Banking Efficiency Analyses: Size, Industry Specialization and Operating Decisions of Agricultural and Non-Agricultural Banks

by

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(Under the Direction of Cesar L. Escalante)

ABSTRACT

This dissertation aims to exploit the U.S. banking efficiency from bank specialization and bank assets. From different aspects, three related studies in the dissertation evaluated the efficiency of the U.S. banks over the period 2000-2005. Study one introduced the Fourier Flexible Cost function to assess the economies of scale and scope along the output expansion path. Study two introduced the application of the Input Distance function to evaluate of the technical efficiency and allocative efficiency from the input aspect. Study three introduced the Stochastic Frontier analysis and Data Envelopment analysis to trace the productivity change from three sources: Technical Efficiency change, Technological Change, and Scale Efficiency change All studies found that the bank efficiency is affected by the bank specialization and bank assets. Agricultural banks will benefit more from the output expansion than non agricultural banks. Agricultural banks are able to thrive more under the specialized mode of the production. Agricultural banks were more technical efficient and allocative efficient but deteriorated faster than non agricultural banks after 2003. Additionally, the technological improvement would be the sustainable source to increase the banks' productivity. Compared to the agricultural banks, non agricultural banks tend to have more incentives and higher capabilities to make the technological innovation.

INDEX WORDS: Economies of scope, Expansion path, Expansion path scale economies, Ray scale economy, Input distance function, Technical efficiency, Allocative efficiency, Data envelopment analysis, Decomposition of total factor productivity change

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DEDICATION

I dedicate my dissertation work to my wife, Xiaohui Deng, my son, Brendon Yu, and my parents, Jikai Yu and Quanrong Geng.

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CHAPTER 1

INTRODUCTION

1.1 Background

The U.S. Banking industry has been undergoing rapid structural transformations in the past two decades. In general, significant transformations have occurred in two aspects: the dramatic decrease in the number of banking organizations and the growing concentration of banking industry assets among large sized banks. Jones and Critchfield (2005), in their account of the banking industry's transformation scenario from 1984 to 2003, found that the number of banks declined by almost 48% and nearly all bank failures were recorded among small banks during this period. Moreover, they contend that the percentage rate of decline in bank numbers was very similar across four different market segments: rural markets, small metropolitan markets, suburban parts of large metropolitan markets, and urban parts of large metropolitan markets. They further reported that the banking industry has become more concentrated as a result of such declining trends as the asset share of the largest bank size group (Total assets>$10 billion) increased dramatically from 42% to 73% during this period. Notably, the rate of decline among surviving banks exhibited a strong cyclical pattern as the rate increased in the 1980s and then started to slow down in the 1990s.

The dramatic decrease in the number of the U.S. banks during the period of mid-1980s to the early 1990s has generated interest in research on trends, determinants and implications of the consolidation of the banking industry since 1990s. In general, studies analyzing the drivers of banking consolidation focused on two major aspects: microeconomic factors (such as operational or business objectives, performance efficiency, and management strategies) and environmental factors (such as legislation, macroeconomic forces, globalization of the marketplace, and overall economic situation).

At the micro level, performance inefficiency was frequently cited as the major reason for bank failures. As a result, efficiency analysis has been widely applied in the banking industry since the 1990s. Many studies have been conducted to measure the efficiency of financial institutions, particularly commercial banks (Berger and Mester, 2003). For example, Berger and Humphrey (1997) compiled the results of 130 efficiency analysis studies on financial institutions in 21 countries. Based on their summary, almost all studies detected some degree of inefficiency. Specifically, Berger and Mester (1997a, 1997b) claimed that the unexpected costs due to inefficiency account for at least 20% of total banking industry costs and erodes the industry's potential profits by about 50%. In addition, many studies also pointed out that banks could improve their operational efficiencies by applying some concrete strategies derived from the efficiency studies. For example, some researchers found that larger banks under a given amount of total assets would perform more efficiently. This implies that expanding the bank size through mergers or acquisition could be an effective strategy to improve the operational efficiency at some specific stage (Berger, 1998; Akhavein et al., 1997; Mitchell and Onvural 1996). In short, in a perfectly competitive market, inefficient firms would finally be driven out by the efficient firms. In this regard, a study on banking efficiency will not only be beneficial to the banks in identifying strategies to survive in a competitive market. Such study could also be useful for the general public, whose confidence in the economy will be influenced by perceptions of the financial health of financial institutions, and policymakers, who are responsible for prescribing banking legislations such as deregulation policies and other more appropriate new banking legislations.

Existing banking legislation has evolved over several decades since 1980. Over time, policymakers have considered imposing fewer operational restrictions on the banking industry and eventually issued more policies of deregulation (Lown and et al., 2000; Kroszner and Strahan, 2000; Montgomery, 2003). These deregulation efforts were especially devoted to relaxing restrictions on permissible banking activities and relaxing the geographic limitations on developing branch networks (Jones and Critchfield, 2005). The most explicit impact of deregulation enhanced competition among banks as barriers to entry in the banking industry are minimized. Thereafter, on one side, more small and community banks disappeared in the market due to their weak competitive ability; on the other side, the greater incidence of bank failures among small banks made it much easier for larger banks to merge and acquire the failed banks at lower costs. The propelling effect of deregulation on consolidation can be more vividly demonstrated by the sharp increase of the bank consolidations right after the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (Riegle-Neal Act) in 1994. The number of mergers among commercial banks was less than 20 in 1994 before the passing of the Reigle-Neal Act. In contrast, this number hit a peak of 189 commercial banks that merged in 1997 (Jones and Critchfield, 2005).

Apparently, the passage of certain banking legislation plays a crucial role in determining the survival of banks, especially small and community banks. While some studies asserted that the deregulation of the legislation will necessarily result in the substantial consolidation of the banking industry (Berger et al., 1995), surprisingly, the community banking sector still accounts for 94% of banking organizations until 2003 (Jones and Critchfield, 2005). This is quite ironic and confusing. However, it is worth noting that most studies analyzed the effects of deregulation under the assumption that the individual bank has no ability to adjust its strategy to deal with competitive pressures of their new environment. Thus, aside from the effects of legislation, the bank's resiliency or ability to quickly adopt strategies to improve efficiency and, hence, their competitive stance in their industries is also extremely important to bank survival. It is in this regard that the evaluation of a bank's performance efficiency and the understanding of strategies implemented by these banks to improve operating efficiencies are important agenda in the study of bank survival in an increasingly competitive environment.

Considering the crucial role of banks in the U.S. financial system, structural changes in the banking industry could significantly affect the U.S. economy. Some studies found that the overall operational efficiency of the banking industry can be enhanced by squeezing out inefficient, less competitive banks. These studies predicted that the transformation of the banking industry through consolidation will continue over a long period of time although the consolidation rate may decrease through time (Hannan and Rhoades, 1992; Nolle, 1995; Berger et al., 1995; Robertson, 2001).

In summary, studies focusing on the efficiency of the banking industry are very important and beneficial. Berger and Humphrey (1997) identified three benefits from banking efficiency analysis. They asserted

"The information obtained from banking efficiency analysis can be used either: (1) to inform government policy by assessing the effects of deregulation, mergers, or market structure on efficiency; (2) to improve managerial performance by identifying 'best practices' and 'worst practices' associated with high and low measured efficiency, respectively, and encouraging the former practices while discouraging the latter; (3) to address research issues by describing the efficiency of the industry, ranking its firms, or checking how measured efficiency may be related to the different efficiency techniques employed (pp.1)."

Various methodologies for implementing efficiency analyses have been developed in theoretical models in the literature that demonstrated their microeconomic, mathematical modeling, and computer technology applications. In general, there are three methodologies that can be used to analyze efficiency: parametric approach, semi-parametric approach, and non-parametric approach.

The parametric approach assumes the most strictly specific functional form. The proper assumptions of the functional form and curvature would be the prerequisites to get unbiased estimates for the parametric method. The semi-parametric approach relaxes the strict functional form requirement of the parametric approach. Particularly, minimal *a priori* assumptions would have to be imposed to guarantee the unbiased estimates (Gallant, 1982). So to some extent, the semi-parametric partially solves the functional form and curvature issues due to more flexible global approximation attributes. But, no matter how few *a priori* assumptions would be imposed, the semi-parametric method, like the parametric approach, would have to assume certain specific functional forms. Compared with these two approaches, the non-parametric technique will not require an explicit functional form. Therefore, the problems associated with the potentially wrong functional forms imposed would be avoided. However, typically, non-parametric techniques only focus on technological optimization but neglect economic optimization by ignoring price information. In addition, the non-parametric method assumes a deterministic procedure instead of a stochastic procedure. In other words, another main drawback of this method is that it usually does not allow for randomness of errors in the data. Thus, in traditional ways, the inferences of the estimated parameters won't be obtained and therefore it won't allow the statistical hypothesis tests (Berger and Mester, 1997a and 1997b; Coelli et al., 2003 ab).

The following are specific applications of the parametric, semi-parametric and non-parametric methodologies, which shall be considered in this study. Stochastic Frontier Analysis (SFA), one of most widely used econometric methods applied to the parametric approach, was introduced as an approach in developing an efficiency analytical framework by Aigner et al. in 1977. The Fourier Flexible Functional Form (FF) is the most widely used functional form in the semi-parametric approach (Mitchell and Onvural, 1996; Huang and Wang, 2004). Data envelopment analysis (DEA) is a non-parametric method to measure the efficiency of a decision-making unit (DMU). DEA was first developed by Charnes et al. in 1978 and was later used by Banker et al. in 1984 to accommodate technologies that exhibit variable returns of scale. Since then, DEA has been widely applied to efficiency analysis. Recently, some studies have explored certain simulation methods to overcome the drawback of DEA's deterministic attribute (Ray, 2004).

1.2 Problem Statement

A bank's survival in an increasingly competitive market environment depends on its ability to formulate short- and long-term strategies that increase its operational efficiency and define its competitive edge. In the short-run, most commercial banks adopt strategies aimed at minimizing costs or maximizing profits. However, not all decisions made by bank managers are rationally consistent with either of these objectives. For example, Penas and Unal (2004) revealed that sometimes, the largest and most complex banking organizations make merger decisions only based on the simple belief in the "Too Big To Fail" syndrome, without even taking into account financial considerations of cost minimization or profit maximization. There are two reasons that may explain such seemingly economically irrational decisions. First, large banks hold tremendous financial resources so that they have enough power to influence or even modify the market structure. In this sense, the budget restriction would not be the effective constraint when they make merger or acquisition decisions. To some extent, the basic limited resource economic assumption is violated in terms of the fluent capital source. Thus, the financial benefit-cost analysis can be easily overlooked in this case. Although the largest banks might still be able to survive in the short term, given that their strong asset base can easily withstand deteriorations in their performance efficiency as a result of their merger decision, this trend of survival is not expected to be sustained in the long run. Aggravated inefficiencies that persist over time can easily lead to a deterioration of their competitive ability, which ultimately could lead to the bank's exit from the industry. Secondly, the largest banks and complex banking organizations usually have very complicated input and output combinations, which make it more difficult for them to implement a more reliable framework for efficiency analysis.

The banking industry displays an increasing trend of concentration as it enters the new millennium. The asset share of large banks (total asset>$10 billion) in the industry has increased dramatically from 42% in 1984 to 73% in 2003. At the end of 2003, the Bank of America Corporation, the largest holder of domestic bank deposits, held $870 billion in total assets, which account for 9.6% of the assets held by the entire U.S. banking industry (Jones and Critchfield, 2005). Considering such a situation that large banks hold more assets in the new century and the fact that these banks tend to make operating decisions that are not based on efficiency considerations, it is therefore imperative to undertake more research efforts that emphasize the significance of efficiency analysis in the survival and improvement of the financial health of financial institutions. It is even more pressing for larger banks to seriously factor efficiency considerations to their operating and strategic decisions, considering that their dominant market shares in the industry translate to their influential roles in the industry that could easily spell the overall financial condition and fate of the entire industry. In this sense, a quantitative and reliable efficiency analysis such as this study aims to accomplish would help bank managers make rational decisions in choosing operating strategies, such as diversification, reallocation of the inputs and outputs that maximize efficiency conditions.

Some studies have established different motivations for bank consolidation decisions across different time periods. Berger (1998) asserted that banks adjusted their operational strategies according to the changing economic and regulatory environment. He observed that the reasons for bank merger decisions in the 1990s are significantly different from those occurring in the 1980s. He claimed that banks were more interested in expanding their geographic bases in the 1980s, since they would like to gain strategic long-term advantage by setting up new businesses in new locations rather than by reducing costs or raising profits in the short term. In contrast, mergers occurring in 1990s were mainly compelled by the objective to improve the operational efficiency and reduce average operational costs in the short run. In the new millennium, new motives for consolidation decisions were uncovered. More recent studies and surveys indicated that the number of banks existing in the market has started to stabilize after 2000 and has even been growing in recent years (Jones and Critchfield, 2005). It is interesting to identify the motivations behind the strategies of banks under the new economic, regulatory, and technological environments of the 2000s. Policymakers and analysts are interested in understanding the reversal in the bank consolidation patterns (where the number of existing banks is increasing instead of decreasing in recent years) in the new millennium. They wanted to evaluate if this reversed structural change in the industry is a result of the banks' greater inclination to implement internal efficiency analyses, from which their operational strategies and decisions have been formulated and implemented.

Over the past decades, a substantial portion of bank efficiency studies were mainly focused on commercial banks. Very little evidence of efficiency analyses among agricultural banks can be found in the literature (e.g., Barry, 1980; Featherstone and Moss, 1994; Neff et al., 1994; Dias and Helmers, 2001). Efficient performance is the key for agricultural banks to successfully deliver their services in the rural financial market. Compared to regular commercial banks, agricultural banks usually have more concerns on liquidity. One-third of all agricultural debts is held by rural banks with assets of less than $50 million (Ellinger, 1994). Thus, agricultural banks are unable to diversify their clientele to include other non-agricultural business clientele due to the shortage of lending funds. The specialized nature of their lending operations results in greater risks and uncertainty. In this regard, results of efficiency analyses based on commercial banking operations have less relevance to agricultural banks as no parallel conclusions can be drawn, given these banks' different styles of lending operations.

Apart from this, in some cases, agricultural banks do not necessarily make decisions in the same fashion as a rational economic decision maker who abides by the dictates of either profit maximization or cost minimization. Sometimes, loan decisions made by certain agricultural lenders do not necessarily follow conventional risk-return principles that usually guide other lenders' decisions on loan applications. Moreover, in contrast to commercial banks, agricultural banks' gains are heavily impacted by the agricultural production and markets. For example, weather risks affecting certain areas leave agricultural banks with not much choice but to offer relatively lower interest rates to clients in the affected areas, usually at the request of some federal authority. Although the government may subsidize the loss between the marketing rate and favorable rate, the consideration of the effectiveness of the lending does distort agricultural banks' behavior. Moreover, if natural disaster is not geographically homogenous or not severe enough to trigger the need for government subsidies, agricultural banks could face a large borrowers' default risk. All these considerations, therefore, might make their operational objective and strategies different from those of the other non-agricultural banks. Given this expectation, it is interesting to analyze the comparative efficiencies of commercial and agricultural banks, and identify operational strategies adopted by agricultural banks and by commercial banks to improve efficiency conditions when covariates are controlled.

Agricultural banks, though generally considered smaller in size and having less industry coverage than most commercial banks, play a vital role in influencing regional flows of funds and influencing the health of rural economies (Samolyk, 1989). It is interesting to note that, in recent years, rural financial markets are also undergoing a period of rapid transition. Changes in the agricultural economy, technological advances, the competitive structure in the financial services industry and changing borrower demands have collectively influenced the delivery of credit to agriculture (Ellinger, 1994). In addition, banking deregulation since 1990 expedited the pace of change in the competitive environment in the rural financial markets. Meanwhile, commercial banks have increasingly been involved in farm lending as agricultural debt comprised 37% of their total loan portfolio (Walraven et al., 1993). These lenders, however, have to contend with competitive pressures from fellow commercial banks as well as captive finance companies and input supply firms which face fewer regulatory hurdles compared to the highly regulated banking industry and Farm Credit System (Ellinger, 1994). In this regard, the relevant issues to investigate include the role of rural financial markets in influencing the availability and delivery of credit to agriculture, the key drivers of productivity change among agricultural banks, and differences in influences of these drivers of change among agricultural banks and commercial banks.

Finally, analysts and researchers have not reached a consensus on a preferred methodology for conducting bank efficiency analysis, given the availability of a number of approaches. First, a limited number of studies have been conducted to compare and contrast the efficiency rankings of banks using different methodologies. In addition, the limited studies drew inconsistent conclusions. Some studies found consistency in efficiency ranking when applying both parametric and non-parametric methodologies. Other studies, however, found very weak proof to support the ranking consistency when applying two different methodologies. For example, Eisenbeis et al. (1996) found that the correlations between the efficiency rankings derived from SFA and DEA varied from 0.44 to 0.59 across four size classes of larger U.S. banks. The same correlations varied from 0.5 to 0.72 for Federal Reserve check processing offices and insurance firms, respectively (Bauer and Hancock, 1993; Cummins and Zi, 1997; Fecher et al., 1993). In contrast, Ferrier and Lovell (1990) found that the correlation derived from SFA and DEA was only around 0.02 and it was statistically insignificantly different from 0 for small U.S. banks. In terms of their findings, the SFA and DEA show the consistent results for efficiency measurements. Although some studies showed the efficiency measures between two methodologies are not highly correlated, it is worthwhile to investigate the correlation between these two methods used for other aspects, such as the productivity change.

1.3 Objectives

The overall objective of this study is to evaluate the efficiency of a sampling of U.S. banks operating continuously over the period 2000-2005 and determine whether efficiency results can be influenced by size attributes and industry specialization.[1] Size and specialization are two attributes that will allow this research to specifically focus on the application of efficiency analyses on agricultural banking operations. In order to address the issues discussed in the earlier section, this study will consider three aspects of banking efficiency analysis: assessing the economies of scale and scope; identifying technical inefficiency and allocative inefficiency; and measuring and decomposing productivity change.

1.3.1 Assessing the Economies of Scale and Economies of Scope

The primary benefits of efficiency analysis can be separated into the efficiencies generated by the scale of production, joint production of outputs, and deviations from an efficient frontier (Ellinger, 1994). Four different cost efficiency measures for banking industry are derived and calculated among different sized banks and between commercial banks and agricultural banks. These four well-known efficiency measures are overall scale economy measure (RSE), expansion path scale economies (EPSE), economies of scope (SCOPE), and expansion path subadditivity (EPSUB), respectively (Mitchell and Onvural, 1996). The first two are the measures of economies of scale and the last two are the measures of economies of scope.

Economies of scale characterizes the reduction in cost per unit resulting from the increase in the output (the number of units produced), realized through operational efficiencies. In contrast, economies of scope characterizes the reduction in cost per unit resulting from widening the range of products rather than increasing the output of the specialized products. Assessing the economies of scale and scope under the new scenario in the new millennium, which constitutes an overall different economic, regulatory, and technological environment from the past two decades, will be helpful to identify the strengths and weaknesses for the banks to expand their

[1] In this study, industry specialization is confined to classifying banks as either agricultural banks or commercial banks.

production units via increasing scale and/or diversify their production via widening scope. On one hand, the results will inform bank managers if the strategies of expanding the scale of operation by merger or acquisition due to the economy of scale or diversifying the joint products due to the economy of scope are more effective. On the other hand, by comparing the change of the economies of scale or scope between the new era and the past two decades, we might also be able to explain significant changes in the trends of bank merger patterns in recent years. In addition, the results will also be meaningful to track the changes and how the banking industry's structure has evolved.

Before the measures of the economies of scale and scope can be evaluated, the cost function needs to be estimated. In order to relax the restrictions on the unknown real function form or proper curvature assumptions imposed on the parametric method, a semi-parametric method will be applied by adopting Fourier Flexible function form (FF) to estimate the cost function. This approach will enable us to test the relative strength and validity of the the more traditional Translog cost functional form, vis-a-vis the more flexible FF functional form, in estimating the banks' cost function.

Finally, some researchers claimed that it would be meaningless to study or measure banking efficiencies if risks are not considered. In this regard, we analyze the effects of loan quality and financial risks on the banking operational cost, which will, in turn, affect the overall banking operational performance.

1.3.2 Identifying Technical Inefficiency and Allocative Inefficiency

The literature on efficiency measurement usually decomposes the operational inefficiency into technical inefficiency and allocative inefficiency. The primary objective of this analysis is to apply the stochastic Translog input distance function to evaluate the operational efficiency and estimate the technical inefficiency and allocative inefficiency for the banking industry.

Distance functions can be used to estimate the characteristics of multiple outputs and input production technologies in the absence of price information and whenever the cost minimization or profit maximization assumptions are inappropriate. Sometimes, the banking industry, unlike other competitive markets, would not set the minimum costs (or maximum profits) as their unique objective, especially for agricultural banks and some other policy banks. In addition, it is obvious that almost all banks would operate in the operational environment with multi-outputs and multi-inputs. Moreover, banks have more power to control over inputs instead of outputs. In this regard, the stochastic input distance function is appropriate in conducting banks' efficiency analysis.

In implementing this analysis, the Stochastic Frontier Analysis (SFA) method will be applied to estimate the stochastic Translog input distance function and calculate the technical inefficiency. The dual Shephard lemma will then be applied on the input distance function to measure the relative allocative inefficiencies and evaluate the extra costs due to the allocative inefficiencies. Then, the effects of the banks' characteristics, such as bank size and bank specialty, on the banks' operational efficiency will be analyzed.

1.3.3 Measuring and Decomposing Productivity Change

This analytical approach is designed to identify sources that influence or determine changes in the banks' productivity levels and estimate their impacts on the banks' productivity growth. The Total Factor Productivity Change (TFPC) measures the rate of productivity growth that banking industry has experienced and provides information whether the banking industry's productivity has experienced significant changes after entering the new millennium. The TFPC can be used to measure the extent to which a particular bank is able to achieve the industry average level of productivity growth. Decomposition of the TFPC will help clarify the contributions of different factors to TFPC and, thus, would help bankers adjust operational strategies and practices to maximize total factor productivity.

Both parametric and non-parametric methods are applied in this analysis in order to enrich the literature by providing and comparing results from different methodologies.

In this analysis, both Stochastic Frontier Analysis (SFA) and Data Envelop Analysis (DEA) methods are applied to estimate the input distance function and evaluate the Total Factor Productivity Change (TFPC) over years. Additionally, the TFPC is decomposed into three sources to evaluate the contributions of each factor causing to the TFPC: technical efficiency change (TEC), technical change (TC), scale efficiency change (SEC).

1.4 Organization

This dissertation is comprised of seven chapters, which are briefly described below.

Chapter 1 provides the rationale for this study and outlines the objectives and structure of the dissertation. This chapter will introduce the background of the banking efficiency analysis, which includes the history of past two decades and the changes occurring in the new millenium. This chapter also reviews the evolution of the microeconomic and macroeconomic factors affecting banking industry and the methodologies applied in the banking efficiency analyses in literature. In discussing the latter, deficiencies in the existing studies are explained to lay out the rationale for conducting further analyses of banking efficiency. This chapter also presents the three major objectives of this research and outlines the organization of this study.

Chapter 2 reviews the relevant literature on the banking efficiency analysis. This chapter is divided into three sections. The first section briefly reviews the banking deregulation trend and investigates the impacts of changes in legislation on bank performance. The second section examines the key studies on banking efficiency analysis. In this section, literatures are further sorted and reviewed in three aspects, each corresponding to an objective defined in the 1st chapter. The third section reviews studies on the application of efficiency analysis models to agricultural banking.

Chapter 3 describes the source of the data, organizes the data, identifies relevant variables used to represent input and output measures, analyzes the data, and present descriptive statistics of the data.

Chapters 4 to 6 separately present the three distinct analyses that correspond to the three major objectives laid out in Chapter 1. Chapter 4 applies the Fourier Flexible functional form, the semi-parametric method, to measure the Economies of Scale and Economies of Scope. Chapter 5 applies the Stochastic Frontier Analysis (SFA), a parametric method, to the input distance function to estimate the technical inefficiency and derives the allocative inefficiency given the input price. Chapter 6 discusses the Data Envelopment Analysis (DEA), a non-parametric method, and presents its application, along with the SFA method, to evaluate the total factor productivity change (TFPC) and the impact by each contributor to TFPC.

Chapter 7 summarizes the results from the three studies, presents the conclusions and discusses other areas warranting further research attention.

CHAPTER 2

LITERATURE REVIEW

2.1 Legislation Evolution and Influence on Efficiency in Banking Industry

Some researchers have found evidence that legislation and regulation play an important role on the bank operational efficiency. For example, Kaufman (1995) indicated that the existing regulatory framework was costly and it imposed inefficiency on the banking industry. His study showed that the regulatory cost of the banking industry ranged between \$7.5 billion and \$17 billion which accounts for between 6% and 17% of the banks' total non-interest expenses. Compared with the strict constraints for bank's business before 1980s, the past two decades saw deregulation as the major emphasis in legislation in the banking industry. In general, the deregulation trend in banking industry occurred before 2000 is mainly reflected on two aspects: geographic deregulation and interest rate ceiling deregulation.

2.1.1 Geographic Deregulation

The National Bank Act of 1874 restricted nationally-chartered banks from operating branches in states. Later, the passage of the McFadden Act of 1927 relaxed this restriction for national banks. Based on the McFadden Act, national banks were granted the same branch opportunities as the state banks, conditional on the permission of the states. Interstate restrictions were further reinforced by the passage of the Bank Holding Company Act in 1956. This regulation prohibited bank holding companies (BHCs) from acquiring banks in other states unless those states allowed such acquisitions. Since then, almost all states forbade interstate banking in the next 20 years until 1978 when Maine became the first state to allow interstate acquisition within its borders (Bernard, 1998).

Some studies reveal that there are mainly two negative effects of geographic restrictions on banking industry. Firstly, banks under the constraints may operate more expensively and less efficiently in terms of cost. For example, Humphrey (1990) found evidence that the limitations on bank branching increase banks' costs. Evanoff and Israilevich (1991) observed diminished operational efficiency for those banks in the states reinforcing the restrictive bank regulatory. Secondly, interstate banking restrictions lead to less competitive financial markets. Laderman and Pozdena (1991) found that liberalizing interstate banking law will reduce the bank stock rates of return. Calem and Nakamura (1993) also found that relaxing the restrictions for interstate branching will reduce the price differentials across local markets.

Since earlier 1980s, banking industry experienced continuous deregulation. About 17 important legislations which are aimed at deregulating the restrictions on banking industry were passed from 1980 to 2001. Jones and Critchfield (2005) summarized those major legislative and regulatory changes in their study. Among them, the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (Riegle-Neal) in 1994 is treated as the watershed of geographic deregulation. Right after the passage of this act, consolidations in banking industry increased dramatically. The main contents of the Riegle-Neal Act are generalized as: (1) permitting banks and BHCs to purchase banks or establish subsidiary banks in any state nationwide; (2) permitting national banks to open branches or convert subsidiary banks into branches across states lines.

Hughes et al. (1996) assessed the impact of the Riegle-Neal Act on risk diversification. In their study, they asserted that increasing geographic and/or depositor's diversification would result in the improvement of the expected returns. Some other researchers explored the impacts of deregulation on bank efficiency. However, the conclusions derived from those literatures are not consistent. Berger and Mester (1997a) estimated the efficiency of 6,000 U.S. commercial banks over a 6-year period from 1990 to 1995. Surprisingly, they found that although efficiency seems to be related to the restrictions of the geographic expansion, the conclusions are inconsistent. On one hand, some researches detected improvement in efficiency due to deregulation. While, on the other side, some researchers claimed no efficiency enhancement caused by deregulation. Moreover, Evanoff (1998) found that allocative inefficiency existing before deregulation is almost disappearing after deregulation. Calem (1994) showed that deregulation forced banks to consolidate to achieve more efficient size induced by economies of scale. But in the meanwhile, Bauer et al. (1993) and Elyasiani and Mehdian (1995) reported that banking efficiency in U.S. was not significantly affected by the deregulation in early 1980s.

2.1.2 Interest Rate Ceiling Deregulation

Interest rate plays an important role on banks because it not only influences the liabilities by affecting the interest rate of deposits but also influences the assets by affecting the interest rate of loans. In the past, interest rate ceiling distorted the financial market since it artificially restricted the volatility of the supply and demand for capital. Interest rate ceiling deregulation caused the increase in banking fund costs and higher volatility of raising funds in the early 1980s because deregulation made the costs of raising funds for commercial banks closely related to interest rates in the money and capital market (Chen, 2001).

In 1980, the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) was passed. The target of the DIDMCA is to relax the restrictions on the interest rate ceiling. The major contents of DIDMCA include: (1) phasing out interest rate ceilings; (2) eliminating usury ceilings; (3) allowing depositories to offer negotiable order of withdrawal (NOW) accounts nationwide; (4) raising federal deposit insurance coverage limit from $40,000 to $100,000.

Lam and Chen (1985) expected varied repercussions of interest rate ceiling deregulation to different sized banks. Brown (1983) found that smaller banks would benefit more from the deregulation because they have more flexibility to adjust their non-interest expenses to a higher efficient level. Humphrey and Pulley (1997) showed that large banks faced more pressure under interest ceiling deregulation during the period between 1977 and 1984. Based on their study, they found that large banks took greater initiative in adjusting the labor and capital inputs, and deposit and loan output prices to deal with the negative effect on the costs due to the interest rate deregulation. Observing this fact, they drew the conclusion that the influence of the business environment on the banks' profit is less to small banks than that to larger banks. In addition, they implied that the volatility of large banks' profit is higher than that of smaller banks after the deregulation of the interest rate ceiling.

2.2 Banking Efficiency Analysis

Efficiency analysis is an efficiency measurement for different performing units. It can be used to gauge the degree of deviation of observed performance from a reference potential performance. Before efficiency analysis was introduced into the banking industry, it has already been widely applied to other industries, such as railroad, hospital, electricity and etc. Facing the increasingly competitive environment, more and more banks realized the importance of efficiency analysis. A variety of the efficiency analyses has been conducted on the banking industry since early 1980s. This study will place an emphasis only on three aspects, each for one of the three objectives, respectively: economies of scale and scope, technical inefficiency and allocative inefficiency, and productivity change. Thus, this section of literature review will focus only on these three aspects.

2.2.1 Assessing the Economies of Scale and Scope

The relaxation of the geographic restrictions on banking industry spurred the banks' enthusiasm to expand the scale and scope of their operations. Given these new opportunities, many empirical studies examined the optimal scale and output mix. It is found that those banks with the most cost-efficient size and product mix acquired the relative cost advantages and increased their competitive abilities. In contrast, those banks operating with less efficient size and product mix were losing their competitive viability. Thus, the economies of scale and scope have been among the most popular and relevant topics for financial institutions. Literature on this topic in banking industry is rich.

Murray and White (1983) analyzed economies of scale and scope for credit unions of British Columbia. However, in their study, they only developed the overall economies of scale and scope measures but failed to identify the product-specific measures. Observing this drawback, Kim (1986) extended Murray and White's study to the product-specific economies of scale and scope measures and compared the empirical results drawn between the overall measures and the product specific measures.

Berger et al. (1987) discovered that the previous measures for economies of scale and scope are too restricted to be held in reality. The two aforementioned measures require: (1) the same product mix (scope) in comparing economies of scale among different companies and (2) the same company size (scale) in comparing economies of scope among different companies. Berger et al. (1987) asserted that those two measures are of little use in evaluating competitive challenges between currently existing banks since banks rarely have the same product mix (scope) or same size (scale). As a contribution, they developed two new multi-product economy measures, expansion path scale economies and expansion path subadditivity, to evaluate the economies of scale and scope. These two new measures do not rely on the assumptions of constant product mix or complete specialization.

Prior to Clark (1996), nobody considered the opportunity costs in the empirical evaluation of banking efficiency. Clark employed the thick frontier methodology to selected U.S. commercial banks for four years 1988-1991(109-110 banks in each year). It is the first study that analyzed the banking efficiency by extending the production costs to economic costs which include not only the explicit production costs but also the potential best alternative risk-adjusted returns. He measured the overall scale efficiency and expansion path subadditivity and then found that the economic cost inefficiency is comparatively small (approximately 3%) and largely invariant with bank size. In contrast, he found that the production cost inefficiency is considerably large (approximately 9%) and increases with bank size. He indicated that this evidence may be used to explain the phenomenon why some banks contributed too much effort on enhancing the production cost efficiency but overlooked the impacts of other attributes, such as risk, which can reflect the economic cost efficiency level.

Literature of empirical studies on bank scale economies generally revealed the evidence of scale inefficiencies for both the smallest and largest banks. Specifically, most studies found increasing returns to scale for smaller banks but decreasing returns to scale for larger banks (Humphrey, 1990; Evanoff and Israilevich, 1991; Berger et al., 1993). However, the consensus regarding optimal bank size has not been reached. Particularly, some studies are unable to determine optimal bank size which benefits from the economies of scale because of sample selection bias. For example, Berger and Humphrey (1991) selected U.S. commercial banks of all sizes and found that scale efficiency hit the peak around $100 million total assets and declines monotonically with further increases in total assets. In contrast, Hunter et al. (1990) and Noulas et al. (1990) found that scale efficiency typically fell in the range of $2 billion to $10 billion when the banks' total assets were restricted above $1 billion. In addition, McAllister and McManus (1993) applied kernel regression to banks with total assets below $10 billion. They found that increasing returns to scale for banks exhausted up to about $500 million in total assets and then kept the constant returns to scale up to the upper limit of the sample selected at $10 billion.

Literature on bank scope economies was ambiguous on the existence or the extent of scope (product mix efficiency). Gilligan et al. (1984), Gilligan and Smirlock (1984), Kim (1986), and Kolari and Zardkoohi (1991) found scope economies for commercial banks. In contrast, Benston et al. (1982) and Berger et al. (1996) found no evidence of scope economy for commercial banks.

Some studies on assessing the economies of scale and scope found that the cost functional form is very important to derive robust conclusions (McAllister and McManus, 1993). In the existing efficiency analysis studies, the most widely used cost functional forms are either Cobb-Douglas or Translog functions because those two functional forms have good characteristics to explain economic theory and are comparatively simpler and easier to estimate (Berger and Humphrey, 1991; Gilligan and Smirlock, 1984; Gropper, 1991; Hunter et al., 1990; Noulas et al., 1990). However, some researchers challenged the validation of these two general functional forms. For example, Coelli et al.(2003ab) pointed out that the assumptions of Cobb-Douglas functional form require that all firms have the same production elasticities and the substitution elasticities of all firms must be equal to one. But in reality, these are too restrictive to be satisfied. McAllister and McManus (1993) questioned the suitability of the Translog cost function for different banking sectors. They concluded that the Translog functional form represents a second-order Taylor series approximation of an arbitrary function at a point. This function, however, forces a symmetric U-shaped average cost curve for both large and small banks without differentiation, which leads to poor approximation of results.

The Fourier Flexible (FF) functional form uses data to infer relationships among variables when the true functional form of the relationships is unknown. In addition, FF functional form can potentially approximate any function well globally for the orthogonality of the trigonometric functions, such as a linear combination of sine and cosine functions named as the Fourier series (Gallant, 1982; Huang and Wang, 2004; Mitchell and Onvural, 1996). So there is no need, when using FF form, to specify the real function form or impose the curvature assumptions before estimating the cost function. Another advantage of FF functional form is that it can measure the bias resulting from the use of the Translog form since the Translog form can be viewed as a special case nested in the FF form. Despite these advantages, very limited studies on FF have been conducted in banking performance analysis. Furthermore, all existing FF studies have thus far been applications to the commercial banking sector (Mitchell and Onvural, 1996; Huang and Wang, 2004).

2.2.2 Identifying Technical Inefficiency and Allocative Inefficiency

Efficiency analysis entails measurement of efficiency of different performing units. It can be used to gauge the degree of deviation of observed performance from a reference potential performance. After the successful application of the efficiency analysis in railroad, hospital, electricity and many other industries, it was introduced to the financial industry in the 1990s. As in any competitive industry, banks have always been pressured to implement innovative business strategies that enhance operating efficiency in order to sustain their competitiveness in the industry. These business strategies are vital to the health of the rural economy, considering the banks' role in influencing regional flows of funds (Samolyk, 1989).

Over the past several years, a number of studies have addressed the measurement of efficiencies of financial institutions, primarily focusing on commercial banking operations (such as Gilligan and Smirlock, 1984; Gropper, 1991; Berger and Humprey, 1991; McAllister and McManus, 1993; Berger and Mester, 1997ab).While in agricultural finance literature, only a few studies have explored the application of efficiency models to agricultural lending (Ellinger and Neff, 1994; Featherstone and Moss, 1994; Neff, Dixon and Zhu, 1994). Compared to the regular commercial banks, agricultural banks tend to have more liquidity concerns. Smaller banks tend to hold more farm loans in their portfolios than their larger counterparts (Stam et al, 2003). Thus, most agricultural banks are unable to diversify their clientele to accommodate businesses from other non-agricultural business clients possibly due to shortage of lending funds. The specialized nature of their lending operations could result in greater risks and uncertainty. In this regard, results of efficiency analyses based on commercial banking operations have less relevance to agricultural banks as no parallel conclusions can be drawn given these banks' different styles of lending operations.

Many studies detected some degree of inefficiency existing in the banking industry. Specifically, Berger and Mester (1997ab) claimed that the unexpected costs due to inefficiency account for at least 20% of total banking industry costs and erodes the industry's potential profits by about 50%. Additionally, some researchers addressed that banks could improve their operational efficiencies by applying some concrete strategies derived from the efficiency studies. They found that larger banks under a given amount of total assets would perform more efficiently. This implies that expanding the bank size through mergers or acquisition could be an effective strategy to improve the operational efficiency at some specific stage (Berger, 1998; Akhavein et al., 1997).

Stochastic Frontier Analysis (SFA) was introduced as an approach in developing an efficiency analytical framework by Aigner et al in 1977. According to Coelli (2000) and Coelli et al (2003b), there are several outstanding merits in the application of the input distance function: (1) it can be used to deal with the production with multi-outputs and multi-inputs; (2) it does not require price information; (3) it will provide robust estimation in case that there are systematic deviations from cost minimizing behavior; (4) it will not encounter the problem of the simultaneous equations bias when firms are cost minimizers or shadow cost minimizers. In addition, it has another important advantage as shown by (Atkinson and Primont, 2002): (5) there is tight relationship between cost function and input distance function according to the duality theory, which indicates the input distance function has meaningful economic explanation. Some special banks, unlike other competitive markets, would not be able to hold the classical economic assumptions. Their behaviors may deviate from the cost minimization or profit maximization paradigms. For example, agricultural banks and some other policy banks have been required to meet the governor's policy goals. Majority of these banks are involved in multiple businesses. Additionally, banks have more power to control over such inputs as labor and loan amounts. So the stochastic input distance function would fully take into consideration these advantages to evaluate bank efficiency.

The discussion of technical efficiency (TE) and allocative efficiency (AE) can be traced back to 1950s. Farrell (1957) proposed that the efficiency of a firm is composed of two components: TE and AE. TE measures the ability of a firm to obtain maximum outputs from a given set of inputs. Equivalently, TE can be treated as measuring the ability of a firm to use minimum inputs for a given outputs. AE measures the ability of a firm to use the inputs in optimal proportions and quantities to achieve the minimum costs given their respective prices and production technology. According to the microeconomics theory, the allocative efficiency is achieved only when the marginal rate of technical substitution (MRTS) between any two of its inputs is equal to the ratio of the corresponding input prices (Wetzstein, 2005).

There is a rich literature on identifying the technical inefficiency and allocative inefficiency for a variety of industries. Atkinson and Cornwell (1994) applied the Translog cost function and panel data to identify the consistent estimation of input and firm-specific allocative inefficiency and firm-specific technical inefficiency for the U.S. airline industry. Coelli and Perelman (2000) assessed the technical efficiency of the European railway system. They used the output distance function and the corrected ordinary least squares (COLS) method in their study and found that the average TE of European railways was around 0.863. Meanwhile, they also detected substantial variability of results across countries.

Recently, efficiency studies have been extended to more industries and more complicated methodologies have been implemented in more applications. Banos-Pino et al. (2002) used a panel data for the period 1955-1995 to estimate the input distance function and measured both the relative and the absolute allocative inefficiency for Spanish public railways. Rodriguez-Alvarez et al. (2004) developed a model allowing the unbiased estimation of allocative inefficiency of input use. In addition to measuring the allocative inefficiency, they evaluated the availability and related costs to adjust the input ratios by analyzing the degree of substitutability. According to the inefficiency scores revealed by these studies on different industries, the conclusions of the efficiency analysis, in terms of both technical and allocative prospective, varied significantly among different industries.

However, in the banking industry, there are fewer studies on allocative inefficiency compared to scale and scope efficiency studies. Although some studies have been done to address technical inefficiencies, they did not study the allocative inefficiencies (Berger and DeYoung, 1997; Berger et al., 1997; Berger and Mester, 1997a and 1997b; DeYoung et al., 1998). To our knowledge, there are only two studies related to this issue and both were conducted for the Taiwan banking industry. The first study was initiated by Huang and Wang in 2003. In this study, they collected the data of 22 Taiwan's domestic banks from 1981 to 1997 and decomposed the overall economic inefficiency into allocative inefficiency (AI) and technical inefficiency (TI). After implementing the Fourier Flexible cost function form and calculating AI and EI, they asserted that AI was more costly than TI in the banking industry. Specifically, they claimed that the TI alone raised banks' cost about 12% and AI alone raised banks' cost about 15%. In addition, they showed that the rise in costs was due to decreasing levels of AI over time. In the second study, Huang and Kao (2006) identified the relationship between bank managers' risk attitudes and TE by estimating a tractable dual cost of frontier. It is the first time that a theoretical model involving production risk and a tractable dual cost frontier, derived under the framework of a certainty equivalent production frontier, are proposed. They calculated the correlation between the efficiency and risk attitudes at around 0.85, indicating that the more risk-averse a bank is, the higher the TE is. This conclusion also indicated that a stable economic environment will more likely benefit the establishment of a highly efficient banking industry. Finally, they showed that the average cost efficiency measure is around 0.48 when potential risks in banking industry are factored in.

2.2.3 Measuring and Decomposing Productivity Change

Productivity has always been one of the important topics for producers. In addition, the decomposition of the total factor productivity change (TFPC) is meaningful because this decomposition will help clarify the contributions of different factors to TFPC and, thus, would help bankers make operating adjustments to maximize the total factor productivity (TFP).

In general, two methods are prevalently applied to construct and estimate the production frontier, which can be used as the yardstick for efficiency analysis. One utilizes the parametric method estimated by the Stochastic Frontier Analysis (SFA). The other one uses the nonparametric method estimated by the Data Envelopment Analysis (DEA). Coelli et al. (2003) commented that these two methods have various advantages and disadvantages, and suggested using both methods for sensitivity testing. According to recent surveys, the percentage of studies applying DEA is higher than those applying SFA. However, limited studies have been conducted to compare the consistency of two different methodologies (Berger and Humphrey, 1997).

The main two approaches to decompose the TFP are the total differential approach (Bauer, 1990; Kumbhakar and Lovell, 2000) and the index number approach (Orea, 2002). SFA is the most prevalent method used in the total differential approach and DEA is mostly used in the index number approach to decompose the TFP. Coelli et al. (2005) derived those two decomposition approaches theoretically and gave examples for the calculations. In their study, under the parametric SFA scheme, they decomposed the TFPC into technical efficiency change (TEC), technical change (TC), and scale efficiency change (SEC). Under the scheme of the non-parametric DEA scheme, they provide the procedures to construct and decompose the Malmquist TFP index.

Although many empirical studies on this topic have been widely conducted on different industries (e.g. Atkinson et al., 2003; Sickles, 2005; Karagiannis et al., 2004; Irz and Thirtle, 2004), relevant research on the banking industry has been limited.

The parametric analyses on measuring and decomposing productivity change are launched a little bit earlier compared to the adoption of the nonparametric analyses. Bauer et al. (1993) and Berger and Mester (1997b) applied the Translog cost functions to calculate and segment the indices of the productivity change. Both studies found that large banks experience greater declines in their cost productivity than small banks.

Nonparametric methods are becoming more widely used recently. Wheelock and Wilson (1999) developed a new more comprehensive decomposition method of the Malmquist productivity index which captures not only the changes in pure technical and scale efficiency but also the adoption of the entire industry's technology innovation. The new decomposition provided additional insights to the banking productivity change during the period of 1984-1993. They found that a large percentage of the increase in inefficiency was attributed to the failure of banks to adopt technological improvements. Notably a few other banks have adopted such improvements to advance in the efficiency frontier. In addition, they showed that productivity changes are different across different bank size groups. Specifically, small banks experienced large decreases in both efficiency and productivity in this period. In 2003, Wheelock and Wilson applied for the first time the robust order m-estimator to examine the evolution of productivity, efficiency and technical progress in the commercial banking industry during the period of 1984-2002. By extending the data to 2002 in their new study, they showed that banks of all sizes exhibited a substantial increase in productivity between 1993 and 2002 and technological progress attributed to a large proportion of the productivity increased during this period.

2.3 Agricultural Banks Efficiency Analysis

The aforementioned literature review indicates that majority of efficiency and related studies have been conducted on commercial banks, with only a few applications on agricultural banks' efficiency analysis. Considering the unique characteristics, positions and roles of agricultural banks in rural financial markets, this section of literature review is specifically dedicated to the efficiency studies on agricultural banks.

Literature on bank behavior, regulation and other related issues indicates that agricultural banks are very different from commercial banks. Swank (1996) generalized two major differences. First, agricultural banks' service is essential for the prosperity of the rural economy. They serve as a bridge between agricultural borrowers and lenders. They also provide reliable sources of investment in agricultural markets. Second, agricultural banks maintain widespread and substantial positions among the so-called interbank market which consists of not only agricultural banks but also commercial banks.

Ellinger (1994) reviewed the potential gains from efficiency analysis of agricultural banks. He asserted that they will benefit from the efficiency analysis by understanding their behavior better. In general, he summarized the importance of the efficiency analysis to agricultural banks as following:

"Greater degrees of efficiency among agricultural banks could result in greater accessibility of loan funds, higher bank profitability, more preferable rates for borrowers and depositors, increased services for customers, and greater probability for long-term viability by using savings-generated efficiencies as a capital cushion. Efficiency linkages to long-term viability are especially critical to rural banks since these banks play a vital role in influencing regional flows of funds. Failures of rural banks can impact funding of local projects and subsequent local economic development and growth (pp.652)."

Neff et al. (1994) examined and discussed both cost efficiency and profit efficiency for agricultural banks. They revealed that inefficiency measured by the profit approach is much higher than those by the cost approach. In addition, the bivariate correlation of inefficiency measures with structural and environmental variables shows that bank size is strongly and negatively related to profit inefficiency while the agricultural loan ratio is positively related to profit inefficiency.

Featherstone and Moss (1994) applied a normalized quadratic cost function with curvature properties imposed to estimate economies of scope and scale in agricultural banking. In their study, they found that the economies of scale is exhausted at the mean size of the banks at $60 million. And this conclusion is consistent regardless of whether the curvature assumptions are imposed or not. However, the measures of both economies of scope and economies of scale indicate slight cost economies at the mean output levels with curvature properties imposed.

Dias and Helmers (2001) applied DEA approach to appraise and compare the productivity change between agricultural and commercial banks. They found the TFC being negative during 1981-1991, which could be explained by the increasing volatility in their productivity growth due to the competitive pressure from restructuring the agricultural credit market. In addition, they revealed that the immediate impact of deregulation affected agricultural banks more than nonagricultural banks in terms of deterioration of the productivity. Finally, they showed evidence that stress the fact that producing agricultural loans actually will help agricultural banks gain the efficiency.

CHAPTER 3

DATA AND SPECIFICATION OF VARIABLES

All three studies in the next three chapters used the same panel data set. They were collected from the Call Report Database from 2000 to 2005 published online by the Federal Reserve Board of Chicago. Data were collected on a quarterly basis and are annualized for the purpose of this study. Data were obtained from consolidated banking financial statements that summarized the annual financial performances of all branches. Only banks that continuously reported their financial conditions in the database during the six-year period were included in this study. Banks with any zero observations for any variable or in any year were discarded. Given these conditions, a total of 383 banks were identified in each year, with 2298 observations in total across 6 years.

In general, there are two criteria to define agricultural banks, Federal Reserve System (FRB) criterion and Federal Deposit Insurance Corporation (FDIC) criterion. FRB classifies a bank as agricultural bank if its ratio of agricultural loans to total loans exceeds the unweighted average of the ratio at all banks. FDIC defines agricultural banks based on the criterion that the agricultural loan ratio was 25% or higher. In our study, FRB's definition is adopted.

The percentages of agricultural banks to the sample size are comparatively stable across 6 years, varying from 16.2% to 17.75%. Drawing upon the earlier studies discussed that establish the role of bank size in determining cost efficiencies, this research considers size as one of the emphases of the analysis of size on banking cost efficiencies. In the next three chapters, the size variable is represented by a 5-group classification system based on the banks' total assets: Banks with total assets less than $1 billion are classified as group 1; Banks with total assets between $ 1 billion and $ 2 billion are classified as group 2; Banks with total assets between $ 2 billion and $ 5 billion are classified as group 3; Banks with total assets between $ 5 billion and $ 10 billion are classified as group 4; Banks with total assets over $ 10 billion are classified as group 5. The distribution of sample banks by specialization (agricultural banks vs. commercial banks) is presented in table3.1 and the distribution of sample banks by total assets (five groups) is shown in table 3.2 and further summarized in figure 3.1.

Bank output data collected include Agricultural Loans (y_1), Non-Agricultural Loans (y_2), Consumer Loans (y_3), Fee-based Financial Services (y_4), and Other Assets that cannot be properly included in any other asset items in the balance sheet (y_5). The main input price data categories considered in this study are: Labor-related Measures (salaries and employee benefits divided by number of full-time equivalent employees, p_1), Physical Capital (occupancy and fixed asset expenditures divided by net premises and fixed assets, p_2), Purchased Financial Capital Inputs (expense of federal funds purchased and securities sold and interest on time deposits of $100,000 or more divided by total dollar value of these funds, p_3), and Deposits (interest paid on deposits divided by total dollar value of these deposits, p_4). The cost of each input is collected and denoted C_1 to C_4 respectively. Cost shares, S_i , are then calculated as $S_i = \frac{C_i}{\sum_{i=1}^{N=4} C_i}$.

Measures of loan quality index (z_1) and financial risk index (z_2) are also included in this analysis to introduce a risk dimension to the efficiency models. The index z_1 is calculated from the ratio of non-performing loans to total loans (NPL) to capture the quality of the banks' loan portfolios[2] (Stirob and Metli, 2003). The index z_2 is based on the banks' capital to asset ratio[3], which is used in the following studies as a proxy for financial risk. The role of equity has been understated in efficiency and risk analyses that focus more on NPL and other liability-related measures. Actually, as a supplemental funding source to liabilities, equity capital can provide cushion to protect banks from loan losses and financial distress. Banks with lower capital to asset ratios (CAR) would be inclined to increasingly rely on debt financing, which, in turn, increases the probability or risk of insolvency. So CAR can be good a proxy to measure the financial risk levels for banks. The statistics for the selected variables are listed in Table 3.3.

[2] $z_1 = 10000 \times \text{NPL} = 10000 \times \frac{\text{nonaccrual loans} + \text{loans 90 days or more past due}}{\text{total loans}}$. The reason to use z_1 but instead of NPL is because ln z_1 is a monotonic transformation of NPL which will only change the magnitude of the NPL but still keep all other properties of NPL. In addition, after the transformation, ln z_1 would be all positive numbers with less extreme values.

[3] $z_2 = 1000 \times CAR = 1000 \times \frac{\text{Equity Capital}}{\text{Total Assets}}$. The reason to develop z_2 is the same as z_1.

Table 3. 1: Distribution of Sample Banks by Specialization

Bank Specialization	Years						Average Across Years
	2000	2001	2002	2003	2004	2005	
Ratio of Agricultural Loan to Total Loans	12.78%	12.48%	12.38%	12.27%	12.02%	11.95%	12.31%
Agricultural Bank	117 (30.55%)	117 (30.55%)	119 (31.07%)	119 (31.07%)	123 (32.11%)	120 (31.33%)	716 (31.11%)
Commercial Bank	266 (69.45%)	266 (69.45%)	264 (68.93%)	264 (68.93%)	260 (67.89%)	263 (68.67%)	1583 (68.89%)
Total	383	383	383	383	383	383	383

Note: In each cell, the upper number is the number of banks in each bank group and the lower number in parenthesis is the percentage of banks in each bank group respectively.

Table 3. 2: Distribution of Sample Banks by Total Assets

Bank Group	Years: 2000	2001	2002	2003	2004	2005	Average Across Years
Group1 (< $1 B[4])	47 (12.27%)	40 (10.44%)	34 (8.88%)	30 (7.83%)	25 (6.53%)	23 (6.01%)	33 (8.66%)
Group2 ($1 to $2 B)	84 (21.93%)	75 (19.58%)	67 (17.49%)	63 (16.45%)	65 (16.97%)	64 (16.71%)	70 (18.19%)
Group3 ($2 to $5 B)	140 (36.55%)	144 (37.60%)	147 (38.38%)	143 (37.34%)	137 (35.77%)	130 (33.94%)	140 (36.60%)
Group4 ($5 to $10 B)	50 (13.05%)	57 (14.88%)	62 (16.19%)	69 (18.02%)	68 (17.75%)	71 (18.54%)	63 (16.41%)
Group5 (> $10 B)	62 (16.19%)	67 (17.49%)	73 (19.06%)	78 (20.37%)	88 (22.98%)	95 (24.80%)	77 (20.15%)
Total	383	383	383	383	383	383	383

Note: In each cell, the upper number is the number of banks in each bank group and the lower number in parenthesis is the percentage of banks in each bank group respectively.

[4] B represents Billion in Dollars

Table 3. 3: Summary of Statistics for Selected Variables

Data Summary				
Variables	Sample Mean	Std. Deviation	Minimum	Maximum
Agricultural loans (y_1)	30,402.670	46,496.240	74.000	586,842.750
Non-agric. loans (y_2)	472,100.910	879,381.000	7819.500	12,123,239.500
Consumer loans (y_3)	65,577.740	134,120.090	905.500	1,323,394.500
Fee-based financial services (y_4)	8,050.260	22,644.190	56.250	384,910.000
Others (y_5)	24,272.180	51,296.880	337.250	713,923.500
Labor (x_1)	289.737	527.087	10.750	4,508.000
Physical capital (x_2)	15,922.560	33,904.210	12.250	460,822.000
Purchased financial inputs (x_3)	151,201.860	299,885.050	3,204.750	3,822,771.000
Deposits (x_4)	666,388.390	1,185,741.760	26,253.750	11,700,000.000
Labwenor (p_1)	27.590	5.211	12.761	74.829
Physical capital (p_2)	0.171	0.239	0.029	6.592
Purchased financial inputs (p_3)	0.022	0.009	0.005	0.061
Deposits (p_4)	0.016	0.007	0.002	0.033
Loan quality index (z_1)	95.668	77.732	3.277	1,038.160
Financial risk index (z_2)	94.858	23.394	48.674	253.241
p_1's cost share (s_1)	8,372.640	16,467.720	195.750	151,362.000
p_2 's cost share (s_2)	2,290.190	4,678.480	30.000	46,518.500
p_3's cost share (s_3)	3,069.290	6,373.110	48.000	73,470.250
p_4's cost share (s_4)	8,825.110	15,287.650	268.750	196,816.750

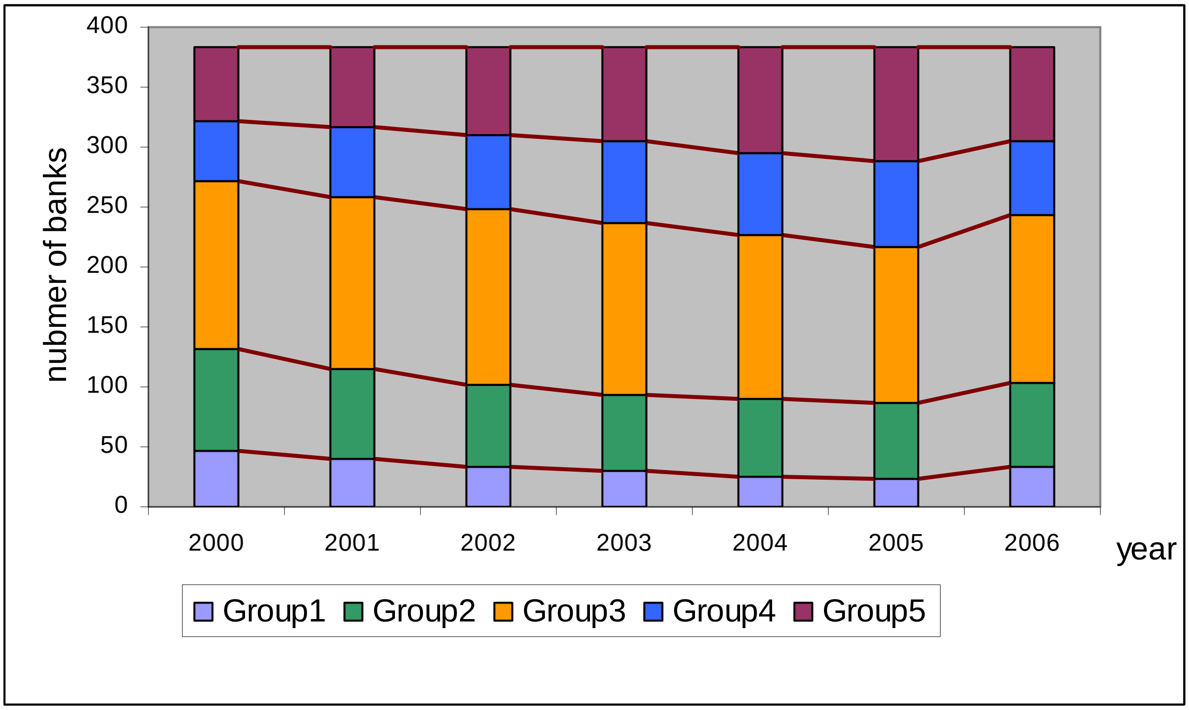

Figure 3. 1: Distribution of Sample Banks by Total Assets

CHAPTER 4

EVALUATING AGRICULTURAL BANKING EFFICIENCY USING THE FOURIER FLEXIBLE FUNCTIONAL FORM

4.1 Introduction

In this study, we employ a semi-parametric cost efficiency analysis using the Fourier Flexible Form function (that shall be from hereon referred to as the FF function), which conveniently allows us to infer relationships among variables when the true functional form of the relationships is unknown. Moreover, this functional form includes trigonometric transformations of the variables that allow for better, global approximation of the underlying true cost function (Gallant, 1982; Huang and Wang, 2004; Mitchell and Onvural, 1996). This means that the FF framework does not require the restrictive conditions of functional form specificity and loose curvature conditions of the parametric approach. In addition, the FF model can measure the bias resulting from the use of the translog form since the latter is actually a special case nested in the FFF form.

To date, the FF framework in bank efficiency analysis have only been applied in a few commercial banking studies (Mitchell and Onvural, 1996; Huang and Wang, 2004) and, to our knowledge, has never been applied in the analysis of agricultural banking efficiency. The application of efficiency models to agricultural banks has usually been complicated by the difficulty of identifying a suitable cost functional form that can accommodate the peculiar lending patterns of these banks.[5] Notably, the FF model potentially has greater relevance in agricultural banking efficiency analyses as it can adapt to the changing financial needs of farm businesses that emanate from the more volatile and uncertain business environments they operate in. Moreover, as previous commercial bank efficiency studies have claimed, the FF provides a better fit to their data due to its global approximation capability (Bauer and Ferrier, 1996; Mitchell and Onvural, 1996).

This study introduces the application of the FF framework in agricultural banking cost efficiency analysis using a panel banking call report dataset from the Federal Reserve Board. In this analysis, an expanded analytical framework is developed to incorporate loan quality and financial risk measures, which seldom are factored into earlier efficiency models. Efficiency measures of scale, scope and specialization are assessed for the FF function and an alternative, competing model based on the translog cost function to illustrate the analytical strengths of the FF framework.

The subsequent sections lay out the theoretical foundations of this study through a discussion of the FFF cost function framework and the efficiency measures considered in this study. The empirical section describes the study's data collection procedures, presents the empirical results and discusses their implications.

4.2 The Fourier Flexible Cost Function

The FF function is a semi-parametric approach that expands the standard translog function by adding a linear combination of sine and cosine functions, referred to as the Fourier series. The non-parametric Fourier component of the expanded translog equation can potentially approximate any well-behaved multivariate function since the sine and cosine terms are mutually

[5] Ellinger and Neff (1994) and Neff, Dixon and Zhu both used the translog cost function; Featherstone and Moss (1994) estimated an indirect multi-product (normalized quadratic) cost function.

orthogonal and function-space-spanning (Huang and Wang, 2004). The FF function can be expressed as[6]:

$$(4.1)\ \ LnC = \beta_0 + \mathbf{x\beta} + (1/2)\mathbf{xAx'} + \mathbf{z\gamma} + \sum_{h=1}^{H}[u_h \cos(\mathbf{xk_h}) + v_h \sin(\mathbf{xk_h})] + \boldsymbol{\varepsilon}$$

where β_0 is a constant to be estimated; $\boldsymbol{\beta} = [\beta_{l1},...\beta_{lN}, \beta_{q1},...\beta_{qM}]'$ is a $(N+M)\times 1$ vector of coefficients to be estimated; N is the number of inputs; M is the number of outputs; $\mathbf{x} = [\mathbf{l'}, \mathbf{q'}]$ is a $QT \times (N+M)$ matrix of rescaled log-input prices $\mathbf{l} = (l_1,...l_N)'$ and scaled log-output quantities $\mathbf{q} = (q_1,...q_M)'$ [7]; Q is the number of firms in each year and T is the number of years in panel data; $\mathbf{A} = \boldsymbol{\beta\beta}' = [a_{ij}]$ is a $(N+M)\times(N+M)$ symmetric matrix of coefficients to be estimated; $\mathbf{z} = [z_1,...z_w]$ is a $QT \times W$ matrix of exogenous variables which can capture the financial risks and loan quality; $\boldsymbol{\gamma} = [\gamma_1,...\gamma_w]'$ is a $W \times 1$ vector of the coefficients to be estimated for $\mathbf{z}$; u_h, v_h are the coefficients to be estimated for Fourier cosine and sine series, accordingly; $\mathbf{k}_h = [k_{h1},...k_{hN}, k_{h,N+1},...k_{h,N+M}]'$ is a $(N+M)\times 1$ elementary multi-index vector (Appendix 1) with integer components chosen by researchers to satisfy the following three criteria (Huang and Wang, 2004):

(i) k_{hi} ,where *i=1,…,N+M*, cannot be a zero vector and its first non-zero element must be positive;

(ii) its elements do not have a common integer divisor; and

(iii) $|\mathbf{k}_h| \le K$ (a constant) are non-decreasing in h, where *h=1,…,H;* and $\boldsymbol{\varepsilon}$ is a $QT \times 1$ random error vector.

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[6] For more details on the derivation of the FF function, please see Chalfant and Gallant, 1985; Gallant and Souza, 1991.

[7] Gallant (1982) claimed that rescaling the data within $[0,2\pi]$ is important for accurate Fourier series to compensate the so-called Gibb's phenomenon.

The translog component that is actually nested in the FFF equation can be derived from (4.1) by dropping the third component involving the sine and cosine series.

Following Gallant's approach (1982), all input and output variables in (4.1) have to be rescaled using the following formulas to ensure that they lie within the range of 0 and 2π:

(4.2) $l_i = \lambda(Lnp_i + w_{pi})$

(4.3) $q_j = \lambda\mu_j(Lny_j + w_{yj})$

(4.4) $w_{pi} = 0.00001 - \min(Lnp_i)$

(4.5) $w_{yj} = 0.00001 - \min(Lny_j)$

(4.6)[8] $\lambda = \dfrac{(2\pi - \varepsilon)}{D} \cong \dfrac{6}{D}$

(4.7) $\mu_j = \dfrac{(2\pi - \varepsilon)}{\lambda[\max(Lny_j) + w_{yj}]} \cong \dfrac{6}{\lambda[\max(Lny_j) + w_{yj}]}$

(4.8) $D = \max\{\max(Lnp_i) + w_{pi}\}$

where i=1,…, N , j=1,…, M, p_i is the price for input i, *and* y_j represents the output j. Equations (4.4), (4.5), (4.6), (4.7), and (4.8) are substituted into (4.2) and (4.3) to calculate the rescaled data which lie within $[0,2\pi]$.

Consistent with microeconomic theory, the cost function is assumed in this analysis to be linearly homogeneous in input prices. The constraints are then set as:

(4.9) $\lambda \sum_{i}^{N} \beta_{li} = 1$

(4.10) $\sum_{j}^{N} a_{ij} = 0, \quad i = 1,\ldots,N + M$

[8] ε in equations (6) and (7) is an arbitrary infinitive small number.

$$(4.11)\quad u_h = v_h = 0 \text{ if } \sum_{j}^{N} k_{hj} \neq 0$$

The third constraint (4.11) requires the sum of the coefficients of input prices for trigonometric functions of sin(.) and cos(.) in equation (4.1) to be zero (Huang and Wang, 2004).

As suggested in previous studies, estimating the cost equation altogether with *N-1* cost share equations could increase the efficiency of estimation for the correlation of the disturbances across equations (Mitchell and Onvural, 1996; Huang and Wang, 2004). The i th cost share equation can be denoted as:

$$(4.12)\quad S_i = \frac{C_i}{C(\mathbf{p},\mathbf{y})} = \frac{p_i x_i}{C(\mathbf{p},\mathbf{y})}\ , \qquad i = 1,\ldots,N$$

where x_i is the cost-minimizing quantity of input i .

By Shephard's Lemma, x_i can be derived as:

$$(4.13)\quad x_i = \frac{\partial C(\mathbf{p},\mathbf{y})}{\partial p_i}, \qquad i = 1,\ldots,N\ .$$

Substituting (4.13) into (4.12), the cost share equations would become:

$$(4.14)\quad S_i = \frac{p_i \left[\dfrac{\partial C(\mathbf{p},\mathbf{y})}{\partial p_i}\right]}{C(\mathbf{p},\mathbf{y})} = \frac{\partial \ln C(\mathbf{p},\mathbf{y})}{\partial C(\mathbf{p},\mathbf{y})} \cdot \frac{\partial C(\mathbf{p},\mathbf{y})}{\partial p_i} \cdot \left(1 \Big/ \frac{\partial \ln p_i}{\partial p_i} \right) = \frac{\partial \ln C(\mathbf{p},\mathbf{y})}{\partial \ln p_i},\ i = 1,\ldots,N$$

Implementing the first partial derivative of the log-cost function (equation 1) to the i^{th} input log-price, $\ln p_i$, and then substituting the result into equation (4.14), the expression of cost share equations would change to:

(4.15)

$$S_i = \frac{\partial \ln C(\mathbf{p},\mathbf{y})}{\partial l_i} \cdot \frac{\partial l_i}{\partial \ln p_i} = \lambda \left\{ \beta_{li} + \sum_{j=1}^{N} a_{ij} l_j + \sum_{j=N+1}^{N+M} a_{ij} q_{j-N} + \sum_{h=1}^{H} \left[-u_h k_{hi} \sin(\mathbf{x}\mathbf{k_h}) + v_h k_{hi} \cos(\mathbf{x}\mathbf{k_h}) \right] \right\}\ ,$$

$$i = 1,\ldots,N$$

To avoid the problem of a singular covariance matrix for the disturbances caused by the perfect collinearity of N cost share equations, one of them must be dropped when estimating the equation system composed of the log-cost function, equation (4.1), and N-1 cost share equations expressed by equation (4.15)[9] . The nonlinear iterative Zellner's seemingly unrelated regression (ITSUR), an estimation method that is asymptotically equivalent to the maximum likelihood method, is applied to the panel data in this study.

Given the panel nature of this study's dataset, the assumptions of fixed effect model need to be tested before implementing the nonlinear ITSUR to estimate the cost and shares equations system. The Hausman specification test compares the fixed versus random effects under the null hypothesis that the individual effects are uncorrelated with the other regressors in the model (Hausman, 1978). If the null hypothesis is rejected, the random effect model would produce biased estimators and hence, the fixed effect model would be preferred. Hausman's essential result is that the covariance of an efficient estimator with its difference from an inefficient estimator is zero (Greene, 2003).

The number of Fourier series chosen for the FF cost functional form would affect the strengths of FF form. Gallant (1981) showed that increasing the number of trigonometric terms included in FF would reduce the approximation error. But too many sine and cosine terms would lead to over-identification and multicollinearity problems. Eastwood and Gallant (1991) have prescribed the following rules to produce consistent and asymptotically normal parameter estimates in the FF function: the number of parameters to be estimated in FF function should be equal to the number of sample observations raised to the two-thirds power. In this study, there are *N* equations in the similar seemingly unrelated regression (SUR) equation system, with

[9] The choice of the cost share equation to be dropped will not significantly influence the results of the estimation.

QT observations for each equation. Therefore, the number of parameters in this analysis, calculated based on the Eastwood and Gallant's formula ($N \cdot QT$), would be:

$$(4.16) \quad NB = \left(N \cdot QT\right)^{\frac{2}{3}}$$

Considering the constraints defined in equations (4.9) to (4.11), the total free unknown parameters to be estimated in the Translog component $\beta_0 + \mathbf{x\beta} + (1/2)\mathbf{xAx'} + \mathbf{z\gamma}$ of the FF log-cost function would be reduced to:

$$(4.17) \quad \begin{aligned} NB\_Trans\log &= 1 + (N+M) - (N+M) + \left[\frac{(N+M)(N+M)-(N+M)}{2} + (N+M)\right] \\ &= 1 + \frac{(N+M)(N+M+1)}{2} \end{aligned}$$

where 1 is the number of estimate for β_0; the first (*N*+*M*) is the number of estimates of $\boldsymbol{\beta}$; the $-(N+M)$ is due to the homogeneity constraints imposed by constraints defined by (4.9) and (4.10); the rest part in [.] gives the number of estimates for $\mathbf{A}$ when the symmetric constraints is imposed on $\mathbf{A}$.

Through equations (4.16) and (4.17) and considering that the numbers of sin(.) and cos(.) are the same, the proper number of Fourier series (H) included in equation (4.1) is derived as:

$$(4.18) \quad H = \frac{1}{2}(NB - NB\_Trans\log) = \frac{1}{2}\left[\left(N \cdot QT\right)^{\frac{2}{3}} - \frac{(N+M)(N+M+1)}{2} - 1\right]$$

4.3 Economies of Scale and Scope Measures

The estimated cost function will be used to develop the following measures that capture efficiencies realized from scale and scope of production, and variations of product specialization schemes of banks (Ellinger, 1994; Mitchell and Onvural, 1996).

Overall scale economy measure

Ray Scale Economy (RSE), a measure developed by Baumol et al (1982), is defined as the elasticity of cost with respect to output given an unchanging output bundle composition. The measure is derived as:

$$(4.19)\quad RSE = \sum_{j=1}^{M} \frac{\partial \ln C}{\partial \ln y_j} = \sum_{j=1}^{M} \frac{\partial \ln C}{\partial q_j} \cdot \frac{\partial q_j}{\partial \ln y_j}$$

Calculating $\frac{\partial q_j}{\partial \ln y_j}$ from equation (4.3) and substituting it into equation (4.19), the RSE equation can thus be rewritten as:

$$(4.20)\quad RSE = \lambda \sum_{j=1}^{M} \mu_j \cdot \frac{\partial \ln C}{\partial q_j} .$$

RSE measures the percentage change in total costs resulting from a percent increase in all outputs. In this measure, the change in output only alters the scale of the outputs' bundle while keeping the output bundle's composition (and respective proportion of the outputs' components) unchanged. Return to scale is increasing, constant, or decreasing when RSE is less than, equal to, or greater than one, respectively. While RSE can provide important implications of the scale effects of banks' efficiency and growth strategies, this measure offers limited insight on cost efficiency when the banks' mix of products and services are allowed to vary.

Expansion path scale economies

Given such limitation of the RSE measure and considering that banks' size expansions usually involves movements along expansion paths connecting output bundles of increasingly larger size and different product mixes, a new measure, expansion path scale economies ($EPSE^{AB}$), was developed by Berger et al. (1986, 1987). $EPSE^{AB}$ is the elasticity of incremental cost with respect to incremental output, allowing variation in the proportion to the output mixes.

$$(4.21) \quad EPSE^{AB} = \sum_{j=1}^{M} \left[\frac{y_j^B - y_j^A}{y_j^B} \cdot \frac{C(\mathbf{y}^B, \mathbf{p})}{C(\mathbf{y}^B, \mathbf{p}) - C(\mathbf{y}^A, \mathbf{p})} \cdot \frac{\partial \ln C(\mathbf{y}^B, \mathbf{p})}{\partial \ln y_j} \right]$$

where y_j^A and y_j^B are the j^{th} outputs in the output bundles at banks A and B, respectively; and $C(\mathbf{y}^A, \mathbf{p})$ and $C(\mathbf{y}^B, \mathbf{p})$ are the total costs to produce the output bundle $\mathbf{y}^A$ in bank A and $\mathbf{y}^B$ in bank B, respectively.

EPSE^{AB} measures the return to scale when expanding from a smaller output bundle $\mathbf{y}^A$ to a larger output bundle $\mathbf{y}^B$ with a different product mix. Return to scale is increasing, constant, or decreasing when EPSE^{AB} is less than, equal to, or greater than one along the expansion path spanning $\mathbf{y}^A$ and $\mathbf{y}^B$.

Economies of Scope

The cost function of the multi-product bank is considered to be sub-additive if the cost of joint production is cheaper than the separate production of its outputs, i.e. $C(\mathbf{y}) < \sum_j C(y_j)$, where $\mathbf{y} = \sum_j y_j$. Hunter et al (1990) pointed out the inadequacy of either the RSE or EPSE measures in explaining the sub-additivity of the banks' cost functions. A measure to address cost sub-additivity was developed using the concept of the economies of scope, which is a necessary condition for subadditivity (Baumol et al., 1982; Kim, 1986; Mester, 1997; Mitchell and Onvural, 1996; Huang and Wang, 2004). This measure, the overall economies of scope (SCOPE) at output bundle $\mathbf{y}$, is defined as:

$$(4.22) \quad \begin{aligned} SCOPE &= \frac{1}{C(\mathbf{y},\mathbf{p})} \left[\sum_{j=1}^{M} C(y_j, \mathbf{p}) - C(\mathbf{y}, \mathbf{p}) \right] \\ &\cong \frac{1}{C(\mathbf{y},\mathbf{p})} \left[\sum_{j=1}^{M} C(y_j - 2y_j^m, \tilde{\mathbf{y}}_j^m, \mathbf{p}) - C(\mathbf{y}, \mathbf{p}) \right] \end{aligned}$$

where $y_j^m = \min(y_j)$, and $\tilde{\mathbf{y}}_j^m = (y_1^m,..., y_{j-1}^m,..., y_M^m)'$ is the output vector whose elements are the minimum values of all *M* outputs except for y_j.

SCOPE measures the percentage of cost saving resulting from the joint (multi-firm) versus specialized (single firm) production of outputs. Scope economies or diseconomies exist if SCOPE is greater than or less than zero respectively. This measure, however, is limited in its application to the standard translog cost function (Hunter et al., 1990; Berger et al., 1987; White, 1980).

Expansion path sub-additivity

Berger et al. (1987) developed the concept of expansion path sub-additivity (EPSUB), a more general measure of scope economies to address such limitation of the SCOPE measure. EPSUB is applicable to banks in different size categories with different proportions of specialization in their product mix. It is calculated using the following expression:

$$(4.23)\quad EPSUB^{AB} = \frac{C(\mathbf{y}^A, \mathbf{p}) + C(\mathbf{y}^D, \mathbf{p}) - C(\mathbf{y}^B, \mathbf{p})}{C(\mathbf{y}^B, \mathbf{p})}$$

where $\mathbf{y}^B$ and $\mathbf{y}^A$ are output bundles for banks B and A, respectively; the residual output bundles $\mathbf{y}^D = \mathbf{y}^B - \mathbf{y}^A$ are produced by bank D; and $C(\mathbf{y}^A, \mathbf{p})$, $C(\mathbf{y}^B, \mathbf{p})$ and $C(\mathbf{y}^D, \mathbf{p})$ are the total costs to produce the product mixes in bank A, B and D, respectively.

Specifically, EPSUB measures the percentage of total cost reduction resulting from the joint production of output bundle $\mathbf{y}^B$ compared to a pair of small “specialized” banks (A and D), which produce the same total amount of the output bundles. The logic behind the EPSUB is to divide $\mathbf{y}^B$ into two smaller “competing banks” including the representative bank producing $\mathbf{y}^A$ along the expansion path connecting $\mathbf{y}^A$ and $\mathbf{y}^B$.

If $EPSUB^{AB}$ is greater than zero, costs are said to be "sub-additive" and implies the realization of scope economies for bank B, which translates to its market competitive edge over the two smaller "specialized" banks A and D. Conversely, if $EPSUB^{AB}$ is less than zero, costs are said to be "super-additive" resulting in scope diseconomies for bank B. Consequently, the odds of survival in the market for bank B are greater as its smaller competitors are able to produce more efficiently the output bundle $\mathbf{y}^B$ separately.

4.4 Data

This study utilized the panel dataset described in Chapter 3. In addition to the variables introduced in Chapter 3, for the specific purpose of this study, all output variables and input price variables are rescaled within $[0,2\pi]$ as $\mathbf{q} = (q_1,...q_5)'$ and $\mathbf{l} = (l_1,...l_4)'$ respectively, using equations (4.2) to (4.8). Table 4.1 presents a comparison of the statistical summaries for the output and input variables before and after data transformation. The transformed data satisfy the data requirement to estimate the FF log-cost function as set by equation (4.1). Also, the number of Fourier series in this analysis (as determined using equation (4.18) with the values N=4, M=5, Q=383, T=6) is $H \cong 197$, where H represents the number of elementary multi-index vectors $\mathbf{k}_h$ to be considered in this analysis.

4.5 Empirical Results

The Hausman hypothesis test for random effects yielded a significant test statistic of 123.21 that indicates that the null hypothesis for random effects can be rejected. This suggests that the nonlinear ITSUR can appropriately be used to estimate the coefficients in the equation system with fixed effects. Table 4.2 provides a comparison of the differences between the estimation results under the FF and translog cost models.[10] The hypothesis that all coefficients of the Fourier series are equal to zero is rejected at 0.01 significant level by an LM test (p-value<0.0001). This, therefore, indicates that the FF is significantly different from the translog function and that the FF cost function could be the proper functional form to estimate the cost function.

The results in table 4.2 indicate that the theoretical assumptions[11] for cost function are generally true for both FF and the translog functions, with a few exceptions. First, the coefficient sign for the purchased financial capital inputs variable (l_3) is significant and negative for both the Fourier and translog models. Both coefficients, however, are small in magnitude and thus, would not amount to a gross violation of the cost theory's condition of non-decreasing in input prices. An interesting result, however, is the significantly negative coefficient for the agricultural loans variable (q_1) in the translog model. This negative coefficient result is inconsistent with standard microeconomic theory and lends support to McAllister and McManus' (1993) previous empirical assertion on the inadequacy of the translog cost function when applied to banking efficiency analysis.

It is worth noting that the coefficients of loan quality index z_1 and financial risk index z_2 are significant for both cost models. The positive sign of z_1 indicates that a deterioration in the quality of loans will cause an increase in bank's total operating costs. The negative sign of z_2 indicates that banks' greater financial risk burdens are usually translated to higher operating costs. These results emphasize the relevance of loan quality and risk measures, which have so often been left out in most efficiency analyses.

[10] For the sake of brevity, the coefficients of Fourier series are not presented in Table 3.
[11] The microeconomic theory requires that the cost function should satisfy: (i) non-decreasing in input prices, (ii) homogeneity of degree one in input prices, (iii) concavity in input prices, and (iv) non-decreasing in outputs.

Table 4.3 summarizes the results for the various efficiency indicators. The RSE results across bank size and specialization groups are all significant, except for Group 5 banks under the FF model. This implies that almost all the sample banks are experiencing increasing returns to scale through proportionate expansions of output bundles without altering product mixes. The trends of the results across bank size and specialization groups are similar regardless of the cost functional forms used. Across bank size groups, the magnitudes of the returns to scale tend to monotonically increase with bank size. This indicates that smaller banks are able to benefit more from increasing returns to scale than larger banks when they expand the outputs in the same proportion. This implies that as banks grow larger, output expansion becomes a less reliable mechanism to further enhance cost efficiency. Specifically, based on the Fourier results, there appears to be no potential benefits from production or output expansion for banks belonging to asset group 5, such that previous trends of increasing returns to scale will collapse to constant returns to scale. Interestingly, this result considerably extends the critical bank size limit for exhausting economies of scale opportunities as established by Featherstone and Moss (1994) at $60 million for banks operating in the 1990s. Apparently, more recent innovative and technological advancements in banks' operating structures realized since the 1990s could have increased these institutions' financial stamina and flexibility.

The bank specialization results provide interesting implications. Based on the absolute values of the RSE statistics, agricultural banks in the study's sample, relative to their non-agricultural counterparts, have demonstrated a stronger tendency to maximize the potentials of increasing returns to scale from output expansion. This trend is attributable to the fact that agricultural banks generally have smaller asset base and scope of operations.

The differences in the RSE results in the FF and translog models reflect these differences in these models' capability to accurately approximate the banks' cost function. Overall, the magnitudes of the RSE results for the translog model are slightly larger than those obtained in the FF model, thus suggesting the latter's greater capability to capture tendencies to attain increasing returns to scale.

All EPSE results in table 4.3 are significantly less than one, which support the earlier results for the RSE measure. The EPSE results indicate that increasing returns to scale are realized when banks expand from a smaller to a larger output bundle under different product mixes. The expansion path is shown in this analysis as a transition from a smaller bank size category to an adjacent (larger) bank size category.

The SCOPE measures derived for all banks in the sample under both cost models are significantly negative (indicating diseconomies and scope) and different from zero. However, the SCOPE measures calculated for the bank size groups under the FF model are not statistically different from zero, suggesting that neither economies nor diseconomies of scope could be verified. These FF results are consistent with those obtained by Mitchell and Onvural (1996) in their application of the FF cost function to U.S. commercial banks.

In the translog cases, the 2nd bank size category registered the only insignificant result. In contrast, group 1 banks exhibit tendencies to realize economies of scope while results for groups 3, 4 and 5 banks suggest the existence of diseconomies of scope. The shift from positive (group 1) to negative (larger groups) results as well as the increasing magnitude in the absolute values of the negative SCOPE estimates both indicate that initially realized economies of scope would tend to diminish and revert to diseconomies of scale as banks expand their operations and increase their asset bases.

Among bank specialization groups, agricultural banks realize diseconomies of scope only under the translog model while non-agricultural banks demonstrate similar tendencies under both the FF and translog models. These results imply the non-agricultural banks' greater vulnerability to realizing diseconomies of scale under expanded, more diversified operations while agricultural banks are able to thrive more under a specialized mode of production.

The results for the final measure, EPSUB, suggest that the costs are slightly "super-additive" along the expansion path from group 2 to 3 and from group 4 to 5 under the translog cost approach. In contrast, the EPSUB results are all insignificant under the FF model. This indicates that neither scope economies nor diseconomies along the expansion path connecting a smaller and a larger bank group are realized. These FF model results reinforce the earlier SCOPE findings.

Table 4. 1: Descriptive Statistical Summary, Before and After Data Transformation

Summary Before Data Transformation					Summary After Data Transformation[a]				
Variables	Sample Mean	Std. Deviation	Minimum	Maximum	Var.	Sample Mean	Std. Deviation	Minimum	Maximum
Agricultural loans (y_1)	30,402.670	46,496.240	74.000	586,842.750	Re-scaled y_1 (q_1)	3.460	0.941	6.68E-06	6.000
Non-agric. loans (y_2)	472,100.910	879,381.000	7819.500	12,123,239.500	Re-scaled y_2 (q_2)	2.692	0.986	8.17E-06	6.000
Consumer loans (y_3)	65,577.740	134,120.090	905.500	1,323,394.500	Re-scaled y_3 (q_3)	2.729	1.050	8.23E-06	6.000
Fee-based financial services (y_4)	8,050.260	22,644.190	56.250	384,910.000	Re-scaled y_4 (q_4)	2.535	0.998	6.79E-06	6.000
Others (y_5)	24,272.180	51,296.880	337.250	713,923.500	Re-scaled y_5 (q_5)	2.593	0.992	7.84E-06	6.000
Labor (p_1)	27.590	5.211	12.761	74.829	Re-scaled p_1 (l_1)	0.833	0.199	1.1E-05	1.953
Physical capital (p_2)	0.171	0.239	0.029	6.592	Re-scaled p_2 (l_2)	1.791	0.517	1.1E-05	6.000
Purchased financial inputs (p_3)	0.022	0.009	0.005	0.061	Re-scaled p_3 (l_3)	1.607	0.459	1.1E-05	2.823
Deposits (p_4)	0.016	0.007	0.002	0.033	Re-scaled p_4 (l_4)	2.031	0.506	1.1E-05	2.979
Loan quality index (z_1)	95.668	77.732	3.277	1,038.160					
Financial risk index (z_2)	94.858	23.394	48.674	253.241					
p_1's cost share (c_1)	8,372.640	16,467.720	195.750	151,362.000					
p_2 's cost share (c_2)	2,290.190	4,678.480	30.000	46,518.500					
p_3's cost share (c_3)	3,069.290	6,373.110	48.000	73,470.250					
p_4's cost share (c_4)	8,825.110	15,287.650	268.750	196,816.750					

Note: [a]The re-scaled q and l variables have been calculated using the data transformation (re-scaling) equations (2) to (8) and using the following derived values: $\lambda = 1.1$, $\mu_1 = 0.61$, $\mu_2 = 0.74$, $\mu_3 = 0.75$, $\mu_4 = 0.62$, $\mu_5 = 0.71$, $w_{y1} = -4.3$, $w_{y2} = -8.96$, $w_{y3} = -6.81$, $w_{y4} = -4.03$, $w_{y5} = -5.82$, $w_{p1} = -2.55$, $w_{p2} = 3.55$, $w_{p3} = 5.35$, $w_{p4} = 6.1$.

Table 4. 2: Estimates of the Fourier[a] and Translog Cost Functions

Parameter	Estimates		Parameter	Estimates		Parameter	Estimates	
	Fourier Cost Function	Tanslog Cost Function		Fourier Cost Function	Tanslog Cost Function		Fourier Cost Function	Tanslog Cost Function
Intercept	5.972***	6.125***	L1*L2	0.025***	0.010***	L1*q4	0.042***	0.046***
	(0.224)	(0.110)		(0.003)	(0.001)		(0.005)	(0.003)
L1	0.510***	0.537***	L1*L3	-0.052***	-0.025***	L1*q5	0.001	-0.015***
	(0.018)	(0.008)		(0.010)	(0.002)		(0.005)	(0.003)
L2	0.100***	0.101***	L1*L4	-0.081***	-0.117***	L2*q2	-0.011***	0.004**
	(0.008)	(0.004)		(0.007)	(0.002)		(0.003)	(0.002)
L3	-0.021***	-0.020***	L2*L3	-0.008***	-0.002**	L2*q3	-0.001	-0.002**
	(0.003)	(0.002)		(0.002)	(0.001)		(0.002)	(0.001)
L4	0.317***	0.288***	L2*L4	-0.023***	-0.030***	L2*q4	0.012***	0.004
	(0.018)	(0.008)		(0.002)	(0.001)		(0.003)	(0.001)
q1	0.072	-0.043*	L3*L4	0.041*	-0.026***	L2*q5	0.002	-0.003**
	(0.075)	(0.026)		(0.024)	(0.003)		(0.002)	(0.001)
q2	0.176	0.318***	q1*q2	-0.043*	-0.022*	L3*q3	0.005	0.001
	(0.181)	(0.047)		(0.023)	(0.011)		(0.004)	(0.002)
q3	-0.134	0.031	q1*q3	0.035***	0.003	L3*q4	-0.008*	-0.011***
	(0.100)	(0.028)		(0.012)	(0.006)		(0.005)	(0.003)
q4	0.333**	0.242***	q1*q4	-0.044**	0.015*	L3*q5	0.001	0.008***
	(0.153)	(0.040)		(0.018)	(0.009)		(0.006)	(0.003)
q5	0.272*	0.105***	q1*q5	0.039**	0.001	L4*q4	-0.046***	-0.039***
	(0.161)	(0.034)		(0.020)	(0.008)		(0.005)	(0.003)
L1^2	0.108***	0.132***	q2*q3	-0.078	-0.041***	L4*q5	-0.004	0.010***
	(0.011)	(0.001)		(0.058)	(0.013)		(0.006)	(0.003)
L2^2	0.006**	0.022***	q2*q4	0.056	0.009	L2*q1	0.001	-0.003***
	(0.003)	(0.001)		(0.092)	(0.016)		(0.002)	(0.001)
L3^2	0.032	0.071***	q2*q5	-0.089	-0.053**	L3*q1	-0.004	0.010***
	(0.027)	(0.003)		(0.237)	(0.022)		(0.003)	(0.002)
L4^2	0.063**	0.173***	q3*q4	-0.156***	-0.062***	L3*q2	0.024***	0.024***
	(0.025)	(0.002)		(0.060)	(0.012)		(0.007)	(0.004)
q1^2	0.005	0.030***	q3*q5	0.092	0.026**	L4*q1	0.000	0.000
	(0.026)	(0.008)		(0.068)	(0.011)		(0.003)	(0.002)
q2^2	0.311	0.223***	q4*q5	-0.005	0.019	L4*q2	0.042***	0.014***
	(0.245)	(0.031)		(0.087)	(0.016)		(0.007)	(0.004)
q3^2	0.156**	0.084***	L1*q1	0.003	-0.007***	L4*q3	0.004	0.001
	(0.071)	(0.011)		(0.003)	(0.002)		(0.004)	(0.002)
q4^2	0.115	0.003	L1*q2	-0.055***	-0.042***	z1	0.012***	0.017***
	(0.135)	(0.018)		(0.006)	(0.004)		(0.003)	(0.003)
q5^2	-0.114	-0.011	L1*q3	-0.008**	0.000	z2	-0.090***	-0.111***
	(0.256)	(0.024)		(0.003)	(0.002)		(0.016)	(0.016)

Note: [a]The 394 coefficients of the Fourier sin(.) and cos(.) series are not reported in this table but will be available from the authors upon request.

*** Significantly different from zero at the 1% level.
** Significantly different from zero at the 5% level.
* Significantly different from zero at the 10% level.

Table 4. 3: Results of Efficiency Analyses[a] for Fourier and Translog Cost Functions

		FF cost function		Translog cost function	
		Estimate	Std. Errors	Estimate	Std. Errors
A. Overall Scale Economy Measure (RSE)					
Bank Size/Total Assets Categories	Group1 (< $1 billion)	0.634***	0.116	0.670***	0.017
	Group2 ($1 to $2 billion)	0.688***	0.082	0.727***	0.014
	Group3 ($2 to $5 billion)	0.754***	0.046	0.791***	0.011
	Group4 ($5 to $10 billion)	0.797***	0.035	0.837***	0.010
	Group5 (> $10 billion)	0.881	0.088	0.936***	0.015
Bank Specialization	Agricultural Banks	0.680***	0.075	0.745***	0.014
	Non-Agricultural Banks	0.814***	0.043	0.859***	0.010
All Banks		0.803***	0.040	0.850***	0.010
B. Expansion Path Scale Economies (EPSE)					
$EPSE^{12}$ (Group1-Group2)		0.579**	0.179	0.669***	0.024
$EPSE^{23}$ (Group2-Group3)		0.575***	0.147	0.658***	0.024
$EPSE^{34}$ (Group3-Group4)		0.542***	0.127	0.629***	0.027
$EPSE^{45}$ (Group4-Group5)		0.696***	0.034	0.760***	0.016
C. Economies of Scope (SCOPE)					
Bank Size/Total Assets Categories	Group1 (< $1 billion)	0.428	0.326	0.523***	0.098
	Group2 ($1 to $2 billion)	-0.001	0.495	0.087	0.097
	Group3 ($2 to $5 billion)	-0.241	0.652	-0.157*	0.097
	Group4 ($5 to $10 billion)	-0.565	0.502	-0.384***	0.086
	Group5 (> $10 billion)	-0.769	0.503	-0.721***	0.068
Bank Specialization	Agricultural Banks	-0.113	0.484	-0.160**	0.074
	Non-Agricultural Banks	-0.739**	0.329	-0.667***	0.074
All Banks		-0.726**	0.323	-0.657***	0.072
D. Expansion Path Sub-Additivity (EPSUB)					
$EPSUB^{12}$ (Group1-Group2)		-0.010	0.281	0.052	0.043
$EPSUB^{23}$ (Group2-Group3)		-0.153	0.355	-0.115**	0.053
$EPSUB^{34}$ (Group3-Group4)		-0.112	0.437	-0.073	0.061
$EPSUB^{45}$ (Group4-Group5)		-0.161	0.272	-0.130***	0.039

Note: [a]All four efficiency measures are measured at sample mean.

*** Significantly less than one for RSE and EPSE measures while significantly different from zero for SCOPE and EPSUB measures at the 1% level.

** Significantly less than one for RSE and EPSE measures while significantly different from zero for SCOPE and EPSUB measures at the 5% level.

* Significantly less than one for RSE and EPSE measures while significantly different from zero for SCOPE and EPSUB measures at the 10% level.

CHAPTER 5

EVALUATING AGRICULTURAL BANKING EFFICIENCY USING THE INPUT DISTANCE FUNCTION

5.1 Introduction

This study introduces the application of the Stochastic Frontier Analysis (SFA) to measure banks' Technical Efficiency and Allocative Efficiency. It uses a panel banking call report dataset from the Federal Reserve Board.

Stochastic Frontier Analysis (SFA) was introduced as an approach in developing an efficiency analytical framework by Aigner et al in 1977. According to Coelli (2000, 2003b), there are several outstanding merits when to apply input distance function: (1) it can be used to deal with the production with multi-outputs and multi-inputs; (2) it does not require price information; (3) it will provide robust estimation in case that there are systematic deviations from cost minimizing behavior; (4) it will not encounter the problem of the simultaneous equations bias when firms are cost minimizers or shadow cost minimizers. In addition, it has another important advantage as showed by (Atkinson and Primont, 2002): (5) there is tight relationship between cost function and input distance function according to the duality theory, which indicates the input distance function has meaningful economic explanation. Some special banks, unlike other competitive markets, would not be able to hold the classical economic assumptions. Their behaviors may deviate from the cost minimization or profit maximization paradigms. For example, agricultural banks and some other policy banks have been required to meet the governor's policy goals. Majority of these banks are involved in multiple businesses. Additionally, banks have more power to control over such inputs as labor and loan amounts. So the stochastic input distance function would fully take into consideration these advantages to evaluate bank efficiency.

The subsequent sections lay out the theoretical foundations of this study through a discussion of the Input Distance Function framework and the efficiency measures considered in this study. The empirical section presents the empirical results and discusses their implications.

5.2 The Input Distance Function

Formally, the Shephard (1953) input distance function is defined as follows:

(5.1) $D^I(\mathbf{x},\mathbf{y}) = \sup_{\rho}\{\rho > 0 : (\mathbf{x}/\rho) \in L(\mathbf{y})\}$

where the superscript I implies that it is the input distance function; the input set $L(\mathbf{y}) = \{\mathbf{x} \in \mathbf{R}_N^+ : \mathbf{x} \text{ can produce } \mathbf{y} \in \mathbf{R}_{\mathbf{M}}^+\}$ represents the set of all input vectors, $\mathbf{x}$, which can produce the output vector, $\mathbf{y}$; ρ measures the possible proportion of the inputs which can be reduced to produce the quantity of the outputs not less than $\mathbf{y}$. So in other word, input distance function is the maximum retraction proportion of inputs to achieve the outputs on the production frontier.

Farrell and Primont (1995) and Cornes (1992) showed and approved the following properties of the input distance function:

(1) $D^I(\mathbf{x},\mathbf{y})$ is dual of the cost function.

(2) $\mathbf{x}$ belongs to the input set of $\mathbf{y}$ (e.g. $\mathbf{x} \in L(\mathbf{y})$) if and only if $D^I(\mathbf{x},\mathbf{y}) \geq 1$.

(3) When a firm operates on the production frontier, isoquant $L(\mathbf{y})$, $D^I(\mathbf{x},\mathbf{y})$ is

equal to 1. In this case, the firm achieves the technical efficiency.

(4) $D^I(\mathbf{x},\mathbf{y})$ is non-decreasing in inputs, $\mathbf{x}$, and non-increasing in outputs, $\mathbf{y}$.

(5) $D^I(\mathbf{x},\mathbf{y})$ is homogeneous of degree 1 in $\mathbf{x}$.

(6) $D^I(\mathbf{x},\mathbf{y})$ is concave in $\mathbf{x}$ and quasi-convex in $\mathbf{y}$.

The stochastic frontier analysis (SFA) approach is introduced to estimate the flexible Translog distance function. The Translog function overcomes the shortcomings of the Cobb-Douglas function form, which assumes that all firms have the same production elasticities, which sum up to 1. The Translog function is more flexible with less restriction on production and substitution elasticities. The flexibility reduces the biased estimate's possibility due to the improper function form's assumption.

The stochastic input distance function for each observation *i* is estimated by:

$$
\begin{aligned}
\ln D_{it}^I = {} & \beta_0 + \sum_{k=1}^{M} \beta_{y_k} \ln y_{k,it} + \frac{1}{2}\sum_{k=1}^{M}\sum_{l=1}^{M} \beta_{y_{kl}} \ln y_{k,it} \ln y_{l,it} + \sum_{j=1}^{N} \beta_{x_j} \ln x_{j,it} + \frac{1}{2}\sum_{j=1}^{N}\sum_{h=1}^{N} \beta_{x_{jh}} \ln x_{j,it} \ln x_{h,it} \\
& + \sum_{j=1}^{N}\sum_{k=1}^{M} \beta_{xy_{jk}} \ln x_{j,it} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{z_d} \ln z_{d,it} + \frac{1}{2}\sum_{d=1}^{P}\sum_{f=1}^{P} \beta_{z_{df}} \ln z_{d,it} \ln z_{f,it} + \sum_{k=1}^{M}\sum_{d=1}^{P} \beta_{yz_{kd}} \ln y_{k,it} \ln z_{d,it} \\
& + \sum_{j=1}^{N}\sum_{d=1}^{P} \beta_{xz_{jd}} \ln x_{j,it} \ln z_{d,it} + \sum_{k=1}^{M} \alpha_k (t \ln y_{k,it}) + \sum_{j=1}^{N} \delta_j (t \ln x_{j,it}) + \sum_{d=1}^{P} \theta_d (t \ln z_{d,it}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\
& + \sum_{g=1}^{G-1} d_g\, dum_{g,it} + d_a\, dum_{a,it}
\end{aligned} \tag{5.2}
$$

where $dum_{g,it}$ is the dummy variable representing the bank size in group *g*; $dum_{a,it}$ is the dummy variable for agricultural banks; *k, l* = 1, … *M* and *M* = 5 (number of outputs); *j, h* = 1, … *N* and *N* = 4 (number of inputs); *d, f* = 1, … *P* and *P* = 2 (number of indexes to measure financial risks and loan's quality), *g* = 1, …(*G-1*) and *G* = 5 (number of groups).

A necessary property of the inputs distance function is homogeneity of degree one in input quantities, which implies that the parameters in equation (5.2) should satisfy the following constraints:

$$\sum_{j=1}^{N} \beta_{x_j} = 1 \qquad \text{(R5.1)}$$

$$\sum_{j=1}^{N} \beta_{x_{jh}} = 0, \qquad \forall\ h = 1,\ldots,N \qquad \text{(R5.2)}$$

$$\sum_{j=1}^{N} \beta_{xy_{jk}} = 0, \qquad \forall\ k = 1,\ldots,M \qquad \text{(R5.3)}$$

$$\sum_{j=1}^{N} \beta_{xz_{jd}} = 0, \qquad \forall\ d = 1,\ldots,P \qquad \text{(R5.4)}$$

$$\sum_{j=1}^{N} \delta_j = 0 \qquad \text{(R5.5)}$$

In addition, the property of homogeneity can be expressed mathematically as:

$$\text{(5.3)}\ \ D_{it}^{I}(\lambda \mathbf{x}, \mathbf{y}) = \lambda D_{it}^{I}(\mathbf{x}, \mathbf{y}), \qquad \forall \lambda > 0$$

Assuming $\lambda = 1/x_{N,it}$ [12], equation (5.3) can be expressed in logarithmic form as:

$$\text{(5.4)}\ \ \ln D_{it}^{I}(\mathbf{x}/x_{N,it}, \mathbf{y}) = \ln D_{it}^{I}(\mathbf{x}, \mathbf{y}) - \ln x_{N,it}$$

According to the definition of the input distance function, the logarithm of the distance function in (5.4) measures the deviation of and observation $(\mathbf{x}, \mathbf{y})$ from the efficient production frontier $L(\mathbf{y})$, ε_{it}.

$$\text{(5.5)}\ \ \ln D_{it}^{I}(\mathbf{x}, \mathbf{y}) = \varepsilon_{it}$$

[12] λ can be selected as arbitrary input to serve as the denominator considering that input distance function is homogeneity of degree one in inputs (here the N^{th} input is selected as the denominator).

Following the literature of the SFA, this deviation from the production frontier can be explained by two components (Irz and Thirtle, 2004). The most extraordinary characteristic of the SFA is that it decomposes ε_{it} as $\varepsilon_{it} = v_{it} - u_{it}$. Then equation (5.5) can be expressed as:

(5.6) $\ln D_{it}^{I}(\mathbf{x},\mathbf{y}) = u_{it} - v_{it}$

where u_{it} measures the technical inefficiency and follows the positive half normal distribution as $u_{it} \overset{iid}{\sim} N^{+}(\mu,\sigma_u{}^2)$; while v_{it} measures the pure random error and follows the normal distribution as $v_{it} \overset{iid}{\sim} N(0,\sigma_v{}^2)$.

Substituting equation (5.6) into equation (5.4), equation (5.4) can be rewritten as:

(5.7) $-\ln x_{N,it} = \ln D_{it}^{I}(\mathbf{x}/x_{N,it},\mathbf{y}) + v_{it} - u_{it}$

Besides the homogeneity restrictions, the symmetric restrictions also need to be imposed in estimating the Translog input distance function. The symmetric restrictions require that the parameters in equation (5.2) should satisfy the following constraints:

$\beta_{y_{kl}} = \beta_{y_{lk}}$, where $k,l = 1,....,M$ (R5.6)

$\beta_{x_{jh}} = \beta_{x_{hj}}$, where $j,h = 1,....,N$ (R5.7)

$\beta_{z_{df}} = \beta_{z_{fd}}$, where d, $f = 1,....,P$ (R5.8)

Imposing restrictions (R5.1) through (R5.8) and equation (5.2) upon equation (5.7) yields the estimating form of the input distance function as follows:

$$
\begin{aligned}
(5.8)\qquad -\ln x_{N,it} =\ & \beta_0 + \sum_{k=1}^{M}\beta_{y_k}\ \ln y_{k,it} + \sum_{j=1}^{N-1}\beta_{x_j}\ \ln x_{j,it}{}^{*} + \sum_{d=1}^{P}\beta_{z_d}\ \ln z_{d,it} \\
& + \frac{1}{2}\left[\sum_{k=1}^{M}\beta_{y_{kk}}(\ln y_{k,it})^2 + \sum_{j=1}^{N-1}\beta_{x_{jj}}(\ln x_{j,it})^2 + \sum_{d=1}^{P}\beta_{z_{dd}}(\ln z_{d,it})^2\right] \\
& + \sum_{k=1}^{M}\ \sum_{l=1,\ for\ l>k}^{M}\beta_{y_{kl}}\ \ln y_{k,it}\ \ln y_{l,it} + \sum_{j=1}^{N}\ \sum_{h=1,\ for\ h>j}^{N-1}\beta_{x_{jh}}\ \ln x_{j,it}{}^{*}\ \ln x_{h,it}{}^{*} + \sum_{d=1}^{P}\ \sum_{f=1,\ for\ f>d}^{P}\beta_{z_{df}}\ \ln z_{d,it}\ \ln z_{f,it} \\
& + \sum_{j=1}^{N-1}\sum_{k=1}^{M}\beta_{xy_{jk}}\ \ln x_{j,it}{}^{*}\ \ln y_{k,it} + \sum_{k=1}^{M}\sum_{d=1}^{P}\beta_{yz_{kd}}\ \ln y_{k,it}\ \ln z_{d,it} + \sum_{j=1}^{N-1}\sum_{d=1}^{P}\beta_{xz_{jd}}\ \ln x_{j,it}{}^{*}\ \ln z_{d,it} \\
& + \sum_{k=1}^{M}\alpha_k(t\ln y_{k,it}) + \sum_{j=1}^{N-1}\delta_j(t\ln x_{j,it}{}^{*}) + \sum_{d=1}^{P}\theta_d(t\ln z_{d,it}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 \\
& + \sum_{g=1}^{G-1} d_g\, dum_{g,it} + d_a\, dum_{a,it} + v_{it} - u_{it}
\end{aligned}
$$

where $x_{j,it}{}^{*} = x_{j,it} / x_{N,it}$ is the normalized input *j*.

After estimating all coefficients in equation (5.8), the coefficients for the N^{th} input can be calculated by the homothetic restrictions (R5.1) to (R5.5).

5.3 Technical and Allocative Efficiency Measures

To better understand the concept of the decomposition of efficiency, consider a scenario of one output with two inputs which can be used to illustrate how the Technical efficiency (TE) and allocative efficiency (AE) is measured in Figure 5.1. Assume that a firm uses input x1 and x2 at point A to produce output *y*. Technical inefficiency would occur since the same amount of the output would be produced with fewer inputs by movement from point A to point C. TE can be calculated as $TE = OC / OA$, which represents the percentage of the input saved. Aligning the definition of the input distance function, it is not hard to find the link between $D^I(\mathbf{x},\mathbf{y})$ and *TE.*

(5.9) $TE = 1/ D^I(\mathbf{x},\mathbf{y})$

where $0 \le TE_{it} \le 1$. The closer TE_{it} is to unity, the more technically efficiently the bank performs.

Aligning with the estimation of the function (5.8), technical efficiency levels can be estimated as

(5.10) $T\hat{E}_{it} = 1/\hat{D}^{I}_{it} = 1/E[\exp(\hat{u}_{it}) \mid v_{it} - u_{it}]$

Considering the panel data utilized in the study, u_{it} will be assumed to follow the distribution below to capture the time effect on the TE level.

(5.11) $\hat{u}_{it} = \exp\{-\eta(t - T_i)\}.\hat{u}_i$

where $u_i \overset{iid}{\sim} N^{+}(\mu, \sigma_{\mu}^{\ 2})$. $\eta = 0$ implies that the distance function will not fluctuate over time series. The model in this case is time-invariant. Otherwise, the model is time-variant. The sign of the η can tell the TE change over times. $\eta > 0$ indicates efficiency achievement. While $\eta < 0$ indicates the TE decay. To get the unbiased estimates, the time-invariant hypothesis H0: $\eta = 0$ will be tested. If the hypothesis is rejected, the time-variant constraint ($\eta \neq 0$) will be necessary to get the unbiased estimates.

Given input prices p_1 and p_2, the AE measure can be illustrated in Figure 5.1. The move from C to D on the isoquantity curve shows that the firm's output is maintained constant while operating at the lower isocost curve *f1*. It implies that the firm could save costs without decreasing output. Following the same concept to calculate TE, AE can be calculated as $AE = OB/OC$. To make this study more realistic, the estimated input distance function will be used to further differentiate technical efficiency and allocative efficiency.

Allocative efficiency can be assessed by estimating shadow prices. Initially, the studies were based on the estimation of the system equations composed by cost function and cost share equations (Atkinson and Halvorsen, 1986; Eakin and Kniesner, 1988). However, the validation of this system equations' estimation requires the assumption of cost minimization. Recently, some researchers provided an alternative method to get shadow prices out of inputs using

Shephard's distance function (Fare and Grosskopf, 1990; Banos-Pino et al., 2002; Atkinson and Primont, 2002; Rodriguez-Alvarez et al., 2003). Under this new scheme, the assumption of cost minimization is not necessary in order to get consistent estimates. They allow the difference between the market prices and shadow prices with respect to the minimum costs. As illustrated in Figure 5.1, shadow price ratio p_1^s / p_2^s is the slope of the isocost curve *f3* which indicates the minimum cost at given level of inputs to produce the same quantity of the outputs. In other words, a firm would be allocative efficient if it could operate at point C which is on the isocost curve *f3* to satisfy the condition required by allocative efficiency. This condition requires that the marginal rate of technical substitution (MRTS) between any two of its inputs is equal to the ratio of corresponding input prices (p_1^s / p_2^s). So the deviation of the market price ratio (p_1 / p_2) from the shadow price ratio (p_1^s / p_2^s) reflects relative allocative inefficiency. The ratio can be expressed as $k_{12} = \frac{p_1^s / p_2^s}{p_1 / p_2}$. Specifically, if the ratio equals to 1, allocative efficiency achieved. Otherwise, allocative inefficiency is detected. The larger $|k_{12}|$ deviates from 1, the larger allocative inefficiency is.

More generally, allocative inefficiency for each observation *i* at time *t* can be measured by relative input price correction indices:

$$(5.11)\quad k_{jh,it} = k_{j,it} / k_{h,it} = \frac{p_{j,it}^s / p_{j,it}}{p_{h,it}^s / p_{h,it}} = \frac{p_{j,it}^s}{p_{h,it}^s} \cdot \frac{p_{h,it}}{p_{j,it}}$$

where $k_{j,it} = p_{j,it}^s / p_{j,it}$ is the ratio of the shadow price, $p_{j,it}^s$, to market price, $p_{j,it}$, for input *j* of the observation *i* at time *t*. If $k_{jh,it} = 1$, there is no allocative inefficiency; If $k_{jh,it} > 1$, input *j* is being underutilized relative to the input *h*; If $k_{jh,it} < 1$, input *j* is being over utilized relative to the input *h*.

Atkinson and Primont (2002) derived the shadow cost function from a shadow distance system. In shadow distance system, the cost function can be expressed as:

$$(5.12)\quad C(\mathbf{y},\mathbf{p}) = \min_{\mathbf{x}}\{\mathbf{px} : D(\mathbf{y},\mathbf{x}) \geq 1\}$$

Implementing the duality theory and imposing input distance function's linear homogeneity property, they showed how to derive the dual Shephard's lemma as:

$$(5.13)\quad \frac{\partial D^I_{it}(\mathbf{x},\mathbf{y})}{\partial x_{j,it}} = \frac{p^s_{j,it}}{C(\mathbf{y},\mathbf{p}^s)}$$

From equation (5.13), the ratio of the shadow prices can be calculated by:

$$(5.14)\quad \frac{p_{j,it}{}^s}{p_{h,it}{}^s} = \frac{\partial D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial x_{j,it}}{\partial D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial x_{h,it}}$$

Applying the derivative envelope theory to the numerator and denominator of the equation (5.14) separately, equation (5.14) can be expressed as:

$$(5.15)\quad \begin{aligned} \frac{p_{j,it}{}^s}{p_{h,it}{}^s} = \frac{\partial D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial x_{j,it}}{\partial D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial x_{h,it}} &= \frac{\left[1\big/\left(D^I_{it}(\mathbf{x},\mathbf{y}) \cdot x_{j,it}\right)\right] \cdot \left[\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{j,it}\right]}{\left[1\big/\left(D^I_{it}(\mathbf{x},\mathbf{y}) \cdot x_{h,it}\right)\right] \cdot \left[\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{h,it}\right]} \\ &= \frac{x_{h,it}}{x_{j,it}} \cdot \frac{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{j,it}}{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{h,it}} \end{aligned}$$

Substituting equation (5.15) into equation (5.11), the relative allocative inefficiency shown by the relative input price correction indices can be expressed as:

$$k_{jh,it} = \frac{p_{h,it}}{p_{j,it}} \cdot \frac{x_{h,it}}{x_{j,it}} \cdot \frac{\partial \ln D^I_{\text{it}}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{j,it}}{\partial \ln D^I_{\text{it}}(\mathbf{x},\mathbf{y}) \big/ \partial \ln x_{h,it}}$$

(5.16)

$$= \frac{p_{h,it} x_{h,it}}{p_{j,it} x_{j,it}} \cdot \frac{\beta_{x_j} + \sum_{h=1}^{N} \beta_{x_{jh}} \ln x_{h,it} + \sum_{k=1}^{M} \beta_{xy_{jk}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{jd}} \ln z_{d,it} + \delta_j t}{\beta_{x_j} + \sum_{j=1}^{N} \beta_{x_{jh}} \ln x_{j,it} + \sum_{k=1}^{M} \beta_{xy_{jk}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{jd}} \ln z_{d,it} + \delta_j t}$$

Since input price is given, the cost of allocative inefficiency level can be evaluated. The optimal input vector to satisfy the cost minimization assumption is defined as $\mathbf{x}^o$. Similar to the allocative inefficiency measure, the input quantity correction ratio is defined as $r_{j,it} = x^o_{j,it} \big/ x_{j,it}$ and the input quantity index is defined as $r_{jh,it} = r_{j,it} \big/ r_{h,it}$, where $x^o_{j,it}$ is the optimized quantity of input x_j for firm *i* at time *t*.

According to equation (5.13), the dual Shephard's lemma can be expressed at optimal input $x^o_{j,it}$ as:

$$(5.20) \quad \frac{\partial D^I_{it}(\mathbf{x},\mathbf{y})}{\partial x^o_{j,it}} = \frac{p_{j,it}}{C(\mathbf{y},\mathbf{p})}$$

Applying derivative envelope theory to the left hand side of equation (5.20),

$$(5.21) \quad \frac{\partial D^I_{it}(\mathbf{x},\mathbf{y})}{\partial x^o_{j,it}} = \frac{\partial D^I_{it}(\mathbf{x},\mathbf{y})}{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y})} \cdot \frac{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y})}{\partial \ln x^o_{j,it}} \cdot \frac{\partial \ln x^o_{j,it}}{\partial x^o_{j,it}} = \frac{D^I_{it}(\mathbf{x},\mathbf{y})}{x^o_{j,it}} \cdot \frac{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y})}{\partial \ln x^o_{j,it}}$$

Substituting equation (5.21) into equation (5.20), (5.20) can be written as:

$$(5.22) \quad x^o_{j,it} = \frac{D^I_{it}(\mathbf{x},\mathbf{y})}{p_{j,it}} \cdot \frac{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y})}{\partial \ln x^o_{j,it}} \cdot C(\mathbf{y},\mathbf{p})$$

Using equation (5.22) to calculate any two arbitrary optimal inputs ratio as:

(5.23)

$$\frac{x^o_{j,it}}{x^o_{h,it}} = \frac{\dfrac{D^I_{it}(\mathbf{x},\mathbf{y})}{p_{j,it}} \cdot \dfrac{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y})}{\partial \ln x^o_{j,it}} \cdot C(\mathbf{y},\mathbf{p})}{\dfrac{D^I_{it}(\mathbf{x},\mathbf{y})}{p_{h,it}} \cdot \dfrac{\partial \ln D^I_{it}(\mathbf{x},\mathbf{y})}{\partial \ln x^o_{h,it}} \cdot C(\mathbf{y},\mathbf{p})} = \frac{[\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{j,it}] / [\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{h,it}]}{p_{j,it} / p_{h,it}}$$

As defined previously, the optimal input *j* can be written as:

(5.24) $x^o_{j,it} = r_{j,it} \cdot x_{j,it}$

Substituting (5.24) into (5.23),

(5.25)
$$\frac{r_{j,it} \cdot x_{j,it}}{r_{h,it} \cdot x_{h,it}} = \frac{[\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{j,it}] / [\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{h,it}]}{p_{j,it} / p_{h,it}}$$
$$\Rightarrow r_{jh,it} = \frac{r_{j,it}}{r_{h,it}} = \frac{[\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{j,it}] / [\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{h,it}]}{x_{j,it} p_{j,it} / x_{h,it} p_{h,it}}$$

Let $F(\mathbf{x},\mathbf{y}) = \partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{j,it}$, considering $D^I_{it}(\mathbf{x},\mathbf{y})$ is linearly homogeneous in input vector $\mathbf{x}$, the following equation can be approved:

(5.26)
$$\begin{aligned} F(\lambda\mathbf{x},\mathbf{y}) &= \partial \ln D^I_{it}(\lambda\mathbf{x},\mathbf{y}) / \partial \ln x^o_{j,it} \\ &= \partial \ln[\lambda D^I_{it}(\mathbf{x},\mathbf{y})] / \partial \ln x^o_{j,it} \\ &= \partial[\ln\lambda + \ln D^I_{it}(\mathbf{x},\mathbf{y})] / \partial \ln x^o_{j,it} \\ &= \partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{j,it} = F(\mathbf{x},\mathbf{y}) \quad ,\forall \lambda > 0 \end{aligned}$$

Equation (5.26) proved that function $F(\mathbf{x},\mathbf{y})$ is homogeneous of degree 0. In this study, we set $\lambda = 1/x^o_{N,it}$, which is the reciprocal value of the N^{th} (*N*=4 in this study) optimal input. Replacing the λ in (5.26) with $1/x^o_{N,it}$, (5.26) gives that

$$\partial \ln D^I_{it}(\mathbf{x},\mathbf{y}) / \partial \ln x^o_{j,it} = \partial \ln D^I_{it}\left(\frac{1}{x^o_{N,it}}\mathbf{x}^o, \mathbf{y}\right) \Big/ \partial \ln x^o_{j,it} \quad \text{and}$$

$\partial \ln D_{it}^{I}(\mathbf{x},\mathbf{y}) \Big/ \partial \ln x_{h,it}^{o} = \partial \ln D_{it}^{I}\left(\frac{1}{x_{N,it}^{o}}\mathbf{x}^{o},\mathbf{y}\right) \Big/ \partial \ln x_{h,it}^{o}$. Replacing them into (5.25), (5.25) can be written as:

$$(5.27)\quad r_{jh,it} = \frac{r_{j,it}}{r_{h,it}} = \frac{\left[\partial \ln D_{it}^{I}\left(\frac{1}{x_{N,it}^{o}}\mathbf{x}^{o},\mathbf{y}\right) \Big/ \partial \ln x_{j,it}^{o}\right] \Big/ \left[\partial \ln D_{it}^{I}\left(\frac{1}{x_{N,it}^{o}}\mathbf{x}^{o},\mathbf{y}\right) \Big/ \partial \ln x_{h,it}^{o}\right]}{x_{j,it}\,p_{j,it} \big/ x_{h,it}\,p_{h,it}}$$

Considering

$$(5.28)\quad \frac{x_{j,it}^{o}}{x_{N,it}^{o}} = \frac{r_{j,it}\,x_{j,it}}{r_{N,it}\,x_{N,it}} = r_{jN,it}\cdot\frac{x_{j,it}}{x_{N,it}} = r_{jN,it}\cdot x_{j,it}^{*}$$

where $x_{j,it}^{*} = \frac{x_{j,it}}{x_{N,it}}$ represents the normalized j^{th} input which is denominated by the N^{th} input.

To avoid the problem of the singularity, the N^{th} equation is dropped so that only *N-1* nonlinear equations in total are represented by equation (5.27). Substituting (5.28) and related partial derivatives into equation (5.27), the *N-1* nonlinear equation system can be expressed in equation (5.29). This nonlinear equation system can be numerically solved. In this study, the SAS procedure is applied to solve this nonlinear optimization problem.

(5.29)

$$\begin{cases} r_{14,it} = \dfrac{\beta_{x_1} + \beta_{x_{11}} \ln(r_{14,it}x^*_{1,it}) + \beta_{x_{12}} \ln(r_{24,it}x^*_{2,it}) + \beta_{x_{13}} \ln(r_{34,it}x^*_{3,it}) + \sum_{k=1}^{M} \beta_{xy_{1k}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{1d}} \ln z_{d,it} + \delta_1 t}{\beta_{x_4} + \beta_{x_{14}} \ln(r_{14,it}x^*_{1,it}) + \beta_{x_{24}} \ln(r_{24,it}x^*_{2,it}) + \beta_{x_{34}} \ln(r_{34,it}x^*_{3,it}) + \sum_{k=1}^{M} \beta_{xy_{4k}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{4d}} \ln z_{d,it} + \delta_4 t} \cdot \dfrac{S_{4,it}}{S_{1,it}} \\ r_{24,it} = \dfrac{\beta_{x_2} + \beta_{x_{12}} \ln(r_{14,it}x^*_{1,it}) + \beta_{x_{22}} \ln(r_{24,it}x^*_{2,it}) + \beta_{x_{23}} \ln(r_{34,it}x^*_{3,it}) + \sum_{k=1}^{M} \beta_{xy_{2k}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{2d}} \ln z_{d,it} + \delta_2 t}{\beta_{x_4} + \beta_{x_{14}} \ln(r_{14,it}x^*_{1,it}) + \beta_{x_{24}} \ln(r_{24,it}x^*_{2,it}) + \beta_{x_{34}} \ln(r_{34,it}x^*_{3,it}) + \sum_{k=1}^{M} \beta_{xy_{4k}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{4d}} \ln z_{d,it} + \delta_4 t} \cdot \dfrac{S_{4,it}}{S_{2,it}} \\ r_{34,it} = \dfrac{\beta_{x_3} + \beta_{x_{13}} \ln(r_{14,it}x^*_{1,it}) + \beta_{x_{23}} \ln(r_{24,it}x^*_{2,it}) + \beta_{x_{33}} \ln(r_{34,it}x^*_{3,it}) + \sum_{k=1}^{M} \beta_{xy_{3k}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{3d}} \ln z_{d,it} + \delta_3 t}{\beta_{x_4} + \beta_{x_{14}} \ln(r_{14,it}x^*_{1,it}) + \beta_{x_{24}} \ln(r_{24,it}x^*_{2,it}) + \beta_{x_{34}} \ln(r_{34,it}x^*_{3,it}) + \sum_{k=1}^{M} \beta_{xy_{4k}} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{xz_{4d}} \ln z_{d,it} + \delta_4 t} \cdot \dfrac{S_{4,it}}{S_{3,it}} \end{cases}$$

After solving for $r_{14,it}$, $r_{24,it}$, and $r_{34,it}$ and considering (5.24) and (5.25), the optimal inputs at can be solved in equation (5.30):

$$(5.30) \begin{cases} x^o_{1,it} = r_{14,it} r_{4,it} x_{1,it} \\ x^o_{2,it} = r_{24,it} r_{4,it} x_{2,it} \\ x^o_{3,it} = r_{34,it} r_{4,it} x_{3,it} \\ x^o_{4,it} = r_{44,it} r_{4,it} x_{4,it} = r_{4,it} x_{4,it} \end{cases}$$

When a firm technically operates efficiently, the inputs will achieve the optimal level and the input distance function is equal to one. So substituting (5.30) into (5.3) and making $D^I_{it} = 1$, $r_{N,it}$ (in this study, it is $r_{4,it}$) can be solved. Other *N-1* $r_{j,it}$ would then be calculated by $r_{j,it} = r_{jN,it} r_{N,it}$. Given the input prices are known, the minimized cost to produce the same outputs with less inputs $x_{j,it}{}^o$ can be calculated as $\cos t^o_{it} = \sum_{j=1}^{N} p_{j,it} x_{j,it}{}^o$.

5.4 Data

This study utilized the panel dataset as described in Chapter 3. The descriptive statistics of the variables used for this study have been presented in Chapter 3.

5.5 Empirical Results

The estimates of the input distance function (5.8) are given in table 5.1. The hypothesis that all coefficients of the distance function are equal to zero is rejected at 0.01 significance level by an LM test (p-value<0.0001).

As explained earlier, the function form will impact the consistency of the estimates. The hypothesis of the acceptability of the Cobb-Douglas function form, which requires that all parameters except for β_{y_k} and β_{j_k} in equation (5.2) equals to 0, is rejected at 0.01 significance level by an LM test (p-value<0.0001). The test result indicates that the flexible Translog function form could be more applicable in this study.

The statistics (p-value>0.1) of η given in Table 5.1 show that it is insignificantly different from 0. It indicates that the hypothesis of time-invariant model cannot be rejected. The overall TE does not change significantly from year to year during the period 2000 to 2005. The significant coefficient estimates of for the agricultural bank (d_a) and bank size (d_g) variables show that the bank's characteristics and size significantly influence TE. Table 5.2 presents the ANOVA summary that can be used to compare TE between agricultural banks and non agricultural banks[13]. The results indicate that both agricultural banks and non agricultural banks are not technically efficient. The efficiency level of agricultural banks is 62% while the efficiency level of non agricultural banks is only 58%. However, a statistical comparison of these results indicate that the TE of agricultural banks is 4% significantly more efficient than non agricultural banks (p-value<0.0001).

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[13] Since the input distance in this study is the time-invariant model, one way ANOVA analysis without time series factor is applied for both bank characteristics and bank size TE comparison.

The results in table 5.3 show that bank size indeed is a factor that can impact the efficiency level at a significance level of 0.0001. All banks selected in the study are under efficient, regardless of bank size. It is may be an implication that the whole banking industry is operating inefficiently. Moreover, in this table, it is evident that smaller banks are more technically efficient than large banks. The differences of the efficiency levels between any two bank size groups are significant. The smallest group1 is 19% more efficient than the largest group5. Graph2 and Graph3 illustrate the TE trend between 2000 and 2005. The trends in the graphs demonstrate that agricultural banks are more efficient than non agricultural banks, and that small banks are more efficient than large banks over time.[14] Additionally, we notice that the time series efficiency trend is quite stable in each classified group. This is another way to graphically demonstrate our early finding that the model is time-invariant.

As previously discussed, $k_{jh,it}$,calculated by equation (5.16), can be used to measure the relative allocative inefficiency level. Tables 5.4 and 5.5 summarize the average k_{jh} over time by bank characteristics and size, respectively.

As can be gleaned from figure 5.4, the inefficiency level may be different over years but relative allocative inefficiency exists widely in both agricultural banks and non agricultural banks between any two inputs. The graph of k_{12} shows the efficiency difference between agricultural and non agricultural as well as the fluctuation between labor input and physical capital input ratio over the years. This phenomenon implies an active adjustment between labor and physical capital. In general, this allocative inefficiency reflects that labor input has been over-utilized vis-à-vis physical capital since $k_{12} < 1$ for all the years except for agricultural banks in 2001. Additionally, agricultural banks have a stronger tendency than non agricultural banks to

[14] There is only one exception in 2000. In this year, the efficiency level of Group5 is higher than Group4.

adjust these two inputs given the more volatile ratio for agricultural banks. This may imply that agricultural banks have more flexibility to adjust physical capital than non agricultural banks. The graph also shows that agricultural banks fluctuate around $k_{12} = 1$ in most years. It may indicate that the efforts made by agricultural banks to adjust labor and physical capital are more effective than those made by non agricultural banks. The graph for the k_{13} trend shows the significant improvement of the allocative efficiency between labor and financial capital inputs over the years by relatively increasing the input of labor and reducing the financial capital. Additionally, it is notable that this adjustment came through two stages. The first stage is the fast adjustment process in the efficient ratio before 2003. It was observed that the sharper slope of k_{13} displays a tendency towards unity. After adjustment at the first stage, the banks seem to have achieved the goals to operate around the optimal input ratio between labor and financial capital. At this stage, agricultural banks are relatively more efficient than non agricultural banks. The second stage then commences after 2003. At the second stage, more efforts are made to keep banks operating around the efficient resource allocation level. At this stage, non agricultural banks are slightly more efficient than agricultural banks. But the difference of the allocative efficiency between these two inputs narrowed down after 2003. $k_{14} < 1$ in all years implies that the labor is over utilized compared to capital input (deposit) for a long time for all banks selected. The graph for k_{14} trend showed that this improper proportion between two inputs is getting worse over years. However, this deteriorating condition has become more stable after 2003 and even showed a potential for improvement in 2005. Meanwhile, agricultural banks consistently allocate these two input resources in a slightly more efficient way over the years. As in the case of k_{14}, k_{23} is less than one during the time period regardless of bank characteristics. This implies that physical capital is over utilized vis-a-vis financial capital for the all banks in the study.

Assuming all banks selected in the study can represent of the whole industry, the conclusion above can be a proxy of the industry's scenario. The graph of k_{23} also demonstrates that 2003 is the point of contra flexure. Before this point, non agricultural banks perform much better than agricultural banks. But after 2003, the disparity in performance is narrowing down until reverting to a trend of higher performance for agricultural banks vis-a-vis non agricultural banks. The graph for k_{24} showed that both agricultural and non agricultural banks perform well below the efficient utilization of physical capital and deposit. Overall, they only reached less than 20% of the allocative efficiency. The physical capital is over utilized compared to deposit. The fact that k_{34} is less than one indicates that financial capital is over utilized compared to the deposit. But the variation of this ratio is relatively small. It means that adjustments between financial capital and deposit were probably seldom made. Notably, agricultural banks allocated these two inputs in more efficient way over the years.

Figure 5.5 presents the graphs for k_{jh} by bank size. All graphs illustrated to some extent the input allocative inefficiency that occurred widely in different bank size groups. Graph k_{12} implies that the labor input is over utilized vis-a-vis physical capitals since $k_{12} < 1$ is true in most years. The banks did make efforts to correct the improper input ratio between labor and physical capital. It was demonstrated by observing that k_{12} for all banks fluctuate around one. The relatively large volatility implies the efforts they made each year in attempting to realize efficient allocation. The crossed line for k_{12} by different sized bank groups implies that bank size has an insignificant influence in differentiating allocative efficiency between labor and physical capital. Graph k_{13} shows movement towards the efficiency reference line at one. It means that the allocative efficiency level between labor and financial capital keep improving over the years. But as in the case of k_{12}, k_{13} does not produce any significant differentiation resulting from variations in bank size. Graph k_{14} clearly demonstrates the different allocative efficiency between labors and deposits by bank size. Smaller banks seem to be more efficient in allocating these two inputs. Meanwhile, labor seems to be over utilized compared to deposits because of $k_{14} < 1$. This inefficient mixture ratio was not corrected and has been observed to get even worse over the years as can be gleaned from the noted deviations from the efficient reference line in each year. The cross line pattern for k_{23} is shown in the graph for k_{23}. This poses difficulty in deriving any conclusion about the role of bank size in the efficient allocation between physical and financial capital. Generally, banks have the tendency to over utilize physical capital regardless of size because $k_{23} < 1$ in most years. Graph k_{24} implies that there is no allocative efficiency difference among different bank size groups. They all performed less efficiently due to the over utilization of physical capital. Graph k_{34} demonstrates that smaller banks tend to realize efficient allocation between financial capital and deposits given the trend of this value more closely approaching one than larger banks. However overall, the banks in our study period seem not to efficiently allocate the financial capital and deposits as a result of over utilizing financial capital. The flat pattern below the unit reference line indicates that the lack of interest and effort in correcting this allocative inefficiency between financial capital and deposits.

The factor r_j introduced in the efficiency measure aims to adjust inputs to the allocative efficient level to minimize the cost. The calculated r_j is summarized in Tables 5.6 and 5.7 by bank characteristics and size. The results reveal that the banks could run the business less costly by retracting the labor, physical capital and financial capital to a certain level without reducing the outputs. Meanwhile, the banks should increase the investments and utilization of the deposit.

After r_j is calculated, the optimal cost $\cos t_{it}^{o}$ when banks operate with allocative efficiency can be assessed. Tables 5.8 and 5.9 provide the comparison between current actual costs and minimal cost that could be achieved after adjusting the inputs to the optimal level.

The results in table 5.8 indicate that cost saving can be realized for both agricultural banks and non agricultural banks. The average costs for agricultural banks over the years will reduce by 5% from 43 MM USD to 41 MM USD. Non agricultural banks will reduce their costs by 9% from 64 MM USD to 58 MM USD. This implies that the input adjustment to efficiency levels will benefit non agricultural banks more than agricultural banks.

Table 5.9 presents the cost savings by bank size. The results indicate that costs can be reduced regardless of bank size. But the cost saving level varies largely by year and bank size. The cost saving rate varies from 2% up to 63%. Specifically, banks with assets less than $1 billion (Group1) could save 29% by reducing the cost from 26 MM USD to 18 MM USD. Banks with assets between $1 billion and $2 billion (Group2) could save 12% by reducing the cost from 44 MM USD to 38 MM USD. Banks with assets between $2 billion and $5 billion (Group 3) could save 4% by reducing the cost from 75 MM USD to 72 MM USD. Banks with assets between $5 billion and $10 billion (Group 4) could save 12% by reducing the cost from 136 MM USD to 120 MM USD. Banks with assets over $10 billion (Group 5) could save 8% by reducing the cost from 251 MM USD to 230 MM USD. The fluctuation of the cost saving rates among different sized banks implies that the bank size would not be necessarily related to the relative potential costs to be saved. So the study does not support the consistent conclusion that the banks size is the factor to impact the cost saving rate by achieve the allocative efficiency.

Figures from 5.6 and 5.10 demonstrate the trends that can deduced from the results presented in Tables 5.8 and 5.9. Figure 5.6 shows that the cost saving rate by achieving the

AE increase year by year for both agricultural banks and non agricultural banks. But the saving rate for agricultural banks increases monotonically from 2000 to 2005 and reach the max 32%. There is a sharp jump in 2004 regarding the saving rate. As for the non agricultural banks, basically the saving rate increases. There is a spike 34% observed in 2003. Thereafter, the saving rate drops to 27% and increases mildly in 2004 and 2005. The increasing potential cost saving rate indicates that the situation of the allocative inefficiency for all bank is not effectively solved but even getting worse over years from 2000 to 2005.

Notably, the potential cost saving rate of the agricultural banks is much lower than non agricultural banks before 2003. But this pattern was reversed after 2003. It may imply that the allocative efficiency for agricultural banks deteriorates faster than non agricultural banks after 2003. Figure 5.7 showed more than millions of dollars loss due to allocative inefficiency. The substantial cost potential savings over years indicates that the banks should pay attention on AIE. Especially, Agricultural banks should make more efforts to correct the deviation from the AE after they are aware of the fast deterioration in recent years. Figure 5.8 showed that the small banks with assets less than two Billions and large banks with assets more than 10 Billions would pay much higher extra cost due to the AIE. In contrast, impact of the AIE on the banks with assets between 2 Billions and 10 Billions are smaller regards of the extra costs they paid for AIE. Additionally, the extra cost paid due to the AIE keeps increasing year by year from 2000 to 2005. This increment is faster for the banks with assets below 2 Billions and more than 10 Billions. Figure 5.9 provides the magnitude of the potential cost gains by achieving the AE for different bank groups classified by their assets. It shows the larger difference of the potential efficient cost and actual cost is smaller for medium banks with assets between 2 Billions and 10 Billions compared to their counterparts falling the group1, group2, and group5 with assets less than 1 Billion, between 1 and 2 Billions, and over 10 Billions respectively. Figure 5.10 illustrates how cost efficiency changes over years from 2000 to 2005. It shows that the actual average cost for all banks selected, if can represent the whole banking industry, went down before 2004 although the pattern of reductions was relatively flat. However, average cost increased steadily from 2004 and a big jump was observed in 2005. Generally, the optimal cost follows the same pattern as actual cost changes over years. Meanwhile, the more apparent fact about the expanding gap between actual and optimal cost implies that the inefficiency issue is not effectively solved but even becomes worse since 2003. Before 2003, the cost inefficiency rate is below 9%, while, after 2003, the inefficiency rate went up to around 20%.

Table 5. 1: Estimates of the Input Distance Function

Estimates of the Input Distance Function									
Intercept	0.553*** (0.062)	$\beta_{x_{44}}$	-0.05 (0.048)	$\beta_{xy_{11}}$	-0.01 (0.01)	$\beta_{yz_{11}}$	0.001 (0.002)	α_3	-0.003* (0.002)
β_{y_1}	-0.054*** (0.006)	$\beta_{z_{11}}$	0.002 (0.005)	$\beta_{xy_{12}}$	-0.009 (0.024)	$\beta_{yz_{21}}$	-0.009 (0.007)	α_4	0.002 (0.002)
β_{y_2}	-0.607** (0.013)	$\beta_{z_{22}}$	-0.09 (0.072)	$\beta_{xy_{13}}$	-0.059*** (0.015)	$\beta_{yz_{31}}$	0.001 (0.004)	α_5	0.001 (0.002)
β_{y_3}	-0.107*** (0.008)	$\beta_{y_{12}}$	0.016*** (0.006)	$\beta_{xy_{14}}$	0.023 (0.018)	$\beta_{yz_{41}}$	0.007 (0.005)	δ_1	-0.009* (0.005)
β_{y_4}	-0.053*** (0.008)	$\beta_{y_{13}}$	-0.006* (0.003)	$\beta_{xy_{15}}$	0.02 (0.025)	$\beta_{yz_{51}}$	0.0003 (0.006)	δ_2	-0.002 (0.002)
β_{y_5}	-0.064*** (0.009)	$\beta_{y_{14}}$	-0.006 (0.004)	$\beta_{xy_{21}}$	-0.007 (0.005)	$\beta_{yz_{12}}$	0.021** (0.01)	δ_3	-0.001 (0.002)
β_{x_1}	0.198*** (0.02)	$\beta_{y_{15}}$	-0.006 (0.004)	$\beta_{xy_{22}}$	-0.04*** (0.014)	$\beta_{yz_{22}}$	-0.118*** (0.026)	δ_4	0.012** (0.005)
β_{x_2}	-0.023* (0.012)	$\beta_{y_{23}}$	0.039*** (0.01)	$\beta_{xy_{23}}$	-0.013 (0.009)	$\beta_{yz_{32}}$	0.02 (0.019)	θ_1	-0.001 (0.001)
β_{x_3}	0.037*** (0.011)	$\beta_{y_{24}}$	0.016 (0.011)	$\beta_{xy_{24}}$	0.026** (0.012)	$\beta_{yz_{42}}$	0.023 (0.019)	θ_2	0.003 (0.005)
β_{x_4}	0.788*** (0.022)	$\beta_{y_{25}}$	0.032** (0.014)	$\beta_{xy_{25}}$	0.01 (0.011)	$\beta_{yz_{52}}$	0.06*** (0.023)	λ_1	0.01*** (0.004)
β_{z_1}	0.002 (0.005)	$\beta_{y_{34}}$	0.022*** (0.007)	$\beta_{xy_{31}}$	0.005 (0.005)	$\beta_{xz_{11}}$	0.0001 (0.013)	λ_2	0.003*** (0.001)
β_{z_2}	0.109*** (0.02)	$\beta_{y_{35}}$	-0.007 (0.008)	$\beta_{xy_{32}}$	-0.011 (0.013)	$\beta_{xz_{21}}$	0.004 (0.006)	d_{g_1}	0.165*** (0.021)
$\beta_{y_{11}}$	-0.019*** (0.003)	$\beta_{y_{45}}$	-0.014 (0.009)	$\beta_{xy_{33}}$	-0.008 (0.009)	$\beta_{xz_{31}}$	0.01 (0.006)	d_{g_2}	0.124*** (0.016)
$\beta_{y_{22}}$	-0.17*** (0.023)	$\beta_{x_{12}}$	-0.104*** (0.025)	$\beta_{xy_{34}}$	0.002 (0.011)	$\beta_{xz_{41}}$	-0.014 (0.014)	d_{g_3}	0.085*** (0.013)
$\beta_{y_{33}}$	-0.077*** (0.009)	$\beta_{x_{13}}$	0.052** (0.02)	$\beta_{xy_{35}}$	0.021* (0.012)	$\beta_{xz_{12}}$	0.061 (0.054)	d_{g_4}	0.057*** (0.009)
$\beta_{y_{44}}$	-0.006 (0.009)	$\beta_{x_{14}}$	-0.032 (0.039)	$\beta_{xy_{41}}$	0.012 (0.011)	$\beta_{xz_{22}}$	-0.047* (0.024)	d_a	0.021* (0.012)
$\beta_{y_{55}}$	-0.003 (0.015)	$\beta_{x_{23}}$	-0.015 (0.012)	$\beta_{xy_{42}}$	0.059** (0.024)	$\beta_{xz_{32}}$	-0.005 (0.026)	η	-0.001 (0.005)
$\beta_{x_{11}}$	0.083 (0.053)	$\beta_{x_{24}}$	0.091*** (0.026)	$\beta_{xy_{43}}$	0.08*** (0.016)	$\beta_{xz_{42}}$	-0.009 (0.052)		
$\beta_{x_{22}}$	0.028** (0.013)	$\beta_{x_{34}}$	-0.009 (0.025)	$\beta_{xy_{44}}$	-0.052*** (0.02)	α_1	0.001* (0.001)		
$\beta_{x_{33}}$	-0.028 (0.018)	$\beta_{z_{12}}$	0.009 (0.013)	$\beta_{xy_{45}}$	-0.051** (0.025)	α_2	0.002 (0.003)		

Note: *** Significantly different from zero at the 1% level.

** Significantly different from zero at the 5% level.

* Significantly different from zero at the 10% level.

Table 5. 2: ANOVA Table for TE Difference between Bank Characteristics

ANOVA Table					
Source of Variation	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	0.37	0.37	39	<.0001
Error	2296	21.86	0.01		
Corrected Total	2297	22.23			

TE Difference Between Agricultural Bank and Non-Agricultural Bank				
Bank Characteristics	Mean	Standard Error		
Ag Bank	0.62	0.09		
NonAg Bank	0.58	0.10		
Comparison	Estimate	Standard Error	t Value	Pr > |t|
Ag Bank – NonAg Bank	0.03	0.01	6.24	<.0001

Table 5. 3: ANOVA Table for TE Difference among Different Bank Sizes

ANOVA Table

Source of Variation	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	6.35	1.59	229.30	<.0001
Error	2293	15.88	0.01		
Corrected Total	2297	22.23			

TE Difference Between Different Sized Banks

Bank Size	Mean	Standard Error
Group1	0.72	0.10
Group2	0.62	0.09
Group3	0.59	0.73
Group4	0.54	0.79
Group5	0.53	0.85

Comparison	Estimate	Standard Error	t Value	Pr > |t|
Group1 – Group2	0.09	0.01	13.25	<.0001
Group1 – Group3	0.13	0.01	19.39	<.0001
Group1 – Group4	0.17	0.01	23.95	<.0001
Group1 – Group5	0.19	0.01	27.07	<.0001
Group2 – Group3	0.03	0.00	6.48	<.0001
Group2 – Group4	0.08	0.01	13.48	<.0001
Group2 – Group5	0.10	0.01	17.10	<.0001
Group3 – Group4	0.05	0.01	9.20	<.0001
Group3 – Group5	0.06	0.00	13.23	<.0001
Group4 – Group5	0.02	0.01	2.82	0.005

Table 5. 4: Summary of k_{jh} by Bank Characteristics over Years

Bank Characteristics	Year	k12	k13	k14	k23	k24	k34
Agricultural Bank	2000	0.29	1.65	0.72	0.15	0.00	0.53
	2001	1.09	1.37	0.67	0.01	0.02	0.59
	2002	0.25	1.13	0.47	0.11	0.12	0.57
	2003	0.92	0.79	0.33	0.17	0.14	0.51
	2004	0.02	0.72	0.26	0.26	0.13	0.47
	2005	0.80	0.81	0.28	0.24	0.13	0.45
Non Agricultural Bank	2000	0.78	2.29	0.57	0.89	0.17	0.37
	2001	0.28	2.08	0.55	0.77	0.10	0.38
	2002	0.07	1.41	0.36	0.44	0.02	0.39
	2003	0.37	1.07	0.26	0.06	0.05	0.40
	2004	0.71	0.87	0.21	0.12	0.06	0.36
	2005	0.66	1.12	0.24	0.14	0.08	0.31

Table 5. 5: Summary of k_{jh} by Bank Size over Years

Bank Size	Year	k12	k13	k14	k23	k24	k34
Group1	2000	0.27	1.75	0.74	0.04	0.07	0.56
	2001	0.03	1.49	0.64	0.14	0.08	0.58
	2002	0.51	1.01	0.53	0.29	0.18	0.58
	2003	0.57	0.79	0.35	0.25	0.15	0.53
	2004	0.83	0.61	0.29	0.24	0.13	0.54
	2005	1.55	0.71	0.30	0.23	0.11	0.50
Group2	2000	0.39	1.89	0.64	0.38	0.07	0.45
	2001	0.20	1.51	0.62	0.01	0.04	0.53
	2002	0.38	1.15	0.46	0.03	0.13	0.52
	2003	0.91	0.79	0.31	0.22	0.18	0.57
	2004	0.13	0.71	0.25	0.18	0.13	0.48
	2005	0.55	0.84	0.28	0.30	0.16	0.46
Group3	2000	1.54	2.21	0.60	0.75	0.18	0.40
	2001	0.14	1.84	0.57	0.59	0.10	0.42
	2002	0.19	1.38	0.37	0.43	0.04	0.42
	2003	0.20	1.14	0.27	0.17	0.03	0.41
	2004	0.94	0.88	0.22	0.13	0.08	0.38
	2005	0.89	1.15	0.24	0.16	0.10	0.33
Group4	2000	0.25	2.42	0.52	1.18	0.23	0.28
	2001	0.60	2.39	0.52	1.11	0.15	0.31
	2002	0.13	1.55	0.31	0.68	0.02	0.32
	2003	0.75	1.04	0.26	0.03	0.06	0.35
	2004	0.23	1.10	0.21	0.00	0.04	0.33
	2005	0.34	1.28	0.24	0.12	0.07	0.28
Group5	2000	0.97	2.83	0.49	1.99	0.21	0.23
	2001	0.70	2.86	0.48	1.67	0.19	0.23
	2002	0.82	1.57	0.27	0.76	0.09	0.28
	2003	0.30	1.08	0.21	0.08	0.03	0.31
	2004	0.49	0.66	0.18	0.28	0.00	0.26
	2005	0.49	1.01	0.21	0.04	0.02	0.21

Table 5. 6: Summary of r_j by Bank Characteristics over Years

Bank Characteristics	Year	r_1	r_2	r_3	r_4
Agricultural Bank	2000	0.01	2.85E-04	0.08	1.99
	2001	0.01	3.02E-04	0.10	1.85
	2002	0.01	2.94E-04	0.09	1.90
	2003	0.01	3.34E-04	0.10	2.00
	2004	0.01	2.36E-04	0.08	1.68
	2005	0.01	2.18E-04	0.07	1.58
Non Agricultural Bank	2000	0.01	1.97E-04	0.06	1.93
	2001	0.01	1.69E-04	0.06	1.99
	2002	0.01	1.85E-04	0.06	1.92
	2003	0.01	1.84E-04	0.06	1.91
	2004	0.01	2.13E-04	0.07	1.91
	2005	0.01	2.09E-04	0.06	1.95

Table 5. 7: Summary of r_j by Bank Size over Years

Bank Size	Year	r_1	r_2	r_3	r_4
Group1	2000	0.01	2.35E-04	0.06	1.51
	2001	0.01	2.42E-04	0.08	1.42
	2002	0.01	2.38E-04	0.07	1.33
	2003	0.01	2.69E-04	0.07	1.35
	2004	0.01	1.92E-04	0.06	1.19
	2005	0.01	1.11E-04	0.05	1.17
Group2	2000	0.01	2.14E-04	0.07	2.06
	2001	0.01	2.27E-04	0.07	1.93
	2002	0.01	2.02E-04	0.07	1.72
	2003	0.01	2.58E-04	0.08	1.70
	2004	0.01	2.26E-04	0.07	1.45
	2005	0.01	2.13E-04	0.05	1.30
Group3	2000	0.01	1.57E-04	0.06	2.41
	2001	0.01	1.78E-04	0.06	2.22
	2002	0.01	2.16E-04	0.07	2.28
	2003	0.01	2.36E-04	0.08	2.25
	2004	0.01	2.19E-04	0.07	2.18
	2005	0.01	2.25E-04	0.07	2.07
Group4	2000	0.02	3.77E-04	0.03	1.52
	2001	0.01	2.82E-04	0.03	1.23
	2002	0.01	1.88E-04	0.05	2.20
	2003	0.01	1.20E-04	0.04	1.79
	2004	0.01	1.37E-04	0.05	2.19
	2005	0.01	1.51E-04	0.05	2.06
Group5	2000	0.02	4.39E-05	0.04	2.83
	2001	0.02	4.57E-05	0.04	2.70
	2002	0.02	4.49E-05	0.04	2.70
	2003	0.02	5.14E-05	0.05	2.75
	2004	0.02	4.55E-05	0.04	2.68
	2005	0.02	4.50E-05	0.04	2.60

Table 5. 8: Comparison between Actual Cost $\cos t$ and Minimal Cost $\cos t^o$ by Bank Characteristics over years

Bank Characteristics	Year	$\cos t$ (MM$)	$\cos t^o$ (MM$)	Cost Save (%)
Agricultural Bank	2000	45.53	44.78	2%
	2001	45.02	42.65	5%
	2002	40.22	37.55	7%
	2003	38.51	34.20	11%
	2004	37.30	25.78	31%
	2005	49.24	33.36	32%
	Average over years	42.62	40.54	5%
Non Agricultural Bank	2000	67.54	67.20	1%
	2001	68.56	61.16	11%
	2002	59.84	49.74	17%
	2003	57.05	37.59	34%
	2004	59.33	43.40	27%
	2005	74.07	51.34	31%
	Average over years	64.19	58.43	9%

Table 5. 9: Comparison between Actual Cost $\cos t$ and Minimal Cost $\cos t^{o}$ by Bank Size over years

Bank Size	Year	$\cos t$ (MM$)	$\cos t^{o}$ (MM$)	Cost Save (%)
Group1	2000	28.43	24.51	14%
	2001	29.03	23.15	20%
	2002	23.72	14.95	37%
	2003	22.41	12.27	45%
	2004	20.54	8.19	60%
	2005	24.87	9.24	63%
	Average over years	25.84	18.34	29%
Group2	2000	56.73	54.26	4%
	2001	54.60	49.59	9%
	2002	40.57	33.18	18%
	2003	35.78	24.41	32%
	2004	32.19	16.78	48%
	2005	36.01	17.91	50%
	Average over years	43.63	38.28	12%
Group3	2000	94.62	92.75	2%
	2001	94.88	91.73	3%
	2002	75.71	70.35	7%
	2003	67.43	60.68	10%
	2004	65.11	50.37	23%
	2005	76.00	60.51	20%
	Average over years	74.95	72.12	4%
Group4	2000	254.65	208.17	18%
	2001	184.53	125.20	32%
	2002	126.04	116.60	7%
	2003	106.81	89.20	16%
	2004	125.52	108.16	14%
	2005	140.45	123.86	12%
	Average over years	135.74	119.69	12%
Group5	2000	221.41	201.92	9%
	2001	229.05	199.92	13%
	2002	201.30	152.75	24%
	2003	192.55	123.49	36%
	2004	199.00	112.09	44%
	2005	250.64	148.99	41%
	Average over years	250.64	229.94	8%

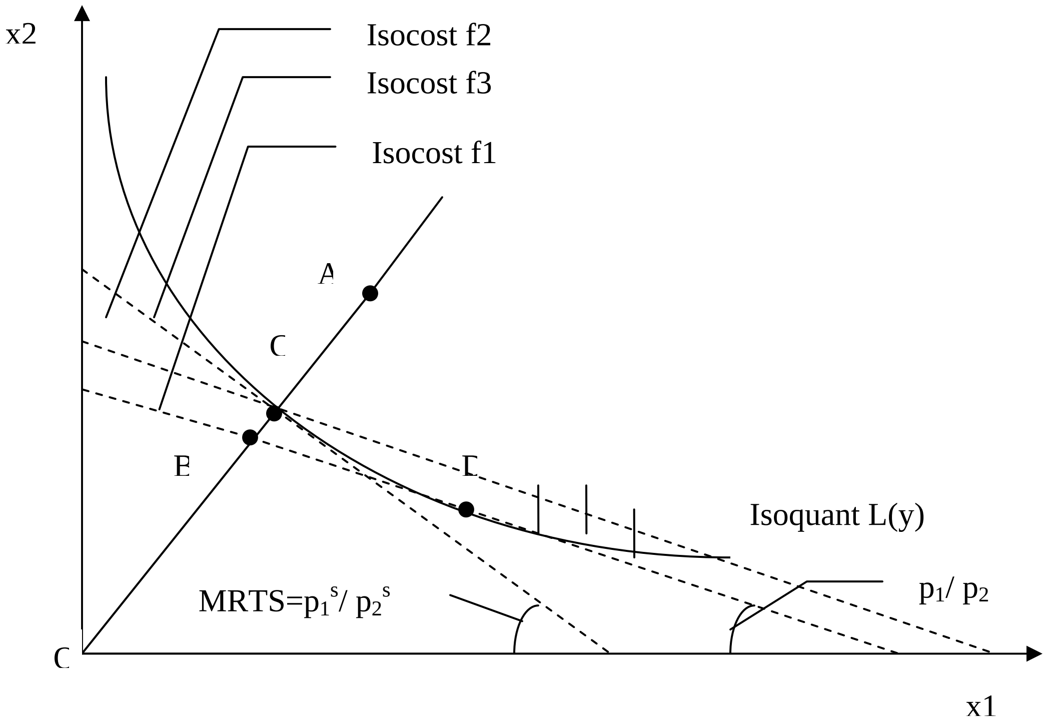

Figure 5. 1: Technical and Allocative Efficiency Identified by Input Distance Function

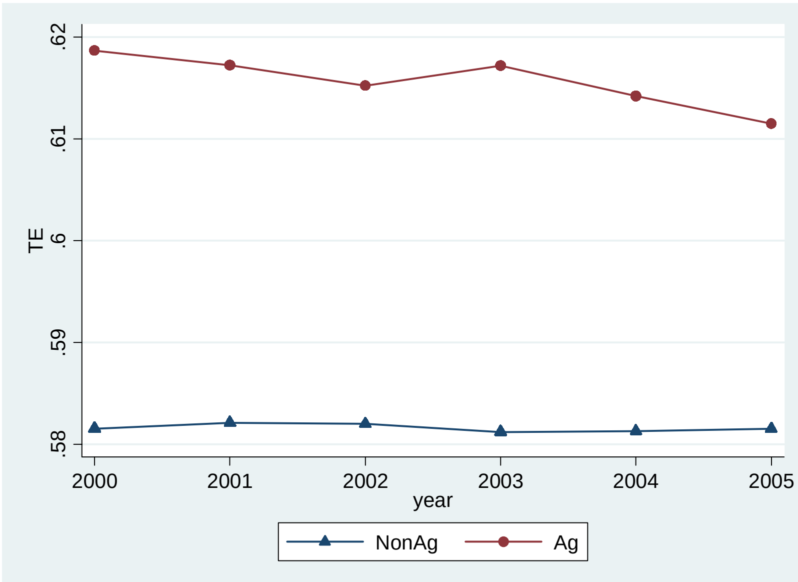

Figure 5. 2: Technical Efficiency Trend by Bank Characteristics

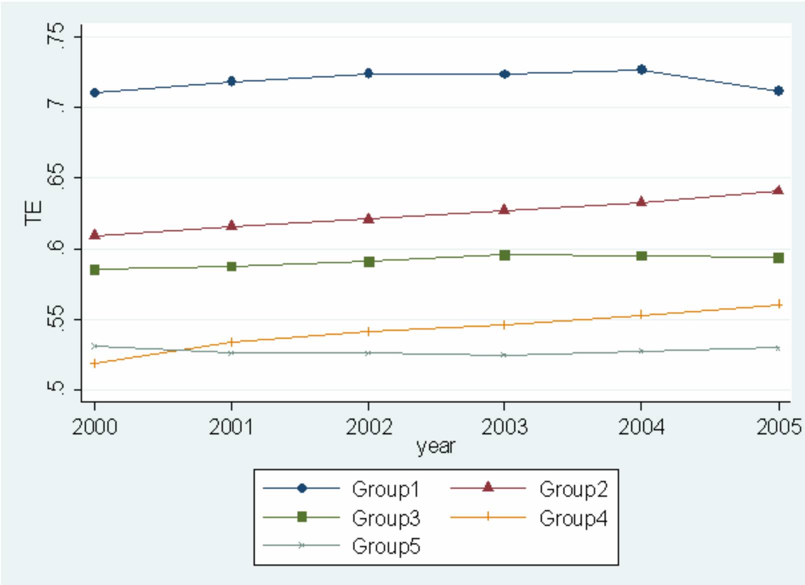

Figure 5. 3: Technical Efficiency Trend by Bank Size

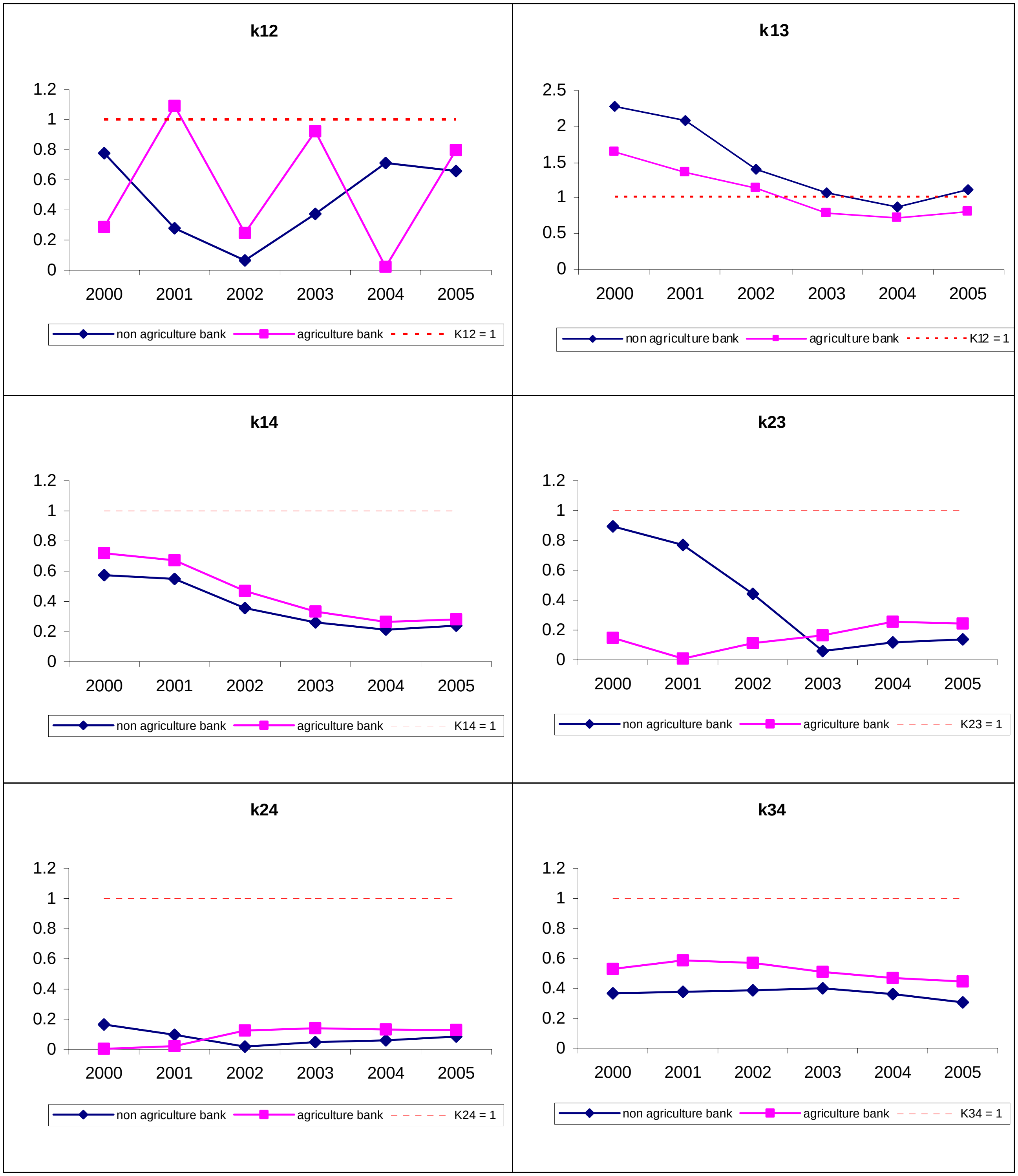

Figure 5. 4: k_{jh} by Bank Characteristics over Years [15]

[15] The subscript of k_{jh} in Figure 5.4 and 5.5 represents the specific input as introduced in the data section. Specifically, 1 is for labor input, 2 is for physical capital input, 3 is for financial capital input, 4 is for debt input

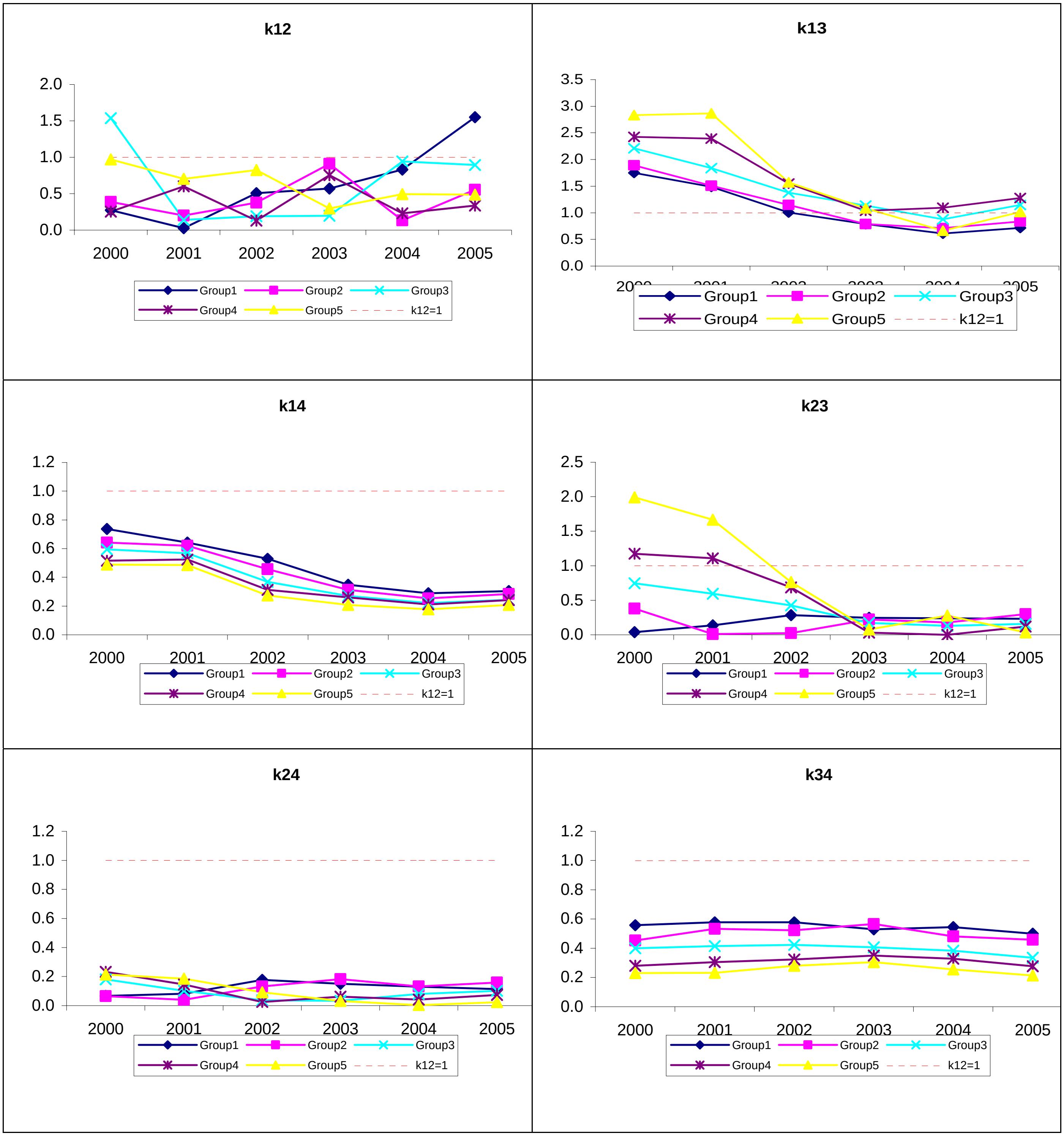

Figure 5. 5: k_{jh} by Bank Size over Years

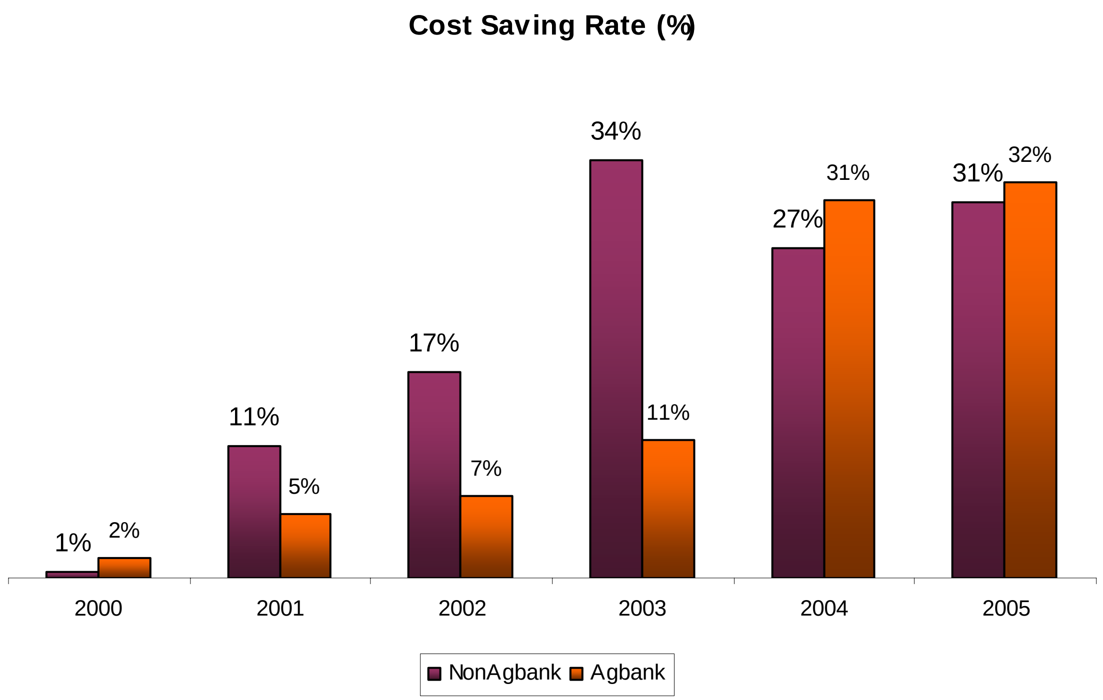

Figure 5. 6: Actual Cost and Optimal Cost Comparison by Bank Characteristics over Years

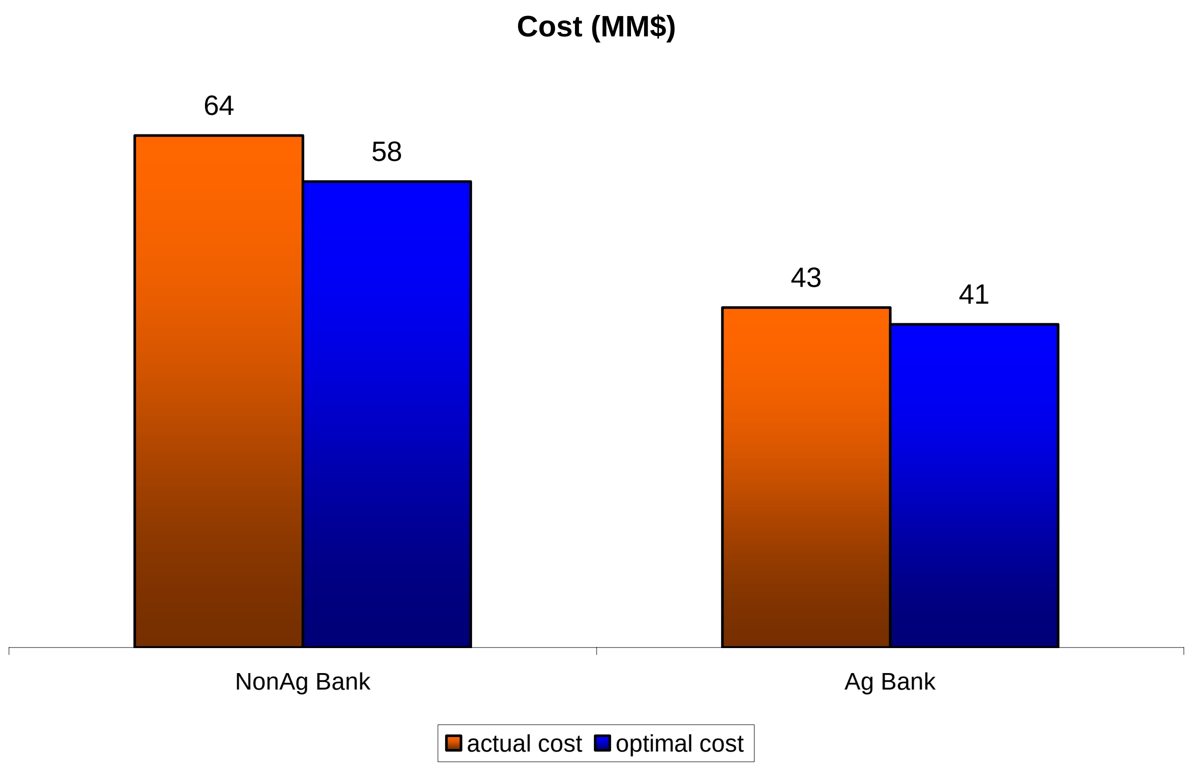

Figure 5. 7: Actual Cost and Optimal Cost Comparison by Bank Characteristics (Average over 2000 – 2005)

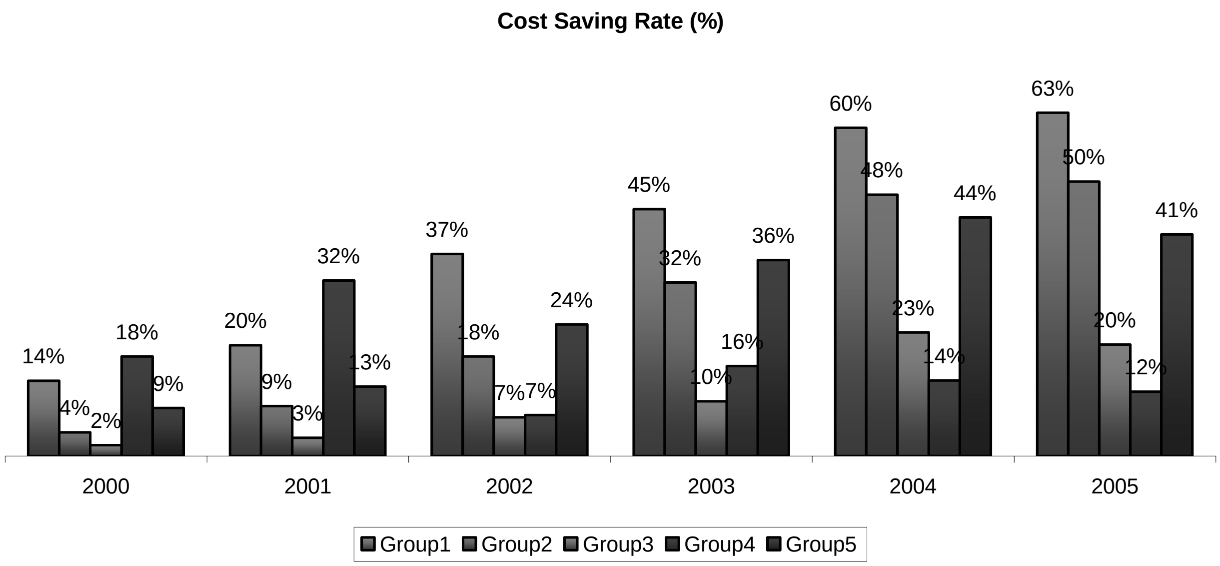

Figure 5. 8: Actual Cost and Optimal Cost Comparison by Bank Size over Years

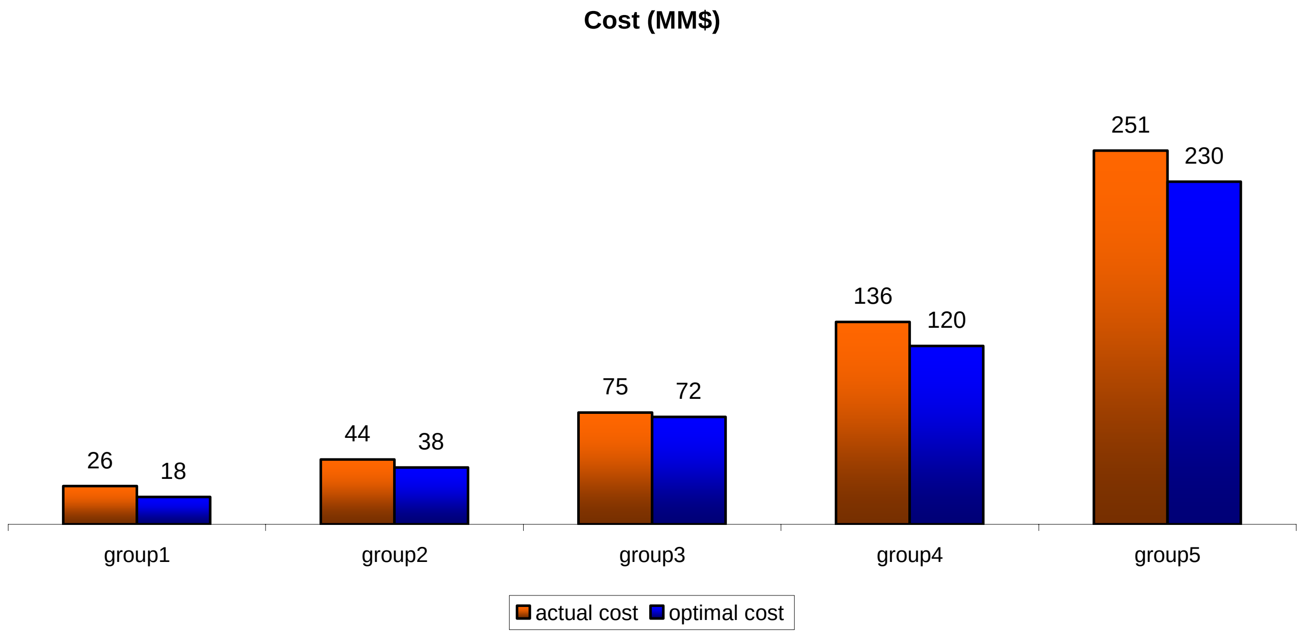

Figure 5. 9: Actual Cost and Optimal Cost Comparison by Bank Size (Average over 2000 – 2005)

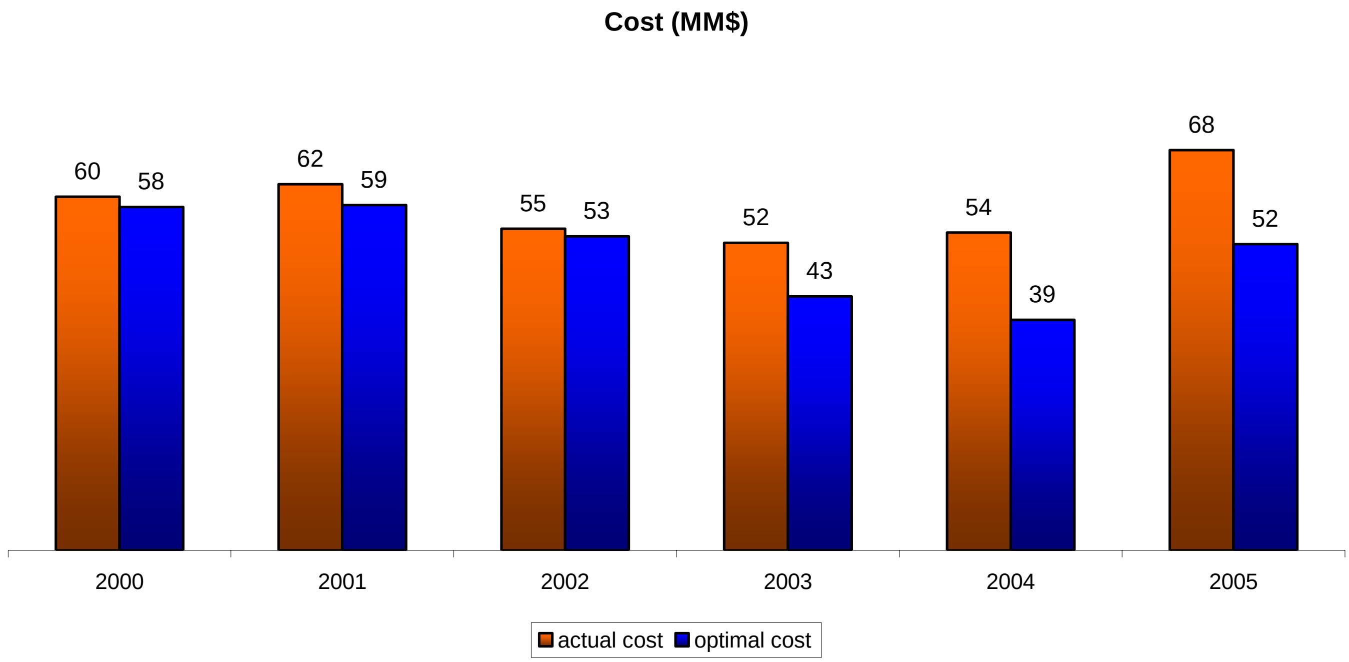

Figure 5. 10: Actual cost and Optimal Cost Comparison over Years for all Banks.

CHAPTER 6

DECOMPOSITION OF THE TOTAL PRODUCTIVITY CHANGE BY SFA AND DEA METHODS

6.1 Introduction

Productivity is an essential concept and measure to assess and compare the firm's operational efficiency. Productivity change can provide meaningful information on the movements in the performance of a firm or an industry over time.

In a situation where a firm only has a single input and output, productivity can be simply treated as the ratio of the output and input. The scale of the ratio for output per unit of input can be used to compare productivity of different firms and analyze productivity changes over time. The larger the ratio is, the higher the productivity. But this analysis can be complicated by the introduction of multiple inputs producing multiple outputs for a firm. In this case, total factor productivity (TFP) would be a more appropriate analytical tool.

TFP can be defined as a ratio of aggregate output produced relative to aggregate input used. But aggregate outputs and aggregate inputs are not just the simple summation of the outputs and inputs, respectively. The "aggregate" measure actually is a weighted summation. So TFP can be expressed as:

$$(6.1)\ TFP = \sum_{k=1}^{M} a_k y_k \Big/ \sum_{j=1}^{N} b_j x_j$$

where a_k and b_j are weights reflecting the relative importance of the different outputs and inputs.

TFP has an important property in which TFP is homogeneous of degree 1 in output and -1 in input. Assuming a firm produces the same output quantities in two periods, t_1 and t_2 (e.g. $t_1<t_2$), the firm's TFP should increase at t_2 if input use decreased at t_2. Similarly, if a firm can use the same quantities of inputs to produce more outputs at t_2, its TFP should also increase at t_2.

Regarding the problem to measure productivity change for a firm from period t_1 to t_2, there are several approaches discussed by Coelli et al. (2005). In this study, the component-based approach to productivity change measurement will be explored.

Balk (2001) describes this approach and asserted that the productivity change can be identified from various sources. The total factor productivity change (TFPC) can be treated as the result of the aggregate effects of those various sources. Generally, TFPC can be segmented as the aggregate effects of technical change (TC), technical efficiency change (TEC), and scale efficiency change (SEC).

TC is used to measure the whole banking industry's technological change. For example, technological innovation will enhance production efficiency. It implies that more outputs will be produced without input reduction. Economically, this change reflects the lifting of the production curve upward.

TEC is used to measure the individual bank's technological change. The movement towards or off of the production curve demonstrates the technical efficiency's improvement and deterioration.

SEC reflects an individual bank's movement toward constant returns of scale level (CRS). If banks move towards CRS, the scale efficiency is improved. Otherwise, the movement results in higher scale inefficiency. It is possible that a firm is technically efficient but the operation scale is not optimal. There are two situations when a firm operates at variant returns of scale

(VRS). If a firm falls within the increasing returns of the scale on the production curve, efficiency can be improved by increasing the entity's size. Conversely, a firm may be too large and operate within the decreasing returns of scale of the production function. In this situation, it should consider decreasing its size.

There are two methodologies which will be applied to estimate the production frontier and identify the sources of the TFPC: Stochastic Frontier Analysis (SFA) and Data Envelope Analysis (DEA). As introduced in Chapter 4, SFA is a parametric estimation method which is based on the assumptions of economics theories. In contrast, DEA is a linear programming method that constructs a non-parametric production frontier by fitting a piece-wise linear surface over data points. Some DMU will be on the frontier (efficient) while others will be inside (inefficient). The technique of DEA produces a deterministic frontier that is generated by observed data. So by construction, some individuals are 'efficient.' This is one of the fundamental differences between DEA and SFA. No formulation has yet been devised that unifies the two into a single analytical framework (Greene, 2008).

The two methods have various advantages and disadvantages. SFA has the advantage to account for noise, while DEA assumes that the data are noise free. Secondly, SFA allows for the conduct of traditional statistical tests of hypotheses, while the traditional technique to estimate DEA does not allow performing such tests (some recent developed advanced mathematical method can do such job, e.g. bootstrapping simulation and Bayesian). However, DEA does not assume a functional form for the frontier or a distributional form for the inefficiency error term. In contrast, SFA needs to specify the functional form and impose the distribution of the error term. The decomposition of the error term into noise and efficiency components may be affected by the particular distributional forms specified and by the related assumption that error skewness is an indication of inefficiency (Coelli et al., 2003). Additionally, SFA is estimated based on inherent economic theory. So any violation of the economic assumptions will lead to biased estimates.

Since there is no evidence that shows the dominance of one methodology over the other, the two methodologies will be discussed in this study. The comparison results will be useful for the sensitivity test for the methodology. The next sections apply the SFA and DEA models to decompose the total productivity change.

6.2 Applying SFA to Decompose Productivity Change

Since chapter 5 has introduced the input distance function and applied SFA to obtain the estimates, this chapter will utilize those results to show how to identify the different factors that contribute to TFPC.

Following the general approach provided by Coelli et al. (2003a), the TFPC between time period t_2 and t_1 (i.e. $t_2 > t_1$) can be calculated as following:

$$\begin{aligned} TFPC &= \ln(TFP_{it_2} / TFP_{it_1}) \\ &= \ln(TE_{it_2} / TE_{it_1}) + \frac{1}{2}[(\partial \ln D^I_{it_1} / \partial t) + (\partial \ln D^I_{it_2} / \partial t)] \\ &\quad + \frac{1}{2}\sum_{k=1}^{M}[(SF_{it_1} e_{k,it_1} + SF_{it_2} e_{k,it_2}) \times (\ln y_{k,it_2} - \ln y_{k,it_1})] \end{aligned} \tag{6.2}$$

where three components on the right hand side of the equation (6.2) are the TEC, TC, and SEC, respectively.

$$TEC = \ln(TE_{it_2} / TE_{it_1}) \tag{6.3}$$

$$TC = \frac{1}{2}[(\partial \ln D^I_{it_1} / \partial t) + (\partial \ln D^I_{it_2} / \partial t)] \tag{6.4}$$

$$SEC = \frac{1}{2}\sum_{k=1}^{M}[(SF_{it_1} e_{k,it_1} + SF_{it_2} e_{k,it_2}) \times (\ln y_{k,it_2} - \ln y_{k,it_1})] \tag{6.5}$$

The technical efficiency levels in each period *t* required to calculate TEC in equation (6.3), TE_{it}, can be calculated by equation (5.10) from chapter 5.

Deriving the first partial derivatives of the Translog input distance function, (5.2) from chapter 5 can be expressed as:

$$(6.6)\quad \partial \ln D_{it}^{I} / \partial t = \sum_{k=1}^{M} \alpha_k \ln y_{k,it} + \sum_{j=1}^{N} \delta_j \ln x_{j,it} + \sum_{d=1}^{P} \theta_d \ln z_{d,it} + \lambda_1 + \lambda_2 t$$

TC can be calculated by substituting equation (6.6) into equation (6.4).

e_{k,it_1} in equation (6.5) is the production elasticities. Considering equation (5.2), it can be derived as:

(6.7)

$$e_{k,it} = \partial \ln D_{it}^{I} / \partial \ln y_{k,it} = \beta_{y_k} + \sum_{l=1}^{M} \beta_{y_{kl}} \ln y_{l,it} + \sum_{j=1}^{N} \beta_{xy_{jk}} \ln x_{j,it} + \sum_{d=1}^{P} \beta_{yz_{kd}} \ln z_{d,it} + \alpha_k t$$

The last unknown parameters in equation (6.5), SF_{it}, is defined as:

$$(6.8)\quad SF_{it} = \left(\sum_{k=1}^{M} e_{k,it} + 1 \right) \Big/ \sum_{k=1}^{M} e_{k,it}$$

Substituting (6.7) and (6.8) into (6.5), SEC can be calculated. After acquiring TEC, TC, and SEC, TFPC can be calculated by substituting them into equation (6.2).

6.3 Applying DEA to Decompose Productivity Change

In this section, the Malmquist TFP index and DEA are introduced to identify the various sources to the productivity change.

The Malmquist TFP index was first proposed by Caves et al. (1982a, 1982b). They defined Malmquist TFP index based on input and output distance function in their studies. In this study, only Malmquist TFP index based on the input distance function will be discussed and implemented to identify the sources of TFPC.

The Malmquist TFP index measures the TFPC between two periods by calculating the ratio of the distances of each data point relative to a common technology. Following Fare et al.(1994), the input-oriented Malmquist TFP is defined as:

(6.9) [16] $$M(t_t, t_2) = TFP_{t_2} / TFP_{t_1} = \left[\frac{D_{t_2}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})}{D_{t_2}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})} \cdot \frac{D_{t_1}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})}{D_{t_1}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})} \right]^{1/2}$$

where $D_{t_2}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})$ represents the distance from observation at period t_1 relative to the technology at period t_2; $D_{t_2}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})$ represents the distance from observation at period t_2 relative to the technology at period t_2; $D_{t_1}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})$ represents the distance from observation at period t_1 relative to the technology at period t_1; $D_{t_1}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})$ represents the distance from observation at period t_2 relative to the technology at period t_1.

Coelli et al. (2003a) decomposed the equation (6.9) as:

(6.10) $$M(t_t, t_2) = TEC \cdot SEC \cdot TC$$

Specifically, TEC, SEC, and TC can be expressed as:

(6.11) $$TEC = \frac{D^V_{t_1}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})}{D^V_{t_2}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})}$$

(6.12) $$SEC = \frac{D^V_{t_2}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})}{D^V_{t_1}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})} \cdot \frac{D^C_{t_1}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})}{D^C_{t_2}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})}$$

(6.13) $$TC = \left[\frac{D^C_{t_2}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})}{D^C_{t_1}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})} \cdot \frac{D^C_{t_2}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})}{D^C_{t_1}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})} \right]^{1/2}$$

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[16] Since all input distance function in this study is input distance function, the superscript *I* indicating input distance function will be omitted for the rest of the formulas or equations.

where the superscript *C* represents constant returns to scale (CRS) technology, while superscript *V* represents the variable returns to scale (VRS) technology. All other denotations are kept the same as defined before.

In order to estimate equation (6.11) through equation (6.13), a set of linear programming (LP) problems need to be solved. Charnes et al. (1978) showed how to apply DEA to solve these LP problems. Following Ferraro (2004), this optimization problem can be expressed as:

$$
\begin{aligned}
& \left[D_{t_1}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})\right]^{-1} = \max_{\theta,\boldsymbol{\lambda}} \theta \\
(6.14)\quad & s.t. \quad -\mathbf{y}_{it_1} + \mathbf{Y}_{t_1}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \theta\mathbf{x}_{it_1} - \mathbf{X}_{t_1}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \boldsymbol{\lambda} \geq \mathbf{0}
\end{aligned}
$$

$$
\begin{aligned}
& \left[D_{t_2}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})\right]^{-1} = \max_{\theta,\boldsymbol{\lambda}} \theta \\
(6.15)\quad & s.t. \quad -\mathbf{y}_{kt_2} + \mathbf{Y}_{t_2}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \theta\mathbf{x}_{jt_2} - \mathbf{X}_{t_2}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \boldsymbol{\lambda} \geq \mathbf{0}
\end{aligned}
$$

$$
\begin{aligned}
& \left[D_{t_1}(\mathbf{y}_{t_2}, \mathbf{x}_{t_2})\right]^{-1} = \max_{\theta,\boldsymbol{\lambda}} \theta \\
(6.16)\quad & s.t. \quad -\mathbf{y}_{kt_2} + \mathbf{Y}_{t_1}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \theta\mathbf{x}_{jt_2} - \mathbf{X}_{t_1}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \boldsymbol{\lambda} \geq \mathbf{0}
\end{aligned}
$$

$$
\begin{aligned}
& \left[D_{t_2}(\mathbf{y}_{t_1}, \mathbf{x}_{t_1})\right]^{-1} = \max_{\theta,\boldsymbol{\lambda}} \theta \\
(6.17)\quad & s.t. \quad -\mathbf{y}_{kt_1} + \mathbf{Y}_{t_2}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \theta\mathbf{x}_{jt_1} - \mathbf{X}_{t_2}\boldsymbol{\lambda} \geq \mathbf{0} \\
& \qquad\quad \boldsymbol{\lambda} \geq \mathbf{0}
\end{aligned}
$$

where $\mathbf{y}_{it} = (y_{1,it} \ldots y_{k,it} \ldots y_{M,it})'$ is $M \times 1$ vector representing the i^{th} firm's outputs at time *t*. $\mathbf{x}_{it} = (x_{1,it} \ldots x_{j,it} \ldots x_{N,it})'$ is $N \times 1$ vector representing the i^{th} firm's inputs at time *t*. $\mathbf{Y}_t$ is a $M \times I$ outputs matrix at time *t*. $\mathbf{X}_t$ is a $N \times I$ outputs matrix at time *t*. I is the total number of firms at each time t. θ is a scalar used to measure the value of the distance function. λ is $I \times 1$ constant vectors which represents the optimized coefficients for inputs and outputs.

6.4 Data

This study utilized the panel dataset described in Chapter 3. Details on the descriptive statistics of the variables used for this study have been presented in Chapter 3.

6.5 Empirical Results

Table 6.1 gives the TFPC decomposition comparison using SFA and DEA methods for this study's sample of banks. Both SFA and DEA results showed an increased TFPC over 6 years from 2000 to 2005. But the results are not consistent under the two methods. The increased TFP calculated by SFA is two times more than the value calculated by DEA. Specifically, the SFA showed that TFPC is 2.5%, while DEA showed that TFPC is only 1.5%. Table 6.1 further demonstrates that the inconsistency does not only occur on the TFPC's magnitude but also on its decomposition source. Moreover, SFA implies that the increase of the TFPC is mainly driven by the higher scale efficiency yields. The contribution of the technical change is small but it is a positive driver. However DEA produces a rather different result. It showed that the technical innovation is the primary factor that led to higher TFPC, given the 2.6% TC increase. From 2000 to 2005, instead of contributing to the increase of the TFPC, scale efficiency offsets the 0.3% gains from the technical enhancement. Meanwhile, it is worth noticing the different levels of TEC measured under SFA and DEA. SFA indicated that there is an insignificant decrease of the technical efficiency change. This result is consistent with our earlier finding that the input distance function is time-invariant model. But the DEA result implies that the technical efficiency decayed significantly during the period selected in the study. Overall, the technical efficiency decreased by 1%. As a result, it offset 50% of the TFPC gains. This result is consistent with the findings by Bauer et al. (1998). They found that DEA approach yields much lower average efficiencies than SFA does. The reason is because the DEA treats the random errors as part of measured inefficiencies (Choi et al. 2007). By comparing the TFPC between adjacent years, the SFA study shows that the highest TFP increase happened between 2004 and 2005. During this period, the banking industry's TFP increased by 3.3%. In contrast, the DEA implies that the highest TFP occurred between 2003 and 2004 when it increased by 2.9%.

Table 6.2 presents the result of the TFPC decomposition by bank characteristics in each method. To better address the impacts of the two methods on different bank characteristics, the discussion will be conducted from two angles. First, we will look at the table vertically for each method to compare the results by bank characteristic. Secondly, we will look at the table horizontally for the same bank characteristics to exploit the impact of the methods.

SFA results in Table 6.2 suggest that the TFPC is different between agricultural banks and non agricultural banks. Overall, the TFP increased 2.93% and 2.46% in agricultural banks and non agricultural banks, respectively. Comparing the contribution of the TEC, TC, and SEC to TFPC between agricultural and non agricultural banks, it is clear that the higher scale efficiency increase in agricultural banks resulted in the higher TFP gains. Specifically, the agricultural banks' SE increased by 0.4% more than non agricultural banks. Comparatively, the TEC and TC are not affected by bank characteristics because there is no significant difference for TEC and TC between agricultural and non agricultural banks. Positive TC contributes to the increase of the TFP, while negative TEC slightly offsets the increase of the TFP. Both agricultural and non agricultural banks yield the highest TFP between 2004 and 2005.

As in the SFA method, DEA results suggest the differentiation by bank characteristics in terms of the TFPC. In the six years between 2000 and 2005, TFP in agricultural banks increased by 2% compared to 1.5% in non agricultural banks. This efficiency gains for both agricultural and non agricultural banks are motivated by adopting better efficient techniques as reflected in the increase of the TC. But the SEC in agricultural banks increased by 1% more than in non agricultural banks. This becomes the motion leading to the higher increase of the TFPC for agricultural banks. Meanwhile, it is noticed that the TEC and SEC made negative contributions to the TFPC. In agricultural banks, TEC and SEC offset the increase of the TFP by 0.9% and 0.1%, respectively. In non agricultural banks, they dragged down the TFP by 0.6% and 0.2%, accordingly. Additionally, we observed one negative TFPC for agricultural banks between 2004 and 2005. Between these two years, the TFP decreased by 1.4% due to 3.4% drop in TC. This is the only exception identified by DEA. This exception indicates that the decomposition of TFP using DEA method implies that agricultural banks may have not fully utilized the benefits brought by the whole industry's technological improvement during 2004 and 2005. Other than that, the TFP is increasing steadily over years for both agricultural and non agricultural banks. But the TFPC in agricultural banks seems to be more volatile than non agricultural banks.

Regardless of bank characteristics, the TFPC comparison between SFA and DEA methods showed that SFA always over estimate TFP increase than DEA. But the level of the over estimation is different across bank characteristics. Agricultural banks have higher over estimation than non agricultural banks. Accordingly, all components of the TFPC, TEC, TC, and SEC are more highly over estimated for agricultural banks in terms of the magnitude.

Table 6.3 compares the decomposition of the TFPC by bank size in the application of the different estimate methods. The table shows that the results given by the DEA method are very volatile. It indicates that DEA may not be a robust method in comparing TFPC by bank size. So the subsequent discussion will focus instead on the SFA method.

SFA method reveals that the smaller bank group may benefit more from the increase of the SE to achieve higher TFP increase. It implies that smaller banks are operating at the increasing returns of scale stage. Their expansion of the bank size should be the easiest way to improve the TFP. The increase in SE over the years indicates that these banks are moving in right direction. Meanwhile, it is notable that the gains from SE increase are diminishing over the years as can be deduced from the decreasing trend noted in the positive SEC magnitude. It indicates that the benefits from the expansion will finally be exhausted. Once they realize constant returns of scale level, any further expansion will lead to a negative SEC. Differently from the SEC, we noticed that the TC is increasing year by year no matter which size groups the banks are from. Meanwhile, the weight of the contribution to the increased TFP is leaning towards positive TC. It indicates that technical innovation should be a sustainable way to increase TFPC. Additionally, it is worth to address the fact that the magnitudes of the positive TC in larger banks are higher than smaller banks. It implies the large banks focus more on technical innovation after scale efficiency gains have been exhausted. It also reflects that large banks have greater capability to implement technical innovation.

Table 6. 1: TFPC Decomposition for Whole Banking Industry

Time Interval	SFA				DEA			
	TEC	TC	SEC	TFPC	TEC	TC	SEC	TFPC
2000-2001	-0.06%	-0.05%	2.54%	2.43%	-2.40%	3.70%	-0.50%	1.20%
2001-2002	-0.06%	0.39%	1.60%	1.93%	-1.30%	2.80%	0.30%	1.50%
2002-2003	-0.06%	0.83%	1.51%	2.28%	-2.70%	3.70%	-1.10%	0.90%
2003-2004	-0.06%	1.27%	1.50%	2.71%	-0.80%	3.80%	-0.50%	2.90%
2004-2005	-0.06%	1.71%	1.69%	3.34%	1.90%	-1.00%	0.40%	0.90%
overall	-0.06%	0.83%	1.77%	2.54%	-1.00%	2.60%	-0.30%	1.50%

Table 6. 2: TFPC Decomposition by Bank Characteristics

Bank Characteristics	Time Interval	SFA				DEA			
		TEC	TC	SEC	TFPC	TEC	TC	SEC	TFPC
Agricultural Bank	2000-2001	-0.05%	0.04%	2.94%	2.93%	-1.50%	7.70%	0.20%	6.10%
	2001-2002	-0.05%	0.46%	2.39%	2.79%	-0.90%	3.60%	-0.40%	2.60%
	2002-2003	-0.05%	0.87%	1.81%	2.63%	-2.20%	3.60%	-0.40%	1.30%
	2003-2004	-0.05%	1.31%	1.63%	2.88%	-1.80%	3.60%	-0.30%	1.70%
	2004-2005	-0.05%	1.74%	1.74%	3.42%	2.00%	-3.40%	0.20%	-1.40%
	overall	-0.05%	0.88%	2.10%	2.93%	-0.90%	3.00%	-0.10%	2.00%
Non Agricultural Bank	2000-2001	-0.06%	-0.06%	2.46%	2.34%	-2.00%	2.20%	-0.30%	0.20%
	2001-2002	-0.06%	0.38%	1.44%	1.76%	-1.10%	2.40%	0.40%	1.30%
	2002-2003	-0.06%	0.82%	1.45%	2.21%	-1.90%	3.20%	-1.20%	1.20%
	2003-2004	-0.06%	1.26%	1.48%	2.68%	-0.20%	3.30%	-0.50%	3.20%
	2004-2005	-0.06%	1.71%	1.68%	3.32%	2.50%	-0.90%	0.90%	1.50%
	overall	-0.06%	0.82%	1.70%	2.46%	-0.60%	2.00%	-0.20%	1.50%

Table 6. 3: TFPC Decomposition by Bank Size

Bank Size	Time Interval	SFA				DEA			
		TEC	TC	SEC	TFPC	TEC	TC	SEC	TFPC
Group1	2000-2001	-0.04%	-0.42%	4.14%	3.68%	1.50%	1.00%	0.60%	2.50%
	2001-2002	-0.04%	0.00%	2.74%	2.69%	-1.50%	-1.10%	-0.80%	-2.60%
	2002-2003	-0.04%	0.40%	2.16%	2.52%	-1.30%	5.80%	-0.90%	4.40%
	2003-2004	-0.04%	0.80%	2.38%	3.14%	-1.90%	2.10%	0.30%	0.10%
	2004-2005	-0.04%	1.19%	1.81%	2.96%	0.80%	-1.70%	0.20%	-0.90%
	overall	-0.04%	0.39%	2.64%	3.00%	-0.50%	1.20%	-0.10%	0.70%
Group2	2000-2001	-0.05%	-0.21%	2.49%	2.23%	-1.20%	2.90%	-1.00%	1.70%
	2001-2002	-0.05%	0.20%	1.66%	1.81%	0.00%	1.80%	-0.30%	1.80%
	2002-2003	-0.05%	0.61%	1.94%	2.49%	-2.50%	4.30%	-0.90%	1.70%
	2003-2004	-0.05%	1.03%	1.57%	2.54%	2.30%	-1.10%	1.30%	1.10%
	2004-2005	-0.05%	1.45%	2.13%	3.53%	2.50%	-1.60%	1.50%	0.80%
	overall	-0.05%	0.62%	1.96%	2.52%	0.20%	1.20%	0.10%	1.40%
Group3	2000-2001	-0.06%	-0.14%	2.80%	2.60%	0.50%	2.20%	0.80%	2.70%
	2001-2002	-0.06%	0.28%	1.88%	2.10%	-0.70%	2.30%	0.00%	1.60%
	2002-2003	-0.06%	0.72%	1.65%	2.31%	-3.20%	7.50%	-1.00%	4.00%
	2003-2004	-0.06%	1.17%	1.70%	2.81%	3.20%	-2.90%	1.40%	0.30%
	2004-2005	-0.06%	1.61%	1.91%	3.47%	1.60%	-2.80%	1.10%	-1.20%
	overall	-0.06%	0.73%	1.99%	2.66%	0.30%	1.20%	0.50%	1.50%
Group4	2000-2001	-0.07%	0.04%	2.96%	2.93%	0.20%	0.00%	0.00%	0.20%
	2001-2002	-0.07%	0.50%	1.53%	1.97%	0.90%	4.20%	1.10%	5.10%
	2002-2003	-0.07%	0.96%	1.69%	2.58%	-1.40%	15.90%	-1.50%	14.30%
	2003-2004	-0.07%	1.41%	1.71%	3.04%	-0.50%	11.40%	0.20%	10.80%
	2004-2005	-0.07%	1.87%	2.02%	3.81%	4.90%	-6.70%	3.10%	-2.10%
	overall	-0.07%	0.95%	1.98%	2.87%	0.80%	4.70%	0.60%	5.50%
Group5	2000-2001	-0.07%	0.36%	1.10%	1.39%	-1.60%	1.50%	-1.00%	-0.20%
	2001-2002	-0.07%	0.83%	0.61%	1.36%	-3.50%	6.30%	-0.60%	2.60%
	2002-2003	-0.07%	1.29%	0.45%	1.67%	2.10%	-0.70%	0.80%	1.40%
	2003-2004	-0.07%	1.75%	0.55%	2.23%	2.70%	0.10%	1.70%	2.80%
	2004-2005	-0.07%	2.22%	0.56%	2.71%	-1.70%	4.70%	-0.60%	2.90%
	overall	-0.07%	1.29%	0.66%	1.87%	-0.40%	2.40%	0.00%	1.90%

CHAPTER 7

SUMMARY AND IMPICATIONS

7.1 The Fourier Flexible Cost Function and Economies Scale and Scope

This study has introduced the application of the FF functional form in the estimation of banks' operating costs and the subsequent analyses of the effects of bank size and product specialization on efficiency measures. Product specialization categories allow the comparative assessments of efficiency between agricultural and non-agricultural banks.

This study's cost estimation results lend support to previous empirical works on commercial banks that establish the FF model's greater capability to produce more plausible results than the translog model. The inclusion of loan quality and financial risk indexes in this study's models reveal these variables' importance in explaining variations in banks' operating costs.

Among the efficiency measures capturing economies of scale and scope, the RSE results under the FF model suggest evidence of increasing returns to scale for small and medium-size banks, with these economies of scale benefits reverting to constant returns to scale for larger banks operating with more than $10 billion assets. In terms of specialization categories, agricultural banks (which operate relatively smaller operations than non-agricultural banks) have demonstrated a stronger tendency to maximize the potentials of increasing returns to scale from output expansion. The EPSE measures obtained confirm these trends under both the FF and translog models. The results indicate that increasing returns to scale are realized when banks expand from a smaller to a larger output bundle under different product mixes. These trends are evident in the proliferation of bank merger and consolidation decisions made in recent years. Through improvements in operating and financial structures and conditions realized from the availability of advance technology and innovations introduced in recent years, the benchmark for realizing favorable returns structure and financial efficiency have been raised significantly. In this study, the critical bank size limit for exhausting economies of scale opportunities is estimated at around $10 billion. Moreover, the smaller operations of agricultural banks offer them more opportunities to realize increasing returns to scale than their larger banking counterparts.

Consistent with the findings of previous studies, the translog model has been shown to produce more intuitive results for the economies of scope analyses. The SCOPE results indicate that economies of scope realized by smaller banks could tend to diminish and revert to diseconomies of scale as banks expand their operations and increase their asset bases. EPSUB results suggest that the banks' costs are slightly "super-additive" along the expansion path from mid- to large size categories.

The SCOPE results for agricultural and non-agricultural banks provide interesting implications. The greater risks and uncertainty usually associated with farm business operations have often raised doubts about the viability of the specialized operations of agricultural banks. This study's results actually prove the naysayers wrong by confirming that agricultural banks are more likely to thrive more efficiently under specialized lending operations while non-agricultural banks are more inclined to realize diseconomies of scale under greater diversification of their services.

This study's initiation of the FF functional model into agricultural banking efficiency analysis paves the way for further research efforts that might want to consider other areas of interests, such as introducing uncertainty, transactions costs, and bank inputs shareability into the model.

7.2 The Input Distance Function and Efficiency Measures

This study has introduced the application of the Input Distance function to measure the banks' operating efficiency and the subsequent analyses of the effects of bank size and product specialization on efficiency measures. Product specialization categories allow the comparative assessments of efficiency between agricultural and non-agricultural banks. The bank size categories allow the comparative assessments of efficiency between large banks and small banks.

The estimation of the input distance function supports the hypotheses that bank characteristics and size have impacts on technical efficiency levels. Specifically, agricultural banks performs have been found to be more technically efficient than non agricultural banks. The TE of agricultural banks is 4% higher than that calculated for non agricultural banks. Small banks are more efficient than large banks in terms of their TE. On average, banks with assets of less than $1 billion can be 19% more efficient than banks with assets of over $10 billion. Meanwhile, the technical efficiency measures showed that the whole banking sample used in this study does not operate close to the efficient path and the nature of the time-invariant input distance function gives evidence that this scenario has not been improved between 2000 and 2005.

Results of the relative allocative efficiency measures suggest that inefficiency due to improper input allocation has been verified to be true for the sample of banks used in this study. Results for some efficiency measures indicate the influence of bank characteristics and size on the measures, although in certain cases, these factors were not significant indicators. A more definitive conclusion cannot be therefore made with respect to efficiency comparisons between agricultural and non agricultural banks across different bank size groups. However, it is notable that all results implied that bank deposits are under utilized as a source of capiptal in the banks. Banks should recognize this relatively cheaper fund source as a potential instrument for achieving input allocative efficiency.

This analysis demonstrated that banks paid a high price for the allocative inefficiency. They could have saved the costs significantly by efficiently allocating their inputs efficiently. Specifically, agricultural banks could have saved 2 MM USD and non agricultural banks could have saved 6 MM USD on average. Different bank size groups could also benefit by achieving allocative efficiency, which would translate to cost savings ranging from 2% to 29%.

7.3 The TFPC decomposition by SFA and DEA

The study introduced the SFA and DEA methods to decompose TFPC into its specific components: TEC, TC, and SEC. The results of this analysis will aid in the evaluation of the current financial industry's policy by helping identify strategies involving the source of TFPV that could be considered in the formulation of future operating policies.

The analysis showed that TFP increased in both SFA and DEA models over the six-year period (2000-2005). But the results revealed by the two different models are not always consistent in terms of both the magnitude and components of the TFPC. As for the magnitude, the SFA produces higher positive estimates for TFPC than DEA. As for the components, SFA showed that the increase in TFPC is mainly due to higher scale efficiency yields. Technical change made a slightly positive contribution. However, DEA showed that the SEC made a negative contribution to the TFPC. Positive TC reflecting technical innovation is the primary driver for higher TFP. In addition, SFA showed that the TE over the years did not change. But DEA claimed that technical efficiency decayed significantly.

Both SFA and DEA showed the influence of bank characteristics on TFPC. The TFPC estimate provided by DEA, however, is more volatile. Meanwhile, both methods indicated that agricultural banks benefit more from larger positive SEC contributions to TFPC. However, SFA produced positive TC and slightly negative TEC contributions, while both TC and TEC are negative evaluated by DEA method.

In terms of the results in this study, the SFA method seems to be a more reliable method that can be recommended for the evaluation of TFPC by bank size. This analysis indicated that smaller banks are more interested in expanding their bank size to fully utilize higher positive SEC contributions to TFPC. In contrast, large banks usually focus more on the contribution of technical innovation to TFPC. Meanwhile, the positive SE contribution will finally be exhausted by expanding bank size. Comparatively, the technical innovation option seems to be a more sustainable alternative to increasing TFP.

7.4 Implications of studies

In general, the three studies discussed the banking efficiencies from different aspects. The studies identified the inefficiency sources and explore the opportunities to operate in more efficient way. This efficiency improvement will be vital to determine if a bank will have better survival odds compared to its counterparts.

The majority of the existing researches are related to the commercial banks. Very limited studies for agricultural banks are conducted. The results revealed in the studies are more meaningful for agricultural banks. The beneficiaries are not only the regulator but also the lenders who are providing the fund for daily business. Today, the financial credit is becoming tighter. The lenders are more cautious for loan's purpose. The safety and profitability are two factors for their decision. Comparing to the other industries, the channels of the agricultural funds are heavily relying on the agricultural banks. So the agricultural banks' confidence for lending is very important for rural economy and even for the entire economy's recovery. Better understanding the efficiency levels and identifying the effective ways to improve the efficiency will be helpful to build this confidence.

The scale and scope economy studies answered if banks have opportunities to expand the outputs scale or business scope to gain better profits. The scale of economy study showed that the agricultural banks have stronger tendency to maximize the potentials of increasing returns to scale from output scale expansion. This finding provides the strong evidence for agricultural banks to expand the agricultural loan size. The result of the scope of economy research also gives agricultural banks' confidence to stay with the specialized mode of production focusing on the agricultural activities.

The technical efficiency and allocative efficiency analysis tried to exploit the inefficiency sources on input aspects. The comparatively higher technical efficiency in agricultural banks than non agricultural banks implies that the agricultural loans specialized future is proper for agricultural banks. However, the technical efficiency decline occurred in agricultural banks over years from 2000 to 2005 sends out the warning. Agricultural banks should pay attention on the diminishing technical efficiency superior. In the meanwhile, the considerable technical inefficiency for agricultural banks reminds that the agricultural banks should make more efforts to improve their technical efficiencies. The widely existing allocative inefficiency in agricultural banks indicates that the correction of the allocation among labor, physical capital, financial capital, and deposits could save the operating cost potentially. Different from the non agricultural banks, agricultural banks may take advantage of comparatively smaller asset and simple business structure to be more flexible for input adjustment. Reduction of the labor and physical capital inputs and raise the financial capital and deposits may be considered. Since the financial capital is more costly and harder to adjust compared to the deposit, agricultural banks may need to think about the effective ways to absorb more deposits. This may bring the issue how to differentiate itself from others by generating higher capital returns and providing higher quality services to the publics. The huge cost saving for agricultural banks by achieving the efficiency shown in the study will stimulate the enthusiasm to make such efforts.

The total factor productivity decomposition study provides a backward looking way to measure the productivity change and different factors' contribution to this change. The results can be used to evaluate the performance in past years and shed the light in the future how to make banks more productive. It is clear that both technological change and scale efficiency change makes the positive contribution to the higher productivity level for agricultural banks. But the gains from the expanding bank scale are decreasing but the gains from the technological innovation are increasing over years. Agricultural banks should be benefit from this study after they realizing that they cannot obtain the consistent productivity gains by expanding the bank size as they were in the past. They are benefiting from the technological innovation in the past and they will be further benefiting in the future. This result will direct them to invest more on the technological innovation in the future.

All studies are also very useful for the banking regulators. These results may make regulators seeking to ensure the efficient and safety banking sector. The efforts to control the credit risks by enforcing more strict regulations may make more available credits migrate to the more efficient agricultural banks. In the meanwhile, the regulators see the bank specification in general will be more efficiently operated. They may constrain the banks to be more focus on the core business. In this case, the deregulation trend in financial industry may be re-investigated in the future. The new policy maybe inclines to the more specialized banking industry. This possible change may provide more opportunities for agricultural banks.

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APPENDICES

Appendix 1: Elementary Multi-Index Vectors K_h

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
q1	1	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0
q2	0	1	0	0	0	-1	0	0	0	1	1	1	0	0	0	1	0	0	0	1	1	1	0	0	0
q3	0	0	1	0	0	0	-1	0	0	-1	0	0	1	1	0	0	1	0	0	1	0	0	1	1	0
q4	0	0	0	1	0	0	0	-1	0	0	-1	0	-1	0	1	0	0	1	0	0	1	0	1	0	1
q5	0	0	0	0	1	0	0	0	-1	0	0	-1	0	-1	-1	0	0	0	1	0	0	1	0	1	1
|kh|	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

h	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50
L1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
L2	-1	0	0	1	1	0	-1	-1	-1	-1	-1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
L3	0	-1	0	-1	0	1	0	0	0	0	0	-1	-1	-1	-1	-1	0	0	0	0	0	-1	-1	-1	-1
L4	0	0	-1	0	-1	-1	0	0	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1	0	0	0	0
q1	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0	0	0
q2	0	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0	0
q3	0	0	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0
q4	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1
q5	0	0	0	0	0	0	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0	-1	0	0	0	0
|kh|	2	2	2	2	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3

h	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75
L1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
L2	1	0	0	0	0	0	-1	-1	-1	-1	-1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
L3	-1	1	1	1	1	1	0	0	0	0	0	-1	-1	-1	-1	-1	0	0	0	0	0	-1	-1	-1	-1
L4	0	-1	-1	-1	-1	-1	0	0	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1	0	0	0	0
q1	0	-1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0
q2	0	0	-1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0
q3	0	0	0	-1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0
q4	0	0	0	0	-1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1
q5	-1	0	0	0	0	-1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0
|kh|	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3

h	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
L1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
L2	1	0	0	0	0	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
L3	-1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

L4	0	-1	-1	-1	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
q1	0	1	0	0	0	0	1	1	1	0	0	0	0	-1	-1	-1	-1	0	0	0	0	0	0	1	1
q2	0	0	1	0	0	0	1	0	0	1	1	1	0	-1	0	0	0	-1	-1	-1	0	0	0	1	0
q3	0	0	0	1	0	0	1	1	0	1	1	0	1	0	-1	0	0	-1	0	0	-1	-1	0	0	1
q4	0	0	0	0	1	0	0	1	1	1	0	1	1	0	0	-1	0	0	-1	0	-1	0	-1	0	0
q5	1	0	0	0	0	1	0	0	1	0	1	1	1	0	0	0	-1	0	0	-1	0	-1	-1	0	0
|kh|	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4	4

h	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120	121	122	123	124	125
L1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L2	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L3	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
L4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
q1	1	1	0	0	0	0	0	0	-1	-1	-1	-1	0	0	0	0	0	0	1	1	1	1	0	0	0
q2	0	0	1	1	1	0	0	0	-1	0	0	0	-1	-1	-1	0	0	0	1	0	0	0	1	1	1
q3	0	0	1	0	0	1	1	0	0	-1	0	0	-1	0	0	-1	-1	0	0	1	0	0	1	0	0
q4	1	0	0	1	0	1	0	1	0	0	-1	0	0	-1	0	-1	0	-1	0	0	1	0	0	1	0
q5	0	1	0	0	1	0	1	1	0	0	0	-1	0	0	-1	0	-1	-1	0	0	0	1	0	0	1
|kh|	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

h	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140	141	142	143	144	145	146	147	148	149	150
L1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
L3	-1	-1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	-1
L4	0	0	0	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0
q1	0	0	0	-1	-1	-1	-1	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	-1	-1
q2	0	0	0	-1	0	0	0	-1	-1	-1	0	0	0	1	0	0	0	1	1	1	0	0	0	-1	0
q3	1	1	0	0	-1	0	0	-1	0	0	-1	-1	0	0	1	0	0	1	0	0	1	1	0	0	-1
q4	1	0	1	0	0	-1	0	0	-1	0	-1	0	-1	0	0	1	0	0	1	0	1	0	1	0	0
q5	0	1	1	0	0	0	-1	0	0	-1	0	-1	-1	0	0	0	1	0	0	1	0	1	1	0	0
|kh|	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

h	151	152	153	154	155	156	157	158	159	160	161	162	163	164	165	166	167	168	169	170	171	172	173	174	175
L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L3	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	0	0	0	0
L4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	-1	-1	-1	-1	-1	-1
q1	-1	-1	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	-1	-1	-1	-1	0	0	0
q2	0	0	-1	-1	-1	0	0	0	1	0	0	0	1	1	1	0	0	0	-1	0	0	0	-1	-1	-1
q3	0	0	-1	0	0	-1	-1	0	0	1	0	0	1	0	0	1	1	0	0	-1	0	0	-1	0	0
q4	-1	0	0	-1	0	-1	0	-1	0	0	1	0	0	1	0	1	0	1	0	0	-1	0	0	-1	0
q5	0	-1	0	0	-1	0	-1	-1	0	0	0	1	0	0	1	0	1	1	0	0	0	-1	0	0	-1
|kh|	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

h	176	177	178	179	180	181	182	183	184	185	186	187	188	189	190	191	192	193	194	195	196	197
L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L2	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
L3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
L4	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
q1	0	0	0	1	1	1	1	0	0	0	0	0	0	-1	-1	-1	-1	0	0	0	0	0
q2	0	0	0	1	0	0	0	1	1	1	0	0	0	-1	0	0	0	-1	-1	-1	0	0

q3	-1	-1	0	0	1	0	0	1	0	0	1	1	0	0	-1	0	0	-1	0	0	-1	-1
q4	-1	0	-1	0	0	1	0	0	1	0	1	0	1	0	0	-1	0	0	-1	0	-1	0
q5	0	-1	-1	0	0	0	1	0	0	1	0	1	1	0	0	0	-1	0	0	-1	0	-1
|kh|	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4