variable rather than as the key factor driving bank efficiency. Vu and Turnell (2010) examine the relationship between cost efficiency and ownership from 2000 to 2006. Over this period joint-stock and foreign banks had a relatively poorer performance with higher cost inefficiencies than state-owned commercial banks. Nguyen and Simioni (2015) measure changes in the total factor productivity of Vietnamese banks by using Färe-Primont indexes. This index method allows the decomposition of productivity change into changes in technical efficiency, mix efficiency, and scale efficiency. The authors found that there existed a deterioration of scale efficiency over the period 2008-2012, meaning that efficiency reduces when banks are bigger. Using a standard two-stage development envelope analysis (DEA) approach, Gardener et al. (2011) investigated the impact of ownership on bank performance in Indonesia, Malaysia, the Philippines, Thailand and Vietnam. The authors control for size and report a negative impact of size on cost efficiency. Stewart et al. (2016) find that large banks are more efficient than small banks in Vietnam from 1999-2009; however, their analysis only considers desirable outputs (i.e. customer loans, other loans and securities) and does not take account of risk.

Pham and Zelenyuk (2017) estimate the slack-based directional distance function using Vietnamese commercial bank data over the period 2008-2014. The authors also compare their empirical results with other approaches including the directional distance function, the enhanced hyperbolic efficiency measure and the Farrell-type technical efficiency. Their findings show the

greater discriminative power of the slack-based directional distance function over the other methods. The empirical results indicate that banks in the period 2008-2011 are more efficient than during the years 2012-2014. However, the authors do not disaggregate total inefficiency into sources of inefficiency related to each input and output thus revealing an empirical gap in the literature which our study seeks to fill.

In sum, several papers have measured bank efficiency and its determinants in Vietnam (Nguyen and Simioni, 2015; Stewart et al., 2016; Vu and Turnell, 2011). These papers, except Pham and Zelenyuk (2017), ignore undesirable outputs in the banking sector. This is an important gap for a developing country such as Vietnam and this paper aims at incorporating non-performing loans as an undesirable output in measuring inefficiency and by decomposing the total inefficiency into contribution of each input, desirable and undesirable output. A better understanding of input waste and output shortage can help bank managers and authorities better identify the sources of the inefficiency of individual banks and the whole bank industry.

3. Background of the Vietnamese banking system

Vietnam is an emerging economy transitioning to full market orientation - a process begun with the implementation of the Doi Moi economic reforms in 1986. Its macroeconomic performance has been impressive with an annual GDP growth rate of 7 percent over the two decades 1990 to 2010 although this growth has slowed since 2010. Major regulatory reforms in the banking system commenced soon after the Asian financial crisis in 1997 with the strengthening of the autonomy and functions of the State Bank of Vietnam and elimination of direct political controls over the interest rate. The banking system then witnessed dramatic growth after joining the WTO in 2007 which stimulated large capital inflows. However, hidden risks generated by financial asset bubbles

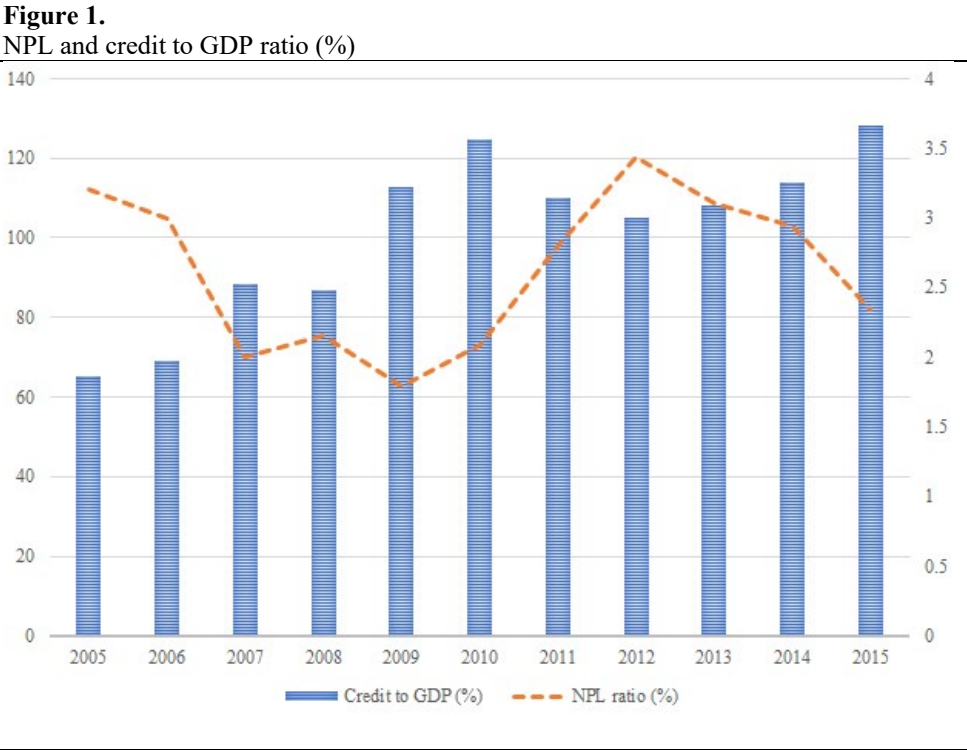
and intra-bank lending activities brought the sector to the brink of collapse in late 2009. Since 2010 a series of measures have been put in place to stabilize the Vietnamese banking system.

One of the most serious risk issue for Vietnam's banking systems during the last 20 years is the level of non-performing loans (NPLs). The literature reveals that due to the extensive investment in real estate by the majority of banks, the collapse in the real estate market in 2009 substantially lowered the value of commercial banks' real estate collateral, leading to loss liquidations and a significant increase in NPL ratios from 2009 to 2012 as shown in Figure 1.

Another distinct feature of Vietnam's banking sector is that the ratio of banks' credit to GDP increased twofold from 65 percent in 2006 to 124 percent in 2010. Since 2010, the banking system's growth has stagnated attributed to the rising levels of bad debts from 1.8 percent in 2009 to 3.4 percent in 2012. The aggregate bank size measured by total assets rose to around USD 250 billion in 2015 from about USD 52 billion in 2006. In terms of banks' total assets, they amounted to 194 percent of GDP in 2015 up from around 90 percent in 2006.

The rapid gain in bank size commenced in 2006 with the release of Government Decree 141 which increased the minimum equity capital levels of all credit institutions from VND70 billion to VND 3 trillion (about USD 150 million) and came into effect in 2008. If they were not able to fulfill this requirement banks would be forced to reduce their scope of activities or even face revocation of their banking operations. In response, Vietnamese banks raised capital from other banks, state-owned enterprises (SOEs) and private business groups leading to a cross-ownership and/or greater interconnectedness in ownership between banks. Consequently, due to cross-ownership between banks and SOEs, a high proportion of total assets of lending banks were in the form of short-term assets which could be used to fund short-term liabilities of borrowing banks. Short-term liabilities amounted to 30 percent of total liabilities by 2015 (ADB, 2015). It is noted that this lending

structure puts the entire banking system in danger of systemic liquidity crises, given the risk that high levels of interbank and short-term liabilities could create a contagious effect throughout the banking system.



Sources: World Bank (2016) world development indicators and State Bank of Vietnam

It is also important to note that the recent growth of Vietnam’s banking sector has been concentrated in a small number of banks. As of 2015, there were 44 commercial banks, including 28 joint-stock banks, 7 state-owned banks, 5 foreign-owned banks and 4 joint-venture banks. Among these, a group of 12 big banks dominates the banking sector. They account for 76 percent of market share in term of total assets, 79 percent of market share in term of loans to customers, and 78 percent of market share in term of deposits from customers. Of this group, 4 state-owned

commercial banks are particularly large having nearly 50 percent of the market share of total assets and over 50 percent of total market share of loans and deposits.

A substantial proportion of banks' loan portfolios are accounted by project loans to SOEs. This both reflects ownership of SOEs by banks and government interventions. It has not been uncommon for the Government to direct banks to meet SOEs' financial needs with the aid of government guarantees (i.e. loans are made without collateral). Credits granted to SOEs account for 60 percent of total credits even though SOEs have generally performed poorly: in 2010 they contributed only one-third of the country's GDP (OECD, 2013). In addition, a significant proportion of bank assets have been allocated to the purchase of government bonds to finance the government's budget deficit and sovereign debt payment. Because of the large concentration of investment in less efficient sectors of the economy, the banking system in Vietnam has failed to achieve a high level of efficiency. In such an environment, the banks have gained in size but have been exposed much greater risk. For example, most non-performing loans are those allocated to SOEs, which are not backed by collateral. So, banks are faced with write-offs of their assets. For this reason, it is desirable to examine the risk-adjusted efficiency performance of banks as well as analyzing the relationship between bank size and level of efficiency.

There have been some papers estimating bank efficiency and its determinants in Vietnam (Nguyen and Simioni, 2015; Stewart et al., 2016; Vu and Turnell, 2011). Most of the previous papers, except Pham and Zelenyuk (2017), ignore undesirable outputs, which are unavoidable in the banking sector, in estimating bank efficiency. This paper is different from most of the previous ones by incorporating non-performing loans as an undesirable output in measuring inefficiency and by decomposing the total inefficiency into contribution of each input, desirable and undesirable output. This difference is important as a key issue of Vietnamese banks is a large volume of non-

performing loans (Dinh and Kleimeier, 2007; Stewart et al., 2016) and the main sources of inefficiency are unknown in the previous studies on bank efficiency in Vietnam.

4. Methodology

We use the non-radial slack-based directional technology distance function (SBM) developed by Färe and Grosskopf (2010) to estimate the efficiency of banks using the data envelopment analysis (DEA) technique³. The distance function has been used in the literature (Pham and Zelenyuk, 2017; Zhu et al., 2015) to incorporate risk into measures of efficiency. Then we conduct the Li-test (Simar & Zelenyuk, 2006) to compare efficiency scores between banks classified into large and small groups.

The traditional DEA-based measures of efficiency including Charnes-Cooper-Rhodes (CCR), Banker-Charnes-Cooper (BCC), and the Russell measures rest on proportional enlargement in outputs or proportional reduction in inputs. Excess in the use of input (i.e. input slacks) or shortage in the output (i.e. output slacks) is often ignored in these conventional measures of efficiency while the SBM accounts for the slacks. Also using the directional distance function, the SBM models incorporate undesired outputs such as risks which are associated with banking lending activity.

In the context of Vietnam, the banking industry is exposed to persistent levels of high credit risk (Dinh and Kleimeier, 2007; Stewart et al., 2016). In fact, high credit risk can lead to the capital shortfall of many banks and this resulted in a series of compulsory restructuring, merging and acquisition of nine banks including commercial banks and banks owned by State Bank of Vietnam. Therefore, the credit risk should be considered in measuring efficiency in the context of Vietnam.

³ As the number of banks and observations are not large (28 banks and 273 observations); hence stochastic frontier analysis is not very suitable. In dealing with a small data set, DEA is more an appropriate technique.

4.1. The non-radial slacks-based measure (SBM) model

The directional distance function is used as this approach allows some good outputs to be expanded and bad outputs to be contracted in any chosen direction. The SBM model is used as it does not assume all inputs and outputs “behave in the proportional way” (Cooper et al., 2011) as is the case in radial models. The SBM model introduced by Tone (2001) proposes a scalar measure of efficiency when utilizing DEA to deal directly with input excess and output shortfall. Thus, the SMB model has an additive structure in which slacks of inputs or outputs can be removed by addition or subtraction from their peer observations.

The following production technology is defined via an input vector $x = (x_1, x_2, \dots, x_N)' \in \mathfrak{R}_+^N$ and an output vector $y = (y_1, y_2, \dots, y_M)' \in \mathfrak{R}_+^M$:

$$T = \{(x, y): x \text{ can produce } y\} \quad (1)$$

When outputs are all desirable, this technology satisfies the strong disposability condition of inputs and outputs. This condition implies that if x can produce y , x can also produce y' if $y' \leq y$. Färe and Grosskopf (2010) introduce a directional vector $g = (g_x, g_y) \in \mathfrak{R}_+^{N+M} : g \neq 0$. Based on this technology, Färe and Grosskopf (2010) propose a directional technology distance function in the form

$$\overline{D}_T(x, y; g) = \max_{\beta} \{\beta \in \mathfrak{R}_+ : x - \beta \times g_x, y + \beta \times g_y \in T\} \quad (2)$$

Färe and Grosskopf (2010) assign the unit vector for $g = (1, \dots, 1)$, transforming Eq.2 into

$$\overline{D}_T(x, y; \mathbf{1}) = \max \left\{ \sum_{n=1}^N \beta_n + \sum_{m=1}^M \gamma_m \in \mathfrak{R}_+ : \begin{array}{l} (x_1 - \beta_1 \times 1, \dots, x_N - \beta_N \times 1, \\ y_1 + \gamma_1 \times 1, \dots, y_M + \gamma_M \times 1) \in T \end{array} \right\} \quad (3)$$

Equation 3 is solved by finding the value of vector $B = (\beta_1, \dots, \beta_N) \geq 0$, $\Gamma = (\gamma_1, \dots, \gamma_M) \geq 0$. These the non-negativity constraints are employed to ensure that the reference point on the frontier is obtained by not decreasing any outputs and by not increasing any of the inputs. The slack-based directional distance function has a different scalar, β_N , for each type of input and a different scalar, γ_M , for each type of output. Based on the calculated values of β_N and γ_M , the total inefficiency level can be quantified as the sum of all slacks from each input and output corresponding to each bank.

The technology with undesirable outputs under a constant return to scale is defined as

$$T^{CRS} = \left\{ \begin{array}{l} (x, y, w) \in \mathbb{R}_+^N \times \mathbb{R}_+^{M_1} \times \mathbb{R}_+^{M_2}: \sum_{k=1}^K \lambda^k x^k \leq x, \theta \sum_{k=1}^K \lambda^k y^k \geq y, \\ \theta \sum_{k=1}^K \lambda^k w^k = w, 0 \leq \theta \leq 1, \\ \lambda^k \geq 0 \forall k = 1, \dots, K \end{array} \right\} \quad (4)$$

where w defines a vector of bad outputs, θ is the abatement factor and $\lambda^k \geq 0 \forall k = 1, \dots, K$ are the intensity variables. Inefficiency can be calculated by solving the following optimization:

$$\bar{D}_T(x, y, w) = \max_{\substack{\beta_1, \dots, \beta_N, \gamma_1, \dots, \gamma_{M_1}, \\ \delta_1, \dots, \delta_{M_2}, \lambda^1, \dots, \lambda^K, \theta}} \left\{ \sum_{i=1}^N \beta_i + \sum_{j=1}^{M_1} \gamma_j + \sum_{l=1}^{M_2} \delta_l \right\} \quad (5)$$

subject to

$$\begin{aligned} x_i - \beta_i \times 1 &\geq \sum_{k=1}^K \lambda^k x_i^k \quad \forall i = 1, \dots, N \\ y_j + \beta_j \times 1 &\leq \theta \sum_{k=1}^K \lambda^k y_j^k \quad \forall j = 1, \dots, M_1 \\ w_l + \delta_l \times 1 &= \theta \sum_{k=1}^K \lambda^k w_l^k \quad \forall l = 1, \dots, M_2 \\ \lambda^k &\geq 0 \quad \forall k = 1, \dots, K; \quad \beta_i \geq 0 \quad \forall i = 1, \dots, N \\ \gamma_j &\geq 0 \quad \forall j = 1, \dots, M_1; \quad \delta_l \geq 0 \quad \forall l = 1, \dots, M_2 \\ 0 &\leq \theta \leq 1 \end{aligned}$$

where (x, y, w) are observed inputs, good outputs and bad outputs of a bank, the optimization is effected over $\beta_1, \dots, \beta_N, \gamma_1, \dots, \gamma_{M_1}, \delta_1, \dots, \delta_{M_2}, \lambda^1, \dots, \lambda^K, \theta$ for constant return to scale (CRS).

Under variable returns to scale (VRS), we can add the constraint $\sum_{i=1}^K \lambda^k = 1$ into Equation 4 and

Equation 5. In this paper, we measure risk-adjusted inefficiency with the amount of nonperforming loans as one bad output using CRS and VRS technologies.

4.2. Testing the equality of distributions of efficiency scores

The Li-test suggested by Simar and Zelenyuk (2006) is known as a nonparametric test for similarity of two unknown density functions. If we have two subgroups A and Z of two random variables $U^A, U^Z \in \mathfrak{R}_+$ with the represented random samples $\{u^{A,k} : k = 1, \dots, n^A\}$ and $\{u^{Z,k} : k = 1, \dots, n^Z\}$ then $f_A(\cdot)$ and $f_Z(\cdot)$ are the density of distributions of U^A and U^Z respectively, and the null and alternative hypotheses would be:

$$\begin{aligned} H_0 &: f_A(u^A) = f_Z(u^Z) \\ H_1 &: f_A(u^A) \neq f_Z(u^Z) \end{aligned}$$

To test this hypothesis, Li (1996) based on the square difference criterion $I \equiv \int (f_A(u) - f_Z(u))^2 dt$ and $I \geq 0$ and $I = 0$ if and only if H_0 is true. Since the density functions $f(\cdot)$ are unknown we use the non-parametric kernel density estimators (KDE) for replacement. K and h are the appropriate kernel function and the smoothing parameter respectively. With the diagonal terms removed for better performance in most of Monte Carlo experiments, the statistics become:

$$\begin{aligned} \hat{I}_{n_A, n_Z, h}^{nd} = & \left\{ \frac{1}{hn_A(n_A - 1)} \sum_{j=1}^{n_A} \sum_{k \neq j, k=1}^{n_A} K\left(\frac{u^{A,j} - u^{A,k}}{h}\right) + \frac{1}{hn_Z(n_Z - 1)} \sum_{j=1}^{n_Z} \sum_{k \neq j, k=1}^{n_Z} K\left(\frac{u^{Z,j} - u^{Z,k}}{h}\right) \right. \\ & \left. - \frac{1}{hn_A(n_A - 1)} \sum_{j=1}^{n_Z} \sum_{k \neq j, k=1}^{n_A} K\left(\frac{u^{Z,j} - u^{A,k}}{h}\right) - \frac{1}{hn_Z(n_Z - 1)} \sum_{j=1}^{n_A} \sum_{k \neq j, k=1}^{n_Z} K\left(\frac{u^{A,j} - u^{Z,k}}{h}\right) \right\} \end{aligned} \quad (6)$$

Letting $\lambda_n = n_A / n_Z$ and assuming $\lambda_n \rightarrow \lambda$ as $n_A \rightarrow \infty$ where $\lambda \in (0, \infty)$ is a constant, the limiting

distribution of Equation (6) is standard normal: $\hat{J}_{n_A, n_Z, h}^{nd} \equiv \frac{n_A h^{1/2} \hat{I}_{n_A, n_Z, h}^{nd}}{\hat{\sigma}_{\lambda, h}} \xrightarrow{d} N(0, 1)$

According to Simar and Zelenyuk (2006), the KDE is unreliable at the boundary while the distribution of efficiency scores is bounded on the left as often seen in the DEA context. The authors used the reflection method of Silverman (1986) to provide symmetric kernels that create the Simar-Zelenyuk-adapted-Li statistic. Basically, this value is similar to that of the original Li-test (1996), with two differences – the inclusion of a factor of $\sqrt{2}$ and the selection of bandwidth from the reflected data $\{u_1, \dots, u_n, 2-u_1, \dots, 2-u_n\}$ instead of the original data $\{u_1, \dots, u_n\}$. In addition, the adaption of the Li-test in the DEA framework also allows better inferences to be obtained by the use of suitable bootstrap techniques in Monte Carlo scenarios. To test the equality of densities, Simar and Zelenyuk (2006) considered two algorithms (Algorithm 1 and Algorithm 2) and proved that Algorithm 2 is more robust where dimensions are increased.

In this paper, we compare the density of slack or inefficiency - as measured by the slack-based directional technology distance function - of two groups: big banks⁴ (BB) and small banks (SB). The null and alternative hypotheses are:

$$H_0 : f_{BB}(SBE^{BB}) = f_{SB}(SBE^{SB})$$

$$H_1 : f_{BB}(SBE^{BB}) \neq f_{SB}(SBE^{SB})$$

Following Simar and Zelenyuk (2006), we estimate densities by using Gaussian kernels and selecting the bandwidth using the methodology of Sheather and Jones (1991). To test the above null hypothesis, we use the bootstrapped p-value of the Li test (Li, 1999). This can be represented by

$$\hat{p} = \frac{1}{B} \sum_{b=1}^B I\{\hat{J}_b > \hat{J}\}$$

⁴ We use size median size for grouping banks each year. A bank is called big when its size is larger than or equal to the size median for each year.

where \hat{J}_b denotes “a consistent bootstrap analogue of the Li-statistic” \hat{J} . Using Algorithm 2 of Simar and Zelenyuk (2006) and selecting the bandwidth using the robust rule of thumb of Silverman, (1986), we replicate 5000 bootstraps ($B = 5000$) to calculate the p-value.

5. Data

As noted, there are 44 commercial banks as of 2015. However, the data available from FitchConnect does not cover all commercial banks in Vietnam. After removing observations with missing values relating to input and output variables, we form an unbalanced panel data over the period 2006-2015⁵. The data set includes 273 observations of 28 banks that represent 80% of the Vietnam banking sector’s total assets.

Table 1 Descriptive statistics, period 2006 - 2015

	Mean	Max	Min	Std.Dev
Inputs				
Deposit	3,900.0	33,935.0	2.5	5,667.0
Fixed assets	67.3	416.0	0.2	81.6
Operating expense	455.7	3,732.0	0.6	633.4
Desirable outputs				
Loan (gross)	3,421.3	27,478.0	4.0	5,408.5
Other earning assets	1,961.1	12,106.0	2.0	2,281.7
Profit before tax	59.2	403.0	-421.3	89.7
Undesirable output				
Non-performing loans (NPL)	107.5	1,700.1	0.1	2,640.1

Note: This table reports the summary average of the variables used in the non-radial slack-based directional technology distance function. This includes the vectors of inputs, desirable outputs and undesirable output over the period 2006-2015. The figures are presented in million U.S. dollars⁶.

⁵ Before 2006, data of Vietnamese banks are very limited on the FitchConnect. Therefore, we use the data from 2006.

⁶ The data on FitchConnect is available in both USD and Vietnam dong (local currency). We collect the data in USD to avoid inflation, which is relatively high during the period.

Kenjegalieva et al. (2009) outline three methods to select inputs and outputs for efficiency analysis in the banking industry, namely the profit/revenue approach, the production approach and the intermediation approach. In the profit/revenue approach outputs are profit or revenue while inputs include labor, operating and other administrative expenses. In the production approach, banks use labor and capital to produce loans and deposits. In the intermediation approach banks are considered as intermediate agents between depositors and borrowers; labor, physical capital, and deposit are viewed as inputs; loans, other earning assets, and income are outputs. We employ the intermediation approach given it is better suited to capture the decisions of banks in the production of intermediation services.

Regarding the undesirable output, this paper focuses on non-performing loans (NPL⁷) although there are multiple types of risk (such as volatility of ROE, ROA, Z-scores and market beta) for three reasons. First, to capture the bad output in the SMB model, we need a quantity of risk in terms of currency to measure the slack of the undesirable output. While volatility of ROE, ROA, Z-scores and market beta are also considered risk, however, these types of risk are not measured as in dollar value. Thus, we use the amount of NPL to proxy for a bad output. Second, a key issue of Vietnamese banks is a large volume of non-performing loans (Stewart et al., 2016). Thus, ignoring the bad debts in measuring efficiency can yield a biased result. And finally, the use of NPL as the bad output is widely supported in the previous studies (Berger and De Young, 1997;

⁷ In Vietnam, debts are classified into 5 groups. Group 1 (standard debts) includes current debts that credit institutions assess as fully and timely recoverable, both principals and interests. Group 2 (debts, which need special attention) includes debts which are overdue for a period of less than 90 days. Group 3 (sub-standard debts) includes debts which are overdue for a period of 90 to 180 days. Group 4 (doubtful debts) includes debts, which are overdue for a period of 181 to 360 days. And Group 5 (potentially irrecoverable debts) includes debts, which are overdue for a period of more than 360 days. Bad debts (NPL) are debts, which have been classified as those in Groups 3, 4 and 5 stipulated in Decision No. 493/2005/QD-NHNN (dated April 22nd 2005), Decision 780/QD-NHNN (dated April 23rd 2012), and Circular No. 14/2014/TT-NHNN (dated May 20th 2014).

Fiordelisi et al., 2011; Koetter et al., 2012). The descriptive statistics of the inputs and outputs for 273 bank-year observations are presented in Table 1.

6. Empirical results

6.1. Inefficiency scores

Inefficiency scores are measured by the accumulated amount of slacks in the SBM model. As NPL is incorporated in the slacks, we call these slacks are risk-adjusted slacks or risk-adjusted inefficiency. We measure the slacks under both constant returns to scale (CRS) and variable returns to scale (VRS) specifications of the production technology⁸. The annual arithmetic average values for risk-adjusted inefficiency over the period 2006-2015 for the two groups of banks are depicted in Figure 2a and 2b.

Figures 2a and 2b show that large banks report greater inefficiency (higher slacks) than small banks using both CRS and VRS technologies in most of the years from 2006-2015. On average, the CRS and VRS slacks of large banks were 2,269.8 million US dollars and 950.1 million US dollars per annum respectively. Whereas, the CRS and VRS slacks of small banks were only 667.0 million US dollars and 382.4 million US dollars per annum respectively. These figures suggest that the slacks of large banks were three times as much as those of small banks. These figures also suggest that a reduction in the inefficiency of big banks would have a greater impact than small banks on the efficiency of the entire banking industry. Given that there are a small number of large banks in Vietnam, this finding suggests that bank regulators in Vietnam should focus on large banks to remove the higher slacks of this group because an inefficiency reduction of this group has a more impact on the overall efficiency of the banking industry as a whole.

⁸ CRS and VRS are two types of frontier scale used in *data envelopment analysis (DEA)*. Under the CRS, efficiency is estimated by a change in inputs results in a proportional change in the outputs. Whereas, under VRS, efficiency is estimated by a change in inputs does not result in a proportional change in the outputs (Cooper, Seiford, and Zhu, 2011).

Figure 2a.
Average CRS inefficiency with bad output (mil. USD)

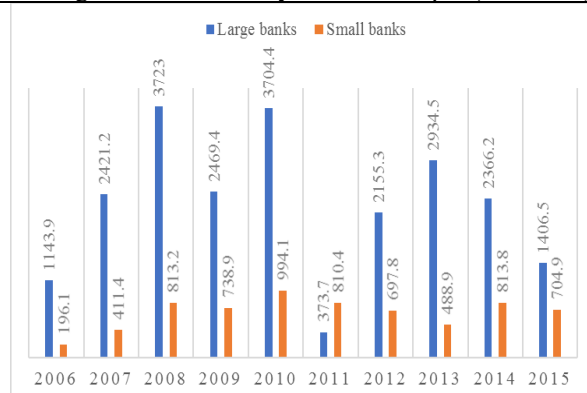
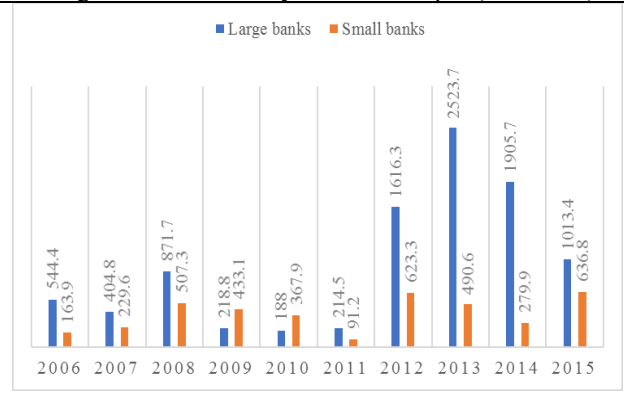


Figure 2b.
Average VRS inefficiency with bad output (mil. USD)



These figures present the average risk-adjusted inefficiency using CRS and VRS for two groups of banks.

However, the inefficiency level of small banks is not always lower than that of large banks for the whole period from 2006-2015. Under the CRS, the average slacks of large banks are lower than those of small banks only in the year 2011. The higher inefficiency of the small banks is related to a sharp rise in the deposit slacks, which accounted for 93.14 percent of the total slacks of the small banks in 2011 (from only 19.41 percent in 2010) as shown in Table 2. The higher deposit slacks in 2011 implies that small banks faced redundancy of deposits. Under the VRS, the slacks of small banks surpass those of big banks on a small scale in the years 2009 and 2010. The higher inefficiency level of small banks in 2009 came from a sudden growth of deposit slacks which accounted for 20.80 percent in 2009, representing a remarking increase from 3.17 percent in 2008 (see Table 3). Whereas the higher inefficiency of small banks in 2010 is connected to a significant increase in other earning asset slacks, which accounted for 81.88 percent (from 62.60 percent in 2009).

Table 2

Decomposition of slacks under CRS

Year	BIG BANKS								SMALL BANKS							
	SC_big	SCdeposit	SCfixed	Scopex	SCloan	SCoea	SCpbt	SCnpl	SC_small	SCdeposit	SCfixed	Scopex	SCloan	SCoea	SCpbt	SCnpl
2006	100	62.77	1.03	0.00	11.87	19.52	0.26	4.55	100	11.96	1.35	0.15	39.69	45.55	0.40	0.90
2007	100	62.08	0.60	0.29	28.84	5.52	0.28	2.39	100	22.44	1.55	0.00	31.65	43.23	0.37	0.76
2008	100	30.05	0.45	1.91	49.37	16.26	0.16	1.79	100	4.84	1.22	2.32	42.84	47.10	0.99	0.68
2009	100	45.59	1.22	1.03	37.69	10.30	1.14	3.02	100	23.54	1.44	0.03	36.16	37.57	0.41	0.85
2010	100	45.68	0.78	1.99	43.23	4.70	0.37	3.25	100	19.41	1.15	0.98	30.30	46.81	0.68	0.67
2006-2010	100	44.70	0.78	1.36	39.11	10.90	0.44	2.70	100	16.53	1.29	0.94	35.71	44.12	0.66	0.75
2011	100	32.74	4.36	2.37	6.39	54.00	0.00	0.15	100	93.14	3.86	0.00	0.00	2.49	0.52	0.00
2012	100	36.16	3.09	1.18	0.28	56.60	0.70	1.98	100	84.42	6.41	2.37	2.33	3.03	1.45	0.00
2013	100	53.98	1.81	1.72	0.00	40.20	1.02	1.28	100	16.77	9.68	1.45	57.39	9.15	4.04	1.52
2014	100	65.13	2.06	0.46	0.66	28.99	1.14	1.56	100	9.93	1.48	0.00	84.89	2.26	0.79	0.65
2015	100	60.46	2.40	0.00	0.00	36.03	0.77	0.35	100	39.55	3.26	1.02	53.63	0.00	1.55	0.99
2011-2015	100	54.31	2.27	1.01	0.41	39.76	0.93	1.31	100	69.58	3.93	3.84	20.69	0.00	1.36	0.59
2006-2015	100	48.81	1.42	1.21	22.54	23.25	0.65	2.11	100	52.83	2.19	0.00	43.28	0.00	1.41	0.29

This table represents the decomposition of slacks (in percentage) of two groups small banks and big banks. The decomposition is the contribution of the wastes of each input, NPL and the shortages of each desirable output, thus the sum of the composition is equal to 100 percent. SC_big and SC_small are the averages of total CRS slacks of big banks and of small banks respectively. SCdeposit, SCfixed, SCopex, SCloan, SCoea, SCpbt, and SCnpl are the averages of CRS slacks of deposits, fixed assets, operating expenses, loans, other earning assets, profit before tax, and non-performing loans respectively.

Table 3

Decomposition of slacks under VRS

Year	BIG BANKS								SMALL BANKS							
	SV_big	SVdeposit	SVfixed	SVopex	SVloan	SVoea	SVpbt	SVnpl	SV_small	SVdeposit	SVfixed	SVopex	SVloan	SVoea	SVpbt	SVnpl
2006	100	41.33	1.45	0.00	3.89	41.64	2.26	9.42	100	11.65	1.59	0.06	36.91	48.38	0.37	1.04
2007	100	60.62	0.74	0.00	2.54	26.58	2.25	7.26	100	18.86	2.05	0.00	28.79	48.95	0.48	0.87
2008	100	8.96	1.45	5.70	18.91	61.25	1.18	2.56	100	3.17	2.05	1.66	20.99	70.49	0.87	0.77
2009	100	2.24	2.42	2.38	7.04	83.95	1.14	0.82	100	20.80	2.29	0.00	12.35	62.60	0.90	1.06
2010	100	10.05	4.41	2.55	6.38	70.05	2.98	3.56	100	0.00	2.74	1.11	12.45	81.88	0.79	1.03
2006-2010	100	23.95	1.80	2.83	10.69	54.68	1.71	4.35	100	9.54	2.24	0.74	18.90	66.85	0.79	0.94
2011	100	33.35	3.96	6.34	3.31	52.01	0.89	0.14	100	8.88	1.86	0.00	6.25	82.57	0.22	0.22
2012	100	37.68	2.41	1.95	4.27	49.42	1.76	2.50	100	9.43	1.04	0.69	2.23	85.72	0.24	0.64
2013	100	52.03	1.58	1.95	1.59	39.97	1.66	1.23	100	37.28	1.79	0.10	0.00	58.66	0.82	1.35
2014	100	58.92	1.79	2.81	2.61	30.96	1.42	1.47	100	60.91	1.68	0.00	0.00	34.80	1.36	1.25
2015	100	46.03	3.03	0.00	0.00	49.57	0.85	0.52	100	44.86	0.94	0.00	6.39	46.26	1.41	0.13
2011-2015	100	49.57	2.06	2.08	2.32	41.02	1.50	1.46	100	32.65	1.33	0.24	2.54	61.64	0.83	0.76
2006-2015	100	44.04	2.00	2.25	4.12	43.96	1.55	2.08	100	22.32	1.74	0.47	9.83	63.98	0.82	0.84

This table represents the decomposition of slacks (in percentage) of two groups small banks and big banks. **The decomposition is the contribution of the wastes of each input, NPL and the shortages of each desirable output, thus the sum of the composition is equal to 100 percent.** SV_big and SV_small are the averages of total VRS slacks of big banks and of small banks respectively. SVdeposit, SVfixed, SVopex, SVloan, SVoea, SVpbt, and SVnpl are the averages of VRS slacks of deposits, fixed assets, operating expenses, loans, other earning assets, profit before tax, and non-performing loans respectively.

To examine the sources of inefficiency, we disaggregated total inefficiency into seven components. These include three components of input waste (i.e. deposits, fixed assets and operating expenses), three shortage components of good outputs (i.e. gross loans, other earning assets, and profit before tax), and one surplus component of undesirable outputs for the two sub-periods (2006-2010 and 2011-2015) under CRS and VRS technologies as shown in Table 2 and Table 3 respectively. Empirical results show that the sources of inefficiency vary between two groups of banks. For big banks, their CRS total inefficiency mainly originates from deposits and loans while their VRS total inefficiency is primarily due to other earning assets over the period 2006-2010. During the same period, the small banks' inefficiency mainly derives from loans and other earning assets under CRS technology and only from other earning assets under VRS technology.

In the period 2011-2015, the main contribution to CRS and VRS total inefficiency for big banks stems from deposits and other earning assets. For the small banks, the main contribution to CRS inefficiency is deposits while the main component of their VRS inefficiency is other earning assets. In sum, over the period 2006-2015, big banks had greater CRS inefficiency in terms of deposits, loans and other earning assets, while that of small banks was in terms of loans and deposits. Under VRS assumptions, other earning assets and deposits are the two main sources of big banks' inefficiency, whereas other earning assets are the dominant driver of small banks' inefficiency. This type of information could help bank managers identify possible ways of reducing their input wastes or output shortages in order to reduce inefficiency. Explaining why small banks and big banks face different sources of inefficiency, however, is worth further investigation but is beyond the scope of the present paper.

6.2. Equality of slack distributions

As shown earlier, small banks on average have small slacks than large banks. However, to examine differences in the annual inefficiency slacks between the two groups across their distribution, we employed Simar-Zelenyuk-adapted-Li test proposed by Simar and Zelenyuk (2006). For this purpose, the Kernel density estimation of inefficient slacks under CRS and VRS were estimated with the inefficiency being bound below by 0 and the bandwidths proposed by Sheather and Jones (1991). *Figures 3a to 3d* exhibit the density estimations corresponding to size, which shows that the density of big banks lies below and skews to the right of the density of small banks under both CRS and VRS during 2006-2010 and 2011-2015⁹. This once again suggests that small banks outperform big banks.

The result of the Simar-Zelenyuk-adapted-Li test provided in Table 4 shows that there is a statistically significant difference in the annual inefficiency levels of the two distributions. As bootstrap p-values are all smaller than 1%, the null hypothesis of identical distribution for inefficiency densities for the two bank groups is rejected. Combining both the density estimation distribution with the Simar-Zelenyuk-adapted-Li test, we can reasonably conclude that small banks operate more efficiently than big banks across the distribution.

This paper provides evidence that small banks outperform large banks in terms of risk-adjusted efficiency. This result is opposite to the two famous hypotheses: SCP and ES. However, our result is in line with the quiet life hypothesis. This hypothesis proposes that large banks with greater market power operate less efficiently than small banks because they do not target to reap all potential rent (Koetter et al., 2012). In competitive markets, bank managers have a strong incentive

⁹ There are three reasons for us to split the whole period into two sub-periods. First, we equally divide 10 years into 5 years each group. Second, CPI is on average 3 times higher in the period 2006-2010 than in the later period. Finally, GDP growth shows its down trend during 2006-2010 while an uptrend during 2011-2015. We believe that the two macro indicators have much impact on banking operation in the country, thus there is necessary to consider bank efficiency separately for each period.

to give their best effort for greater efficiency. But in oligopolistic markets, managers of large banks may not be motivated by achieving greater efficiency and may choose to enjoy the “quiet life.” The norm “quiet life” refers to a situation when managers of large banks avoid making hard decisions or taking on difficult tasks. In the context of Vietnam, the hard decisions are those related to non-performing loans and to solve these bad loans.

Figure 3a.
Density of inefficiency under CRS 2011-2015

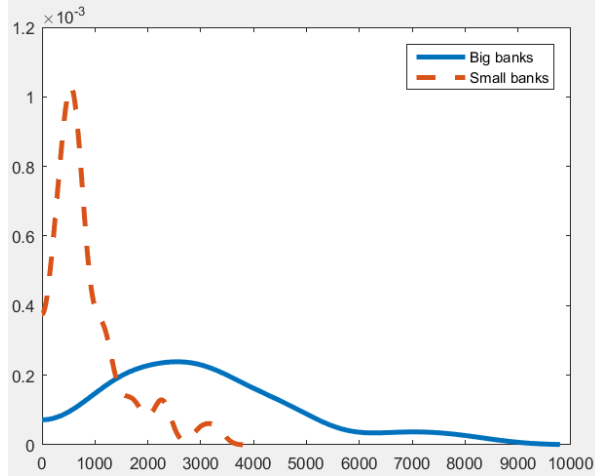


Figure 3b.
Density of inefficiency under CRS 2006-2010

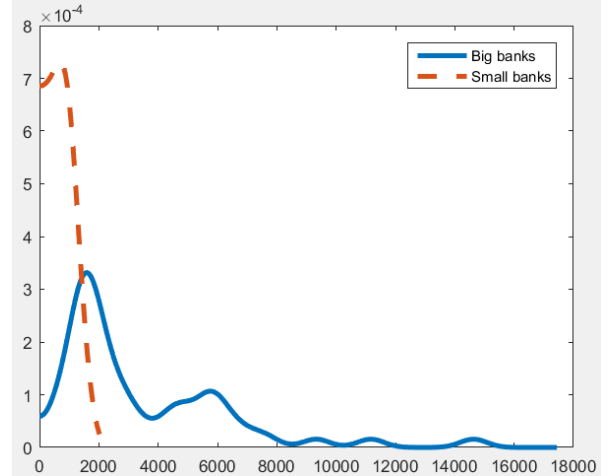


Figure 3c.
Density of inefficiency under VRS 2011-2015

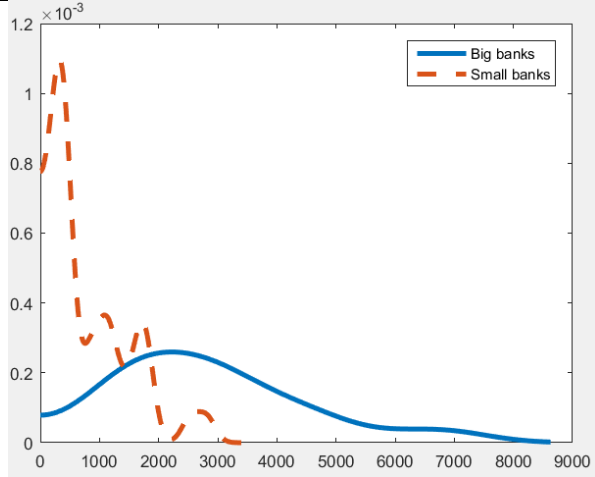
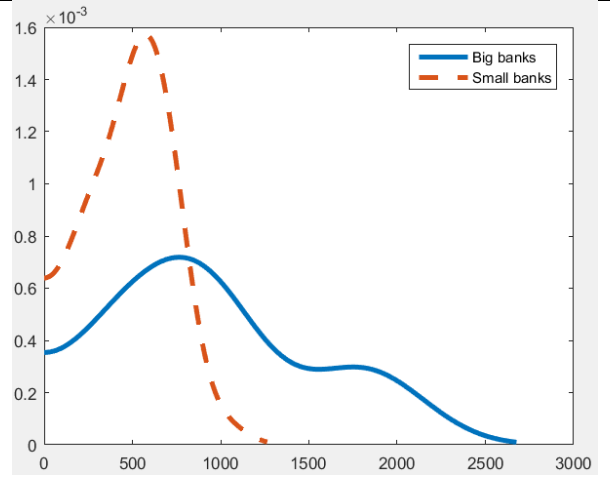


Figure 3d.
Density of inefficiency under VRS 2006-2010



As Vietnam is a so-called socialist country, banks are subject to the intervention by the State with its multiple objectives, ranging from economic to social development. For example, the State encourages or even assigns large banks to provide favorable loans to farmers and fishermen. These loans have a long-term maturity at low-interest rates. Rural activities relating to farming and fishing have low turnover and high risk because they heavily depend on weather conditions. In addition, some large state-owned banks partially aim at maximizing social welfare of the State by granting credits to state-owned enterprises (SOEs). And majority loans granted to SOEs are unsecured (without collateral). In Vietnam, many SOEs are poorly managed and suffer huge losses. Because of the two reasons, it is difficult for Vietnam banks to avoid nonperforming loans.

The Vietnamese banking system has struggled to recover from the non-performing loan (NPL) hangover because mechanisms to solve the bad loans are difficult. Before The Vietnamese National Assembly's Resolution 42/2017/QH14 on dealing with bad debts of credit institutions, there have been two mechanisms to recover from NPL. First, banks can liquidate collaterals. But this task is difficult as large banks have a close relationship with SOEs and grant unsecured loans to SOEs. Second, banks can sell their NPL to the Vietnam Asset Management Company (VAMC) (set up in 2013) in exchange for special bonds that matured in five years. This mechanism enables banks to provision for the NPLs over a five-year period, VAMC was merely a warehousing structure to house the NPLs before returning them to the bank's balance sheets. As a true secondary market for trading NPLs in Vietnam does not work, banks have to buy back their NPLs when maturity comes.

Table 4: Simar-Zelenyuk-adapted-Li test for distributions of CRS and VRS inefficiency

	CRS 2011- 2015	VRS 2011- 2015	CRS 2006- 2010	VRS 2006- 2010
Bootstrap Li-statistic \hat{f}	12.3258	3.5430	12.3148	7.8456
Bootstrap p value	0.0000	0.0040	0.0000	0.0000
Reject H_0	Yes	Yes	Yes	Yes

Our results are in line with the study of Gardener et al. (2011) who find a negative effect of size on cost and allocative efficiency. The authors conclude that large banks are not as good as small banks in cost management. In efficient in cost management then leads to lower levels of profits for large banks. However, this paper's results are different from Stewart et al. (2016) who classify Vietnamese banks into four groups: very large, large, medium and small banks and conclude that very large and large banks are more efficient than medium and small banks. Our paper is different from Stewart et al. (2016) in terms of taking NPL as an undesirable output and providing statistical test for the difference of inefficiency distribution. These differences are important for two reasons. First, we have known that ignoring risk in measuring efficiency can lead to biased estimation. Specifically, exclusion of bad outputs is subject to overestimate efficiency scores (Färe et al., 2005; Huang et al., 2015). Second, the test for the equality of inefficiency distribution is important because the test provides statistical evidence on the significance of inefficiency difference. Without the test, we cannot conclude the average efficiency for one group may be statistically higher or lower.

7. Conclusion

The literature has shown that size and efficiency are associated. However, empirical studies rarely investigate the relationship between size and efficiency with the presence of bad outputs. This paper extends the literature by re-examining the relationship when efficiency is adjusted for undesirable outputs. We use the amount of non-performing loans as a bad output, which is a widely used indicator of credit risk. The empirical results show that, on average, the inefficiency level of a large bank was three times as much as those of a small bank for the period 2006-2015 in Vietnam, a transitional economy. The level under CRS (VRS) was 2,269.8 (950.1) million US dollars for a large bank, whereas the level is 667.0 (382.4) million US dollars for a small bank per annum. As

large banks caused a major proportion of total inefficiency level, bank regulators in the country should focus on large banks to improve the overall efficiency of the banking industry as a whole.

In addition, by disaggregating inefficiency into three categories of input wastes, three categories of desirable outputs shortages, and one undesirable output, our empirical results show the contribution of input wastage and output shortage for each input and each output in the total inefficiency level for two groups of banks (i.e. small and large banks) under both CRS and VRS. For example, deposit waste contributed the largest share in total inefficiency for large banks under VRS during the period 2006-2015. However, a shortage from other earning assets was the main inefficiency among small banks. By examining the contribution of each input and output into total inefficiency for two sub-periods 2006-2010 and 2011-2015, we have found that the contribution varies between the two periods for each group. For instance, the shortage of other earning assets was the main inefficiency for small banks under CRS in 2006-2010; however, deposit waste then became the main source of inefficiency in 2011-2015.

Besides the two implications relating to the main source of inefficiency from large banks and the components of inefficiency for each bank group, this paper also proposes a stricter monitoring and arranging mechanism from the State Bank of Vietnam to successfully form a real secondary market for NPL trading. The Resolution 42/2017/QH14 has set forth a framework for a secondary market for NPL trading. The goal of this market is to align the interests of VAMC and banks (in selling NPLs) and debt traders (in investing in NPLs). However, the market has not contributed much to the alignment due to a lingering question of pricing NPLs is unanswered. Sellers (VMAC and banks) and buyers of bad debts (traders or investors) often have different viewpoints on pricing these debts. Sellers expect a higher price on their NPLs while buyers disagree. This kind of

disagreement raises a need on a mechanism from the State Bank of Vietnam to trade bad debts successfully.

Future analysis could consider why the sources of inefficiency vary between small banks and large banks and between the two periods. Such an analysis would provide bank managers and regulators with further detailed information on causes of inefficiency. For example, deposit waste, which is identified as the main source of inefficiency for large banks, poses the question of whether this could be due to the lack of competition in the deposit market.

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