A COMPARATIVE ANALYSIS OF THE OPERATING AND ECONOMIC EFFICIENCY OF CHINA'S MICROFINANCE INSTITUTIONS, TRADITIONAL CHINESE AGRICULTURAL LENDERS, AND COUNTERPART INDIAN MICROFINANCE INSTITUTIONS

by

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(Under the Direction of Cesar L. Escalante)

ABSTRACT

This dissertation evaluates the efficiency of microfinance institutions (MFIs) in China relative to other Chinese agricultural lending institutions and the more established Indian MFIs. Microfinance institutions provide financial services to the low income population as a partial solution to capital shortages among poor households. In comparing Chinese MFIs and agricultural lending institutions, the Input Distance function was employed to evaluate of the technical efficiency and allocative efficiency from the input aspect while Data Envelopment Analysis techniques were used to further decompose the technical efficiency into pure technical efficiency and scale efficiency. This research also compared the technical efficiency of Chinese microfinance institutions with the more established Indian microfinance institutions and identified the different factors significantly affecting the efficiency of microfinance institutions in these two countries. The results indicate that there is no significant difference between Chinese commercial banks and microfinance institutions in terms of technical efficiency while

Chinese commercial banks achieved higher level of allocative efficiency than microfinance institutions. After further decomposing technical efficiency into pure technical efficiency and scale efficiency and comparing with more established Indian microfinance institutions, the results show that overall Chinese microfinance institutions have lower level of technical efficiency, pure technical efficiency, and scale efficiency than Indian microfinance institutions. The results also indicate that the efficiencies of Chinese and Indian microfinance institutions are influenced by different sets of factors that define these institutions' differing operating goals.

INDEX WORDS: Microfinance, Stochastic Frontier Analysis, Input distance function, Technical efficiency, Allocative efficiency, Data Envelopment Analysis, Pure Technical Efficiency, Scale Efficiency, Seemingly Unrelated Regression

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DEDICATIONS

Dedicated to My Husband, Jimmy Shi, My Parents, Huaiqing Wu and Cuiju Li, my brother, Jie Wu, and my nephew, Bozhi Wu

For Their Love and Support

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INTRODUCTION

Throughout the world, poor people are usually excluded from the traditional borrowing clientele of the formal financial system. The exclusion of poor borrowers from the banking clientele ranges from partial exclusion in developed countries to full or nearly full exclusion in less developed countries. Deprived of adequate access to the formal financial services, the poor have instead resorted to a wide variety of informal community based financial arrangements to meet their financial needs (Brau and Woller, 2004). Prior to the introduction of the microfinance movement in developing countries, the poor households have relied mostly on usurious informal lenders that charge exorbitant rates and contributed instead to the deterioration of the financial conditions of poor households. Under such lending arrangements, the poor became even poorer as their financial obligations skyrocket to unaffordable levels.

1.1 Background

Microfinance, regarded as the effective remedy to the poor's financial needs, refers to intended provision of financial services to the middle and low income population. The microfinance movement is a more comprehensive, encompassing program than its predecessor program involving microcredit, which only entailed providing credit services for the above economic groups. The essential characteristic of microfinance is that its designated target customers are the middle and low income population, who usually are considered as non-creditworthy and excluded from formal financial service.

In general, all microfinance models are defined by a two-pronged mission: maximizing social outreach potentials and at the same time realizing financial sustainability. The first aspect of their mission is social outreach, which implies that a large number of poor and low income people should be provided with credit or financial services. The challenge here is to extend financial assistance to a wider base of borrowers, consciously adapting their financial services and products to the needs of their poor clientele, and hoping that such services will eventually effectively help lift their poor borrowing clientele out of poverty. The second is financial profitability wherein microfinance organizations aspire to achieve financial sustainability and independence. This dimension of their organizational goals marks the essential difference between microfinance institutions and government subsidized development projects and traditional poverty-alleviation projects.

In China, however, microfinance is more of a recent phenomenon as it was introduced only in the 1990s, after the microfinance movement has already taken great strides in its development, especially in South Asia. The implementation of microfinance in China presents some unique challenges not necessarily experienced in other countries owing to the extent and nature of government involvement in agricultural and rural lending activities. In a nutshell, there currently exists a four-tier banking system in China. The Agricultural Bank of China (ABC), Agricultural Development Bank of China (ADBC) and Rural Credit Cooperatives (RCCs) are considered as the traditional agricultural lenders that assume the role of financing China's agricultural sector. Currently, the Agricultural Bank of China (ABC) and the Agricultural Development Bank of China (ADBC) are the major sources of loans to agricultural enterprises, rural cooperatives, and village organizations. Meanwhile, Rural Credit Cooperatives (RCCs), which had been the core of the rural financial system since their initiation in1950s, are currently the major source of formal loans to rural households.

1.2 Problem Statement

This study is specifically designed to understand the predicament of the relatively younger microfinance institutions in China as they operate under an established lending regime and deal with any existing operating constraints established by the Chinese government. This study approaches this issue from the operating efficiency perspective through a comparative analysis of these institutions' efficiencies.

Since the late 1970s, reforms in China's banking system were carried out with a view to improve efficiency and resource allocation. The efficiency of banking industry was initially not a concern under the planned economy, but only attracted more attention after the reform. The structural changes brought by the reform are expected to affect banking industry performance in many ways. Therefore, studies focusing on the efficiency of the banking industry are very important and beneficial. As Berger and Humphrey (1998) stated, there are 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"(P. 175).

Commercial banks usually adopt strategies aimed at minimizing costs or maximizing profits. Berger (1998) asserted that banks adjusted their operational strategies according to the changing economic and regulatory environment.

While there are a few studies that provide empirical evidence on the efficiency and performance of Chinese financial institutions, a substantial portion of them are devoted to commercial banking analyses. There is a dearth of literature on Chinese agricultural banking efficiency analysis.

Efficient performance is a key factor for traditional agricultural lenders to successfully deliver their services in the rural financial market. Compared to regular commercial banks, traditional agricultural lenders usually have more concerns on liquidity. In particular, ADBC and RCCs 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 traditional agricultural lenders as no parallel conclusions can be drawn given these banks' different styles of lending operations.

In some cases, traditional agricultural lenders do not necessarily make decisions in the same fashion as a rational economic decision maker that is either a profit maximizer or a cost minimizer. Sometimes, loan decisions made by certain traditional agricultural lenders were policy-driven and do not necessarily follow conventional risk-return principles that usually guide other lenders' decisions on loan applications. Also traditional agricultural lenders' gains are heavily impacted by the agricultural production markets. They could face a large borrowers' default risk in bad harvest year. Therefore, all these factors might make their operational objective and strategies different from those of the commercial banks.

Given these constraints affecting the lenders' operating policies and environments, it would be interesting to analyze and compare the comparative efficiencies of commercial banks and traditional agricultural lenders, and identify operational strategies adopted by both of them to improve efficiency conditions when covariates are controlled.

1.3 Objectives

The overall objective of this study is to evaluate the comparative efficiency performance of selected commercial banks, traditional agricultural lenders, and microfinance institutions in China over the period 2004-2008. The specific objectives of this study are to:

a. Perform a comparative technical and allocative efficiency analysis of the three groups of financial institutions in China (selected commercial banks, the RCCs, and the MFIs) in order to determine the relative efficiency of Chinese MFIs vis-à-vis the other providers of agricultural credit in the country;
b. Decompose and compare the technical efficiencies of Chinese MFIs and RCCs to determine specific sources of inefficiency in the contrasting operations of these two sets of institutions;
c. Using the more established Indian MFI system as a vantage point, evaluate the efficiencies of Chinese MFIs by analyzing the effects of structural differences between Chinese and Indian MFIs as they affect the technical efficiencies of the operations of these two sets of MFIs.

This study will help to fill some of gaps in literature on microfinance. The results of this study are expected to offer important insights into possible sources of Chinese financial institutions' inefficiency. Specifically, the comparative analysis will shed light on the effect of government restrictions and involvement on the cost efficiency of three sources of micro loans in China. We will also analyze the impacts of the micro lending and agricultural components of these institutions' lending operations on their efficiency. Through the inclusion of commercial banking units, this analysis will also address the issue of whether the concentration of micro and agricultural loans in lending portfolios will favorably enhance the cost efficiencies of these lending institutions. As the scarcity of agricultural capital is restricting China's agricultural development, this study should offer some valuable insights on sustaining the viability and survival of these rural micro- and agricultural-related lending institutions.

The efficiency problem can be analyzed using either of three general approaches: parametric approach, semi-nonparametric approach, and nonparametric approach. The parametric approach assumes the most strictly specific functional form, a restriction that is relaxed in the semi-nonparametric approach. Particularly, the minimal *a priori* assumptions would have to be imposed to guarantee the unbiased estimates (Gallant, 1982). The need to assume a functional form of the underlying technology and distribution for the inefficiency term makes the parametric and semi-nonparametric methods less flexible. In contrast, the nonparametric approach does not require specifying an explicit functional form. However, there are drawbacks of using the nonparametric technique. First, it only focuses on the technological optimization but neglects economic optimization. Second, it assumes a deterministic procedure instead of a stochastic procedure. Thus, there is no way to derive inferences of the estimated parameters or conduct the statistical hypothesis tests. Some recent studies are exploring some simulation methods to overcome the drawback of the deterministic approach (Ray, 2004).

The parametric and non-parametric methods will be considered to derive the efficiency measurements in this study. Specifically, Stochastic Frontier Analysis (SFA, parametric approach) is employed in identifying technical and allocative inefficiency, and data envelopment analysis (DEA, non-parametric approach) is employed to decompose the technical inefficiency into pure technical inefficiency and scale inefficiency.

The following subsections discuss in detail the procedures and approaches to be used in addressing the above specific research goals.

1.3.1 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 part is to apply the stochastic Translog input distance function to evaluate the operational efficiency and estimate the technical inefficiency and allocative inefficiency for the three groups of financial institutions in China.

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 traditional agricultural lenders and policy banks. Moreover, banks have more power to control over inputs instead of outputs. In this regard, the stochastic input distance function is appropriate in conducting efficiency analysis in this study.

This study introduces the application of the Stochastic Frontier Analysis (SFA) to measure selected Chinese financial institutions' technical efficiency and allocative efficiency. In implementing this analysis, the Stochastic Frontier Analysis (SFA) method will first 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.

1.3.2 Decomposing Technical Efficiency

Technical efficiency is comprised of two components: Pure technical efficiency (PTE) and Scale efficiency (SE). Pure technical efficiency measures how far off a DMU is from the production frontier. It indicates the potential reduction in inputs a DMU could achieve by adopting the best production practice of the best performance DMU. Scale efficiency measures the proportional reduction in input usage that is achieved by a DMU which operating at constant return to scale (Dong and Featherstone, 2004). The decomposition will help clarify the contributions of different factors to technical inefficiency.

In this study, we will focus on evaluating and comparing technical efficiency measurements derived from nonparametric method, which is often referred to as data envelopment analysis (DEA). DEA is often used to measure technical efficiency of firms, which are called Decision-Making Units (DMUs). DEA constructs a best-performance benchmark from the observed input-output bundles of the firms in the sample. A DMU's efficiency is a relative measure. It compares a DMU's performance to the best performance benchmark from the observed data on input-output combinations.

In this part, first, Data Envelopment Analysis (DEA) method is applied to estimate the pure technical efficiency measure. Second, the technical efficiency can be obtained by solving the DEA model with different restraints. Third, after estimating both the pure technical efficiency and technical efficiency, the scale efficiency will be obtained as the ratio of the technical efficiency and pure technical efficiency. Finally, bootstrapping can be utilized to investigate sampling properties of DEA estimators and to perform inference for efficiency measures.

1.3.3 Technical Efficiency of Microfinance Institutions in China and India

The operation of microfinance institutions (MFIs) varies significantly in India versus China (Tsai, 2004). This is due in part to differences in the policy environment for both NGOs and nonbanking financial institutions. Overall, MFIs in India have not been subjected to stringent regulations. Chinese MFIs, on the other hand, have to contend with more restrictive government policies that affect their decisions and operations.

In this analysis, we will use the DEA method to evaluate and compare the technical efficiencies of MFIs in India and in China. The pure technical efficiency and technical efficiency will be estimated by solving the DEA model with different restraints. Then the scale efficiency will be obtained as the ratio of technical efficiency and pure technical efficiency. After estimated the technical efficiency scores, the SUR (Seemly Unrelated Regression) will be used to see whether the different characteristics of Chinese and Indian MFIs affect technical efficiency differently.

1.4 Organization

This dissertation is comprised of six chapters. Chapter 1 provides the rationale for this study and outlines the objectives and structure of the dissertation.

Chapter 2 presents industry/historical backgrounds and a literature review. This chapter is divided into two sections. The first section will introduce the background of this study, which includes the history of microfinance industry and the development of microfinance in China. This section also reviews restrictions on agricultural lending in China, the difference between RCCs and MFIs in China, and the difference between MFIs in China and India. The second section briefly reviews the efficiency analysis of Chinese financial institutions. This section also examines the key studies on microfinance institutions' efficiency analysis. In this section, the literature are further sorted and reviewed in two aspects which are, first, microfinance industry development in China and Chinese characteristics on microfinance institutions; second, Indian microfinance institutions' efficiency analysis.

Chapter 3 presents the Stochastic Frontier Analysis (SFA), a parametric method which is applied to the input distance function to estimate and calculate both technical inefficiency and allocative inefficiency. The source of the data, definition of variables, and the summary of result are also discussed in this chapter.

Chapter 4 discusses the Data Envelopment Analysis (DEA), a non-parametric method, which will be applied to estimate technical efficiency and then decompose it into two components: pure technical efficiency and scale efficiency. The source of the data, definition of variables, and the summary of result are also discussed in this chapter.

Chapter 5 discusses and compares the efficiency performances of MFIs in China and India. The technical efficiency measures will then be regressed on explanatory variables to address what’s the factor attribute such difference. The source of the data, definition of variables, and the summary of result are also discussed in this chapter.

CHAPTER 2

LENDING INDUSTRY OVERVIEW AND RELATED EFFICIENCY ANALYSES

This chapter is divided into two major sections. The first section provides an overview of the agricultural lending industry in China (including the microfinance sector) and India's microfinance lending operations. The discussions will trace historical developments and rationale of lending programs introduced in China, along with the introduction of microfinance in the country.

The second section will present discussions of previous studies conducted on several issues related to this research. A review of studies on the efficiency of Chinese financial institutions will set the tone for the analysis of specific Chinese lenders considered in this study. This will be followed by a review of various studies on the microfinance industry and its relevance to the poor, developing economies. Specific studies on the performance and efficiency of Chinese and Indian microfinance operations will also be presented. These two groups of MFI operations are a bit differentiated in their operating structures, although both are designed to realize the common goals of social outreach and financial sustainability.

2.1 Industry and Historical Backgrounds

In order to better appreciate a comparative analysis of lending institutions within China as they relate to each other and vis-à-vis the more established microfinance firms in India, this section will trace the historical developments of these institutions. In these discussions, their operating rationale and environments will be laid to provide bases for the discussion of this study's results and implications.

2.1.1 The Origins of Global Microfinance

It is generally accepted that the effective microfinance system started in the 1970s, and its origins are the result of many individuals and organizations. In 1971, Al Whittaker and David Bussau individually began funding microloans in Colombia and Indonesia respectively. Later on, they formed the international organization, Opportunity International, which operates offices in Australia, Great Britain, Canada and United States. In 1973, Accion International introduced a new pilot project to provide economic opportunity for the poor in Brazil through microloans. By 1977, they had provided 885 loans with a repayment rate of over 90%. Today, Accion International works in India, United States, South and Central America, and Africa.

Meanwhile, in 1974, Dr. Muhammed Yunus, founder of the Grameen Bank, began providing micro loans to promising entrepreneurs with inadequate start-up funds in the amount of USD$27 to USD$42 in Bangladesh. Due to the success of these loans, Grameen Bank was founded in 1976. Since Grameen is the first bank to provide these microloans in a large scale (USD$ 5 billion since inception), it is perceived as the 'true' developer of the microcredit system. In fact, the Grameen website states that they have "reversed conventional banking practice by removing the need for collateral and created a banking system based on mutual trust, accountability, participation and creativity" (http://www.grameen-info.org/index.php?Itemid=164&task=blogsection&option=com_content&id=5).

During the 1980's, the microcredit program reevaluated its operating framework and introduced certain modifications to increase its efficiency and effectiveness. At this time, regular lending channels, like commercial banks, have started taking notice of the feasibility and apparent success of microcredit and microfinance institutions (MFIs). The MFI experience also made a strong impression to the world about the poor's untapped potentials as a viable borrowing clientele as MFIs registered amazing records of high loan repayment records among its poor household borrowers and the benefits of MFI financial sustainability arising from such successful loan transactions.

During the 1990's, the microcredit revolution changed from a grass roots type of organization to a financial structure recognized worldwide by banks and other lending institutions. There are some cases where MFIs turned into full-fledged commercial banks while other commercial banks started offering microfinance services themselves. Furthermore, many grass-root MFIs are creating linkages with regional and national markets through secondary markets. Traditionally, microcredit provided a very standardized credit product. But the poor needed a diverse range of financial instruments, such as savings and insurance, to be able to build assets, stabilize consumption and protect themselves against risks. The current challenge is to find efficient and reliable ways to provide a richer menu of microfinance products.
As stated by Kofi Annan, former United Nations Secretary-General, ‘Microfinance is an idea whose time has come’. The United Nations declared the year 2005 as the International Year of Microcredit. In 2006, the Noble Peace Prize was awarded to the Grameen Bank for its role in initiating the microcredit scheme on a larger scale in the 1980s.

2.1.2 Microfinance in China

Microfinance was introduced in China in the early 1990s. The development of the microfinance industry in China has undergone three phases. During the 1st Phase (early 1994 to October 1996), funding mainly came from international donation and soft loans, without any infusion of capital funds from the government. At this time, the focus was to explore the feasibility of establishing a Bangladesh “Grameen Bank” style in China. In the 2nd Phase (October 1996 to 2000), the government started becoming actively involved in providing capital, manpower and organization. At this time, the government consciously attempted to pursue the goal of poverty alleviation through microfinance. During the current phase (3rd Phase since 2000 to the present), Rural Credit Cooperatives (RCCs) started to become involved in the microfinance industry. The RCCs since then have gradually become the main providers of microloans to rural households (Du, 2003).

The United Nations was the first international organization that introduced microfinance in China. Since the 1980s, UNIFEM, IFAD, and UNFPA have included the provision of financial services in their programs promoting poverty alleviation or agricultural development in China. Some international NGOs, such as Worldvision, also followed suit as microfinance activities became integrated into their poverty alleviation and community development projects directed towards the poor population of China.

Researchers at the Chinese Academy of Social Science (CASS) have earlier explored the possibility of adopting the microfinance program and their investigations resulted in initial introduction of a Bangladesh Grameen Bank type of operations, an international standardized microfinance model, into China in 1994. Later, “Funding Poor Cooperatives (FPC)” was created by the Institute of Rural Development of CASS. It launched microcredit projects in 6 counties with a capital outlay sourced from various donations and low interest loans. Hence, “microfinance” became a terminology for extending financial services to the poor and became associated with poverty alleviation objectives in China.

An Australian-funded “China Qinghai Community Development” project started its microfinance operation in 1995. The project was mainly carried out by the Agricultural Bank of Haidong with an operating capital of 14 million Chinese Yuan. Meanwhile, UNDP microfinance poverty alleviation projects have been carried out in 48 counties and cities in China's 17 provinces. Later, an urban microfinance project for laid-off workers was carried out in Tianjin Municipality and some cities in Henan province. The project followed the Grameen Bank style, but was operated by Rural Development Associations run by local governments.

In 1997, the Chinese government evaluated previous lending experiences from the various microfinance pilot projects. As a result of this evaluation, the government decided to implement a government-oriented microfinance project on a much wider scope in 1998. In general, microfinance was mainly a poverty alleviation discount lending program where loans were subsidized by the Central Treasury and distributed via the Funding Poor Cooperatives (FPC) mechanism, which was an agent of Agricultural Development Bank (later transferred to the Agricultural Bank of China). But this arrangement was changed in 1999 when the loans were serviced and the program was disbursed to the farmers directly by the Agriculture Bank of China since then. However, the microfinance business shrank in scale later and then experienced a number of ups and downs in terms of varying scale of operations.

At the end of 1999, the Rural Credit Cooperatives (RCCs) also started their involvement in the microfinance industry. Initially, their funding source was the relending fund from People's Bank of China (PBC) that were made available to them as capital funds with preferential costs (interest rates). Microloans and co-guarantee loans for rural households were launched on a national scale in 2002. From then on, the RCCs are gradually becoming the major formal source of microloans to rural households in China.

China was the first country where the government itself has initiated large-scale microfinance program (Park and Ren, 2001). In general, there are four types of microfinance organizations in China:

(1) Bilateral or multi-lateral projects set up to manage and disburse or lend donated funds according to the requirements and regulations of donor organizations. Such projects include UNDP project, UNICEF project, Australian-aid Qinghai Project, and Xinjiang Project by Canada's CIDA.

(2) Non-government organizations (NGOs) operating microfinance for the purpose of poverty alleviation. These include such projects as "Poverty alleviation Association" by CASS and Oxfam Hong Kong.

(3) Particular projects set up by the government to manage and operate discount lending programs to aid the poor, such as the government poverty alleviation projects in Shaanxi, Yunnan, Sichuan provinces and Guangxi Autonomous Region.

(4) Microfinance projects directly operated by financial institutions. For example, an Australian-aided project operated by a local agricultural bank after the expiration of the project and household credit loans and group guaranteed loans provided by RCCs.

Projects implemented with different organizational structures focus on different development goals or objectives. In general, non-government institution and foreign aid focus on social development and sustainability while government- operated projects emphasize the need to address the speed and scale of development. Financial institutions, on the other hand, put more weight on sustainability and risk control (Du, 2003).

Initially, microfinance projects in China, including the program designed and introduced by the Chinese government, imitated the Grameen Bank model. In general, most of the microfinance projects for poverty alleviation are group collateral based that emphasize cooperation and monitoring by group members. In addition, some microfinance projects in China extend loans directly to individual. Moreover, some of the poverty alleviation projects only emphasize credit services; some are only part of a more comprehensive project; and others provide not only credit services but also other financial services related to promoting social and economic development.

Microcredit services provided by the Rural Credit Cooperatives (RCCs) do not really serve as poverty alleviation mechanisms. Their lending programs are implemented by first classifying the rural households into different credit rating classes within their area and use such rating class to determine the loan amount (various from ￥1,000 to ￥20,000). The loans provided by the RCCs under this arrangement are usually expected to be repaid by a single repayment at the end of the loan cycle. Like the Grameen Bank model, the RCC lending scheme adopts the group guarantee scheme of borrowing that enforces social pressure on individuals to repay their loans on time.

2.1.3 Chinese Banking System and Rural Financial System

In considering the appropriate role of microfinance in China, one must begin with describing of China's banking system and rural financial system. China has substantially boosted lending to farmers and agribusiness in recent years. Policymakers have encouraged financial institutions to channel more capital to the agricultural sector as part of its general policy aimed at raising rural incomes and improving farm productivity. From 2001 to 2005, the aggregate loan exposure to farmers has been doubled. Although China is trying to remold rural banks and credit cooperatives into financial intermediaries to allow them to operate more like commercial banks, rural financial institutions are still subjected to certain governmental restrictions that regulate the lenders' activities and decisions, such that the lending practice remains largely policy-driven. As such, these institutions' lending decisions often reflect the government's policy initiatives and development strategies (Gale and Collender, 2006).

Chinese banking system reform began in late 1970s. The most noticeable change was that the People's Bank of China (PBC) was separated from the Ministry of Finance. Thereafter, three new banks (Agricultural Bank of China, Bank of China, and China Construction Bank) were founded to diversify the PBC's monopoly of the lending industry. Later in 1982, the PBC was converted into China's Central Bank. Meanwhile, its deposit and lending activities were taken over by the newly founded Industrial and Commercial Bank of China (Empel and Smit, 2003).

Currently, the Chinese banking system is based on a four-tier system.

1^{st}	Four state-owned commercial banks (Agricultural Bank of China, Bank of China, China Construction Bank, and Industrial and Commercial Bank of China), also known as 'Big Four'; 67% market share;
2^{nd}	Three policy or specialized banks (Export-Import Bank, Agricultural Development Bank of China, and China Development Bank), founded in 1993 to take over the policy lending function of 1^{st} tier banks; 10% market share;
3^{rd}	Ten nation-wide joint-stock commercial banks (JSCBs) and commercial banks;
4^{th}	Large number of city commercial banks, urban credit cooperatives, rural credit cooperatives, foreign financial institutions, trust and investment companies, finance companies, and leasing companies;

The operating policies of China's banking system, including the setting of interest rates, are regulated by the central government. The financial system was originally designed to serve the State-Owned Enterprises (SOEs). Banks lent money to the SOEs at below-market rates. The four 1^{st} tier commercial banks, which hold together two-thirds of all deposits in Chinese banking system, play an insignificant role in financing the needs of private sectors, especially of the Small and Medium Enterprises (SMEs) and individual households. After the four 1^{st} tier commercial banks withdrew their operations in most townships and rural areas to focus on more profitable operations in the urban areas, Rural Credit Cooperatives (RCCs) took over the burden of financing rural households.

Since their establishment in the 1950s, Rural Credit Cooperatives (RCCs) have serviced the financial needs of the agricultural sector and have been one of the regular, constant providers of rural finance. By 1956, around 90 percent of rural households were RCC members and they relied on the RCCs for small amount loans for both production activities and personal needs. RCCs were originally under the People's Bank of China. Then, after its restoration in 1979, it was placed under the Agricultural Bank of China. During this period, RCCs' independent existence was little more than 'in name only' (Yi, 1986) (not in governance). Their management systems, interest rates, loan terms, and deposit procedures became as the same as other banks, but not as a cooperative. They collected deposits from farmers and extended loans to support agricultural production. Meanwhile, they were required to hold a substantial reserve, usually 20-30 percent of total RCCs deposit, in Agricultural Bank of China. This reserve deposit requirement substantially reduced the amount of funds RCCs could lend out to agricultural sectors. Although RCCs were allowed to vary their interest rates over official PBC rates, their services are not much different from other banks and the only thing that distinguished them from others was their wide clientele network that stretched from townships to villages (Watson, 2003). RCCs are the only financial institutions with branches extending to most villages.

Formal efforts to reform the RCCs were made after 1983. The strategic goal is to restore the 'three characteristics' of RCCs: mass character as a cooperative, democratic nature as an organization run by its own members, and flexible operations. However, subsequent reports indicated that little progress has been made until the launching of the banking reforms after 1994.

RCCs were managed by the Agricultural Bank of China prior to 1996, then separated and reconstructed as a separate set of independent institutions afterwards and under the administrative supervision of People's Bank of China and China Banking Regulatory Commission. A microloan scheme was introduced in this reform, with some provisions for support for agricultural lending from the Central Bank, the People's Bank of China (PBC). Although this reform improved access to RCC loans for rural households, the system was riddled with some problems, including the high demand for microloans and subsequent accumulation of financial losses (Dong and Featherstone, 2004).

2.1.4 Agricultural Lending in China

As discussed earlier, Agricultural Bank of China (ABC), Agricultural Development Bank of China (ADBC), and Rural Credit Cooperatives (RCCs) are regarded as traditional agricultural lenders which provide financial services to the agricultural sector. Agricultural Bank of China (ABC) provides majority of the loans to agricultural enterprises, rural cooperatives, and village organizations, but not usually to individual rural households. ABC was created in 1970s to carry out rural policy but became a commercial bank serving both rural and urban markets since reforms in 1994. Agricultural Development Bank of China (ADBC) is a policy bank created by Chinese government in 1994 to make loans for commodity, agribusiness, and rural infrastructure. Rural Credit Cooperatives (RCCs) accept deposits from local residents and make loans to households, business, and other entities. There are more than 30,000 rural credit cooperatives and each of China's 40,000 townships is served by an RCC.

These traditional agricultural lenders are effectively controlled by government and their lending decisions often reflect policy initiatives and development strategies. Chinese policymakers hold the view that rural poverty can be solved by an infusion of cheap credit and they are attempting to reverse the historic outflow of funds from rural savers to urban borrowers (Huang, Rozelle, and Wang, 2003; He and Feng). Loans to improve infrastructure and provide production credit are also seen as a means of boosting grain production, another important priority for China's policymakers. As one of the measures taken to solve China's "three rural problems," the agricultural lending has been boosted in recent years. "Three rural problems" refers to "raise rural income, improve agricultural production, and develop rural area." Rural Credit Cooperatives (RCCs) are pushed by government to make more loans to farmers and rural households. Some other loans from Agricultural Bank of China (ABC) and Agricultural Development Bank of China (ADBC) are specially targeted for agribusiness and rural infrastructure projects (Gale and Collender, 2006).

An infusion of cash into China's agricultural sector of the magnitude has a major impact on agricultural production by enabling farmers to invest in fixed assets such as greenhouses and finance purchases of seeds, fertilizer, livestock, machinery, and other inputs. The quality and standardization of farm products is being improved and farms are diversifying into new enterprises. Irrigation, water management, and other infrastructure are improving too.

Not all agricultural loans are used in agricultural purposes. According to Gale and Collender (2006), China's agricultural input expenditures and investment in agricultural fixed assets rose from $59 billion in 2001 to $64.5 billion in 2003 while agricultural loans issued shot up from $53 billion in 2001 to $99 billion in 2003. The large margin between "agricultural" loans and agricultural expenditures indicates that many or most "agricultural" loans in China are used for nonagricultural purposes such as house construction, school fees, health care costs, or nonfarm business expenses. For example, Peoples Bank of China guidelines for micro loans specify that micro loans may be used for “agricultural production; purchase of small farming machinery; services before, during or after agricultural production; or housing, medical service, education and consumption.” The guidelines emphasize agricultural production, but the fourth category seems to allow loans to be used for nearly any purpose.

Financial institution reforms have reduced the influence of local officials over lending decisions, a practice that contributed to the buildup of nonperforming loans during the 1990s. However, agricultural banks and RCCs are still subject to Communist Party and government directives (Heilmann, 2005). The ABC remains state-owned and it is not clear who owns RCCs. Board members include representatives of the Communist Party and government. Board members and managers must have the approval of The China Bank Regulatory Commission (CBRC), also an arm of the government. Agricultural related banks still receive instructions to make loans in support of policies set by the government (Shih, 2004). The CBRC, in addition to monitoring the performance of institutions, also issues guidance on government policy. For example, in 2004, the CBRC issued documents directing RCCs to expand group guarantee loans and gave instructions about how to manage the group-lending program (Xin, 2004).

Interest rates do not reflect capital scarcity and risk in rural China. Rates are set by the central bank and RCC loan rates are lower than rates charged by underground private lenders, suggesting that they are below market-clearing rates. RCCs are now allowed to set interest rates on loans up to double the officially set rate. The rural market is segmented by geography and type of borrower. RCCs must operate within their home county, where they have a monopoly on formal lending to rural households (Zhou and Lin, 2005). The entry of new lenders in a geographic area is not permitted. Agricultural financial institutions cannot be taken over by another institution, although mergers of RCCs into larger unions may be designed to combine weak institutions with stronger ones (Gale and Collender, 2006). The government also uses its influence over bank lending as a macroeconomic management tool. When the economy appeared to be overheating in mid-2004, the central bank ordered banks to cut back on lending to certain sectors in order to cool off the economy.

2.1.5 Rural Credit Cooperatives and Microfinance Institutions in China

Rural Credit Cooperatives (RCCs) is the core of Chinese rural financial system since 1950s and the current major source of formal loans to rural households. RCCs were originally under the People's Bank of China and then were placed under the Agricultural Bank of China in 1979. After separated from Agricultural Bank of China and reconstructed as a separate set of independent institutions in 1996, RCCs were put under the administrative supervision of People's Bank of China and China Banking Regulatory Commission. RCCs launched microloans and co-guarantee loans for rural households in 2002. Their initial funding source was the relending fund from People's Bank of China (PBC) with preferential interest rates and the central government has committed roughly $20 billion to clean up old nonperforming loans in RCCS. Moreover, the deposits they collected from local residents are used as the loan source within the designed region too.

However, RCCs' microcredit services do not really serve as poverty alleviation mechanisms. It's worthy noticing that rural households are not the only clientele RCCs serve. The major responsibility of RCCs is to serve agricultural sector. Other than provide rural households loans, RCCs also provide loans and other financial services to township and village enterprises and agribusiness. The RCCs located at suburb or urban area provides loans and financial services to urban households and local small to medium enterprise too. By the end of

June 2009, the agricultural related loan amount accounted for about 45% of the total outstanding loan amount of RCCs (http://www.21jrr.com/news/guanfangshuju/2009/0806/4585.html).

The rural households are first classified into different credit rating class within each area. The loan amounts are then determined based on each household's rating class (various from ￥1,000 to ￥20,000). The loans provided by the RCCs under this arrangement are usually expected to be repaid by a single repayment at the end of the loan cycle. Rural households are allowed to obtain more loans after they repay their initial loan on time. The RCC lending scheme adopts the group guarantee scheme of borrowing that enforces social pressure to individuals to repay their loans on time.

In contrast, microfinance institutions (MFIs) in China are focusing in rural areas in western and central regions where the majority of poor live. By providing the poor with credit access, these microfinance programs are expected to aid the poor in farm productivity, and eventually lift them from poverty. The target customers of MFIs are the poor in these designed areas.

The fund source of the MFIs in China can be classified as either from donors or from domestic poverty funds. By proving loan capital and technical support, donor agencies have so far played an important role for the rapid expansion of microfinance program in China. Such donors include the UNDP, the World Bank, AusAID, Oxfam, and etc. The domestic government agency, the Poverty Alleviation and Development Offices, have adopted some mechanisms of microfinance for poverty alleviation since 1996. Such agencies include the Poverty Alleviation and Development Offices in Shaanxi, Sichuan, and Yunnan Provinces.

Initially, MFIs projects in China imitated the Grameen Bank model. In general, most of the microfinance projects for poverty alleviation are group collateral based that emphasize cooperation and monitoring by group members. There are also some changes and adaptations have been made to the Gameen bank model. The intervals of meeting and loan repayment have extended from weekly to half-monthly or monthly. In addition, some microfinance projects in China extend loans directly to individual, although the principle of group guarantee still applies.

2.1.6 Microfinance Institutions in China and India

In analyzing and evaluating the performance of Chinese MFIs, it might be necessary to use a reliable vantage point with which to compare the results of the Chinese MFI analyses. As Indian MFIs have been in existence much earlier than the advent of the MFI movement in China, this study will look into the Indian MFIs as its vantage point in the efficiency analyses.

India is a major player in the global microfinance industry. Over 500 million households have been estimated to have benefited from microcredit loans worldwide (Helms, 2006). The majority of microloans in developing countries occur in India where approximately 18% of the population has taken a microloan (Christen, Rosenberg, and Jayadeva, 2004).

India has three main structures for MFIs: (1) Grameen model, (2) Self Help Group (SHG) model, and (3) shareholder model. Each model has its attributes and drawbacks. Although the effectiveness of each model may not be the same, they all aspire to realize the same goal: local development in rural areas. MFIs under any model will offer three to five group loan cycles. Each successive cycle has larger loans and longer repayment schedules. There is also more flexibility in the later cycles for borrowers facing unexpected hardships. Once the group loan cycles have been exhausted, individual loans for members become available. These individual loans, also known as “entrepreneurial loans", are significantly larger than the group loans with amounts up to Rs. 200,000 (USD$ 5128).

The operation of microfinance institutions (MFIs) varies significantly in India vis-a-vis the MFI operations in China (Tsai, 2004). This is due in part to differences in the policy environment for both Non-government Organizations (NGOs) and nonbanking financial institutions. Overall, MFIs in India have not been subjected to stringent regulations. Given the developmental contribution of MFIs, the restriction which prohibits savings mobilization from the public without the permission of the Reserve Bank of India (RBI) has not been enforced. Furthermore, interest rate controls on microcredit have been loosened, which offers MFIs in India enough leeway to package their loans in a financially self-sustainable manner. While the government of India has promoted the growth of self-governing MFIs and encouraged domestic development finance institutions to collaborate with them, China's MFIs are sponsored by a particular government unit (making them government-organized NGOs rather than pure NGOs) or established by international donors. To date, India's MFIs have had more extensive reach in microfinance than their counterparts in China. In both countries, however, few MFIs are financially sustainable while the market for MFIs remains vast.

In contrast to the MFIs in India, China's policy environment is much more restrictive. All NGO MFIs in China must have an official government unit sponsor their application to register as "social organizations" with the Civil Affairs Bureau (Saich, 2000). As such, China does not have purely nongovernmental organizations engaged in microfinance even though they may be functionally equivalent to NGOs.

Initially, microfinance projects in China, including the program designed and introduced by the Chinese government, imitated the Grameen Bank model. The introduction of the Grameen model of microfinance provides a good example of the close relationship between government entities and NGO MIFs in China. Researchers at the Chinese Academy of Social Science

(CASS) introduced the Bangladesh Grameen Bank type of operations, an international standardized microfinance model, into China in 1994. Later, “Funding Poor Cooperatives (FPC)” was created to launch microcredit projects in 6 counties with a capital outlay sourced from various donations and low interest loans. Besides the FPC, international donors have initiated over 200 microfinance programs throughout central and western China (Cheng, 2003). The donors have all implemented their projects with different local governmental partners. With few exceptions, the donor-initiated programs have been structured as projects with a limited lifespan rather than as MFIs aiming for sustainability (Cheng, 2003; Park & Ren, 2001).

Furthermore, as distinct from rural India, China’s poor areas are located mainly in remote and mountainous areas with low population density. Microfinance program are found almost exclusively in rural areas particularly the state designated poor counties in western and central regions, where the majority of the poor live. The off-farm investment opportunities are very limited and the returns on farm investment are very low. These conditions only aggravate operational and borrowing costs. The geographical constraint also makes it impossible to have weekly meetings as Indian MFIs would normally do in their borrowing communities. Thus, many programs extend the loan repayments from weekly to half-monthly or monthly.

Microloans in China have also been disbursed to individuals rather than to groups, although the principle of group guarantee still applies (Cheng, 2003). While the target MFI clientele in India are poor households in general, the majority of the target customers of microloans in China are farmers. The new poor in urban areas, the unemployed and retrenched state workers are not yet serviced to the same extent (Cheng, 2003).

2.2 A Review of Past Empirical Works

This study draws upon previous studies that have analyzed the efficiency and operating environments of Chinese financial institutions. There is also considerable work already done that shed light on the operating structures, goals and challenges of microfinance firms. The Indian model has drawn much attention owing to their wealth of experience given their relatively longer history. Given the collection of studies presented in this discussion, this study has developed its own agenda based on what has not been covered by the studies presented in this discussion.

2.2.1 The Efficiency of Chinese Financial Institutions

There are some empirical studies that analyzed the efficiency and performance of Chinese banks and financial institutions. Analyzing the profit and cost efficiency of banks representing 95% of commercial banking assets, Berger et. al.,(2006) found that the Big Four state-owned banks are by far the least efficient, and that minority foreign ownership of other banks is associated with significantly improved efficiency. To detect the determinants of bank performance in China, Heffernan and Fu (2008) suggested that economic value added and the net interest margin are the best dependent variables, as against the conventional measures of profitability, return on average assets (ROAA) and return on average equity (ROAE). They also found that the two main indicators of reform (bank listing and foreign equity investment) have no significant influence on performance. By constructing an index of relative risk management practice and risk organizational practice for a sample of Chinese banks, Matthews (2010) found no significant direct relationship between the measures of risk management practice and risk management organization and an objective measure of performance of the bank such as ROA. He also argued that the information content of the risk management practice and risk management organization measures is indirect and is better revealed within a network DEA framework.

However, a substantial portion of bank efficiency studies were mainly focused on commercial banks. Very little evidence of efficiency analyses focusing traditional agricultural lenders can be found in the literature. Banking operation in urban areas is believed to be more profitable and more preferred by commercial banks. As we defined before, traditional agricultural lenders (Agricultural Bank of China (ABC), Agricultural Development Bank of China (ADBC), and Rural Credit Cooperatives (RCCs)) are the primary providers of financial services to the agricultural production, agribusiness, and rural household sectors. Among them, only the ABC and ADBC have sub-branches at the township level in some provinces and focus on serving agricultural enterprises, rural cooperatives, and village organizations. RCCs are the only ones that extended their operations from townships to villages and serve as the major source of formal loans to rural households. Since they operate a large amount of retail banking business (as opposed to larger scale, wholesale banking) across the countryside, their operation and staffing costs were very high (Watson, 2003).

2.2.2 The Microfinance Framework

The United Nations estimates that about 500 million households have benefited from the financial services of microfinance institutions (MFIs) with millions more also potentially benefiting from microfinance in the near future (Helms, 2006). As major providers of financial services for the poor, MFIs play a significant role in the development of poor rural communities worldwide. MFIs struggle to reach a harmonious balance between profit maximization and social outreach; however, some MFIs achieve this goal more efficiently.

Christen, Rosenberg, and Jayadeva (2004) define MFIs as a movement where “a world in which as many poor and near-poor households as possible have permanent access to an appropriate range of high quality financial services, including not just credit but also savings, insurance, and fund transfers.” (pp. 2-3) Microfinance attempts to provide the poor and near-poor access to credit for sustainable ventures and thereby achieve their goals of outreach. However, the goals of profitability have been more elusive for MFIs, with less than 5% being self-sustainable (Hudon and Traca, 2006). This means that more than 95% of the MFIs still sustain themselves, at least partially, through subsidies, grants and loans. All this controversy surrounding the financial performance of MFIs has led to a plethora of recent literature surrounding MFI efficiency. Most of the recent papers on the efficiency of MFIs either utilize a financial efficiency approach (Hartarska, Caudill, and Gropper, 2006) or an outreach approach (Ahlin and Jiang, 2008), or analyze techniques in achieving efficiency (Gutierrez-Nieto, Serrano-Cinca, and Molinero, 2007).

With financial services as a key component of MFI operations, it is understandable why researchers would focus on financial efficiency. Recent work by Hartarska, Caudill, and Gropper (2006) suggests that labor, physical capital, and financial capital all significantly determine the financial efficiency of the MFI. Gutierrez-Nieto, Serrano-Cinca, and Molinero (2007) contend that the specification of the inputs and outputs drastically affects the results of the efficiency analysis. In their analysis, they looked at different combinations of inputs and outputs and found that none of the 30 MFIs scored the highest total efficiency in all combinations. While the findings stated in these articles provide useful information, the question of how efficient MFIs that strive to achieve both financial and social outreach remains unanswered. Moreover, with over 7,000 MFIs serving several countries all over the world and over 500 million estimated households benefiting from microcredit loans, an accurate estimation of the efficiency of MFIs (taking into account the dualistic goals) is more relevant than ever (Helms, 2006).

2.2.3 The Chinese Microfinance Model

Several studies have analyzed the operations of microfinance institutions in China. Most of them focused on analyzing the rationale for introducing microfinance in China and probing into the development and policy implications of providing microfinance services to Chinese rural households. Du (2003) summarized the various aspects of microfinance practice in China, such as the mode and scale of operations, targeted populations, organization management, development, and the funding sources. He also identified and discussed different types of microfinance programs in China, how they have grown, trends, problems, and future prospects of microfinance in China. Park, Ren and Wang (2003) examined the potential role of microfinance for poverty alleviation and financial reform in China in the light of the country's accumulated experience in MFI operations and ongoing changes in China's economic, institutional, and policy environment. They also cited that the uncertain legal status of NGOs, a strict financial regulatory environment, and inadequate financial management capacity could pose as barriers to MFI program expansion in China. In their assessment report, He, Du, Bai, and Li (2009) provided the most complete review of microfinance industry in China. Their discussions covered the development phase of the MFI movement in the country, market supply and demand, the industry's impact on development, legal and policy framework, opportunities, threats, and provided several policy suggestions.

There is, however, a dearth in literature that shed light on the efficiency assessment of microfinance institutions (MFIs) in China. As MFIs aspire for financial sustainability and independence, these goals can only be realized if MFIs consciously implement policies and actions which geared at attaining and maintaining acceptable levels of operating efficiency. Only Park and Ren (2001) empirically contrasted the implementation of microfinance services provided by non-government MFIs and those supplied by the Chinese Government. They found that microfinance services from NGOs are more effective in realizing their clientele targeting, financial sustainability, and economic impact goals. In contrast, their analysis revealed that the corresponding government programs addressing the same issues are less successful in attaining such goals. Their results support the notion that efficient MFI management contributes significantly to accomplishing microfinance objectives.

2.2.4 The Indian Microfinance Model

Microfinance institutions (MFIs) are contributing significantly to the reduction of poverty by providing microloans to those neglected by commercial banks. Microloans are quickly becoming a crucial development tool that is heavily utilized throughout the world, especially in impoverished nations. In India alone, over 1000 organizations routinely provide microcredit to those in need. Though not all organizations offering microcredit are considered MFIs; MFIs offer more financial services than merely microcredit (Karnani, 2007).

In India, MFIs adopt a nontraditional approach by lending to groups rather than individuals, utilizing a collective collateral system. To form lending groups, field managers and branch workers are assigned a village to study, determine the village’s financial and developments needs, and establish training programs to educate villagers in the ways of loan management. Groups are formed after villagers have completed the training program and these groups agree on a set of terms of contract covering the borrowing transactions (Sa-Dhan, 2003(b)). The collective responsibility of the group serves as collateral for the loan. This means that while each individual receives the same amount and uses the loan for individual purposes, the group is liable for the whole loan (Wydick, 2001). If one member defaults, then it is the responsibility of the other members to repay the amount in arrears. If the whole group loan is not repaid, the other members of the group cannot take out any more loans. Because of these restrictions, there is substantial group pressure to keep payments and encourage repayment amongst the members (Wydick, 2001). If the collective responsibility does not work, then the MFI will often send field officers to remind the borrowers of their responsibilities. While MFIs usually boast of greater than 90% repayment rate, this rate usually comes at the cost of time and field staff resources (Field and Pande, 2008). Furthermore, there is no guarantee for the MFIs that their eventual repayments will cover their costs at the margin.

In microfinance, a credit rating system often has to be developed for each MFI through debt capacity and repayment performance. Once a borrower's credit rating has been established by a MFI, the borrower can often access repeat loans (Rozycki, 2006; Ross and Savanti, 2005(a)). In terms of loan size, microfinance loans are small in value and often used for working capital, which means the interest earned on each loan by itself is likely small. Moreover, the loans are often the bulk of the transactions and portfolio of an MFI (Ananth, 2005). Therefore, choosing the right group and group policy can benefit MFIs greatly. This makes it even more important to understand what variables are characteristic of an efficient borrowing group.

There is no current literature that examines how the structure affects the efficiency of MFIs. However, literature profiling the different Indian MFI models and borrowing group characteristics is plentiful. Field and Pande (2008) find that there is no difference in repayment between borrower weekly and monthly repayment terms; however, this finding is not examined for its effect on MFIs. Whereas Ross and Savanti (2005(b)) look at loan size and purpose, they primarily look at the variables as they affect the borrowers in their current state through survey data and simple statistics.

CHAPTER 3

IDENTIFYING TECHNICAL AND ALLOCATIVE INEFFICIENCIES

The literature on efficiency measurement usually decomposes operational inefficiency into technical inefficiency and allocative inefficiency (Farrel, 1957). The primary objective of this part is to apply the stochastic Translog input distance function to evaluate operational efficiency and estimate technical inefficiency and allocative inefficiency scores for the three categories of financial institutions.

Allocative efficiency (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 (Farrell, 1957). Technical efficiency (TE) measures the ability of a firm to obtain optimal outputs from a given set of inputs (Drake and Hall, 2003). In summary,

Productive Efficiency (PE) = Allocative Efficiency (AE) × Technical Efficiency (TE)

3.1 Methodology

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 arenot applicable. This study introduces the application of the Stochastic Frontier Analysis (SFA) to measure selected Chinese financial institutions' technical efficiency and allocative efficiency.

The Shephard input distance function is defined as:

$$D^I(\mathrm{x}, \mathrm{y}) = \sup_{\rho}\{\rho > 0 : (\mathrm{x}/\rho) \in L(\mathrm{y})\} \tag{3.1}$$

where the superscript *I* implies that it is the input distance function; the input set $L(\mathrm{y}) = \{\mathrm{x} \in R_N^+ : \mathrm{x}$ can produce $\mathrm{y} \in R_M^+\}$ represents input vector, x, that can produce the output vector, y; ρ measures the possible proportion of the inputs which can be reduced to produce the quantity of the outputs not less than y. In other word, input distance function is the maximum proportion of the reduction in inputs necessary to achieve the outputs on the production frontier.

The following properties have been utilized by Farrell and Primont (1995) and Cornes (1992):

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

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

(3) When a firm operates on the production frontier, isoquant $L(\mathrm{y})$, $D^I(\mathrm{x}, \mathrm{y})$ is equal to 1. In this case, the firm achieves the technical efficiency.

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

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

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

The stochastic frontier analysis 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 that sum up to 1. The translog function is more flexible with less restriction on production and substitution elasticities. The flexibility reduces the biases estimate’s possibility due to the improper function form’s assumption.

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

$$
\begin{aligned}
\ln D_{it}^{I} = \beta_0 &+ \sum_{k=1}^{M}\beta_{y_k} \ln y_{k,it} + \frac{1}{2}\sum_{k=1}^{M}\sum_{l=1}^{M}\beta_{y_{kl}} \ln y_{k,it} \ln y_{l,it} + \sum_{j=1}^{N}\beta_{x_j} \ln x_{j,it} \\
&+ \frac{1}{2}\sum_{j=1}^{N}\sum_{h=1}^{N}\beta_{x_{jh}} \ln x_{j,it} \ln x_{h,it} + \sum_{j=1}^{N}\sum_{k=1}^{M}\beta_{xy_{jk}} \ln x_{j,it} \ln y_{k,it} + \sum_{k=1}^{M}\alpha_k (t \ln y_{k,it}) \\
&+ \sum_{j=1}^{N}\delta_j (t \ln x_{j,it}) + \lambda_1 t + \frac{1}{2}\lambda_2 t^2 + d_m dum_m \qquad (3.2)
\end{aligned}
$$

where $dum_{g,it}$ is the dummy variable representing the different type of financial institutions in group g; k,l =1,…M (number of outputs); j,h = 1, …N (number of inputs); g = 1,…(G-1), G is number of groups).

The input distance function is homogeneous to degree one in input quantities, which implies that the parameters in equation (3.2) should satisfy the following constraints:

(R3.1) $\sum_{j=1}^{N}\beta_{x_j} = 1$

(R3.2) $\sum_{j=1}^{N}\beta_{x_{jh}} = 0, \quad \forall h = 1,..., N$

(R3.3) $\sum_{j=1}^{N}\beta_{xy_{jk}} = 0, \quad \forall k = 1,..., N$

(R3.4) $\sum_{j=1}^{N}\delta_j = 0$

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

$$D_{it}^{I}(\lambda \mathrm{x}, \mathrm{y}) = \lambda D_{it}^{I}(\mathrm{x}, \mathrm{y}), \quad \forall \lambda > 0 \qquad (3.3)$$

Assuming $\lambda = 1/x_{N,it}$, equation (3.3) can be expressed in logarithmic form as:

$$\ln D_{it}^{I}(\mathrm{x}/x_{N,it}, \mathrm{y}) = \ln D_{it}^{I}(\mathrm{x}, \mathrm{y}) - \ln x_{N,it}) \qquad (3.4)$$

According to the definition of the input distance function, the logarithm of the distance function in (3.4) measures the deviation of an observation (x,y) from the efficient production frontier L(y), ε_{it}.

$$\ln D_{it}^{I}(\mathrm{x},\mathrm{y}) = \varepsilon_{it} \tag{3.5}$$

Following the literature on 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 $\varepsilon_{it} = u_{it} - v_{it}$. Then the equation (3.5) can be expressed as:

$$\ln D_{it}^{I}(\mathrm{x},\mathrm{y}) = u_{it} - v_{it} \tag{3.6}$$

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 (3.6) into equation (3.4) and equation (3.4) can be rewritten as:

$$-\ln x_{N,it} = \ln D_{it}^{I}(\mathrm{x}/x_{N,it}, \mathrm{y}) + v_{it} - u_{it} \tag{3.7}$$

Aside from the homogeneity restrictions, the symmetric restrictions also need to be imposed in estimating translog input distance function. The symmetric restrictions require that the parameters in equation (3.2) should satisfy the following constraints:

(R3.5) $\beta_{y_{kl}} = \beta_{y_{lk}}$, where $k, l = 1,..., M$

(R3.6) $\beta_{x_{jh}} = \beta_{x_{hj}}$, where $j, h = 1,..., N$

Imposing restrictions (R3.1) through (R3.6) and equation (3.2) upon equation (3.7) yields the estimating form of the input distance function as follows:

$$-\ln x_{N,it} = \beta_0 + \sum_{k=1}^{M} \beta_{y_k} \ln y_{k,it} + \sum_{j=1}^{N-1} \beta_{x_j} \ln x_{j,it} + \frac{1}{2}\left[\sum_{k=1}^{M} \beta_{y_{kk}} (\ln y_{k,it})^2 + \sum_{j=1}^{N-1} \beta_{x_{jj}} (\ln x_{j,it})^2 \right]$$

$$+ \sum_{k=1}^{M} \sum_{l=1, for\, l>k}^{M} \beta_{y_{kl}} \ln y_{k,it} \ln y_{l,it} + \sum_{j=1}^{N} \sum_{h=1, for\, h>j}^{N-1} \beta_{x_{jh}} \ln x_{j,it}^{\;*} \ln x_{h,it}^{\;*}$$

$$+ \sum_{j=1}^{N-1} \sum_{k=1}^{M} \beta_{xy_{jk}} \ln x_{j,it}^{\;*} \ln y_{k,it} + \sum_{k=1}^{M} \alpha_k (t \ln y_{k,it}) + \sum_{j=1}^{N-1} \delta_j (t \ln x_{j,it}^{\;*})$$

$$+ \lambda_1 t + \frac{1}{2} \lambda_2 t^2 + d_m dum_m + v_{it} - u_{it} \qquad (3.8)$$

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

After estimating all coefficients in equation (3.8), the coefficient for the N^{th} input can be calculated by the homothetic restriction (R3.1) to (R3.4).

To simplify the analysis and better understand the concept of the decomposition of efficiency, consider a scenario of one output with two inputs (assume a firm uses input x1 and x2 to produce output y). The estimated input distance function will be used to further differentiate technical efficiency and allocative efficiency.

Based on the definition of the input distance function, it is not hard to find that:

$$TE = 1 / D^I (\mathrm{x}, \mathrm{y}) \qquad (3.9)$$

where $0 \le TE_{it} \le 1$. The closer TE_{it} is to 1, the more technically efficient the firm's performance is.

Aligning with the estimation of the function (3.8), technical efficiency levels can be estimated as

$$T\hat{E}_{it} = 1 / \hat{D}_{it}^I = 1 / E\left[\exp(\hat{u}_{it}) \,|\, v_{it} - u_{it}\right] \qquad (3.10)$$

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

$$\hat{u}_{it} = \exp\{-\eta(t - T_i)\} \cdot \hat{u}_i \tag{3.11}$$

where $u_i \overset{iid}{\sim} N^+(\mu, \sigma_u^2)$. $\eta = 0$ implies that the distance function will not fluctuate over time series and 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 time. $\eta > 0$ indicates efficiency achievement, while $\eta < 0$ indicates TE decay. To get the unbiased estimates, the time-invariant hypothesis H_0: $\eta = 0$ will be tested. If the hypothesis is rejected, the time-variant constraint ($\eta \neq 0$) will be necessary to get the unbiased estimates.

The allocative efficiency can be assessed by estimating shadow prices. Initially, previous empirical works on the AE concept were based on the estimation of a system of equations composed of the cost function and cost share equations (Atkinson and Halvorsen, 1986; Eakin and Kniesner, 1988). However, the validation of this system of equations' estimation requires the assumption of cost minimization. Recently, some researchers provided an alternative method to obtain shadow prices from 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 market prices and shadow prices with respect to the minimum costs. Given input prices p_1 and p_2, 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 $k_{12} = \dfrac{p_1^s / p_2^s}{p_1 / p_2}$. Specifically, if the ratio equals to 1, allocative efficiency is achieved. Otherwise, allocative inefficiency is detected. The larger $|k_{12}|$ deviates from 1, the larger allocative inefficiency is. Generally, allocative inefficiency for each observation *i* at time *t* can be measured by relative input price correction indices:

$$k_{jh,it} = k_{j,it} / k_{h,it} = \frac{p^s_{j,it} \big/ p_{j,it}}{p^s_{h,it} \big/ p_{h,it}} = \frac{p^s_{j,it}}{p^s_{h,it}} \cdot \frac{p_{h,it}}{p_{j,it}} \tag{3.12}$$

where $k_{j,it} = p^s_{j,it} / p_{j,it}$ is the ratio of the shadow price, $p^s_{j,it}$, to market price, $p_{j,it}$, for the 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 input *h*; if $k_{jh,it} < 1$, input *j* is being over utilized relative to 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:

$$C(\mathrm{y}, \mathrm{p}) = \min_{\mathrm{x}} \{\mathrm{p}\mathrm{x} : D(\mathrm{y}, \mathrm{x}) \geq 1\} \tag{3.13}$$

Implementing the duality theory and imposing input distance function's linear homogeneity property, they showed the derivation of the dual Shepherd's lemma as:

$$\frac{\partial D^I_{it}(\mathrm{x}, \mathrm{y})}{\partial x_{j,it}} = \frac{p^s_{j,it}}{C(\mathrm{y}, \mathrm{p}^s)} \tag{3.14}$$

From equation (3.1.14), the ratio of the shadow prices can be calculated by:

$$\frac{p^s_{j,it}}{p^s_{h,it}} = \frac{\partial D(x, y) / \partial x_{j,it}}{\partial D(x, y) / \partial x_{h,it}} \tag{3.15}$$

Applying the derivative envelope theory to the numerator and denominator of the equation (3.15) separately, equation (3.15) can be expressed as: x

$$\frac{p^s_{j,it}}{p^s_{h,it}} = \frac{\partial D(\mathrm{x},\mathrm{y})/\partial x_{j,it}}{\partial D(\mathrm{x},\mathrm{y})/\partial x_{h,it}} = \frac{\left[1/\left(D^I_{it}(\mathrm{x},\mathrm{y})\cdot x_{j,it}\right)\right]\cdot\left[\partial \ln D^I_{it}(\mathrm{x},\mathrm{y})/\partial \ln x_{j,it}\right]}{\left[1/\left(D^I_{it}(\mathrm{x},\mathrm{y})\cdot x_{h,it}\right)\right]\cdot\left[\partial \ln D^I_{it}(\mathrm{x},\mathrm{y})/\partial \ln x_{h,it}\right]}$$

$$= \frac{x_{h,it}}{x_{j,it}}\cdot\frac{\partial \ln D^I_{it}(\mathrm{x},\mathrm{y})/\partial \ln x_{j,it}}{\partial \ln D^I_{it}(\mathrm{x},\mathrm{y})/\partial \ln x_{h,it}} \tag{3.16}$$

Substituting equation (3.16) into equation (3.12), the relative allocative inefficiency shown by the relative input price correction indices can be expressed as:

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

$$= \frac{p_{h,it}x_{h,it}}{p_{j,it}x_{j,it}}\cdot\frac{\beta_{x_j} + \sum_{h=1}^{N}\beta_{x_{jh}}\ln x_{h,it} + \sum_{k=1}^{M}\beta_{xy_{jk}}\ln y_{k,it} + \delta_j t}{\beta_{x_j} + \sum_{h=1}^{N}\beta_{x_{jh}}\ln x_{j,it} + \sum_{k=1}^{M}\beta_{xy_{jk}}\ln y_{k,it} + \delta_j t} \tag{3.17}$$

3.2 Data and Variables

Berger and Humphrey (1992) have identified three alternative methods of defining bank inputs and outputs. They are the asset approach, user cost approach, and value-added approach. It is argued that the value-added approach is the best method for accurately estimating changes in bank technology and efficiency over time. However, Sealey Jr. and Lindley (1977) suggested that the researcher can adopt any measure of output for a financial firm as long as the measure is consistent with the researcher's goal.

This study will derive and decompose efficiency measures across commercial banks, and microfinance institutions in China. There are 12 commercial banks and 4 microfinance institutions (MFIs) included in this study. The microfinance institutions included in this study are: China Fund for Poverty Alleviation (CFPA), Chifeng Zhaowuda Women's Sustainable Development Association (CZWSDA), PATRA Hunchun, and PATRA Yanbian.

The financial data for the commercial banks are obtained from Almanac of China's Finance and Banking (various years) and annual reports of individual bank from their websites. Information of the microfinance institutions in China are collected from MixMarket.org. The study period is from 2004 to 2007.

In this study, the inputs are defined as total assets (x_1) and number of employee (x_2) while the output is the gross loan portfolio (y). The cost of each input is collected and denoted as c_1 and c_2. Specifically, c_1 includes operating and administrative expenditures while c_2 represents labor-related expense (salaries and employee benefits). The input price p_1 is then calculated as operating and administrative expenditures divided by total assets, while input price p_2 is salaries and employee benefits divided by number of employees. The cost shares, s_i, are then calculated as $s_i = \frac{c_i}{\sum_{i=1}^{2} c_i}$. The summary statistics are provided in Table 3.1.

3.3 Empirical Results

The estimates of the input distance function (3.8) are presented in Table 3.2. Based on the summary, 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 functional 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_{x_j} in equation (3.2) equal 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 would be more applicable in this study.

The coefficient estimate for microfinance institutions is not significant. This indicates that the commercial banks and microfinance institutions do not have significantly different TE levels.

Table 3.3 presents the ANOVA summary that can be used to compare the TE levels of commercial banks and MFIs. The results indicate that both commercial banks and MFIs are not technically efficient. The efficiency level of commercial banks is 51% while the efficiency level of MFIs is only 50%. A statistical comparison of these results indicate that the TE levels of commercial banks and MFIs are not statistical significantly different from each other (p-value=0.8307).

The annual average TE of commercial banks and MFIs from 2004 to 2007 are presented in Figure 5.1. Throughout the study period, commercial banks registered a fairly stable trend of TE values that fluctuated within a narrow range of values between 0.5 and 0.52. However, the TE levels of MFIs fluctuated over a wider range, starting from 0.48 in 2004 and jumping to 0.56 in 2005, and then dropping back to 0.48 in 2006. Overall, the TE levels of commercial banks and MFIs are not significantly different from each other, which coincide with the results from the ANOVA analysis as explained earlier.

As previously discussed, the variable $k_{jh,it}$, calculated by equation (3.17), can be used to measure the relative allocative inefficiency level. The average k_{jh} over time for commercial banks and MFIs in summarized in Table 3.4.

As can be gleaned from Figure 3.2, the inefficiency level may be different over years but relative allocative inefficiency exists widely in both commercial banks and MFIs between two inputs. The graph shows the efficiency difference between commercial banks and MFIs as well as the fluctuation between labor input and asset input ratio over the years. Overall, commercial banks achieve higher allocative efficiency level than MFIs.

For MFIs, the allocative inefficiency reflects that asset input has been over-utilized vis-à-vis labor input since $k_{12} < 1$ for all the years. The graph showed that MFIs performs well below the efficient utilization of asset input and labor input. Overall, they only reached about 20% of the allocative efficiency.

For commercial banks, the allocative inefficiency fluctuates throughout the study period. The graph also shows that commercial banks moves towards $k_{12} = 1$ in 2005. It may indicate that the efforts made by commercial banks to adjust labor and asset input are more effective than those made by MFIs. The allocative inefficiency reflects that asset input has been over-utilized vis-à-vis labor input since $k_{12} < 1$ in 2004 while asset input has been under-utilized vis-à-vis labor input since $k_{12} > 1$ in 2006 and 2007. Overall, commercial banks have a stronger tendency than MFI to adjust these two inputs. This may imply that commercial banks have more flexibility to adjust asset capital than MFIs.

Table 3.1. Summary Statistics of Commercial Banks and Microfinance Institutions, 2004-2007

Variable	Minimum	Maximum	Mean	Standard Deviation
Commercial Banks				
Y-Loan	660	565363	157838	179610
X1-Total Asset	147000	1240000	304000	351000
X2- Number of Employees	256	489425	119819	164006
P1- Physical Expenditure	0.004	0.020	0.013	0.005
P2- Labor Expenditure	1224	35090	12302	8044
S1- Physical Cost Share	0.193	0.974	0.789	0.193
S2 - Labor Cost Share	0.025	0.654	0.211	0.193
Microfinance Institutions				
Y-Loan	0.075	9.59	1.33	2.39
X1-Total Asset	0.123	10.39	1.58	2.63
X2- Number of Employees	3	151	43	53
P1- Physical Expenditure	0.085	0.156	0.111	0.025
P2- Labor Expenditure	545	7445	2413	1677
S1- Physical Cost Share	0.582	0.767	0.675	0.058
S2 - Labor Cost Share	0.418	0.233	0.325	0.058

Note: All financial values are in millions U.S. Dollar ($1,000,000).

Table 3.2. Estimates of the Input Distance Function

Estimates of the Input Distance Function					
	estimate	std		estimate	std
Intercept	2.494	3.681	$\beta_{xy_{11}}$	-0.017	0.023
β_{y_1}	-0.836***	0.151	$\beta_{xy_{21}}$	0.017	0.023
β_{x_1}	0.002	0.575	α_1	-0.008	0.008
β_{x2}	0.998	0.575	σ_1	-0.002	0.022
$\beta_{y_{11}}$	0.007	0.011	σ_2	0.002	0.022
$\beta_{x_{11}}$	0.103	0.074	λ_1	0.193	0.191
$\beta_{x_{22}}$	0.103	0.074	λ_2	0.037	0.047
$\beta_{x_{12}}$	-0.007	0.011	d_m	1.468	1.087
$\beta_{x_{21}}$	-0.103	0.074			

Note: '***' significant at 0.01, '**' significant at 0.05, '*' significant at 0.10

Table 3.3. ANOVA Table for TE Difference between Commercial Bank and MFI

ANOVA Table

Source of Variation	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	0.0004	0.0004	0.05	0.8307
Error	62	0.4875	0.0079		
Corrected Total	63	0.4879			

TE Difference Between Commercial Banks and MFIs

	Mean	Standard Error
Commercial Banks	0.51	0.09
MFIs	0.50	0.07

Comparison	Estimate	Standard Error	t Value	Pr>|t|
Commer. vs MFIs	-0.0055	0.0256	-0.21	0.8307

Table 3.4. Summary of k_{12} (Asset to Labor) of Commercial Banks and MFIs

	Year	k_{12}		Year	k_{12}
Commercial Banks	2004	0.76	MFIs	2004	0.08
	2005	1.00		2005	0.15
	2006	1.35		2006	0.24
	2007	1.53		2007	0.20

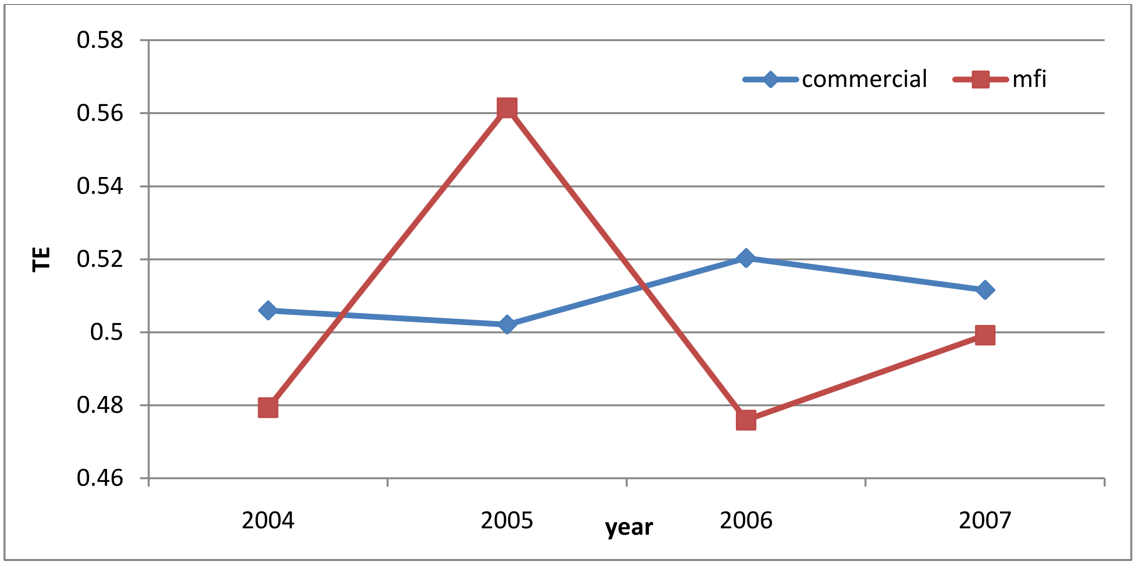
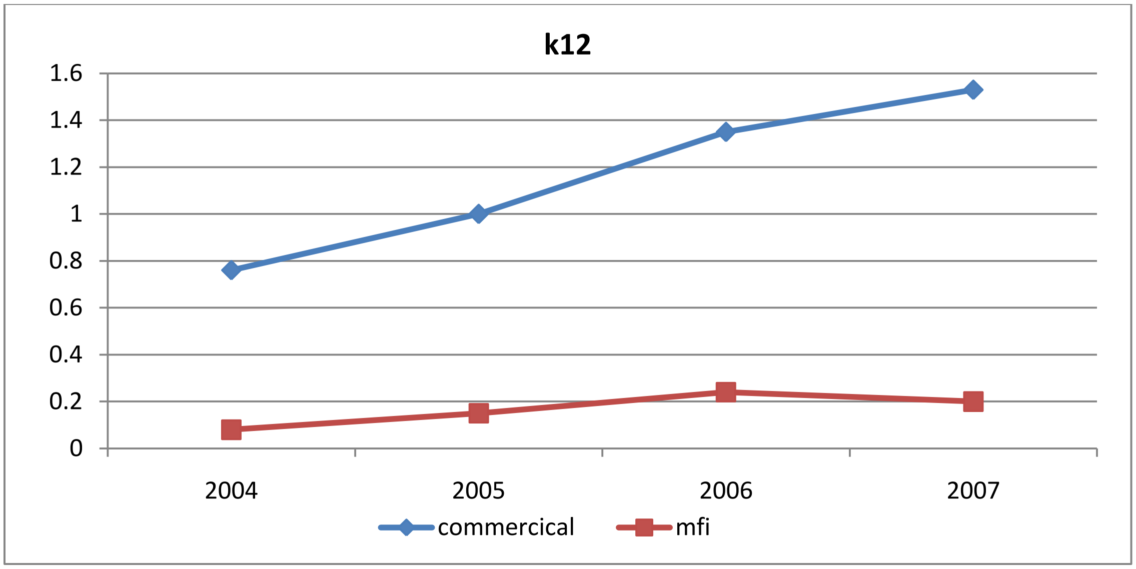


Figure 3.1. Technical Efficiency of Commercial Banks and MFIs in China



Note: K_{12} is the deviation of the market price ratio (P_1/P_2) from shadow price ratio (P_1^s/P_2^s) where P_1 is physical expenditure and P_2 is labor expenditure.

Figure 3.2. k_{12} **of Commercial Banks and MFIs over Years**

CHAPTER 4

DECOMPOSING TECHNICAL EFFICIENCY

Technical efficiency is comprised of two components: Pure technical efficiency (PTE) and Scale efficiency (SE). Pure technical efficiency measures how far off a DMU is from the production frontier. It indicates the potential reduction in inputs a DMU could achieve by adopting the best production practice to produce optimal performance DMU. Scale efficiency measures the proportional reduction in input usage that is achieved by a DMU that operates at constant return to scale (Dong and Featherstone, 2004). In other words,

Technical Efficiency (TE) = Pure Technical Efficiency (PTE) ×

Scale Efficiency (SE)

In this study, we will focus on evaluating and comparing technical efficiency measurements derived from nonparametric method, which is often referred to as data envelopment analysis (DEA). DEA is often used to measure technical efficiency of firms, which are called Decision-Making Units (DMUs). DEA constructs a best-performance benchmark from the observed input-output bundles of the firms in the sample. The constructed relative efficiency frontiers are non-statistical in the sense that they are constructed through the envelopment of the DMUs, with the best practice DMUs forming the frontier (Drake and Hall, 2003).

A DMU's efficiency is a relative measure. It compares a DMU's performance to the best performance benchmark from the observed data on input-output combinations. If many of the DMUs producing multiple outputs from multiple inputs, the bench mark will be made up of more than one DMU unless the DMU has the best performance in producing all outputs. Usually, a single DMU does not have the best performance in producing all outputs. So the best-performance benchmark of a DMU may include a number of DMUs that have the best performance in producing one or more outputs (Dong and Featherstone, 2004).

4.1 Methodology

Consider the case where there are *k* DMUs in the sample, each producing *m* outputs $[Y_1, Y_2, ..., Y_k]$ by using *n* input $[X_1, X_2, ..., X_k]$, where Y_i ($i = 1, ..., k$) is the (m×1) vector of outputs and X_i ($i = 1, ..., k$) is the (n×1) vector of inputs. The outputs and inputs are represented by the *k*-column matrices: X and Y. The input requirement set can be represented by the free disposal convex hull of the observations. The smallest convex set contains the observations with the least input requirement set for the certain level of outputs.

The pure technical efficiency is obtained by solving the following DEA model:

$$
\begin{aligned}
&\min\ \theta_i \\
&\text{subject to:} \\
&z_1 y_{11} + z_2 y_{12} + ... + z_k y_{1k} \geq y_{1i} \\
&z_1 y_{21} + z_2 y_{22} + ... + z_k y_{2k} \geq y_{2i} \\
&\qquad\qquad\cdots\cdots \\
&z_1 y_{m1} + z_2 y_{m2} + ... + z_k y_{mk} \geq y_{mi} \\
&\theta_i x_{1i} - z_1 x_{11} - z_2 x_{12} - ... - z_k x_{1k} \geq 0 \\
&\theta_i x_{2i} - z_1 x_{21} - z_2 x_{22} - ... - z_k x_{2k} \geq 0 \\
&\qquad\qquad\cdots\cdots \\
&\theta_i x_{ni} - z_1 x_{n1} - z_2 x_{n2} - ... - z_k x_{nk} \geq 0 \\
&z_i > 0,\ (i = 1,2,...,k) \\
&z_1 + z_2 + ... + z_k = 1
\end{aligned}
\tag{4.2.1}
$$

where x_{ij} (*i*=1, …, n; *j*=1, …, k) is the *i*th input used by the *j*th DMU; and y_{ij} (*i*=1, …, m; *j*=1, …, k) is the *i*th output produced by the *j*th DMU. θ_i (*i*=1, …, k) is the measure of pure technical efficiency for the *i*th DMU. The technical efficiency, denoted as λ_i, can be obtained by solving the DEA model in equation (1) without the constraint $\sum z_1 = 1$. The scale efficiency is the ratio of the technical efficiency and pure technical efficiency:

$$S_i = \frac{\lambda_i}{\theta_i} \tag{4.2.2}$$

If S_i is equal to 1, then the DMU is scale efficient; if S_i is less than1, then the DMU is inefficient. The source of scale inefficiency can be identified by estimating the DEA model in equation (1) with the constraint $\sum z_1 \leq 1$ instead of $\sum z_1 = 1$; that is, the technology is non-increasing returns to scale (NIRS). If the objective function of the DEA model under NIRS (labeled γ_i) is equal to pure technical efficiency (θ_i), decreasing returns to scale exist; otherwise, increasing returns to scale exist (Färe, Grosskopf, and Lovell, 1985).

4.2 Data and Variables

Berger and Humphrey (1992) have addressed that there are three alternative methods of defining bank inputs and outputs. They are the asset approach, user cost approach, and value-added approach. It is argued that the value-added approach is the best method for accurately estimating changes on bank technology and efficiency over time. However, Sealey Jr. and Lindley (1977) suggested that the researcher can adopt any measure of output for a financial firm as long as the measure is consistent with the researcher's goal.

This study will derive and decompose the efficiency measures across commercial banks, traditional agricultural lenders, and microfinance institutions in China. Because of the different data forms, we are unable to get the same definition of the input and output across commercial banks, traditional agricultural lenders, and microfinance institutions in China. Therefore, there are two pairwise comparisons conducted: efficiency comparison between commercial banks and traditional agricultural lenders (including RCCs), and efficiency comparison between Rural Credit Cooperatives (RCCs) and microfinance institutions (MFIs).The input and output definitions are slightly different for the two pairs.

The financial data for the commercial banks and traditional agricultural lenders of China are obtained from Almanac of China's Finance and Banking (various years) and annual reports of individual bank from their websites. Information of the microfinance institutions in both India and China are collected from MixMarket.org. The study period is from 2004 to 2007.

There are 13 commercial banks, 3 traditional agricultural lenders, and 4 microfinance institutions (MFIs) included in this study. The traditional agricultural lenders considered in this analysis are: Agricultural Bank of China, Agricultural Development Bank of China, and Rural Credit Cooperatives (RCCs). The microfinance institutions included in this study are: China Fund for Poverty Alleviation (CFPA), Chifeng Zhaowuda Women's Sustainable Development Association (CZWSDA), PATRA Hunchun, and PATRA Yanbian.

Commercial Banks & Traditional Agricultural Lenders

The output measures used are loans, investments, and claims on other banks. The inputs are deposits, fixed assets, and number of employees. This study includes thirteen commercial banks and three traditional agricultural lenders covering the period from 2004 to 2007. There are a total of 64 observations. The summary statistics are provided in Table 4.1.

Rural Credit Cooperatives & Microfinance Institutions

The outputs are loans and other asset. The inputs are liabilities and number of employees. This study includes RCCS and four microfinance institutions (MFIs) in years ranging from 2004 to 2007. There are a total of 20 observations. The summary statistics are presented in Table 4.2.

4.3 Empirical Results

DEA, as discussed in 4.1, is implemented to the objective on the comparative efficiency analysis of commercial banks and traditional agricultural lenders (including RCCs), Rural Credit Cooperatives (RCCs) and microfinance institutions (MFIs). The following describes the analytical procedures and presents the preliminary results in Table 4.3 to Table 4.8.

Commercial Banks & Traditional Agricultural Lenders in China

First, we calculated and compared the efficiency measures between commercial banks and traditional agricultural lenders (including RCCs). The summary statistics for technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) are provided in Table 4.3, Table 4.4 and Table 4.5, respectively.

With respect to technical efficiency, commercial banks exhibit higher mean score than traditional agricultural lenders through the study period (2004-2007). The mean scores of commercial banks are all above 0.9 with the highest 0.9631 in 2004 and the lowest 0.9007 in 2005. On the other hand, the mean scores of traditional agricultural lenders are all less than 0.9 with the highest 0.8760 in 2004 and the lowest 0.6726 in 2005. This suggests that the traditional agricultural lenders could make significant reductions in input utilization (given the output level) and achieve significant cost savings. Both commercial banks and traditional agricultural lenders experienced the same trend through the study period: decreasing efficiency from the highest level achieved in 2004 and reaching the lowest efficiency level in 2005, then increasing steadily through the rest of the study period.

In regards to pure technical efficiency, there is no significant difference in the results obtained for commercial banks and traditional agricultural lenders. The mean scores are all above 0.9 throughout the study period (2004-2007). For each year, the mean score of commercial banks is slightly higher than the mean score of traditional agricultural lenders.

The scale efficiency comparison provides similar results as technical efficiency. Commercial banks exhibit higher mean score of scale efficiency than traditional agricultural lenders through the study period (2004-2007). The mean scores of commercial banks are all above 0.9 with the highest 0.9802 in 2006 while the mean scores of traditional agricultural lenders are all less than 0.9 with the lowest 0.6953 in 2005. Both commercial banks and traditional agricultural lenders experienced their lowest scale efficiency levels in 2005 with mean scores of 0.9469 and 0.6953, respectively.

It is worth of noting that, for both commercial banks and traditional agricultural lenders, the bulk of the overall technical inefficiency is attributed to scale inefficiency rather than pure technical inefficiency. The mean DEA scores of pure technical efficiency are all higher than the mean DEA score of scale efficiency. This contrasts with recent US evidence which typically finds that X-inefficiency (failure to minimize costs for a given level of output) is a much more serious problem than scale inefficiency (Berger and Humphrey, 1997).

Rural Credit Cooperatives & Microfinance Institutions

Now we focus on the efficiency measures of Rural Credit Cooperatives (RCCs) and microfinance institutions (MFIs). The summary statistics for technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) are provided in Table 4.6, Table 4.7 and Table 4.8, respectively. It is clear that RCCs and CFPA are the most efficient institutions, with efficiency scores of 1 through the study period (2004-2007).

For CZWSDA, the overall technical inefficiency is mostly attributed to scale inefficiency rather than pure technical efficiency. The only exception is year 2005 when the pure technical efficiency score is 0.6296, which is much lower than its scale efficiency score 0.9968. Pure technical inefficiency contributed most of the bulk of CZWSDA's overall technical inefficiency in 2005.

The pure technical efficiency scores are all 1 throughout the study period (2004-2007) for PATRA Hunchun. Since scale efficiency is the ratio of the technical efficiency and pure technical efficiency, PATRA Hunchun's technical efficiency and scale efficiency scores are the same for each year. Both of the efficiencies experienced decreasing trend from 2004 to 2007.

The pure technical efficiency scores are all 1 though the study period (2004-2007) for PATRA Yanbian. Again, since scale efficiency is the ratio of the technical efficiency and pure technical efficiency, PATRA Yanbian's technical efficiency and scale efficiency scores are the same for each year. Both of the efficiencies experienced V shape trend, decreasing from 2004 to 2006 and then increasing from 2006 to 2007.

4.4 Implications

Throughout the study period (2004-2007), commercial banks achieved higher level of technical efficiency, pure technical efficiency and scale efficiency than traditional agricultural lenders (including RCCs). The source of the overall technical inefficiency is attributed to the scale inefficiency rather than pure technical inefficiency for both commercial banks and traditional agricultural lenders.

RCCs and one of the selected MFIs are the most efficient institutions with all efficiency scores equal to 1 while other MFIs experienced some overall technical inefficiency and scale inefficiency through the study period (2004-2007).

Since the inputs and outputs are defined slightly different between the two pairwise comparisons, the calculated efficiency scores are not directly comparable across these two pairs. The direct comparison of efficiency scores across three categories (commercial banks, traditional agricultural lenders and microfinance institutions) will be more meaningful and insightful if the necessary financial information for defining output and input variables are available.

Table 4.1. Summary Statistics of Chinese Commercial Banks and Traditional Agricultural Lenders, 2004-2007

Variable	Minimum	Maximum	Mean	Standard Deviation
Y1-Loan[a]	46.23	39,575.42	10,680.62	11,408.88
Y2-Investment[a]	10.03	25420.24	4533.53	6866.40
Y3-Claims on other financial banks[a]	24.3	11717.52	2537.35	2879.03
X1-Deposit[a]	53.14	68984.13	16146.74	19192.88
X2-Fixed asset[a]	4.34	1197.84	266.81	331.13
X3-Number of Employees	256	651664	134178	192670
N-observation number	64			

a: All financial values are in hundreds of millions Chinese Yuan (￥100,000,000).

Table 4.2. Summary Statistics of Chinese RCCs and MFIs, 2004-2007

Variable	Minimum	Maximum	Mean	Standard Deviation
Y1-Loan[a]	0.0062	24121.61	4136.19	8542.47
Y2-Other assets[a]	0.0035	16974.13	2806.47	5825.68
X1-Liability[a]	0.0116	41095.74	6942.60	14362.19
X2-Number of employees	3	651664	123097	253167
N-observation number	20			

a: All financial values are in hundreds of millions Chinese Yuan (￥100,000,000).

Table 4.3. Technical efficiency of Chinese Commercial Banks & Traditional Agricultural Lenders, 2004-2007

	2004	2005	2006	2007
Commercial Banks				
mean	0.9631	0.9007	0.9414	0.9570
Standard deviation	0.0708	0.1001	0.1007	0.0761
minimum	0.8133	0.7608	0.6384	0.7433
maximum	1	1	1	1
Rural Financial Institutions				
mean	0.8760	0.6726	0.7846	0.7643
Standard deviation	0.1429	0.3796	0.2244	0.2733
minimum	0.7198	0.2565	0.5522	0.4648
maximum	1	1	1	1

Note: A “1” indicates that the institution is the most efficient relative to other institutions included in this study.

Table 4.4. Pure Technical Efficiency of Chinese Commercial Banks & Traditional Agricultural Lenders, 2004-2007

	2004	2005	2006	2007
Commercial Banks				
mean	0.9904	0.9509	0.9608	0.9936
Standard deviation	0.0347	0.0700	0.0993	0.231
minimum	0.8750	0.8260	0.6456	0.9167
maximum	1	1	1	1
Rural Financial Institutions				
mean	0.9711	0.9301	0.9554	0.9566
Standard deviation	0.0501	0.1211	0.0772	0.0752
minimum	0.9133	0.7902	0.8662	0.8697
maximum	1	1	1	1

Note: A "1" indicates that the institution is the most efficient relative to other institutions included in this study.

Table 4.5. Scale Efficiency of Chinese Commercial Banks & Traditional Agricultural Lenders, 2004-2007

	2004	2005	2006	2007
Commercial Banks				
mean	0.9726	0.9469	0.9802	0.9634
Standard deviation	0.0639	0.0724	0.0359	0.0753
minimum	0.8113	0.8188	0.9002	0.7433
maximum	1	1	1	1
Rural Financial Institutions				
mean	0.8988	0.6953	0.8131	0.7876
Standard deviation	0.1063	0.3425	0.1815	0.2354
minimum	0.7881	0.3246	0.6375	0.5345
maximum	1	1	1	1

Note: A “1” indicates that the institution is the most efficient relative to other institutions included in this study.

Table 4.6. Technical efficiency of Chinese RCCs and MFIs, 2004-2007

	2004	2005	2006	2007
RCC	1	1	1	1
CFPA	1	1	1	1
CZWSDA	0.9281	0.6276	0.8298	0.9107
PATRA Hunchun	1	1	0.6286	0.5255
PATRA Yanbian	0.7380	0.5983	0.5771	0.7369

Note: A "1" indicates that the institution is the most efficient relative to other institutions included in this study.

Table 4.7. Pure Technical Efficiency of Chinese RCCs and MFIs, 2004-2007

	2004	2005	2006	2007
RCC	1	1	1	1
CFPA	1	1	1	1
CZWSDA	0.9844	0.6296	1	1
PATRA Hunchun	1	1	1	1
PATRA Yanbian	1	1	1	1

Note: A “1” indicates that the institution is the most efficient relative to other institutions included in this study.

Table 4.8. Scale Efficiency of Chinese RCCs and MFIs, 2004-2007

	2004	2005	2006	2007
RCC	1	1	1	1
CFPA	1	1	1	1
CZWSDA	0.9427	0.9968	0.8298	0.9107
PATRA Hunchun	1	1	0.6286	0.5255
PATRA Yanbian	0.7380	0.5983	0.5771	0.7369

Note: A “1” indicates that the institution is the most efficient relative to other institutions included in this study.

CHAPTER 5

TECHNICAL EFFICIENCY OF MICROFINANCE INSTITUTIONS IN CHINA AND INDIA

China and India are both developing countries with huge population, with a significant portion of their population living in rural areas and subsisting on low incomes. The economic and demographic characteristics of their populations make them ideal breeding grounds for the operation of microfinance programs.

Microfinance was introduced in India earlier than in China and the majority of microloans in developing countries occur in India. Nowadays, there are more than 100 organizations in India that provide microloans to those in need. Interestingly, approximately 18% of the Indian population has taken a microloan (Christen, Rosenberg, and Jayadeva, 2004).

After its introduction in China in the 1990s, the microfinance industry has experienced ups and downs. It was initially adopted as financial tool aimed at poverty alleviation and eventually developed as China's microfinance industry with its own characteristics.

The operation of microfinance institutions (MFIs) varies significantly between India and China (Tsai, 2004). This is due in part to differences in the policy environment for both NGOs and nonbanking financial institutions. Overall, MFIs in India have not been subject to stringent regulations. In contrast to the MFIs in India, China's fiscal and economic policy environment is much more restrictive. China's MFIs are sponsored by a particular government unit. As such, China does not have purely nongovernmental organizations engaged in microfinance even though they may be functionally equivalent to NGOs. To date, India's MFIs have had more extensive reach in microfinance than their counterparts in China.

As emphasize earlier in this thesis, the goal of sustainability and achieving strong impact through wider social outreach can only be realized if MFI operations are highly efficient. This chapter will present a comparative efficiency analysis of MFIs in India and in China, with the basic goal of determining the relative efficiency of the much younger (inexperience) Chinese MFIs vis-à-vis the more established (experienced) Indian MFIs. After estimating the technical efficiency scores, Seemingly Unrelated Regression (SUR) techniques will be used to determine the factors that can explain any significant differences between Chinese and Indian MFIs.

5.1 Technical Efficiency

Technical efficiency measures how far a decision-making unit (DMU) is from the production frontier. Technical efficiency is comprised of two components: Pure technical efficiency (PTE) and Scale efficiency (SE). To compare the efficiency of Chinese and Indian MFIs, DEA will be used to calculate technical efficiency and further decompose it into pure technical efficiency and scale efficiency.

5.1.1 Methodology

To calculate the technical efficiency, the non-parametric method, DEA, discussed in **4.2** is employed here again. Consider the case where there are *k* DMUs in the sample, each producing *m* outputs [$Y_1, Y_2, ..., Y_k$] by using *n* input [$X_1, X_2, ..., X_k$], where Y_i ($i = 1, ..., k$) is the (m$\times$1) vector of outputs and X_i ($i = 1, ..., k$) is the (n$\times$1) vector of inputs. The outputs and inputs are represented by the *k*-column matrices: X and Y. The input requirement set can be represented by the free disposal convex hull of the observations. The smallest convex set contains the observations with the least input requirement set for the certain level of outputs.

The pure technical efficiency is obtained by solving the following DEA model:

$$\begin{aligned}
&\min\ \theta_i \\
&\text{subject to:} \\
&z_1 y_{11} + z_2 y_{12} + \ldots + z_k y_{1k} \geq y_{1i} \\
&z_1 y_{21} + z_2 y_{22} + \ldots + z_k y_{2k} \geq y_{2i} \\
&\qquad\qquad \cdots\cdots \\
&z_1 y_{m1} + z_2 y_{m2} + \ldots + z_k y_{mk} \geq y_{mi} \\
&\theta_i x_{1i} - z_1 x_{11} - z_2 x_{12} - \ldots - z_k x_{1k} \geq 0 \\
&\theta_i x_{2i} - z_1 x_{21} - z_2 x_{22} - \ldots - z_k x_{2k} \geq 0 \\
&\qquad\qquad \cdots\cdots \\
&\theta_i x_{ni} - z_1 x_{n1} - z_2 x_{n2} - \ldots - z_k x_{nk} \geq 0 \\
&z_i > 0,\ (i = 1,2,\ldots,k) \\
&z_1 + z_2 + \ldots + z_k = 1
\end{aligned} \tag{5..1}$$

where x_{ij} (i=1, …, n; j=1, …, k) is the ith input used by the jth DMU; and y_{ij} (i=1, …, m; j=1, …, k) is the ith output produced by the jth DMU. θ_i (i=1, …, k) is the measure of pure technical efficiency for the ith DMU. The technical efficiency, denoted as λ_i, can be obtained by solving the DEA model in equation (5.1) without the constraint $\sum z_1 = 1$.

The scale efficiency is the ratio of the technical efficiency and pure technical efficiency:

$$S_i = \frac{\lambda_i}{\theta_i} \tag{5.2}$$

If S_i is equal to 1, then the DMU is scale efficient; if S_i is less than1, then the DMU is inefficient. The source of scale inefficiency can be identified by estimating the DEA model in equation (1) with the constraint $\sum z_1 \leq 1$ instead of $\sum z_1 = 1$; that is, the technology is non-increasing returns to scale (NIRS). If the objective function of the DEA model under NIRS (labeled γ_i) is equal to pure technical efficiency (θ_i), decreasing returns to scale exist; otherwise, increasing returns to scale exist (Färe, Grosskopf, and Lovell, 1985).

5.1.2 Data and Variables

For the inputs, we used the suggested categories found in commercial banking efficiency papers (Giradone, Molyneux, and Gardner, 2004): fixed assets, funding, and risk. Usually labor is included in large commercial bank financial estimations, but since the MFIs used in this study are significantly smaller than commercial banks, labor would not be expected to influence ROE and number of borrowers. Since labor is often a measure of the size of the financial institution, the gross loan portfolio will instead be used as a measure of the size of the MFI, as it would influence the outputs (ROE and number of borrowers).

The other inputs are fixed assets, funding and risk. Owing to limited balance sheet data information available, the fixed assets variable was estimated as: Fixed Assets = Total Assets - Gross Loan Portfolio. For the funding variable, the debt-to-equity ratio was used. The debt-to-equity variable was chosen because it captures two sources of funding that MFIs use: loans, which are a majority of their debt, and their own equity. The use of the ratio explains how they are managing their funds – i.e. if they are taking on a lot of debt (as compared to the equity) or if they are keeping their debt at low levels (as compared to equity).

Risk was added to the equation to ensure that the precautions that MFIs take against poor repayment are considered. In more recent papers, including the risk factor when looking at banking institutions has become the norm (see Black, Kunze and Salvanes, 2004). For the risk variable, the loan-loss-provision ratio was used in this analysis. This variable was chosen as it reflects how strongly the MFIs feel about their borrowers' repayment ability. This ratio is usually influenced by the MFI's previous loan repayment experiences and their assessments of the potentials of their current loan portfolios. The higher the loan-loss-provision ratio, the less confident the MFI is about their borrowers' capability to repay their loans.

MFIs have to balance two parallel, sometimes seemingly contradictory, goals: financial profitability and social outreach. In this analysis, the return on equity (ROE) is used as a financial indicator and the number of active borrowers as the social outreach indicator. ROE is defined as the ratio of the difference of net operation income and taxes over average total assets by MixMarket. The ROE is often used in financial efficiency estimation (Giradone, Molyneux, and Gardner, 2004) as an output. The number of active borrowers was chosen for the social outreach indicator because MFIs are challenged with reaching as many borrowers as possible. We therefore are assuming that MFIs only lend to borrowers that are near the poverty level (Field and Pande, 2008). It is also assumed that the more active borrowers the MFI has, the more the MFI is achieving the social outreach goal.

Both dual-output and single-output modeling methods are used in this study. In dual-output modeling method, both outputs, return on equity (ROE) and number of borrowers, are signed the same weight through the programming. By using dual-output method, we will be able to evaluate the overall efficiency performance of MFIs in China and India. Then we use one of these two defined outputs along with the inputs to calculate technical efficiency scores of MFIs in China and India. The single-output approach should aim to reveal whether Chinese and Indian MFIs have different focus on their operations. The inputs used in both dual-output and single-output modeling methods are the same as we defined earlier.

There are 12 MFIs in China and 35 MFIs in India included in this study. All financial data and information are collected from MixMarket. The study period is from 2005 to 2009. The summary statistics of MFIs in China and India are presented in Table 5.1 and Table 5.2, respectively.

Based on the summaries of descriptive statistics for the Indian and Chinese MFI datasets (Tables 5.1 and 5.2), Indian MFIs tend to dominate their Chinese counterparts in the output measures (ROE and number of borrowers), although with larger standard deviations. In term of inputs, Indian MFIs have larger average and deviation in fixed assets, gross loan portfolio, debt to equity, and loan loss provision.

5.1.3 Empirical Results

First, we calculated and compared the efficiency measures between MFIs in China and India by using the dual-output modeling method. The summary statistics for technical efficiency (TE), scale efficiency (SE), and pure technical efficiency (PTE) are provided in Table 5.3, Table 5.4 and Table 5.5, respectively. We also present the comparison of annual average efficiency scores (TE, SE, and PTE) of Chinese and Indian MFIs in Figure 5.1, Figure 5.2, and Figure 5.3.

In order to isolate the two mission goals of MFIs, we then used the single-output approach to calculate the technical efficiency scores of MFIs in China and India. The results of using ROE as single output are presented in Figure 5.4 while the results of using number of borrowers as single output are presented Figure 5.5.

Dual-Output: Technical Efficiency (TE)

Looking at the annual average level of technical efficiency (Table 5.3 & Figure 5.1), the Indian and Chinese MFIs had two contrasting starting levels in 2005 when Indian MFIs registered a TE level of 0.2553 (coincidentally its lowest point) whereas Chinese MFIs started at their highest TE level of 0.7724. Indian MFIs, however, realized their highest TE level of 0.7718 in 2006 while Chinese MFIs dropped from their highest point in 2006. The technical efficiency of both

Indian and Chinese MFIs steadily dropped through 2006 to 2008, and then both registered improvements in their TE levels in 2009.

Overall, Chinese MFIs have lower annual average technical efficiency scores than Indian MFIs. But at the same time, the technical efficiency of Chinese MFIs experienced larger deviations than Indian MFIs throughout the study period (2005-2009).

Dual-Output: Pure Technical Efficiency (PTE)

The trends for the PTE results are quite different from the previous TE trends discussed earlier. As presented in Table 5.4 and Figure 5.2, PTE values for both Chinese and Indian MFIs tend to fluctuate only between a narrow range of (0.6 to 0.8). Chinese MFIs started with a higher pure technical efficiency in 2005 than Indian MFIs and continued such trend until 2007. The average pure technical efficiency of Chinese and Indian MFIs are very close at 0.7371, and 0.7138, respectively. Indian MFIs are able to register a higher PTE in 2008 than Chinese MFIs afterwards. This trend would continue till the end of the sample period.

Overall, Indian MFIs have slightly higher annual average pure technical efficiency scores than Chinese MFIs. But at the same time, the pure technical efficiency of Chinese MFIs experienced larger deviation than Indian MFIs throughout the study period (2005-2009).

Dual-Output: Scale Efficiency (SE)

The pattern of the results of scale efficiency scores is very similar to what we found for technical efficiency. As presented in Table 5.5 and Figure 5.3, Indian MFIs registered their lowest SE level of 0.3817 in 2005 while Chinese MFIs started at its highest point (0.8580). Indian MFIs then started to register improvements in their SE scores and reached their highest point of 0.9714 in 2006 while Chinese MFIs experienced deterioration in their SE scores starting in 2006. The technical efficiency of both Indian and Chinese MFIs steadily dropped through 2006 to 2008, before improving their SE levels in 2009.

Overall, for dual-output approach, Chinese MFIs have lower annual average scale efficiency scores than Indian MFIs. At the same time, the scale efficiency of Chinese MFIs experienced larger deviation than Indian MFIs throughout the study period (2005-2009). These results indicate that more mature Indian MFIs were able to operate more efficient when both missions are treated equally.

Single-Output: Technical Efficiency (TE)

As presented in Figure 5.4, when ROE is treated as single output, the technical efficiency performances of Chinese MFIs are better than Indian MFIs for all years. Comparing with their counterpart Indian MFIs, Chinese MFIs are newer and still in the early stage of the operations. So they are more struggling with realizing financial sustainability to survive in the market. This explains why Chinese MFIs operated more efficiently when ROE is the single output in the analysis. Figure 5.5 presents the technical efficiency performances of Chinese and Indian MFIs when number of borrowers is treated as single output. The technical efficiency performances of Indian MFIs are better than Chinese MFIs except in 2005. This is understandable that more established Indian MFIs were able to thrive in the market and then be able to more focus on their social outreach mission: to reach as many borrowers as possible.

This single-output approach provides us a good perspective of understanding that Chinese MFIs and Indian MFIs may have different focus point in their operations. However, social outreach and financial sustainability are two-pronged missions for all MFIs and any MFI cannot be classified as a MFI if they realize only one of these two missions. So the efficiency performances we got from dual-output approach are more representative. So our next step in this study of comparison of Chinese and Indian MFIs will use the efficiency scores we got from dual-output approach.

5.2 Seemingly Unrelated Regression

As we discussed in 5.1, the same set of inputs and outputs have been used to calculate the technical efficiency scores of MFIs in China and India. We already observed that there are significant difference of TE, PTE, and SE existing for MFIs in China and India. Now we are going to see whether the characteristics of Chinese and Indian MFIS affect the efficiency measurements differently. For this analysis, a Seemingly Unrelated Regression (SUR) is implemented as follows:

5.2.1 Methodology

In a seemingly unrelated equation system, the equations are related in one or both of the following ways. First, the error terms in the different equations are related. The error terms are correlated if there are common unobserved factors that influence the dependent variables in the equations. Second, the parameters in the different equations are related. This occurs if the same parameter(s) appears in more than one equation, or if the parameter(s) in one equation is a linear or nonlinear function of the parameter(s) in the other equations.

Consider the case where we have M-equations that are related because the error terms are correlated. This system of M seemingly unrelated regression equations can be written in matrix format as follows.

$$
\begin{aligned}
y_1 &= X_1\beta_1 + \mu_1 \\
y_2 &= X_2\beta_2 + \mu_2 \\
y_3 &= X_3\beta_3 + \mu_3 \\
&\ldots\ldots \\
y_M &= X_M\beta_M + \mu_M
\end{aligned}
\tag{5.3}
$$

Using more concise notation, this system of M-equations can be written as

$$y_i = X_i\beta_i + \mu_i \quad \text{for } I = 1, 2, \ldots, \text{M} \tag{5.4}$$

Where y_i is a $T \times 1$ column vector of observations on the *ith* dependent variable; X_i is a $T \times K$ matrix of observations for the *K-1* explanatory variables and a column vector of 1's for the *ith* equation; β_i is the $K \times 1$ column vector of parameters for the *ith* equation; and μ_i is the $T \times 1$ column vector of error terms for the *ith* equation.

The assumptions of SUR are as following:

A1. The functional form of the equation (5.4) is linear in parameters.

$\mathbf{y} = \mathbf{X\beta} + \boldsymbol{\mu}$

A2. The error term in the equation (5.4) has a normal distribution with mean zero.

$\boldsymbol{\mu} \sim \text{N}$ and $\text{E}(\boldsymbol{\mu}) = \mathbf{0}$

A3. The error term in the equation (5.4) is uncorrelated with each explanatory variable..

$\text{Cov}(\boldsymbol{\mu},\mathbf{X}) = \mathbf{0}$

A4. The errors in the equation (5.4) satisfy the following assumptions and imply the variance-covariance matrix of errors as $\text{Cov}(\boldsymbol{\mu}) = \text{E}(\boldsymbol{\mu\mu}^{\text{T}}) = \mathbf{W} = \mathbf{\Sigma} \otimes \mathbf{I}$

a. The error variance for each individual equation is constant (no heteroscedasticity).

b. The error variance may differ for different individual equations.

c. The errors for each individual equation are uncorrelated (no autocorrelation)

d. The errors for different individual equations are contemporaneously correlated.

There are two important cases when the SUR estimates turn out to be equivalent to the equation-by-equation OLS, so that there is no gain in estimating the system jointly. These cases are: C1, when the matrix **Σ** is known to be diagonal, that is, there are no cross-equation correlations between the error terms. In this case the system becomes not seemingly but truly unrelated. C2, when each equation contains exactly the same set of regressors, that is $X_1 = X_2 = \ldots = X_m$. Then the estimators turn out to be numerically identical to OLS estimates follows from Kruskal's theorem (Davidson and MacKinnon, 1993).

An often used specification test for the SUR model is the Breusch-Pagan Test of Independent Errors. The Breusch-Pagan Test is used to test the assumption that the errors across equations are contemporaneously correlated. The null hypothesis is no contemporaneous correlation. The alternative hypothesis is contemporaneous correlation. For a two equation SUR model, the test statistic is the following Lagrange multiplier statistic that has a chi-square distribution with 1 degree of freedom.

$$LM = Tr_{12}^2 \sim \chi^2(1) \quad \text{where} \quad r_{12}^2 = (\sigma_{12})^2 / (\sigma_{11}\sigma_{22})$$

where T is the sample size, σ_{12} is the sample covariance of the errors for the two equations, and σ_{11} and σ_{22} are the sample error variances for the two equations. This test statistic can be generalized for more than two equations.

5.2.2 Data and Variables

The explanatory variables include: funding source, year of establishment, the percentage of women borrowers, size, personnel allocation, and profitability variables. This set of variables will capture several possible sources of deviations in Chinese and Indian MFI structures. The data on the MFI characteristics are obtained from MixMarket.org. The summary statistics of all explanatory variables of Chinese and Indian MFIs are presented in Table 5.6.

The funding sources were included to see if MFIs are more efficient if they resort to raising lending funds through borrowings instead of maintaining their reliance on grants. The capability to accommodate increasing liabilities would actually indicate the MFIs greater financial maturity as dependence on grants is expected to be more prevalent only for younger MFIs. To analyze the effect of dependence on borrowed funds, the funding category was divided into three groups: no loans included (0), dependence on loans plus other sources (1), and reliance on loans as the only funding source (2). It is expected that the funding coefficient will be positively related to MFI efficiency, as greater reliance on lending funds should reflect greater financial maturity that can be achieved through greater efficiency.

The year of establishment was included to determine the effect of the experience on efficiency. The expectation is for more experienced MFIs to demonstrate higher levels of efficiency.

A variable capturing the proportion of women borrowers to the MFIs' total borrowers is included to determine the extent of client targeting employed by Indian and Chinese MFIs. As the established MFI lending paradigm contends, targeting women as preferred borrowers can be an effective strategy to enhance the MFIs financial sustainability objective as women borrowers tend to have good borrowing records as well as realizing the MFIs desire to empower women in the rural communities they operate in. Women are more trustworthy to devote their loans to reliable and more productive activities of their small businesses, thus ensuring the timely repayment of their loans. The percentage of women borrowers is expected to positively affect the MFI's efficiency.

Total assets is the sum of all cash, investments, furniture, fixtures, equipment, receivables, intangibles, and any other items of value owned by each MFI. We used total assets as a proxy variable to capture the MFI size effect.

Personnel allocation variables will be represented by average loan per borrower, borrower per staff, and personnel allocation ratio while the personnel allocation ratio is defined as the ratio of number of loan officers over number of personnel.

Profitability variables will be represented by return on assets (ROA) and cost per borrower (which is the flipside of the profit margin). ROA is defined as the ratio of the difference of net income and taxes over average total assets and is expected to positively affect the dependent variable while the cost variable will have a negative effect.

5.2.3 Empirical Results

The SUR is applied to three efficiency scores we calculated in 5.1, TE, PTE, and SE. For each efficiency score, it is a two equation SUR, one for China and one for India. The results are presented in Tables 5.7, 5.8, and 5.9.

Technical Efficiency (TE)

Technical efficiency measures how far a decision-making unit (DMU) is from the production frontier, i.e. if the DMU is maximizing output with given inputs and after having chosen technology.

The bottom of Table 5.7 provides a Breusch-Pagan test of whether the error terms from the two equations are independent. The large P-value (p=0.599) indicates that there is no contemporaneous correlation. In other word, there is no cross-equation correlation between the error terms. As we discussed, there are two cases when the SUR estimates turn out to be equivalent to the equation-by-equation OLS. One of them is that there are no cross-equation correlations between the error terms. So in this case of technical efficiency, there is no gain in estimating the system jointly. The SUR estimates are equivalent to the separate OLS for China and India, respectively.

Efficient Indian MFIs are more dependent on loans, which means that their cash flow generating capability is adequate to afford the more costly option of incurring liabilities and better increase their gross loan portfolio. Indian MFIs also are more efficient when dealing with smaller loan requests from their clientele.

For Chinese MFIS, the longer the MFI established the better technical efficiency level it achieves which is as what we expected as more experience results in higher efficiency. These MFIs also are more efficient when dealing with smaller loan requests from their clientele

The contrasting results for borrower per staff and personnel allocation ratios for the two countries tell an interesting story. Indian MFIs are more efficient when their staff members can handle more borrowers and their personnel allocation ratio is low. On the other hand, Chinese MFIs become more efficient when their staff members handle a smaller set of borrowers and their personnel allocation ratio is high. These contrasting results imply that Indian MFIs have most likely realized the benefits of economies of scale where they can thrive with a smaller personnel force to handle efficiently a greater workload. The longer experiences of Indian MFIs in handling client transactions enable them to achieve economies of scale with such working arrangement (less staff, more borrower clients). On the other hand, the results for the Chinese MFIs reveal that the Chinese MFI industry is relatively younger and has less experience in handling large volumes of transactions. As Chinese MFIs are still in the learning stage, the more efficient arrangement for them is to have their staff members handle a smaller set of borrowers at first. They are also inclined to hire more employees (personnel allocation ratio) that they can train and rely on to implement their lending operations. Also, as Chinese MFIs are still in the learning stage, they tend to be more efficient when they operate smaller operations (total assets result).

Scale Efficiency (SE)

SE measures a firm's productivity at a given point with respect to what it could accomplish if it operated at the most productive scale size where average productivity reaches a maximum level.

The bottom of Table 5.8 provides a Breusch-Pagan test of whether the error terms from the two equations are independent. The large P-value (p=0.537) indicates that there is no cross-equation correlation between the error terms. So in this case of scale efficiency, there is no gain in estimating the system jointly. The SUR estimates are equivalent to the separate OLS for China and India, respectively.

The results for borrower per staff and personnel allocation ratios are consistent with the findings for the technical efficiency SUR model. Chinese MFIs tend to hire more staff workers to become more efficient while Indian MFIs tend to hire fewer personnel. These results indicate the greater business maturity of Indian MFIs relative to the Chinese MFIs since these Indian lenders have been in existence for a much longer time.

The interesting result here is that Indian MFIs, like Chinese MFIs in the previous summary, would tend to maintain smaller operations (total assets) in order to enhance scale efficiency. This means that although the clientele of Indian MFIs may be larger, they tend to keep their asset expenses (and thus, their overhead expenses) low in order to continue operating efficiently.

Although Chinese MFIs are still in the learning stage, in term of scale efficiency, they tend to be more efficient as they gain more years in operation in microfinance industry which is as what we expected as more experience results in higher efficiency.

As what we found for technical efficiency, Indian MFIs tend to be more efficient when each staff member is dealing with larger number of borrowers.

Pure Technical Efficiency (PTE)

Pure technical efficiency measures how far off a DMU is from the production frontier. It indicates the potential reduction in inputs a DMU could achieve by adopting the best production practice of the best performance DMU.

The bottom of Table 5.9 provides a Breusch-Pagan test of whether the error terms from the two equations are independent. The large P-value (p=0.216) indicates that, in this case of pure technical efficiency, there is no gain in estimating the system jointly. The SUR estimates are equivalent to the separate OLS for China and India, respectively.

More efficient Indian MFIs again tend to have their staff members handle smaller loan requests, as probably dictated by the loan demand of their clientele (i.e. they operate in very rural areas where loan requests are generally small amounts). The contrasting result (vis-à-vis previous results in scale efficiency model) is the sign of the total asset variable. The result here suggests that more efficient Indian MFIs tend to have larger operations (total assets).

The results for the Chinese MFIs are interesting. Targeting women borrowers can seem to enhance pure technical efficiency of Chinese MFIs. This means that the much newer Chinese

MFI operations (less experience) must have probably not saturated yet the female segment of the rural borrowing population. The result here suggests that Chinese MFIs can benefit much if they continue to target women borrowers whose impressive repayment records confirmed from the more established operations of Indian and Bangladeshi MFIs can definitely enhance the technical efficiency potentials of Chinese MFIs.

Chinese MFIs are also less dependent on loans. This is understandable as Chinese MFIs are newer in the MFI industry so they rely more on grants while building up their financial sustainability potentials that should eventually allow them to accommodate more loans as source of funding for their operations.

The other results confirm the earlier trends noted in the other efficiency SUR models. More efficient Chinese MFIs tend to have their staff members handle a smaller number of clients. By keeping their operations at a smaller scale, Chinese MFIs are able to attain greater efficiency.

5.3 Implications

The more established Indian microfinance institutions achieved higher technical efficiency and scale efficiency than Chinese microfinance institutions. The difference of pure technical efficiency between Indian and Chinese microfinance institutions is not significant. At the same time, Chinese MFIs experienced larger deviations than Indian MFIs in terms of all three efficiency measurements. The results indicate that more experienced Indian MFIs perform better and more stable than their counterpart Chinese MFIs though the study period.

After estimating the technical efficiency scores, Seemingly Unrelated Regression (SUR) is used to determine the factors that can explain any significant differences between Chinese and

Indian MFIs. The results of Breusch-Pagan test indicate that there is no contemporaneous correlation existed for all three efficiency measurements. So there is no gain in estimating the system jointly. The SUR estimates are equivalent to the separate OLS for China and India, respectively.

In term of technical efficiency, efficient Indian MFIs are more dependent on loans while efficient Chinese MFIs are more dependent on the year of experience. Both Indian and Chinese MFIs are more efficient when dealing with smaller loan requests from their clientele. Indian MFIs are more efficient when their staff members can handle more borrowers and their personnel allocation ratio is low. The longer experiences of Indian MFIs in handling client transactions enable them to achieve economies of scale with such working arrangement (less staff, more borrower clients). On the other hand, Chinese MFIs become more efficient when their staff members handle a smaller set of borrowers and their personnel allocation ratio is high. This reveals that the Chinese MFI industry is relatively younger and has less experience in handling large volumes of transactions.

As for scale efficiency, the results indicate the greater business maturity of Indian MFIs relative to the Chinese MFIs since these Indian lenders have been in existence for a much longer time. Although the clientele of Indian MFIs may be larger, they tend to keep their asset expenses (and thus, their overhead expenses) low in order to continue operating efficiently. Although Chinese MFIs are still in the learning stage, they tend to be more efficient as more years in operation in microfinance industry which is as what we expected as more experience results in higher efficiency.

More efficient Indian MFIs, in term of pure technical efficiency, again tend to have their staff members handle smaller loan requests, as probably dictated by the loan demand of their clientele. The result also suggests that more efficient Indian MFIs tend to have larger operations (total assets). Targeting women borrowers can seem to enhance pure technical efficiency of Chinese MFIs. The result suggests that Chinese MFIs can benefit much if they continue to target women borrowers whose impressive repayment records confirmed from the more established operations of Indian and Bangladeshi MFIs can definitely enhance the technical efficiency potentials of Chinese MFIs.

Table 5.1. Summary Statistics of MFIs in China, 2005-2009

Variable	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Y1- Return to Equity	-2.11	0.62	-0.02	0.41
Y2- Number of Borrowers	407	36080	5178	8877
X1- Fixed Assets ($1,000)	1	2908	537	792
X2- Gross Loan Portfolio ($1,000)	153	27521	3001	5720
X3- Debt to Equity	-154.89	32.56	-6.32	28.93
X4- Loan loss Provision	-0.011	0.032	0.005	0.009
N-observation number	60			

Note: Return to Equity is defined as (net operation incomes - taxes)/total average equity, the negative ROE indicates that the MFIs have negative net operation incomes.

Table 5.2. Summary Statistics of MFIs in India, 2005-2009

Variable	Minimum	Maximum	Mean	Standard Deviation
Y1- Return to Equity	0.05	9.57	0.23	1.21
Y2- Number of Borrowers	441	5795028	328237	694055
X1- Fixed Assets ($1,000)	583	200321	6902	26120
X2- Gross Loan Portfolio($1,000)	47	960794	47065	115967
X3- Debt to Equity	4.96	630.16	28.04	73.16
X4- Loan loss Provision	0.002	0.062	0.009	0.012
N-observation number	175			

Note: Return to Equity is defined as (net operation incomes - taxes)/total average equity, the negative ROE indicates that the MFIs have negative net operation incomes.

Table 5.3. Technical Efficiency of MFIs in China and India, 2005-2009

	2005	2006	2007	2008	2009
INDIA					
Mean	0.2553	0.7718	0.5754	0.3939	0.7584
Standard deviation	0.2217	0.2306	0.2915	0.2693	0.2198
Minimum	0.0350	0.1851	0.0857	0.1050	0.3160
Maximum	1.0000	1.0000	1.0000	1.0000	1.0000
CHINA					
Mean	0.7724	0.6267	0.5247	0.2359	0.5159
Standard deviation	0.4553	0.3461	0.4392	0.3091	0.4690
Minimum	0.0895	0.2834	0.1448	0.0048	0.0157
Maximum	1.0000	1.0000	1.0000	1.0000	1.0000

Table 5.4. Pure Technical Efficiency of MFIs in China and India, 2005-2009

	2005	2006	2007	2008	2009
INDIA					
mean	0.7229	0.7919	0.7138	0.6768	0.8185
Standard deviation	0.3282	0.2272	0.3071	0.3154	0.1997
minimum	0.0385	0.1977	0.0971	0.1052	0.3158
maximum	1.0000	1.0000	1.0000	1.0000	1.0000
CHINA					
mean	0.8018	0.8230	0.7371	0.5475	0.6247
Standard deviation	0.3965	0.2993	0.3820	0.4240	0.4683
minimum	0.2071	0.3091	0.1619	0.0597	0.1115
maximum	1.0000	1.0000	1.0000	1.0000	1.0000

Table 5.5. Scale Efficiency of MFIs in China and India, 2005-2009

	2005	2006	2007	2008	2009
INDIA					
mean	0.3817	0.9714	0.8159	0.6441	0.9208
Standard deviation	0.2348	0.0445	0.1797	0.2952	0.0930
minimum	0.1271	0.8340	0.4769	0.2332	0.6788
maximum	1.0000	1.0000	1.0000	1.0000	1.0000
CHINA					
mean	0.8580	0.7752	0.7324	0.4281	0.7116
Standard deviation	0.2839	0.2781	0.3578	0.3349	0.3571
minimum	0.4322	0.3987	0.1606	0.0388	0.1387
maximum	1.0000	1.0000	1.0000	1.0000	1.0000

Table 5.6. Summary Statistics of Explanatory Variables in SUR, 2005-2009

Variable	Minimum	Maximum	Mean	Standard Deviation
Indian MFIs				
Funding source	0	2	1.25	0.55
Year of establishment (yr)	4	30	13.74	5.61
Women borrower percent (%)	0	1	0.91	0.19
Total assets ($1,000)	133	897871	53933	121108
Average loan per borrower ($)	0.13	4.81	1.35	0.68
Borrowers per staff	0	14.3	2.83	2.25
Personal allocation ratio	0	1.22	0.63	0.23
Return on assets	-30.3	30.82	2.04	5
Cost per borrower ($)	0	7.5	1.40	1.26
Chinese MFIs				
Funding source	0	2	0.45	0.62
Year of establishment (yr)	2	14	7.19	3.45
Women borrower percent (%)	0.05	1	0.69	0.32
Total assets ($)	212	30429	3537	6389
Average loan per borrower ($)	1.42	101.93	13.42	26.06
Borrowers per staff	0.13	2.61	0.99	0.62
Personal allocation ratio	013	2.66	0.66	0.45
Return on assets	-8.14	12.39	0.91	3.53
Cost per borrower ($)	1.1	80.4	12.11	19.03

Note: Return to assets is defined as (net operation incomes - taxes)/total average asset, the negative ROA indicates that the MFIs have negative net operation incomes.

Table 5.7. SUR Results of Technical Efficiency (China and India)

	India		China	
	Coefficients	P-value	Coefficients	P-value
Intercept	0.276 (0.317)	0.387	0.033 (0.263)	0.900
Funding	0.197 (0.089)	0.031**	-0.178 (0.117)	0.133
Establishment	0.011 (0.011)	0.356	0.058 (0.024)	0.022**
Women	0.215 (0.240)	0.374	0.263 (0.197)	0.189
Total assets	-0.0003 (0.0004)	0.418	-0.026 (0.008)	0.002***
Loan Per Borrower	-0.172 (0.100)	0.091*	0.003 (0.003)	0.356
Borrower Per Staff	0.053 (0.022)	0.024**	-0.169 (0.092)	0.073*
Personnel Allocation Ratio	-0.421 (0.158)	0.011**	0.275 (0.115)	0.021**
Return to Assets	0.007 (0.008)	0.370	-0.021 (0.020)	0.298
Cost Per Borrower	0.030 (0.052)	0.565	-0.002 (0.005)	0.772
Breusch-Pagan Test	Test Statistic=0.275		P-value=0.599	

Note: '***' significant at 0.01, '**' significant at 0.05, '*' significant at 0.10

Table 5.8. SUR Results of Scale Efficiency (China and India)

	India		China	
	Coefficients	P-value	Coefficients	P-value
Intercept	0.549 (0.277)	-.053*	0.230 (0.225)	0.312
Funding	0.123 (0.076)	0.120	-0.058 (0.100)	0.566
Establishment	-0.007 (0.010)	0.510	0.045 (0.021)	0.034**
Women	0.151 (0.210)	0.476	0.124 (0.168)	0.465
Total assets	-0.001 (0.0003)	0.007***	0.003 (0.007)	0.708
Loan Per Borrower	0.089 (0.087)	0.312	0.002 (0.003)	0.573
Borrower Per Staff	0.041 (0.020)	0.047**	-0.064 (0.003)	0.421
Personnel Allocation Ratio	-0.367 (0.138)	0.011**	0.209 (0.098)	0.038**
Return to Assets	0.004 (0.007)	0.556	-0.016 (0.017)	0.357
Cost Per Borrower	0.043 (0.046)	0.352	-0.006 (0.005)	0.236
Breusch-Pagan Test	Test Statistic=0.382		P-value=0.537	

Note: '***' significant at 0.01, '**' significant at 0.05, '*' significant at 0.10

Table 5.9. SUR Results of Pure Technical Efficiency (China and India)

	India		China	
	Coefficients	P-value	Coefficients	P-value
Intercept	0.656 (0.269)	0.019**	0.347 (0.217)	0.111
Funding	0.073 (0.075)	0.342	-0.338 (0.095)	0.0008***
Establishment	0.016 (0.010)	0.098*	0.056 (0.020)	0.007***
Women	0.125 (0.204)	0.544	0.429 (0.160)	0.010**
Total assets	0.0007 (0.0003)	0.023**	-0.032 (0.007)	0.0000***
Loan Per Borrower	-0.283 (0.085)	0.002***	0.004 (0.003)	0.164
Borrower Per Staff	0.022 (0.020)	0.269	-0.141 (0.075)	0.065*
Personnel Allocation Ratio	-0.113 (0.134)	0.405	0.008 (0.093)	0.934
Return to Assets	0.004 (0.006)	0.534	-0.030 (0.016)	0.075*
Cost Per Borrower	-0.003 (0.044)	0.947	0.001 (0.004)	0.772
Breusch-Pagan Test	Test Statistic=1.528		P-value=0.216	

Note: ‘***’ significant at 0.01, ‘**’ significant at 0.05, ‘*’ significant at 0.10

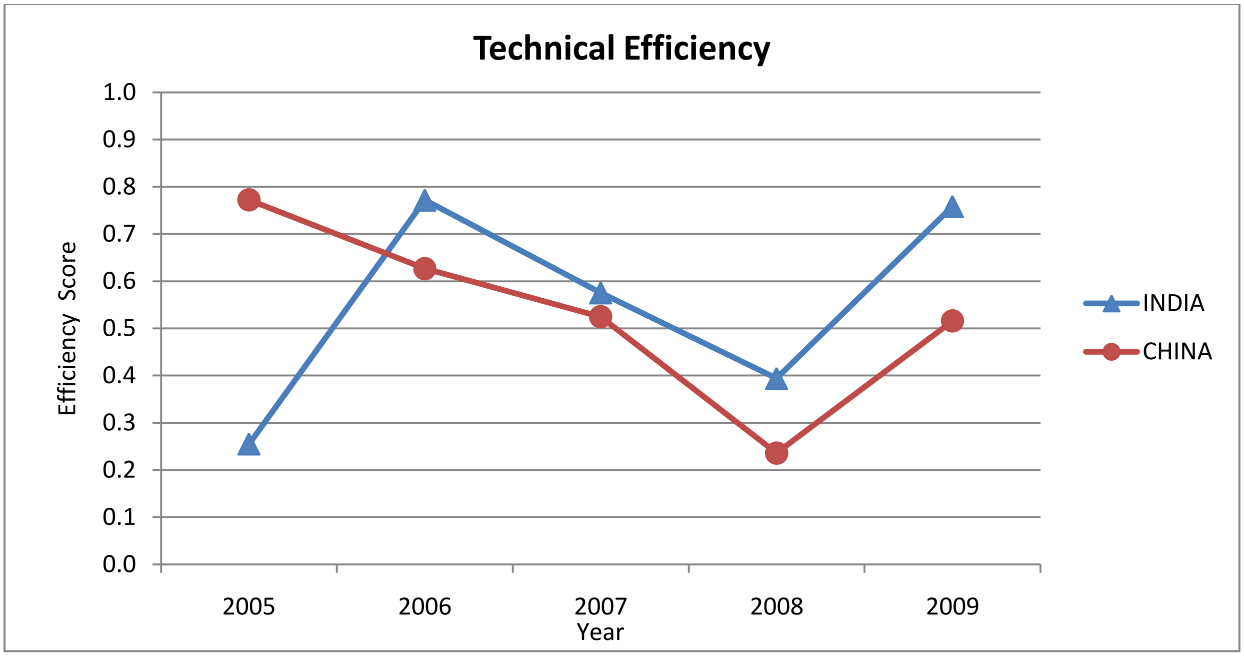


Figure 5.1. Technical Efficiency of MFIs in China and India, 2005-2009

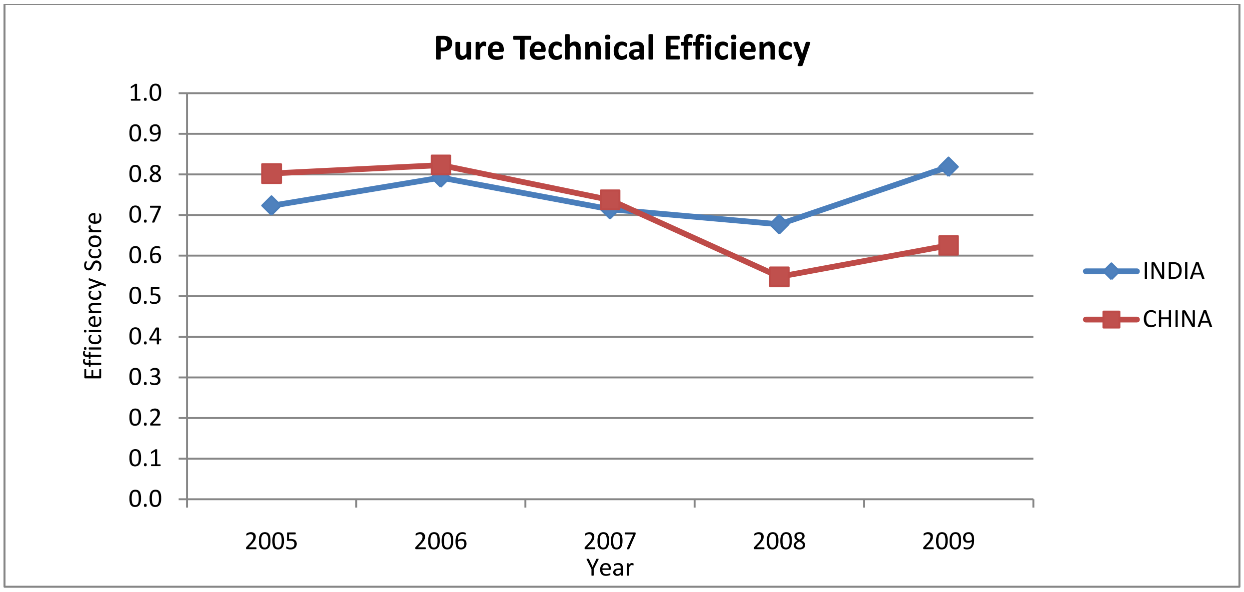


Figure 5.2. Pure Technical Efficiency of MFIs in China and India, 2005-2009

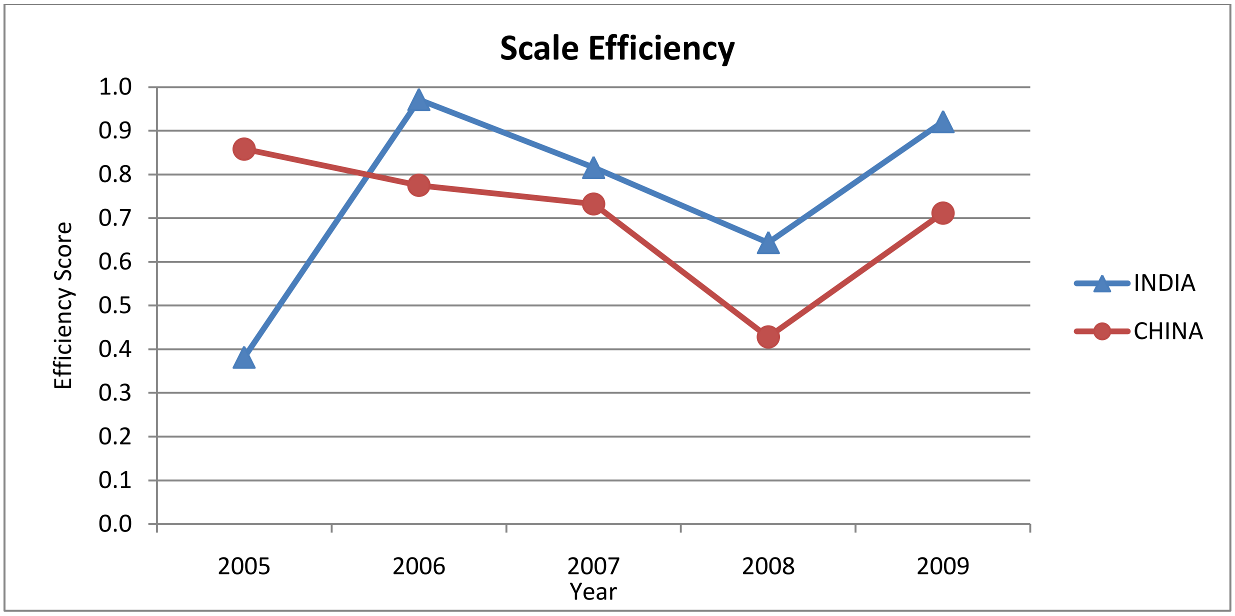


Figure 5.3. Scale Efficiency of MFIs in China and India, 2005-2009

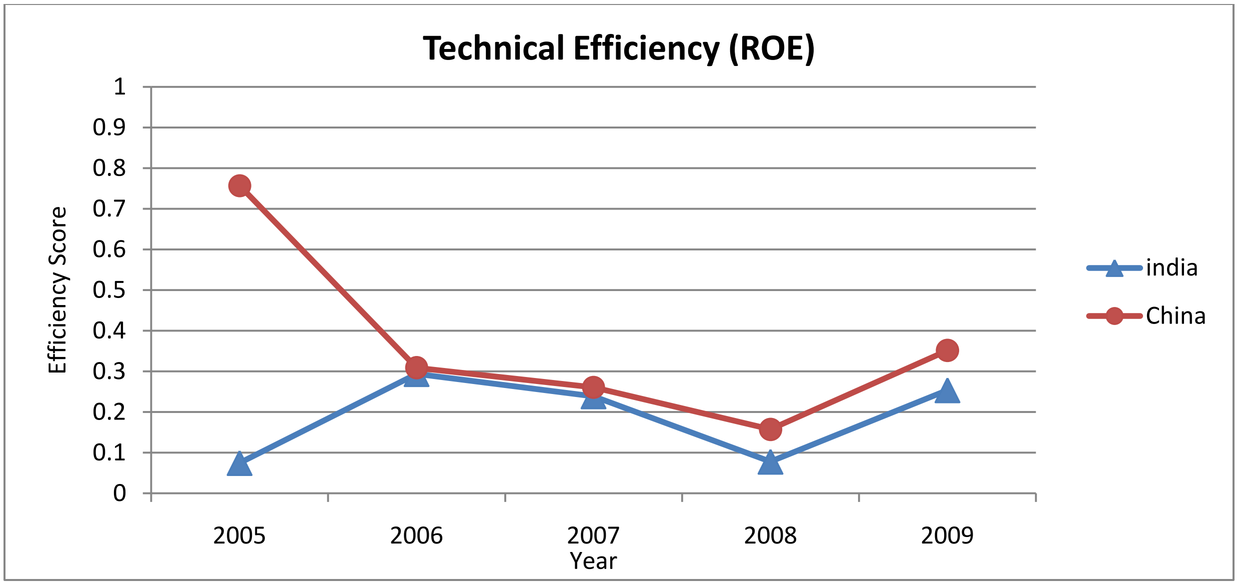


Figure 5.4. Technical Efficiency of MFIs in China and India (ROE), 2005-2009

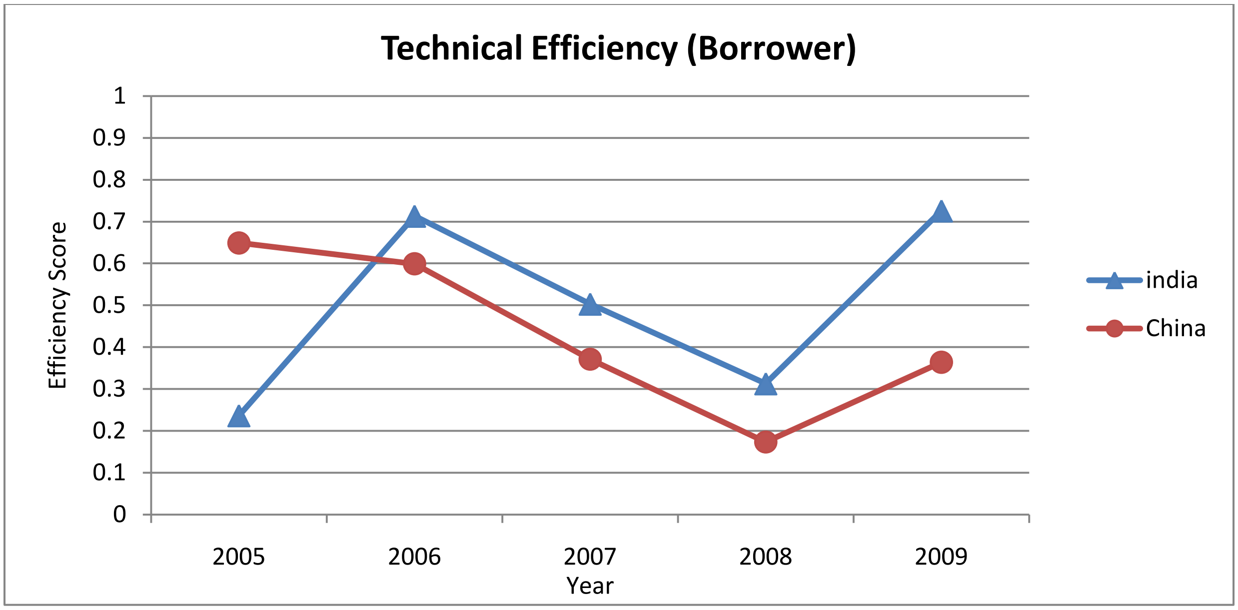


Figure 5.5. Technical Efficiency of MFIs in China and India (Number of Borrowers), 2005-2009

CHAPTER 6

CONCLUSION

This study's primary goal is the understanding of the challenges faced by microfinance firms in China as well as uncovering trends in their operating goals and decisions, especially at such early stages of their existence. This study realized this goal through a comparative analysis of efficiency conditions and strategies implemented by such Chinese MFIs vis-à-vis competing commercial and traditional agricultural or rural lenders in China as well as counterpart MFIs in India. The comparisons with competing Chinese lenders were designed to uncover the effects of differing operating structures and governmental restrictions on operating decisions and strategies. The Indian MFI comparison, on the other hand, was intended to assess the operational progress and values placed on typical microfinance mission goals of the relatively newer (less experienced) Chinese MFIs compared to the Indian MFI benchmark, chosen by virtue of these institutions' wealth of longitudinal experience in micro lending.

6.1 Major Findings

In this study, we use the input distance function to estimate the technical efficiency and allocative efficiency of microfinance institutions and commercial banks in China. In term of technical efficiency, the results indicate that both MFIs and commercial banks are not technically efficient. A statistical comparison of these results indicate that the TE levels of MFIs and commercial banks are not statistical significantly different from each other. The allocative inefficiency levels vary over years but relative allocative inefficiency exists widely in both commercial banks and MFIs between two inputs (assets and labor). Overall, commercial banks have achieved higher allocative efficiency levels than MFIs.

The nonparametric approach, data envelopment analysis, is employed to further decompose the technical efficiency into pure technical efficiency and scale efficiency. Throughout the study period (2004-2007), commercial banks achieved higher level of technical efficiency, pure technical efficiency and scale efficiency than traditional agricultural lenders (including RCCs). RCCs and one of the selected MFIs are the most efficient institutions with all efficiency scores equal to 1 while other MFIs experienced some overall technical inefficiency and scale inefficiency through the study period (2004-2007).

We used more established Indian MFIs as vantage point to compare the technical efficiency results of Chinese MFIs. Indian microfinance institutions are found to achieve higher technical efficiency and scale efficiency than Chinese microfinance institutions while Chinese MFIs experienced larger deviations than Indian MFIs in terms of all three efficiency measurements. The results indicate that more experienced Indian MFIs perform better and are more stable than their counterpart Chinese MFIs thoughout the study period.

Seemingly Unrelated Regression (SUR) is used to determine the factors that can explain any significant differences between Chinese and Indian MFIs. In term of technical efficiency, Indian MFIs are more efficient when their staff members can handle more borrowers and their personnel allocation ratio is low. The longer experiences of Indian MFIs in handling client transactions enable them to achieve economies of scale with such working arrangement (less staff, more borrower clients). On the other hand, Chinese MFIs become more efficient when their staff members handle a smaller set of borrowers and their personnel allocation ratio is high.

This reveals that the Chinese MFI industry is relatively younger and has less experience in handling large volumes of transactions.

As for scale efficiency, the results indicate the greater business maturity of Indian MFIs relative to the Chinese MFIs since these Indian lenders have been in existence for a much longer time. Although the clientele of Indian MFIs may be larger, they tend to keep their asset expenses (and thus, their overhead expenses) low in order to continue operating efficiently.

More efficient Indian MFIs, in term of pure technical efficiency, again tend to have their staff members handle smaller loan requests, as probably dictated by the loan demand of their clientele. The result also suggests that more efficient Indian MFIs tend to have larger operations (total assets). Targeting women borrowers can seem to enhance pure technical efficiency of Chinese MFIs. The result suggests that Chinese MFIs can benefit much if they continue to target women borrowers whose impressive repayment records confirmed from the more established operations of Indian and Bangladeshi MFIs can definitely enhance the technical efficiency potentials of Chinese MFIs.

6.2 Study's Implications and Future Research Direction

This study's results provide important implications on the nature of challenges faced by MFIs in China. In the Chinese financial environment, there are several forms of governmental restrictions that can affect a financial institution's quest for survival and financial sustainability: limits on geographical coverage of operations, more specific client or industry targeting restrictions, interest rate ceilings, and, for MFIs, the added challenge of reaching out to remote (hardly accessible) clients in rural areas.

It is therefore not surprising that commercial banks (which are the least restricted among Chinese financial institutions) would be more capable of realizing efficiencies in their operations or that the traditional Chinese agricultural or rural lenders (which are government-owned and operated) would have a significant edge over the younger Chinese MFIs that have to aggressively source for cheaper funds to finance their operations. Moreover, the Indian MFIs are naturally expected to have already acquired or learned strategies to maintain operating efficiencies, not only by virtue of their wealth of experience but because of their more flexible operating environments (less government intervention) and more accessible clientele (sans the physical geographical challenges for access in China).

Given all these considerations, it is therefore hardly an understatement to declare that there can be no greater challenge in setting up an MFI operation than establishing one in China instead of anywhere else in the world. Previous studies have shown that one of a start-up MFI's greatest challenges is attaining financial sustainability as the social outreach goal is usually relegated to the backseat in the early years of operations. In China, newer MFIs struggle with fund sourcing concerns and must confront the more difficult challenge of sustaining their operations within limits imposed by the Chinese government, especially on loan pricing. In other countries, newer MFIs charge relatively higher interest rates in order to pay for higher initial operating costs and remain in business. Notably, these newer MFIs' interest rates are still significantly lower than those charged in informal credit markets, but a bit higher than those charged by more experienced MFIs in India, for example. But new Chinese MFIs do not have loan pricing flexibilities as they have to be cognizant of the government-imposed ceiling on interest rates.

This study has shed important light on the predicament of MFIs in China relative to their lending competitors in China and their peers in India. As data issues have usually been difficult to resolve in empirical studies requiring information from Chinese financial institutions, the models used in this study can be improved by expanding the input and output datasets to include other parameters in lending operations. A complementary study that analyzes the efficiency problem from the borrowers' point of view could also provide important results that could corroborate the lenders' study results.

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