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สัญญาเลขที่ MRG5380107

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สนับสนุนโดยสำนักงานคณะกรรมการการอุดมศึกษาและสำนักงานกองทุนสนับสนุนการวิจัย

Decomposition Productivity Growth from the Output Distance Function using Unbalance FE-IV Approach: The Case Study of Thai Commercial Banks[1]

Abstract

Subsequent the Asian Financial Crisis, Thailand commercial banking industry have gone through a reconstructing period via the Financial Sector Master Plan (FSMP), which was formulated to strengthen the banking industry. This study aims to decompose the Total Factor Productivity growth (TFP) for Thailand commercial banking industry with an output distance function, where the data adopted in this study covers the period before and after of implementation of FSMP. With an unbalanced panel dataset, we used the Fixed Effect (FE) model with Instrumental Variables (IV) to estimate the TFP growth empirically. The results show that FSMP succeeded in reinforcement of the technical inefficiency change effect, scale effect, and output price effect of the Thai banking industry. Furthermore, the productivity growth of the small size banks was majorly improved by the positive impact of scale effect; while that of the large and medium size banks was significantly worsened by this effect.

Key words: Productivity Growth, Fixed Effect, Instrumental Variables, Distance Function, Thai Commercial Banks.

[1] This research was supported by The Thailand Research Fund (TRF), contract number MRG5380107.

1. Introduction

Investigation of productivity growth is beneficial not only for firms to adjust their management toward productivity improvement, but also for their governments to make policies promoting the productivity growth and strengthening an industry in their countries. A large number of studies contributed to this topic across many industries, such as, Atkinson and Primont (2002); Atkinson et al. (2003); Saal et al. (2007); and Wales et al. (2005). Many productivity growth studies are for banking industry, such as Chaffai et al. (2001), Kumbhakar and Wang (2007), Rezitis (2008), and Koutsomanoli-Filippaki et al. (2009).

According to Kumbhakar and Lovell (2000), productivity growth can be measured by the difference between the rates of change in output and input indices. This growth can be decomposed into four components: (i) technical inefficiency change component, (ii) technical change component, (iii) scale component, and (iv) allocative inefficiency component. The last three components are normally estimated through the parameters of the distance function with panel data models, while the first component is often estimated from the unobserved effects of the models.

Three parametric methods for panel data, fixed effect, random effect, and maximum likelihood, are widely adopted to obtain the parameters and unobserved effects. Examples of application in the fixed effect model are Atkinson et al. (2003), and Atkinson et al. (2003). Papers applying the random effect method include Chaffai et al. (2001), Sickles et al. (2002), and Karagiannis et al. (2004). Studies using the maximum likelihood include Brummer et al. (2002), Cuesta and Orea (2002), Rezitis (2008), Jiang et al. (2009) and Rahman (2010).

None of the maximum likelihood studies recognized and dealt with the endogeneity problem in productivity growth. Among those who did, Sickles et al. (2002) used multivariate kernel estimators for the joint distribution of the multiple outputs and potentially correlated firm random effect, and Atkinson and Primont (2002), Atkinson (2003), Atkinson et al.

(2003), and Karagiannis et al. (2004) used instrumental variables[2] to correct the endogeneity problem from the unobserved effects and idiosyncratic disturbances. However, the consideration of selectivity bias is ignored when unbalance panel data[3] are applied.

According to Wooldridge (2005), although the endogeneity is corrected, the biased of parameters will arise if there exists correlation between selection and the unobserved effects. In this paper, we will concern both the selectivity biased and the endogeneity problem. These issues can be dealt with by the method proposed by Semykina and Wooldridge (2010). When the hypothesis of no selection biased is failed to reject, Semykina and Wooldridg (2010) suggested a procedure of fixed effect 2SLS; otherwise, a correction procedure based on the pooled 2-Stage-Least-Square is applied.

This paper tries to apply the FE-IV method with consideration of selectivity bias to investigate banking productivity growth. Thailand banking industry is selected as a case study. After the Asian financial crisis in 1997, the industry has been reinforced especially in upgrading the regulatory and supervisory to the banking industry through the Thailand's Financial Sector Master Plan (FSMP) which has been implemented since 2004. We segment the banks into three groups: large size, middle size, and small size. The effectiveness of the plan to each size will be evaluated by decomposing the productivity growth of the industry. The selected unbalanced panel data of 14 Thai commercial banks is adopted. The parameters from the distance function are estimated in accompany with allowing explanatory variables correlate to unobserved effects and idiosyncratic error.

The remainder of this paper is as follows. Section 2 presents the literature reviews on measuring of banking performance. Section 3 presents the model and the estimation

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[2] The output quantities, output prices, input prices, and technology index were chosen as instrumental variables

[3] Karagiannis et al. (2004) applied unbalanced panel data and the balanced panel data was used in Sickles et al. (2002), Atkinson et al. (2003), and Atkinson et al. (2003).

method. Section 4 presents the background of the Thai banking industry and data. Section 5 presents the results and section 6 concludes.

2. Literature Reviews on Banking Performance

The standard tool extensively used to measure firms' performance is total factor productivity (TFP) growth decomposition. In most measuring of banking performance papers, nonparametric procedure and parametric one are popular econometrics methodologies to measure the TFP.

The mostly adopted nonparametric approach is the TFP Malmquist index computed by Data Envelopment Analysis (DEA). Examples for this application are Tsionas et al. (2003) and Chortareas et al. (2009) for the Greek banking system; Isik and Hassan (2003) for the Turkish banks; Guzman and Reverte (2008) for Spain; Sufian (2009) Malaysian banking sector.

More advanced techniques to measure Malmquist index have been adopted. For instance, Matthews and Zhang (2010) used bootstrap for the Malmquist index to the nationwide banks of China and a sample of city commercial banks for 1997–2007. This technique enables us to test for sensitivity of the index. Brissimis et al. (2008) examined the relationship between banking sector reform and bank performance of ten newly acceded EU countries by applying a doubled bootstrap procedure to account for endogeneity.

New procedures are also being developed to estimate TFP Malmquist index. For example; Portela et al. (2006) estimated TFP Malmquist index which relied on geometric distance function (GDF), based on observed value only. They applied this procedure to bank branches in Portugal. Portela and Thanassoulis (2010) developed a method computing meta-Malmquist indices and meta–Luenberger indicators for measuring productivity change over time and productivity differences between units in multi-input / multi-output contexts allowing for negative values.

The cost, production, and distance function are parametric approaches broadly adopted to decompose TFP. Examples of TFP measures from the cost function are Sensarma

(2006), Kondeas et al. (2008). They applied stochastic frontier translog cost function to extract productivity for commercial banks in India and 15 nations in the European Union, respectively. Huang and Fu (2009) used translog cost function under uncertainty to estimate TFP in Taiwan banking industry. The parameters in the cost function are mostly estimated by maximum likelihood.

When the cost function is applied to analyze the productivity growth, the inputs prices are required. On the other hand, when the production function is applied to decompose TFP, no prices are required. For example, Nakane and Weintraub (2005) used Cobb–Douglass production function and Huang (2005) used translog production function to decomposed TFP of the banking industry in Brazil and Taiwan, respectively.

The outputs and inputs used in these studies, except for Sensarma (2006), are based on 'intermediation' approach, which treat deposits as an input, to produces loans, an output. In opposition to these studies, Sensarma (2006) treats deposits and loans as output, and labor and capital as inputs; this selection is based on the 'value added' approach, which is more appropriate when the main objective of a bank is to boost its loans and deposits. We follow the value added approach in this study, as it is more suitable to Thai banking industry.

Unfortunately, although the application of production function does not require prices, the only single output is restricted. The requirement of single output is unrestricted when the distance function is adopted to decompose TFP. Most of the studies mentioned in the first section took the distance function to investigate TFP growth, because it can dealt with multiple outputs and inputs, and because it does not involve cost minimization or profit maximization explicitly thus requiring no price information in the model estimation. In this paper, we extend the literature in measure of bank performance using the output distance function approach, estimated with the FE-IV technique.

3. Model and Estimation Method

Model

As mentioned earlier, the output distance function is often used to investigate TFP when multiple outputs are produced by several inputs. The method only requires input and output quantity data, but not prices.

Let Time is denoted by the subscript *t*. y^t be a *m*-vector of outputs ($y^t \in \mathbb{R}_+^m$), x^t is a *k*-vector of inputs ($x^t \in \mathbb{R}_+^k$), $P^t(x^t) = \{y^t : (x^t, y^t) \in S^t\}$ represents the set of all output vectors that can be produced with the input vector *x* under the technology set, S^t.

Following Fare and Primont (1995), we assumed that the output distance function, which describes the structure of production technology, is given by

$$D_O^t(x^t, y^t) = inf_\mu \left\{\mu > 0 : \left(\frac{y^t}{\mu}\right) \in P^t(x^t)\right\} \text{ for all } x^t \in \mathbb{R}_+^k \quad (1)$$

The output distance function, $D_O^t(x^t, y^t)$, represents a proportional expansion of all the outputs, y^t, that are still able to be produced by the given inputs, x^t. $D_O^t(x^t, y^t)$ is non-decreasing, convex, and linearly homogeneous in outputs, and it is decreasing and quasi-concave in inputs.

To summarize the concept of the output distance function, we follow the same procedure as Brummer et al. (2002). It is illustrated by figure 1. Assuming there are two outputs (y_1 and y_2), and the output set $P^t(x^t)$ corresponds to a given input vector x^t. The value of $D_O^t(x^t, y^t)$ projects the output vector, y^t, along the ray from the origin through y^t on the boundary of $P^t(x^t)$ and thus $D_O^t(x^t, y^t) \leq 1$, which implies that the distance function will take a value which is less than or equal to unity, depending on whether the output vector, y^t, is located below or on the boundary of $P^t(x^t)$.[4]

[4] Because it is infeasible for output distance to be greater than unity, in empirical analysis we only observe data in the range of distance less than or equal to unity.

Brummer et al. (2002) estimated technical progress change by including the time trend as another exogenous variable. Hence, the output distance function is written as $D_O(t, x, y)$. For the technical efficiency measurement, Kumbhakar and Lovell (2000) showed that this can be measured by the output distance function in the logarithm form. Accordingly, in this paper, replacing the ln(*TE*) with a non-positive random error, *u*, we have

$$\ln(TE) = \ln D_O(t, x, y) = u. \tag{2}$$

and the measure of technical efficiency can be estimated from $TE = \exp(u)$.

Because of its flexibility and convenience to impose restrictions, this paper adopted the translog function as the output distance function (see appendix A) and the parameters of the output distance function can be shown in a matrix form as follow,

$$-\ln y_{iM}^{t} = \alpha_0 + \boldsymbol{x_i^t \beta} - u_i^t + v_i^t \tag{3}$$

where $\boldsymbol{x_i^t}$ and $\boldsymbol{\beta}$ are, respectively, the vectors of all explanatory variables in their corresponding algebraic forms and of their coefficients in equation (A3); v_i^t are the idiosyncratic errors accounting for irregular event affecting to firms; u_i^t are non-positive unobserved effects which are used to capture the technical inefficiency in output; v_i^t and u_i^t are independent and subscript *i* is the i^{th} firm.

Let T_i be the time period for the i^{th} firm, $u_i^t = \varphi_{i0} + \varphi_1 \sin(\phi\tau_i) + \varphi_2 \cos(\phi\tau_i)$, where τ_i is the time periods, which may be differently started in each firm, until its last time period T_i . The parameters φ_{i0}, φ_{i1}, and φ_{i2} describes how the behavior of the i^{th} firm affects its non-positive unobserved structure, which might be concave or convex. Finally, ϕ is the common scaling factor, which makes the value of $\phi\tau_i$ span the interval $(0,2\pi)$. Gallant (1982) suggested $\phi = \frac{6}{\max_i T_i}$. Plugging it back to equation (3), we get

$$ly_{iM}^{t} = \boldsymbol{w_i^t \varphi_i} + \boldsymbol{x_i^t \beta} + v_i^t \tag{4}$$

where $ly_{iM}^{t} = -\ln y_{iM}^{t}$, $\boldsymbol{w_i^t} = (1, -\sin(\phi\tau_i), -\cos(\phi\tau_i))$ and $\boldsymbol{\varphi_i} = (\varphi_{i0}^{*}, \varphi_{i1}, \varphi_{i2})'$, $\varphi_{i0}^{*} = \alpha_0 - \varphi_{i0}$.

The output distance function can be used to extract the four components of productivity change (see appendix B), which are (i) technical inefficiency change, (ii) technical progress change, (iii) scale effect, and (iv) allocative effects regarding inputs and outputs price changes. The translog form of the output distance function is briefed in Appendix A, where y_1 is selected as normalized output variable.

Technical inefficient effects are evaluated at every firm from TE_{it}=$\exp\{\hat{u}_i^t\}$, where $\hat{u}_i^t = \hat{u}_i^{t*} - u_i^{0t}$ and we may estimate $\hat{u}_i^{t*}$ from $\hat{u}_i^{t*} = \hat{\varphi}_0^* + \hat{\varphi}_1 \sin(\phi\tau_i) + \hat{\varphi}_2 \cos(\phi\tau_i)$, $u_i^{0t} = \max_{i=1,\dots,N} \hat{u}_i^{t*}$. Thus at least one firm must have 100% average technical efficiency for each period. Technical inefficient change effects of Thai commercial banks is estimated by $\frac{\partial \hat{u}_i^t}{\partial \tau_i} = \hat{\varphi}_1 \phi\cos(\phi\tau_i) - \hat{\varphi}_2 \phi\sin(\phi\tau_i)$.

The technical progress change effects are also evaluated at the values of inputs and outputs in every firm from the following equation,

$$-\frac{\partial \ln D_O(.)}{\partial t} = -\left(\hat{\delta}_0 + \hat{\delta}_{y2} \ln y_2^t - \hat{\delta}_{y2} \ln y_1^t + \hat{\delta}_{x1} \ln x_1^t + \hat{\delta}_{x2} \ln x_2^t + \hat{\delta}_{11} t \right).$$

The scale effects are *RTS* at the value of inputs and outputs from $(RTS-1)\sum_{k=1}^{2} \lambda_k \dot{x}_k$, where $RTS = -\sum_{k=1}^{2} \frac{\partial \ln D_O(x,y)}{\partial \ln x_k} = -\left(\hat{\beta}_1 + \hat{\beta}_{11} \ln x_1^t + \hat{\beta}_{12} \ln x_2^t + \hat{\delta}_{x1} t + \hat{\gamma}_{11} \ln \frac{y_2^t}{y_1^t}\right) - \left(\hat{\beta}_2 + \hat{\beta}_{22} \ln x_2^t + \hat{\beta}_{12} \ln x_1^t + \hat{\delta}_{x2} t + \hat{\gamma}_{12} \ln \frac{y_2^t}{y_1^t}\right)$. Finally, the allocative effects are composed of output price effects $\left(\sum_{m=1}^{M} (R_m - \mu_m) \dot{y}_m\right)$ and input price effects $\left(\sum_{k=1}^{K} (\lambda_k - S_k) \dot{x}_k\right)$. As in the previous effects, we calculate the allocative effects at the values of outputs and inputs, where $\mu_1 = \frac{\partial \ln D_O(.)}{\partial \ln y_1} = -\alpha_1 + \alpha_{22} \ln y_1 - \alpha_{22} \ln y_2 - \delta_{y1} t - \gamma_{11} \ln x_1 - \gamma_{12} \ln x_2$, $\mu_2 = \frac{\partial \ln D_O(.)}{\partial \ln y_2} = \alpha_1 + \alpha_{22} \ln y_2 - \alpha_{22} \ln y_1 + \delta_{y1} t + \gamma_{11} \ln x_1 + \gamma_{12} \ln x_2$, and $\lambda_k = \frac{\partial \ln D_O(.)}{\partial \ln x_k} / RTS$.

Estimation Method

According to equation (4), the exogeneity assumption might be violated since the normalized output appears in regressors. Moreover, we have unbalanced panel data that the number of time periods is not the same across all firms resulting from the firms' entry or exit of the market. This paper follows fixed effect instrumental variable (FE-IV) proposed by Semykina and Wooldridge (2005, 2010) and Wooldridge (2002), to estimate the model as shown in equation (4). This method allows the unobserved effects to correlate to explanatory variables, and instrumental variables, and it even allows correlations between some explanatory variables and idiosyncratic errors. The estimation method is concluded as follows. For any random draw i from the population, let $\boldsymbol{s_i} = (s_i^1,\ldots, s_i^{Ti})'$ denotes the $T_i\times 1$ vector of selection indicators, where $s_i^t = 1$ if $(\boldsymbol{x_i^t}, ly_{iM}^t)$ is observed and zero otherwise. It tells us which time period is missing for each i. If we define $\boldsymbol{W_i}$ as the $T_i\times 3$ matrix with tth row as $\boldsymbol{w_i^t}$, and $\boldsymbol{X_i}$ as the $T_i\times K$ matrix with tth row as $\boldsymbol{x_i^t}$, where $T_i = \sum_{t=1}^{T} s_i^t$ and $\boldsymbol{M_i} = \boldsymbol{I_T} - \boldsymbol{W_i}(\boldsymbol{W_i'}\boldsymbol{W_i})^{-1}\boldsymbol{W_i'}$. The equation (4) can be written as

$$\boldsymbol{ly_{iM}} = \boldsymbol{W_i}\boldsymbol{\varphi_i} + \boldsymbol{X_i}\boldsymbol{\beta} + \boldsymbol{v_i} \qquad (5)$$

Multiplying M_i through equation (5),

$$\boldsymbol{l\ddot{y}_{iM}} = \boldsymbol{\ddot{X}_i}\boldsymbol{\beta} + \boldsymbol{\ddot{v}_i} \qquad (6)$$

where $\boldsymbol{l\ddot{y}_{iM}}$ and $\boldsymbol{\ddot{X}_i}$ are the residuals from the time series regression of $\boldsymbol{ly_{iM}}$ and $\boldsymbol{X_i}$ on $\boldsymbol{W_i}$, respectively. To achieve consistency estimator, when there exist a correlation between some explanatory variables and the idiosyncratic errors, a $1\times L$ vector of instrument variables $\boldsymbol{z_i^t}$ is required. The FE-IV estimator on unbalanced panel data is

$$\boldsymbol{\widehat{\beta}_{FE-IV}} = \left[\left(N^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} s_i^t \boldsymbol{\ddot{x}_i^{t\prime}}\boldsymbol{\ddot{z}_i^t}\right)\left(N^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} s_i^t \boldsymbol{\ddot{z}_i^{t\prime}}\boldsymbol{\ddot{z}_i^t}\right)^{-1}\left(N^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} s_i^t \boldsymbol{\ddot{z}_i^{t\prime}}\boldsymbol{\ddot{x}_i^t}\right)\right]^{-1} \times$$

$$\left[\left(N^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} s_i^t \boldsymbol{\ddot{x}_i^{t\prime}}\boldsymbol{\ddot{z}_i^t}\right)\left(N^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} s_i^t \boldsymbol{\ddot{z}_i^{t\prime}}\boldsymbol{\ddot{z}_i^t}\right)^{-1}\left(N^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} s_i^t \boldsymbol{\ddot{z}_i^{t\prime}}\boldsymbol{l\ddot{y}_{iM}^t}\right)\right]$$

(7)

where $\ddot{\boldsymbol{z}}_{\boldsymbol{i}}^{\boldsymbol{t}}$ is the residuals from the time series regression of $\boldsymbol{z}_{\boldsymbol{i}}^{\boldsymbol{t}}$ on $\boldsymbol{w}_{\boldsymbol{i}}^{\boldsymbol{t}}$, t=1,…,T; $\ddot{\boldsymbol{x}}_{\boldsymbol{i}}^{\boldsymbol{t}}$ and $\ddot{\boldsymbol{y}}_{\boldsymbol{i}}^{\boldsymbol{t}}$ are the t^{th} row of $\ddot{\boldsymbol{X}}_{\boldsymbol{i}}$ and $\boldsymbol{l}\ddot{\boldsymbol{y}}_{\boldsymbol{iM}}$, respectively. The unbiased estimators of $\boldsymbol{\varphi}_{\boldsymbol{i}}$ are obtained from

$$\widehat{\boldsymbol{\varphi}}_{\boldsymbol{i}} = \left[\left(\sum_{\boldsymbol{t}=\boldsymbol{1}}^{\boldsymbol{T}} s_i^t \boldsymbol{w}_i^{\boldsymbol{t}\prime} \boldsymbol{w}_i^t\right)^{-\boldsymbol{1}}\right] \left[\sum_{\boldsymbol{t}=\boldsymbol{1}}^{\boldsymbol{T}} s_i^t \boldsymbol{w}_i^t (\boldsymbol{l}\boldsymbol{y}_{\boldsymbol{iM}} - \boldsymbol{X}_{\boldsymbol{i}}\widehat{\boldsymbol{\beta}}_{\boldsymbol{FE-IV}})\right] \tag{8}$$

4. Background and Data

In the decade after the 1997 Asian Financial Crisis, financial institutions in Thailand faced foreign debt crisis, because Thai government adopted the floating exchange rate policy for the Baht. Several commercial banks were ordered to write down capital and to recapitalize, or merged with other domestic or foreign banks in 1998. As a result, there were only thirteen commercial banks left in Thailand at the end of 1999, all of which were public owned.

Thai commercial banks have been gradually recovered from the financial crisis since 1999. As reported by IMF (2009)[5], Thai banks are reporting solid profitability and improved solvency, due to higher interest margins and strong loan growth. In addition, better credit underwriting and efforts by the Bank of Thailand to improve provisioning coverage against distressed assets have lowered the overall risk profile of the Thai banking sector. After the return of banking profitability in 2001, the central bank of Thailand set a new goal, which was to provide the system with sufficient resiliency to withstand new competitive forces brought about through trade liberalization and appropriation of traditional banking services by non–bank entrants[6]. Subsequently, the Financial Sector Master Plan (FSMP) was formulated by the central bank and Ministry of Finance as the medium – term development for financial institutions under the supervision of the central bank. The main objective of the FSMP is to re-engineering of the financial institution landscape through the promotion of competency driven consolidation and modification of relevant prudential guidelines. The FSMP Phase 1, started from 2004 to 2008, expressed three visions: (1) Broaden Access to Financial Service, (2) Increase Efficiency of Financial Sector, and (3) Measures to Improve

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[5] Thailand: Financial System Stability Assessment, IMF Country Report No. 09/147, May 2009.

[6] "Thailand's Financial Sector Master Plan Handbook", Bank of Thailand, downloaded from http://www.bot.or.th/THAI/FINANCIALINSTITUTIONS/HIGHLIGHTS/MASTERPLAN/Pages/MPHandbook.aspx.

Consumer Protection. According to the plan, several new banks, originally operated as financial companies and were already publicly owned, were emerged in the industry[7]. However, many banks that couldn't recover from the crisis had to be merged with domestic or foreign banks[8].

As classified by the Bank of Thailand, 14 commercial banks operated in Thailand by the end of 2007,[9] and all of them are included in this analysis. We consider two outputs, value of loans (y_1) and total deposits (y_2)[10], and two inputs, personnel expenses (x_1) and premise and equipment expenses (x_2) [11]. Data are collected from the first quarter of 1999 to the second quarter of 2008 from the banks' balance sheets and income statements available from the Stock Exchange of Thailand (SET). Therefore, this data set can be used to evaluate the effective of FSMP Phase 1. Descriptive statistics of these variables are summarized in Table 1. This shows that at least 80 percent for both outputs and inputs are in the traditional banks which data are available for the whole period of this study, while less than 20% for those variables are in the new banks which data are not available for this whole period. The total value of the outputs and inputs are shown in figures 2 and 3, respectively. These figures show that the total value of loans is generally greater than the total deposits since 2000; and

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[7] TISCO Bank (July 1, 2005), Kiatnakin Bank (October 3, 2005), and ACL Bank (December 23, 2005).

[8] Bangkok Metropolitan Bank was merged with Siam City Bank on April 1, 2002. DBS Thai Danu Bank and Industrial Finance Corporation of Thailand (IFCT) were merged with Thai Military Bank on September 1, 2004. Bank of Asia was merged with UOB Radanasin Bank and changed its name to United Overseas Bank (Thai) on November 28, 2005. Standard Chartered Nakornthon Bank was merged with Standard Charter Bank (Bangkok Branch) and changed its name to Standard Chartered Bank (Thai) on October 1, 2005.

[9] They are ACL Bank (ACL), Bangkok Bank (BBL), Bank of Ayudhya (BAY), Bank Thai (BT), Kasikornbank (KBANK), Kiatnakin Bank (KK), Krung Thai Bank (KTB), Siam Commercial Bank (SCB), Standard Chartered Bank (Thai) (SCBT), Thanachart Bank (TBANK), Siam City Bank (SCIB), TISCO Bank (TISCO), TMB BANK (TMB), and United Overseas Bank (Thai) (UOBT).

[10] According to the FSMP Phase 1, aiming to broaden access to financial services of loans and deposits; hence, the outputs and inputs adopted are based on the 'value added' approach as in Sensarma (2006). Then loans and deposits are appropriate outputs; and labor and capital are inputs.

[11] We use personnel expenses (x_1) and premise and equipment expenses (x_2) to represent for labor and capital, respectively.

the whole value of personnel expenses is always greater than premise and equipment expenses. Each variable shows a gradually increasing trend.

5. Results

5.1 FE-IV Estimates

We use the value of loans (y_1) as the normalized output variable. The instrumental variables used in this paper are the one period lagged values of the normalized regressors. We also test for selection bias by adding the regressor $\sum_{r=t+1}^{T} s_{ir}$ or the number of periods the bank remain in the data set into equation (5) as suggested in Semykina and Wooldridge (2005 and 2010) and found that its coefficient of the regressor is 2.516 but statistically insignificant different from zero. That is non-random selection has no effect on our model. The first order serial correlation is also tested by using residuals of equation (6), denoted by $\widehat{\boldsymbol{v}}_{\boldsymbol{i}}^{\boldsymbol{t-1}}$, $i = 1,\ldots, N$. Then the following pooled ordinary least square is estimated, $\boldsymbol{l\ddot{y}_{iM}} = \ddot{\boldsymbol{X}}_{\boldsymbol{i}}\boldsymbol{\beta} + \rho\widehat{\boldsymbol{v}}_{\boldsymbol{i}}^{\boldsymbol{t-1}} +$ residual, $i = 1,\ldots, N$. The $\hat{\rho}$ is 2.2480 and its t- statistics is extremely high indicating the existence of a first order serial correlation at 0.01 significant level.

Hence, we use the robust standard variances of coefficient estimators, V = $\left[\left(\ddot{\boldsymbol{X}}'\ddot{\boldsymbol{Z}}\right)\left(\sum_{i=1}^{N}\ddot{\boldsymbol{Z}}_i'\widehat{\boldsymbol{v}}_i\widehat{\boldsymbol{v}}_i'\ddot{\boldsymbol{Z}}_i\right)\left(\ddot{\boldsymbol{Z}}'\ddot{\boldsymbol{X}}\right)\right]^{-1}$, to calculate robust t-statistics. The FE-IV estimators and their p-values, calculated from the robust t-statistics of equation (6), are shown in Table 2, indicating they are all significant at 0.01 level. This means that the 'value added' approach has described a reasonable input-output relationship for the Thai banking industry. Equation (6), representing equation (A3), has the homogeneity property in output imposed. The property of nondecreasing in output y_2[12] is mostly held; nonincreasing in x_1 is often held in large and medium banks; and nonincreasing in x_2 is mostly held in medium and small banks. Since only two outputs are adopted and one is restricted for homogeneity, the convexity in output is violated.

[12] Since y_1 is used as the normalized variable, we consider only the output y_2.

5.2 Decomposition Productivity Growth Estimates

The banks are classified based on their sizes of loans in the studied periods into three segments: large, medium, and small size[13]. The statistical description of technical efficiency scores, return to scales, and the productivity growth's components of these three classifications are reported in Table 3.

Technical Inefficient Change Effects

Figure 4 shows that the large bank's technical efficiency scores move constantly below but in a similar pattern with the medium banks, increasing from 1999 to 2003 decreasing after 2004. These scores of the small size banks were one from 1999 to the first quarter of 2002 and they decreased quickly at second quarter of 2002 and the fourth quarter of 2005. A possible reason for dramatic fell is that there was an additional small bank (TBANK), with lower efficiency score, included in the group at the second quarter of 2002, and two more small banks (ACL, KK) added into the group at the fourth quarter of 2005. It is noticed that the highest technical efficiency scores always belong to the small banks; while the large banks' technical efficiency scores have the lowest variance. The movement of the average technical efficiency scores is dominated by the pattern of large and medium banks.

The technical inefficiency change effects are depicted in Figure 5. Although technical efficiency scores of the small banks were one from 1999 to the first quarter of 2002, its technical inefficiency change effects shows a decreasing trend and this trend immediately converts to a rise in the second quarter of 2002. The variation of this effect in the large and medium banks is much lower than that in the small banks. Moreover, as seen from that figure, the technical inefficiency change effects of large and medium banks are opposite in direction decreasing for large ones and increasing for medium ones. However, the movement of the average of all size banks' technical inefficiency change effects was similar to that of

[13] The large size banks are BBL, KTB, KBANK, and SCB; the medium size banks are BAY, TMB, SCIB, BT, and UOBT; the small size banks are TBANK, TISCO, SCBT, KK, and ACL.

the large size banks. This means that the technical inefficiency change effects of the banking industry suffered from the Asian financial crisis in 1997, which is confirmed by the negative value of the average technical inefficiency change until the fourth quarter of 2003. However, the average technical inefficiency change effect switched to positive value since 2004, which would be the results of success implementation FSMP Phase 1, started from 2004 – 2008, this plan aimed to enhance financial system's efficiency, strength, and access. Nevertheless, the medium size banks did not attain benefit from the plan.

Technical Progress Effects

The technical progress effects are similar for all bank sizes, uniformly decreasing over time, which are likely the result of technology spilled over to all banks. This effects exhibited positive effects until 2004 and negative effect since 2005. This informs us that, although the new information technology infrastructure was used, it did not response to borrowers and lenders' needs; hence, loans and deposits did not increase, this worsened the productivity growth. Furthermore, the technology improvement to the banking system was not the main content in the FSMP Phase 1.

Scale Effects

The scale effects are derived from the returns to scale, which is shown in figure 7. The figure indicates that banking industry of Thailand experienced the decreasing return to scale with average value for overall banks of 0.2386. Furthermore, the small banks has the highest return to scale ranging from 0.2353 to 0.6051, the large banks' returns to scale rose above that of the medium banks after the second quarter of 2005. An application of Thailand's FSMP Phase 1, such as restructure commercial banks licensing regime into two types of financial institutions: commercial banks and retail commercial banks, reduce number of deposit-taking financial institutions within the same conglomerate under "One–Presence" policy, resulted in higher return to scale for the large and small banks. However, the medium banks' return to scale suffered when the plan was applied.

The scale effects of the small banks were more stable over the study period; while those effects of the large and medium banks experienced the most fluctuate between the fourth quarter of 2000 and the second quarter of 2002. This fluctuation was possible from the result of the payment in the early retirement program for voluntary staffs of banks in both groups. The average of scale effects for the small size banks is positive value, 9.6141; while these for the large and medium size banks are negative value, –79.9323 and –9.8771, respectively.

Allocative Effect

The allocative effects are composed of output and input price effects. As can be seen in Table 3, the large, medium, and small sizes have positive output price effects, the small and large size banks have the highest and lowest values of 5.6251 and 1.2880, respectively. After the FSMP Phase 1 adopted in 2004, the output price effects for large and medium banks were more stable than those before 2004, however, the small size banks had higher fluctuation of the effects in those periods. The possible cause of this higher fluctuation is that new banks that were qualified by the Trust and Credit Foncier companies to improve their status to commercial banks entered the market, leading to higher loans and deposits for small banks in the period of FSMP Phase 1.

The average of input price effect for all sizes banks is negative in the studied periods; where medium and small sizes banks were the highest and lowest input price effects with the value of 3.6363 and –23.2742, respectively. As can be noticed from Figure 10, the input price effects show the same movement as in the scale effects, they oscillated from the fourth quarter of 2000 to the second quarter of 2002, this would be from the same reason as the scale effects. Furthermore, we found that the input price effects dominate the output price effects; hence the allocative effects tend to have similar movement to the input price effects as seen in Figure 11.

The nonzero of the average output price effects implies that the prices set up by the Thai banking industry did not satisfy the profit maximization. In other words, since the loan's and deposit's interests might be considered as their prices, the interests were not determined by the demand for and supply of loan and deposit markets. Thai commercial banks set their interest rates signaled by the policy interest rate from the central bank. Moreover, that the wage rates did not reflect to the true employees' productivity resulted in the nonzero of the average input price effect.

Total Factor Productivity Growth

Figure 12 indicates that the medium and small sizes banks' productivity growths experienced the lower fluctuated after application of FSMP Phase 1. Table 3 shows that the negative of scale effects was the major result in negative productivity growth of the large and medium sizes banks, while the negative of input price effects were the major cause of negative productivity growth of the small banks sizes. On the other hand, the positive of input prices effects were the most contributed to the positive productivity growth of the large and medium sizes banks, while the positive of scale effects were the major consequence of positive productivity growth of the small banks sizes. The output price effects were the greater contributed to positive effects of all sizes banks' productivity growths than the technical progress effects. Technical inefficiency effects showed a little negative impact to large and medium sizes banks' productivity growth and slightly positive impact to small size banks' productivity growth.

6. Conclusion

This research decomposed TFP growth of Thai commercial banking industry using unbalanced panel data during the decade of the Asian Financial Crisis in 1997 and the Global Financial Crisis in 2008. In the meantime, FSMP Phase 1 was adopted From 2004 to 2008. The output distance function was estimated by FE-IV to extract the components of TFP growth into the changes in technical inefficiency effect, technical change effect, scale effect, and allocative effect (inputs and outputs price change effects). We found that there is no selectivity bias in the data applied to the output distance function. Hence, the results can imply for the whole Thai banking industry.

The results indicated that, after the implementation of FSMP Phase 1 in 2004, Thai banking industry experienced an improvement of the technical inefficiency change effect, scale effect, and output price effect. This indicates the success of implementation of the FSMP Phase 1, which aimed to enhance efficiency and economy of scale. However, the plan did not contribute to technical progress effect and input price effect. Although the scale effect was improved, it was the major cause of worsening in the productivity of Thai banking industry. That is, the policies in the next period should continue to focus on the improvement of economy of scales. Moreover, our results suggest that the policies of technology progress should be more concerned; otherwise the productivity might be destroyed by technical regress.

In this paper, we segmented the banking industry into three groups: large, medium, and small sizes. We found that the technical inefficiency change effects of small banks were not stable comparing to the large and medium ones. This might be the results of FSMP Phase 1 which induced qualified Trust and Credit Foncier companies to improve their status to commercial banks. The productivity growth of the small banks was extremely worsened by the negative impact of input price effect, while that of the large and medium banks was mostly enhanced by this effect. This implies that remuneration for inputs in large and medium banks induced more efficient inputs than that in small banks. On the other hand, the productivity growth of the small banks was primarily improved by the positive impact of scale effect, while that of the large and medium banks was significantly worsened by this effect. That is, to achieve higher outputs, the small banks might increase its inputs, while the large and medium banks should not extend their inputs.

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Figure 1. The Output Distance Function and Productivity Change

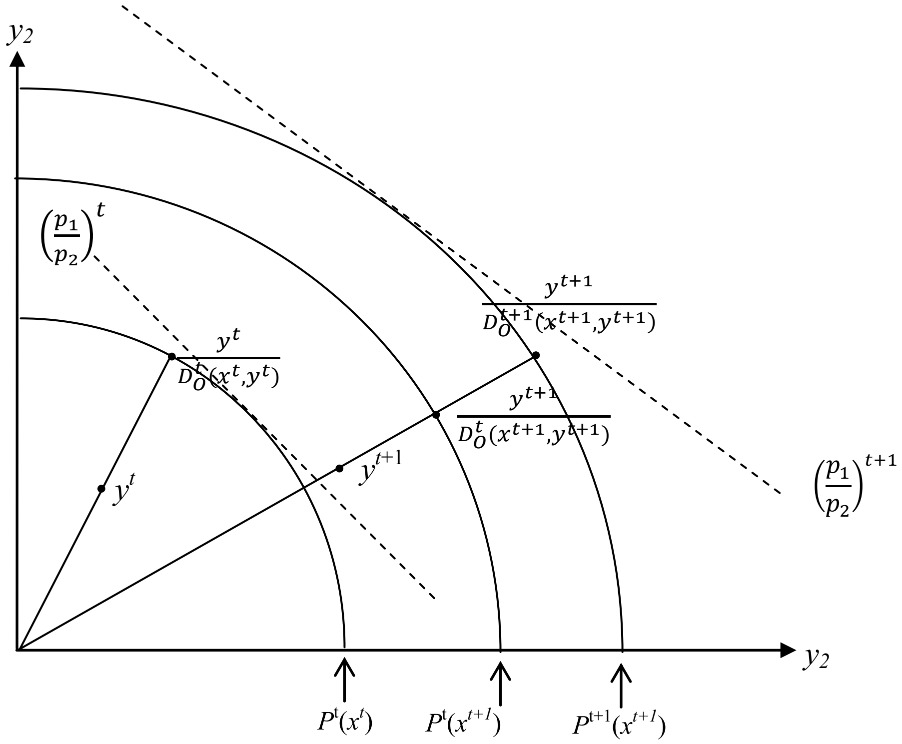

Figure 2. The total values of loans (Y_1) and deposits (Y_2)

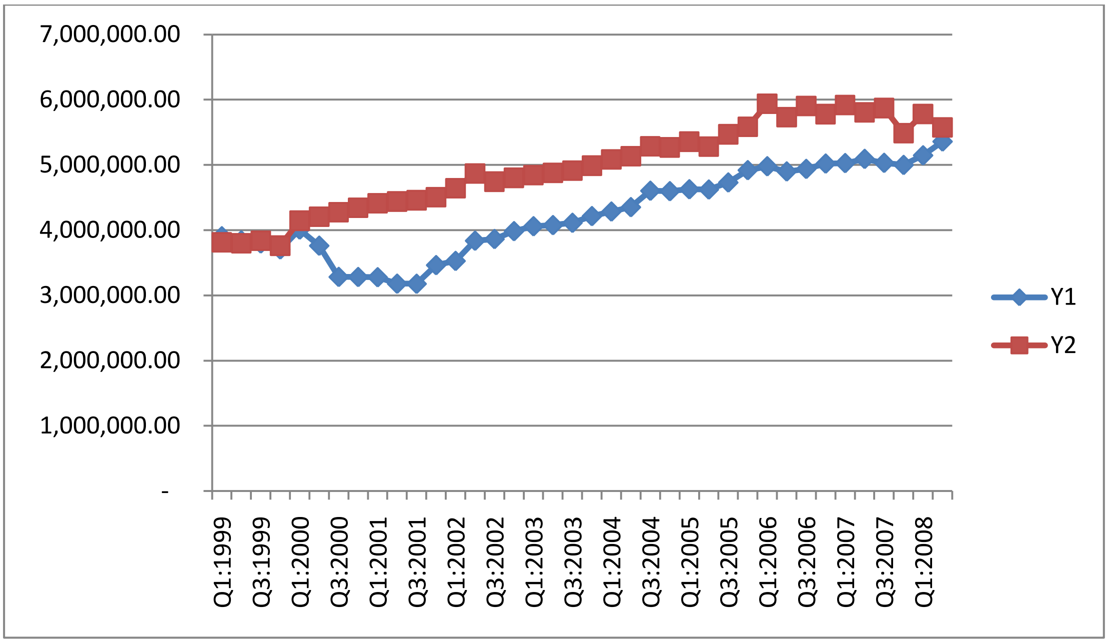

Figure 3. The total values of personnel expenses (X_1) and premise and equipment expenses (X_2)

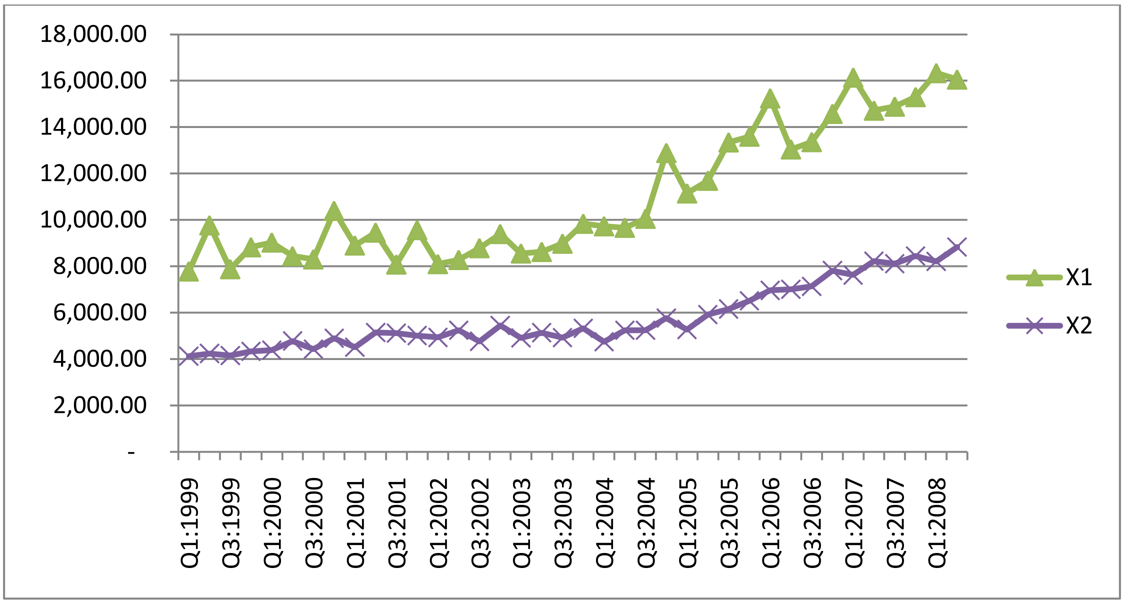

Figure 4: Technical Efficiency Scores

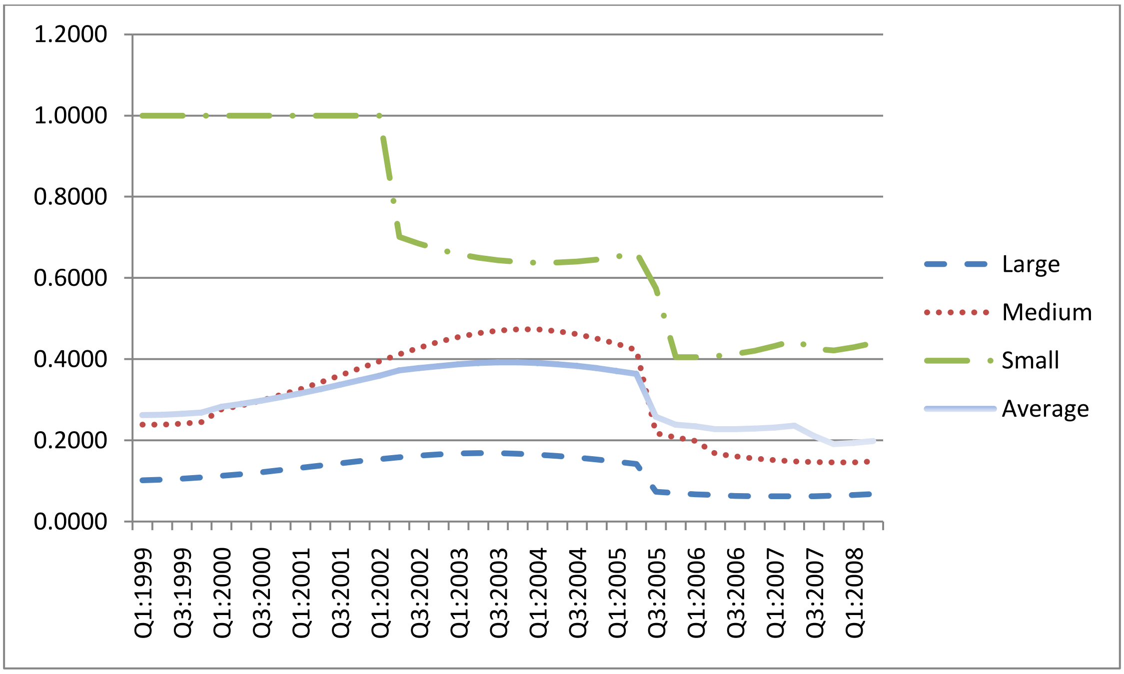

Figure 5: Technical Inefficiency Change Effect

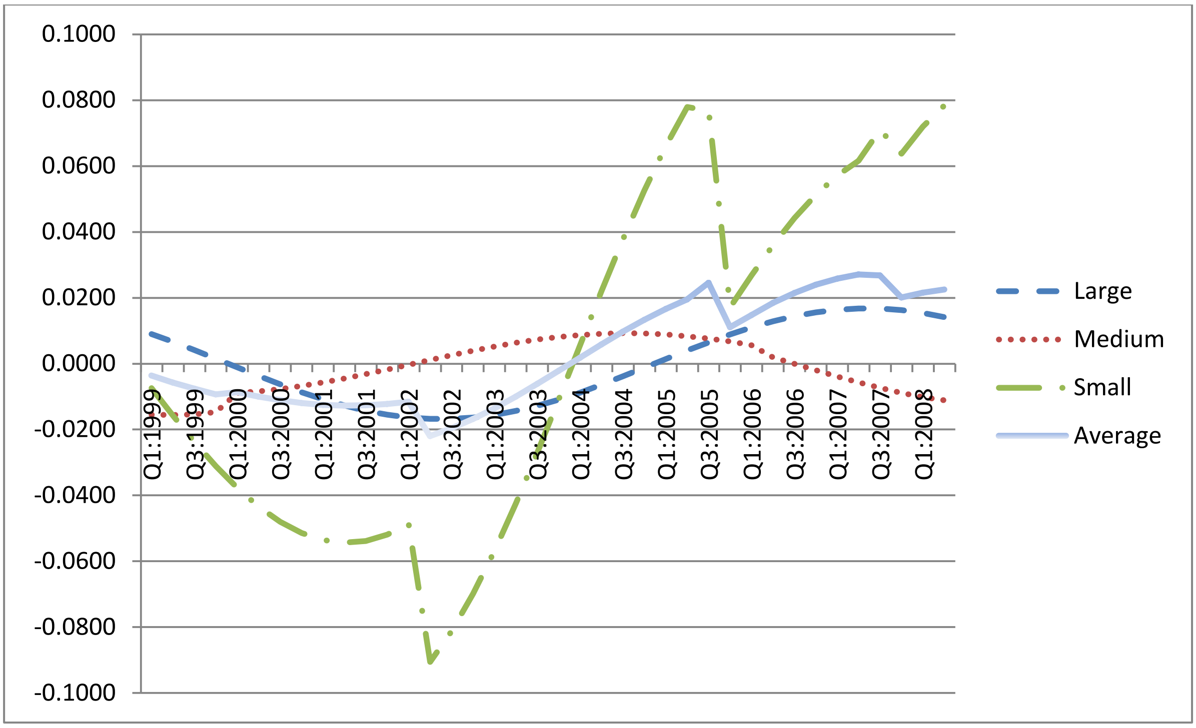

Figure 6: Technical Progress Effect

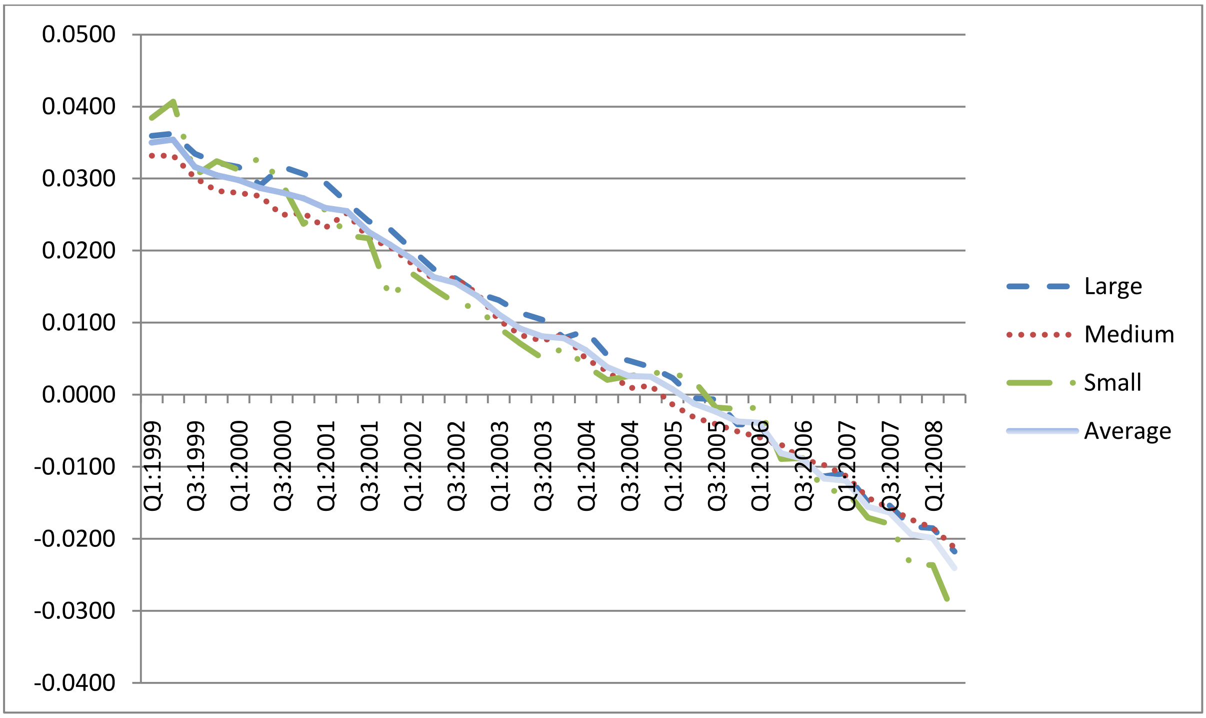

Figure 7: Return to Scale

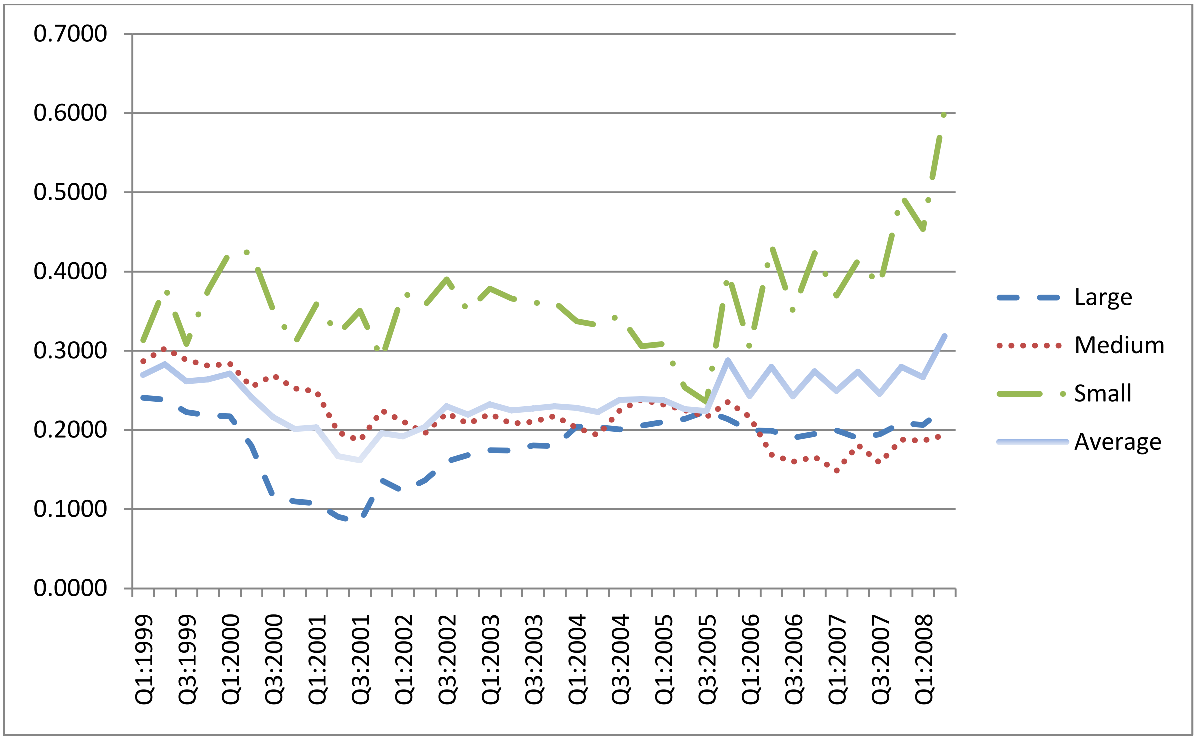

Figure 8: Scale Effects

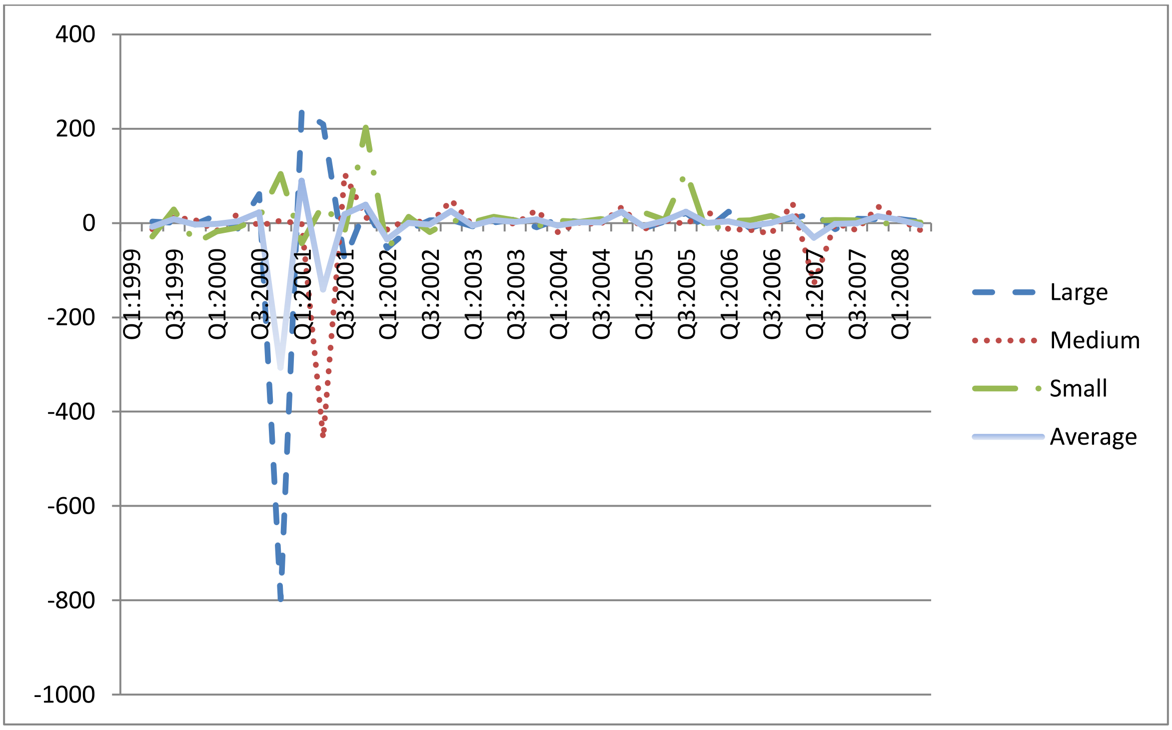

Figure 9: Output Price Effects

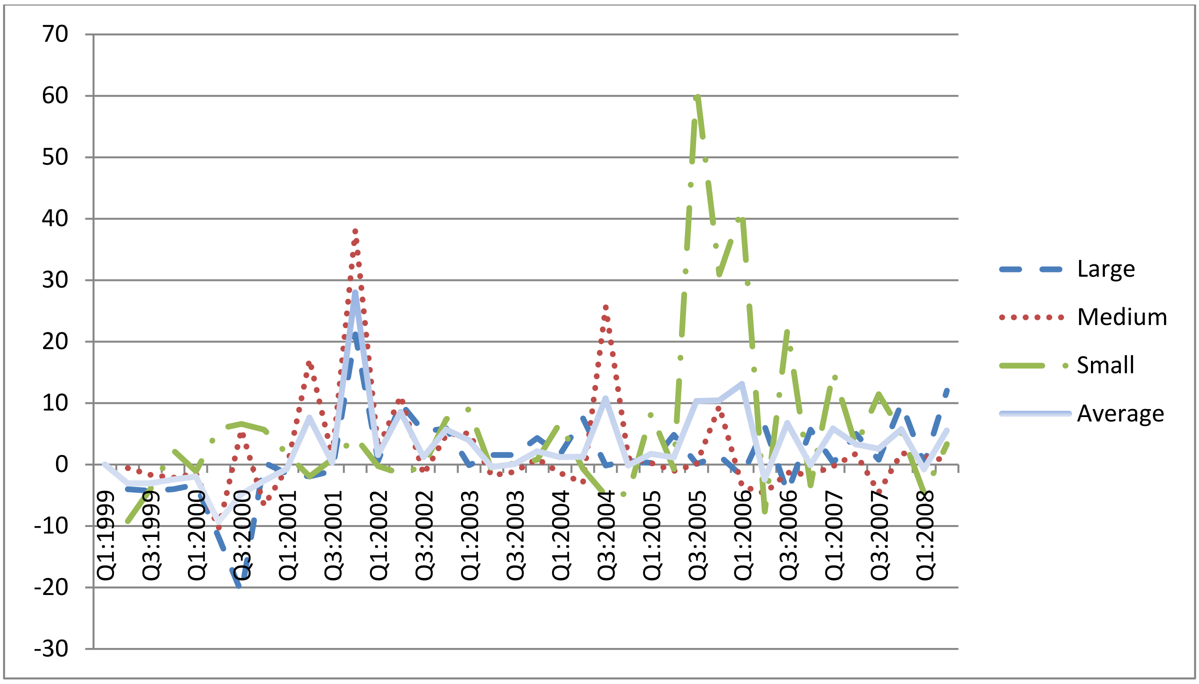

Figure 10: Input Price Effects

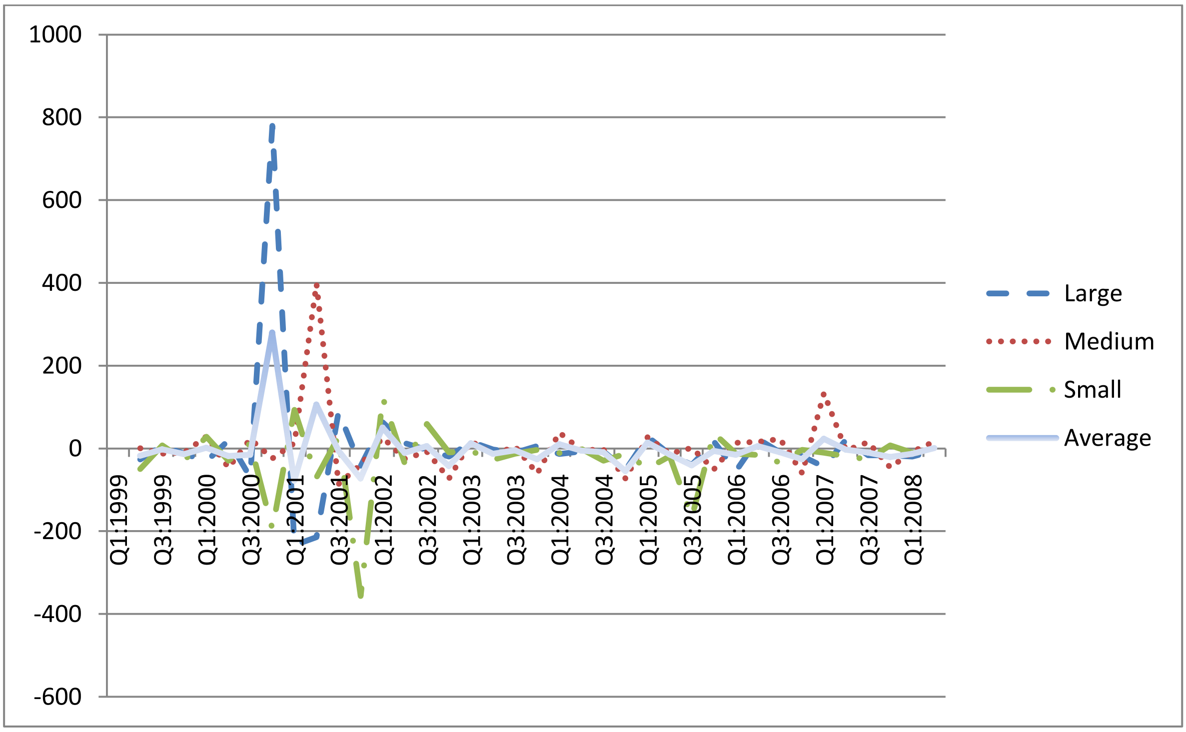

Figure 11: Allocative Effects

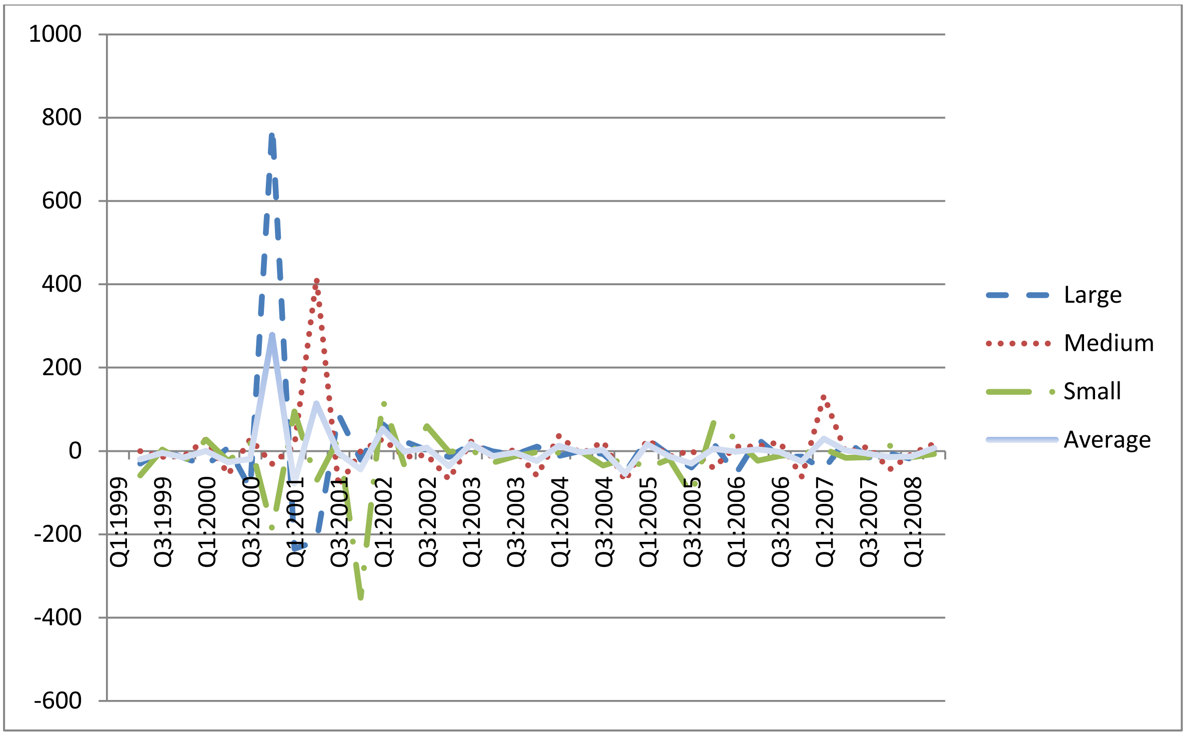

Figure 12: Productivity Growth

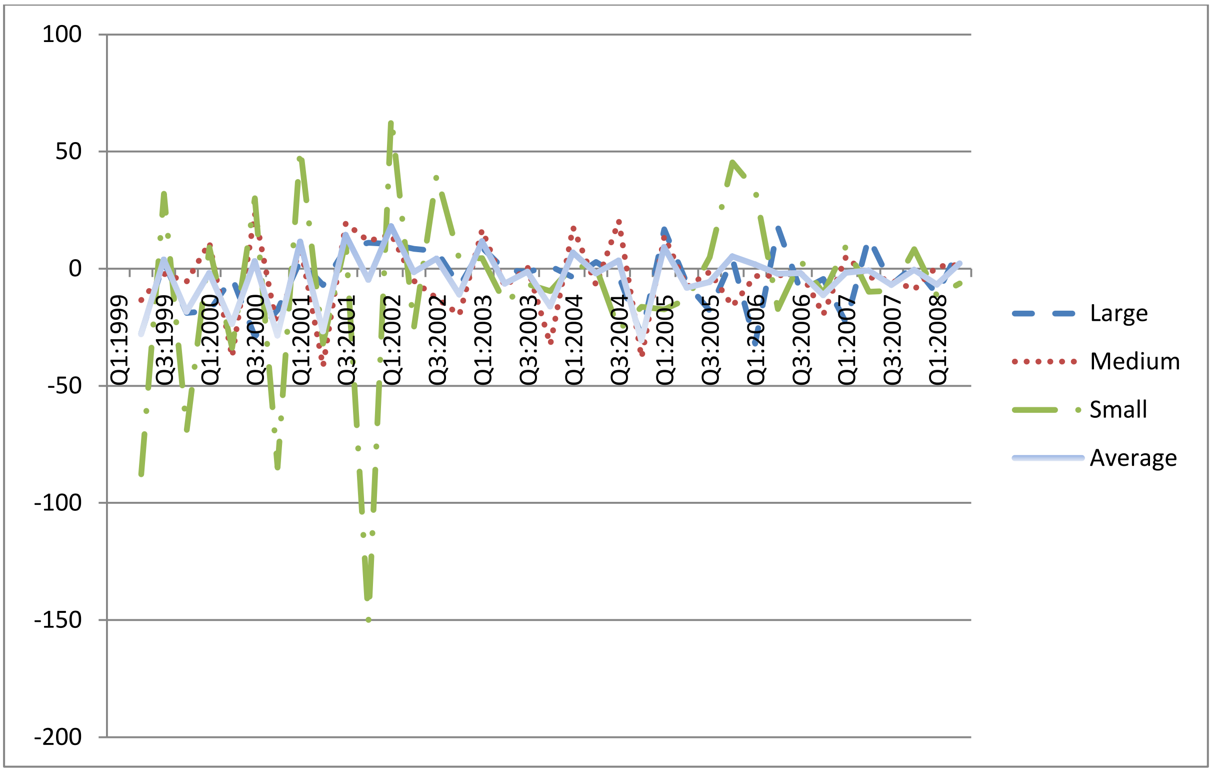

Table 1: Summary of Descriptive Statistics in variables

Unit: Millions of Baht

Variables	Observation	Number of banks	Mean	SD	Min	Max
Y_1	Full	7	558,905.00 (86.25%)	246,855.52	1,161,692.32	72,539.89
	Partial	7	89,111.14 (13.75%)	45,791.26	212,085.19	24,114.07
Y_2	Full	7	653,701.14 (86.30%)	287,108.17	1,286,743.96	193,755.53
	Partial	7	103,739.51 (13.70%)	62,874.55	220,706.01	19,864.60
X_1	Full	7	1,415.83 (82.96%)	781.32	3,925.43	232.43
	Partial	7	290.89 (17.04%)	146.72	642.15	31.10
X_2	Full	7	746.90 (84.15%)	386.60	1,858.46	149.27
	Partial	7	140.67 (15.85%)	80.24	336.58	15.46

Notes: BBL, BAY, KBANK, KTB, SCB, SCIB, and TMB have full observation banks which cover from the first quarter of 1999 to the second quarter of 2008; while BT,ACL, KK, SCBT, UOBT, TBANK, and TISCO have partial observations during the same period.

Table 2: FE-IV Estimators of equation (6)

Variables	Parameters	FE-IV estimators	Variables	Parameters	FE-IV estimators
$\ln (\frac{y_{i2}^t}{y_{i1}^t})$	α_1	–0.0295 [0.0000]***	$(\ln x_{i1}^t)t$	δ_{X1}	– 0.0093 [0.0000] ***
$\ln x_{i1}^t$	β_1	0.6784 [0.0000] ***	$(\ln x_{i2}^t)t$	δ_{X2}	0.0087 [0.0000] ***
$\ln x_{i2}^t$	β_2	–1.1255 [0.0000] ***	$\ln \frac{y_{i2}^t}{y_{i1}^t} \ln x_{i1}^t$	γ_{11}	–1.1224 [0.0000] ***
t	δ_0	–0.0275 [0.0000] ***	$\ln \frac{y_{i2}^t}{y_{i1}^t} \ln x_{i2}^t$	γ_{12}	1.4699 [0.0000] ***
$0.5\left[\ln \frac{y_{i2}^t}{y_{i1}^t}\right]^2$	α_{22}	–0.4605 [0.0000] ***	$0.5t^2$	δ_{11}	0.0016 [0.0000] ***
$\ln \frac{y_{i2}^t}{y_{i1}^t} t$	δ_{y1}	–0.0137 [0.0000] ***			
$0.5(\ln x_{i1}^t)^2$	β_{11}	–0.1313 [0.0000] ***			
$0.5(\ln x_{i2}^t)^2$	β_{22}	0.0142 [0.0000] ***			
$\ln x_{i1}^t \ln x_{i2}^t$	β_{12}	0.0767 [0.0000] ***			

The numbers in the square brackets [ ]are *p-value* which calculated from *robust t–statistics*

*** denotes significant at 0.01 level

Table 3: Technical Efficiency Scores, RTS, and Productivity Growth's Components of Thai Banking Industry between Q1:1999and Q2:2008

		Large	Medium	Small	Overall
Technical Efficiency Scores					
	Average	0.1182	0.3104	0.7038	0.3048
	Max	0.1688	0.4738	1.0000	0.3925
	Min	0.0622	0.1458	0.4048	0.1912
Return to Scale					
	Average	0.1827	0.2186	0.3656	0.2386
	Max	0.2406	0.3028	0.6051	0.3182
	Min	0.0834	0.1484	0.2353	0.1617
Technical Inefficiency Effect					
	Average	–0.0006	–0.0013	0.0005	0.0027
	Max	0.0168	0.0093	0.0784	0.0271
	Min	–0.0168	–0.0156	–0.0905	–0.0220
Technical Progress Effect					
	Average	0.0095	0.0076	0.0074	0.0082
	Max	0.0363	0.0332	0.0407	0.0354
	Min	-0.0218	-0.0212	-0.0309	-0.0241
Scale Effect					
	Average	-7.9323	-9.8771	9.6141	-6.2892
	Max	238.4436	104.2795	202.1652	89.8208
	Min	-797.6528	-456.3901	-57.4294	-306.2476
Output Price Effect					
	Average	1.2880	2.1493	5.6251	2.8710
	Max	21.1803	38.1229	61.5934	27.9810
	Min	-20.8442	-10.3939	-9.2373	-9.3467
Input Price Effect					
	Average	2.5720	3.6365	-23.2742	-0.7095
	Max	779.7397	397.6363	122.7955	280.2997
	Min	-233.5374	-86.1776	-356.8459	-77.6213
Productivity growth					
	Average	-4.0643	-4.0855	-8.0243	-4.1169
	Max	17.5707	23.4595	65.0461	18.1127
	Min	-32.0014	-41.6730	-150.2450	-30.6882

Appendix A

Translog Functional Form of the Output Distance Function

To estimate the parameters in the output distance function, the translog functional form is adopted here. This form is widely adopted in most studies since it is flexible and convenient to impose restrictions. It is written as

$$\begin{aligned}\ln D_O(t, x_i, y_i) = {} & \alpha_0 + \textstyle\sum_{m=1}^{M} \alpha_m \ln y_{im}^t + \sum_{k=1}^{K} \beta_k \ln x_{ik}^t + \delta_0 \mathrm{t} \\ & + \frac{1}{2}\sum_{l=1}^{M}\sum_{m=1}^{M} \alpha_{lm} \ln y_{il}^t \ln y_{im}^t + \sum_{m=1}^{M} \delta_{ym} \ln y_{im}^t\, t \\ & + \frac{1}{2}\sum_{j=1}^{K}\sum_{k=1}^{K} \beta_{jk} \ln x_{ij}^t \ln x_{ik}^t + \sum_{k=1}^{K} \delta_{xk} \ln x_{ik}^t\, t \\ & + \sum_{m=1}^{M}\sum_{k=1}^{K} \gamma_{mk} \ln y_{im}^t \ln x_{ik}^t + \frac{1}{2}\delta_{11} t^2 \end{aligned} \tag{A1}$$

where the subscript *i* represents for the i^{th} firm where $i=1,2,\ldots,N$; and t represent for time where $t=1,2,..,T$ and α, β, γ, and δ are parameters. As we know that the output distance function is homogeneity of degree 1 in outputs, so we rewrite $D_O\,(t, y/y_M, x) = D_O\,(t, y, x)/y_M$. Hence the M^{th} output-normalized distance function can be represented by

$$\begin{aligned}\ln \frac{D_O(t, x_i, y_i)}{y_{iM}^t} = {} & \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{y_{im}^t}{y_{iM}^t} + \sum_{k=1}^{K} \beta_k \ln x_{ik}^t + \delta_0 t \\ & + \frac{1}{2}\sum_{l=1}^{M-1}\sum_{m=1}^{M-1} \alpha_{lm} \ln \frac{y_{il}^t}{y_{iM}^t} \ln \frac{y_{im}^t}{y_{iM}^t} + \sum_{m=1}^{M-1} \delta_{ym} \ln \frac{y_{im}^t}{y_{iM}^t}\, t \\ & + \frac{1}{2}\sum_{j=1}^{K}\sum_{k=1}^{K} \beta_{jk} \ln x_{ij}^t \ln x_{ik}^t + \sum_{k=1}^{K} \delta_{xk} \ln x_{ik}^t\, t \\ & + \sum_{m=1}^{M-1}\sum_{k=1}^{K} \gamma_{mk} \ln \frac{y_{im}^t}{y_{iM}^t} \ln x_{ik}^t + \frac{1}{2}\delta_{11} t^2 \end{aligned} \tag{A2}$$

Combining equations (2) and (A2), we obtain the stochastic output distance function as

$$
\begin{aligned}
-\ln y_{iM}^{t} = {} & \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln \frac{y_{im}^{t}}{y_{iM}^{t}} + \sum_{k=1}^{K} \beta_k \ln x_{ik}^{t} + \delta_0 t \\
& + \frac{1}{2} \sum_{l=1}^{M-1} \sum_{m=1}^{M-1} \alpha_{lm} \ln \frac{y_{il}^{t}}{y_{iM}^{t}} \ln \frac{y_{im}^{t}}{y_{iM}^{t}} + \sum_{m=1}^{M-1} \delta_{ym} \ln \frac{y_{im}^{t}}{y_{iM}^{t}} t \\
& + \frac{1}{2} \sum_{j=1}^{K} \sum_{k=1}^{K} \beta_{jk} \ln x_{ij}^{t} \ln x_{ik}^{t} + \sum_{k=1}^{K} \delta_{xk} \ln x_{ik}^{t}\, t \\
& + \sum_{m=1}^{M-1} \sum_{k=1}^{K} \gamma_{mk} \ln \frac{y_{im}^{t}}{y_{iM}^{t}} \ln x_{ik}^{t} + \frac{1}{2} \delta_{11} t^2 - u_i^t + v_i^t
\end{aligned}
\tag{A3}
$$

Appendix B

Components of Productivity Change

Kumbhakar and Lovell (2000) explained that productivity change occurs when an index of outputs changes at a different rate than the index of input changes. This may refer to the total factor productivity ($T\dot{F}P$) change defined as the difference between the rate of change of an output quantity index ($\dot{Y}$) and the rate of change of an input quantity index ($\dot{X}$), or

$$T\dot{F}P = \dot{Y} - \dot{X} \tag{B1}$$

where the dot over a variable indicates its rate change, e.g. $\dot{Y} = \frac{1}{Y}\frac{dY}{dt} = \frac{d\ln Y}{dt}$. When multiple outputs and inputs are considered, the rate of change of outputs and inputs can be measured by the conventional Divisia index as follows: $\dot{Y} = \sum_{m=1}^{M} R_m \dot{y}_m$ and $\dot{X} = \sum_{k=1}^{K} S_k \dot{x}_k$, where $R_m = \frac{p_m y_m}{\sum_m p_m y_m}$ is the observed revenue share of output y_m, $S_k = \frac{w_k x_k}{\sum_k w_k x_k}$ is the observed cost share of input x_k, and $p = (p_1, \ldots, p_M)$, $w = (w_1, \ldots, w_K)$ are the price vectors of outputs and inputs, respectively. $\dot{y}_m$ and $\dot{x}_k$ are the growth rate of output m $\left(\frac{dy_m/dt}{y_m}\right)$ and input k $\left(\frac{dx_k/dt}{x_k}\right)$, respectively. Therefore, the total factor productivity change can be expressed as

$$T\dot{F}P = \sum_{m=1}^{M} R_m \dot{y}_m - \sum_{k=1}^{K} S_k \dot{x}_k \tag{B2}$$

If we totally differentiate equation (2), the results are exposed into:

$$\sum_{m=1}^{M} \frac{\partial \ln D_O(.)}{\partial \ln y_m} \dot{y}_m + \sum_{k=1}^{K} \frac{\partial \ln D_O(.)}{\partial \ln x_k} \dot{x}_k + \frac{\partial \ln D_O(.)}{\partial t} - \frac{\partial u}{\partial t} = 0 \tag{B3}$$

Now we define $\frac{\partial \ln D_O(.)}{\partial \ln y_m} = \mu_m$ and $\frac{\partial \ln D_O(.)}{\partial \ln x_k} = -\lambda_k \cdot \text{RTS}$, where RTS is return to scale defined as in Fare and Primont (1995) [14], and combine it with equation (B2), we obtain

$$T\dot{F}P = \sum_{m=1}^{M} \left(R_m - \mu_m\right)\dot{y}_m + \sum_{k=1}^{K} (RTS \cdot \lambda_k - S_k)\dot{x}_k - \frac{\partial \ln D_O(.)}{\partial t} + \frac{\partial u}{\partial t}$$

$$= \sum_{m=1}^{M} \left(R_m - \mu_m\right)\dot{y}_m + \sum_{k=1}^{K} (\lambda_k - S_k)\dot{x}_k + (RTS - 1)\sum_{k=1}^{K} \lambda_k \dot{x}_k - \frac{\partial \ln D_O(.)}{\partial t} + \frac{\partial u}{\partial t} \quad \text{(B4)}$$

The productivity change can be decomposed into four components: (i) change in technical inefficiency, (ii) technical progress change, (iii) scale effect, and (iv) allocative effects regarding inputs and outputs price changes[15]. According to equation (B4), we follow Brummer et al. (2002) to explained that allocative effects include an output price effect $\left(\sum_{m=1}^{M}(R_m - \mu_m)\dot{y}_m\right)$ and an input price effect $\left(\sum_{k=1}^{K}(\lambda_k - S_k)\dot{x}_k\right)$, the scale effect is $\left((RTS - 1)\sum_{k=1}^{K}\lambda_k \dot{x}_k\right)$, the technical change effect is $\left(-\frac{\partial \ln D_O(.)}{\partial t}\right)$, and change in technical efficiency effect is $\left(\frac{\partial u}{\partial t}\right)$.

These four components can also be explained by figure 1. When technology progresses from period t to t+1, the output boundary shifts from $P^t(x^t)$ to $P^{t+1}(x^{t+1})$, and the technical change effect can be observed from the output distance function changing from $D_O^t(x^{t+1}, y^{t+1})$ to $D_O^{t+1}(x^{t+1}, y^{t+1})$. Technical efficiency change from period t to period $t+1$ is represented by a change from $D_O^t(x^t, y^t)$ to $D_O^{t+1}(x^{t+1}, y^{t+1})$. Figure 1 also indicates the return to scale effect, since the increase from x^t to x^{t+1} does not lead to an equal proportionate shift in the output boundary.

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[14] Returns to scale (RTS) are estimated from the negative sum of distance elasticities with respect to the inputs.

[15] Karangiannis et al. (2004) argued that allocative inefficiency effect developed in Brummer et al. (2002) is irrelevant to the degree of allocative inefficiency defined by Farrell (1957) and Koop (1981).

Allocative effects, or allocative inefficiency, for outputs and inputs occurs when $R_m - \mu_m \neq 0$ and $S_k - \lambda_k \neq 0$, respectively. Brummer et al. (2002) showed that these effects can be clarified by deriving the stationary solution of the profit maximization:

$$\max_{y,x} \sum_m p_m y_m - \sum_k w_k x_k \text{ s.t. } D_O(x, y) - 1 = 0.$$

The resulting $M+K+1$ first-order conditions from the corresponding Lagrangian are (i) $p_m - \theta \partial D_O(x,y)/\partial y_m = 0$, $m = 1,\ldots,M$; (ii) $-w_k - \theta \partial D_O(x,y)/\partial x_k = 0$, $k = 1,\ldots,K$; and (iii) $D_O(x, y) - 1 = 0$.

From the first order condition for outputs (i), adding up the M equations and utilizing the Euler's theorem and linear homogeneity in outputs of the distance function, we can show that the total revenue equal to the Lagrange multiplier: θ,

$$\begin{aligned} \sum_m p_m y_m &= \theta \sum_m \frac{\partial D_O(x,y)}{\partial y_m} y_m \\ &= \theta\, D_O(x,y) && \text{(from Euler's theorem)} \\ &= \theta && \text{(from condition (iii) } D_O(x, y) = 1\text{)} \qquad \text{(B5)} \end{aligned}$$

Then, it can be proved that the revenue share of output m, R_m, in the terms of the logarithmic derivative of the distance function:

$$R_m = \frac{y_m \theta \partial D_O(x,y)}{\partial y_m} \Big/ \theta D_O(x,y) = \frac{\partial \ln D_O(x,y)}{\partial \ln y_m} = \mu_m \qquad \text{(B6)}$$

Equation (B6) implies that the slope of the distance function at the observed outputs must be equal to the price ratio of the output prices (under profit maximization). Then, observed output vectors y^t and y^{t+1} are not allocative efficient as shown in Figure 1, because the assumption of profit maximization is violated.

The similar procedure can be applied to the first order condition for inputs (ii), except for the Euler's theorem, since there are no homogeneity restrictions on inputs. Hence, the term with the sum of the partial derivatives does not vanish but is substituted by the return to scale term. It can be proved that the total cost is the multiplication of the Lagrange multiplier and the return to scale,

$$\sum_k w_k x_k = \theta \sum_k \frac{\partial D_O(x,y)}{\partial x_k} x_k = \theta \cdot \mathrm{RTS} \qquad \text{(B7).}$$

Then, the cost share of input k, S_k , can be expressed in the terms of the negative of the corresponding logarithmic derivative of the distance function divided by RTS:

$$S_k = -\frac{x_k \theta \partial D_O(x,y)}{\partial x_k} / \theta \cdot \mathrm{RTS} = -\frac{\partial \ln D_O(x,y)}{\partial \ln x_k} / \mathrm{RTS} = \lambda_k \qquad \text{(B8)}$$

Therefore, the allocative effects for output m and input k can be concluded that $(R_m - \mu_m)$ and $(S_k - \lambda_k)$ are both zeros when the profit maximization first order conditions for output m and input k hold, while $(R_m - \mu_m)$ or $(S_k - \lambda_k)$ is not zero if the profit maximization first order condition for output m or input k is violated. The allocative components account for the differences between observed value shares of outputs and inputs and their corresponding shadow shares, as derived from the distance function elasticities. Hence, it may imply that the allocative effect does not affect total factor productivity growth if the profit maximization behavior occurs.