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Productivity growth decomposition with FE-IV approach: Rethinking Thai commercial banks after the financial crisis

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ABSTRACT

To cope with the Asian Financial Crisis, Thai commercial banks have gone through a reconstructing period. This study aims to decompose the Total Factor Productivity growth (TFP) for Thai commercial banking industry with an output distance function. With an unbalanced panel dataset, we used the Fixed Effect (FE) model with Instrumental Variables (IV) to estimate the TFP growth empirically. We found the technical inefficiency change and scale effects were the two major contributors to the recent growth, while the input price effect of the premises and equipment was the major preventer of the growth. Moreover, the Thai commercial banking industry produced in decreasing return to scale, and the input–output allocation was not at the profit maximization optimum under the exogenous prices.

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. (2003a); Saal et al. (2007); and Nemoto and Goto (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. (2003a,b). 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 et al. (2003a,b), 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 (1995), 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 Wooldridge (2010) suggested a procedure of fixed effect 2SLS; otherwise, a correction procedure based on the pooled 2-Stage-Least-Square is applied.

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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. (2003a,b).

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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 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 and Thanassoulis (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

3.1. 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 $\left(y^t \in \mathbb{R}_+^m\right)$, x^t is a k-vector of inputs $\left(x^t \in \mathbb{R}_+^k\right)$, $P^t(x^t) = \{y^t : (x^t, y^t) \in S^t\}$ 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

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

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 Fig. 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]

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 $TE = \exp(u)$.

[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.