Empirical Analysis of Technical Efficiency and Productivity in Post-Reform China

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神戸大学大学院経済学研究科

経済学専攻

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改革開放後中国における技術的効率性と生産性の実証分析

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Abstract

This dissertation mainly presents three essays providing empirical evidence on technical efficiency and productivity in post-reform China.

The first essay uses a household-level data—Chinese Household Income Project (CHIP) surveys—to investigate regional technical efficiency, technology gaps, and their determinants in rural China. The findings show that the Southeast always has the highest technology gap ratio, while the Southwest has an increasing meta-frontier technical efficiency. On the contrary, the Northwest always lags behind with respect to the technical efficiency and the technology gap ratio. The results also show that intra-regional technical efficiency, rather than technology gaps contribute to the disparities of meta-frontier technical efficiency level across regions in rural China. In addition, the results of the determinant models indicate that the quality of agricultural labor, agricultural infrastructure, natural conditions, and farmer's political status have strong positive effects on a farm's technical efficiency and technology gap ratio, while the illiteracy rate, off-farm activities, lagged natural conditions, and lower economic development level are found to have a negative effect on a farm's technical efficiency and technology gap ratio.

The second essay uses firm-level data to investigate the regional technical efficiency, technology gaps, total factor productivity (TFP) change, and their determinants in Chinese state-owned manufacturing enterprises during the period of 1980-1994. The results indicate that Jiangsu has the highest mean technology gap ratio while Sichuan has the highest mean technical efficiency value. The results also show that enterprises in all regions experienced positive TFP change in the early reform period, where the TFP growth attributed to technical efficiency change in the first ten years, then to technical change in the subsequent five years. Next, the results of the determinant models show that reform measures (management form dummies, bonus system) contributed greatly to TFP growth and technical efficiency improvement. Engineering personnel share and export ratio are also found to have strong positive effect on TFP growth, and technical efficiency improvement.

In contrast to the stochastic meta-frontier analysis approach used in previous essays, the third essay employs a different methodology—a two-stage data envelopment analysis–to investigate the linkage between openness and DEA technical efficiency in

Chinese manufacturing industry using the World Bank Investment Climate Survey. The results indicate that the firms involved in international trade and foreign capital participation are more efficient than others. The findings in the two-stage bootstrap estimation also show that international trade have positive effect on technical efficiency in Chinese manufacturing industry.

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Chapter 1

Introduction

China has been called the “miracle economy” for its great economic achievement since it launched the Reform and Opening-Up policy in 1978. Because of this, it is customary for researchers to use its major economic indicators in 1978 as a benchmark. As Figure 1.1 shows, during the 30 years between 1978 and 2008, China enjoyed sustained economic growth at an annual average rate of 9.8%; in other words, its real gross domestic product (GDP) in 2008 was 16.5 times its 1978 level. When population growth is taken into account, the per capita GDP grew 8.6% per year. China’s “miracle economy” has captured a great deal of attention from researchers. In particular, Lin et al. (1996) addressed a number of questions: Why did China initiate reform at the end of the 1970s? How did the reform proceed? What did the reform achieve? How could the reform continue? Chow (2002) presented a detailed interpretation of the process by which China transitioned from a planned economy to a market-oriented one. However, what were the important factors that contributed to China’s economic growth “miracle” during this reform period? Wu (2004, p1) argues that China’s economic growth has been driven by the development of the rural non-farming sector, a massive inflow of foreign capital, structural transformation, reform-induced efficiency improvement and the promotion of trade. This dissertation will investigate reform-induced efficiency improvement in three respects.

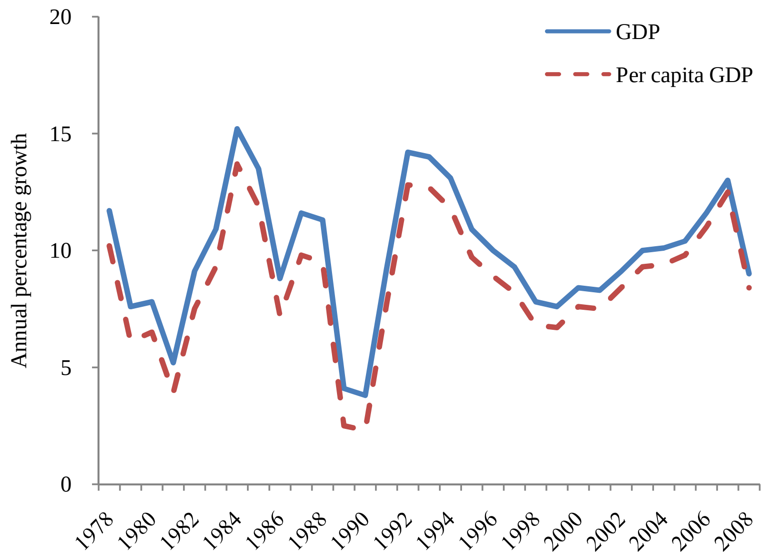

Figure 1.1: The growth rate of Chinese economy, 1978–2008

Source: National Bureau of Statistics of China (2010).

1.1 China's economic reform and opening up

After the People's Republic of China was founded in 1949, the new government turned to the former Soviet Union as its primary model and developed a highly centralized planned economic system characterized by (1) a heavy-industry-oriented development strategy, (2) a macro policy environment with low interest rate, low exchange rate, low wage, and low commodity price, (3) a planned resource allocation system, and (4) a micro management institution known as State Ownership and People's Commune (Lin et al., 2003). However, the government ignored the economic situation presented by China's abundant labor force but shortage of capital in these early, foundational years. China thus moved away from any comparative advantage it may have enjoyed.[1] As a result, the heavy-industry-oriented development strategy and distorted macro policy environment led to low and instable economic growth, and the planned resource allocation system and micro management institution led to inefficient resource allocation, lack of competition, poor incentives, and low productive efficiency. At the same time, neighboring countries and areas, such as Japan, South Korea, Singapore, Hong Kong, and Taiwan, which had adopted a market economy, achieved great success in economic development. China's own economic failure,

[1] China should develop labor-intensive industries in that period, but it had given much concern to heavy industries, which is typically capital-intensive.

coupled with the economic successes of its neighbors, induced the country to make change.

In December 1978, at the Third Plenary of the Eleventh Central Committee of the Chinese Communist Party (CCP), the Party publicly rejected the principle of class struggle as the key determinant of policy and took a more pragmatic approach to addressing the country's concerns—one based on economic principles. China then initiated the Reform and Opening Up policy to transition from a planned economy to a market-oriented one.

1.1.1 Agriculture reform

The reform began in the agricultural sector with the implementation of the "Household Responsibility System" (Jiating Lianchan Chengbao Zerenzhi), which successfully brought incentives back to the marketing system. At the end of 1978, 18 Xiaogang villagers made a household contract, under which land was leased to families in return for delivery of fixed output quotas. The household contract marked the beginning of China's agricultural reform. The abundant harvest of the Xiaogang village in 1979 led to the implementation of the Household Responsibility System in more and more villages. Next, rural markets began to reopen. Farmers were permitted to deal with their own output in rural markets after fulfilling their output quotas. Rural households were also allowed to engage sideline activities, such as handicraft, and raise chickens and livestock, activities that were banned under the commune system. In 1982, the Central Committee of the CCP approved the "National Rural Work Meeting Minutes" and pointed out that the current responsibility systems in operation in rural areas were the production responsibility systems under the socialist collective economy. This declaration meant that the Household Responsibility System became a main measure of agricultural reform, and it further promoted the system's implementation. At the end of 1983, the Household Responsibility System had been adopted by 98 percent of rural production teams in China (Lin, 1992).

The Household Responsibility System prompted an increase in agricultural production through productivity gains. According to statistical data, during the period from 1978 to 1984, when the Household Responsibility System was dominant, agricultural output grew 42.23%, at annual rate of 6.05%. Lin (1992) showed that 46.89% of the total agricultural output increase in that period can be attributed to the Household Responsibility System. However, even though China's agricultural output experienced high growth after the reform, the growth was not stable (see Figure 1.2).

In particular, the growth decreased after 1984 when the focus of reform was turned from the rural sector to state-owned enterprises and coastal areas.

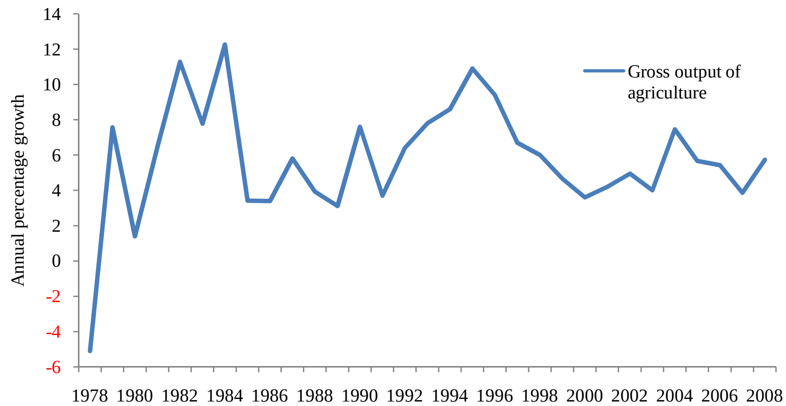

Figure 1.2: The growth rate of Chinese agriculture, 1978–2008

Source: National Bureau of Statistics of China (2010).

In 1985, the fourth "No 1 central documents" was issued by the Central Committee of the CCP. The government proposed two important measures to liberalize the grain market. First, the system of unified purchase was replaced by contract procurement, and the new contract procurement price was set at a weighted average of the previous quota and above-quota prices. Second, the grain-rationing system was abandoned, and consumers could no longer buy a fixed amount of grain at a low price as they had before 1985. These measures allowed farmers to develop a connection with market.

In 1993, because the 20-year land leases introduced in 1978 were set to expire in the coming years, the central government proposed extending them for another 30 years to stabilize the rural land contracting relationship and endow farmers with long-term, guaranteed land-use rights. In addition, transfer of these land-use rights was permitted with compensation. This allowed the most important factor for agricultural production—land—to be allocated according to the market rule. These measures resulted in improved agricultural productivity.

In general, agricultural growth is attributed two major factors: input growth and productivity improvement. Fan et al. (2004) point out that rural reforms had accounted for more than 60% of the total growth of Chinese agricultural production over the 1978–1984 period, but their impact on the growth of agricultural total factor productivity (TFP) was not significant between 1985 and 2000. Considering the fact that some agricultural production resources, such as cultivated land, irrigated water and the rural agricultural labor force, are decreasing as its economy further develops, China must improve its agricultural TFP to raise its agricultural output. Furthermore, TFP improvement is theoretically attributed to efficiency improvement (catching up) and technological progress (innovation). Thus, improving agricultural technical efficiency can be a very important approach to raising agricultural TFP. In addition, China's vast geographical area is characterized by regional disparities in natural resources, physical capital stocks, and agricultural technological changes. Hence, the reform may have different impact in different regions. Therefore, the first essay of this dissertation attempts to compare the agricultural technical efficiency and technology gaps across regions and their determinants in the Chinese post-reform period.

1.1.2 Reform of state-owned enterprises

Just as the People's Communes (Renmin Gongshe) were instrumental in the agricultural sector during the pre-reform period, the State-Owned Enterprises (SOEs) were the most important production units in the manufacturing and service sectors. Chinese SOEs came from the SOEs owned by the former government and private enterprises in the period of "Socialist Reform" (Shehui Zhuyi Gaizao). When the process of the "Socialist Reform" was completed at the end of 1957, almost 90% of the gross industrial output value came from SOEs. Ever since, SOEs have played a very significant role in China's economic development (see Figure 1.3). However, following the socialist economic principles, SOEs were aimed at output maximization rather than profit maximization or cost minimization. They performed government planning, producing the maximum output to satisfy the planning authorities, submitting all profits to the government and having all expenses covered by the government. For incentive mechanisms, SOEs relied on political propaganda and rank promotion, instead of explicit material rewards, to motivate managers and workers. As a result, the problems of inefficient production and other economic failures in Chinese SOEs became increasingly serious. To remedy this, China also began market-oriented reforms focused on efficiency and productivity improvements and economic growth in state-owned sector after the Third Plenary of the Eleventh Central Committee of the CCP was held in 1978.

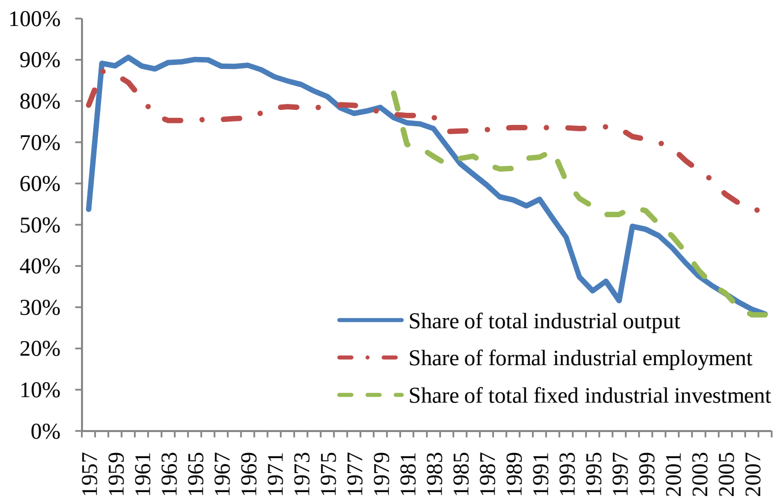

Figure 1.3: The importance of SOEs in Chinese economy
Notes and Source: The share figures are calculated using information from *China Compendium of Statistics 1949-2008* (National Bureau of Statistics of China, 2010) for industrial output and formal industrial employment, *China Statistical Yearbook* (National Bureau of Statistics of China, 2006, 2007, 2008, 2009) for total fixed industrial investment.

The reform process of China's SOEs has been gradual with different measures being proposed in different stages. Many researchers have discussed the reform stages of SOEs (e.g., Qian, 2000; Lin and Liu, 2000; Wang, 2005). According to Lin and Liu (2000), the SOEs' reform in the early period was divided into three stages:[2] the first stage, from 1978 to 1986, expanded SOEs' autonomy and introduced profit retention; the second stage, from 1987 to 1992, promoted the contract responsibility system; and the third stage, from 1993 to 1997, experimented with "Grasping the Large and Letting Go the Small" (Zhuada Fangxiao) and constructed a modern enterprise system.

The reform of SOEs began with the experiment of expanding enterprises autonomy and introducing profit retention in Sichuan province in October 1978. By 1980, about 60% of SOEs (in terms of output value) had joined the experiments and obtained some limited autonomy (Qian, 2000). The SOEs' expanded autonomy included the right to produce and sell products to the market after fulfilling plan quotas, and the

[2]Lin and Liu (2000) divided SOEs reform into four stages,thus taking an approach that differs from this paper's. They divided the period of 1978–1986 into two stages: the stage of expanding SOEs autonomy and introducing profit retention (1978–1982) and the stage of replacement of profit by tax (1983–1986). Nevertheless, the objective of replacement of profit by tax was also to enlarge enterprise autonomy and to incentive enterprise by profit, which was the same as the period between 1978 and 1982. Wang (2005) also treated the period of 1978–1986 as one stage.

authority to promote mid-level managers without government approval. They also developed profit retention schemes that allowed them to retain some profits after fulfilling the plan quotas. In 1983 and 1984, the central government carried out two-step "replacement of profit by tax" measures to clarify the relationship between the state's fiscal revenue and the SOEs' disposable income, so that the SOEs could operate in a perfectly competitive market and under an impartial tax system. In May 1984, the State Council issued a document entitled "On Regulations of Further Expanding Autonomy of State-Owned Enterprises" to expand SOEs' autonomy in ten areas (known as "Ten Articles for Expanding Rights", in Chinese: Kuoquan Shitiao).

However, the SOEs' autonomy was rather limited and profit retention was negotiated on an annual basis. To address the financial incentive problem, the government began promoting the "Contract Responsibility System" (Chengbaozhi) in January 1987 . Under this system, contracts lasted for at least 3 years to avoid annual bargaining. Compared with the previous rounds of enterprise reform, the contract responsibility system delegated more control rights to managers. By the end of 1987, about 80% of large and medium-sized SOEs had adopted the contract responsibility system, and almost all SOEs had adopted it by 1993 (Qian, 2000).

In December 1993, the Company Law of the People's Republic of China was issued to construct a modern enterprise system with clearly defined property rights, clear powers and responsibilities, separation of government from enterprises, and scientific management. Later, the central government promoted reform through the measure of "Grasping the Large and Letting Go the Small". "Grasping the Large" meant that only about 1000 large SOEs would remain state owned, and "Letting Go the Small" meant privatization of some medium-sized and small SOEs. By the end of 1996, up to 70% of small SOEs had been privatized in a few provinces, such as Shandong, Guangdong, and Sichuan, and about half were privatized in many other provinces (Qian, 2000).

How did SOEs' productivity and efficiency changed in the early reform period? What main factors affected SOEs' productivity and efficiency when Chinese SOEs experienced various reform measures? These questions have attracted considerable attention from researchers, most of whom have argued that reform contributed to the improvement of SOEs' productivity and efficiency in the early reform period. As previous studies have showed (see Table 1.1), Chinese SOEs experienced positive TFP growth in the early reform period. Nevertheless, TFP improvement in SOEs might be accompanied by increasing spatial disparity. Therefore, the regional analysis of Chinese SOEs' TFP and technical efficiency may shed light on the TFP and technical efficiency literature of Chinese SOEs.

Table 1.1: Chinese SOEs' TFP growth in some studies

Publication	Period	TFP growth
Chen et al. (1988)	1978-1985	4.8-5.9%
Dollar (1990)	1975-1982	4.70%
Gordon and Li (1995)	1983-1987	4.60%
Jefferson et al. (1992)	1980-1988	2.40%
Li (1997)	1980-1989	4.68%
Wan (1995)	1980-1988	2.50%

Source: The corresponding papers of the authors.

1.1.3 Opening up policy

The success of agricultural reform encouraged the government to pursue further reform. Faced with the reality that it was short of the capital needed to develop in the beginning of the reform, China started to open up by attracting foreign investment and promoting foreign trade, which allowed it to further integrate into the world economy. Under the principle of gradual reform, China's efforts to open up were initially limited to two coastal provinces. Guangdong and Fujian, but gradually extended to larger areas. The opening up process developed in four stages.

Experimental stage, early 1980s. In 1979, the central government decided to allow Guangdong province to adopt "Special Policies" (Teshu Zhengce) and implement "Flexible Measures" (Linghuo Cuoshi). At the same time, the government began to set up four Special Economic Zones: Shenzhen, Zhuhai, and Shantou in Guangdong province and Xiamen in Fujian province (see Table 1.2). As the experimental fields and the benchmark for future implementations of the opening up policy in other regions, these special economic zones provided investors with various preferential tax treatments and exemptions, import license exemptions for capital goods, low land-use fees, and other preferential policies designed to attract foreign investment and promote foreign trade.

Table 1.2: Timeline of China's regional preferential policies: 1979-1994

Year of approval	Number and type of opened zone	Location
1979	3 Special Economic Zones	Guangdong
1980	1 Special Economic Zone	Fujian
1984	14 Coastal Open Cities	Liaoning, Hebei, Tianjin, Shandon, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Guangxi
	10 Economic and Technological Development Zones	Liaoning, Hebei, Tianjin, Shangdong, Jiangsu, Zhejiang, and Guangdong
1985	1 Economic and Technological Development Zone	Fujian
	3 Coastal Open Economic Zones	Pearl River delta, Yangtz River delta, and Fujian
1986	2 Economic and Technological Development Zone	Shanghai
1988	Open Coastal Belt	Liaoning, Shandong, Guangxi, and Hebei
	1 Special Economic Zone	Hainan
	1 Economic and Technological Development Zone	Shanghai
1990	Pudong New Area	Shanghai
1992	13 bonded areas in major coastal port cities	Tianjin, Guangdong, Liaoning, Shandong, Jiangsu, Zhejiang, Fujian, and Hainan
	10 major cities along Yangtze River	Jiangsu, Anhui, Jiangxi, Hunan, Hubei, and Sichuan
	13 Border Economic Cooperation Zones	Mongolia, Xinjiang, Yunnan, and Guangxi
	All capital cites of inland provinces and autonomous regions	
	5 Economic and Technological Development Zones	Fujian, Liaoning, Jiangsu, Shandong, and Zhejiang
1993	12 Economic and Technological Development Zones	Anhui, Guangdong, Heilongjiang, Hubei, Liaoning, Sichuan, Fujian, Jilin, and Zhejiang
1994	2 Economic and Technological Development Zones	Beijing and Xinjiang

Source: Demurger et al., 2002.

Developmental stage, mid and late 1980s. The great success of special zones, especially the success of Shenzhen encouraged the central government to expand its opening up policy.[3] In 1984, fourteen cities along the coast were designated as the Economic and Technological Development Zones. The open areas were subsequently expanded in 1985 to four economic development areas—the Changjiang delta, Zhujiang delta, Xiamen-Zhangzhou-Quanzhou Triangle in south Fujian (Minnan triangle), Shandong Peninsula and Liaodong Peninsula (Bohai area). Further, Hainan province became the biggest special economic zone in 1988. In 1990, the government established the Pudong New Area in Shanghai.

Acceleration stage, after 1992. After Deng Xiaoping's "Southern Tour Speech" (Nanxun Jianghua) in 1992, more and more inland regions began opening up to the word economy in various ways, includint Border Economic Cooperation Zones, Economic and Technological Development Zones, and Capital Cites of Inland Provinces. In addition to the official policy launched by the central government, all of the provinces, and hundreds of counties began to formulate their own preferential policies in specific development zones to attract foreign investment.

Integrating into the world economy, after 2001. In December 2001, China became a member of the World Trade Organization (WTO). The WTO accession meant a further opening up of the domestic market of China; the boundary between the Chinese domestic market and the international market became even more blurred. It also meant that China became an international production location. After the WTO accession, China attracted more foreign investment and intensely promoted international trade. As Figure 1.4 shows, in the early period of Reform and Opening Up, China had very little amount of foreign trade and foreign direct investment (FDI). China only exported US$ 6.9 billion in merchandise in 1978, 0.79% of the total world exports. The FDI from 1979 to 1982 was less than US$ 1.8 billion, an average of about US$ 0.6 billion per year. In 2008, China exported US$ 1428.7 billion, imported US$ 1131.6 billion in merchandise, and received US$ 92.4 billion in FDI, and therefore became the second largest exporter, the third largest importer, and the third largest FDI recipient in the world. As a result, the Reform and Opening Up policy has dramatically contributed to China's rapid economic growth.[4]

[3]In the period of 1979–1985, the gross regional product of Shenzhen grew about 15 times (from RMB 0.2 billion to 3.0 billion), while the per capita GDP increased from RMB 0.6 thousand to 4.8 thousand. Source: Shenzhen Bureau of Statistics, 2000.

[4]The annual average growth of real GDP from 1979 to 2008 is 9.8%, while the rat between 1953 and 1978 is 6.7% (National Bureau of Statistics of China, 2010). Wu (1996, 2004) argues that FDI was an engine of China's economic growth during the post-reform period.

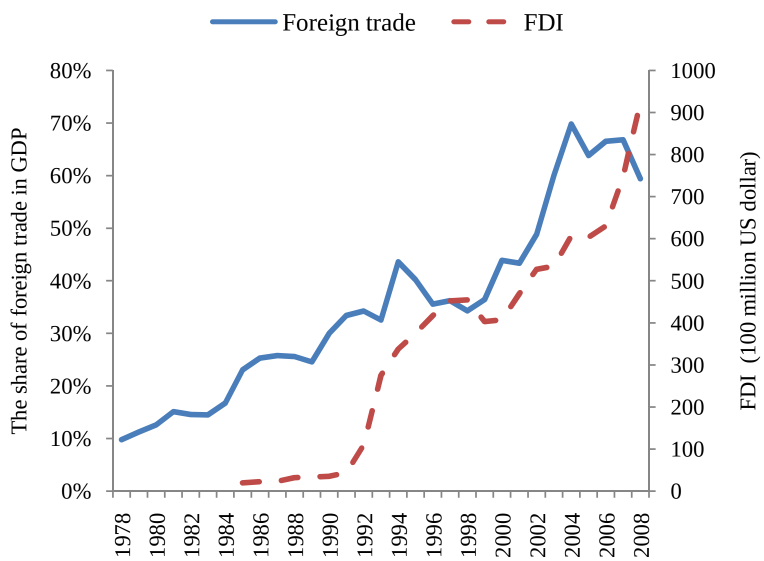

Figure 1.4: Foreign trade and FDI in China, 1978–2008

Source: National Bureau of Statistics of China (2009).

The increasing FDI has provided not only capital, new technology, and training for labor to China, but also modern managerial systems, business practices, and a legal framework for conducting business transactions. At the same time, the improvements in foreign trade increased competition not only between domestic and foreign companies but also among the domestic companies themselves. Therefore, the technology and knowledge diffusion, and the increasing competition through FDI and foreign trade would probably improve the productivity and technical efficiency of Chinese production sectors. While the FDI and foreign trade were mainly promoted in secondary industry, this paper also investigates the opening up effect on technical efficiency in the Chinese manufacturing industry.

1.2 Measures of technical efficiency and TFP change

The theoretical literature on technical efficiency first appeared in the work of Koopmans (1951), who provided the following definition of technical efficiency: A producer is technically efficient if, and only if, it is impossible to produce more of any output without producing less of some other output or using more input. Later, Farrell (1957) introduced an empirical measure of technical efficiency, which employed linear programming techniques to estimate the frontier production function. Under the influence of the classic work of Farrell (1957), Charnes et al. (1978) developed data envelopment analysis (DEA), a non-parametric approach to estimate technical efficiency. Today, DEA is a well-established technical efficiency measurement technique and is widely used in empirical papers. Meanwhile, Farrell's work also inspired the studies of Aigner and Chu (1968), Timmer (1971), and Afriat (1972), whom directly influenced the development of the parametric approach to measuring technical efficiency known as—stochastic frontier analysis (SFA). In 1977, SFA was first presented in three papers: Meeusen and van den Broeck (1977), Aigner et al. (1977), and Battese and Corra (1977). Both DEA and SFA suppose that not all producers are always successful in utilizing their inputs to produce maximum outputs under a given technology; in other words, not all producer are always technically efficient. Both DEA and SFA assumed that all producers operate either along the production frontier or in the interior of a potential production frontier, with the producers operating along the production frontier considered technically efficient and the producers operating in the interior of the production frontier are considered technically inefficient.

Figure 1.5 illustrates the concept of production frontier, technical efficiency, and TFP change. The curves of OF_t and OF_{t+1} denote the production frontier in period t and $t+1$ respectively. The slope of a ray from the origin to a particular data point shows the measures of productivity of that point. For example, in period t, the points along OF_t define the efficient subset of the feasible production set. The producer at point A is technically inefficient while the producer at point B is technically efficient. If a producer move from point A to B, the slop of the ray will be greater, implying higher productivity at point B. This productivity growth come from improved technical efficiency. Technical change between periods is illustrated by the movement from point B to C. Thus, the productivity growth from point A to C comprises the technical efficiency improvement from point A to B and the technical progress from B to C.

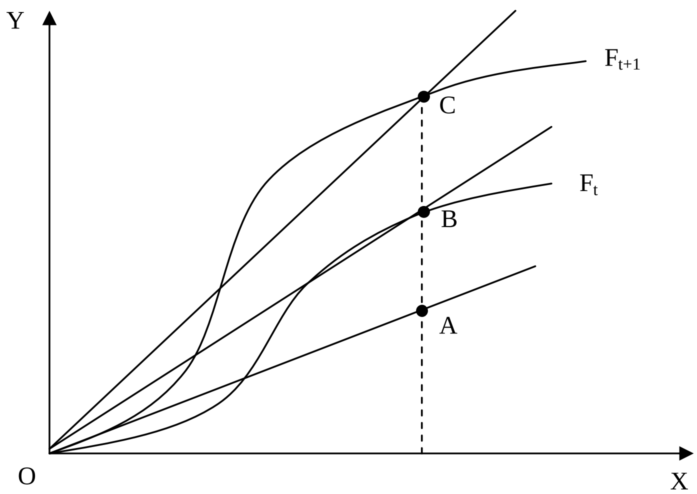

Figure 1.5: Production frontier, technical efficiency and TFP change

1.2.1 Data envelopment analysis

The DEA approach usually assume that all production units within a group have access to the same technology. For each production unit i $(i = 1, 2, \ldots, n)$, the technology in a given industry can be characterized by a technology set T that transform a nonnegative vector of inputs, $X = (X_1, \ldots, X_N) \in \Re_+^N$, into a nonnegative vector of outputs, $Y = (Y_1, \ldots, Y_M) \in \Re_+^M$. it is defined as

$$T \equiv \{(X_i,\, Y_i) \mid X_i \,\text{can produce}\, Y_i\}\,, \tag{1.1}$$

Equivalently, the same technology can be characterized by the output set

$$P \equiv \{Y_i \mid X_i \,\text{can produce}\, Y_i\}\,, \tag{1.2}$$

The boundary of P is referred as the technology or the production frontier. The distance from the actual point of each unit in the production set P to the frontier of P is treated as the inefficiency of each unit. In other words, since each unit has specific characteristics, some units may operate along the production frontier while others operate at the points in the interior of the production frontier. The former units are considered technically efficient, while the latter units are considered technically inefficient. The technical efficiency is defined as

$$TE_i \equiv \max \{\theta \mid (X_i,\, \theta Y_i) \subseteq P\}\,. \tag{1.3}$$

When $TE_i = 1$, the production unit is considered technically efficient, while technically inefficient when $TE_i > 1$.[5]

Since true production sets can not be observed, we use the most common DEA procedure (constant returns to scale) to estimate the best-practice (observed) frontier from the observed input-output combinations (X_i, Y_i), which is defined as

$$\begin{aligned}\hat{P} = \ & \Bigg\{ Y \mid Y_m \leqslant \sum_{i=1}^{n} q_i Y_i^m,\ m = 1, \ldots, M, \\ & X_j \geqslant \sum_{i=1}^{n} q_i X_i^j,\ j = 1, \ldots, N, \\ & q_i \geqslant 0,\ i = 1, \ldots, n \Big\}\,,\end{aligned} \tag{1.4}$$

where $\hat{P}$ is the DEA estimate of the true production frontier of P, q_i are intensity variables that indicate a particular unit's intensity in the production set.[6] Then, the DEA estimate of individual technical efficiency at any point (X_i, Y_i) can be derived by solving the following linear programming problem

$$\hat{TE}_i = TE\left(X_i, Y_i \mid \hat{P}\right) = \max_{\theta, q_1, \ldots, q_n} \left\{\theta \mid \theta Y_i \in \hat{P}\right\}. \tag{1.5}$$

The linear programming solution in EDA model makes user can calculate the efficiency score of each production unit without regard to the specific production, cost, or profit function of the group. Meanwhile, the linear programming solution leads to the non-statistical feature of DEA. However, DEA can not yield standard errors then leaves no room for hypothesis testing that is well established in econometric literature. Then, several approaches were proposed to address the non-statistical drawback of DEA. For example, Banker (1993) proposed a convex and monotonic nonparametric frontier with a one-side disturbance term and showed that the DEA estimator converges in distribution to the maximum likelihood estimators. Simar and

[5] Note that $0 < (1/TE_i) \leqslant 1$, the reciprocal of TE_i represents the relative percent level of the technical efficiency of Unit i relative to the production frontier of P.

[6] Constant returns to scale may be relaxed to non-increasing returns to scale or variable returns to scale by adding the restriction of $\sum_{i=1}^{n} q_i \leqslant 1$ or $\sum_{i=1}^{n} q_i = 1$, respectively.

wilson (1998, 2000b) developed a bootstrap DEA approach to generate statistical distributions of the efficiency measures of individual production unit.[7]

1.2.2 Stochastic frontier analysis

On the contrary to DEA, SFA based on a production, cost, or profit function as traditional econometric model did. However, stochastic frontier production (cost or profit) is different from traditional production (cost or profit) function. The error term in stochastic frontier function comprises not only a symmetric random error but also a non-negative technical inefficiency term. Following Battese and Coelli (1992), the panel data version of stochastic frontier production is specialized as

$$\begin{aligned} Y_{it} &= f\left(X_{it},\, \beta,\, t\right) e^{V_{it}-U_{it}}, \\ i &= 1, 2, \ldots, N,\ t = 1, 2, \ldots, T, \end{aligned} \tag{1.6}$$

where Y_{it} denotes the output for the ith producer at the tth time;

X_{it} denotes a vector of values inputs of production for the ith producer at the tth time;

β is a vector of unknown parameters to be estimated;

V_{it} is assumed to be identically and independently distributed as $N(0,\, \sigma_V^2)$ random variables;

$U_{it} = U_i exp\left(-\eta\left(t - T\right)\right)$, where the U_i is non-negative random variable which is assumed to account for technical inefficiency and is assumed to be *iid* as truncations at zero of the $N(0,\, \sigma_U^2)$ distribution, and U_{it} is independent of V_{it};

η is a scalar parameter to be estimated, where $\eta > 0$, $\eta = 0$, or $\eta < 0$ mean that U_{it} decrease, remain constant, or increase as t increases.

Then, The technical efficiency (TE_{it}) for the ith firm at the tth time is defined as

$$TE_{it} = exp\left(-U_{itj}\right), \tag{1.7}$$

Function (1.6) and (1.7) can be estimated by maximum likelihood method, which is done with calculation the maximum likelihood estimates σ and γ, where $\sigma^2 = \sigma_V^2 + \sigma_U^2$, $\gamma = \sigma_U^2/\sigma^2$. γ is also used to test whether any form of stochastic frontier production is required by the null hypothesis that γ equals zero, if is accepted, this would indicate

[7]See Ray (2004, p5) for a review.

that σ_U^2 is zero and hence that U_{it} term should be removed form the model, then the model can be consistently estimated using ordinary least squares.

To measure TFP change, we start from the partial derivatives of the logarithm of Equation (1.6) with respect to time t,

$$\frac{\dot{Y_{it}}}{Y_{it}} = \left(e_{f/x} \times \frac{\dot{X_{it}}}{X_{it}} + \dot{v_{it}} \right) + e_{f/t} - \dot{u_{it}}, \tag{1.8}$$

where $e_{f/x}$ and $e_{f/t}$ denote respectively the output elasticities of $f\,(X_{it},\, \beta^*,\, t)$ with respect to X_{it} and t, and dotted variables indicate time derivatives. Since V_{it} is distributed as $N(0,\, \sigma_V^2)$, the effect of the random error V_{it} is equal to zero and can be ignored. $e_{f/t}$ is the rate of the technological change corresponding to the shifts of the frontier, and $-\dot{u_{it}}$ represents the technical efficiency change. Following Coelli et al. (2005), the technical change index (TC) between the adjacent periods is calculated as the exponential of the geometric mean of two partial derivatives,

$$TC = exp \left\{ \frac{1}{2} \left(e_{f/t} + e_{f/t-1} \right) \right\},\ t = 2, 3, \ldots, T, \tag{1.9}$$

and the technical efficiency change index (TEC) is defined as:

$$TEC = TE_{it}/TE_{it-1}. \tag{1.10}$$

Then, the Malmquist TFP index[8] can be obtained by multiplying Equation (1.9) and Equation (1.10),

$$Malmquist\ TFP = TC \times TEC. \tag{1.11}$$

[8]The Maimquist TFP index was defined as the geometric mean of two distance indices, which was introduced by Caves et al. (1982) after Sten Maimquist proposed constructing quantity indexes as ratios of distance functions. For more information on Maimquist TFP index, see Coelli et al. (2005).

1.3 Review of the relevant literature

In the beginning of the reform, Deng Xiaoping—the chief designer of the Reform and Opening Up policy—made a famous proclamation: “It doesn't matter if a cat is black or white, so long as it catches mice.” This is usually interpreted as pragmatism, but it also reflects the principle of the reform: give priority to efficiency. The efficiency and productivity gains from the reform have garnered much attention. This section discusses the technical efficiency literature of Chinese agriculture, the technical efficiency and productivity literature of Chinese SOEs, and the openness effect on technical efficiency literature.

1.3.1 Technical efficiency in China's agriculture

According to the methodology, the literature on Chinese agricultural technical efficiency can be classified into two main groups. The first group refers to the studies that employed the SFA approach, while the second group refers to the studies that employed the DEA approach (see Table 1.3).

Table 1.3: Selected studies on technical efficiency in Chinese agriculture

Publication	Model	Type of data	Object	Region	TE
Chen et al. (2006)	SFA	County-level 2002 counties 1999	Agriculture	National	0.80
Chen and Song (2008)	SFA	County-level 2002 counties 1999	Agriculture	National	0.752
				East	0.940
				Central	0.625
				West	0.761
				Northeast	0.639
Chen et al. (2009)	SFA	Household-level 591 households 1995–1999	Agriculture	North	0.80
				Northeast	0.85
				East	0.73
				Southwest	0.69
Hu and McAleer (2005)	SFA	Provincial-level 30 provinces 1991–1997	Agriculture	National	0.60
				East	0.73
				Central	0.58
				West	0.51
Huang and Kalirajan (1997)	SFA	Household-level 1000 households 1993–1995	Maize	Sichuan	0.65
				Shandong	0.68
				Jilin	0.71
			Rice	Guangdong	0.86
				Sichuan	0.69
			Wheat	Shandong	0.73
Liu and Zhuang (2000)	SFA	Household-level 7927 households 1990	Crops	Sichuan	0.773
				Jiangsu	0.553
Tian and Wan (2000)	SFA	Provincial-level 1983–1996	Indica rice	National	0.946
			Japonica rice		0.905
			Wheat		0.862
			Corn		0.853
Wang et al. (1996a)	SFA	Household-level 1786 households 1991	Crops and livestock	National	0.62
Wang et al. (1996b)	SFA	Household-level 1889 households 1990	Crops and livestock	National	0.611
WU (1995)	SFA	Provincial-level 1985–1991	Agriculture	National	0.55
			Rural industry		0.58
			State industry		0.53
Xu and Jeffrey (1998)	SFA	Household-level 180 households Jiangsu 1986	Hybrid rice	South	0.85
				Central	0.78
				North	0.74
			Conventional rice	South	0.94
				Central	0.91
				North	0.87
Yao and Liu (1998)	SFA	Provincial-level 30 provinces 1987–1992	Grain products	National	0.63
Yao et al. (2001)	SFA	Provincial-level 30 provinces 1987–1992	Grain products	National	-3.17%
				East	-3.00%
				Central	-2.81%
				West	-4.23%
Chen et al. (2008)	DEA	Provincial-level 29 provinces 1990–2003	Agriculture	National	-2.6%
Mao and Koo (1997)	DEA	Provincial-level 30 provinces 1984–1993	Agriculture	National	-1.37%
Monchuk et al. (2010)	DEA	County level 2028 counties 1999	Grain and meat	National	0.968

Source: The corresponding papers of the authors.

Notes:

1. The percent value means the average annual change rate of technical efficiency.

2. The DEA technical efficiency score in Monchuk et al. (2010) is 1.033, its reciprocal is the the commonly used measure of technical efficiency that has a score between 0 and 1.

In the SFA literature, all the studies listed in Table 1.3 used a stochastic frontier production function except the studies of Wang et al. (1996a, 1996b), which employed a stochastic shadow price profit function. Wang et al. (1996a, 1996b) showed that profit maximization based on market prices is inappropriate and that farmers' resource endowment and education influence their productive efficiency. In other SFA studies, Wu (1995) and Yao and Liu (1998) decomposed the TFP change into technical change and technical efficiency change using provincial-level panel data. Even though they used different period data, both reached similar results: China's agriculture experienced a positive TFP growth in the reform period, but the technological progress was the main source of the TFP growth—in other words, technical efficiency decreased in their reference period. Instead of measuring technical efficiency, some papers (e.g., Huang and Kalirajan, 1997; Xu and Jeffrey, 1998; Yao and Liu, 1998; Liu and Zhuang, 2000; Tian and Wan, 2000; and Chen et al., 2009b) investigated the determinants of the technical efficiency of Chinese agriculture. Among these two-stage studies,[9] Huang and Kalirajan (1997), Xu and Jeffrey (1998), Liu and Zhuang (2000), and Chen et al. (2009b) employed household-level data, while Yao and Liu (1998) and Tian and Wan (2000)employed provincial-level data. Both Huang and Kalirajan (1997) and Xu and Jeffrey (1998) found that household's human capital stock (i.e., household members' education), land size and market-oriented reform contributed positively to agricultural technical efficiency. Yao and Liu (1998) found that irrigation and chemical fertilizer have positive impact on farms' technical efficiency, while labor congestion has a negative effect. On the contrary, Tian and Wan (2000) argued that agricultural production growth can no longer be driven by chemical fertilizer usage and that enlarging farm size and promoting agricultural R&D are conductive to efficiency improvement. Liu and Zhuang (2000) proposed that better access to credit and education attainment are positively related to technical efficiency and that nutrition intake can improve farms' technical efficiency in less-developed regions and low-income households. In addition, Chen et al. (2009b) pointed out that using machinery and eliminating land fragmentation bring efficiency gains for Chinese farms.

In consideration of the huge geographical area of China and the regional disparity of agricultural production, Wu (1995), Yao et al. (2001), and Hu and McAleer (2005) presented comparison of three regions—East (Coastal), Central, and West.

[9] The estimation of stochastic frontier production function and the calculation of technical efficiency score of each observation occurred in the first stage, and the regression of the technical efficiency determinant model occurred in the second stage.

Wu (1995) and Hu and McAleer (2005) both found that the East enjoys the highest agricultural technical efficiency, while the West trailed behind other two regions. On the contrary, Yao et al. (2001) found that the Central region has the highest technical efficiency score and has experienced the slowest increase rate. Both Chen and Song (2008) and Chen et al. (2009b) divided China into four agricultural regions (see Table 1.3), but their results are inconsistent. Chen and Song (2008) showed that the East has the highest technical efficiency score and that the technical efficiency score of the Northeast is only higher than the Central regions, while Chen et al. (2009b) indicated that the Northeast has the highest technical efficiency score and that the East is only more efficient than the Southwest. The different results of these two studies may be attributed to the different type of data.[10] However, it is noteworthy that Chen and Song (2008) employed a developed SFA approach—stochastic metafrontier analysis—that can compare technical efficiency across producers operating under different technologies. Because the regional comparisons of technical efficiency in the traditional SFA literature neglected the fact that the farms in different regions obviously use different technologies for different natural endowment and economic development levels, Chen and Song (2008) contributed to the empirical literature about the regional comparison of China's agricultural technical efficiency. In addition, based on the results of SFA analysis, Chen and Huffman (2006) employed a first-order spatial autocorrelation model and found a strong spatial dependence among county-level technical efficiency scores.

Relative to the amount of SFA literature, there is little DEA literature about China's agricultural technical efficiency. Mao and Koo (1997) and Chen et al. (2008) measured the output-oriented Malmquist productivity indexes (Malmquist TFP) and decomposed TFP change into technical change and technical efficiency change using the DEA approach. Both studies reached similar results: the major source of China's agricultural TFP growth is technical progress over time, while technical efficiency has deteriorated in the same period. Their findings are in line with those of Wu (1995) and Yao and Liu (1998) who employed the SFA approach. Recently, Monchuk et al. (2010) investigated the relationship between China's agricultural technical efficiency and some determinant factors using a two-stage semi-parametric bootstrap DEA approach. They found that a heavy industrial presence and a large percentage of the rural labor force in one county have negative effects on agricultural production efficiency. They suggested that the environmental consequence of pollution from in-

[10]Chen and Song (2008)used county-level data from 2002 counties in 31 provinces; Chen et al. (2009b) used household-level data from 29 randomly selected villages within 9 provinces.

dustrial production should be considered in the future, and moreover, that nurturing and promoting growth of non-primary agriculture may lead to more efficient use of labor resources in agriculture and consequently, may improve China's agricultural technical efficiency.

1.3.2 Technical efficiency and TFP change in Chinese SOEs

As the central government turned its attentions to reforming the SOEs in the late 1980s, many researchers also turned their attention to Chinese SOEs' productive performance in the transition period. Some investigated Chinese SOEs' TFP change, while others measured Chinese SOEs' technical efficiency (see Table 1.4 and Table 1.5).

In the TFP literature, some researchers such as Chen et al. (1988)), Jefferson et al. (1992) and Wan (1995) measured the macro level TFP of the Chinese state industrial sector employing the conventional production function approach. All of these studies found a substantial acceleration of TFP growth after reform. Jefferson et al. (1992) and Wan (1995) found that technological progress has undoubtedly contributed to the TFP growth after reform. Furthermore, using time-series aggregate level data, Lau and Brada (1990) measured the TFP growth rate of state-owned industries, and decomposed TFP growth into technical efficiency change and technological change by estimating a frontier production function. They showed that Chinese state-owned industries have been characterized by a high growth rate of technological progress, but both technical efficiency and TFP increased appreciably in the period of 1978–85.

Table 1.4: Selected studies on TFP growth in Chinese SOEs

Publication	Model	Type of data	Period or sector	TFP growth
Chen et al. (1988)	PF	Country-level	1953–1985	1.9–2.8%
		1952–1985	1978–1985	4.8–5.9%
Dollar (1990)	PF	Firm-level	1975–1982	4.7%
		20 firms		
		1975–1982		
Gordon and Li (1995)	PF	Firm-level	1983–1987	4.6%
		285 firms		
		1983–1987		
Jefferson et al. (1992)	PF	County-level	1980–1988	
		293 counties	SOEs	2.40%
		1984, 1987	collective	4.63%
Kong et al. (1999)	SFA	Firm-level	1990–1994	
		94 firms	Building materials	-0.6%
		1990–1994	Chemicals	-3.3%
			Machinery	1.5%
			Textiles	-3.8%
Lau and Brada (1990)	FPF	Country-level	1978–1985	>0%
		1953–1985		
Li (1997)	PF	Firm-level	1980–1989	4.68%
		769 firms	To incentive	2.29%
		1980–1989	To reallocation	1.79%
Wan (1995)	PF	Country-level	1957–1978	1.3%
			1978–1985	2.6%
Zheng et al. (2003)	DEA	Firm-level	1980–1989	3–12%
		681 firms	1990–1994	3–8%
		1980–1994		

Source: The corresponding papers of the authors.
Note: DEA, FPF, PF, SFA in column 2 are the abbreviations of data envelopment analysis, frontier production function, production function, and stochastic frontier analysis.

However, macro level measurements of TFP are likely to be biased because the reform measures were not implemented systematically and were carried out at different paces in different sectors and regions. To investigate the firm-level productive performance of different industries and regions, researchers turned to micro data models. For example, based on various kind of firm-level data, Dollar (1990), Woo et al. (1993), Jefferson and Xu (1994), Gordon and Li (1995), and Li (1997) investigated Chinese SOEs' TFP growth by estimating production function. Dollar (1990) found that SOEs' TFP has grown rapidly and that TFP dispersion across firms declined from 1978 to 1982. Jefferson and Xu (1994) also found the convergence of SOEs'

TFP from 1980 to 1989 among three kinds of SOEs—sales 100% within plan, sales partially within plan, and sales not within plan. Gordon and Li (1995) found that Chinese SOEs' TFP increased by 4.6% per year from 1983 to 1987 and that half of the growth due to the rapidly improving education level of the labor force. Similarly, Li (1997) found a substantial TFP growth from 1980 to 1989; in particular, he showed that over 87% of the TFP growth was attributed to improved incentives, intensified product market competition, and improved factor allocation. On the contrary, Woo et al. (1993) showed that TFP growth in SOEs has at best been zero in the 1984–88 period. Furthermore, Kong et al. (1999) investigated Chinese SOEs' TFP growth and decomposed TFP change into technical efficiency change and technical change using the SFA approach. They found negative TFP growth in the chemicals, machinery and textiles industries from 1990 to 1994, which they attributed mainly to the significant reduction in technical efficiency. Employing the DEA model, Zheng et al. (2003) also decomposed TFP change into technical efficiency change and technical change. They found a positive TFP change in the period of 1980–1989, but the TFP growth was accomplished mainly through technical progress rather than through efficiency improvement.

Table 1.5: Selected studies on technical efficiency in Chinese SOEs

Publication	Model	Type of data	Period or sector	TE
Kalirajan and Yong	SFA	Firm-level	large	0.63
(1993)		94 firms	middle	0.61
		1988	small	0.58
Kong et al.	SFA	Firm-level		
(1999)		94 firms	Building materials	0.678
		1990–1994	Chemicals	0.415
			Machinery	0.437
			Textiles	0.757
Lau and Brada	FPF	Country-level		
(1990)		1953–1985	1978–1985	>0%
Liu and Liu	SFA	Firm-level	1980–1989	
(1996)		382 firms	Chemicals	1.0%
		1980–1989	Textiles	-0.7%
			Food	-0.8%
			Metallurgy	1.9%
			Materials	-0.1%
			Machinery	3.2%
			Electronics	3.5%
Murakami et al.	PF	Firm-level	SOEs	0.48
(1994)		111 firms	Urban COE	0.57
		1990	Independent TVE	0.68
			Cooperative TVE	0.92
			Joint venture	1.00
Zhang et al.	SFA	Firm-level	Average	0.66
(2003)		8341 firms		
		1995		
Zheng et al.	DEA	Firm-level	1980–1989	-6.0–-1.0%
(2003)		681 firms	1990–1994	-6.0–-5.0%
		1980–1994		
Zheng et al.	DEA	Firm-level	SOE	0.77
(1998)		1759 firms	COE	0.80
		1986–1990	TVE	0.84

Source: The corresponding papers of the authors.
Notes:
1. The percent value of TE is the efficiency change rate of the period of each study.
2. DEA, FPF, PF, SFA in column 2 are the abbreviations of data envelopment analysis, frontier production function, production function, and stochastic frontier analysis.
3. SOE, COE, TVE in column 2 are the abbrevaiations of state-owned enterprise, collective-owned enterprise, and township-village enterprise.

In the technical efficiency literature, many studies employed the SFA approach.

Kalirajan and Cao (1993) examined the productive efficiency of the Chinese iron and steel industry using firm-level data. They decomposed productive efficiency into technical, allocative and scale efficiencies, and found that the Chinese iron and steel industry achieved about 60% of its potential output in 1988. Liu and Liu (1996) showed that reform-induced gains in technical efficiency were significant in all seven state-owned manufacturing industries and that the average level of technical efficiency of Chinese SOEs grew from 43% in 1980 to 59% in 1989, amounting to an increase of 1.6% per annum. Wu (1996) examined both the macro and micro levels of technical efficiency of Chinese industries. At the macro level, he measured the technical efficiency of both rural and urban industries based on the provincial-level panel data in the period of 1985–1990 and found significant technical efficiency improvement over time. At the micro level, he examined the firm-level technical efficiency of the coal, iron and steel, and textile industries, and he found that the incentive system had positive effect on firms' technical efficiency. Wen et al. (2002) estimated the stochastic frontier production functions of six industries using firm-level panel data, and they found that the firms with foreign related or private ownership are more efficient than those with state ownership, domestic collective ownership, and joint domestic ownership. They suggested that further privatization of SOEs, deregulation of other ownership forms, and reduction of government intervention in the economy are desirable for improving efficiency.

In addition, based on an estimation of the average growth of factor productivity (labor, capital, and material), Jefferson and Xu (1991) presented an empirical analysis of 20 enterprises (13 SOEs and 7 collective-owned enterprises) located in Wuhan city. They found that reform initiatives motivated economizing behavior and raised factor efficiency and that resources became more efficiently allocated between the industrial branches and enterprises during the reform period. Moreover, Zheng et al. (1998) employed the DEA approach to compare technical efficiency across Chinese SOEs, collective-owned enterprises, and township-village enterprises. They found that the collective-owned enterprises were less efficient than the township-village enterprises, but more efficient than the SOEs. Relative to those studies that utilized micro data, Shiu (2002) used provincial-level data to compare technical efficiency across industries and regions. He showed that non-state-owned enterprises are more efficient than the state-owned enterprises and that the economic gap between the western and coastal regions was related to the varying performances of ownership types in these regions.

1.3.3 Opening up and technical efficiency

In contrast to the large number of empirical studies on the technical efficiency of agricultural and state-owned industries, there are only a few empirical papers focused on the link between openness and technical efficiency in Chinese industries. Sun et al. (1999) measured the technical efficiency of Chinese manufacturing industries and investigated the openness effect on technical efficiency using data on 28 manufacturing industries across 29 provinces and the DEA approach. They found that trade openness had a positive effect on technical efficiency in Chinese manufacturing industries. Based on a panel of data of 126 countries during the period 1970–1998, Liu et al. (2005) investigated the impact of openness on the technical efficiency improvement of the world economy and compared the link between openness and performance in India and China. They found that FDI and its interaction with labor quality improvement play significant roles in improving efficiency, and that China has experienced a higher degree of openness and has therefore caught up with the world's best practices at a faster rate. In addition, using a two-digit industrial level panel data from 1990 to 1997, Fu (2005) employed two-stage DEA approach to decompose the TFP change of Chinese industries into technical change and technical efficiency change and to evaluate the export effect on these changes. He did not find a positive export effect on TFP growth, but he found that export-oriented industries are more efficient than non-export industries.

In addition to the technical efficiency literature, Chuang and Hsu (2004) investigated the international trade effect on firms' productivity using a data containing about 450,000 firms from the Third National Industrial Census of China. They found that China's imports from OECD and the four Asian Tigers (South Korea, Taiwan, Hong Kong and Singapore), and exports to OECD had positive effects on domestic firms' productivity.

1.4 Outline of the dissertation

This dissertation contains five chapters. However, three essays are mainly presented in Chapter 2, 3 and 4 to provide empirical evidence on the regional technical efficiency of Chinese agriculture, the regional technical efficiency and TFP change in Chinese SOEs, and the linkage between openness and the technical efficiency of Chinese manufacturing industry, respectively.

The second chapter uses household-level data from the Chinese Household Income

Project (CHIP) surveys to investigate regional technical efficiency, technology gaps, and their determinants in rural China. The stochastic meta-frontier analysis approach is employed to estimate the score of the technical efficiency and the technology gap ratio of each household in rural China. The main findings are as follows: First, the Southeast (the developed region) always has the highest technology gap ratio, while the Southwest (the developing region) has a rising score of meta-frontier technical efficiency. However, the Northwest (the poorest region) always lags behind its counterparts with respect to technical efficiency and technology gap ratio. Second, it is intra-regional technical efficiency, rather than technology gaps, that contributes to the disparities in the meta-frontier technical efficiency levels across regions. Finally, the quality of agricultural labor, agricultural infrastructure, natural conditions, and the farmer's political status have strong positive effects on a farm's technical efficiency and technology gap ratio, while the illiteracy rate, off-farm activities, lagged natural conditions, and lower economic development level are found to have a negative effect on a farm's technical efficiency and technology gap ratio.

In the third chapter, firm-level panel data are used to investigate regional technical efficiency, technology gaps, TFP change, and their determinants in Chinese state-owned manufacturing enterprises in the early reform period. The stochastic meta-frontier production function approach is employed to fit the scores of meta-frontier technical efficiency and the technology gap ratio of the Chinese SOEs in four regions. Further, TFP change is calculated by using the estimated regional frontier parameters. The findings indicate that Jiangsu has the highest mean technology gap ratio while Sichuan has the highest mean technical efficiency value. The results also show that enterprises in all regions experienced positive TFP change in the early reform period, while TFP growth attributed to technical efficiency change in the first ten years, then to technical change in the subsequent five years. Next, the results of the determinant models show that the reform measures such as management form dummies and bonus systems, contributed greatly to TFP growth and technical efficiency improvement. Engineering personnel share and export are also found to have strong positive effect on TFP growth and technical efficiency improvement.

Based on the World Bank Investment Climate Survey, the fourth chapter provides an empirical evidence of the link between openness and technical efficiency in Chinese manufacturing industries. A new two-stage data envelopment analysis approach is employed to calculate the technical efficiency value of each firm and to simultaneously estimate the determinants of technical efficiency in Chinese manufacturing industry. The results indicate that the firms involved in international trade and foreign capital participation are more efficient than others. The results of determinant models also show that international trade participation has positive effects on technical efficiency in Chinese manufacturing industries.

The last chapter summarize the findings and policy implications of the previous chapters to project the potential areas of improvement in terms of technical efficiency and TFP change in China's economy. In addition, it discusses the direction of the further research.

Chapter 2

Regional technical efficiency and technology gaps in rural China: Evidence from CHIP surveys

2.1 Introduction

In 1978, China started market-oriented reforms by implementing the "Household Responsibility System" in the rural sector. This system prompted an increase in agricultural production through productivity gains. Meanwhile, a high rate of economic growth and a remarkable improvement in living standards led to a rapidly growing demand for protein-rich diets, composed particularly of livestock products. The increasing demand for agricultural products and continuous population growth have evoked debates on how well China can feed itself in the future (Brown, 1995).

In order to achieve food self-sufficiency under the constraint of limited cropland and per capita inputs, China needs to promote agricultural productivity. Much has been written about the agricultural productivity of China (See a review in Chen et al., 2008). Since improvements in productivity are theoretically attributed to improvements in technical efficiency and technological progress, several studies have focused on the role of efficiency in the improvement of agricultural productivity. In particular, the literature examining Chinese agricultural technical efficiency can be classified into two main groups: the first group includes studies that employ the stochastic frontier analysis approach, and the second group consists of studies that adopt data envelopment analysis approach. In first group, Wu (1995), Yao and Liu (1998), Tian and Wan (2000), and Chen and Huffman (2006) investigated the technical efficiency of Chinese agriculture using provincial or county-level data. Huang and Kalirajan (1997), Xu and Jeffrey (1998) and Liu and Zhuang (2000) estimated the technical efficiency associated with several types of crops using houselold-level data. In addition, Wang et al. (1996a,1996b) employed a shadow-price profit stochastic frontier function to investigate the profit efficiency of crops and livestock in China using household-level data. In the second group, Mao and Koo (1997) analyzed the TFP growth, technical change, and technical efficiency change in Chinese agricultural production from 1984 to 1993 using provincial-level data. They found that Chinese agricultural TFP growth can mainly be attributed to technical progress, rather than to technical efficiency improvement. Recently, Monchuk et al. (2010) investigated the county-level technical efficiency of Chinese agriculture and its determinants using a two-stage data envelopment analysis approach.

The level of agricultural development differs across the various regions of China's vast geographical area. Yao et al. (2001), Chen and Song (2008), and Chen et al. (2009b) investigated regional technical efficiency of Chinese agriculture using a stochastic frontier analysis approach. In particular, Chen and Song (2008) provided an empirical study of the technical efficiency and technology gaps in China's agriculture across four regions using a new stochastic frontier analysis approach—stochastic meta-frontier analysis. They found that the eastern region has the highest mean regional technical efficiency score, while the northeastern region has the lowest mean regional technical efficiency score. They also suggested that technology and knowledge diffusion within a region might help to improve the technical efficiency and output of the agricultural sector.

Nevertheless, several issues were disregarded in these regional comparisons. First, these studies classified China into three regions or four regions when considering the regional level of economic development. For instance, Yao et al. (2001) divided China into three regions: East, Central, and West; Chen and Song (2008) and Chen et al. (2009b) divided China into four regions: Northeast, East, Central, and West. However, the climate, soil conditions, hydrological conditions, and institutions vary across regions. If only economic development level is consider to classify agricultural region, the agricultural technology may be different in one region. According to the hypothesis of stochastic frontier analysis, every regional frontier should share the same potential technology when comparing regional levels of technical efficiency. Therefore, the regional division of China in the study of the regional technical efficiency should be reconsidered. Second, even though household-level data was used to investigate Chinese agricultural technical efficiency in previous studies, the data consisted of small sample sizes or was selected from several special provinces. Thus, a reexamination of Chinese agriculture using a large data set with broad geographical coverage may contribute to the empirical study of regional technical efficiency and technology gaps in rural China.

In this paper, following Chen and Song (2008), we employ a new stochastic frontier analysis approach—stochastic meta-frontier analysis Battese et al. (2004)—to investigate regional technical efficiency, technology gaps, and meta-frontier technical efficiency in rural China using large household-level surveys—Chinese Household Income Project (CHIP)—from 1988, 1995, and 2002.[1] Our article differs from the previous literature in two respects. First, we divide China into six regions to enable the consideration of both economic development and geographic conditions when examining different regions in rural China. Second, we provide evidence on regional technical efficiency, technology gap ratio, and meta-frontier technical efficiency in rural China drawing on the famous household-level surveys—CHIP. These surveys allow us to investigate the determinants of regional technical efficiency, technology gap ratio, and meta-frontier technical efficiency by controlling for the characteristics of agricultural labors and rural households.

Our main findings are as follows. Firstly, the Southeast (developed region) always has the highest technology gap ratio, while the Southwest (developing region) has an increasing meta-frontier technical efficiency. However, the Northwest (the poorest region) always lags behind with respect to the technical efficiency and the technology gap ratio. These results indicate a negative relationship between regional technical efficiency and technology gap ratio for all regions, with the exception of the Northwest. Secondly, it is intra-regional technical efficiency, rather than technology gaps that contribute to differences in the meta-frontier technical efficiency level across regions. Thirdly, the technical efficiency of all regions improved remarkably from 1988 to 2002, but the technology gap ratios across regions changed only slightly in the same period. Finally, the quality of agricultural labor, agricultural infrastructure, and natural conditions have strong positive effects on a farm's technical efficiency and technology gap ratio, while the illiteracy rate, off-farm activities, lagging natural conditions, and lower economic development level are found to have a negative effect on a farm's technical efficiency and technology gap ratio.

The rest essay is organized as follows. In Section 2, we briefly describe the methodology used to estimate the regional technical efficiency and technology gaps under

[1] The three surveys are taken from Griffin and Zhao (1993a); Riskin et al. (2000); and Li (2008), respectively.

different technologies. The data and empirical specifications are briefly summarized in Section 3. Section 4 reports the empirical results of the regional technical efficiency and technology gaps in rural China, together with the determinants of the regional technical efficiency and technology gaps. Finally, some concluding remarks are presented in Section 5.

2.2 The stochastic meta-frontier methodology

The stochastic frontier production function has been widely used in the study of technical efficiency. The difference between the stochastic frontier production function and the traditional production function is that the error term in the stochastic frontier production function includes a symmetric random error term and a non-negative technical inefficiency term. As not all producers are always successful in utilizing the given inputs to maximize output under a given technology, namely, not all producers are always technically efficient, the stochastic frontier analysis is more realistic. However, stochastic frontier analysis assumes that all producers operate under a given production technology, and thus, cannot be used to compare the performance of producers operating under different technologies. In order to address this issues, Battese et al. (2004) have developed a stochastic meta-frontier approach to investigate technical efficiencies and technology gaps across different groups.

In this study, following Battese et al. (2004), the stochastic frontier production function for the jth region is specified as

$$Y_i = f\left(X_i,\, \beta_j\right) e^{V_{ij}-U_{ij}},\ i = 1, 2, \ldots, N,\ j = 1, 2, \ldots, M, \tag{2.1}$$

where Y_i denotes the output for the ith rural household in the jth region; X_i denotes a vector of inputs; β_j is the parameter vector; V_{ij} is assumed to be identically and independently distributed as $N(0,\, \sigma_{vj}^2)$ random variables; U_{ij} is independent of V_{ij}, and is defined as the truncation (at zero) of $N(\mu_{ij},\, \sigma_{uj}^2)$ distributions, where μ_{ij} is an inefficiency term, and $\gamma_j = \sigma_{uj}^2 / \left(\sigma_{uj}^2 + \sigma_{vj}^2\right)$. For the sake of simplicity, the model is specified as

$$Y_i = f\left(X_i,\, \beta_j\right) e^{V_{ij}-U_{ij}} = e^{X_i\beta_j + V_{ij} - U_{ij}}. \tag{2.2}$$

The meta-frontier production function, which is assumed to envelop all the jth regional frontiers, is expressed by

$$Y_i^* = f\left(X_i,\, \beta^*\right) = e^{X_i\beta^*},\; i = 1, 2, \ldots, N = \textstyle\sum_{j=1}^{M} N_j \tag{2.3}$$

$$s.t.\; X_i\beta^* \geqslant X_i\beta_j, \tag{2.4}$$

where Y_i^* and β^* denote the output and the parameters of the meta-frontier function.

Battese et al. (2004) present two criteria for the estimation of the meta-frontier function. One is the minimum sum of absolute deviations, and parameters can be obtained by solving the following linear programming problem:

$$Min\; L \equiv \sum_{i=1}^{N} \left| X\beta^* - X_i\hat{\beta}_j \right| \tag{2.5}$$

$$s.t.\; X_i\beta^* \geqslant X_i\hat{\beta}_j,\; j = 1, 2, \ldots, M. \tag{2.6}$$

The other is the minimum sum of the squares of deviations, and parameters can be obtained by solving the following quadratic programming problem:

$$Min\; L \equiv \sum_{i=1}^{N} \left(X\beta^* - X_i\hat{\beta}_j \right)^2, \tag{2.7}$$

subject to the restrictions of Equation (2.6).

Rewriting Equation (2.2) as

$$Y_i = e^{-U_{ij}} \times \frac{e^{X_i\beta_j}}{e^{X_i\beta^*}} \times e^{X_i\beta^* + V_{ij}}, \tag{2.8}$$

where the first term on the right-hand side of Equation (2.8) is the technical efficiency relative to the stochastic frontier for the jth region,

$$TE_i = \frac{Y_i}{e^{X_i\beta_j + V_{ij}}} = e^{-U_{ij}}. \tag{2.9}$$

The second term on the right-hand side of Equation (2.8) is the technology gap ratio (TGR), which measures the ratio of the output of the jth region's frontier production function relative to the potential output of the meta-frontier production function.

$$TGR_i = \frac{e^{X_i\beta_j}}{e^{X_i\beta^*}}. \tag{2.10}$$

The technical efficiency relative to the meta-frontier (TE_i^*, meta-frontier technical efficiency), is defined as

$$TE_i^* = \frac{Y_i}{e^{X_i\beta^* + V_{ij}}}. \tag{2.11}$$

Then, from Equation (2.8), (2.9), (2.10), and (2.11), we obtain

$$TE_i^* = TE_i \times TGR_i. \tag{2.12}$$

2.3 Data and empirical Specification

The data used in this paper come from three household income surveys conducted by the CHIP team at the Chinese Academy of Social Sciences, with assistance from the National Bureau of Statistics, for the reference years of 1988, 1995, and 2002.[2] The sample in each survey was drawn from the large-scale annual household survey of the National Bureau of Statistics using the Probability Proportionate to Size method. There are two parts in CHIP 1988 and 1995, namely, rural sample and urban sample, and three parts in CHIP 2002, namely, rural sample, urban sample, and urban migrant sample. The datasets in this study contain only the rural parts of the three surveys (See Table 2.1).

[2]For more information on the first survey, see Khan et al. (1992); on the second, see Khan and Riskin (1998); and on the third, see Gustafsson et al. (2008).

Table 2.1: Comparison of CHIP samples for 1988, 1995 and 2002

	1988	1995	2002
Rural Samples of CHIP			
Number of persons	51,352	34,739	37,969
Number of households	10,258	7,998	9,200
Number of provinces	28	19	21
Working samples in this study			
Number of persons	37,655	34,353	30,367
Number of households	7,615	7,888	7,474
Number of provinces	19	19	19

Source: CHIP 1988, 1995, and 2002.

Note: Observations with missing values are removed from working samples.

The CHIP surveys were mainly used for the study of income distribution and income inequality in China. The CHIP teams' research results can be found in three volumes, Griffin and Zhao (1993b), Riskin et al. (2001), and Gustafsson et al. (2008). The surveys can also be used to investigate technical efficiency in agriculture, since the rural samples remain the available sources of nation-wide household-level data on production factors and other household characteristics. In addition, the surveys are closely related to the National Bureau of Statistics household surveys, which were selected on the condition that they should represent the economic characteristics in rural China's various regions (Gustafsson et al., 2008). Therefore, it is safe to argue that the surveys can be employed for a regional analysis of agricultural technical efficiency and technology gaps. Then, we select nineteen provinces, which are consistent in the three years' rural samples, as our working samples to investigate the regional technical efficiency and technology gaps during the three reference years.

In contrast of the regional classification of China used in previous studies, we divide China into six regions to allow for consideration of both the level of economic development and agricultural conditions.[3] This classification satisfies the hypothesis that farms conform to a uniform technology in a region, but employ different technologies across regions. The six regions are divided as follows: the Northeast includes Liaoning and Jilin; the North includes Beijing, Hebei, and Shandong; the Central includes Henan, Anhui, Hubei, Hunan, and Jiangxi; the Southeast includes Jiangsu,

[3]In this study, the regional economic development level is considered according to the prevalent Chinese regional economy studies, while geographic conditions are considered mainly according to the classification of the National Commission of Agricultural Division (1991, p.50-57) that divided the mainland of China into ten first-level agricultural regions, on the principle that agricultural production should be consistent with (1) regional natural conditions such as climate, soil conditions, and hydrological conditions and (2) regional economic conditions.

Zhejiang, and Guangdong; the Southwest includes Sichuan, Yunnan, and Guizhou; and the Northwest includes Gansu, Shaanxi, and Shanxi (See Figure 2.1).

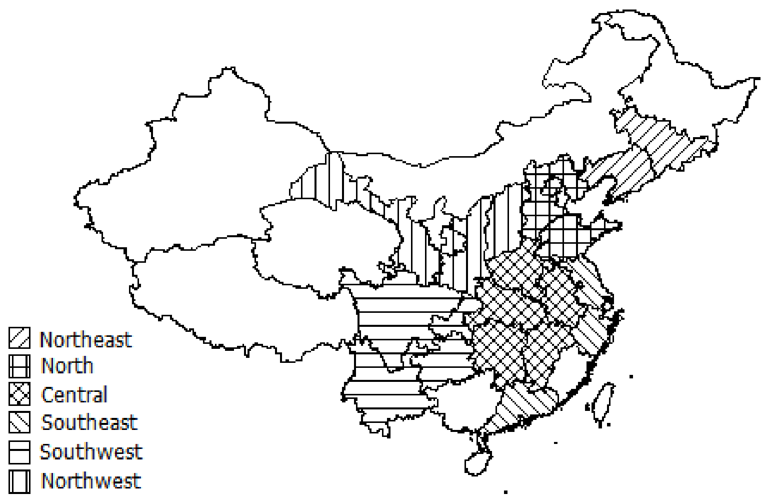

Figure 2.1: Six agricultural regions in this study

The translog stochastic frontier production function of region j is specialized as

$$y_i = \beta_0 + \sum_{m=1}^{3} \beta_m x_{mi} + \sum_{m=1}^{3} \sum_{k \geqslant m}^{3} \beta_{mk} x_{mi} x_{ki} + V_i - U_i, \tag{2.13}$$
$$i = 1, 2, \ldots, N_j,\ j = 1, 2, \ldots, 6,$$

where y_i denotes the natural logarithm of the gross value of agricultural output (the total value of production from farming, forestry, animal husbandry, fishing, and sideline activities; in RMB Yuan) for the ith rural household; x_{1i} denotes the natural logarithm of the total value of the agricultural production cost (including seeds, fertilizers, pesticides, agricultural machinery; in RMB Yuan); x_{2i} denotes the natural logarithm of the total number of labors in a household that mainly engage in agricultural production; x_{3i} denotes the natural logarithm of the sown area (in mu $= 0.0667$ hectares) of a household. The summary statistics on rural households in different regions are presented in Table 2.2. V_i is the white noise, and U_i is the inefficiency term.

Table 2.2: Summary statistics on households in rural China

Region	Year	Output (RMB Yuan)	Production cost (RMB Yuan)	Labor (Person)	Sown area (Mu)	Number of obs.
North	1988	1709.79	947.55	2.76	10.73	1295
		(1685.29)	(1351.71)	(1.34)	(44.66)	
	1995	7057.53	2143.16	2.42	6.99	1238
		(6351.21)	(4691.61)	(1.16)	(4.61)	
	2002	7385.40	2879.27	2.65	6.39	911
		(13128.70)	(8473.63)	(0.98)	(4.62)	
Northeast	1988	2553.65	1240.50	2.60	23.62	512
		(1852.65)	(1211.82)	(1.10)	(44.22)	
	1995	9203.23	3305.62	2.51	14.27	592
		(5544.28)	(4398.21)	(1.08)	(8.34)	
	2002	9976.10	3378.92	2.69	15.62	910
		(7611.55)	(4238.20)	(0.91)	(10.41)	
Central	1988	1800.19	919.52	3.01	7.62	2371
		(1380.51)	(1265.19)	(1.33)	(5.65)	
	1995	7382.84	2266.54	2.51	6.86	2397
		(4695.78)	(4960.61)	(1.07)	(4.86)	
	2002	7175.37	2073.82	2.95	7.59	2100
		(5177.68)	(2194.87)	(1.09)	(6.42)	
Southeast	1988	2545.00	1400.74	2.77	7.31	1204
		(2382.74)	(2344.88)	(1.41)	(36.58)	
	1995	9672.91	3196.81	2.11	4.77	1373
		(16086.80)	(8534.21)	(1.05)	(3.34)	
	2002	9823.70	3897.41	2.87	5.87	1253
		(19466.70)	(12649.01)	(1.10)	(9.98)	
Southwest	1988	1443.97	846.62	3.14	10.68	1348
		(1613.30)	(1377.33)	(1.39)	(51.24)	
	1995	6140.29	2541.89	2.79	5.92	1393
		(3774.43)	(3780.64)	(1.21)	(5.56)	
	2002	7520.58	2782.85	2.87	7.83	1237
		(4587.77)	(2270.63)	(1.06)	(9.94)	
Northwest	1988	1189.33	662.57	2.88	13.01	885
		(1974.05)	(1136.80)	(1.36)	(8.51)	
	1995	4910.74	1871.39	2.68	12.60	895
		(3713.36)	(2916.48)	(1.29)	(7.98)	
	2002	6185.20	2096.90	2.74	10.73	1063
		(7283.93)	(4651.49)	(1.08)	(7.20)	

Source: CHIP 1988, 1995, and 2002.

Note: Standard deviations are reported in parentheses.

Having specified the stochastic frontier production function, we now turn our attention to factors that may affect regional technical efficiency and technology gaps. Given data availability, we assume that regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio are affected by two levels of explanatory variables: individual-level and household-level variables.

As summarized in Table 2.3, individual-level variables come from rural individual datasets that describe the characteristics of agricultural labors in each household. The following individual-level variables are employed in this study: the average age of agricultural labor in a household reflects the working experience of agricultural labor; the illiteracy rate of a household; the dummy variable indicating township or village cadre that may partially capture the the effect of political status on agricultural production; the dummy variable indicating worker in a household that captures the time lost in agricultural production.

Table 2.3: Description and summery statistics of variable for determine model

Variables	Description	Mean	St. Dev.
Individual level variables			
Average age	Total age of agriculture labors divided by the number of agriculture labor in a household	37.378	8.839
Illiteracy rate	The share of illiterate members to the total household members	0.128	0.179
Township or village cadre	=1 if there a township or village cadre in the household, 0 otherwise	0.061	0.239
Worker	=1 if there are one or more household members working as ordinary worker, temporary or short-term contract worker, 0 otherwise	0.322	0.467
Household level variables			
Agriculture labor share	The ratio of agriculture labor to the total household members	0.634	0.226
Non-agriculture income ratio	The ratio of non-agriculture income to gross imcome of a household	0.243	0.264
Terrain variables			
Flat	=1 if the household locates in flat area, 0 otherwise	0.469	0.499
Hilly	=1 if the household locates in hilly area, 0 otherwise	0.306	0.461
Mountainous	=1 if the household locates in mountainous area, 0 otherwise	0.224	0.417
Impoverished region	=1 if the household locates in impoverished region, 0 otherwise	0.262	0.440
Electricity	=1 if the household access to electricity, 0 otherwise	0.947	0.223

Source: CHIP 1988, 1995, and 2002.

Note: The number of observation is 22883 after removed the observations with missing values.

Household-level variables come from rural household datasets that describe the characteristics of households. We employ the following household level variables: the agricultural labor share; non-agriculture income share; the dummy variables for flat, hilly, and mountainous terrain that reflect where the household is located and can be regarded as proxy variables for geographical conditions; the dummy variable of impoverished counties;[4] the dummy variable of electricity, which is regarded as a

[4] At first, 258 counties were designated as national poor counties in 1986 by the Leading Group for Economic Development in Poor Areas of China, according to the standard that the rural net

proxy variable for physical infrastructure and is assumed to have a positive effect on technical efficiency.

In addition, regional dummy and year dummy variables are employed for the analysis of regional effects and time effects.

2.4 Empirical results

2.4.1 Regional technical efficiency, technology gap ratio, and meta-frontier technical efficiency

The regional frontier production functions were estimated by maximum likelihood using the FRONTIER 4.1 programme (Coelli, 1996). Then, three generalized likelihood ratio tests were taken to demonstrate whether the estimated regional stochastic frontier functions are appropriate (see Table 2.4).[5]

First, the null hypothesis that the Cobb-Douglas production function is an adequate representation of our samples was rejected for all regions. Next, the hypothesis that the technical inefficiency term is not present in a given region, was rejected for all regions at the significance level of 0.05, with the exception of the southwest in 2002.[6] The results suggest that the technical inefficiencies terms were present in the samples of all regions. Finally, the hypothesis that all regions share the same technology was also rejected in every reference year, which indicates that the regional stochastic frontiers are different across all six regions in the three reference years.

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income per capita of a county was below 150 RMB Yuan in 1985. Then, the number of national poor counties increased to 592 in 1993. In addition, in 1988, 370 counties were designated as provincial poor counties by different provincial standards Park et al. (2002).

[5] For the detailed steps of the test, see Battese et al. (2004).

[6] Since the P-value of the test for southwest stochastic frontier in 2002 is 0.224, we think that the inefficiency term was present.

Table 2.4: Test of hypotheses for the estimates of translog stochastic frontier models in six regions

Null hypothesis							
1. Cobb-douglas production function is adequate for every regional frontier, $H_0 : \beta_{mk} = 0$.							
		North	Northeast	Central	Southeast	Southwest	Northwest
Likelihood ratio	1988	275.135(0.000)	85.863(0.000)	525.513(0.000)	191.110(0.000)	315.034(0.000)	208.367(0.000)
statistic	1995	89.363(0.000)	33.691(0.000)	219.737(0.000)	59.886(0.000)	89.563(0.000)	61.621(0.000)
	2002	110.401(0.000)	75.422(0.000)	162.165(0.000)	205.087(0.000)	76.429(0.000)	145.400(0.000)
2. The inefficiency is absent in every regional frontier, $H_0 : \gamma = \delta = 0$.							
		North	Northeast	Central	Southeast	Southwest	Northwest
Likelihood ratio	1988	325.846(0.000)	79.486(0.000)	573.061(0.000)	223.906(0.000)	369.532(0.000)	198.630(0.000)
statistic	1995	8.339(0.015)	10.739(0.005)	129.642(0.000)	12.043(0.002)	34.903(0.000)	15.285(0.000)
	2002	46.884(0.000)	26.617(0.000)	47.011(0.000)	113.514(0.000)	2.991(0.224)	88.091(0.000)
3. All regions share the same technology.							
Likelihood ratio	1988	339.432(0.000)					
statistic	1995	1030.491(0.000)					
	2002	559.015(0.000)					

Note: P value is presented in parentheses. The likelihood ratio satistic obey the chi-squre distribution, and the degree of freedom is 6, 2, and 65 in hypothesis 1, 2, and 3 respectively.

Table 2.5: Estimation results of stochastic frontier and metafrontier for rural China

Variable	Coeff.	National(SFA)[a]	Meta(LP)[b]	Meta(QP)[c]
1988				
Constant	β_0	5.873(0.205)	8.227(0.057)	7.434(0.423)
x_1	β_1	-0.173(0.059)	-0.973(0.090)	-0.635(0.076)
x_2	β_2	1.099(0.122)	1.624(0.126)	1.406(0.044)
x_3	β_3	-0.118(0.066)	0.196(0.000)	-0.071(0.000)
$(x_1)^2$	β_{11}	0.064(0.005)	0.140(0.004)	0.104(0.006)
$(x_2)^2$	β_{22}	-0.062(0.028)	0.006(0.000)	0.010(0.001)
$(x_3)^2$	β_{33}	0.020(0.007)	0.088(0.000)	0.069(0.006)
$x_1 \times x_2$	β_{12}	-0.121(0.019)	-0.237(0.032)	-0.204(0.021)
$x_1 \times x_3$	β_{13}	0.022(0.011)	-0.058(0.003)	-0.003(0.000)
$x_2 \times x_3$	β_{23}	-0.008(0.024)	0.036(0.000)	0.054(0.005)
1995				
Constant	β_0	7.765(0.058)	8.018(0.108)	8.000(0.410)
x_1	β_1	-0.003(0.012)	0.023(0.000)	0.026(0.003)
x_2	β_2	0.699(0.061)	0.899(0.012)	0.874(0.031)
x_3	β_3	0.400(0.034)	0.141(0.000)	0.170(0.004)
$(x_1)^2$	β_{11}	0.008(0.001)	0.006(0.000)	0.007(0.001)
$(x_2)^2$	β_{22}	-0.060(0.027)	-0.074(0.000)	-0.087(0.007)
$(x_3)^2$	β_{33}	-0.027(0.008)	0.141(0.000)	0.129(0.006)
$x_1 \times x_2$	β_{12}	-0.013(0.007)	-0.017(0.000)	-0.018(0.000)
$x_1 \times x_3$	β_{13}	0.011(0.004)	0.017(0.000)	0.011(0.001)
$x_2 \times x_3$	β_{23}	-0.182(0.023)	-0.322(0.004)	-0.289(0.022)
2002				
Constant	β_0	6.296(0.116)	7.828(0.407)	7.804(0.326)
x_1	β_1	-0.115(0.030)	-0.452(0.025)	-0.449(0.006)
x_2	β_2	0.517(0.102)	0.075(0.000)	0.098(0.013)
x_3	β_3	0.430(0.046)	0.666(0.048)	0.673(0.039)
$(x_1)^2$	β_{11}	0.054(0.002)	0.080(0.000)	0.080(0.004)
$(x_2)^2$	β_{22}	-0.031(0.030)	0.252(0.021)	0.254(0.018)
$(x_3)^2$	β_{33}	0.003(0.006)	0.061(0.005)	0.064(0.004)
$x_1 \times x_2$	β_{12}	-0.038(0.015)	-0.041(0.000)	-0.043(0.003)
$x_1 \times x_3$	β_{13}	-0.031(0.007)	-0.070(0.000)	-0.073(0.004)
$x_2 \times x_3$	β_{23}	-0.035(0.021)	-0.102(0.014)	-0.107(0.005)

Notes:

1. Standard errors in parentheses. Statistical significance is at *10%, **5%, and ***1% levels.

[a]Estimates of the stochastic frontier production function for rural China obtained by pooled data.

[b]Estimates of metafrontier production function obtained by linear programming.

[c]Estimates of metafrontier production function obtained by quadratic programming.

The estimates of the meta-frontier obtained by linear programming and quadratic programming, together with the estimates of the stochastic frontier production function for rural China obtained by pooled data in every reference year, are presented in Table 2.5. The parameters of the meta-frontier production functions and their standard errors were obtained using MATLAB, while the standard errors were obtained from 5000 times bootstrapping procedures. Table 2.5 shows that there is insignificant differences between linear programming and quadratic programming estimates for the parameters of the meta-frontiers. Then, the quadratic programming estimates were used to calculate the technology gap ratio and the meta-frontier technical efficiency of each household. The estimated regional technical efficiency, technology gap ratio, and meta-frontier technical efficiency are summarized in Table 2.6.

There are several points to be taken from Table 2.6. First, in spite of the fact that the Southeast (economic developed region) always had the highest technology gap ratio, its meta-frontier technical efficiency changed from the highest to the lowest. On the contrary, the Southwest (economic developing region) always had a low technology gap ratio, but its rank in meta-frontier technical efficiency increased from number four to number one. However, the Northwest (the poorest region) always lags behind on both technical efficiency and technology gap ratio.

Second, the mean technology gap ratio of Chinese rural households changed slightly over the three years (decreased from 0.962 in 1988 to 0.941 in 1995, then returned to 0.962 in 2002). All six regions exhibited the same fluctuation in mean technology gap ratio over the three years. It is noticeable that the Southeast always leads with respect to the technology gap ratio, while the Northwest always lags behind the other regions.

Third, the mean values of the meta-frontier technical efficiency increased in each period (0.572, 0.712, 0.734 in the years 1988, 1995, 2002, respectively), while variations in meta-frontier technical efficiency of each region were rather different over the three sample years. Although the mean values for meta-frontier technical efficiency in four of all regions, namely, the Northeast, the Central, the Southwest, and the Northwest increased in each period, the mean values of the meta-frontier technical efficiency in the North and the Southeast increased from 1988 to 1995, then decreased in 2002. In particular, the Southwest and the Northwest had a faster rate of growth in meta-frontier technical efficiency (47.68% and 34.65% from 1988 to 2002, respectively) than other regions, but the meta-frontier technical efficiency of the southeast increased at a rate of 18.61% from 1988 to 1995, and then decreased at a rate of 6.79% from 1995 to 2002.

Table 2.6: Summary statistics of regional technical efficiency, technology gap ratio, and metafrontier technical efficiency in rural China

		1988				1995				2002			
Region	Statistic	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
	TE	0.561	0.220	0.013	0.916	0.759	0.085	0.194	0.924	0.720	0.131	0.083	0.932
North	TGR	0.970	0.021	0.678	0.992	0.948	0.028	0.756	1.000	0.961	0.017	0.847	1.000
	TE^*	0.544	0.214	0.012	0.895	0.720	0.083	0.185	0.889	0.692	0.127	0.080	0.903
	TE	0.610	0.197	0.018	0.924	0.787	0.087	0.168	0.934	0.774	0.107	0.109	0.932
Northeast	TGR	0.965	0.022	0.869	1.000	0.932	0.025	0.795	1.000	0.959	0.013	0.846	1.000
	TE^*	0.589	0.190	0.018	0.904	0.734	0.082	0.140	0.901	0.742	0.104	0.107	0.895
	TE	0.627	0.196	0.013	0.941	0.744	0.125	0.039	0.947	0.812	0.080	0.086	0.953
Central	TGR	0.968	0.012	0.860	1.000	0.959	0.011	0.904	1.000	0.969	0.017	0.781	1.000
	TE^*	0.608	0.190	0.012	0.897	0.714	0.120	0.038	0.915	0.787	0.079	0.083	0.953
	TE	0.630	0.191	0.025	0.930	0.741	0.082	0.077	0.911	0.688	0.143	0.027	0.914
Southeast	TGR	0.989	0.017	0.747	1.000	0.980	0.023	0.696	1.000	0.984	0.025	0.764	1.000
	TE^*	0.624	0.190	0.024	0.929	0.727	0.082	0.075	0.911	0.677	0.141	0.025	0.906
	TE	0.586	0.208	0.011	0.941	0.796	0.085	0.080	0.955	0.871	0.044	0.505	0.946
Southwest	TGR	0.956	0.020	0.776	0.984	0.936	0.015	0.843	1.000	0.950	0.008	0.884	0.974
	TE^*	0.560	0.199	0.010	0.892	0.745	0.080	0.074	0.906	0.827	0.043	0.481	0.902
	TE	0.546	0.212	0.012	0.913	0.705	0.120	0.121	0.907	0.718	0.128	0.016	0.914
Northwest	TGR	0.925	0.026	0.786	1.000	0.892	0.028	0.713	0.967	0.947	0.018	0.860	0.986
	TE^*	0.505	0.197	0.011	0.851	0.629	0.109	0.113	0.821	0.680	0.122	0.015	0.874

Note: The quadratic programming estimates for the metafrontier coefficients are used in this table.

In addition, there are several differences between our findings and the findings of Chen and Song (2008). They found that the Northeast has the highest TGR (0.985), and the East has the highest regional technical efficiency value (1.000). The difference in results may arise for three reasons: first, we used household-level data, while they used county-level data; second, we used a different regional division; third, Chen and Song (2008) employed traditional production function (no inefficiency term) for the regional frontier estimation of the eastern region because the likelihood ratio test could not rejected the hypothesis that the inefficiency term was not present in the production frontier of this region. Thus, all farms in the eastern region have the highest technical efficiency scores, in other words, the regional technical efficiency score of each eastern farm equals 1 in Chen and Song (2008)'s study. However, both studies conclude that the West has the lowest technology gap ratio.[7]

2.4.2 Determinants of regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio

To discern the sources of technical efficiency, the indexes (TE, TE^*, and TGR) were regressed on the set of explanatory variables we described in the previous section. The econometric analysis was conducted by pooling data across all three years. Since all the three indexes have 1 as the upper bound and 0 as the lower bound, Tobit models are employed in this study.[8] In addition, since the inefficiency term U_i is assumed to be a truncated normal distribution, the quantile regression may be used to obtain efficient estimation (Jacobs et al., 2004). In this study, the quantile regression and Tobit yield identical sign and significance level. These results indicate that the Tobit models are robust. The Tobit and the quantile regression results for regional technical efficiency, meta-frontier technical efficiency, the technology gap ratio are reported in Table 2.7 and Table 2.8, respectively.

[7] In this study, both the Northwest and the Southwest have the lowest TGR.

[8] The Tobit model was employed by Chavas et al. (2005) and Chen and Song (2008) for the efficiency determinant function, while maximum likelihood estimation was employed by Yao and Liu (1998), and OLS estimation, by Tian and Wan (2000). In this study, Tobit and OLS estimators are identical in the TE and the TE^* models since there is no censored observation. Further, the estimators in the TGR model are also similar between Tobit and OLS estimates since there are only 30 right-censored observations in all 22853 observations.

Table 2.7: Tobit estimates of TE, TE*, and TGR

Dependent variable	TE	TE^*	TGR
Individual level variables			
Average age	0.12***	0.16***	0.063***
	(0.040)	(0.038)	(0.0061)
Square of average age	-0.0012**	-0.0017***	-0.00080***
	(0.00050)	(0.00048)	(0.000077)
Illiteracy rate	-2.43***	-2.75***	-0.61***
	(0.51)	(0.49)	(0.078)
Township or village cadre	1.67***	1.56***	-0.094*
	(0.36)	(0.35)	(0.055)
Worker	-0.79***	-0.75***	-0.022
	(0.19)	(0.19)	(0.030)
Household level variables			
Agriculture labor share	-3.44***	-2.91***	0.53***
	(0.40)	(0.38)	(0.061)
Non-agriculture income ratio	-28.20***	-27.50***	-0.67***
	(0.35)	(0.34)	(0.054)
Terrain variables			
Hilly	-0.95***	-1.03***	-0.21***
	(0.21)	(0.20)	(0.032)
Mountainous	-2.67***	-2.93***	-0.57***
	(0.25)	(0.24)	(0.038)
Impoverished region	-2.49***	-2.43***	-0.11***
	(0.22)	(0.21)	(0.034)
Electricity	6.25***	6.21***	0.42***
	(0.41)	(0.39)	(0.063)
Regional dummies			
North	1.30***	3.52***	3.51***
	(0.34)	(0.32)	(0.052)
Northeast	2.02***	3.60***	2.69***
	(0.39)	(0.37)	(0.059)
Central	4.91***	7.48***	4.11***
	(0.29)	(0.28)	(0.045)
Southeast	3.75***	7.72***	6.11***
	(0.33)	(0.32)	(0.051)
Southwest	8.59***	9.74***	2.51***
	(0.32)	(0.31)	(0.050)
Year dummies			
1995	9.45***	7.73***	-1.85***
	(0.23)	(0.22)	(0.035)
2002	13.80***	13.10***	-0.22***
	(0.25)	(0.24)	(0.038)
Constant	61.60***	56.30***	91.60***
	(0.97)	(0.93)	(0.15)
No. Obs.	22883	22883	22883

Note: Standard errors in parentheses. The coefficient estimates and standard errors are given to two-significant digits. Statistical significance is at * 10%, ** 5%, and *** 1% levels. Dependent variables are multiplied by 100. Both regional and year dummies are jointy statistically significant by likelihood-ratio test.

Table 2.8: Quantile regression results of TE, TE*, and TGR

Dependent variable	TE	TE^*	TGR
Individual level variables			
Average age	0.094***	0.15***	0.034***
	(0.034)	(0.034)	(0.0037)
Square of average age	-0.00078*	-0.0016***	-0.00044***
	(0.00043)	(0.00043)	(0.000046)
Illiteracy rate	-2.56***	-2.71***	-0.26***
	(0.43)	(0.43)	(0.047)
Township or village cadre	1.01***	1.10***	-0.063*
	(0.31)	(0.31)	(0.034)
Worker	-0.81***	-0.69***	-0.0072
	(0.17)	(0.17)	(0.018)
Household level variables			
Agriculture labor share	-3.21***	-2.40***	0.35***
	(0.34)	(0.34)	(0.037)
Non-agriculture income ratio	-20.90***	-20.60***	-0.24***
	(0.30)	(0.30)	(0.033)
Terrain variables			
Hilly	-0.93***	-1.02***	-0.070***
	(0.18)	(0.18)	(0.019)
Mountainous	-2.28***	-2.57***	-0.44***
	(0.21)	(0.21)	(0.023)
Impoverished region	-2.07***	-2.10***	-0.0028
	(0.19)	(0.19)	(0.021)
Electricity	7.06***	6.86***	0.16***
	(0.35)	(0.35)	(0.038)
Regional dummies			
North	1.73***	4.15***	3.48***
	(0.29)	(0.29)	(0.032)
Northeast	3.02***	4.64***	2.60***
	(0.33)	(0.33)	(0.036)
Central	5.46***	8.22***	3.97***
	(0.25)	(0.25)	(0.027)
Southeast	2.16***	6.76***	6.18***
	(0.28)	(0.28)	(0.031)
Southwest	9.96***	11.10***	2.20***
	(0.28)	(0.28)	(0.030)
Year dummies			
1995	8.92***	7.05***	-1.57***
	(0.19)	(0.19)	(0.021)
2002	12.80***	12.10***	-0.23***
	(0.21)	(0.21)	(0.023)
Constant	61.60***	55.60***	92.60***
	(0.82)	(0.83)	(0.090)
No. Obs.	22883	22883	22883

Note: 0.5 quantile regression (median) is employed. Standard errors in parentheses. The coefficient estimates and standard errors are given to two-significant digits. Statistical significance is at * 10%, ** 5%, and *** 1% levels. Dependent variables are multiplied by 100. Both regional and year dummies are jointy statistically significant by likelihood-ratio test.

Table 2.7 shows that the estimated coefficients in the meta-frontier technical efficiency model have the same sign and statistical significance as the corresponding regional technical efficiency model. Moreover, the magnitudes of the coefficients changed slightly between the TE and TE^* models. This change in magnitudes stems from from the fact that the meta-frontier technical efficiency is theoretically decomposed into two components: the distance from an input-output point to the regional frontier (regional technical efficiency), and the distance between the regional frontier and the meta-frontier (technology gap). In this study, the mean value of the technology gap ratio (0.958) is close to the upper bound value. Thus, the meta-frontier technical efficiency is mainly affected by the regional technical efficiency.

As shown in Table 2.7, the quadratic structure of agricultural labor's average age has statistically significant and negative marginal effects on regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio, whereas farmers' average age has a positive effect on regional technical efficiency and meta-frontier technical efficiency for averages below 50 and a negative effect above 50. With respect to the technology gap ratio, the turning point is 39. This result is consistent with the findings of Liu and Zhuang (2000) where although farmers become more skillful as they grow older, the learning-by-doing effect decreases as their physical strength begins to decline.

The illiteracy rate is found to have a negative and significant impact on regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio. These findings are in line with the expectation that a higher illiteracy rate leads to lower technical efficiency and technology gap ratio. Township or village cadre is found to have a positive and significant impact on regional technical efficiency and meta-frontier technical efficiency, but a negative effect on technology gap ratio. These results indicate that the higher political status of a rural household can improve the technical efficiency, but cannot change the production environment. In addition, worker is shown to have a negative and significant impact on regional technical efficiency and meta-frontier technical efficiency, a negative but insignificant impact on technology gap. This may stem from the fact that most migrant labors are youth and have relatively high education levels in rural China, the remaining labors in the rural sector are less efficient because they are slower to adopt existing technologies.

In line with priori expectations, agricultural labor share has a strong negative effect on regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio. This finding is in line with Yao and Liu (1998), who proposed that a higher share of agricultural labor has a negative effect on efficiency because of labor congestion. Non-agricultural income ratio is also found to have a strong negative effect on regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio. These results reflect the fact that non-agricultural activities distract farmers' attention from agricultural production. The estimated coefficients on terrain variables (flat is base group) show that better geographical conditions contribute to more efficient agricultural production. In addition, impoverished region is found to have a negative and significant impact on regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio, which reflects the fact that the farmers in impoverished area are at a disadvantage with respect to the agricultural production environment.

As a proxy variable of physical infrastructure, access to electricity is found to have a positive and significant effect on regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio. The results support the recommendation in previous studies (e.g. Yao and Liu, 1998; Tian and Wan, 2000) that agricultural infrastructure investment will improve both agricultural technical efficiency (catching up) and agricultural technology level (innovation).

In the TE model, the estimated coefficients on regional dummy variables show that the southwest is the most efficient region in agricultural production, and the Central, the Southeast, the Northeast, and the North are sorted by their marginal effects. A similar finding is observed in the TE^* model, except for a changed rank order between the Central and the Southeast. In the TGR model, however, the marginal effects with respect to the Southeast, the Central, the North, the Northeast, and the Southwest are sorted from high to low. These findings are in accordance with the results in Section 4.1. These findings also reveal the true picture of regional agricultural production in China. Since the Northwest is the poorest in natural endowments (e.g. soil condition, hydrological condition) and infrastructure (e.g. irrigation system, road, electricity), its agricultural production frontier is the farthest from the meta-frontier and thus has the lowest technology gap ratio. In addition, since the stochastic frontier analysis approach is an input-output based procedure for technical efficiency estimation, an output shock will lead to a low technical efficiency score. Agricultural production in northwest China is severely affected by drought, which may be the explanation for inefficient agricultural production. On the contrary, the southeast has priority in natural endowments, infrastructure, marketing facilities, and technical service. Thus, its frontier is the closest to the meta-frontier. And since the Southeast always experiences faster technical progress, the feasible regional production frontier shifts outwards more quickly than those of other regions, and consequently ordinary farms find it difficult to catch up with the best performing farms. Therefore, the Southeast has a lower regional technical efficiency. For the Southwest, poor infrastructure keeps the agricultural production frontier well below the meta-frontier. On the contrary, because of the southeast's slow technical progress, ordinary farms find it is easier to catch up with the best performing farms. Thus, the Southeast's average regional technical efficiency level is higher. Moreover, differences in the regional technical efficiencies of the Southwest and the Northwest may be associated with the fact that the Southwest is seldom affected by output shocks, since it has better natural endowments (fertile soil and higher annual precipitation).

The estimated coefficients on year dummies in the TE and TE^* models show that farms in China became increasingly efficient from 1988 to 2002, which is in line with Yao et al. (2001) who report that the national average level of technical efficiency increased from 1987 to 1992. In the TGR model, however, year dummies are found to have a negative and significant effect on the technology gap ratio, which means that technology gaps across regions increased over time. Thus, considerable attention should be paid to rising regional technology gaps, especially the gap between developed and developing regions.

2.5 Concluding Remarks

This essay attempts to investigate regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio in rural China using household-level data. A stochastic meta-frontier analysis approach is employed to calculate the score of the regional technical efficiency, the meta-frontier technical efficiency, and the technology gap ratio of each rural household. Our findings are as follows.

Firstly, there is a negative relationship between the technology gap ratio and regional technical efficiency for all regions except the Northwest. For instance, the Southeast (economic developed region) always had the highest technology gap ratio, while the Southwest (economic developing region) had an increasing meta-frontier technical efficiency. The Northwest (the poorest region), however, was always legging in both technical efficiency and technology gap ratio. This result is consistent with the findings of Yao et al. (2001) that technical efficiency is negatively correlated with technological progress. Meanwhile, this result suggests that the regions with high technology gap ratios (Southeast, Central, and North) should focus on the improvement of intra-region efficiency gaps among households. Efficiency improvement can be brought about through technology diffusion within region. On the other hand, regions with low technology gap ratios (Northeast, Northwest, and Southwest) should pay more attention to the improvement of their agricultural production environment, since their regional frontiers are farther away from the meta-frontier than their counterparts. The agricultural production environment can be improved through infrastructural construction (road, irrigation, etc.) and human capital investment (education and training).

Secondly, if the meta-frontier technical efficiency in rural China is decomposed into two parts, the distance between actual production and the regional frontier (regional technical efficiency), and the technology gap between the regional frontier and the meta-frontier (technology gap ratio), it is regional technical efficiency rather than the technology gap ratio that contributes to the meta-frontier technical efficiency level, since the technology gap ratio is close to 1 in all regions. This finding indicates that policy should focus on the improvement of intra-regional disparities in efficiency among households in rural China. Improvements in efficiency can be made through the diffusion of technology within regions.

Finally, the mean values of regional technical efficiency and meta-frontier technical efficiency increased considerably over time, especially from 1988 to 1995, but the technology gap ratio decreased slightly over time. These trends suggest that intra-region efficiency in rural China converged after reform, but inter-region efficiency diverged. Therefore, the efforts to narrow regional technology gaps are also necessary for improving agricultural technical efficiency in China.

This study also attempts to explain the determinants of regional technical efficiency, meta-frontier technical efficiency, and technology gap ratio in rural China. The empirical evidence suggests that the working experience of agricultural labor and infrastructure have a strong positive effect on both technical efficiency and technology gap ratio, while the illiteracy rate of a household, off-farm activities, lagging natural conditions (e.g. terrain variables), and lower economic development (e.g. impoverished) have negative effect on technical efficiency and technology gap ratio. Thus, improvements in technical efficiency and outward shifts in regional frontiers can be brought about by increasing agricultural infrastructure investment and improving intangible human qualities in rural areas, especially in the developing rural areas (Northwest and Southwest). Besides, political status (e.g. township or village cadre) is found to have a positive effect on technical efficiency, but a negative effect on technology gap ratio. Therefore, social status equality among rural households is likely to improve technical efficiency and decrease technology gaps in rural China.

Chapter 3

Regional technical efficiency, technology gaps, and TFP change in Chinese SOEs during the early reform period

3.1 Introduction

Chinese SOEs have played a significant role in China's economic development since "the socialist reform" accomplished in 1957.[1] However, Chinese SOEs experienced inefficient production and other economic failures under the planned economy. China thus began market-oriented reform in 1978. The reform has focused on improving efficiency and stimulating economic growth. Many measures were proposed to fulfill these goals in SOEs, where different stages of the reform aimed at different aspects of objective.[2] There has been substantial research on the performance of Chinese SOEs, while most of them showed that the reform had made achievements in improving SOEs' productivity and efficiency during the early reform period. However, productivity and efficiency improvement in SOEs has also been accompanied by increasing spatial disparity.[3] This imbalance of regional productivity in SOEs has in fact emerged as one disturbing factor affecting SOEs' development in China. Therefore, this essay attempts to investigate the regional disparity of technical efficiency, technology gaps, and TFP in Chinese SOEs in the early reform period, and

[1]The annual mean share of SOEs' output value to gross industrial output value is 86.11% from 1958 to 1978. Source: National Bureau of Statistics of China (2010).

[2]For more information on the reform stage of SOEs, see Lin and Liu (2000) and Qian (2000).

[3]Computing from the macro data (National Bureau of Statistics of China, 1999, p.A27-28), the standard deviations of SOEs' labor productivity among regions increased from 0.104 in 1978 to 0.483 in 1995.

to investigate what may influence the technical efficiency, technology gaps, and TFP change.

Much has been written about the technical efficiency and productivity of Chinese SOEs during the reform period. Several studies concentrated on the measurement of aggregate level TFP of Chinese SOEs employing conventional production function approach (e.g. Chen et al., 1988; Jefferson et al., 1992; and Wan, 1995). However, Aggregate level measurements cannot be used to investigate the specific reform effects on different industries and regions as reforms were not implemented systematically and were carried out at different paces in different industries and regions. Some studies have examined differences in technical efficiency and TFP across firms using firm-level panel data. Dollar (1990) found that SOEs' TFP has grown rapidly and TFP dispersion across firms declined from 1978 to 1982. Jefferson and Xu (1994) observed a tendency of convergence of technical efficiency among large and medium-sized SOEs over the period 1980–1989. Murakami et al. (1994) showed that SOEs were less efficient than cooperative township-village enterprises and joint ventures in the case of the garment industry. Gordon and Li (1995) found that Chinese SOEs' TFP increased by 4.6% per year from 1983 to 1987 and half of this growth due to the rapidly improving education of the labor force. Further, using a stochastic frontier analysis approach, Lau and Brada (1990), Kalirajan and Cao (1993), Wu (1996) measured the TFP change in Chinese SOEs and decomposed the TFP change into technical efficiency change and technical change. They found that reform was significant in promoting SOEs' technical efficiency. In particular, Liu and Liu (1996), and Kong et al. (1999) employed Battese and Coelli (1995)[4] model to investigate SOEs' TFP and technical efficiency.

In addition, several studies have employed DEA approach. Zheng et al. (1998) analyzed technical efficiency and its determinants among Chinese state, collective, and township-village enterprises. Zheng et al. (2003) investigated the productivity performance of SOEs and found that productivity growth was accomplished mainly through technical progress rather than through improvement in technical efficiency.

Nevertheless, the regional analysis of technical efficiency and TFP change for Chinese industry was limited. Tong and Chan (2003) examined regional disparity in technical efficiency across Chinese township and village enterprises and found that regional disparity in Chinese township and village enterprises' technical efficiency was increasing. Recently, Chen et al. (2009a) analyzed the inequality of Chinese industry

[4]Battese and Coelli (1995) developed a simultaneous approach of SFA to gain the consistent estimates of technical efficiency score and the determinants technical efficiency.

productivity between coastal and non-coastal provinces using provincial data from 1996 to 2004. However, regional differences in Chinese SOEs have not received much attention.

Since we attempt to contribute to the literature of Chinese SOEs reform by offering some insights into regional technical efficiency and productivity performance, this paper employs the developed SFA approach—stochastic meta-frontier analysis (Battese et al., 2004))—to investigate regional technical efficiency, technology gaps, and TFP change in Chinese state-owned manufacturing enterprises using a sample of approximately 600 enterprises from 1980 to 1994. We found that the manufacturing production frontier of Jiangsu (the Eastern region) is the closest to meta-frontier while the frontier of Shanxi (the Northwest area) is the farthest. However, the firms in Sichuan and Shanxi (the Western region) have higher regional technical efficiency scores than their counterparts. Our findings also show that SOEs in all regions experienced positive TFP change in the early reform period while TFP growth attributed to technical efficiency change in the first ten years, then to technical change in the next five years. In addition, the regression results of the determinant models suggest that the reform measures contributed technical efficiency improvement and TFP growth, but enlarged the regional disparity of technology level in Chinese state-owned manufacturing enterprises.

The rest of the essay is organized as follows. In Section 2, we describe the methodology used to estimate regional technical efficiency and technology gaps, and to measure the TFP growth. The data, variables, and empirical specifications are briefly summarized in Section 3. Section 4 reports the empirical results of the regional technical efficiency, technology gaps, and TFP change in Chinese state-owned manufacturing enterprises, together with the major determinants of regional meta-frontier technical efficiency, technology gaps, and TFP change in the early reform period. Finally, some concluding remarks are presented in Section 5.

3.2 The stochastic meta-frontier methodology

The SFA approach is a well-established technical efficiency measurement technique and is widely used in empirical papers. Some empirical studies about the technical efficiency and productivity performance have already employed this approach (see literature review in previous section). The difference between stochastic frontier production function and traditional production function (e.g. Cobb-Douglas production function) is that the error term in stochastic frontier production function comprises a symmetric random error and a non-negative technical inefficiency term. Since not all producers are always successful in utilizing the given inputs to produce maximum outputs under given technology, namely, not all producer are always technically efficient, the stochastic frontier analysis is more realistic. However, stochastic frontier analysis assumes that all producers operate under a given production technology. It can not be used to compare the performance of producers operating under different technologies. Battese et al. (2004) thus developed the stochastic meta-frontier approach to investigate technical efficiencies and technology gaps across different groups.

In this study, following Battese and Coelli (1995), a simultaneous stochastic production frontier and inefficiency model for jth region is specified as

$$Y_{it} = f\left(X_{it},\, \beta_j,\, t\right) e^{V_{itj}-U_{itj}} = e^{X_{it}\beta_j+V_{itj}-U_{itj}}, \tag{3.1}$$

$$U_{itj} = Z_{itj}\delta_j + W_{itj}, \tag{3.2}$$

$$i = 1, 2, \ldots, N_j,\; t = 1, 2, \ldots, T,\; j = 1, 2, \ldots, M,$$

where Y_{it} denotes the output for the ith firm at the tth time; X_{it} denotes a vector of values inputs of production for the ith firm at the tth time; β_j is a vector of unknown parameters to be estimated; V_{itj} is assumed to be identically and independently distributed as $N(0,\, \sigma_{vj}^2)$ random variables; U_{itj} is defined as inefficiency terms of production of jth region, and it is independent of V_{itj}; Z_{itj} is a vector of explanatory variables associated with the technical inefficiency of each firm, and W_{it} is defined by the truncation (at zero) of $N(0,\, \sigma_j^2)$ distributions, δ_j is a vector of unknown coefficient. The expression of Equation (3.1) assumes that the exponent of the frontier production is linear in the parameter β_j.

The technical efficiency (TE_{itj}) for the ith firm at the tth time in jth region is defined as

$$TE_{itj} = exp\left(-U_{itj}\right) = exp\left(-Z_{itj}\delta_j - W_{itj}\right), \tag{3.3}$$

The method of maximum likelihood is proposed for simultaneous estimation of the stochastic frontier production function and the inefficiency model. The likelihood function is expressed in terms of the variance parameters, $\sigma_{sj}^2 \equiv \sigma_{vj}^2 + \sigma_j^2$ and $\gamma_j \equiv \sigma_j^2/\sigma_{sj}^2$.

The meta-frontier production function is assumed to envelop all the regional frontiers. It is expressed by

$$Y_{it}^{*} = f\left(X_{it},\, \beta^{*},\, t\right) = e^{X_{it}\beta^{*}}, \tag{3.4}$$
$$i = 1, 2, \ldots, N = \textstyle\sum_{j=1}^{M} N_j,\ t = 1, 2, \ldots, T,$$
$$s.t.\ X_{it}\beta^{*} \geqslant X_{it}\beta_j, \tag{3.5}$$

where Y_{it}^{*}, β^{*} denote the output, and the vector of parameters of the meta-frontier function.

Battese et al. (2004) presented two criteria to estimate the meta-frontier function by solving optimization problem: one is minimum sum of absolute deviations, parameters can be obtained by solving linear programming problem:

$$Min\ L \equiv \sum_{t=1}^{T} \sum_{i=1}^{N} \left| X_{it}\beta^{*} - X_{it}\hat{\beta}_j \right| \tag{3.6}$$
$$s.t.\ X_{it}\beta^{*} \geqslant X_{it}\hat{\beta}_j,\ j = 1, 2, \ldots, M, \tag{3.7}$$

the other is minimum sum of squares of deviations, parameters can be obtained by solving quadratic programming problem:

$$Min\ L \equiv \sum_{t=1}^{T} \sum_{i=1}^{N} \left(X_{it}\beta^{*} - X_{it}\hat{\beta}_j \right)^{2}, \tag{3.8}$$

subject to the restrictions of Equation (3.7).

Rewriting Equation (3.1) as

$$Y_{it} = e^{-U_{itj}} \times \frac{e^{X_{it}\beta_j}}{e^{X_{it}\beta^{*}}} \times e^{X_{it}\beta^{*} + V_{itj}}, \tag{3.9}$$

where the first term on the right-hand side of Equation (3.9) is the technical efficiency relative to the stochastic frontier of the jth region. The second term on the right-hand side of Equation (3.9) is the technology gap ratio (TGR_{it}), which measures the ratio of the output that is defined by the jth regional frontier function relative to the potential output that is defined by the meta-frontier function,

$$TGR_{it} = \frac{e^{X_{it}\beta_j}}{e^{X_{it}\beta^*}}. \tag{3.10}$$

The technical efficiency of the ith firm, relative to the meta-frontier (TE_{it}^*), is defined as

$$TE_{it}^* = \frac{Y_{it}}{e^{X_{it}\beta_j + V_{itj}}}. \tag{3.11}$$

It can also be expressed by an alternative expression

$$TE_{it}^* = TE_{it} \times TGR_{it}. \tag{3.12}$$

Further, in order to measure TFP change, we start from the partial derivatives of the logarithm of equation (1) with respect to time t,

$$\frac{\dot{Y_{it}}}{Y_{it}} = \left(e_{f/x} \times \frac{\dot{X_{it}}}{X_{it}} + \dot{v_{it}} \right) + e_{f/t} - \dot{u_{it}}, \tag{3.13}$$

where $e_{f/x}$ and $e_{f/t}$ denote respectively the output elasticities of $f\left(X_{it},\, \beta^*,\, t\right)$ with respect to X_{it} and t. Dotted variables indicate time derivatives. Since V_{it} is distributed as $N(0,\, \sigma_v^2)$, the effect of the random error V_{it} is equal to zero and can be ignored. $e_{f/t}$ is the rate of the technological change corresponding to the shifts of the frontier, and $-\dot{u_{it}}$ represents the technical efficiency change. Following Coelli et al. (2005), the technical change index (TC) between the adjacent periods is calculated as the exponential of the geometric mean of two partial derivatives,

$$TC = exp\left\{ \frac{1}{2}\left(e_{f/t} + e_{f/t-1} \right) \right\},\ t = 2, 3, \ldots, T, \tag{3.14}$$

and the technical efficiency change index (TEC) is defined as:

$$TEC = TE_{it}/TE_{it-1}. \tag{3.15}$$

Then, Malmquist TFP index[5] is obtained by multiplying Equation (14) and Equation (15),

$$Malmquist\,TFP = TC \times TEC. \tag{3.16}$$

3.3 Data and empirical specification

The data used in this paper come from a matched panel survey of Chinese SOEs cover the period of 1980 to 1994.[6] The data for the entire period of 1980 to 1994 has been used by Li and Liang (1998), Lee (1999), Dong and Putterman (2001), andZheng et al. (2003). The data covers four provinces: Jiangsu, Sichuan, Shanxi, and Jilin, which represent four economic in China (East, Southwest, Northwest, and Northeast).[7] The coverage of industries are grouped into five major industrial categories: mining and utility, heavy manufacturing, light manufacturing, chemical, and others. We only use manufacturing category (both heavy and light manufacturing) in our study. After excluding missing observations, we had a smaller data set with 228 enterprises. Summary statistics of the main variables are reported in Table 3.1. Output and inputs in stochastic frontier production function are selected and measured as follows:

[5] The Maimquist TFP index was defined as the geometric mean of two distance indices, which was introduced by Caves et al. (1982) after Sten Maimquist proposed constructing quantity indexes as ratios of distance functions. For more information on Maimquist TFP index, see Coelli et al. (2005).

[6] The first survey covers 1980 to 1989 and the second survey covers 1990 to 1994, and about 681 enterprises had valid replies in both surveys Li and Liang (1998).

[7] A detailed discussion about regional sampling is presented by Dong et al. (1995, P524-527).

Table 3.1: Summary statistics of the main variables on SOEs in China

Variable	Jiangsu	Sichuan	Shanxi	Jilin
Y	4211.82	3317.04	2673.51	2458.11
	(5335.39)	(6855.13)	(5133.18)	(4278.32)
X_1	2297.34	1874.48	1120.36	1307.80
	(3230.68)	(3143.94)	(1795.55)	(2724.77)
X_2	196.05	101.70	171.22	233.16
	(507.16)	(136.10)	(319.03)	(819.84)
X_3	1112.77	1604.81	2147.79	1557.51
	(1213.75)	(2630.67)	(3507.15)	(2619.91)
X_4	1538.62	2371.83	2507.48	1676.52
	(1476.33)	(3144.45)	(3287.91)	(1736.12)
z_0	0.39	0.43	0.43	0.34
	(0.49)	(0.50)	(0.50)	(0.48)
z_1	0.059	0.036	0.067	0.10
	(0.24)	(0.19)	(0.25)	(0.30)
z_2	0.47	0.44	0.46	0.48
	(0.50)	(0.50)	(0.50)	(0.50)
z_3	0.13	0.14	0.091	0.11
	(0.34)	(0.34)	(0.29)	(0.32)
z_4	0.37	0.39	0.34	0.39
	(0.17)	(0.14)	(0.18)	(0.17)
z_5	0.048	0.059	0.052	0.049
	(0.031)	(0.036)	(0.031)	(0.033)
z_6	0.23	0.23	0.17	0.11
	(0.42)	(0.42)	(0.38)	(0.31)
Number of firms	68	33	33	94
Number of obs.	1020	495	495	1410

Note: The values of Y, X_1,X_2, and X_3 are expressed in ten thousands of 1980 RMB, X_4 is expressed in person. Standard deviations are reported in parentheses.

Y_{it}: Output is measured as the gross industrial output value at fixed 1980 prices. We use the out deflators that are calculated directly from the data set. Different methods in dealing with output deflators were proposed in the previous three studies which used the same surveys. Lee (1999) used the firm specific price index reported in the survey, but did not give a detailed interpretation. Dong and Putterman (2001) used the industrial product price indexes from China's Statistical Yearbook, to deflate real output. Nevertheless, since enterprises' output price information were presented in the surveys, the deflators from the surveys are more accurate to reflect the real output price of every enterprise. Zheng et al. (2003) interpreted that output at fixed 1980 price came directly from the data set. However, output at fixed 1980 price only was reported in the first survey (1980-1989), while the second survey (1990-1994) reported output at fixed 1990 price, and Zheng et al. (2003) did not give a discussion on matching the price indexes. In this study, indices of gross industrial output value (IGIOV) (Preceding Year=100) is calculated as

$$IGIOV_t = \frac{GIOVC_t}{GIOVC_{t-1} \times (GIOVF_t/GIOVF_{t-1})} \times 100, \qquad (3.17)$$
$$t = 1981, 1982, \ldots, 1994,$$

where $IGIOV_{1980} = 100$, $GIOVC_t$ denotes gross industrial output value at current price of each enterprise in the tth year, $GIOVF_t$ denotes gross industrial output value at fixed 1980 price from the period of 1981 to 1989, and at fixed 1990 price from 1990 to 1994. Unfortunately, $IGIOV_{1990}$ cannot gained from equation (3.17) for the two different fixed price standard (fixed price of 1980 and 1990 in two surveys). Therefore, based on the assumption that the price indexes of each enterprise changed continuously over year, we employ an alternative approach that use the arithmetic mean of $IGIOV_{1989}$ and $IGIOV_{1991}$ of each enterprise to represent $IGIOV_{1990}$. Then, real output at 1980 price is calculated by deflating $IGIOV_t$.

X_{1it}: Intermediate input of total material costs at fixed 1980 price. The material deflator comes from the China Statistical Yearbook (National Bureau of Statistics of China, 1996). Here, we use the overall industrial products producer price indexes to represent material price indexes because the purchasing price indexes of raw material were not reported in the China Statistical Yearbook before 1989. In addition, even annual growth rate of the material price is reported in the survey, there are too much missing values of the variable. Thus, this study use the deflator from China Statistical Yearbook.

X_{2it}: Total energy costs at fixed 1980 price. The deflator for energy is also from the China Statistical Yearbook (National Bureau of Statistics of China, 1996). The producer price indexes of coal and electricity in China Statistical Yearbook, and the consumption share of coal and electricity in the survey are used to construct real energy consumption.

X_{3it}: Capital stock at fixed 1980 price. it is constructed using perpetual inventory method, which defined as

$$K_t = K_{t-1} + I_t, \qquad (3.18)$$

where K_t denotes capital and I_t denotes investment in tth year, and

$$I_t = (B_t - B_{t-1}) / P_t, \tag{3.19}$$

where B_t denotes nominal fixed capital formation, and P_t denotes investment goods price in tth year from Data of Gross Domestic Product of China Xu (2007). The net book value of fixed capital B_0 in the data is used as K_0 in the base year.

X_{4it}: Labor, which is constructed by the annual average number of full-time employees without any modification. Kong et al. (1999) used yearly actual total working hours as proxy of labor in the second survey. However, we found that the yearly actual total working hours are not continuous between the two surveys, which may result from different statistics standard of working hours items between two surveys. Therefore, employee number is used as the proxy of labor.

The production frontier of jth region is assumed as a translog functional form,

$$\begin{aligned}
y_{it} &= \beta_{0j} + \sum_{m=1}^{4} \beta_{mj} x_{mit} + \sum_{m=1}^{4} \sum_{k \geqslant 1}^{4} \beta_{mkj} x_{mit} x_{kit} && (3.20) \\
&\quad + \beta_{tj} t + \beta_{ttj} t^2 + \sum_{m=1}^{4} \beta_{tmj} t x_{mit} + V_{itj} - U_{itj}, \\
i &= 1, 2, \ldots N_j,\ j = 1, 2, 3, 4,\ t = 1, 2, \ldots, 15, \\
U_{itj} &= \delta_{0j} + \sum_{r=1}^{6} \delta_{rj} z_{rit} + W_{itj},\ r = 1, 2, \ldots, 6, && (3.21)
\end{aligned}$$

where y_{it} denotes the natural logarithm of output at 1980 price for the ith firm in the tth year; x_{mit} denotes the natural logarithm of the mth input variable for the ith firm in the tth year (one output and four inputs—material, energy, capital, and labor); t is a time trend representing technical change; z_{rit} are firms' characteristic variables that are supposed to influence the technical efficiency; βs, δs are unknown parameters to be estimated; V_{itj}, U_{itj}, W_{itj} are as defined in the previous section. To put z_{rit} more specifically, z_{1it}, z_{2it}, z_{3it} denote SOEs' management form dummy variables of contract system, corporation or shareholding system, and other kind of management forms respectively, where the factory director responsibility system is treated as the base group because it was the main system in the pre-reform period. These dummy variables are supposed to capture the effect of SOEs' management system reform. z_{4it} is the proportion of bonuses and overtime payments in the total wage bill. The bonus system was adopted in the reform period to motivate employees. z_{5it} is the share of engineering technical personnel to the total employees. z_{6it} is the export dummy that equals 1 if the enterprise exported, and 0 otherwise.

3.4 Empirical results

3.4.1 Estimation of regional frontiers and meta-frontier

In this study, the FRONTIER 4.1 program (Coelli, 1996) is used to estimate the regional stochastic frontier production functions. Furthermore, the technical efficiency score of each SOE is calculated by Equation (3.3). The null hypothesis that the Cobb-Douglas production function is an adequate representation of our samples is rejected by generalized likelihood ratio tests for all regions (see Table 3.2). Then, the second generalized likelihood ratio test results suggest that the technical inefficiency effect is present in all regional frontiers. The third null hypothesis that the inefficiency effects are not stochastic is also strongly rejected for all regions.

Table 3.2: Tests of hypotheses for the parameters of translog stochastic frontier models in four regions

Null hypothesis	Jiangsu	Sichuan	Shanxi	Jilin
Translog stochastic production function				
LR value	-621.24	-198.90	-167.76	-518.44
1.Cobb-douglas production function, $H_0 : \beta_{mk} = \beta_{mt} = \beta_{tt} = 0$				
LR value	-723.11	-261.18	-207.53	-610.65
Test statistic	203.75***	124.57***	79.54***	184.42***
χ^2 (0.90) value	22.31	22.31	22.31	22.31
2. The ineffciency effects are absent models, $H_0 : \gamma = \delta_r = 0$				
LR value	-640.91	-211.30	-175.01	-611.87
Test statistic	39.34***	24.79***	14.50*	186.87***
χ^2 (0.90) value	13.36	13.36	13.36	13.36
3. The inefficiency effects are not stochastic, $H_0 : \gamma = 0$				
LR value	-625.18	-201.99	-172.75	-587.39
Test statistic	7.87**	6.17**	9.99***	137.90***
χ^2 (0.90) value	4.61	4.61	4.61	4.61

Note: LR test is used for all the null hypltheses. Asterisks ***, **, and * on the value of test statistic indicate that the null hypothesis is rejected at 0.01, 0.05, and 0.1 significance levels respectively.

The Likelihood-ratio test is also used to examine if all regions share the same technology. The Likelihood-ratio statistics (749.62) is calculated after estimating the stochastic frontier by pooling the data from all four regions.[8] This result strongly suggests that the four regional stochastic frontiers for SOEs in China are different from each other.

The maximum-likelihood estimates for the parameters of four regional stochastic frontier production functions are presented in Table 3.3. The estimated coefficients of reform variables in these inefficiency models are of particular interest. Firstly, the coefficients of SOEs' management form dummy variables differ among regions, but half of them are found to have positive and significant effect on technical efficiency.[9] As is expected, this result indicate that managerial mechanism changes contributed to the improvement of Chinese SOEs' technical efficiency during the early reform period. In addition, the positive impact of bonus proportion on technical efficiency is found to be statistically significant in Sichuan, Shanxi, and Jilin. it is still positive but insignificant in Jiangsu. This result implies that more bonuses in relation to base wages tended to generate a higher level of technical efficiency. This finding is consistent with the findings in previous studies, e.g., Liu and Liu (1996), and Kong et al. (1999).

[8]For detail steps on the test, see Battese et al. (2004). The degree of freedom for the Chi-square distribution is 90—the difference between the sum of parameters of all four regional stochastic frontiers and the number of parameters estimated under the full sample.

[9]A negative sign in the inefficiency model means positive effect on technical efficiency. In Table 3.3, ten out of twelve coefficients have a negative sign.

Table 3.3: ML estimates of stochastic frontier and inefficiency determine function

Variable	Jiangsu	S.E.	Sichuan	S.E.	Shanxi	S.E.	Jilin	S.E.
Stochastic frontier function								
Constant	8.87***	1.15	3.18***	0.88	8.27***	0.98	4.17***	0.95
x_1	0.44**	0.22	0.89***	0.26	1.15***	0.26	0.63***	0.13
x_2	0.73***	0.16	0.73***	0.20	0.61***	0.19	0.87***	0.18
x_3	-1.48***	0.34	-2.22***	0.30	1.45***	0.44	-0.38*	0.22
x_4	-0.76	0.47	1.16**	0.50	-3.73***	0.63	-0.79**	0.35
t	0.018	0.048	-0.012	0.026	-0.11**	0.043	0.059**	0.029
$(x_1)^2$	0.051***	0.017	0.090***	0.012	0.099***	0.027	0.077***	0.0094
$(x_2)^2$	-0.023	0.018	0.017	0.026	-0.021	0.013	0.028***	0.010
$(x_3)^2$	0.19***	0.051	-0.21***	0.052	0.033	0.080	-0.11***	0.025
$(x_4)^2$	0.077	0.068	-0.27***	0.072	0.56***	0.13	0.016	0.035
t^2	-0.00051	0.0012	-0.0013	0.0011	0.0012	0.0011	-0.00024	0.00062
$x_1 \times x_2$	0.061**	0.026	0.037	0.034	-0.10***	0.031	0.00079	0.013
$x_1 \times x_3$	-0.19***	0.050	-0.048	0.035	0.069	0.066	-0.071***	0.021
$x_1 \times x_4$	0.084	0.061	-0.17***	0.060	-0.24***	0.091	-0.076***	0.024
$x_1 \times t$	-0.017***	0.0052	-0.014***	0.0045	-0.015***	0.0057	-0.0011	0.0030
$x_2 \times x_3$	0.14***	0.045	0.0046	0.053	0.15**	0.063	-0.0022	0.024
$x_2 \times x_4$	-0.25***	0.045	-0.14**	0.061	-0.098	0.076	-0.15***	0.033
$x_2 \times t$	-0.019***	0.0051	-0.0034	0.0063	-0.0025	0.0051	-0.0035	0.0030
$x_3 \times x_4$	-0.0050	0.091	0.72***	0.064	-0.39**	0.18	0.31***	0.048
$x_3 \times t$	-0.0075	0.010	0.042***	0.0079	0.020**	0.0099	0.029***	0.0047
$x_4 \times t$	0.035***	0.012	-0.021***	0.0062	0.014	0.014	-0.029***	0.0066
Inefficiency determine function								
Constant	0.31***	0.095	0.97***	0.22	0.43***	0.094	-0.32	0.29
z_1	-0.0068	0.048	-0.052	0.12	-0.13*	0.077	-0.12*	0.066
z_2	-0.39	0.25	-1.03***	0.15	-0.62**	0.25	1.17***	0.18
z	-0.18**	0.093	-0.21	0.21	0.038	0.10	-1.12***	0.20
z_4	-0.057	0.18	-1.81***	0.49	-1.66***	0.56	-4.87***	0.56
z_4	-1.09	0.93	-2.88***	1.07	0.64	1.32	-5.92***	1.67
z_5	-0.87	0.78	-0.21**	0.085	0.028	0.13	-1.56***	0.17
σ^2	0.21***	0.012	0.14***	0.016	0.13***	0.0093	0.86***	0.15
γ	0.083**	0.067	0.188**	0.19	0.18***	0.067	0.92***	0.015
Mean TE	0.849		0.859		0.904		0.788	

Notes:

1. According to Coelli et al. (2005), t-test is suitable for testing hypotheses concerning individual parameter, because unconstrained ML estimators are asympototically normally distributed when the sample size is large. Therefore, t-test were used in this study.

2. Standard errors in parentheses. Statistical significance is at *10%, **5%, and ***1% levels.

The estimates of meta-frontier obtained by linear and quadratic programming in MATLAB programming language, together with the estimates of the stochastic frontier production function for China obtained by pooled data on all SOEs, are presented in Table 3.4.

Table 3.4: ML estimates of stochastic frontier for China, together with estimates of metafrontier production function

Variable	SFA		Meta(QP)	Meta(LP)
Frontier production function				
Constant	4.59***	(0.43)	8.65	8.57
x_1	0.72***	(0.077)	0.80	0.74
x_2	0.55***	(0.08)	0.96	0.90
x_3	-0.51***	(0.14)	-1.46	-1.71
x_4	-0.54***	(0.20)	-1.15	-0.90
t	-0.012	(0.017)	0.042	0.082
$(x_1)^2$	0.071***	(0.0064)	0.10	0.10
$(x_2)^2$	-0.014**	(0.0066)	0.022	0.033
$(x_3)^2$	-0.12***	(0.019)	0.072	0.13
$(x_4)^2$	-0.022	(0.025)	0.13	0.13
t^2	-0.00083*	(0.00047)	0.0016	0.0017
$x_1 \times x_2$	-0.0015	(0.0081)	0.0021	0.0043
$x_1 \times x_3$	-0.07***	(0.016)	-0.099	-0.12
$x_1 \times x_4$	-0.066***	(0.018)	-0.11	-0.089
$x_1 \times t$	-0.011***	(0.002)	-0.016	-0.011
$x_2 \times x_3$	0.083***	(0.018)	0.063	0.057
$x_2 \times x_4$	-0.12***	(0.018)	-0.21	-0.21
$x_2 \times t$	-0.0086***	(0.0021)	-0.0092	-0.0087
$x_3 \times x_4$	0.30***	(0.034)	0.14	0.100
$x_3 \times t$	0.037***	(0.0036)	0.0060	0.0036
$x_4 \times t$	-0.015***	(0.0044)	0.0076	-0.00010
Inefficiency determine function				
Constant	0.40***	(0.099)		
z_1	-0.043	(0.04)		
z_2	0.031	(0.051)		
z_3	-0.57***	(0.11)		
z_4	-1.58***	(0.29)		
z_4	-4.43***	(0.93)		
z_5	-1.1***	(0.20)		
σ^2	0.28***	(0.037)		
γ	0.43***	(0.083)		

Notes:

1. Standard errors in parentheses. Statistical significance is at *10%, **5%, and ***1% levels.

2. The coefficient estimates and SF standard errors are given to two-significant digits behind the decimal points.

3. SF indicates the SFA estimate, which is obtained by pooled data on all SOMEs.

We notice that there are insignificant differences between the linear programming and quadratic programming estimates for the parameters of the meta-frontier function, but there are significant differences between the meta-frontier coefficients and their corresponding coefficients of the stochastic frontier for pooled data. This indicates that the latter estimates gave unsatisfactory results for TE^* and TGR. Therefore, quadratic programming estimates are used to compute TE^* and TGR for all SOEs. Basic summary statistics for these measures are presented in Table 3.5. The mean value of TGR vary from 0.920 (Shanxi) to 0.972 (Jiangsu) among regions, while SOEs in Jiangsu and Jilin have higher TGR value than those in Sichuan and Shanxi. These results indicate that, on average, the regional frontier of Jiangsu is the closest to meta-frontier, and Shanxi is the farthest, which also mean that SOEs in Jiangsu and Jilin are superior to Sichuan and Shanxi in technology level. These findings are consistent with the practice of SOEs in the reform period, Jiangsu (Eastern region) was the first open area since the "Reform and Opening Up" policy was implemented, SOEs in Jiangsu thus have better access to marketing facilities, technical service, infrastructure, which pushed the Southeast frontier close to the meta-frontier. The mean values of TE^* in each region are different from the value of TGR, since SOEs in Jiangsu and Shanxi have higher TE^* value than those in Sichuan and Jilin.

Table 3.5: Summary statistics of regional TE, TGR, and TE* in Chinese SOEs

Region	Statistic	Mean	St. Dev.	Minimum	Maximum
	TE	0.849	0.084	0.690	0.985
Jiangsu	TGR	0.972	0.016	0.911	1.000
	TE*	0.825	0.084	0.671	0.975
	TE	0.859	0.092	0.542	0.981
Sichuan	TGR	0.939	0.028	0.783	0.987
	TE*	0.807	0.092	0.473	0.962
	TE	0.904	0.068	0.602	0.982
Shanxi	TGR	0.920	0.043	0.752	1.000
	TE*	0.832	0.076	0.531	0.943
	TE	0.788	0.131	0.116	0.949
Jilin	TGR	0.964	0.028	0.833	1.000
	TE*	0.760	0.128	0.113	0.937

Note: The QP estimates for the metafrontier coefficients are used in this table.

3.4.2 TFP change across regions

Annual percentage change measure of TFP change, which can be decomposed into technical efficiency change and technical change, is calculated for each enterprise in each pair of adjacent years using the method described in Section 3.3. These measures are presented in Figure 3.1 and Figure 3.2. A number of points can be made regarding the results in Figure 3.1 and Figure 3.2.

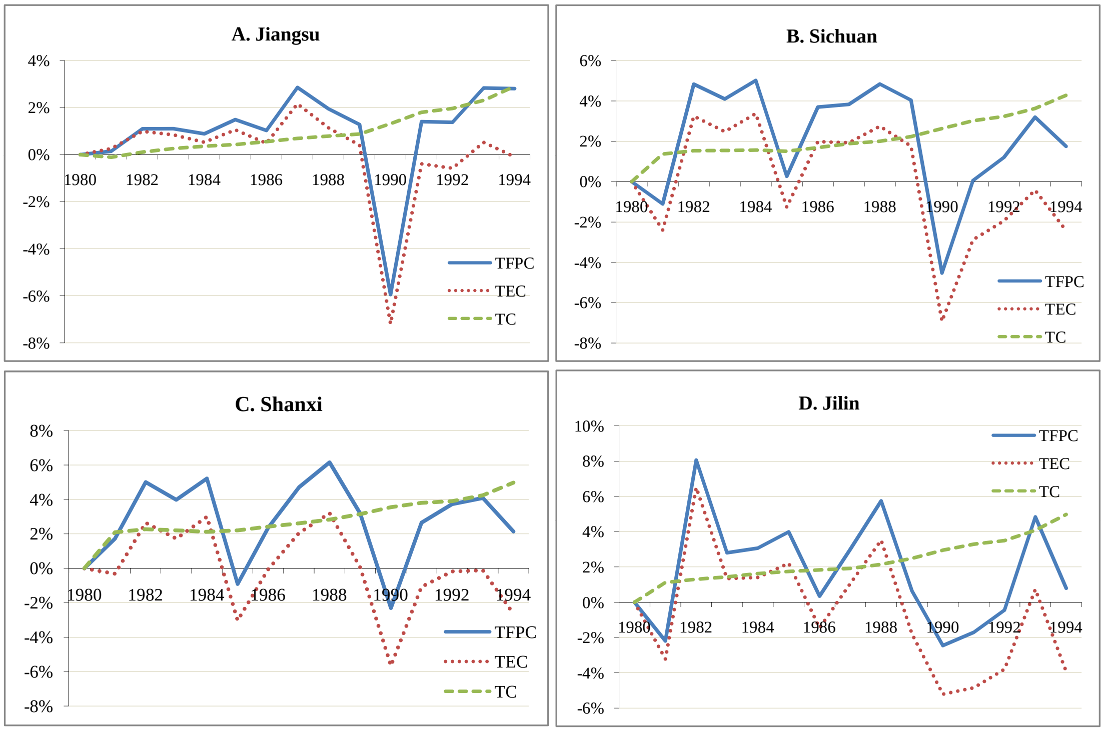


Figure 3.1: TFP change, technical efficiency change, and technical change in SOEs

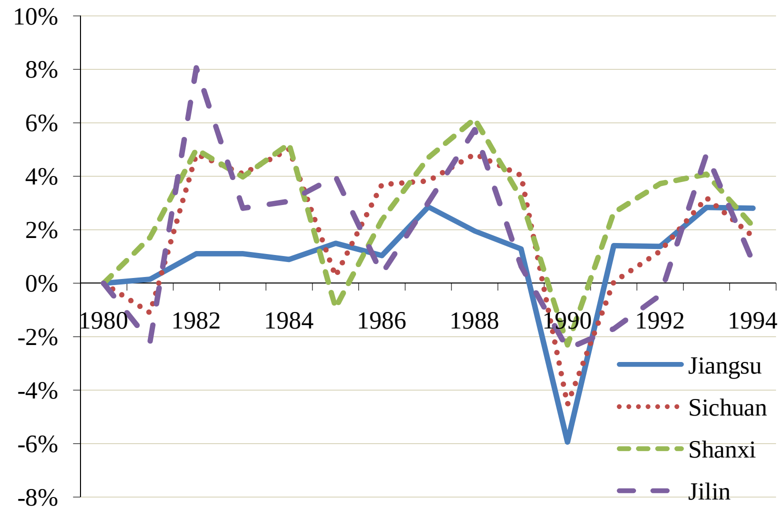


Figure 3.2: Regional comparison of TFP change in SOEs

Firstly, in the early reform period, the SOEs in all four regions experienced positive average annual TFP growth, where Shanxi was the fastest (2.78%), and Jiangsu was the slowest (0.95%). This result shows a natural process of convergence, which the regions with a low level of TFP catch up to the regions with a high level of TFP (Fare et al., 1994). Since the initial value of SOEs' TFP in Shanxi and Sichuan, was smaller than that in Jiangsu, Shanxi and Sichuan enjoyed a faster TFP growth rate.

Secondly, average annual growth rate of TFP and technical efficiency were higher in 1980s than in the early 1990s for all regions. This indicates that the reform measures such as contract responsibility system, and other incentive measure, have had positive effect on the improvement of SOEs' TFP and technical efficiency in 1980s, but the effect decreased in the early 1990s. The findings about SOEs' TFP change in 1980s are consistent with the results of previous studies such as Dollar (1990), Jefferson et al. (1992), Groves et al. (1994), Liu and Liu (1996), and Zheng et al. (2003). However, in this study, the decomposition of TFP change almost equally to technical efficiency change and technical change in 1980s, which differs from the finding in Zheng et al. (2003), whom found that the decomposition of TFP growth attributes overwhelmingly to technical progress rather than to technical efficiency improvement. Besides, we find a positive TFP growth that includes a positive technical change but a negative technical efficiency change in the early 1990s. This finding is in line with the result of Zheng et al. (2003), but contradict the result in Kong et al. (1999) who argued that SOEs' TFP decreased from 1990 to 1994.

Thirdly, TFP change of each region is quite stochastic, which is primarily due to the stochastic technical efficiency change, while technical change is increasing gradually for all regions. The stochastic behaviour of technical efficiency change and stationary behaviour of technical change reflect the fact that SOEs' technology improved continuously after reform, while the technical efficiency was sensitive to some factors such as reform measures, industrial environment, or SOEs' specific characters.

Finally, both TFP change and technical efficiency change in all regions decreased sharply from 1989 to 1990. The sharply TFP and technical efficiency decrease may be attribute to the production shocks in 1989 and 1990. The production shocks may be related to the failure of the wholesale price reform in 1988. To further promote the economic reform, the government started the wholesale price reform in May 1988. However, the price reform resulted in panic buying and runaway inflation after "the preliminary proposal of price and wage reform" was proposed in August 1988. Therefore, the government slowed down the reform to stabilize price and brake the overheating economy. As a result, SOEs' production was shocked by the slowing domestic demand and economic recession in the following two years. Furthermore, the price reform failure and high inflation, together with the corruption that resulted from the double-track price system induce many remonstrance in most big cities, and the remonstrances finally lead to the Tiananmen Square incident in 1989. The remonstrances themselves made many SOEs cannot concentrate on production. Besides, the further conservative economic policy after the incident might gave another shock on SOEs' production.

3.4.3 Determinants of TFP change, technology gap ratio, and meta-frontier technical efficiency

To discern regional disparities of the TFP change ($TFP\,change$), the technology gap ratio (TGR), and the technical efficiency relative to meta-frontier (TE^*) for Chinese state-owned manufacturing enterprises, and the reform effect on these indexes, the three indexes are regressed on the explanatory variables used in regional inefficiency functions. For the $TFP\,change$ regression, the Hausman test result suggests that a random effect model would not obtain consistent parameter estimates. Then, a two-stage estimation approach is employed to deal with the problem that the time invariant variables in fixed effect model are "swept away" by the within estimator of the coefficients on the time varying covariates.[10] The regression results are reported

[10]The regional dummies are time invariant variables in this study. A detailed discussion about time invariant variables in panel data is presented by Krishnakumar (2006).

in Table 3.6.

Table 3.6: Two-step estimates of TFP change

	(1)		(2)	
	First step[a]	Second step[b]	First step[a]	Second step[b]
Constant	-3.24***	-0.85***	-4.56***	-0.83***
	(0.72)	(0.32)	(0.88)	(0.31)
Sichuan	-	0.87	-	0.74
	-	(0.56)	-	(0.54)
Shanxi	-	2.30***	-	2.24***
	-	(0.56)	-	(0.54)
Jilin	-	0.95**	-	0.97**
	-	(0.42)	-	(0.41)
Contract system	0.65		1.01**	
	(0.44)		(0.46)	
Corperation or	2.56***		1.63**	
shareholding systems	(0.79)		(0.78)	
Other system	2.11***		1.94***	
	(0.66)		(0.66)	
Bonuses proportion	8.34***		8.47***	
	(1.25)		(1.40)	
Technical personnel share	11.7		21.1*	
	(8.81)		(11.0)	
Export	2.99***		2.76***	
	(0.64)		(0.64)	
Year dummies	No		Yes	
R^2	0.03	0.0051	0.073	0.005
Hausman test: $\chi^2(df)^c$	84.41		70.10	

Notes:

1. Standard errors in parentheses. Statistical significance is at *10%, **5%, and ***1% levels.

[a]Dependent variable is TFP change.

[b]Dependent variable is is fixed effects parameters from first stage regression.

[c]df equals 6 in model (1), and 20 in model (2). The Hausman test reveals that fixed effects model would obtain consistent estimates.

The results in model (1) and (2) are obtained by controlling year dummies and not respectively. The parameters in model (2) show that year effects are present in this regression. The positive coefficient of regional dummies, Sichuan, Shanxi, and Jilin, indicate that SOEs in these three regions had faster TFP growth than in Jiangsu, while Shanxi was the fastest. This supports the findings in previous section, that SOEs in developing region has higher average annual TFP growth rate than those in developed region.

The positive impact of management form dummies (contract system, corporation or shareholding system, and other systems) on TFP growth are found to be statistically significant, which show that new management forms (compared with the form of factory director responsibility system) contributed to SOEs' TFP growth in the early reform period. This finding can be interpreted as follow: First, under new management form, SOEs had an expanded autonomy to motivate managers and workers using more effective incentive mechanism. Under factory director responsibility system, enterprise managers were appointed by administrative departments and they relied on political propaganda and ranking promotion, rather than operating performance. Whereas, under contract system or other new system, managers' promotion were determined by operating performance, moreover, top manager had an enlarged right to promote middle level managers without approval from the administrative department. Therefore, the new system could make both manager and employee more productive. Second, under new management form, SOEs could keep more revenue if they gained enough that exceeded the part should turn over to the government, thus, they had more room to motivate managers and workers by material rewards.

The positive impacts of bonus proportion on SOEs' TFP growth are also found to be statistically significant, which means that SOEs are more productive if more bonuses were used to motivate employee. This result supports the findings in some previous studies such as Groves et al. (1994) and Zheng et al. (2003), whom argued bonus has a significant positive impact on SOEs' TFP growth and technical efficiency.

In line with priori expectations, engineering technical personnel share has a strong positive effect on SOEs' TFP growth, which implies that enterprise with more share of engineering technical personnel to the total employees tend to be more productive.

Finally, export dummy has a significant positive effect on TFP growth, which implies that export firms are more productive than non-export firms This result is also in accord with expectations, that international competition makes export firms have to improve their product quality and reduce cost by improving technology or effectively utilizing the existing technology, thus export firms have faster TFP growth than non-export firms.

For the regressions of TGR and TE^*, Tobit model was regressed for the reason that TGR and TE^* have 1 as an upper bound and 0 as a lower bound. Linear models of TGR and TE^* are also estimated by normal panel regression. We reached similar results between the two regressions in the sign, statistical significance, and magnitude of estimated coefficients. This may due to the the fact that there are only 25 out of 3420 observations have TGR upper bound value. In addition, the Hausman test results suggest that a random effect model is suitable for the determinant models of TGR and TE^*. For the sake of brevity, we only present the estimations of the random effect models for TGR and TE^* are presented in Table 3.7. Columns 1, and 3 give the estimation results as the year dummy variables (1980 is the base year) are included, while the results in columns 2 and 4 did not include year dummy variables.

Table 3.7: Random effect estimates of TGR and TE

Dependent variable	TGR		TE*	
	(1)	(2)	(3)	(4)
Constant	0.97***	0.96***	0.70***	0.72***
	(0.0030)	(0.0031)	(0.0089)	(0.0096)
Sichuan	-0.034***	-0.034***	-0.025*	-0.028**
	(0.0049)	(0.0049)	(0.013)	(0.013)
Shanxi	-0.051***	-0.052***	0.021	0.017
	(0.0048)	(0.0049)	(0.013)	(0.013)
Jilin	-0.0072**	-0.0070*	-0.056***	-0.056***
	(0.0036)	(0.0037)	(0.010)	(0.010)
Contract system	-0.0029***	-0.0013*	0.016***	0.025***
	(0.00074)	(0.00076)	(0.0029)	(0.0030)
Corperation or	-0.0033**	-0.0023*	0.0058	0.0045
shareholding systems	(0.0013)	(0.0013)	(0.0052)	(0.0052)
Other system	0.0015	0.00046	0.059***	0.052***
	(0.0011)	(0.0011)	(0.0044)	(0.0044)
Bonuses proportion	0.0060***	-0.0037	0.20***	0.17***
	(0.0021)	(0.0023)	(0.0084)	(0.0093)
Technical personnel share	0.045***	0.065***	0.16***	0.48***
	(0.015)	(0.018)	(0.056)	(0.067)
Export	0.0061***	0.0052***	0.098***	0.093***
	(0.0011)	(0.0011)	(0.0042)	(0.0042)
Year dummies	No	Yes	No	Yes
R^2	0.29	0.31	0.31	0.34
Hausman test: $\chi^2(df)^a$	6.01	5.90	10.19	2.11

Notes:
1. Standard errors in parentheses. Statistical significance is at *10%, **5%, and ***1% levels.
[a] df equals 6 in model (1) and (3), and 20 in model (2) and (4). The Hausman test reveals that random effects model is suitable.

In the TGR regressions, the two estimations (with and without year dummies) show that aggregate trends in TGR have little effect on estimation, since the sign, statistical significance, and magnitude of the coefficients in two estimations changed little. The coefficients on Jilin, Sichuan, and Shanxi indicate that the TGR value in all of them are substantially lower than that in Jiangsu, which supports the findings in previous section that SOEs' production frontier in developed region (Jiangsu) is closer to meta-frontier than those in developing regions (Sichuan and Shanxi).

Somewhat surprisingly, the coefficients on contract system, and corporation or shareholding systems are negative and significant; besides, the coefficient on other management forms is positive but insignificant, which means that new management forms (compared with the factory director responsibility system) have a negative effect on TGR. These results suggest that these reform measures did not push the regional production frontiers of SOEs close to the meta-frontier, on the contrary, they made the regional production frontiers far from the meta-frontier. In other words, these measures enlarged the disparities of technology level across regions.

Bonus proportion is found to have a significantly positive effect on TGR as the the year dummies are not controlled, but have a insignificantly negative effect as the year dummies are controlled. This result cannot reveal a positive effect of bonus system on TGR, that is to say, even higher bonus proportion can motivate SOEs' workers to be more productive, it cannot push the regional production frontier close to the meta-frontier.

As is expected, engineering technical personnel share has strong positive effect on TGR. Since the share of engineering technical personnel of a SOE reflect the firm's human capital level. Higher engineering technical personnel share make the firm to be more innovative, thus improve the firm's technology level, and push its regional production frontier close to the meta-frontier. Export is also found to have strong positive effect on TGR, which is in line with expectations that international competition makes export enterprises improve their product quality and reduce cost by improving technology, thus the regional production frontier shift outwards.

The TE^* regression results are reported in columns 3 and 4 of table 3.7. It is consistent whether the year dummies are controlled or not. The coefficients on Sichuan and Jilin are negative and statistically significant, while the coefficient on Shanxi is positive but insignificant. It is surprising that SOEs in Shanxi are more efficient than those in Sichuan and Jilin, since Shanxi fall behind its counterparts in economic development level. The result seems to be contrary to common sense, but may be related to the meta-frontier measurement that technical efficiency relative to meta-frontier is calculated by multiplying TGR and regional technical efficiency. Even Shanxi has the lowest average TGR value, it has the highest average regional technical efficiency value, then Shanxi is superior in TE^* to its counterparts. This result may reflect the actuality of SOEs' development in the early reform period. SOEs in Shanxi experienced slower technical progress, the feasible regional production frontier shifts outwards less quickly than its counterparts, then ordinary enterprises find it is easy to catch up with the best performing enterprises. Therefore, Shanxi has a higher average regional efficiency level but less technology level.

The three management form dummy variables (contract system, corporation or shareholding systems, and other systems) have expected sign, and the former two variables are statistically significant. Finally, the statistically significant coefficients of bonus, engineering technical personnel share, and export are also in line with expectations that higher bonus share, higher engineering technical personnel share, contribute to SOEs' technical efficiency relative to meta-frontier, and export enterprises are more efficient than non-export ones.

3.5 Concluding remarks

The lower efficiency and productivity of Chinese SOEs has garnered concern for policy makers in China. In addition, the regional inequality has persistently been a problem in Chinese SOEs. Using a panel data from 1980 to 1994, this paper has examined the regional technical efficiency, technology gaps, and TFP change in Chinese state-owned manufacturing enterprises. Our findings are as follows.

First, according to the meta-frontier methodology, the technical efficiency relative to meta-frontier can be decomposed into two parts: one is the gap between actual production and potential production on the regional frontier, the other is the technology gap between regional frontier and meta-frontier. We found that the SOEs in Jiangsu (Eastern region) have the highest average technology gap ratio and higher TE^* value, but those in Shanxi (Western region) have the lowest average technology gap ratio. The findings suggest that more efforts should focus on the improvement of intra-region efficiency gaps among SOEs in the eastern regions of China, while technical efficiency improvement can be made by technology or knowledge diffusion within region. On the other hand, in the western regions, technical improvement measures such as infrastructural investment, introduction of new technology and technicians, should be taken to narrow the technology gap between regional frontier and meta-frontier.

Second, the SOEs in all four regions experienced positive average annual TFP growth (1.72%) though out the reference period, while regional inequality in terms of TFP growth rate was harmonized in the early reform period. This may due to the natural process of convergence, as regions with a low level of TFP catch up to those with a high level of TFP.

Third, SOEs' TFP increased faster in 1980s than that in the early 1990s, which means that some incentive measures, e.g., contract responsibility system, bonus system, had contributed greatly on SOEs' TFP in the early stage of reform, but had little effect after 1990.

Finally, TFP change comprise two terms—technical efficiency change and technical change. In our findings, more TFP change is propelled by technical progress (1.95%), and the technical efficiency change has an adverse effect (-0.21%). However, in the first ten years, both technical change (1.30%) and technical efficiency change (0.96%) contributed to TFP growth (2.29%). This finding shows that the technical efficiency on Chinese SOEs increased in 1980s, but decreased sharply in the early 1990s.

This paper also attempts to explain the determinants of the TFP change, technology gaps, and technical efficiency relative to meta-frontier. The empirical evidence suggests that: compared with the SOEs in coastal region (Jiangsu), those in non-coastal regions (Sichuan, Shanxi, and Jilin) have priority in TFP growth and technical efficiency improvement, but they fall behind in technology levels.

In terms of management form dummy variables, and bonus system, reform measures are found to have positive effect on SOEs' TFP growth and technical efficiency improvement, but they are not found to have effect on the technology gap ratio level; in other words, these reform measures had motivated the managers and employee in SOEs to be more efficient and productive in the early reform period, but they had little effect on the improvement of SOEs' technology level. In addition, Engineering technical personnel share that represents human capital level, and Export dummy that represents international competition, both of them are found to have strong positive effect on TFP growth and technical efficiency improvement.

Chapter 4

Openness and technical efficiency in Chinese manufacturing industry: A two-stage bootstrap data envelopment analysis

4.1 Introduction

Since the Reform and Opening Up policy was adopted in 1978, China began to transit from a planned economy to a market-oriented one. Then, it increasingly integrated into world economy through foreign trade and foreign investment. Especially, China became a member of the World Trade Organization in December 2001. Ever since, China became a major player in the world economy. In the early period of Reform and Opening Up, China had very little foreign trade and FDI. China only exported US$ 6.9 billion in merchandise in 1978, 0.79% of the total world exports. The FDI from 1979 to 1982 was less than US$ 1.8 billion, an average of about US$ 0.6 billion per year. In 2008, China exported US$ 1428.7 billion, imported US$ 1131.6 billion in merchandise, and received US$ 92.4 billion in FDI, China became the second largest exporter, the third largest importer, and the third largest FDI recipient in the world. As a result, the Reform and Opening Up policy has dramatically contributed to China's rapid economic growth.[1] However, did the Reform and Opening Up influence the productivity of the production sectors in China? In other words,

[1]The annual average growth of real GDP from 1979 to 2008 is 9.8%, while the rate between 1953 to 1978 is 6.7%. Source: China Compendium of Statistics 1949-2008 (National Bureau of Statistics of China, 2010).

did China's economic growth come form productivity improvement or input increase? This question has been an hot topic since China transited from a closed economy to an open one. Since productivity improvement theoretically attributes to technical efficiency improvement (catching up) and technological progress (innovation), technical efficiency improvement probably is an important factor that affect economic growth. Therefore, this essay attempts to present an empirical evidence on the relationship between openness and technical efficiency using a Chinese manufacturing industry survey.

Much has been written about the openness effect on economic growth and TFP growth. In the new growth theories, Lucas (1988) argued that openness (international trade) can positively affect physical and human capital accumulation, therefore contribute to economic growth. Grossman and Helpman (1991) and Barro and Sala-i Martin (2004) have showed that more open economies have greater ability to absorb advanced technologies generated in developed countries. This technology transfer or technology diffusion leads to faster growth of TFP, hence, encourages economic growth. On the empirical side, a large number of studies showed that openness could contribute to TFP growth.[2] Dollar (1992) developed a cross-country measure of outward orientation in 95 developing economies and suggested that trade liberalization could dramatically improve economic performance in many developing countries. Edwards (1998) constructed six alternative openness index on the total factor productivity growth of 93 countries. He showed that open countries experienced faster productivity growth than non-open ones. Recently, Chang et al. (2009) provided an empirical evidence that openness may significantly contribute to economic growth if certain complementary reforms are undertaken. To sum up, both of these theoretical and empirical studies have showed a positive relationship between openness and productivity growth. In order to interpret this positive relationship, Sun et al. (1999) summarized five explanations: openness may lead to economies of scale, openness may intensify market competition, openness may accelerate technology transfer and diffusion, openness may have spillover effect, and openness may act as catalyst in the process of market liberalization.

In contrast to the research on the openness effects on economic growth and TFP growth, the relationship between openness and technical efficiency has not gained much attention. The existing literature proceeded along two main lines. One employed SFA approach (e.g., Brada et al., 1997; Liu et al., 2005; Mastromarco and Ghosh, 2009; Liu and Nishijima, 2010), the other employed DEA approach (e.g., Sun

[2]See a survey by Edwards (1993).

et al., 1999; Fu, 2005; Christopoulos, 2007). The difference of the two approach is that the former approach employs a parametric method to estimate production frontiers, while the later employs a non-parametric method. Nevertheless, both approaches have the same tasks: First, estimation of production frontiers and efficiency score of each decision making unit (firm, region, country, etc.) in a sample relative to the estimated frontier. Second, subsequent analysis of potential causes of decision making units' efficiencies. To analyze the effect of openness on efficiency, these previous studies used foreign trade or FDI as the proxies of openness. And they reached similar result that openness has positive effect on technical efficiency, except that Brada et al. (1997) found export orientation had no effect on firm's efficiency using a firm level data for Czechoslovakia and Hungary.

As the largest transitional economy in the world, China has created an economic miracle since it opened up to the world. Thus, the empirical study about the economic openness effect on Chinese manufacturing firms' efficiency may contribute to the literature that examine economic openness effects on firm's efficiency in transitional economies. In this paper, we employ a new DEA approach—two-stage bootstrap DEA (Simar and Wilson, 2007)—to investigate the economic openness effect on Chinese manufacturing firms' technical efficiency using a firm-level data collected by World Bank (Investment Climate Survey 2003). Even Sun et al. (1999) have empirically analyzed the relationship between openness and technical efficiency in Chinese manufacturing industries, our article differs form their study in two respects. First, Sun et al. (1999) employed a traditional two-stage DEA approach that estimate efficiency score by DEA model in the first stage, then regress a censored (Tobit) model (the estimated DEA efficiency in the first stage is the dependent variable) in the second stage. However, Simar and Wilson (2007) argued that the traditional two-stage DEA approach has a serious problem—the second stage estimation is inconsistent since the DEA efficiency estimates are serially correlated. Thus, Simar and Wilson (2007) proposed the two-stage bootstrap DEA approach to solve this problem. Therefore, we employed the two-stage bootstrap DEA approach to gain a consistent empirical result. Second, Sun et al. (1999) used aggregate industry data while we used firm-level data. The firm-level data enables us to control firm heterogeneity.

Our main findings are as follows. First, the results obtained by group-wise heterogeneous bootstrap of aggregate DEA efficiency show that the firms engaged in international economic activities are efficient than those did not. Further, the previous findings are confirmed through the two-stage bootstrap DEA estimation results. Concretely speaking, two proxies of openness—import and export—in the two-stage bootstrap DEA estimation are found to have positive and significant effects on firm's technical efficiency. These findings also support the findings in previous literature (e.g., Sun et al., 1999; Liu et al., 2005; Fu, 2005; Christopoulos, 2007) that economic openness can contribute to manufacturing firms' efficiency improvement in transitional China. Second, we find that research and development expenditures (R&D) and innovation have positively relationship with efficiency.[3] Finally, firm age is found to have a negative effect on firm's efficiency, while firm size is found to have a positive effect.

The rest of the essay is organized as follows. In section 2, We describe the analytic framework and methodology used to estimate the bootstrap DEA efficiency and the efficiency determinant model. The data, variables, and empirical specifications are briefly summarized in Section 3. Section 4 reports the empirical results of openness effect on Chinese manufacturing firms' efficiency. Besides, the robust test is presented in this section. Finally, some concluding remarks are presented in Section 5.

4.2 Methodology

4.2.1 DEA Estimation of technical efficiency

The DEA approach usually assume that all firms within an industry have access to the same technology. For each firm i ($i = 1, 2, \dots, n$), the technology in a given industry can be characterized by a production set P that transform a nonnegative vector of inputs, $X = (X_1, \dots, X_N) \in \Re^N_+$, into a nonnegative vector of outputs, $Y = (Y_1, \dots, Y_M) \in \Re^M_+$. it is defined as

$$P \equiv \{(X_i,\, Y_i) \mid X_i \,\text{can produce}\, Y_i\}\,, \tag{4.1}$$

where each firm faces certain environmental variables, $z = (z_1, \dots, z_Q) \in \Re^Q_+$ that are expected to influence firms' performance. The boundary of P is referred to as the technology or the production frontier. The distance from the actual point of each firm in the production set P to the frontier of P is treated as the inefficiency of each firm, where this distance is determined by the firm's environmental variables z. In other words, since each firm has specific characteristics (represented by environmental

[3] As Fajnzylber and Fernandes (2009) described, R&D and innovation measure the learning and absorptive capacity of firms since developing absorptive capacity is a motivation for firms to engage in R&D. If a firm is more likely to learn and absorb new knowledge, it will be more efficient.

variables), some firms may operate along the production frontier while others operate at the points in the interior of the production frontier. The former firms are considered technically efficient, while the latter firms are considered technically inefficient.

To measure such technical efficiency, we employ the Farrell (1957) output oriented measure of productive efficiency, which is defined as

$$TE_i \equiv \max \{\theta \mid (X_i,\, \theta Y_i) \subseteq P\}\,. \tag{4.2}$$

When $TE_i = 1$, the firm is considered technically efficient, while technically inefficient when $TE_i > 1$.[4]

Since the true production sets can not be observed, we use the most common DEA procedure (constant returns to scale) to estimate the best-practice (observed) frontier from the observed input-output combinations (X_i, Y_i), which is defined as

$$\begin{aligned}\hat{P} = \quad & \Big\{ Y \mid Y_m \leqslant \sum_{i=1}^{n} q_i Y_i^m,\, m = 1, \ldots, M, \\ & X_j \geqslant \sum_{i=1}^{n} q_i X_i^j,\, j = 1, \ldots, N, \\ & q_i \geqslant 0,\, i = 1, \ldots, n \Big\}\,,\end{aligned} \tag{4.3}$$

where $\hat{P}$ is the DEA estimate of the true production frontier of P, q_i are the intensity variables that indicate a particular firm's intensity in the production.[5] Then, the DEA estimate of individual technical efficiency at any point (x_i, y_i) be derived by solving the following linear programming problem

$$\hat{TE}_i = TE\left(X_i, Y_i \mid \hat{P}\right) = \max_{\theta, q_1, \ldots, q_n} \left\{\theta \mid \theta Y_i \in \hat{P}\right\}. \tag{4.4}$$

Since $\hat{P} \subseteq P$, $\hat{TE}_i$ is a downward-baised estimator of δ_i. Then, some DEA literature (e.g., Simar and Wilson, 2000a; Henderson and Zelenyuk, 2007; Simar and Zelenyuk, 2007) developed a bootstrap DEA procedure to address the problem.

[4]Note that $0 < (1/TE_i) \leqslant 1$, the reciprocal of TE_i represents the relative percent level of the technical efficiency of Firm i relative to the production frontier of P.

[5]Constant returns to scale can be relaxed to non-increasing returns to scale or variable returns to scale by adding the restriction of $\sum_{i=1}^{n} q_i \leqslant 1$ or $\sum_{i=1}^{n} q_i = 1$, respectively.

4.2.2 Group-wise heterogeneous sub-sampling bootstrap of aggregate DEA efficiency

Since we attempt to investigate the openness effects on firms' technical efficiency, in aggregate level, we divide the sample into two groups—Open group and Non-open group,[6] then compare the aggregate EDA efficiency score of the two groups to see whether the Open group is more efficient than the Non-open group or not. Recently, Simar and Zelenyuk (2007) showed that the common practice (comparing the simple average efficiency scores of different groups) can not gain a satisfying result, and proposed a new approach—Group-wise heterogeneous sub-sampling bootstrap of aggregate DEA efficiency. Therefore, We use this developed DEA approach to compare the efficiency between the Open firms and Non-firms in our study. For group $l\,(l = 1, 2, \ldots, L)$, represented by a sub-sample $i_l = 1, 2, \ldots, n_l\,(\leqslant n)$ of the original sample with n firms, the weighted group aggregate technical efficiency is defined as

$$\overline{TE^l} = \sum_{i_l=1}^{n_l} TE_{i_l}^l \times S_{i_l}^l, \tag{4.5}$$

where $S_{i_l}^l = \frac{py_{i_l}^l}{p\overline{y^l}}$, $\overline{y^l} = \sum_{i_l}^{n_l} y_{i_l}^l$, $S_{i_l}^l$ is the weights, p is the vector of output price, $\overline{y^l}$ is the sum of output over the firms in group l.

In practice, the two bootstrap procedures (Simar and Zelenyuk, 2007) are used to obtain bias-corrected subgroup aggregate DEA efficiency scores and bootstrap confidence intervals.

4.2.3 Determinants of DEA efficiency

Further, in order to evaluate the openness effects on firms' efficiency more specifically, we employ the two-stage bootstrap DEA approach. The determinant model of DEA efficiency is specialized as.

$$TE_i = z_i\delta + \varepsilon_i, \tag{4.6}$$

where $TE_i = TE\left(X_i, Y_i \mid \hat{P}\right)$, as is defined in Equation (4.4); δ is a vector of parameters that we aim to estimate; z_i is a vector of firm environment variables that may

[6] We will give a description about the group classification in the next section.

affect the ith firm's efficiency; ε_i is the white noise.

The traditional two-stage DEA literature typically employs censored (Tobit), sometimes OLS regression to estimate Equation (4.6). However, Simar and Wilson (2007) argued that the traditional estimators are inappropriate because (1) they have not provide a coherent description of a data-generating process that would make such regressions sensible, and (2) standard DEA efficiency estimates are serially correlated, consequently, the traditional two-stage DEA estimation is inconsistent in the second stage regression. Thus, they proposed a two-stage bootstrap DEA approach to gain a consistent regression. This essay employs one of their bootstrap procedure—Algorithm 2 (Simar and Wilson, 2007, p42),

(1) For each firm in the sample $\{(X_i, Y_i), i = 1, 2, \ldots, n\}$, compute $\hat{TE}_i$ for each firm using equation (5).

(2) Use the method of maximum likelihood to obtain an estimate $\hat{\delta}$ of δ, and $\hat{\sigma}_\varepsilon$ of σ_ε.

(3) For each firm $i = 1, 2, \ldots, n$, loop over the next 4 steps B_1 times to obtain a set of bootstrap estimates $\left\{\hat{TE}^*_{ib},\, b = 1, 2, \ldots, B_1\right\}$:

i Draw ε_i from the $N(0, \hat{\sigma}^2_\varepsilon)$ distribution with left truncation at $\left(1 - z_i\hat{\delta}\right)$.

ii Compute $TE^*_i = z_i\hat{\delta} + \varepsilon_i$.

iii Set $X^*_i = X_i$, $Y^*_i = Y_i\hat{TE}_i/TE^*_i$.

iv Compute $\hat{TE}^*_i$ on the set of pseudo data .

(4) For each firm i, compute the bias-corrected estimate $\hat{\hat{TE}}_i = \hat{TE}_i - \hat{bias}\left(\hat{TE}_i\right)$, where $\hat{bias}\left(\hat{TE}_i\right) = (1/B_1)\sum_{b=1}^{B_1}\left(\hat{TE}^*_{ib} - \hat{TE}_i\right)$. . (5) Use the the method of maximum likelihood to estimate the truncated regression of $\hat{\hat{TE}}_i$ on z_i, yielding estimates $\left(\hat{\hat{\delta}}, \hat{\hat{\sigma}}\right)$.

(6) For each firm i, loop over the next 3 steps B_2 times to obtain a set of bootstrap estimates :

i Draw ε_i from the $N\left(0, \hat{\hat{\sigma}}^2_\varepsilon\right)$ distribution with left truncation at $\left(1 - z_i\hat{\hat{\delta}}\right)$.

ii Compute $TE^{**}_i = z_i\hat{\hat{\delta}} + \varepsilon_i$.

iii Use the method of maximum likelihood to estimate the truncated regression of TE^{**}_i on z_i, yielding estimates $\left(\hat{\hat{\delta}}^*, \hat{\hat{\sigma}}^*\right)$.

(7) Use the bootstrap results to get confidence intervals.

4.3 Data and empirical specification

The data used in this paper comes from the World Bank Investment Climate Survey, which use standardized survey instruments and a uniform sampling methodology to analyze firm performance and the business environment of most developing countries.[7] The survey of China 2003 was conducted by the Investment Climate Survey Group of Word Bank with assistance from the Enterprise Survey Organization of the Chinese National Bureau of Statistics, for the reference year of 2002. In the survey, 2400 firms are randomly sampled from both manufacturing (1616 firms) and services industries (784 firms) in eighteen cities that represent the five main regions in China.[8]

According to the hypothesis of DEA theory, all firms within an industry should have access to the same technology. In our sample, manufacturing industry is classified into ten sub-industries,[9] which obviously operate at different technology. Therefore, it is reasonable to estimate the production frontier of each sub-industry. After excluding the observations with missing value of output and input variables, we chose five sub-industries, each of which has more than 100 observations as our working sample.

Given data availability, we employ one *Output*—value of total sales (in 1000 Yuan), and three inputs—*Material, Capital, Labor*, to estimate the efficiency score of each firm using bootstrap DEA procedure. *Material* is defined as total material costs (in 1000 yuan); *Capital* is proxyed by the book value of fixed asset (in 1000 yuan); *Labor* is the total number of employees. Descriptive statistics of output and inputs of each sub-industry are presented in Table 4.1. It is notable that the *Output* (value of total sales) and the input variables of *Material* and *Capital* contain price information, which may have effect on the allocation of outputs and inputs, consequently on efficiency. As a result, the efficiency score obtained from these variables is the enlarged definition of the technical efficiency that includes both technical and allocate efficiency, rather than the original Farrell (1957) productive efficiency.[10] However, there is a benefit to use the aggregated (with prices) output and inputs in DEA model since such measurement of outputs and inputs enlarge the meaning of technology

[7] More information on the survey can be found at https://www.enterprisesurveys.org. The survey of China 2003 could be accessed at the website before 2009, but is currently not available. Furthermore, the subsequent surveys of China are not appeared on the website.

[8] Ayyagari et al. (2010) provided a detail description of the World Bank Investment Climate Survey of China 2003.

[9] The ten sub-industries are: Garment & leather products, Electronic equipment, Electronic parts making, Household electronics, Auto & auto parts, Food processing, Chemical products & medicine, Biotech products & Chinese medicine, Metallurgical products, and Transportation equipment.

[10] In practice, the aggregated (with prices) variables were widely used in DEA technical efficiency empirical literature (e.g., Sun et al., 1999; Fu, 2005; Christopoulos, 2007).

from engineering to a broader one—"'use money to make more money', regardless of particular engineering, managerial and other features of business," (Zelenyuk and Zheka, 2006). Therefore, it is safe for us to estimate the specific production frontier of a manufacturing industry with different types of firms that may operate under different technologies.[11] Our empirical procedure is specialized as follows.

Table 4.1: Summary statistics of each sub-industry

Variables	Mean	Std. dev.	Min.	Max.	No. of obs.
Garment & leather products					
Output	38678.59	104471.30	9.50	911610.00	293
Material	22856.17	67439.95	3.10	601431.00	293
Capital	21113.56	61976.94	12.70	791538.00	293
Labor	335.58	624.79	12.00	5690.00	293
Electronic equipment					
Output	417871.80	1115893.00	273.54	7125799.00	160
Material	251967.50	795973.50	22.00	5167263.00	160
Capital	116248.30	283467.20	39.00	1742915.00	160
Labor	580.39	1080.94	12.00	6300.00	160
Electronic parts making					
Output	102124.20	430510.10	141.00	4630020.00	244
Material	61762.24	308940.70	20.00	3510391.00	244
Capital	75501.84	307595.30	23.00	3752570.00	244
Labor	390.49	822.67	13.00	7245.00	244
Auto & auto parts					
Output	233305.10	736041.30	75.00	7555244.00	317
Material	140502.40	482766.50	3.00	4760431.00	317
Capital	131676.70	385786.70	70.00	4455954.00	317
Labor	676.82	1165.71	15.00	8688.00	317
Metallurgical products					
Output	37547.67	170580.60	54.00	1599230.00	134
Material	15103.20	73530.59	3.00	821656.00	134
Capital	32210.99	131464.60	66.88	1331777.00	134
Labor	342.25	727.36	8.00	6582.00	134

In our first stage (DEA efficiency estimation), we estimate the best-practice frontier of each sub-industry, then gain the bais-corrected efficiency score of each firm

[11] For example, auto firms and auto parts firms are treated as one sub-industry in the survey, but they may operate under different technology level.

relative to their sub-industry frontier using bootstrap DEA procedure. We estimate the sub-industry frontiers rather than the meta-frontier of the whole manufacturing industry so that the key hypothesis of DEA approach can be satisfied in our estimation, that is to say, the firms in one production set should have access to the same technology level.[12]

Further, we divide each sub-industry sample into two groups—Open group and Non-open group. Open group includes the firms that have engaged in international economic activities (export final products, import material, or have foreign capital), while Non-open group includes the remaining firms. If openness has positive effect on firms' efficiency, then the Open group is expected to be more efficient than the Non-open group.

In the second stage, we estimate the efficiency determinant model using the two-stage bootstrap DEA approach. Generally, firms' efficiency level may be determined by various environment variables. Since we attempt to investigate the hypothesis that openness can affect the efficiency of Chinese manufacturing firms, we assume that firms' efficiency is influenced by the following variables.

Foreign, *Import*, and *Export*, three dummy variables that are used as the proxy of openness. We choose these three variables for the considerations of (1) FDI, import, and export were widely used to proxy openness in previous empirical studies (e.g. Sun et al., 1999; Liu et al., 2005; Christopoulos, 2007; Mastromarco and Ghosh, 2009) and (2) international trade and FDI have played an important role in China's transition period. For characterizing the ownership, we use the state ownership share of each firm. In the transition period of China, most state-owned firms performed mainly according to the politic propaganda of the administrative department, rather than to market rules. As a result, state-owned firms generally less efficient than other kind of firms. Therefore, *State* is expected to be negatively related to firms' efficiency. *Innovation* and *R&D* dummies are used to capture the learning and absorptive capacity of firms. A higher innovation and R&D level of a firm indicate the firm prefer to learn new things (Fajnzylber and Fernandes, 2009), then contribute to efficiency improvement. In addition, we include logarithm of employee number (*Log(labor)*) for size effect, *Firm_age* for age effect, and industry dummies for industry specifics. Definitions and descriptive statics of main variables are presented in Table 4.2.

[12]Even we enlarged the definition of technology in this study, the labor-intensive industries (e.g. Garment & leather products industry) are different from capital-intensive industries (e.g. Auto & auto parts industry) in technology level. Actually, we estimated the meta-frontier but gained strange DEA efficiency scores (very large mean and variance).

Table 4.2: Description of variables

Variable	Definition	Mean	St. Dev.	Min	Max
Firm_age	The difference between the current year (2002) and the firm's established year.	15.056	13.454	2.000	52.000
State	The share of a firm is owned by government.	0.173	0.364	0.000	1.000
Foreign	The share of a firm is owned by foreign individuals or orgnization.	0.105	0.263	0.000	1.000
Import	The share of imported raw material cost in total material cost.	0.071	0.203	0.000	1.000
Export	The share of total exports value in total sales value.	0.131	0.304	0.000	1.000
Innovation	=1 if a firm has introduced new products, new business line, new process, new management techniques, or new quality controls in production since 1999, 0 otherwise.	0.777	0.417	0.000	1.000
R & D	=1 if a firm has R & D expenditures, 0 otherwise.	0.454	0.498	0.000	1.000
Industry_GL	=1 if a firm belongs to garment & leather products industry.	0.256	0.437	0.000	1.000
Industry_EE	=1 if a firm belongs to electronic equipment industry.	0.138	0.345	0.000	1.000
Industry_EP	=1 if a firm belongs to electronic parts making industry.	0.212	0.409	0.000	1.000
Industry_AA	=1 if a firm belongs to auto & auto parts industry.	0.278	0.448	0.000	1.000
Industry_MP	=1 if a firm belongs to metallurgical products industry.	0.116	0.321	0.000	1.000

Note: The number of observations is 981.

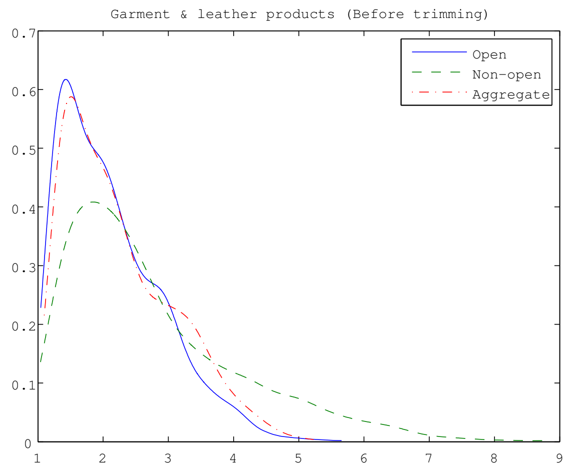
4.4 Empirical results

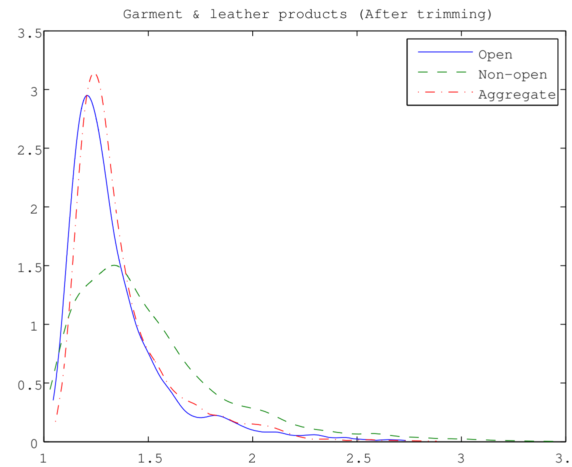
4.4.1 Estimation of DEA efficiency

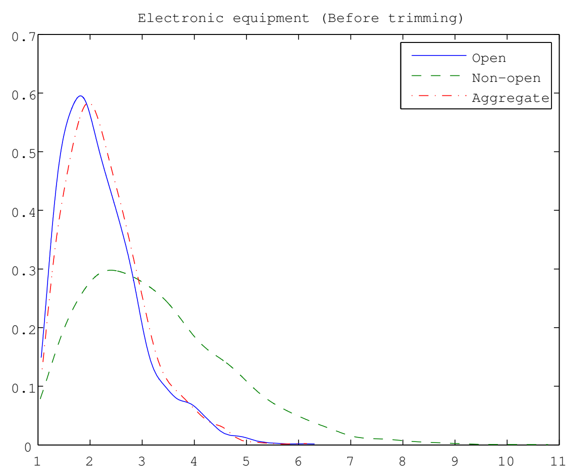
In the first stage, the technical efficiency score of each firm in each sub-industries is estimated by solving the linear programming problem of Equation (4.4). Then, Kernel density estimator is used to obtain the density of efficiency scores of each sub-industry. The estimated efficiency scores and their densities look suspicious for every sub-industry especially for Metallurgical products industry.[13] These results suggest that there may be some outliers in the sample of each sub-industry, especially in the Metallurgical products industry. As argued by Zelenyuk and Zheka (2006), efficiency outliers may due to three reasons. First, the firms with efficiency outliers follow a different distribution of efficiency, namely, these firms operate under different production frontier. Second, all firms follow the same distribution but external shock (e.g., strike, unexpected incidents) make some firms appear far in the tail of the distribution. Finally, the firms with recording error (extra digits) for some output or input variables lead to extreme efficiency scores. In our study, outliers may due to the last two reasons since there are some firms with unusual output and inputs.[14] As these outliers may disturb the estimation of the frontier, we trim about 15% of firms with extreme efficiency score in each sub-samples. The Kernel density distribution of the original samples (before trimming) and the trimmed samples (after trimming) are presented in Figure 4.1.

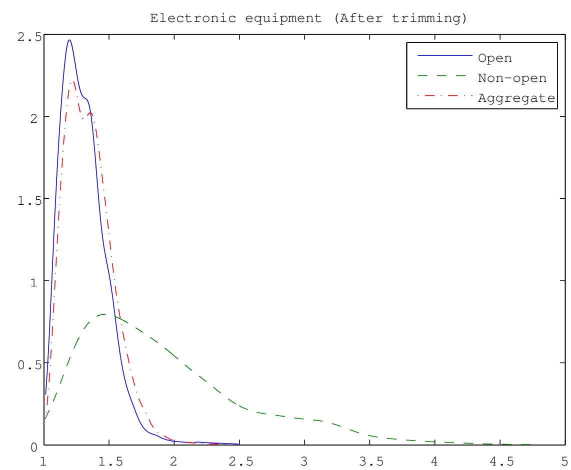
[13] The average efficiency score is too large in each sub-industry especially in the Metallurgical products industry. For example, the average efficiency score of the Metallurgical products industry is 62.600, while the maximum score is 123.594.

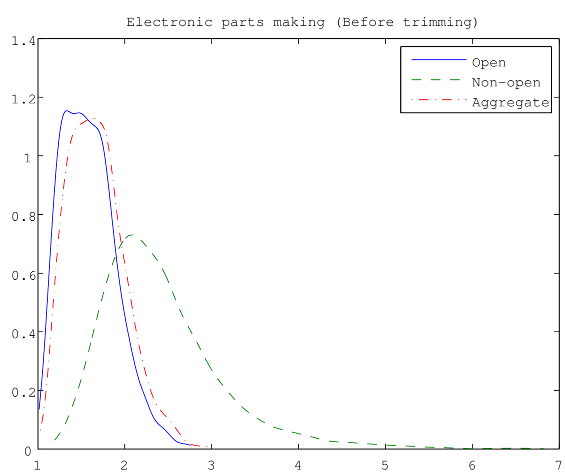
[14] These firms have large amounts of output but small amounts of inputs, or small amounts of output but large amounts of inputs. Besides, some variables (i.e., total sales, employee) of a firm changed unreasonably (sharp increase or decrease) across years.

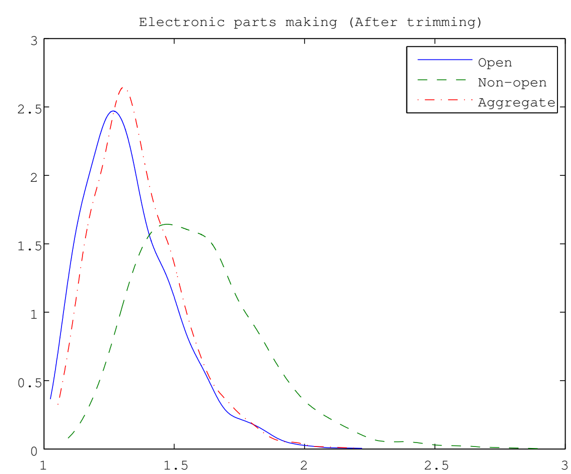

Garment & leather products (Before trimming)
Open
Non-open
Aggregate
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
1 2 3 4 5 6 7 8 9


Garment & leather products (After trimming)
Open
Non-open
Aggregate
0 0.5 1 1.5 2 2.5 3 3.5
1 1.5 2 2.5 3 3.5


Electronic equipment (Before trimming)
Open
Non-open
Aggregate
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
1 2 3 4 5 6 7 8 9 10 11


Electronic equipment (After trimming)
Open
Non-open
Aggregate
0 0.5 1 1.5 2 2.5
1 1.5 2 2.5 3 3.5 4 4.5 5


Electronic parts making (Before trimming)
Open
Non-open
Aggregate
0 0.2 0.4 0.6 0.8 1 1.2 1.4
1 2 3 4 5 6 7


Electronic parts making (After trimming)
Open
Non-open
Aggregate
0 0.5 1 1.5 2 2.5 3
1 1.5 2 2.5 3

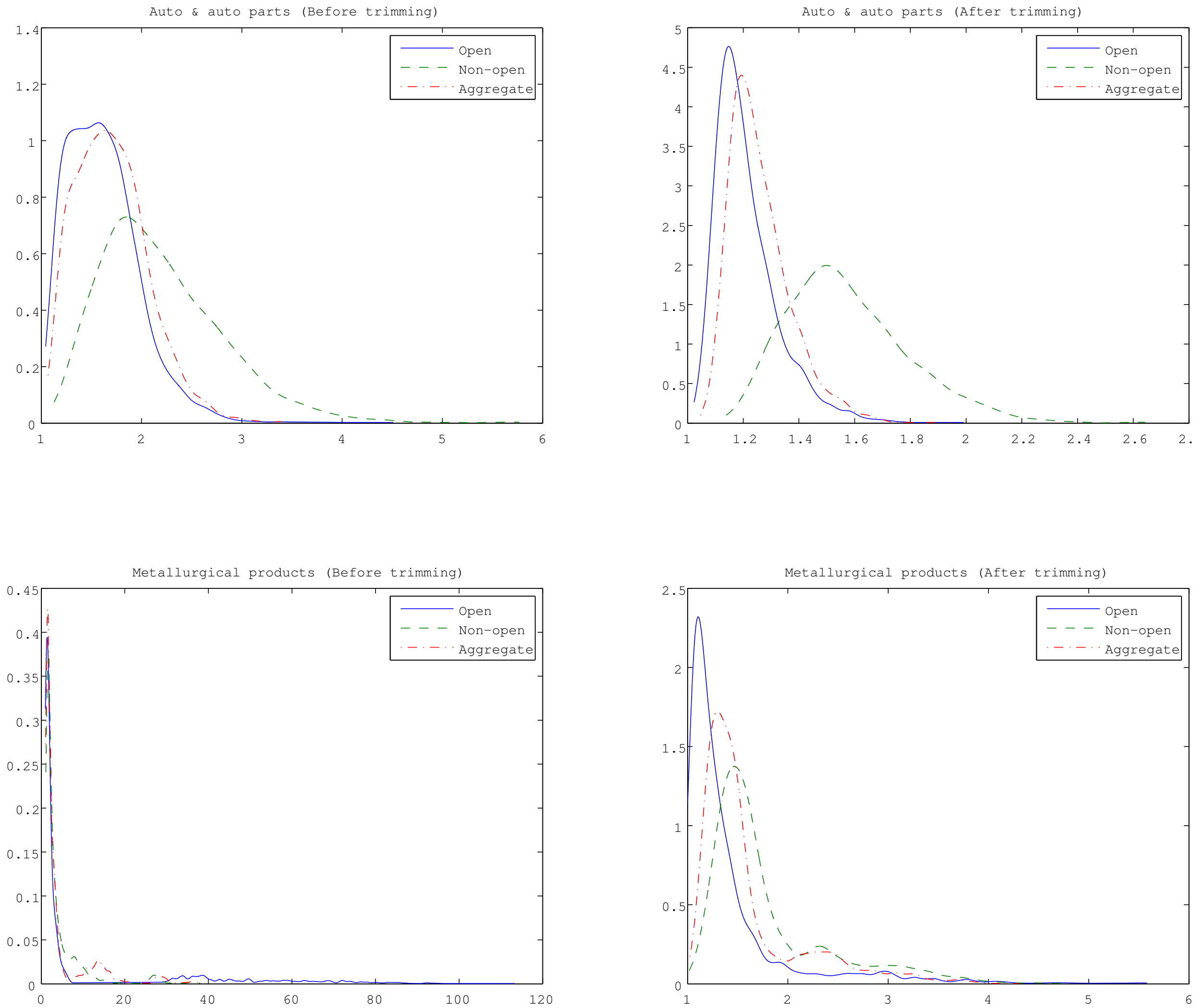


Figure 4.1: Kernel density distribution of Bootstrap DEA efficiency

The trimmed samples may generate reasonably distribution of efficiency scores, but readers may argue that can the trimmed samples represent the distribution of the original samples or not. Fortunately, Simar-Zelenyuk-adapted Li Test (Simar and Zelenyuk, 2006) can be used to answer this question. As shown in Table 4.3, the Simar-Zelenyuk-adapted Li Test results in all sub-industries cannot reject the hypotheses that the distributions of original and trimmed samples are equal. Therefore, it is safe for us to use the trimmed samples for the two-stage bootstrap DEA estimation.

Table 4.3: Simar-Zelenyuk-adapted Li Test for equality of efficiency distributions between original and trimmed sample

Industry	Original sample	Trimmed sample	Bootstrap P_value
Garment & leather products	293	251	0.420
Electronic equipment	160	135	0.824
Electronic parts making	244	208	0.593
Auto & auto parts	317	273	0.545
Metallurgical products	134	114	0.691

Note: The number of firms in each sample is presented in column 2 and 3.

Then, the original DEA efficiency, bias-corrected EDA efficiency of each firm, together with the weighted efficiency of each group in each sub-industry are estimated using a Matlab program—group-wise heterogeneous sub-sampling approach (Simar and Zelenyuk, 2007). Output shares are used to obtain the weights of aggregation. The estimated aggregate efficiency scores of the Open group and Non-open group, and their confidence intervals are reported in Table 4.4.

Table 4.4: Estimation results of bootstrap DEA efficiency

Industry	DEA estim.	St. dev.	Bias corr. estim.	95% CI bounds Lower	95% CI bounds Upper	90% CI bounds Lower	90% CI bounds Upper	99% CI bounds Lower	99% CI bounds Upper
Garment & leather products									
Open	1.713	0.248	2.078	1.343	2.331	1.579	2.314	1.033	2.366
Non-open	1.910	0.368	2.317	1.269	2.744	1.549	2.721	0.883	2.773
Aggregate	1.772	0.234	2.175	1.501	2.423	1.674	2.406	1.262	2.455
RD	0.897	0.218	0.862	0.394	1.233	0.503	1.186	0.065	1.289
Electronic equipment									
Open	1.770	0.172	2.232	1.849	2.473	1.919	2.460	1.595	2.502
Non-open	2.912	0.626	3.902	2.397	4.681	2.775	4.649	1.704	4.763
Aggregate	1.836	0.181	2.324	1.912	2.588	1.996	2.569	1.685	2.624
RD	0.608	0.189	0.482	0.122	0.829	0.158	0.773	-0.063	0.891
Electronic parts making									
Open	1.566	0.179	1.801	1.361	2.064	1.440	2.046	1.170	2.096
Non-open	1.933	0.250	2.269	1.687	2.655	1.783	2.619	1.273	2.723
Aggregate	1.620	0.169	1.880	1.475	2.142	1.549	2.123	1.295	2.174
RD	0.810	0.145	0.772	0.479	1.030	0.508	0.999	0.354	1.105
Auto & auto parts									
Open	1.336	0.114	1.460	1.159	1.606	1.220	1.595	0.880	1.629
Non-open	1.834	0.219	2.094	1.595	2.427	1.673	2.406	1.302	2.511
Aggregate	1.426	0.111	1.592	1.312	1.743	1.365	1.734	1.127	1.781
RD	0.728	0.122	0.674	0.413	0.886	0.464	0.861	0.225	0.973
Metallurgical products									
Open	1.941	0.601	2.451	0.594	2.861	1.026	2.848	-0.383	2.877
Non-open	2.864	0.609	3.934	2.266	4.554	2.516	4.511	1.604	4.625
Aggregate	2.615	0.518	3.630	2.123	4.118	2.434	4.098	1.479	4.158
RD	0.678	0.229	0.538	-0.006	0.917	0.150	0.838	-0.316	1.015

Notes:

1. Estimation is according to Simar and Zelenyuk (2007) group-wise heterogeneous sub-sampling approach, with 2000 bootstrap replications for bias correction estimation and confidence intervals (CI); Sub-sample size for each group $l\,(l = 1, 2)$ is determined as $n_l^{0.7}$.
2. Open, Non-open, and Aggregate denote the weighted aggregate efficiency of open group, non-open group, and a sub-industry, respectively.
3. RD is used to test the equality of aggregate efficiencies between Open and Non-open group.

As shown in Table 4.4, the Open group is more efficient than the Non-open group for each sub-industry (the Open group has a smaller aggregate efficiency score relative to the Non-open group in each sub-industry). However, since the bootstrap estimated confidence intervals are quite wide in all sub-industries, it is not safe to draw a conclusion from the aggregate efficiency score alone. Thus, RD-statistic (Simar and Zelenyuk, 2007) is used to test whether the aggregate efficiencies of two groups are different or not. If the bootstrap confidence interval of RD-statistic does not cover unity, then the null hypothesis that the aggregate efficiencies of two groups are equal can be rejected. Fortunately, the RD-statistics in Table 4.4 rejected the null hypothesis in all sub-industries except Garment & leather products industry at 90% confidence level. When the confidence level increased to 95% and 99%, the RD-statistics still rejected the null hypothesis in three sub-industries (Electronic equipment, Auto & auto parts, and Metallurgical products) and two sub-industries (Electronic equipment and Auto & auto parts), respectively. These results suggest that the openness effects on firms' technical efficiency are obvious in those capital-intensive industries (Electronic equipment, Electronic parts making, Auto & auto parts, and Metallurgical products), meanwhile, it is not obvious in labor-intensive industry (Garment & leather products).

In addition, Table 4.4 indicate that the aggregate efficiencies obtained by bootstrap bias-corrected estimation are larger than those obtained by original DEA estimation. These results are in line with the theory of bootstrap DEA literature that the original DEA estimates are biased downward. Besides, We should notice that the estimated efficiency score of each firm are gained from the distance between the firm's actual production point and the best-practice frontier of one sub-industry, rather than the distance between the firm's actual production point and the meta-frontier of the whole manufacturing industry, accordingly, the aggregate efficiencies of each sub-industry are based on different production frontier. As a result, we cannot compare the aggregate efficiencies across sub-industries in Table 4.4. However, it is does not matter since the efficiency comparison across sub-industries is not our intent.

Finally, even we can learn from Table 4.4 that the open firms are more technically efficient than non-open firms in most sub-industries, the widely estimated confidence intervals also suggest that the efficiency may be affected by some firm specific characteristics. Therefore, we will give a further analysis in the second stage.

4.4.2 Determinants of DEA efficiency

In the second stage, the efficiency determinant model (Equation 4.6) is estimated using a Matlab program proposed by Zelenyuk and Zheka (2006), while the parameters and the confidence intervals are gained from 2000 times bootstrapping procedures. Specifically, the bias-corrected efficiency scores gained from the first stage are pooled cross sub-industries, then they are regressed on firms' environment variables and industry dummies using Algorithm 2 of Simar and Wilson (2007), with 2000 bootstrap replication both for bias correction and for confidence intervals of the estimated coefficients. The results are presented in Table 4.5. Considering the fact that the variables of *Foreign*, *Export*, and *Import* correlate highly with each other, we regressed several specifications for robustness. The first regression includes 12 regressors, while the rest regressions exclude some of these highly correlated variables. Fortunately, all the regressions yielded quantitatively similar results for all variables except for *Import*, size variable (*Ln(employee)*) and *Industry_EP*.

Table 4.5: Truncated bootstrap regression of the determinants of DEA efficiency

	Reg.1	Reg.2	Reg.3	Reg.4
Constant	1.601***	1.005***	0.298***	1.003***
Firm age	0.161***	0.168***	0.166***	0.166***
Ln(employee)	-0.334***	-0.263***	-0.095***	-0.234***
State	3.060***	2.990***	2.932***	3.015***
Foreign	0.061	0.096		
Import	-0.737***		-2.479***	
Export	-0.407***			-0.294***
Innovation	-2.194***	-2.075***	-2.223***	-2.119***
R & D	-1.878***	-1.847***	-2.021***	-1.896***
Industry_EE	-6.776***	-7.279***	-7.074***	-7.401***
Industry_EP	0.525***	0.040	0.031	0.120***
Industry_AA	-1.422***	-1.633***	-1.593***	-1.738***
Industry_MP	3.260***	3.184***	3.180***	3.158***
σ_ε	6.040***	6.102***	6.184***	6.098***

Notes:

1. The dependent variable is the bootstrap bias-corrected DEA estimate of efficiency score.
2. ***, **, and * indicate statistically significant at 0.01, 0.05, and 0.1 significance levels respectively, according to bootstrap confidence intervals.

As shown in Table 4.5, the two openness indicators—*Export* and *Import*—have negative and statistically significant coefficients, while *Foreign* has a positive but insignificant coefficient.[15] The results of *Export* and *Import* are consistent with the findings in Sun et al. (1999) and Fu (2005) that trade openness has positively influenced the technical efficiency of Chinese manufacturing industry. However, the result of *Foreign* differs the result of Sun et al. (1999), whom found foreign capital has a positive effect on firms' technical efficiency in China's manufacturing sector, but we did not find a positive effect in our regressions since the sign of *Foreign* is positive and insignificant.

Noteworthy, *State* is found to have a negative and significant effect on firms' technical efficiency, which suggests that the more a firm is owned by state, the less the firm is technically efficient. This finding confirmed previous findings by Jefferson and Xu (1991), Zheng et al. (1998) and Wen et al. (2002) for China. It also explained the economic failures of state-owned firms during the transition period, which is often characterized by low profitability, large deficit and a large amount redundant staff.

As is expected, *Innovation* and *R&D* are found to have significantly positive effect on technical efficiency in every regressions. The results confirmed the innovation literature of Cohen and Levinthal (1989) that innovation and R&D not only generate new technology but also enhance firms' ability to assimilate and exploit existing technology. As a result, innovative firms are more technically efficient than non-innovative ones.

Since firm size is defined by the number of employees when the survey was constructed, we use the logarithm of employee number to control the size effect. The results in our regressions are in line with some previous studies (e.g., Brada et al., 1997; Zheng et al., 1998; Sun et al., 1999; Zelenyuk and Zheka, 2006), which suggest that larger firms are more efficient than the smaller ones.

Finally, the coefficient of *Firm_age* is positive and significant in all regressions. The results indicate that older firms intend to be less technically efficient than younger ones. This may relate to the fact that older firms are more likely to be slower in accepting new information and management style. Thus, they are less than younger firms.

To compare the estimation results that obtained from two-stage bootstrap DEA approach and form traditional two-stage DEA approach, we present the Tobit estimation results in Table 4.6. Even all the regressors except for *Foreign* and *Industry_EP* have similar sign between the two-stage bootstrap DEA estimations and the tra-

[15] According to the DEA efficiency measurement, larger efficiency score of a firm means less efficient production of the firm. Therefore, the negative coefficients in the regressions mean the positive effect on firm's technical efficiency.

ditional two-stage DEA estimations, the significance level and magnitude changed dramatically for the three openness indicators—*Foreign*, *Export* and *Import*. The coefficients of all these openness indicators have negative sign but they are insignificant even in 10% level. Thus, we can not draw a conclusion that openness has positive on the efficiency of Chinese manufacturing firms from the traditional two-stage DEA estimations. A possible explanation is that the traditional two-stage DEA approach can not yield a consistent result, as is argued by Simar and Wilson (2007). Another reason may due to the endogenous variable of *Foreign*, *Export* and *Import*. We should notice that the foreign oriented firms seem to be more efficient, at the same time, more efficient firms are more likely to attract foreign capital and trade with foreign partners.

Table 4.6: Tobit estimation of the determinants of DEA efficiency

	Reg.1	Reg.2	Reg.3	Reg.4
Constant	5.520***	5.493***	5.498***	5.533***
	(0.442)	(0.442)	(0.442)	(0.441)
Firm age	0.056***	0.057***	0.058***	0.057***
	(0.009)	(0.009)	(0.009)	(0.009)
Ln(employee)	-0.063	-0.09	-0.097	-0.069
	(0.087)	(0.085)	(0.084)	(0.087)
State	1.308***	1.058***	1.079***	1.052***
	(0.307)	(0.307)	(0.305)	(0.306)
Foreign	-0.214	-0.384		
	(0.448)	(0.400)		
Import	-0.002		-0.330	
	(0.579)		(0.518)	
Export	-0.488			-0.552
	(0.399)			(0.369)
Innovation	-0.689***	-0.672***	-0.682***	-0.696***
	(0.258)	(0.258)	(0.258)	(0.258)
R & D	-0.580***	-0.555**	-0.54**	-0.574**
	(0.224)	(0.223)	(0.222)	(0.223)
Industry_EE	-1.578***	-1.493***	-1.476***	-1.597***
	(0.357)	(0.345)	(0.348)	(0.349)
Industry_EP	-0.086	-0.003	-0.005	-0.097
	(0.306)	(0.298)	(0.299)	(0.305)
Industry_AA	-0.609**	-0.486*	-0.497*	-0.622**
	(0.298)	(0.281)	(0.282)	(0.296)
Industry_MP	1.157***	1.265***	1.263***	1.149***
	(0.369)	(0.359)	(0.359)	(0.368)
σ_ε	3.109	3.111	3.112	3.109

Notes:

1. The dependent variable is the traditional DEA estimate of efficiency score.

2. Standard errors in parentheses. ***, **, and * indicate statistically significant at 0.01, 0.05, and 0.1 significance levels respectively.

4.4.3 Robust test by SFA

To verify whether the two-stage bootstrap DEA results is robust or not, we re-estimate the inefficiency function by a alternative approach—SFA. Following Battese and Coelli (1995), the simultaneous stochastic frontier production and inefficiency model are specified as

$$y_i = \beta_0 + \sum_{m=1}^{3} \beta_m x_{mi} + \sum_{m=1}^{3} \sum_{k \geqslant m}^{3} \beta_{mk} x_{mi} x_{ki} + V_i - U_i, \tag{4.7}$$

$$U_i = \delta_0 + \sum_{j=1}^{J} \delta_j z_{ji} + W_i, \tag{4.8}$$

$$i = 1, 2, \ldots, N, \ j = 1, 2, \ldots, J,$$

where y_{it} denotes the natural logarithm of *output* for the ith firm; x_{1i}, x_{2i}, and x_{3i} denote the natural logarithm of *Material, Capital, Labor* respectively; z_{ji} are the environment variables that are used in the previous determinant model; β and δ are the unknown parameters to be estimated; V_i are assumed to be identically and independently distributed as $N(0,\, \sigma_v^2)$ random variables; U_i are defined as inefficiency terms of production, and they are independent of V_i; and W_{it} is defined by the truncation (at zero) of $N(0,\, \sigma_2)$ distributions.

The FRONTIER 4.1 program (Coelli, 1996) is used to estimate the simultaneous stochastic production frontier and inefficiency model. The estimation results of stochastic frontier production and inefficiency functions are presented in Table 4.7. The null hypothesis ($\gamma = \delta_j = 0$) that the technical inefficiency effects are not present in the stochastic frontier production function is rejected for all regressions.

As shown in Table 4.7, all the regressions by SFA approach have yielded similar results. Somewhat surprisingly, even the three openness indicators—*Foreign*, *Export* and *Import* have the expected sign, but they are insignificant. These results are similar with the result in the Tobit estimations, but differ from the one in the two-stage bootstrap DEA estimations. However, we have the robust results on the variables of *Firm_age*, *Innovation*, *R&D*, and industry dummies. Thus, the SFA estimation confirmed again that the three openness indicators—*Foreign*, *Export* and *Import*, are endogenous in this sample.

Table 4.7: Estimation results of SFA inefficiency functions

	Reg.1	Reg.2	Reg.3	Reg.4
Constant	0.767***	0.828***	0.716***	0.514***
	(0.204)	(0.227)	(0.16)	(0.063)
Firm age	0.006***	0.006***	0.006***	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)
Ln(employee)	-0.053	-0.069	-0.046	-0.004
	(0.038)	(0.043)	(0.032)	(0.003)
State	0.046	0.031	0.046	0.048
	(0.057)	(0.054)	(0.054)	(0.056)
Foreign	-0.086	-0.135		
	(0.118)	(0.114)		
Import	-0.148		-0.175	
	(0.140)		(0.133)	
Export	-0.025			-0.004
	(0.085)			(0.010)
Innovation	-0.145***	-0.130***	-0.145***	-0.139***
	(0.049)	(0.050)	(0.05)	(0.046)
R & D	-0.127**	-0.122**	-0.123**	-0.122***
	(0.053)	(0.050)	(0.054)	(0.041)
Industry_EE	-0.691***	-0.687***	-0.689***	-1.039***
	(0.144)	(0.144)	(0.122)	(0.115)
Industry_EP	-0.155**	-0.147**	-0.145**	-0.120**
	(0.065)	(0.064)	(0.062)	(0.055)
Industry_AA	-0.074	-0.068	-0.072	-0.059
	(0.062)	(0.060)	(0.061)	(0.050)
Industry_MP	0.021	0.024	0.025	0.039
	(0.071)	(0.071)	(0.071)	(0.060)
σ^2	0.157***	0.150***	0.158***	0.159***
	(0.008)	(0.008)	(0.008)	(0.008)
γ	0.056	0.051	0.051	0.058***
	(0.098)	(0.078)	(0.086)	(0.014)
Log-likelihood	-487.050	-488.141	-486.711	-468.500
LR-test: $\chi^2(df)^a$	159.194	157.012	159.871	196.293

Notes:

1. The Battese and Coelli (1995) model is employed to estimate the stochastic production function and the technical inefficiency determinant function, where a translog stochastic production function is selected by LR test. For the sake of brevity, only the coefficients of the technical inefficiency determinant function are presented in this table.

2. Standard errors in parentheses. ***, **, and * indicate statistically significant at 0.01, 0.05, and 0.1 significance levels respectively.

[a]The test is used for the hypotheses that the inefficiency effects are absent in the model. *df* equals 14 in Reg.1, and 12 in Reg.2, Reg.3, and Reg.4.

4.5 Concluding remarks

Based on the World Bank Investment Climate Survey, this essay present an empirical study on the relationship between openness and technical efficiency in Chinese manufacturing industry using the two-stage bootstrap DEA approach. The results reveal a positive relationship between openness and technical efficiency in Chinese manufacturing industry during the transition period. Concretely speaking, the aggregate DEA efficiency scores of each sub-industry obtained by group-wise heterogeneous bootstrap procedure show that the Open firms are more technically efficient than the Non-open firms. Further, the findings in the second stage estimation show that two international economic activities—import and export—have strong positive effect on firms' technical efficiency. This results support the findings in previous works (e.g., Sun et al., 1999; Liu et al., 2005; Fu, 2005; Christopoulos, 2007) that opening-up policy has played an important role in improving the technical efficiency of Chinese manufacturing industries. However, another openness indicator—foreign capital—is not found to have effect on firms' technical efficiency. We re-estimated the inefficiency model by SFA approach, but the results are not significant. This may due to the endogeneity problem of these openness indicators.

In addition, state share of a firm is found to have strong negative effect on firms' technical efficiency, which suggests that the more a firm is owned by state, the less the firm is technically efficient. Further, firms' learning and absorptive capacity, which is indicated by *Innovation* and *R&D* is found to have significantly positive effect on technical efficiency in this study. This suggest that innovation and R&D can improve not only firms' technology level but also firms' technical efficiency level. We also find that firm size is positively related to technical efficiency, while firm age is negatively related to technical efficiency.

To sum up, we provide an empirical evidence that openness is positively related to technical efficiency in Chinese manufacturing industry. Nevertheless, the evidence is not strong for the endogeneity problem of these openness indicators. Unfortunately, the current two-stage bootstrap DEA approach can not deal with the endogeneity problem. Therefore, the endogeneity problem in the two-stage bootstrap DEA model will be a challenging task in our further research.

Appendix 4.1

Table A1: Bootstrap estimated confidence intervals for Reg.1 in Table 4.5

Variable	Coeff.	Bounds of the bootstrap estimated confidence intervals					
		Lower 5%	Upper 5%	Lower 1%	Upper 1%	Lower 10%	Upper 10%
Constant	1.601	-1.497	5.119	-2.548	6.414	-1.060	4.381
Firm age	0.161	0.106	0.218	0.086	0.235	0.115	0.210
Ln(employee)	-0.334	-0.936	0.256	-1.110	0.500	-0.832	0.146
State	3.060	1.282	4.933	0.786	5.424	1.575	4.590
Foreign	0.061	-3.214	3.427	-4.139	4.711	-2.647	2.905
Import	-0.737	-4.770	4.146	-6.192	6.026	-4.114	3.067
Export	-0.407	-3.065	2.502	-3.867	3.331	-2.646	1.925
Innovation	-2.194	-3.792	-0.631	-4.138	0.039	-3.573	-0.896
R & D	-1.878	-3.341	-0.335	-3.750	0.340	-3.109	-0.608
Industry_EE	-6.776	-9.895	-3.150	-10.684	-1.836	-9.466	-3.847
Industry_EP	0.525	-1.510	2.448	-2.339	3.053	-1.198	2.117
Industry_AA	-1.422	-3.346	0.563	-3.863	1.221	-3.117	0.241
Industry_MP	3.260	1.080	5.402	0.432	6.093	1.451	5.088
σ_ε	6.040	5.301	6.748	4.878	6.872	5.463	6.648

Table A2: Bootstrap estimated confidence intervals for Reg.2 in Table 4.5

Variable	Coeff.	Bounds of the bootstrap estimated confidence intervals					
		Lower 5%	Upper 5%	Lower 1%	Upper 1%	Lower 10%	Upper 10%
Constant	1.005	-2.244	4.472	-3.221	5.476	-1.773	3.813
Firm age	0.168	0.113	0.222	0.097	0.236	0.122	0.216
Ln(employee)	-0.263	-0.847	0.318	-1.006	0.488	-0.759	0.224
State	2.990	1.251	4.808	0.515	5.302	1.567	4.535
Foreign	0.096	-2.660	3.379	-3.471	4.474	-2.221	2.648
Innovation	-2.075	-3.673	-0.414	-4.091	0.274	-3.451	-0.713
R & D	-1.847	-3.390	-0.323	-3.855	0.306	-3.180	-0.549
Industry_EE	-7.279	-10.460	-3.878	-11.183	-2.704	-9.994	-4.455
Industry_EP	0.040	-1.903	1.939	-2.618	2.496	-1.604	1.665
Industry_AA	-1.633	-3.562	0.292	-4.103	0.939	-3.201	-0.048
Industry_MP	3.184	1.085	5.314	0.445	6.045	1.499	4.994
σ_ε	6.102	5.342	6.810	4.854	6.921	5.494	6.700

Table A3: Bootstrap estimated confidence intervals for Reg.3 in Table 4.5

Variable	Coeff.	Bounds of the bootstrap estimated confidence intervals					
		Lower 5%	Upper 5%	Lower 1%	Upper 1%	Lower 10%	Upper 10%
Constant	0.298	-3.055	3.742	-4.072	5.238	-2.648	3.078
Firm age	0.166	0.108	0.222	0.091	0.239	0.119	0.215
Ln(employee)	-0.095	-0.661	0.518	-0.885	0.678	-0.564	0.423
State	2.932	1.130	4.759	0.459	5.257	1.392	4.511
Import	-2.479	-6.506	2.199	-7.389	3.922	-5.927	1.405
Innovation	-2.223	-3.846	-0.533	-4.323	-0.102	-3.616	-0.824
R & D	-2.021	-3.635	-0.341	-4.162	0.125	-3.404	-0.673
Industry_EE	-7.074	-10.217	-3.495	-10.983	-2.293	-9.812	-4.135
Industry_EP	0.031	-2.000	1.989	-2.632	2.771	-1.599	1.741
Industry_AA	-1.593	-3.533	0.409	-4.146	1.090	-3.228	0.068
Industry_MP	3.180	1.021	5.395	0.073	6.069	1.420	5.031
σ_ε	6.184	5.352	6.881	4.837	7.010	5.525	6.809

Table A4: Bootstrap estimated confidence intervals for Reg.4 in Table 4.5

Variable	Coeff.	Bounds of the bootstrap estimated confidence intervals					
		Lower 5%	Upper 5%	Lower 1%	Upper 1%	Lower 10%	Upper 10%
Constant	1.003	-2.199	4.463	-2.970	5.562	-1.725	3.783
Firm age	0.166	0.111	0.225	0.092	0.241	0.121	0.216
Ln(employee)	-0.234	-0.825	0.346	-1.003	0.510	-0.721	0.267
State	3.015	1.238	4.885	0.702	5.304	1.511	4.587
Export	-0.294	-2.767	2.346	-3.552	3.194	-2.464	1.951
Innovation	-2.119	-3.653	-0.557	-4.180	0.033	-3.436	-0.797
R & D	-1.896	-3.487	-0.394	-4.023	0.149	-3.219	-0.620
Industry_EE	-7.401	-10.471	-3.955	-11.529	-2.435	-10.036	-4.589
Industry_EP	0.120	-1.808	2.147	-2.622	2.681	-1.516	1.833
Industry_AA	-1.738	-3.730	0.362	-4.395	1.193	-3.365	-0.051
Industry_MP	3.158	1.009	5.510	0.197	6.000	1.387	5.100
σ_{ε}	6.098	5.302	6.763	4.839	6.892	5.471	6.696

Chapter 5

Epilogue

Over the last three decades, China has been experiencing important transition from a planned economy to a market-oriented one. As a result of the transition, China achieved a sustained high economic growth. What were the sources of this outstanding growth have gained considerable attention from researchers over the last thirty yeas. In economic growth theory, economic growth may come from capital (physical and human capital) accumulation or TFP growth. Many studies showed that the reform-induced TFP growth has contributed greatly to China's economic growth. e.g. McMillan et al. (1989), Lin (1992), and Fan et al. (2004) empirically showed that the reform has contributed significantly to China's agricultural growth. Dollar (1990) and Jefferson and Xu (1991) found that reform affected the individual performance and the overall performance of the industrial economy, substantially motivated enterprises to be more productive. However, TFP growth theoretically attributes to technical efficiency improvement (catching up) or technological progress (innovation). Thus, technical efficiency improvement probably was an important factor that contributes to China's outstanding economic growth during the reform period. Many researchers provided empirical works on the technical efficiency of China's economy (see the survey in Chapter 1). Considering the increasing regional disparities of China's economy and the increasing integration of China into the world economy, the previous chapters reflect some of the major concerns centered on the analysis of the regional technical efficiency of Chinese agriculture and Chinese SOEs, and on the analysis of the linkage between openness and the technical efficiency of Chinese manufacturing industry. In this chapter, the major findings of this dissertation are summarized and further extensions are discussed for future research.

5.1 Technical efficiency in Chinese agriculture

It was generally recognized that Chinese agriculture experienced inefficient production under the commune system during the pre-reform period. Then, China started the well-known economic reform by implementing the "Household Responsibility System" in the rural sector in 1978. The reform prompted an increase in agricultural production through productivity gains. Considering the fact that the levels of agricultural development differ across the various regions of China's vast geographical area, Chapter 2 presented a regional analysis of the technical efficiency of Chinese agriculture during the post-reform period.

In Chapter 2, based on a household-level data, the stochastic meta-frontier analysis approach enable us to analyze the technical efficiency of each region relative to the meta-frontier production function of rural China. The technical efficiency relative to the meta-frontier can be decomposed in to two parts—the technical efficiency relative to the regional frontier and the technology gap ratio of each regional frontier relative to the meta-frontier. The results show a negative relationship between the technology gap ratio and the regional technical efficiency for all regions except the Northwest. For example, the Southeast (developed region) has a higher technology gap ratio but has a lower regional technical efficiency; on the contrary, the Southwest (developing region) has a lower technology gap ratio but has a higher regional technical efficiency. This result suggests that the regions with high technology gap ratios (Southeast, Central, and North) should focus on the improvement of intra-region efficiency gaps among households. Efficiency improvement can be brought about through technology diffusion within region. On the other hand, the regions with low technology gap ratios (Northeast, Northwest, and Southwest) should pay more attention to the improvement of their agricultural production environment, since their regional frontiers are farther away from the meta-frontier than their counterparts. The agricultural production environment can be improved through infrastructural construction (road, irrigation, etc.) and human capital investment (education and training). In addition, the results indicate that it is the intra-regional technical efficiency rather than the technology gaps across regions that contributed to disparities of the meta-frontier technical efficiency across regions. Therefore, policy makers' effort should focus focus on the reduction of intra-regional disparities in efficiency among households. Reduction of regional efficiency disparities can be made through the diffusion of technology within regions. Finally, the results show that the meta-frontier technical efficiency improved remarkably from 1988 to 2002 for all regions, but the technology gap ratios changed slightly in the same period.

The determinants of regional technical efficiency and technology gap ratio were also investigated in the rest of Chapter 2. The regression results suggest that the working experience of agricultural labor and infrastructure have strong positive effect on both technical efficiency and technology gap ratio, while the illiteracy rate of a household, off-farm activities, lagging natural conditions (e.g. terrain variables), and lower economic development (e.g. impoverished) have negative effect on technical efficiency and technology gap ratio. Therefore, the improvements of technical efficiency and the outward shifts of regional frontiers can be brought about by increasing agricultural infrastructure investment and improving intangible human qualities in rural areas, especially in developing rural areas (Northwest and Southwest). Political status (e.g. township or village cadre) is found to have a positive effect on technical efficiency, but a negative effect on technology gap ratio. Therefore, the equality of social status among rural households is likely to improve technical efficiency and decrease technology gaps in rural China.

5.2 Technical efficiency and TFP change in Chinese SOEs

The same as the rural sector, Chinese SOEs also experienced inefficient production during the pre-reform period. Therefore, SOEs' reform was also an important part of the whole economic reform. Since SOEs' reform measures were unevenly implemented across regions, the aggregate level analysis may not reveal the reform effect on Chinese SOEs' productive performance across regions. Using a firm-level panel data, Chapter 3 investigated the regional technical efficiency, technology gaps, TFP change, and their determinants in Chinese SOEs during the early reform period. The stochastic meta-frontier production function approach is employed to fit the scores of meta-frontier technical efficiency and technology gap ratio of each SOEs in four regions. Further, TFP change is calculated using the estimated regional frontier parameters.

The estimation results show that the SOEs in Jiangsu (Eastern region) have the highest average technology gap ratio and higher TE^* value, but those in Shanxi (Western region) have the lowest average technology gap ratio. The findings suggest that more efforts should focus on the improvement of intra-region efficiency gaps among SOEs in the eastern regions of China, where efficiency improvement can be achieved by technology or knowledge diffusion within region. On the other hand, in the western regions, technical improvement measures, e.g., infrastructural investment, introduction of new technology and technicians, should be taken to narrow the technology gap between regional frontier and meta-frontier.

We also found that the TFP of the SOEs in our sample increased at annual rate of 1.72% from 1980 to 1994, and the TFP growth converged across regions. However, the growth rate is faster in the 1980s than that in the early 1990s. Besides, in the first ten years, both technological change (1.30%) and technical efficiency change (0.96%) contributed to TFP growth (2.26%), but in the whole period from 1980 to 1994, the TFP change is propelled mainly through technological progress (1.95%), and the technical efficiency change has an adverse effect (-0.21%).

The results of the determinant models show that the reform measures (management form dummies, bonus system) have positive effect on SOEs' TFP growth and technical efficiency improvement, but they are not found to have effect on the technology gap ratio level, namely, these reform measures had motivated the managers and employee in SOEs to be more efficient during the early reform period, but they did not decrease the technology gaps of SOEs among regions. In addition, Engineering technical personnel share that represents human capital level, and Export dummy that represents international competition, both of them are found to have strong positive effect on TFP growth, technical efficiency improvement.

5.3 Opening up and technical efficiency

It is well-know that one of the key reform initiatives in China is opening up to the world. As a result, China's economic takeoff during the reform period has been accompanied by rapid expansion of international trade and FDI. Chapter 4 employed a two-stage bootstrap DEA approach to investigate the impact of openness on the technical efficiency of manufacturing industry.

The results reveal a positive relationship between openness and technical efficiency in Chinese manufacturing industry during the transition period. Concretely speaking, the aggregate DEA efficiency scores of each sub-industry obtained by group-wise heterogeneous bootstrap procedure show that the Open firms are more technically efficient than Non-open firms. Further, this findings are confirmed by the two-stage bootstrap DEA model. Two international economic activities—import and export—that are supposed to represent openness level, have strong positive effect on firms' technical efficiency, but foreign capital is not found to have effect on firms' technical efficiency. Policy implication can be drawn from the results is that opening-up policy has played an important role in improving the technical efficiency of Chinese manufacturing industries. In addition, state share of a firm is found to have strong negative effect on firms' technical efficiency, which suggests that the more a firm is owned by state, the less the firm is technically efficient. Further, firms' learning and absorptive capacity, which is indicated by *Innovation* and *R&D* is found to have significantly positive effect on technical efficiency in this study. The result suggests that innovation and R&D can improve not only firms' technology level but also firms' technical efficiency level. We also find that firm size is positively related to technical efficiency, while firm age is negatively related to technical efficiency.

5.4 Research extensions

Although the results of this dissertation provide some insight into technical efficiency and productivity in Chinese rural sector and SOEs, and into openness impact on technical efficiency in Chinese manufacturing industry, there are several extensions for future work.

In Chapter 2 and 3, stochastic frontier production function is employed to estimate regional technical efficiency score and TFP change rate. However, as first discussed by Marschak and Andrews Jr (1944), ordinary estimation of production functions faces an endogeneity problem since there may be potential correlation between input levels and the unobserved firm-specific productivity shocks in the estimation of production function parameters. For example, firm will choose the level of inputs according to their own level of productivity. Therefore, dealing with unobserved production shock in stochastic frontier production function will be a possible research extension. Many approaches have been proposed to address this problem. Specially, Olley and Pakes (1996) use investment as a proxy for the unobserved productivity shocks, Levinsohn and Petrin (2003) use intermediate inputs to solve this simultaneity problem. Both Olley-Pakes and Levinsohn-Petrin approaches assumed that the error term in production function has two components—a transmitted productivity component that is correlated with input choices and an i.i.d. component that is uncorrelated with input choices. While in SFA model, the error term is also assumed to be separable in two components—an inefficiency term component and a white noise. Therefore, we cannot use Olley-Pakes or Levinsohn-Petrin approach directly in a stochastic frontier production function. Then, how to control the unobserved productivity shocks in a stochastic frontier production function will be a challenging task both in theoretical and empirical sides.

In Chapter 4, the two-stage bootstrap DEA approach is employed to investigate the openness effect on the technical efficiency of Chinese manufacturing industry. But we notice that the key explanatory variables—*Foreign, Import* and *Export*—seem to be endogenous explanatory variables. To the best of my knowledge, the current two-stage bootstrap DEA approach cannot solve the endogeneity problem. Therefore, the endogeneity problem in the two-stage bootstrap DEA model will also be a challenging task in the further research.

In addition, in Chapter 2 and 3, reform measures in rural sector and state-owned industry have been found to have positive effect on technical efficiency of farms and SOEs. As a result, the reform freed up a substantial amount of surplus labor in rural sector and state-owned industry. These surplus labor, who is called "Migrant Workers (Nongmingong)" or "Laid-off Workers (Xiagang Gongren)", have to move around in search of new employment opportunities. According to the study of Yang (2009), the number of the migrant workers in China increased from 30 million in 1978 to 246 million in 2007. Most of the migrant workers moved to the labor-intensive industries, which improved the comparative advantage of China in the world market. The mobility of labor in China's economy obviously affect the industry structure, consequently affect the productive performance of producer. Therefore, the study of the relationship of labor migrant and the technical efficiency change is another dimension of future research.

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