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Incorporating risk into technical efficiency for Vietnam's and ASEAN banks

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Abstract

Purpose – The purpose of this paper is to incorporate risk in technical efficiency of ASEAN banks in a panel data framework for the period 2000 to 2015.

Design/methodology/approach – The directional distance function and semi-parametric framework are employed to estimate efficiency scores for two scenarios, one with only good outputs and the other with a combination of good and bad outputs.

Findings – The findings show there is no evidence of technological progress for banks in ASEAN and concerns about the outperformance of Vietnam's banks. In addition, performance of Vietnam's banks tends to be distorted by low level of loan loss reserves.

Practical implications – To reflect the true performance and shorten the period of removing bad assets, the State Bank of Vietnam can request banks in Vietnam to book more loan loss reserves.

Originality/value – By examining such a new approach, this study makes an early attempt to incorporate credit risk into the banking efficiency in ASEAN region.

Keywords Risk, Bank efficiency, Directional distance function, Semi-parametric estimation of stochastic frontier models

Paper type Research paper

1. Introduction

We try to incorporate risk into measuring technical efficiency of banking institutions in the Association of Southeast Asian Nations (ASEAN)[1] alliance. Our motivation commences from a gap that, in the literature searching of efficiency analysis in ASEAN banking sector, risk is ignored in examining efficiency in articles of Wong and Deng (1999), Karim (2001), Gardener *et al.* (2011), Williams and Nguyen (2005), Sarifuddin *et al.* (2015) and Chan *et al.* (2015). We have evidences that efficiency is specious and biased if risk is disregarded. Berger and Humphrey (1997) argue that banking efficiency would be underestimated if the risk was ignored. Meanwhile, some included risk as an environmental variable or regarded it as exogenous in the analysis of efficiency effect, such as Khan (2014) and Yueh-Cheng Wu *et al.* (2016). According to Laeven (1999), whereas loans are usually chosen as an output variable in the intermediation approach to modeling bank production, non-performing loans are chosen as a proxy for risk, and then they regress efficiency scores followed by



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environmental variables, including risk, there is likely risk to be endogenous that is influenced by bad management or controlling of the loan portfolio. Sarmientoa and Galán (2015) also found out that cost and profit efficiency are over- and underestimated when risk measures are not accurately modeled.

In the circumstance that financial liberalization is an inevitable trend of global and regional integration, it is very meaningful to properly incorporate risk in banking efficiency analysis for policy implications. At the end of 2015, the creation of ASEAN Economic Community (AEC) has spread out both chances and challenges for nation members on the road to achieve a highly integrated and cohesive economy in ASEAN. To support for economic development, the banking systems in many ASEAN countries are still a primary source for raising capital. Banking assets made up more than 82 percent of total financial assets in ASEAN in 2009 and for the BCLMV[2], the figure was even higher, at 98 percent, according to a study of ADB (2013). Making a push for ASEAN in financial integration, ASEAN members implemented the ASEAN Banking Integration Framework in December 2014, allowing banks satisfying certain criteria (Qualified ASEAN Banks – QABs) to open their activities in other member nations and be equally treated as domestic banks.

Once the AEC is in implementation, domestic banks could have more chances to attract capital flows from foreign investors to raise their legal capitals for the QABs' requirements. However, the deeper integration in banking sector, the greater competition and improved quality of services, the higher pressure for commercial banks in ASEAN region to adapt and operate efficiently so that they can shorten competitiveness gaps in the common playground. Since one of QABs' basic standards is that banks must meet appropriate risk management and internal control fit for the size and complexity of its operation, the matter of risk and efficiency is becoming more important than ever before. Greater banking openness, on the other hand, could lead to greater vulnerability as risks to financial stability in one country can spill over more quickly to another. The stories about the regional financial crisis in 1997 and the global economic downturn in 2008 remind us that information on incorporating risk in banking efficiency when compared across ASEAN nations is not only important for financial intermediaries but also for supervising sectors to build safe and sound policies for ASEAN banking system.

This paper, therefore, does not only aim to measure the efficiency of the commercial banks in ASEAN, but also incorporating risk into efficiency level. This purpose can be solved by applying the directional distance function (DDF) originally proposed by Färe *et al.* (2005) and customized by Huang *et al.* (2015) under two frameworks of parametric (Stochastic Frontier Analysis (SFA)) and semi-parametric estimation of stochastic frontier models (SEMSFA). As SFA requires production functions, however, these functions are considered too restrictive, even inappropriate. Hence, we apply SEMSFA, a new approach of SFA by using a generalized additive model (GAM), developed by Vidoli and Ferrara (2015).

The remainder of this paper is organized as follows. In Section 2, the literature on incorporating risk in banking efficiency analysis in ASEAN region is reviewed. In Section 3, we describe the methodology used in the paper and Section 4 discusses the data and input/output selection. Section 5 presents the empirical results and, finally, the conclusion and future research are given in Section 6.

2. Literature on incorporating risk in banking efficiency in ASEAN

There are two main streams in literature of efficiency estimation: nonparametric (or deterministic) and parametric (or stochastic) method. In which of the nonparametric methods, data envelopment analysis (DEA) is the most widely used while stochastic parametric methods are famous for SFA. Narrowing down to research articles concerning risk in efficiency estimation, we classify those relating to incorporating risk in the banking efficiency and those dealing this issue in the ASEAN banks.

2.1 Incorporating risk into bank efficiency

There are two strands of focusing on the incorporating risk in efficiency. One regards risk as exogenous to analyze efficiency effects and another way is to incorporate endogenous risk into the production analysis (Chang and Chiu, 2006). Berger and DeYoung (1997) consider risk as an exogenous in a Granger-causality model to examine the relationship between risk and cost efficiency. By a totally different way, Chang (1999) follows the nonparametric model proposed by Färe et al. (1985), treats risks as endogenous and undesirable outputs, namely, NPLs, allowance for loan losses and risky assets. To test the statistically significant differences between efficiency scores when employing three risk indicators alternatively, he uses ANOVA, Kruskal-Wallis and Wilcoxon rank-sum methods. Zhu et al. (2016) call on the advantages of both parametric and non-parametric DDF to estimate technical efficiency of 44 Chinese commercial banks during 2004-2011 and use NPLs as a proxy for risk as one undesirable output, to freely adjust direction vectors to incorporate bank's risk preferences. Collecting unbalanced panel data over the period 1995–2008 from 17 Central and Eastern European countries, Huang et al. (2015) develop a new meta-frontier directional technology distance function under a SFA framework and regard NPLs as an undesirable output in cost efficiency estimation.

Whereas most studies in existing literature use credit risk indicators to explain bank efficiency scores. Chang and Chiu (2006) consider both credit and market risks associated with a bank's efficiency. They employ a DEA model and Tobit regression to investigate the bank efficiency index incorporated both two types of risk. Information disclosed in annual financial reports of Taiwan's banking industry from 1996 to 2000 is used to apply value at risk as the market risk measure and NPLs is regarded as the proxy for bank credit risk. The bank efficiency index is calculated in four different scenarios: without risk, with credit risk or market risk only, with both risk types and then the Wilcoxon matched-pairs signed-ranks test is used to test statistically significant differences in efficiency index of each scenario. Sarmientoa and Galán (2015) propose a SFA model with random inefficiency parameters to capture the influence of risk-taking on cost and profit efficiency of different types of Colombian banks for the period 2002-2012. The inference of the model is carried out via Bayesian method to formally incorporate parameter uncertainty and to derive bank-specific distributions of efficiency and risk random coefficients. As risk exposure measures with different effects on bank-specific inefficiency, they include measures of credit risk, liquidity, capital and market risk in accordance Colombian financial regulation and the Basel III standards.

2.2 Incorporating risk into bank efficiency in ASEAN banking sector

In this section, we try to sort out the studies related to incorporating risk in efficiency analysis of banking institutions in the ASEAN alliance. To have a better glance for this issue, we also direct our attention to East Asian studies of banking efficiency where necessary.

The matter of incorporating risk in banking efficiency estimation in ASEAN banks is related in some ways. Followed by the SFA approach, Karim *et al.* (2010) examined the relationship between efficiency and NPLs of banks in Malaysia and Singapore between 1995 and 2000. They use normal- γ efficiency distribution model proposed by Greene (1990) to estimate cost efficiency scores and then regressed them against NPLs and other control variables. The relationship between NPLs and efficiency is believed as two-way direction, hence a Tobit simultaneous equation regression model is used for the simultaneity effect. Manlagnit (2011) examines the cost efficiency of Philippine commercial banks in the period from 1990 to 2006, using stochastic cost frontier

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analysis and specifically incorporating risk (ratio of loan loss provisions to total loans) and asset quality measures in the estimation. Consistent with earlier findings, the results show substantial inefficiencies among domestic banks and that risk and asset quality affect the efficiency of banks.

The DEA approach is employed by many researchers for its flexibility in not requiring the pre-specification of production function, its linearity and its suitability for relatively small data size for each banking system (Gardener *et al.* (2011)). Khan (2014) proposes the intermediation DEA approach with input-oriented model to incorporate the influences of the external variables on Southeast Asian banking efficiency. With using data from five banks in the region from 1999 to 2005 in a four-stage DEA procedure, they allow slack or surpluses due to the environment variables and use it to calculate adjusted values for the primary inputs.

Laeven (1999) also applies the DEA technique to estimate the inefficiencies of banks in Indonesia, Korea, Malaysia, the Philippines and Thailand for the pre-crisis period 1992— 1996 with some adjustments. Choosing the intermediate approach but differently from other researches, he bases on the output orientation to calculate technical efficiency, instead of aiming to input minimization. He also points out that, due to weak enforcement of banking regulation, bad loan data may not be inadequately reported as NPLs so applying this data in efficiency models might lead to incorrect conclusions. In the case of East Asia, until 1997, loans were not classified as NPLs until no payments were made for over one year. In such countries, a bank efficiency model might estimate a bank to be in better shape than they actually are. Therefore, he chooses excessive loan growth as a good proxy for bank risk-taking, instead of NPLs. However, in his research, Laeven (1999) also shows some weaknesses of DEA such as the difficulty to use DEA to compare efficiency among firms due to its estimation only for upper bound; not considering statistical noise which means that all the error term in the estimation is attributed to inefficiency and measuring DEA efficiency in small samples is sensitive to the difference between the number of firms and the sum of inputs and outputs used. Hence, Yueh-Cheng Wu et al. (2016), instead of choosing a traditional DEA, apply newly developed dynamic network DEA formulated by Tone and Tsutsui (2014) to deal with inefficiencies of interacting divisions that are embedded inside the banks' production process and use loan loss provision as a proxy for risk.

2.3 Applying the DDF under parametric and semi-parametric framework to incorporate risk into measuring ASEAN banking efficiency

The literature of incorporating risk in banking efficiency almost propose either DEA or SFA or combine both of them for comparison purpose. As pointed out by Andor and Hesse (2014), DEA is a linear-based technique that constructs a nonparametric envelopment frontier over the data points. As a DEA's advantage, it does not require the pre-specification of production function but it estimates efficiency without considering statistical noise and is thus deterministic. Conversely, SFA requires an assumption about the functional form of the production function and allows measuring efficiency while simultaneously considering the existence of statistical residuals. Because of their methodological differences and equivalent advantages and disadvantages, they are the two of the most popular approaches for measuring efficiency.

According to a comprehensive survey of frontier efficiency analysis in financial institutions, mostly banking, by Berger and Humphrey (1997), DEA is the most frequently used approach for efficiency evaluation. However, according to Yueh-Cheng Wu et al. (2016), the traditional DEA models are not sufficient to measure the banks' complex production process because these models assume the system as a single black box that converts inputs to outputs. As a result, the banks' complex production process

requires more sophisticated techniques to account for internal structures within the black box. In regards to traditional SFA, since the traditional stochastic frontier model[3] also cannot solve the multi-output production, which is very common in the banking industry, some researchers apply the DDF to freely adjust direction vectors such as Huang *et al.* (2015) and Zhu *et al.* (2016). Huang *et al.* (2015) apply DDF under SFA framework whereas Zhu *et al.* (2016) compare efficiency indexes under both parametric and non-parametric framework. The DDF is useful in modeling undesirable outputs in a different manner of desirable outputs while other inefficiency measurements only permit either inputs savings or output expansion, but not both simultaneously. Allowing dealing with a multiple-input, multiple-output production technology, DDF can support for simultaneously quantifying input saving and output expansion.

Recently introduced by Kuosmanen and Kortelainen (2012) and combined the strengths of the SFA and DEA methods, the Stochastic Non-smooth Envelopment of Data method is stochastic and semi-parametric, requiring no *a priori* explicit assumption about the functional form of the production function. This method is employed in some researches related to efficiency analysis in farming (Vidoli and Ferrara, 2015), electricity distribution (Kuosmanen, 2012) and sales roles of bank branches (Eskelinen and Kuosmanen, 2013) but it is not seen in incorporating risk into banking efficiency. In this study, we would employ the DDF under both parametric (SFA) and semi-parametric (SEMSFA) framework and then compare efficiency scores with risk adjusted in two scenarios. To the best of the authors' knowledge, this study makes an early attempt by examining this new approach to the banking efficiency in ASEAN region. The next section provides more details about our methodology for measuring ASEAN's banking efficiency while concerning to risk.

3. Methodology

To incorporate undesirable outputs into inefficiency, we rely on the DDF measures that treat both sets of outputs differently. This requires a redefinition of the production technology where outputs $y \in \mathfrak{R}_{-}^{M}$ is partitioned into desirable and undesirable outputs $y, w = (y, b), y \in \mathfrak{R}_{+}^{D}, b \in \mathfrak{R}_{+}^{U}$. Then, the production technology with undesirable outputs is given by:

$$T = \{(x, (y, b): x \text{ can be used by banks to produce } (y, b))\}.$$
 (1)

The DDF measure can be extended in the way that maximizes the radial increase in good outputs as well as the radial decrease in both inputs and bad outputs along the directional vector $g = (g_x, g_y, g_b) \in \mathbb{R}^N_+ \times \mathbb{R}^D_+ \times \mathbb{R}^D_+ : g \neq 0$:

$$\overrightarrow{D_T}\left(x,y,b;g_x,g_y,g_b\right) = \max_{\xi} \left\{ \xi \in \Re_+ \colon x - \xi g_x, y + \xi g_y, \ b - \xi g_b, \ \in T \right\}. \tag{2}$$

To solve this optimization, there are two options. First, one can follow non-parametric approach, which finds β that maximizes the Equation (2). Second, one can choose parametric approach by following functional form with translation property:

$$\overrightarrow{D_T}\left(x - \xi g_x, y + \xi g_y, \ b - \xi g_b; g_x, g_y, g_b\right) = \overrightarrow{D_T}\left(x, y, b; g_x, g_y, g_b\right) - \xi. \tag{3}$$

This property means that if we translate the vector (x, y, b) into $(x-\xi g_x, y+\xi g_y, b-\xi g_b)$, then the value of the distance function is reduced by the scalar ξ . The translation property is used to transform the DDF into an estimable regression equation.

Following Färe *et al.* (2005) and Huang *et al.* (2015), we arbitrarily choose $\xi = y_1$ to translate the quadratic DDF into:

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$$-y_{1} = \overrightarrow{D_{T}} \left(x - \beta g_{x}, y + \beta g_{y}, b - \beta g_{b}; 1, 1, 1, t, \theta \right) + v - u$$

$$= \alpha_{0} + \sum_{n=1}^{N} \alpha_{n} (x_{n} - y_{1}) + \sum_{m=2}^{M} \beta_{n} (y_{m} + y_{1}) + \sum_{j=1}^{J} \lambda_{j} (b_{j} - y_{1})$$

$$+ \frac{1}{2} \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{nn'} (x_{n} - y_{1}) (x_{n'} - y_{1}) + \frac{1}{2} \sum_{m=2}^{M} \sum_{m'=2}^{M} \alpha_{mm'} (y_{m} + y_{1}) (y_{m'} + y_{1})$$

$$+ \frac{1}{2} \sum_{j=1}^{J} \sum_{j'=1}^{J} \lambda_{jj'} (b_{j} - y_{1}) (b_{j'} - y_{1}) + \sum_{n=1}^{N} \sum_{m=2}^{M} \gamma_{nm} (y_{m} + y_{1}) (x_{n} - y_{1})$$

$$+ \sum_{n=1}^{N} \sum_{j=1}^{J} a_{jn} (b_{j} - y_{1}) (x_{n} - y_{1}) + \sum_{m=2}^{M} \sum_{j=1}^{J} c_{jm} (b_{j} - y_{1}) (y_{m} + y_{1}) + \delta_{1}t + \frac{1}{2} \delta_{2}t^{2}$$

$$+ \sum_{n=2}^{N} \psi_{n} t (x_{n} - x_{1}) + \sum_{m=2}^{M} \mu_{m} t (y_{m} + x_{1}) + \sum_{j=1}^{J} c_{j} t (b_{j} - x_{1}) + \varepsilon, \tag{4}$$

where $\theta = (\alpha, \beta, \lambda, \gamma, a, c, \delta, \psi, \mu)$ is a vector of parameters to be estimated and $\varepsilon = u - v$ is the composed error term. Hence, $\overrightarrow{D_T}(\cdot)$ is the translated DDF that will be estimated later in our empirical study. In addition, $u = \overrightarrow{D_T}(x, y, b; 1, 1, 1, t, \theta)$ is treated as a non-negative random variable, reflecting technical inefficiency of the firm under consideration, and v is a two-sided, normally distributed error with a mean of zero and a constant variance σ_n^2 , which is traditionally assumed to be independent of u.

Similar to Koutsomanoli-Filippaki *et al.* we specify the inefficiency term u as $u = \alpha'z + w \ge 0$, where z is vector of bank characteristics (equity/total asset ratio and liquid assets/total assets) and macro environment variables (GDP growth, Herfindall-Hirschman index (HHI) index, a dummy variable of unlisted, listed and delisted banks), α denotes the corresponding unknown parameters and w is assumed to be $w \sim N(0, \sigma_w^2)$.

We employ the maximum likelihood to estimate parameters in the Equation (4). Relying on the estimated parameters, we compute the conditional expectation that serves as a point estimator for technical inefficiency as:

$$E(u|\varepsilon) = \alpha' z + \mu_* + \sigma_* \frac{\phi\left(\frac{-\alpha' z - \mu_*}{\sigma_*}\right)}{1 - \phi\left(\frac{-\alpha' z - \mu_*}{\sigma_*}\right)},\tag{5}$$

where $\mu_* = -(\varepsilon \sigma_w^2/\sigma^2)$, $\sigma_*^2 = (\sigma_v^2 \sigma_w^2/\sigma^2)$, $\sigma^2 = \sigma_v^2 + \sigma_w^2$ and $\varepsilon = v - w$. The conditional expectation in the Equation (4) is non-negative. The higher the value of $E(u|\varepsilon)$ is, the higher technically inefficient the bank is.

In applications, forcing to belong to a parametric family of functions like Translog, Cobb-Douglas may lead to a serious modeling bias and hence misleading conclusion about the link between x_I and other variables in Equation (4). To overcome these drawbacks, we use a GAM framework for the estimation of stochastic production frontier models. A GAM fits a response variable x_1 using a sum of smooth functions of the explanatory variables.

In a regression context with Normal response, the model is:

$$\mu = E(x_1|X = x) = \alpha + \sum_{j=1}^{p} f_j(X_j),$$
 (6)

where the $f_j(\cdot)$ denotes standardized smooth functions so that $E[f_i(X_j)] = 0$. GAM can provide useful approximations to the regression surface, but relaxing the linear (polynomial) structure of the additive effects.

In a panel regression setting, Equation (4) becomes:

$$x_{1it} = f(x_{it}) + v_{it} + u_{it}, \quad i = 1, \dots, n,$$
 (7)

where we employ GAM to model the unknown function $f(\cdot)$ in order to relax the linear assumption between inputs and outputs. We estimate the conditional expectation of the mean frontier $E(x_1|X=x)$ and two error term parameters (σ_v, σ_u) . To guarantee the smoothness of the fitted production frontier, we use thin plate regression splines to represent the f_j 's smooth function with smoothing parameters selected by generalized cross validation criterion: $n \times (D/(n-DoF)^2)$ where D is the deviance; n the number of data; and DoF, the effective degrees of freedom of the model.

Once obtaining the mean frontier $E(x_1|X=x)$, the estimation of the production function $f(\cdot)$ will be achieved by shifting the estimation of the conditional expectation in an amount equal to the average estimate of the expected value of the term of inefficiency.

We will consider the estimation of model (7) with unknown $f(\cdot)$ modeled using a penalized regression splines with penalty by introducing effects of interactions among covariates in following way:

In step 1, we use the semiparametric or nonparametric regression techniques to relax parametric restrictions of the functional form representing technology:

$$f(\cdot) = \alpha + \sum_{j=1}^{p} f_j(x_j) + \sum_{j=1}^{p} \sum_{k < p}^{p} f_{kj}(x_k, x_j).$$
 (8)

In step 2, we estimate variance parameters by pseudolikelihood estimators:

$$\min_{\alpha,\beta,\delta,f} \left\{ \left\langle \sum_{i}^{n} \left(y_{i} - \widehat{f}_{i} \right)^{2} \middle| \begin{array}{l} \widehat{f}_{i} = \alpha_{i} + \beta_{i}' x_{i}, \forall i = 1, \dots, n \\ \alpha_{i} + \beta_{i}' x_{i} \leqslant \alpha_{h} + \beta_{h}' x_{i}, \forall h = 1, \dots, n \end{array} \right\rangle \right\},$$

$$\beta_{i} \geqslant 0, \ \forall i = 1, \dots, n$$
(9)

where δ represents the average effect of contextual variables z_i on performances and $z_i'\delta - u_i$ can be seen as the overall efficiency of bank i, where the term $z_i'\delta$ represents technical inefficiency that is explained by the contextual variables; and the component u_i , the proportion of inefficiency that remains unexplained.

4. Data statistics

The data used in this study are taken from FitchConnect, which is a rich source for balance sheet and profit and loss account data for individual banks across the world. Our main target is unlisted and listed banks from ASEAN countries. Relying on the FitchConnect database, we compile unbanlanced panel data from 2000 to 2015 from eight ASEAN countries, including Brunei, Cambodia, Indonesia, Laos, Malaysia, the Philippines, Thailand and Vietnam. We exclude bank-year observations with not available value for our input and output variables, forming a sample of 331 unique banks and 2,805 bank-year observations.

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The whole sample includes 1,523 unlisted bank-year observations, 1,076 listed bank-year observations and 206 delisted bank-year observations.

We identify inputs and outputs in accordance with the intermediation approach. For the inputs of banks, we select labor expense (x_1) , fixed assets as physical capital (x_2) and borrowed funds (x_3) which is total deposits and short-term borrowings. For the desirable outputs, we employ total loans (y_1) , investment (y_2) and noninterest income (y_3) . In addition to these good outputs, we consider provision for loan loss (b) as a proxy for undesirable output. We also include micro and macro environmental factors to reflect the different atmospheres to explain technical inefficiency. The micro factors include ratio of equity to total assets (z_1) and liquidity position (z_2) which is the ratio of liquid assets to total assets. The macro environment factors are GDP growth (z_3) and the HHI competition index (z_4) . We use GDP growth to represent the overall economic condition, influencing the bank activities and this efficiency. HHI is used to measure the market concentration or competition pressure where banks operate.

Table I shows the sample statistics for inputs, outputs and environmental factors. The average amounts of good outputs, including loans, investments, noninterest income are 5,208, 1,721 and \$102m, respectively. The mean of bad output (loan loss reserves) is equal to \$189m. Three inputs have means at 81, 86, and \$1,740 m, respectively. The micro environmental factors reveal banks in ASEAN with equity and liquid ratio, showed by 13.39 and 25.8 percent, respectively. Finally, the macro environment factors suggest a highly concentrated market with HHI index at 1,068 and relatively high GDP growth rate at 5.25 percent.

5. Estimation results

5.1 Primary results: no evidence of technological progress?

We estimate ASEAN bank efficiency by DDF and SEMSFA. We use the results of DDF to compare with that of SEMSFA because the later method includes two stages, in which the first stage measure parameters relying on the semiparametric regression, which is almost "similar" to the quadratic regression in DDF. Hence, technical efficiencies measured by the two methods are expected to be also akin.

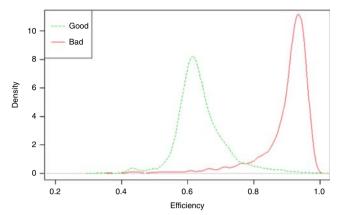
Efficiency estimations from both DDF and SEMSFA are presented in Figures 1 and 2 correspondingly. For the DDF approach, we estimate efficiency from the coefficients of Equation (4). The Equation (4) estimates a translog production frontier with bank-year

| Variables (\$ million) | Symbol | Mean | SD |
|--|------------------|----------|-----------|
| Outputs | | | |
| Loans | y_1 | 5,208.06 | 12,823.80 |
| Investment | y_2 | 1,721.42 | 5,145.48 |
| Noninterest income | y_3 | 102.93 | 239.96 |
| Undesirable (loan loss reserves) | b | 189.46 | 397.23 |
| Inputs | | | |
| Labor | x_1 | 81.28 | 174.00 |
| Physical capital | x_2 | 86.26 | 171.83 |
| Borrowed funds | $\overline{x_3}$ | 1,740.39 | 14,262.77 |
| Environment | | | |
| Equity/Total assets (%) | z_1 | 13.39 | 11.35 |
| Liquidity (%) | z_2 | 25.8 | 16 |
| GDP growth (%) | z_3 | 5.25 | 2.04 |
| НН | z_4 | 1,068.54 | 2,744.99 |
| Source: Authors' computation from Fig. | tchConnect | | |

Table I. Descriptive statistics for the sample

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Figure 1. Efficiency under DDF



Source: Authors' computation from FitchConnect

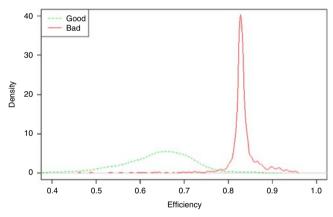


Figure 2. Efficiency under SEMSFA

Source: Authors' computation from FitchConnect

observation efficiencies that account for non-constant rates of technological change as well as biased technological change. To test for the suitability of the translog production function, we employ likelihood ratio test. The value of χ^2 test statistic on one-sided error is 1,374.2 for good output model and 741.6 for bad output model. The χ^2 test statistics clearly reject the OLS stochastic frontier model and support for a translog production model. We show DDF regression results and the χ^2 test statistics at the appendices.

Technical efficiency is the outcome of comparing one bank to the best performing bank on the frontier line. Our efficiency estimations are displayed in Figures 1 and 2. Both approaches yield the efficiency with provision for loan loss (as a proxy for an undesirable output) that is higher the efficiency without the bad output. Their corresponding efficiencies are 89 and 64 percent under DDF, and 83 and 67 percent under SEMSFA. Figures 1 and 2 show the densities of efficiency, in which the density of efficiency with bad output (the red line) lies to the right of the density of efficiency with good outputs (the green line). The difference looks illogic because efficiency with bad output should be lower than that with good ones.

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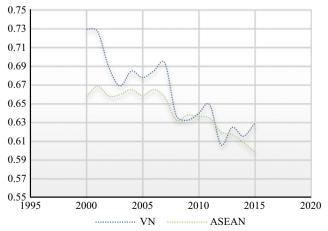
Reason for the illogic difference originates from the adjustment of performance of the best banks in term of risk. The adjustment degrades the performance of the best bank so that the frontier line moves toward the coordinate angle. Once the performance of the benchmark decreases, the performance of other banks upgrades. From the degradation of the best performing bank and the upgradation of the rest of the banks when we take risk into account, we can conclude that the best performer faces higher risk. Hence, it is necessary to incorporate risk into examining bank performance.

When outputs are all good, most coefficients from the regression results are significant, except for time variables (t and t^2). As the coefficients of t and t^2 are not significant, one interesting finding from the model is that there is no significant evidence of technological progress in ASEAN banks. The same finding for the case of bad output model, the coefficient of variable t is not significant, but t^2 has a significantly negative coefficient, implying a long-term technological regress. The retreating performance of ASEAN banks is exhibited in Figure 4 and in Table AII.

The means of efficiency under both methods for good and bad outputs are not much different, but the trend of efficiency is much different under each method. While the DDF method yields a reduction of efficiency in ASEAN (as shown in Figures 3 and 4), the SEMSFA shows a stable trend in the good output scenario (in Figure 5) and even increasing tendency of efficiency in bad output scenario (in Figure 6). The divergence of tendency under the two methods shows disadvantage of parametric DDF approach and highlights the advantage of nonparametric/semi-parametric SEMSFA. For a parametric model to estimate efficiency, knowing just the parameters (which is measured from the mean value of observation) from translog regression is enough. However, the SEMSFA helps us to measure efficiency by relying not just on the parameters (actually the parameters change in corresponding to each observation) but also in the current state of data that has been observed. By capturing the current state of data, the SEMSFA helps us to gain more correct efficiency estimation.

5.2 Vietnam's banks: outperforming?

The second finding from both DDF and SEMSFA is that banks in Vietnam outperform their peers in ASEAN nations. Regardless the difference in efficiency trend under both methods, the average efficiency level of Vietnam's banks lies above the average level of ASEAN

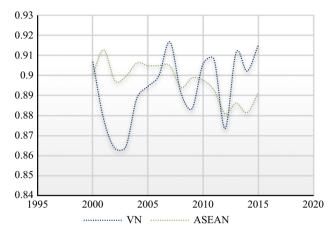


Source: Authors' computation from FitchConnect

Figure 3. DDF's efficiency without risk

12

Figure 4. DDF's efficiency with risk



Source: Authors' computation from FitchConnect

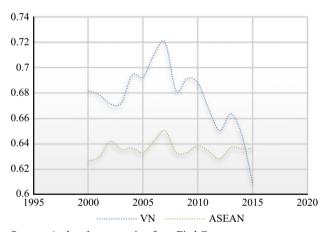


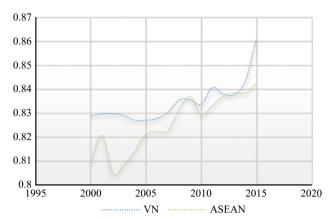
Figure 5. SEMSFA's efficiency without risk

Source: Authors' computation from FitchConnect

banks as shown in Figures 3–6. Our estimation supports the outperformance of banks in Vietnam even taking risk into account. In other words, banks in Vietnam are both more efficient and safer than their peers in ASEAN.

Regardless the better performance, the efficiency of banks in Vietnam ignites two concerns. Our first concern is that both methods show a drop in efficiency of Vietnam's banks under the good output scenario. The speed of efficiency reduction of banks in Vietnam exceeds the average speed reduction of their competitors in ASEAN. In the SEMSFA method, Vietnam's banks have shown a persistently reducing performance since 2005 and commence a lower efficiency in 2005 (Figure 7).

Our second concern is about the amount of loan loss reserve of banks in Vietnam. Our data show Vietnam's banks have used much lower capital resources to reserve for loan loss. During 2000–2015, the loan loss reserve ratio of total gross loan is stable around 2 percent for banks in Vietnam. We are doubtful about the amount loan loss reserves of banks in Vietnam. The amount of reserves is set up relying on their nonperforming loans.

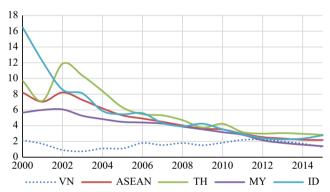


Source: Authors' computation from FitchConnect



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Figure 6. SEMSFA's efficiency with risk



Source: Authors' computation from FitchConnect

Figure 7. Loan loss reserves (as % of total gross loan)

Our suspicion originates from the very low nonperforming loans that are disclosed by both banks and the State Bank of Vietnam. As the non-performing loans are underestimated, the disclosure does not capture the real risk of banks in the country and banks in Vietnam may become riskier as their low provision for loan loss. If their clients cannot pay loans on due, the banks may have not enough resources to deal with the credit risk and liquidity risk. To stop "systemic risk" among banks, the State Bank of Vietnam has recently acquired five distressed banks. The acquisition supports our skepticism about the fact that nonperforming loan ratio of banks in Vietnam is "flatten."

Our skepticism is also supported by Moody's report[4] as "the banks' loan loss reserves and capital are likely insufficient to absorb potential losses on problem assets." Moody's report also mentions that the problem assets ratio[5] should be 6.9 percent at the end 2015. If it is true, the loan loss provision in the country accounts for about one-third of the total credit risk. The benefit of recording low level of loan loss reserves helps to boost profitability in the short-term; but the long-term adverse effect is that it will take the banks many years before legacy problem assets are prudently covered by reserves and/or written off. In sum, we emphasize that low level of loan loss provision is a root of this instability and it takes longer period for Vietnam's banks to have enough loan loss provision to remove the true high level of bad loans.

6. Conclusion

In this paper, risk is incorporated into efficiency measurement by DDF and SEMSFA. Thanks to the two methods, we can point out the performance of banks in Vietnam and their peers in ASEAN countries. Our research has two interesting findings that are no evidence of technological progress for banks in ASEAN and concerns about the outperformance of Vietnam's banks. For the technological regress problem, ASEAN banks can improve efficiency via investing more on technology and management. For the concern of the performance of banks in Vietnam, the State Bank of Vietnam can request banks in Vietnam to book more loan loss reserves to shorten the period of removing bad assets.

Notes

- Originally established in Bangkok in 1967 and consisted of five member countries (Indonesia, Malaysia, Philippines, Singapore and Thailand), the Association of Southeast Asian Nations (ASEAN) is nowadays a diverse group of five original states (ASEAN-5) and five newer members: Brunei Darussalam, Cambodia, Lao PDR, Myanmar and Vietnam (BCLMV), aiming towards a politically cohesive, economically integrated, and socially responsible community.
- Brunei Darussalam, Cambodia, the Lao People's Democratic Republic (Lao PDR), Myanmar and Vietnam.
- 3. The SFA model is defined as $y_{it} = f(x_{ii}, \beta) + v_{it} u_{it}$, where $Y_{it} \in \mathbb{R}_+$ is the outputs of bank i at time $t, X_i \in \mathbb{R}_+^p$ is the vector of inputs, $f(\cdot)$ defines a production (frontier) relationship between inputs X and the outputs $Y, v_i \sim N(0, \sigma_v^2)$ is a symmetric two-side error representing random effects and $u_i > 0$ is one-side error term representing technical inefficiency $(u_i \sim N(0, \sigma_u^2))$.
- The report is summarized at www.moodys.com/research/Moodys-changes-outlook-for-Vietnamese-banking-system-to-stable-from-PR_314709
- The non-performing asset ratio is collected from www.moodys.com/research/Moodys-Outlook-for-Vietnam-banks-stable-supported-by-the-countrys-PR_358832

References

- ADB, A. (2013), "The road to ASEAN financial integration: a combined study on assessing the financial landscape and formulating milestones for monetary and financial integration in ASEAN", Asian Development Bank, Manila.
- Andor, M. and Hesse, F. (2014), "The StoNED age: the departure into a new era of efficiency analysis? A Monte Carlo comparison of StoNED and the 'oldies' (SFA and DEA)", *Journal of Productivity Analysis*, Vol. 41, pp. 85-109.
- Berger, A.N. and DeYoung, R. (1997), "Problem loans and cost efficiency in commercial banks", Journal of Banking & Finance, Vol. 21, pp. 849-870.
- Berger, A.N. and Humphrey, D.B. (1997), "Efficiency of financial institutions: international survey and directions for future research", European Journal of Operational Research, Vol. 98, pp. 175-212.
- Chan, S.-G., Koh, E.H.Y., Zainir, F. and Yong, C.-C. (2015), "Market structure, institutional framework and bank efficiency in ASEAN 5", Journal of Economics and Business, Vol. 82, pp. 84-112.
- Chang, C.-C. (1999), "The nonparametric risk-adjusted efficiency measurement: an application to Taiwan's major rural financial intermediaries", American Journal of Agricultural Economics, Vol. 81, pp. 902-913.
- Chang, T.-C. and Chiu, Y.H. (2006), "Affecting factors on risk-adjusted efficiency in Taiwan's banking industry", Contemporary Economic Policy, Vol. 24, pp. 634-648.
- Eskelinen, J. and Kuosmanen, T. (2013), "Intertemporal efficiency analysis of sales teams of a bank: stochastic semi-nonparametric approach", *Journal of Banking & Finance*, Vol. 37, pp. 5163-5175.

Incorporating

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- Färe, R., Grosskopf, S. and Lovell, C.K. (1985), The Measurement of Efficiency of Production, Kluwer-Nijoff Publishing, Boston, MA.
- Färe, R., Grosskopf, S., Noh, D.W. and Weber, W. (2005), "Characteristics of a polluting technology: theory and practice", *Journal of Econometrics*, Vol. 126 No. 2, pp. 469-492.
- Gardener, E., Molyneux, P. and Nguyen-Linh, H. (2011), "Determinants of efficiency in South East Asian banking", *The Service Industries Journal*, Vol. 31, pp. 2693-2719.
- Greene, W.H. (1990), "A Gamma-distributed stochastic frontier model", *Journal of Econometrics*, Vol. 46 Nos 1-2, pp. 141-163, available at: https://doi.org/10.1016/0304-4076(90)90052-U
- Huang, T.-H., Chiang, D.-L. and Tsai, C.-M. (2015), "Applying the new metafrontier directional distance function to compare banking efficiencies in central and eastern European countries", *Economic Modelling*, Vol. 44, pp. 188-199.
- Karim, M.Z.A. (2001), "Comparative bank efficiency across select ASEAN countries", ASEAN Economic Bulletin, Vol. 18, pp. 289-304.
- Karim, M.Z.A., Sok-Gee, C. and Sallahudin, H. (2010), "Bank efficiency and non-performing loans: evidence from Malaysia and Singapore", *Prague Economic Papers*, Vol. 2, pp. 118-132.
- Khan, S.J.M. (2014), "Bank efficiency in Southeast Asian countries: the impact of environmental variables", *Handbook on the Emerging Trends in Scientific Research*, PAK Publishing Group, pp. 658-672.
- Kuosmanen, T. (2012), "Stochastic semi-nonparametric frontier estimation of electricity distribution networks: application of the StoNED method in the Finnish regulatory model", *Energy Economics*, Vol. 34, pp. 2189-2199.
- Kuosmanen, T. and Kortelainen, M. (2012), "Stochastic non-smooth envelopment of data: semi-parametric frontier estimation subject to shape constraints", *Journal of Productivity Analysis*, Vol. 38, pp. 11-28.
- Laeven, L. (1999), Risk and Efficiency in East Asian Banks, World Bank, Financial Sector Strategy and Policy Department, Washington, DC.
- Manlagnit, M.C.V. (2011), "Cost efficiency, determinants, and risk preferences in banking: a case of stochastic frontier analysis in the Philippines", *Journal of Asian Economics*, Vol. 22, pp. 23-35.
- Sarifuddin, S., Ismail, M.K. and Kumaran, V.V. (2015), "Comparison of banking efficiency in the selected ASEAN countries during the global financial crisis", PROSIDING PERKEM, Vol. 10, pp. 286-293.
- Sarmientoa, M. and Galán, J.E. (2015), "The influence of risk-taking on bank efficiency: evidence from Colombia", CentER discussion paper, pp. 2015-2036.
- Tone, K. and Tsutsui, M. (2014), "Dynamic DEA with network structure: a slacks-based measure approach", Omega, Vol. 42 No. 1, pp. 124-131, available at: https://doi.org/10.1016/j.omega.2013.04.002
- Vidoli, F. and Ferrara, G. (2015), "Analyzing Italian citrus sector by semi-nonparametric frontier efficiency models", Empirical Economics, Vol. 45, pp. 641-658.
- Williams, J. and Nguyen, N. (2005), "Financial liberalisation, crisis, and restructuring: a comparative study of bank performance and bank governance in South East Asia", *Journal of Banking and Finance*, Vol. 29, pp. 2119-2154.
- Wong, W.P. and Deng, Q. (1999), "Efficiency analysis of banks in ASEAN countries", *Benchmarking: An International Journal*, Vol. 23, pp. 1798-1817.
- Yueh-Cheng Wu, I.W.K.T., Lu, W.-M., Nourani, M. and Kweh, Q.L. (2016), "The impact of earnings management on the performance of ASEAN banks", *Economic Modelling*, Vol. 53, pp. 156-165.
- Zhu, N., Wang, B., Yu, Z. and Wu, Y. (2016), "Technical efficiency measurement incorporating risk preferences: an empirical analysis of Chinese commercial banks", *Emerging Markets Finance* and Trade, Vol. 52, pp. 610-624.

Appendix 1

| | _ |
|---|----------------------------|
| 1 | $\boldsymbol{\mathcal{C}}$ |
| | n |
| | |

| Variables | Coef. | SE | Variables | Coef. | SE | Variables | Coef. | SE |
|-----------------------|------------|-------|---|------------|--------|-------------|------------|--------|
| Intercept | -0.5052*** | 0.023 | y_1t | 0.0013* | 0.0007 | x_2t | 0.0015** | 0.0007 |
| y_1 | -0.3847*** | 0.009 | y_{2}^{2} | -0.0345*** | 0.0018 | x_{3}^{2} | 0.0756*** | 0.0039 |
| y_2 | -0.0898*** | 0.007 | <i>y</i> ₂ <i>y</i> ₃ | -0.0077*** | 0.0023 | x_3t | 0.0011 | 0.0010 |
| <i>y</i> ₃ | -0.0319*** | 0.009 | y_2x_2 | 0.0070*** | 0.0023 | t^2 | -0.0005 | 0.0003 |
| x_2 | -0.0195** | 0.009 | y_2x_3 | -0.0007 | 0.0025 | GDP | 0.0028** | 0.0011 |
| x_3 | 0.4578*** | 0.012 | y_2t | -0.0024*** | 0.0005 | HHI | 0.0000 | 0.0000 |
| t | 0.0022 | 0.003 | y_3^2 | -0.0184*** | 0.0039 | Equity | 0.0066*** | 0.0003 |
| y_1^2 | -0.0784*** | 0.003 | y_3x_2 | -0.0091*** | 0.0029 | Liquid | -0.6375*** | 0.0182 |
| y_1y_2 | 0.0417*** | 0.002 | y_3x_3 | 0.0027 | 0.0034 | Unlisted | 0.5228*** | 0.0201 |
| <i>y</i> 1 <i>y</i> 3 | 0.0305*** | 0.003 | y_3t | 0.0023*** | 0.0008 | Listed | 0.5070*** | 0.0201 |
| y_1x_2 | 0.0021 | 0.003 | x_2^2 | 0.0127*** | 0.0038 | Delisted | 0.4959*** | 0.0223 |
| y_1x_3 | 0.0032 | 0.003 | x_2x_3 | -0.0055* | 0.0028 | σ^2 | 0.0153*** | 0.0004 |
| | | | | | | γ | 0.0000*** | 0.0000 |
| 37 . 37 | 1 (1 | . • | 0.005.11 | | 1.00 | O TD (2 . | | |

Table AI.DDF regression for only good output

Notes: Number of observations = 2,805; log-likelihood function = 1,880; LR (χ^2) test statistic on one-sided error = 1,374.2. *,***,***Denote significance at the 10, 5 and 1 percent levels, respectively

Appendix 2

| Variables | Coef. | SE | Variables | Coef. | SE | Variables | Coef. | SE |
|-----------------------|------------|--------|--|------------|--------|-------------|------------|---------|
| Intercept | 0.9563*** | 0.1546 | y_2^2 | -0.0558*** | 0.0046 | x_{3}^{2} | 0.2002*** | 0.0126 |
| y_1 | -0.2029*** | 0.0287 | <i>y</i> ₂ <i>y</i> ₃ | 0.0300*** | 0.0076 | x_3b | 0.0166 | 0.0086 |
| y_2 | -0.2093*** | 0.0327 | y_2x_2 | -0.0166*** | 0.0049 | | 0.0109** | 0.0033 |
| <i>y</i> ₃ | 0.2213** | 0.0720 | y_2x_3 | -0.0218** | 0.0084 | b^2 | 0.0054 | 0.0081 |
| x_2 | 0.0791 | 0.0446 | y_2b | 0.0014 | 0.0052 | bt | -0.0024 | 0.0017 |
| x_3 | 0.5312*** | 0.0579 | y_2t | 0.0015 | 0.0012 | t^2 | -0.0019* | 0.0008 |
| b | -0.0345 | 0.0446 | $y_2 t \\ y_3^2$ | -0.0.004 | 0.0180 | GDP | -0.0102** | 0.0033 |
| t | 0.0147 | 0.0134 | y_3x_2 | -0.0070 | 0.0104 | HHI | -0.0001*** | 0.0000 |
| y_1^2 | -0.0673*** | 0.0033 | y_3x_3 | -0.1188*** | 0.0167 | Equity | -0.0173*** | 0.0008 |
| y_1y_2 | 0.0583*** | 0.0038 | y_3b | -0.0005 | 0.0103 | Liquid | 0.2596*** | 0.0538 |
| y_1y_3 | -0.0226** | 0.0069 | | -0.0005 | 0.0031 | Unlisted | 1.0778*** | 0.0447 |
| y_1x_2 | 0.0163*** | 0.0046 | $\begin{array}{c} y_3t \\ x_2^2 \end{array}$ | 0.0450*** | 0.0084 | Listed | 1.0861*** | 0.0443 |
| $y_1 x_3$ | 0.0441*** | 0.0077 | x_2x_3 | 0.0247* | 0.0105 | Delisted | 1.1192*** | 0.0518 |
| y_1b | -0.0158*** | 0.0046 | x_2b | -0.0143* | 0.0064 | σ^2 | 0.0660*** | 0.0022 |
| y_1 t | -0.0000 | 0.0011 | x_2t | -0.0005 | 0.0017 | γ | 0.0000 | 2.3107e |

Table AII.DDF regression for both good and bad outputs

Notes: Number of observations = 2,805; log-likelihood function = 1,730.2; LR (χ^2) test statistic on one-sided error = 741.6. *,***,****Denote significance at the 10, 5 and 1 percent levels, respectively

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