TECHNICAL AND ALLOCATIVE EFFICIENCY IN CHINESE MANUFACTURING INDUSTRIES

A Thesis in
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by
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ABSTRACT

Since the economic reform in the late 1970s, the Chinese enterprises have undergone a great transformation, changing from non-profit-seeking entities to profit-seeking entities. However, it is still unknown whether this transformation is complete. To answer this question, I evaluate the cost-minimizing behavior of 12 Chinese manufacturing industries using shadow prices and allocative efficiency. With survey data for large- and medium-firms, I find the average allocative efficiency to be only 67% of its potential. Capital and energy are found to be greatly overused, while labor is slightly underused compared to materials. Another goal of this study is to find whether there is significant difference in the performance of different industry sectors. This is measured by industry-specific technical efficiency. It is found that industries differ in their relative performance. Chemical, food, machinery and rubber industries present the highest technical efficiency, while electricity, petroleum and other industries present the lowest technical efficiency, with mining, metals, nonmetals, textiles and timber falling in-between. A correlation analysis reveals that technical efficiency is highly correlated with foreign capital intensity in the industry.
# TABLE OF CONTENTS

LIST OF FIGURES .................................................................................................................... vi

LIST OF TABLES ......................................................................................................................... vii

ACKNOWLEDGEMENTS ........................................................................................................... viii

Chapter 1 Introduction .............................................................................................................. 1

  1.1 Research question to address .......................................................................................... 2
  1.1 Background ..................................................................................................................... 3
    1.2.1 Historical review of Chinese economic reform ......................................................... 3
    1.2.2 Foreign Direct Investment in China ......................................................................... 5
    1.2.3 WTO entry .............................................................................................................. 6
  1.3 Objective of the thesis ...................................................................................................... 6

Chapter 2 Literature Review .................................................................................................... 8

  2.1 Cost efficiency in regulated industries .......................................................................... 9
    2.1.1 Cost efficiency, allocative efficiency and technical efficiency ............................... 9
    2.1.2 The shadow price approach and imperfect market conditions ......................... 10
  2.2 Efficiency studies on Chinese manufacturing industries ............................................. 12
  2.3 FDI in China .................................................................................................................. 15

Chapter 3 Model specification, Data Description and Estimation Results ......................... 17

  3.1 Model specification ........................................................................................................ 18
  3.2 Data description ............................................................................................................. 23
  3.3 Estimations ..................................................................................................................... 24
  3.4 Results ............................................................................................................................ 24
    3.4.1 Economies of scale and input demand elasticities ................................................. 25
    3.4.2 Shadow prices and allocative efficiency ............................................................... 26
    3.4.3 Relative technical efficiency in different manufacturing sectors ....................... 28
    3.4.4 Explaining the difference in technical efficiency in different manufacturing sectors .......................................................................................................................... 29
  3.5 Summary ......................................................................................................................... 29

Chapter 4 Efficiency Results and Policy Implications ......................................................... 38

  4.1 Understanding the efficiencies ....................................................................................... 39
    4.1.1 Allocative efficiency ............................................................................................... 39
    4.1.2 Technical efficiency ............................................................................................... 42
  4.2 Policy implications ......................................................................................................... 43
Chapter 5  Conclusion........................................................................................................44

5.1 Summary of empirical findings..................................................................................45
5.2 Suggestions for future studies ..................................................................................45

References:......................................................................................................................47
LIST OF FIGURES

Figure 3-1: The shadow price approach for measuring technical efficiencies and allocative efficiencies..............................................................30
LIST OF TABLES

Table 3-1: Characteristic statistics for output quantities, input prices and total expenditure ..31
Table 3-2: Number of observations in different sectors.........................................................32
Table 3-3: Estimation results from a translog shadow price model......................................33
Table 3-4: Sector-specific intercept estimates in the expenditure equation.............................34
Table 3-5: Morishima elasticity of substitution $\sigma_{ij}$ and own price elasticity $\varepsilon_{ij}$ ........35
Table 3-6: Technical efficiency, allocative efficiency and cost efficiency by sectors...............36
Table 3-7: Technical efficiency, mean capital share and mean foreign capital intensity for each industry and their correlation coefficients...............................................................37
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Chapter 1

Introduction
1.1 Research question to address

The reforms since 1979 changed the landscape of the Chinese economy leading to a transformation from a central planned economy to a market-oriented economy. Before the reform era, the Chinese enterprises had limited autonomy and did not operate under incentives such as profit maximization or cost minimization. Instead, they need to meet output quotas set by the government and play non-profit roles such as providing social welfare. During the reform era, great efforts were made to transform these enterprises into profit-seeking entities. Meanwhile, new profit-seeking entities were encouraged to enter the market. Substantial improvement was realized in the overall performance of the Chinese enterprises. However, it is still unknown whether the Chinese enterprises are completely transformed into profit-seeking or cost-minimizing entities comparable to those in the western economy. This study attempts to answer this question by evaluating their cost minimization behavior. Using a generalized cost function, I estimate shadow prices and allocative efficiency to measure how well the enterprises allocate their input uses according to market prices. The effects of incomplete enterprise transformation and distortionary factors such as regulations will be reflected in shadow prices and allocative efficiency.

Although most reform measures target enterprises in all industries in general, industry sectors may differ in their performances due to various reasons such as industry-specific policies. The second goal of this study is to examine whether there is significant difference in performance among different industry sectors. This is realized by estimating technical efficiency for each industry after adjusting for allocative inefficiency. Factors related to the performance difference are also investigated as a primary attempt to identify the underlying reasons.
This study has two goals: a) to evaluate cost-minimizing behavior; and b) to compare industry performances. These two goals are realized by measuring the average allocative efficiency and the industry-specific technical efficiency. These two efficiencies will be estimated simultaneous in a generalized cost function.

1.1 Background

1.2.1 Historical review of Chinese economic reform

The Chinese economy before the reforms in 1979 was well known for its central planned system. Under this system, prices were set by the central planning authority. The state-owned enterprise was the major ownership type. State-owned enterprises accounted for 78% of the economy and the remaining 22% was composed of collectively-owned enterprises (China Statistical Yearbook, various years). Both types of enterprises were under close control of either central authorities or local authorities. Governments were involved not only in the appointment of major positions inside the enterprises, but also in their operations (Groves et al, 1994). For example, government officials set the output quotas for the enterprises and decided their procurement. In addition, these enterprises did not operate as a profit maximization entity, but rather served multiple roles such as providing social welfare services. For example, many state enterprises were responsible for providing housing, schooling, medical care and retirement funds to their employees (Jefferson and Xu, 1991). In this sense, the enterprises prior to the reform era hardly behaved as profit-seeking entities similar to the firms in the western economy.

Early reforms since 1979 attempted to give incentives to the enterprises and increase their autonomy. Under these reform measures, the state enterprises were allowed to retain partial profit or excess revenue after meeting the output quotas set by the authorities (Otsuka et al, 1998). This
allowed them to follow price signals to adjust production. Meanwhile, prices were allowed to deviate from central planning and to be determined by markets gradually (Otsuka et al, 1998). A two-tier price system was used at the beginning, when the central planned price and the market price coexisted. Later, the central planned prices were completely replaced by prices set by the market. In addition, other forms of enterprises, such as private-owned enterprises and joint ventures were granted permission to engage in commercial activities (Otsuka et al, 1998). One particular form of collectively owned enterprises, township-village enterprises, developed quickly in the early 1990s. The township-village enterprises, as well as foreign investment, usually in the form of joint ventures, became strong competitors with state enterprises and challenged their monopoly position.

Although the reforms in the 1980s allowed more freedom for the state enterprises and they became more competitive than before, state enterprises still lagged behind township-village enterprises and joint ventures (Otsuka et al, 1998). Reforms in the late 1990s further restructured the state-owned enterprises by converting them into limited liability companies or joint stock share companies (Movshuk, 2004). The subsequent policy of “grasping the large and releasing the small” retained large state enterprises within state support while releasing the small- or medium-sized state enterprises for privatization or other ownership type transformation. These reform measures further promoted the transformation of the state enterprises into profit seeking entities and increased their competitiveness. By the end of the 1990s, the output from state enterprises dropped from 78% from 1978 to 28% in 1999, and ownership types other than state-owned enterprises or collectively-owned enterprises grew from zero to 44% of the economy (China Statistical Yearbook, various years).
1.2.2 Foreign Direct Investment in China

Foreign direct investment (FDI) is a major form of foreign capital in China. FDI increased dramatically after reforms, especially between the mid-1980s and the mid-1990s. Annual contractual FDI grew from $0.1 billion in 1979 to $45 billion in 1996 (China Statistics Yearbook, various years). China has become the largest recipient of FDI among developing countries since 1994. FDI is considered to be an important force driving the rapid growth of the Chinese economy, filling the capital shortage that the Chinese economy suffered at the beginning of its economic reform. In addition, FDI brought other benefits such as technology spillovers, training of human capital and increased degree of competition in the domestic market.

The policies for attracting foreign capital experienced roughly three stages (Fung et al, 2002). In the first stage, cautious and limiting policies lasted from the late 1970s to the early 1980s, during which foreign-invested firms were permitted for the first time. Special Economic Zones (SEZs) were set up in several coastal cities, where joint ventures using foreign capitals were permitted. FDI was granted legal status under these policies. However, many limitations remained. The fear of losing assets or worries about the political stability still prevented further investment. The second stage policies from the mid-1980s to the mid-1990s proactively encouraged FDI. More SEZs were set up in the coastal cities to attract FDI. Meanwhile, more measures were taken to encourage FDI, such as preferential tax rates, freedom to import inputs, and simplified licensing procedures. During this stage, FDI increased dramatically and reached its peak in 1996. In the third stage, the policies started to put emphasis on providing incentives for FDI that aligned well with the growth objective of the Chinese economy. Several sectors such as agriculture, hydropower, and those with advanced technologies were favored by these policies.

Early on, FDI came mostly from developing countries in Asia. This FDI was mainly targeted at labor intensive and export-oriented industries, such as the textile and footwear
industries. By the end of the 1990s, FDI from Europe, US and Japan increased. This FDI was targeted more at the domestic market rather than export (Lemoine, 2000). Sectors receiving the FDI were more likely to be capital-intensive.

1.2.3 WTO entry

China became a formal member of the World Trade Organization (WTO) in December 2001. WTO accession is considered to help integrate the Chinese economy into global markets (Rumbaugh and Blancher, 2004). Under the accession agreement, China agreed to lower its average tariff to 9.4% by 2005. In return, China is able to enjoy the privileges as a WTO member, such as the permanently most-favored-nation treatment. More access to the foreign market is predicted to have a positive effect on China’s export. For example, the removal of quotas on textile and footwear exports from China should boost its export of related products. On the other hand, WTO membership also means more legal and institutional adjustments in China.

WTO entry is also considered to bring more opportunities for FDI in China. Industries used to be heavily occupied by state enterprises such as banking, telecommunication and insurance, are now open to foreign capital under the WTO agreement. This will certainly bring more competition and help to restructure these industries. The discipline of the competitive market environment has the potential to lead to greater firm production efficiency.

1.3 Objective of the thesis

The major goals of this study are to examine the cost minimization behavior of Chinese manufacturing enterprises and to compare the relative performance of different industry sectors. These two goals are realized by measuring the overall allocative efficiency for all manufacturing
sectors and the average technical efficiency for enterprises in different sectors. A shadow price model is applied to estimate the two efficiencies. A dataset containing a survey of the large- and medium-sized enterprises in 12 manufacturing industries are analyzed for the years 1999-2004.

This thesis is organized as follows. Chapter 2 reviews the previous literature on methodologies to estimate efficiency, with special emphasis on Chinese manufacturing industries and FDI. Chapter 3 specifies the model and presents the estimation result. Chapter 4 discusses the policy implications of the findings. Chapter 5 concludes the study.
2.1 Cost efficiency in regulated industries

2.1.1 Cost efficiency, allocative efficiency and technical efficiency

The concept of production efficiency was originally proposed by Farrell (1957). The primal, production efficiency and its dual, cost efficiency (CE), are measured as the distance to the frontier firm, or the best practice firms. Cost efficiency can be further decomposed into technical efficiency (TE) and allocative efficiency (AE). Technical efficiency can be measured in two ways. The output-oriented efficiency measures the distance of the optimal output level at a given input level, while the input-oriented technical efficiency measures the distance of firm’s input use from the minimum input required for a given output level. Allocative efficiency, on the other hand, measures whether the resources are allocated in accordance with firms’ economic objective.

Under Farrell’s framework, production efficiencies and its dual counterpart, cost efficiency, have been the focus of empirical investigation. Among the different schools of methods developed, stochastic frontier method features econometric measurement of efficiency and allows for statistical testing. This approach can be further divided into the error-component approach and the shadow price approach. The error-component approach, initially developed by Aigner et al (1977) and Meeusen and van den Broeck (1977), treats the error term in a production function as a combination of a two-sided error and a one-sided error. The two-sided error can be either positive or negative, capturing idiosyncratic shocks. The one-sided error is always positive, capturing firms’ technical efficiency. This method is practical for estimation of technical efficiency and cost efficiency. However, when allocative efficiency is taken into account and treated as additional sets of errors, it greatly increases the complexity of the composite error, making it difficult to separate the three error terms. Although it is still tractable (Schmidt and
Lovell, 1979), it is computationally inconvenient. The shadow price approach, on the other hand, is more convenient in dealing with adding allocative efficiency and decomposing cost efficiency. It introduces a parameter rather than an error term to capture allocative efficiency. These parameters, also called the shadow price ratios, reflect the difference between the observed prices and a hypothetical set of prices under which the firm’s input use observed is an optimal decision. Compared with the error component approach, the shadow price approach is easier to implement when dealing with the decomposition of cost efficiencies.

2.1.2 The shadow price approach and imperfect market conditions

Shadow prices are defined to be a set of hypothetical prices that allow the marginal productivity ratios of inputs to equal the hypothetical price ratios. It captures the inequality relationship between the marginal product and the observed input price, and is usually conceived as a measure of inefficient decisions in resource allocation. However, there are multiple reasons for the existence of shadow prices, such as price uncertainty and unobserved input quality. Among these reasons, distortions caused by regulation can be an important factor resulting in the divergence between the real price and the shadow price. Consequently, the shadow price approach is applied extensively in the literature studying the behavior of firms in regulated or imperfect market conditions.

Lau and Yotopoulos (1971) are the first to use shadow prices to measure the performance of Indian farmers. They find that Indian farmers are poor but efficient in allocating resources. Toda (1976) uses the shadow price to study a cost function in Soviet manufacturing industries during 1958-1971, a period when the Soviet economy was under strong government intervention and firms’ behavior deviated from profit maximization or cost minimization rationales. By assuming shadow prices and analyzing a generalized cost function, Toda measures the shadow
price ratios, or the relative price efficiencies, in each of the eight manufacturing industries in Soviet Union and finds that the shadow price ratio for capital to labor is significantly lower than the observed price ratio for three out of the eight industries.

Similarly, Atkinson and Halvorsen (1984) evaluate the distortions in efficiency caused by government regulation in the U.S. electric power generation industry. They estimate a generalized cost function by assuming shadow prices. The assumption of cost minimization subject to market price is substituted by the assumption of cost minimization under shadow prices. They point out that the shadow price approach originally proposed by Lau and Yotopoulos (1971) can be considered to be a first-order Taylor approximation to the price distortion caused by general regulations. Since no specific form of regulation is specified in the constraint, firm behavior under a wide range of regulation can be studied with the shadow price approach. This allows the classical theoretical framework of cost minimization or profit maximization to be extended to firms whose behavior might be distorted.

Sickles et al (1986) uses shadow prices in a generalized profit function and the derived systems of equations to study the effect of deregulation on reducing the total cost and allocative distortions in the U.S. airline industry during 1970-1981. Shadow price are used to capture the price distortions and an error component is used to characterize the firm-specific heterogeneity. By specifying the shadow price ratio to be a function of time and applying the model to panel data, this model allows for tracing the effect of deregulation on price efficiencies. They find evidence that deregulation helps to reduce cost and to improve price efficiency in input allocation.

Although these studies all carried the idea of allocative efficiency, it was not until the paper by Atkinson and Cornwell (1994) that Farrell’s definition of allocative efficiency and technical efficiencies are formally blended with shadow prices. In this paper, they combine the shadow price approach to characterize allocative efficiency and use an error term to specify technical efficiency. The model is applied to panel data of U.S. airlines and the cost efficiency
and its two components are estimated. Balk (1997) and Kumbharkar (1997) further developed formulae to decompose cost efficiency into technical efficiency and allocative efficiency.

In studying Chinese manufacturing industries, one issue is the existence of vast distortions in the Chinese economy. For example, mobility of labor is restricted by the registration (Hu Kou) system (Cheng and Selden, 1994). Bank loans favor large state enterprises, even a high percentage of these loans are not performing (Bhattasali, 2002). Government has monopolistic power in leasing land to commercial users (Su, 2008). Electricity prices are regulated and kept below the production cost (Lam, 2005). These distortions not only make it essential to take allocative inefficiency into account when evaluating performances, but also add additional complexity in interpreting allocative efficiency. Allocative efficiencies in the Chinese economy can be a result of not only the management deficiencies, but also the distortionary factors in the economy. One advantage of the shadow price approach is that it does not have restrictions on the forms of distortion existing in the economy (Atkinson and Halvorsen, 1984). This, along with its computational convenience, makes it an appropriate tool to study the efficiencies in Chinese manufacturing industries. In this study, I use the shadow price approach to account for the allocative efficiency and a fixed effect to measure technical efficiency in Chinese manufacturing sectors.

2.2 Efficiency studies on Chinese manufacturing industries

Efficiency studies in Chinese manufacturing industries have been a focus for various reasons. It is important for evaluating the effectiveness of economic reform and identifying directions for future policy development. Accordingly, efficiency studies are closely related to the economic reforms around the study period. For example, some studies on efficiency in the late 1980s and early 1990s placed considerable emphasis on the township-village enterprises, which
were growing rapidly during that period. As foreign investment increased in the 1990s, studies attempted to estimate efficiencies for foreign invested firms and to evaluate their impact on local firms. Ownership types have been discussed extensively in the literature, since the ownership transformation is a focus of the economic reform throughout the time.

The iron and steel industry is an example of heavily studied industry for efficiency analysis. Wu (1995, 1996) finds an average of 66% technical efficiency by analyzing 87 iron and steel enterprises in 1988. He identifies several firm attributes related to technical efficiency, such as firm age. Kalirajan and Yong (1993) finds the efficiency averages 60% in the iron and steel industry in 1988. Zhang and Zhang (2001) uses the same stochastic frontier method, but with data for large- and medium-sized iron and steel enterprises in 1995. Their result shows an average of 54.6% for technical efficiency, with state enterprises having a 10% lower efficiency level compared to share-holding enterprises and foreign invested enterprises. Movshuk (2004) studies technical efficiency in the iron and steel industry from 1988 to 2000 and tries to differentiate technical efficiency change and technology change. Despite significant technological progress, he finds that technical efficiency does not increase but rather deteriorate in the middle of the study period. He argues that this might be a result of technical progress, as the gap between the best practice firm and average firm widens. His result is consistent with Wu (1995) who analyzes productivity growth and efficiency growth using provincial statistics from 1985-1991. He finds that the technical efficiency growth is relatively small or none, contributing little to the overall total factor productivity growth compared to technological progress. He also finds the average technical efficiency is 50% -60% for the state industry, rural industry and agricultural sectors.

Technical efficiency studies in other industries are relatively scarce. An example is Shi and Grafton (2009), who study technical efficiency in the coal industry in China during 2000 - 2005. In his study, technical efficiency averages 77.4%, but declines over the study period. He
argues that this may be due to technical progress which causes more dispersion between the frontier firm and poor performing firms.

Most studies on efficiencies in Chinese manufacturing industries only address technical efficiency. These studies neglect an important fact that input may not be allocated efficiently according to their marginal productivity, especially in transitioning economies. Only a few studies address allocative inefficiency. Murakami et al (1994) estimates both technical efficiency and allocative efficiency in Chinese garment industry in the early 1990s using survey data. The objective is to compare the performance of different ownership types, mainly state enterprises, urban collective, township-village, and joint venture. With allocative efficiency measured as an underpayment or overpayment to labor, he finds large excessive payment to labor as well as significantly low technical efficiency in the state enterprises and urban collectives. Joint venture and cooperative township-village are most efficient both in terms of technical efficiency and allocative efficiency. Parker (1995) attempts to evaluate firms’ general response to reform by testing whether the factor price inefficiencies converge. He finds that the hypothesis of price efficiency is strongly rejected. Although there is evidence suggesting improved price efficiency, no evidence supports convergence of factor price efficiency. Parker (1997) addresses the debate on the effectiveness of economic reform for the state enterprises. The sector for analysis is the construction industry over the years 1985-1991. He finds large firms having less price efficiencies than medium-sized firms, and that both profits and efficiency fall during the period studied. He argues that this could be a result of state enterprise autonomy that allows these enterprises to be less efficient. Parker (1999) uses the shadow price approach to study the wage efficiency in the machine building industry in China over the period 1980-1992, finding that although wages increase during the studied time period, the marginal productivity of labor stagnates. He concludes that wage increase is not due to increased labor productivity but rather loss of labor monopsony for the state enterprises.
All of the studies above evaluate the performance of the Chinese enterprises by estimating technical or allocative efficiencies. Most of them evaluate only technical efficiencies. Only a few studies address firms’ imperfect responses to price signals by assuming allocative inefficiency. Yet these studies are for the late 1980s to the early 1990s and the data used are limited in terms of industry or region. This study features comprehensive survey data from National Bureau of Statistics (NBS), containing large- and medium-firms for 12 manufacturing sectors and covering the period 1998-2004. This dataset allows more recent and more comprehensive evaluation of the overall performance of Chinese manufacturing sectors.

2.3 FDI in China

One important factor contributing to the fast economic growth in China is foreign direct investment. As the major form of foreign capital in China, FDI filled the capital shortage in the early stage of the reform. Meanwhile, it brought other benefits such as introducing technologies and increasing market competition. Economic studies on FDI in China go in different directions. One stream of literature examines GDP growth and income growth associated with FDI. Evidence is found for a positive correlation between high income growth and high foreign investment in the coastal regions (Dayal-Gulati and Husain, 2000, Lemoine, 2000). Liu et al (2002) evaluates the causal relationship between economic growth, export and FDI, and finds evidence for bi-directional causality. He concludes that economic growth, exports and FDI are mutually reinforcing factors.

Another stream of literature examines the spillover effect of FDI. Eden et al (1997) argue that FDI can spill over to the host country in several ways, including training of the local workers, demonstration of product, interaction with local suppliers and buyers, and increasing competition. The results of the studies examining the spillover effect of FDI in China are mixed. Young and
Lan (1997) find FDI only brings modest technology transfer. But a study by Cheung and Lin (2004) finds a positive impact of FDI on domestic patent application. Buckley et al (2002) examine the spillover effect of FDI on local manufacturing firms and finds that Chinese firms differ in their ability in absorbing spillover benefits. State-owned enterprises experience no benefits, while the collectively owned firms gain positive spillover effects.

Several studies focus on the relationship between FDI and productivity. Two hypotheses on FDI’s effect on productivity growth exist. One is that FDI may decrease its efficiency because lack of rivalry. The other is that domestic enterprises may increase their efficiency facing competition from FDI. Zhu and Tan (2000) find a positive correlation between FDI intensity and labor productivity. But they find no evidence for FDI as the cause of the labor productivity increase. Liu and Wang (2003) find FDI has a positive effect on total factor productivity in Chinese industrial sectors. However, it does not show that the growth of total factor productivity comes from local firms or FDI firms themselves.

Another stream of literature examines the determinants of FDI location. Sun et al (2002) analyze provincial data and find that the determinants of FDI change through the time. FDI before 1991 has different features than FDI after 1991. In the early stage, there is no significant relationship between FDI and provincial GDP, while in the later stage there is a positive correlation between the two. Wage has a positive relationship with FDI in the first stage, while it has a negative relationship in the second stage.

FDI is generally considered to play a positive role in the Chinese economy. Yet discrepancies exist in the empirical studies investigating the mechanism of how FDI benefits host countries. In this study, I investigate the link between FDI and technical efficiencies in different industries as an attempt to understand the underlying factors causing the difference in technical efficiency.
Chapter 3

Model specification, Data Description and Estimation Results
In this chapter, the shadow price model is used to estimate average allocative efficiencies for all industries and technical efficiency for each industry. The econometric model is specified in 3.1, followed by a description of dataset in 3.2 and estimation details in 3.3. Section 3.4 presents the results.

3.1 Model specification

The estimated model follows the shadow price model presented in Kumbhakar and Lovell (2000). Figure 3-1 illustrates the basic idea of the shadow price model. L(y) is the input requirement set for output level y. Point D is the cost efficient input bundle for the output level y and the observed input prices, \( w_1 \) and \( w_2 \). The observed input use, point A (\( x_1, x_2 \)), is neither on the isoquant for output level y, nor at the tangency of the isocost line and the isoquant. So point A is neither technical efficient nor allocative efficient. To measure technical efficiency, consider a scalar \( \varphi \) such that the contracted input use \( C(\varphi x_1, \varphi x_2) \) is on the isoquant for y. \( \varphi \) is called the input-oriented technical efficiency whose value is equal to \( \frac{OC}{OA} \). To measure allocative efficiency, consider a scalar \( \theta \), such that the isocost line with the slope \( \frac{\theta w_1}{w_2} \) is tangent to the isoquant for y at point C. \( \theta \) is called shadow price ratio, while \( w_1^* = \theta w_1 \) is called shadow price. The tangency at point C implies that the contracted input use C is allocatively efficient under the shadow price. Allocative efficiency is then measured as the ratio of the lowest cost under the real prices \( w_1 \) and \( w_2 \) (the cost for point D) to the lowest cost under the shadow prices (the cost for point C). In the graph, allocative efficiency equals \( \frac{OB}{OC} \).
Mathematically, this model can be expressed as follows. For a firm with N inputs, the shadow price for input n in firm i, \( w_{in}^* \), is the product of shadow price ratio \( \theta_n \) and the observed price \( w_{in} \).

\[
(3.1) \quad w_{in}^* = \theta_n \times w_{in}
\]

where \( \theta_n \) is positive with its value ranging from zero to one. \( \theta_n > 1 \) indicates input n is relatively underused compared to the standard input. \( \theta_n < 1 \) indicates input n is relatively overused. \( \theta_n = 1 \) implies that use of input n is allocatively efficient. Note that \( \theta_n \) is a coefficient reflecting relative efficiency compared to an arbitrarily selected input as a standard of measure.

Technical inefficiency can be specified to be either output-oriented or input-oriented. For cost minimization, the input-oriented approach has a greater computational advantage than the output approach\(^1\) (Kumbhakar and Lovell 2000). Following this idea, I use the input-oriented technical inefficiency. For all sectors, I assume a single production frontier \( f(x; \beta) \) which is specified by the parameter \( \beta \) and represents the maximal output level given input level at the observed input level, \( x \). Then the observed firm’s output level should be no more than the maximum output level at \( x \).

\[
(3.2) \quad y_i \leq f(x_i; \beta)
\]

This inequality relationship can be transformed into an equality relationship by using technical efficiency \( \varphi \).

\[
(3.3) \quad y_i = f(\varphi, x_i; \beta)
\]

---

\(^1\) The input-oriented technical efficiency enters only the expenditure function as an intercept term, while the output-oriented technical efficiency enters both the expenditure function and the cost share equations in a nonlinear form. Therefore, the model with input-oriented technical efficiency is easier to estimate. For more details in the output-oriented approach, see Kumbhakar and Lovell (2000).
where \( \varphi_j \) is defined to be the input-oriented technical efficiency for firms in industry \( j \). Then the contracted input use \( \varphi_j x_i \) and output level \( y_i \) for firm \( i \) in industry \( j \) should satisfy the production function.

The shadow cost function is defined to be the minimum cost at price \( \frac{w^*_i}{\varphi_j} \) and output level \( y_i \).

\[
(3.4) \quad c \left( \frac{w^*_i}{\varphi_j}, y_i; \beta \right) = \min_{\varphi_i, \varphi_j, \varphi^*_i, \varphi^*_j} \left( \frac{w^*_i}{\varphi_j} \right)^T \varphi_j x_i : f \left( \varphi_j x_i; \beta \right) = y_i
\]

According to Shephard’s Lemma and the property of being homogeneous of degree one on prices for cost functions, the cost minimization input use \( \varphi_j x_{in} \) can be expressed as

\[
(3.5) \quad \varphi_j x_{in} = \frac{\partial c \left( w^*_i, y_i; \beta \right)}{\partial w^*_{in}}
\]

Rearrange Eq. (3.5), the observed input use can be expressed with a shadow cost share function, a shadow cost function and technical efficiency.

\[
(3.6) \quad x_n \left( w^*_i, y_i; \beta \right) = \frac{1}{\varphi_j} \frac{\partial c \left( w^*_i, y_i; \beta \right)}{\partial w^*_{in}} = \frac{S_n \left( w^*_i, y_i; \beta \right) c \left( w^*_i, y_i; \beta \right)}{\varphi_j w^*_{in}}
\]

The observed total expenditure can be expressed as sum of the expenditure on each input.

Substituting \( x_i \) in the total expenditure equation with Eq (3.6) yields

\[
(3.7) \quad E_j = \sum_{n=1}^{N} w^*_{in} x_{in} = \sum_{n=1}^{N} \frac{S_n \left( w^*_i, y_i; \beta \right) c \left( w^*_i, y_i; \beta \right)}{\varphi_j \varphi^*_{in}} c \left( w^*_i, y_i; \beta \right) = \frac{c \left( w^*_i, y_i; \beta \right)}{\varphi_j} \sum_{n=1}^{N} \frac{S_n \left( w^*_i, y_i; \beta \right)}{\varphi^*_{in}} \theta_n
\]
Eq. (3.7) allows expressing the observed total expenditure with a shadow cost function, $c\left(w_i^*, y_i; \beta\right)$, shadow cost share functions for each input, $S_n\left(w_i^*, y_i; \beta\right)$, technical efficiency, $\varphi_j$, and shadow price ratios, $\theta_n$.

Further, the observed cost share can also be expressed with the shadow cost share function for each input and shadow price ratios. This is realized by dividing the expenditure on input $i$ by the total expenditure and substituting the observed input use by Eq. (3.6) and the observed expenditure by Eq. (3.7).

$$S_n^i = \frac{w_{in} x_{in}}{E_i} = \frac{S_n\left(w_i^*, y_i; \beta\right)c\left(w_i^*, y_i; \beta\right)}{\varphi_j \theta_n} = \frac{\theta_n^{-1} S_n\left(w_i^*, y_i; \beta\right)}{\sum_{k=1}^{N} \theta_k^{-1} S_k\left(w_i^*, y_i; \beta\right)}$$

To allow more flexibility in the substitution patterns, I specify a translog functional form for the shadow cost function. This yields the shadow cost function to be

$$\ln c\left(w_i^*, y_i; \beta\right) = \alpha + \sum_n \beta_n \ln w_n^* + \frac{1}{2} \sum_n \sum_{k, l} \beta_{nl} \ln w_n^* \ln w_l^* + \beta_y \ln y_i + \frac{1}{2} \beta_{y^2} (\ln y_i)^2 + \ln y \sum_n \beta_{yn} \ln w_n^*$$

Accordingly, the shadow cost share function can be derived by applying Shephard’s lemma.

$$S_n\left(w_i^*, y_i; \beta\right) = \frac{\partial \ln c\left(w_i^*, y_i; \beta\right)}{\partial \ln w_{in}^*} = \beta_n + \sum_k \beta_{nk} \ln w_{ik}^* + \beta_{yn} \ln y_i$$

Substituting Eq. (3.9) and Eq. (3.10) into Eq. (3.7) and Eq. (3.8) yields the observed total expenditure equation and the observed cost share equations to estimate.
\[
\ln E_i = \alpha + \sum_n \beta_n \ln w^{*}_{in} + \frac{1}{2} \sum_n \sum_k \beta_{nk} \ln w^{*}_{nk} + \beta_i \ln y_i + \frac{1}{2} \beta_{yy} (\ln y_i)^2 + \ln y_i \sum_n \beta_i \ln w^{*}_{in} \\
+ \ln \left( \sum_{n=1}^{N} \theta_n^{-1} \left( \beta_n + \sum_k \beta_{nk} \ln w^{*}_{nk} + \beta_{yn} \ln y_i \right) \right) - \ln \varphi_j
\]

\[
S^{a}_{in} = \frac{\theta^{-1}_n S_n \left( w^{*}_i, y_i; \beta \right)}{\sum_{k=1}^{N} \theta^{-1}_k S_k \left( w^{*}_i, y_i; \beta \right)} = \frac{\theta^{-1}_n \left( \beta_n + \sum_l \beta_{nl} \ln w^{*}_{in} + \beta_{yn} \ln y_i \right)}{\sum_{k=1}^{N} \theta^{-1}_k \left( \beta_k + \sum_l \beta_{kl} \ln w^{*}_{ik} + \beta_{yn} \ln y_i \right)}
\]

In addition, the cost function needs to satisfy the property of being homogeneous of degree one on input prices. The homogeneity constraints are imposed as:

\[
(3.13) \quad \sum_n \beta_n = 1 \\
\sum_n \beta_{nk} = 0 \quad \text{for each } k = 1, \ldots, N \\
\sum_n \beta_{yn} = 0
\]

The symmetry constraints are imposed as:

\[
(3.14) \quad \beta_{nk} = \beta_{kn} \text{ for any } n = 1, \ldots, N \text{ and } k = 1, \ldots, N
\]

As long as the symmetry constraints and N-1 out of the N constraints of \(\sum_n \beta_{nk} = 0\) are satisfied, the remaining constraint will hold. Therefore, only N-1 out of the N constraints of \(\sum_n \beta_{nk} = 0\) will be imposed during estimation.
3.2 Data description

The dataset used in the study is firm-level survey data from China’s National Bureau of Statistics (NBS), which is made available through an ongoing research collaboration between Penn State University, Brandeis University and NBS. It contains survey data for large and medium-sized enterprises from 12 manufacturing sectors over the period from 1999 to 2004. The 12 manufacturing sectors include chemicals, electricity, food, machinery, metals, mining, nonmetals, petroleum, timber, rubber, textiles and other industries.

Input prices are calculated as the ratio of input value to physical quantity. Except for the price of materials, all input prices are calculated similar to Fisher-Vanden and Jefferson (2008). The price of capital is computed as value added less salary payment and welfare benefit, divided by the total value of fixed assets. The price of labor is calculated as the sum of salary payment and welfare benefit divided by total employment. The price of energy is calculated by dividing total value of expenditure on energy by total energy consumed in the unit of standard coal equivalent units. The price of materials is calculated as the weighted average of industry prices using input-output shares from China’s national accounts.

The prices for capital, labor, and energy are firm-specific. However, the price for materials is the same across firms in the same industry. Table 3-1 produces summary statistics for the output quantity, input prices and total expenditure.

Some observations contain missing values and these observations are deleted. This results in a total of 7402 observations in the sample. The number of observations for each sector is listed in Table 3-2.
3.3 Estimations

Estimation of the shadow prices by industries presented difficulties as estimation for each industry fails to converge. This might be a result of limited variation in the price of materials, or limited number of observations in each sector. Consequently, a single frontier for all the 12 manufacturing industries is estimated. The shadow price ratio is assumed to be uniform across different sectors and constant during the studied period. Technical efficiency is allowed to vary for different sectors but stays constant during the studied period. Industrial dummies are added in the expenditure equations to capture technical efficiency.

The equations to estimate are the observed expenditure equation, Eq. (3.11), and the three cost share equations, Eq. (3.12). In this study, the four inputs are capital, labor, energy and materials. To avoid multicollinear residuals, the share equation for labor is dropped. The three shadow cost share equations estimated are associated with capital, energy and materials. The homogeneity constraints and the symmetry constraints defined in Eq. (3.13) and Eq. (3.14) are imposed. Since all four equations are nonlinear, estimation is carried out using Nonlinear Seemingly Unrelated Regression in STATA.

3.4 Results

Both nonlinear estimation iterations and FGLS iterations converge successfully. A total of 29 parameters are estimated simultaneously, including 14 frontier coefficients, 3 shadow price ratio coefficients and 12 industry-specific intercepts. The frontier parameters and the shadow prices are listed in Table 3-3 and the industry-specific intercepts are listed in Table 3-4.

The $R^2$ for the expenditure equation and the three cost share equations are 0.559, 0.800, 0.637 and 0.941, respectively, suggesting the model is a good fit overall. All the cost frontier
parameters are significant except for $\beta_y$. Changes in different combinations of the shadow cost share equations do not change the estimated coefficients and their significance if the convergence is successful. However, excluding the cost share equation for capital does cause the estimation fail to converge at the FGLS stage.

### 3.4.1 Economies of scale and input demand elasticities

Economies of scale reflect whether firms are operating at their optimal scale. Increasing or decreasing returns to scale can be reflected by cost elasticities less than one or greater than one. For the shadow price approach, there are two cost elasticities to measure: the actual cost elasticity and the shadow cost elasticity (Atkinson and Halvorsen 1984). These two elasticities reflect the returns to scale observed either from an econometrician’s point of view, or from the firm’s point of view, who observes its shadow prices. The actual cost elasticities can be calculated by taking the derivative of the actual expenditure with respect to output, while the shadow cost elasticity can be calculated by taking the derivative of the shadow cost function with respect to output. The actual cost elasticity is calculated as follows:

\[
\frac{\partial \ln E_i}{\partial \ln y_i} = \beta_y + \beta_{yy} \ln y_i + \sum_n \beta_{ny} \ln \theta_n w_n + \sum_n \theta_n^{-1} \beta_{ny} \theta_n^{-1} S_{in}
\]

The shadow cost elasticity is calculated as:

\[
\frac{\partial \ln c_i}{\partial \ln y_i} = \beta_y + \beta_{yy} \ln y_i + \sum_n \beta_{ny} \ln \theta_n w_n
\]

The actual cost elasticity ranges from 0.64 to 1.12, with an average of 0.85, while the shadow cost elasticity ranges from 0.68 to 1.17, with an average of 0.89. Both average cost elasticities are less than one, suggesting the enterprises are operating at increasing returns to scale.
on average. $\beta_{yx}$ is significantly greater than zero, suggesting a non-homothetic production function and the scale economies decrease as output increases.

Input demand elasticities are calculated by following the same method as Atkinson and Halvorsen (1984). The Morishima elasticities of substitution, $\sigma_{ij}$, and own price elasticity, $\varepsilon_{ii}$, are listed in Table 3-5. The own price elasticities for capital, labor and energy are close, with values ranging from 0.6 to 0.7. The price elasticity for materials is relatively low, at 0.1, suggesting firms are less sensitive to the price of materials than the other inputs. The Morishima elasticities $\sigma_{LK}$ and $\sigma_{LE}$ are relatively large, suggesting greater substitution for labor versus capital, and labor versus energy. The Morishima elasticities $\sigma_{MK}$ and $\sigma_{KE}$ have the lowest scores, suggesting that capital versus materials, and capital versus energy are complements. These results are not surprising since more capital input, such as machine, usually needs more energy to operate, and more labor can serve as a substitute for machine as well as energy.

3.4.2 Shadow prices and allocative efficiency

The shadow price ratios are presented in Table 3-3. The two shadow price ratios, $\theta_e$ and $\theta_m$, are statistically significant. The variance for the shadow price ratio for labor $\theta_e$ is not generated. Generally, $\theta < 1$ indicates overuse, while $\theta > 1$ implies underuse. Since the shadow price ratio here only reflects the relative price efficiency for each input rather than the absolute efficiency, I need to take the standard input into account. Here, capital is standardized to be 1 during estimation. However, the historical evidence suggests that the capital used in Chinese enterprises, especially in state enterprises, is not usually efficient. For example, government subsidies or preferential loans from national banks allow the state enterprises to gain capital more easily even when they are making losses. Material use, on the other hand, is relatively stable.
From Parker’s (1999) estimates, the shadow price ratio for materials has little change, with its value around 10% over the 12 year period. Therefore, I use materials as a standard and recalculate the shadow price ratios to be $\frac{\theta_k}{\theta_m} = 0.023$, $\frac{\theta_l}{\theta_m} = 1.46$, $\frac{\theta_e}{\theta_m} = 0.014$. These results suggest that energy and capital are greatly overused, while labor is slightly underused, if materials are assumed used efficiently.

To evaluate the overall efficiency loss as a result of input allocation deviated from cost-minimizing input allocation, allocative efficiency is calculated based on shadow price ratios. Using the fact that cost efficiency is the product of allocative efficiency and technical efficiency, allocative efficiency can be calculated by dividing cost efficiency by technical efficiency (Kumbhakar and Lovell 2000). The expression for calculating allocative efficiency is

\[
\ln AE_i = \sum_n \beta_n \ln \theta_n + \sum_n \sum_k \beta_{nk} \ln w_{nk} \ln \theta_k + \frac{1}{2} \sum_n \sum_k \beta_{nk} \ln \theta_n \ln \theta_k + \ln y_i \sum_n \beta_{yn} \ln \theta_n \\
+ \ln \left( \sum_{n=1}^N \theta_n^{-1} \left( \beta_n + \sum_{nk} \beta_{nk} \left( \ln w_{nk} + \ln \theta_k \right) + \beta_{yn} \ln y_i \right) \right)
\]

The averaged allocative efficiencies for each industry are listed in table 3-6. The average allocative efficiency for all industries is 0.67. Notice that there is no great variation among the allocative efficiencies for different industries. This is due to the fact that the shadow price ratios $\theta_1$, $\theta_e$, $\theta_m$ are the same for all observations. The variations in the calculated allocative efficiency mainly come from different input prices for each observation.

---

2 The formula in Kumbharkar and Lovell (2000, P234) is incorrect. Following the book, Eq. (6.2.32) is based on Eq. (6.2.28) and Eq. (6.2.30). But Eq. (6.2.32) will not hold unless the nonlinear term $\sum_{n=1}^N \theta_n^{-1} \left( \beta_n + \sum_{nk} \beta_{nk} \left( \ln w_{nk} + \ln \theta_k \right) + \beta_{yn} \ln y_i \right)$ is added to the right-hand-side of Eq. (6.2.32). Accordingly, allocative efficiency should be calculated as the third term in Eq. (6.2.32) plus this nonlinear term.
3.4.3 Relative technical efficiency in different manufacturing sectors

Technical efficiency $\varphi_j$ is captured in the industry-specific intercept and can be recovered by taking the exponential of the difference between the intercept for a particular industry and that of the most efficient industry (The industry with the minimum intercept).

\[ (3.18) \quad TE_j = \varphi_j = e^{u_0-u_j} \]

where $u_j$ is the intercept for industry $j$ in the cost function and $u_0 = \min \{u_j\}, \ j = 1 \sim 12$

Table 3-4 lists all the sector-specific intercept estimates and their significance levels. The chemical industry has the minimum intercept and is normalized to be zero in the table. This implies that the chemical industry achieves the highest level of technically efficiency. The intercepts for other industries listed in the table are the relative values compared to the chemical industry. Most of the intercept estimates for these industries are significant. Only three sectors, food, machinery and rubber, have intercepts not significantly different than zero, indicating that the three sectors are nearly as technically efficient as the chemical industry. Based on the calculated technical efficiency and allocative efficiency, cost efficiency can be computed as their product. Table 3-6 lists the estimated technical efficiencies and cost efficiencies for each industry.

Based on their technical efficiencies, these sectors can be roughly divided into three groups. High efficiency group has TE close to 1, including chemicals, food, machinery and rubber. The second group has TE between 0.5 and 0.9, which includes mining, metals, nonmetals, textiles and timber. The third group has TE lower than 0.5, which includes electricity, petroleum and other industries.
3.4.4 Explaining the difference in technical efficiency in different manufacturing sectors

To further understand the nature of the variations in technical efficiency in different manufacturing industries, the correlation coefficient between the technical efficiency and capital share or foreign capital intensity is calculated and listed in Table 3-7. It is shown that there is no significant correlation between capital share and technical efficiency. However, the correlation between foreign capital intensity and technical efficiency is high, at 0.75. Using the three-group ranking rather than number generates a similar correlation. This indicates that there is close connection between foreign capital intensity and the technical efficiency variations in different manufacturing sectors. Sectors with high foreign capital tend to exhibit higher efficiency.

3.5 Summary

In this chapter, I present the econometric models, the data and the estimation results. The estimation result suggests overall increasing returns to scale for Chinese manufacturing industries. The estimates for shadow price ratios indicate that capital and energy are greatly overused, and that labor is relatively underused compared to materials. Average allocative efficiency is 0.67. Technical efficiency differs across industries, ranging from 0.36 to 1. A correlation analysis reveals a positive relationship between foreign capital intensity and technical efficiency. In the next chapter, I will discuss these results and the policy implications.
Figure 3-1: The shadow price approach for measuring technical efficiencies and allocative efficiencies.
Table 3-1: Characteristic statistics for output quantities, input prices and total expenditure.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output (Million yuan)</td>
<td>0.821</td>
<td>2.82</td>
<td>0.005</td>
<td>169.8</td>
</tr>
<tr>
<td>Price of capital</td>
<td>0.474</td>
<td>0.833</td>
<td>0.000</td>
<td>38.7</td>
</tr>
<tr>
<td>Price of labor</td>
<td>17.3</td>
<td>14.3</td>
<td>0.195</td>
<td>181.6</td>
</tr>
<tr>
<td>Price of energy</td>
<td>1.18</td>
<td>2.11</td>
<td>0.005</td>
<td>51.5</td>
</tr>
<tr>
<td>Price of materials</td>
<td>8.97</td>
<td>0.38</td>
<td>7.81</td>
<td>11.91</td>
</tr>
<tr>
<td>Total expenditure</td>
<td>0.472</td>
<td>1.08</td>
<td>0</td>
<td>17.5</td>
</tr>
</tbody>
</table>
Table 3-2: Number of observations in different sectors

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total observations</th>
<th>Percentage of total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemicals</td>
<td>1481</td>
<td>20.0</td>
</tr>
<tr>
<td>Electricity</td>
<td>1030</td>
<td>13.9</td>
</tr>
<tr>
<td>Food</td>
<td>523</td>
<td>7.1</td>
</tr>
<tr>
<td>Machinery</td>
<td>769</td>
<td>10.4</td>
</tr>
<tr>
<td>Metals</td>
<td>526</td>
<td>7.1</td>
</tr>
<tr>
<td>Mining</td>
<td>485</td>
<td>6.6</td>
</tr>
<tr>
<td>Nonmetals</td>
<td>946</td>
<td>12.8</td>
</tr>
<tr>
<td>Other industries</td>
<td>289</td>
<td>3.9</td>
</tr>
<tr>
<td>Petroleum</td>
<td>170</td>
<td>2.3</td>
</tr>
<tr>
<td>Rubber</td>
<td>165</td>
<td>2.2</td>
</tr>
<tr>
<td>Textiles</td>
<td>674</td>
<td>9.1</td>
</tr>
<tr>
<td>Timber</td>
<td>344</td>
<td>4.6</td>
</tr>
<tr>
<td>Total</td>
<td>7402</td>
<td>100</td>
</tr>
</tbody>
</table>
Table 3-3: Estimation results from a translog shadow price model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient estimate</th>
<th>Standard error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{l}$</td>
<td>0.548</td>
<td>0.063</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{e}$</td>
<td>0.015</td>
<td>0.002</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{m}$</td>
<td>0.416</td>
<td>0.066</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{ll}$</td>
<td>0.027</td>
<td>0.004</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{le}$</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{lm}$</td>
<td>-0.028</td>
<td>0.004</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{ee}$</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{em}$</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{mm}$</td>
<td>0.032</td>
<td>0.004</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{ly}$</td>
<td>-0.031</td>
<td>0.004</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{ey}$</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{my}$</td>
<td>0.032</td>
<td>0.004</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\theta_{l}$</td>
<td>63.5</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\theta_{e}$</td>
<td>0.593</td>
<td>0.071</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\theta_{m}$</td>
<td>43.9</td>
<td>6.25</td>
<td>0.000**</td>
</tr>
<tr>
<td>$\beta_{y}$</td>
<td>0.205</td>
<td>0.121</td>
<td>0.091</td>
</tr>
<tr>
<td>$\beta_{yy}$</td>
<td>0.057</td>
<td>0.009</td>
<td>0.000**</td>
</tr>
</tbody>
</table>
Table 3-4: Sector-specific intercept estimates in the expenditure equation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient estimate</th>
<th>Standard error</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity</td>
<td>0.707</td>
<td>0.051</td>
<td>0.000**</td>
</tr>
<tr>
<td>Food</td>
<td>0.002</td>
<td>0.057</td>
<td>0.979</td>
</tr>
<tr>
<td>Machinery</td>
<td>0.026</td>
<td>0.052</td>
<td>0.613</td>
</tr>
<tr>
<td>Metals</td>
<td>0.448</td>
<td>0.058</td>
<td>0.000**</td>
</tr>
<tr>
<td>Mining</td>
<td>0.568</td>
<td>0.059</td>
<td>0.000**</td>
</tr>
<tr>
<td>Nonmetals</td>
<td>0.110</td>
<td>0.004</td>
<td>0.000**</td>
</tr>
<tr>
<td>Other industries</td>
<td>0.885</td>
<td>0.081</td>
<td>0.000**</td>
</tr>
<tr>
<td>Petroleum</td>
<td>1.027</td>
<td>0.091</td>
<td>0.000**</td>
</tr>
<tr>
<td>Rubber</td>
<td>0.010</td>
<td>0.093</td>
<td>0.917</td>
</tr>
<tr>
<td>Textiles</td>
<td>0.253</td>
<td>0.052</td>
<td>0.000**</td>
</tr>
<tr>
<td>Timber</td>
<td>0.194</td>
<td>0.067</td>
<td>0.004**</td>
</tr>
</tbody>
</table>
Table 3-5: Morishima elasticity of substitution $\sigma_{ij}$ and own price elasticity $\varepsilon_{ii}$.

<table>
<thead>
<tr>
<th></th>
<th>Capital</th>
<th>Labor</th>
<th>Energy</th>
<th>Materials</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital</td>
<td>-0.595</td>
<td>0.609</td>
<td>0.406</td>
<td>0.598</td>
</tr>
<tr>
<td>Labor</td>
<td>1.07</td>
<td>-0.661</td>
<td>1.039</td>
<td>0.794</td>
</tr>
<tr>
<td>Energy</td>
<td>0.576</td>
<td>0.703</td>
<td>-0.695</td>
<td>0.698</td>
</tr>
<tr>
<td>Materials</td>
<td>0.444</td>
<td>0.779</td>
<td>0.645</td>
<td>-0.139</td>
</tr>
</tbody>
</table>
Table 3-6: Technical efficiency, allocative efficiency and cost efficiency by sectors

<table>
<thead>
<tr>
<th>Sector</th>
<th>Technical Efficiency</th>
<th>Average allocative efficiency</th>
<th>Average cost efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemicals</td>
<td>1</td>
<td>0.681</td>
<td>0.681</td>
</tr>
<tr>
<td>Electricity</td>
<td>0.493</td>
<td>0.637</td>
<td>0.314</td>
</tr>
<tr>
<td>Food</td>
<td>0.999</td>
<td>0.665</td>
<td>0.664</td>
</tr>
<tr>
<td>Machinery</td>
<td>0.974</td>
<td>0.689</td>
<td>0.672</td>
</tr>
<tr>
<td>Metals</td>
<td>0.639</td>
<td>0.707</td>
<td>0.452</td>
</tr>
<tr>
<td>Mining</td>
<td>0.567</td>
<td>0.684</td>
<td>0.387</td>
</tr>
<tr>
<td>Nonmetals</td>
<td>0.896</td>
<td>0.653</td>
<td>0.586</td>
</tr>
<tr>
<td>Other industries</td>
<td>0.413</td>
<td>0.606</td>
<td>0.250</td>
</tr>
<tr>
<td>Petroleum</td>
<td>0.358</td>
<td>0.674</td>
<td>0.241</td>
</tr>
<tr>
<td>Rubber</td>
<td>0.990</td>
<td>0.692</td>
<td>0.686</td>
</tr>
<tr>
<td>Textiles</td>
<td>0.776</td>
<td>0.681</td>
<td>0.529</td>
</tr>
<tr>
<td>Timber</td>
<td>0.824</td>
<td>0.674</td>
<td>0.555</td>
</tr>
<tr>
<td>Average</td>
<td>0.793</td>
<td>0.670</td>
<td>0.533</td>
</tr>
</tbody>
</table>
### Table 3-7: Technical efficiency, mean capital share and mean foreign capital intensity for each industry and their correlation coefficients.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Technical Efficiency</th>
<th>Capital share</th>
<th>Foreign capital intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemicals</td>
<td>1</td>
<td>0.142</td>
<td>0.033</td>
</tr>
<tr>
<td>Electricity</td>
<td>0.493</td>
<td>0.217</td>
<td>0.018</td>
</tr>
<tr>
<td>Food</td>
<td>0.999</td>
<td>0.300</td>
<td>0.112</td>
</tr>
<tr>
<td>Machinery</td>
<td>0.974</td>
<td>0.162</td>
<td>0.137</td>
</tr>
<tr>
<td>Metals</td>
<td>0.639</td>
<td>0.139</td>
<td>0.029</td>
</tr>
<tr>
<td>Mining</td>
<td>0.567</td>
<td>0.204</td>
<td>0.000</td>
</tr>
<tr>
<td>Nonmetals</td>
<td>0.896</td>
<td>0.159</td>
<td>0.057</td>
</tr>
<tr>
<td>Other industries</td>
<td>0.413</td>
<td>0.248</td>
<td>0</td>
</tr>
<tr>
<td>Petroleum</td>
<td>0.358</td>
<td>0.107</td>
<td>0.025</td>
</tr>
<tr>
<td>Rubber</td>
<td>0.990</td>
<td>0.168</td>
<td>0.163</td>
</tr>
<tr>
<td>Textiles</td>
<td>0.776</td>
<td>0.154</td>
<td>0.042</td>
</tr>
<tr>
<td>Timber</td>
<td>0.824</td>
<td>0.196</td>
<td>0.069</td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td>0.053</td>
<td>0.75</td>
</tr>
</tbody>
</table>
Chapter 4

Efficiency Results and Policy Implications
In the last chapter, I find that significant allocative inefficiency exists in Chinese manufacturing industries and that technical efficiency varies across manufacturing sectors. In this chapter, I discuss what impacts the allocative inefficiency and the factors underlying the differences in technical efficiency in different sectors. Policy implications based on the findings are also discussed.

4.1 Understanding the efficiencies

4.1.1 Allocative efficiency

I find the average allocative efficiency to be approximately 0.67, indicating significant deviation from optimal factor use. In a competitive market, the deviation of the observed input use from cost-minimizing input use is usually interpreted as a result of managerial defects. However, in the context of the transitioning economy in China, the inefficient input use is more likely to be a result of multiple institutional reasons such as incomplete enterprise role transformation, government intervention or defects in market functioning.

It is found that compared to materials, capital and energy are relatively overused and labor is relatively underused. The estimated relative shadow price ratio is almost close to zero,

\[ \frac{\theta_k}{\theta_m} = 0.023 \]. But it is very close to the shadow price estimated by Parker (1999), who finds

\[ \frac{\theta_k}{\theta_m} = \frac{0.086}{1.337} = 0.064 \]

in Nanjing machine-building state enterprises in 1992. He also finds that the shadow price ratio for capital is even negative during 1980-1989, although the trend is increasing. Both studies suggest great overuse of capital. Overuse of capital is not surprising given state enterprises had a long history of soft-budget constraint before the reform era. Even
after the transformation in the late 1990s, the state enterprises that are retained by the government still benefit from considerable subsidies or enjoy preferential loans from state-owned banks. In 1999, state enterprises accounted for only 28% of total output, but absorbed 47% of total investment (China Statistical Yearbook, various years). The state directed investment may be a major contributing factor leading to the overuse of capital. On the other hand, the low price efficiency for capital is also observed in pre-reform Soviet manufacturing industries. Toda (1976) estimates the shadow price ratio in eight Soviet manufacturing industries and finds that three out of the eight industries have significant shadow price disparity and that all the three industries have shadow price ratio for capital less than 1.

Meanwhile, \( \frac{\theta}{\theta_m} = 1.46 \) suggests that labor is relatively underused, or labor is underpaid compared to its marginal productivity. This result is to the contrary of the findings by Murakami et al (1994) and Parker (1999). Murakami et al (1994) find an overpayment to labor, or overuse of labor in the state enterprises compared to other ownership types in the garment industry in 1991. Parker (1999) finds that the shadow price ratio dropped from 1.9 to 0.8 from 1980 to 1992, suggesting the trend shifts from underpaying labor toward overpaying labor. His interpretation of the trend is that state enterprises are losing labor monopsony throughout the time and wages are raised to retain skilled workers. The finding of this study provides evidence for a somewhat reversed trend; that is, labor is relatively underpaid. Notice that the studied period for this work is from 1999 to 2004, later than the studied period for Murakami et al (1994) and Parker (1999). This reversed trend may be a result of oversupply of labor in the late 1990s. The massive layoff during late 1990s from state enterprises and migration of labor from the rural areas to the urban areas may both lead to the oversupply of labor.
There are relatively few studies on the shadow prices on energy. This study shows strong evidence of overuse of energy, $\frac{\theta_c}{\theta_m} = 0.014$. The low shadow price ratios for both energy and capital are not surprising given that energy and capital are complements, and therefore low return to capital is likely to be coupled with low return to energy. Moreover, the low energy efficiency in China could also be a contributing factor for the low shadow price ratio for energy. For example, as the most available resource, coal is China’s dominant energy source (China Statistics Yearbook, various years). The use of low quality coal makes China’s energy efficiency lower than most developed countries (Lam 2005). The low energy efficiency is also found in literature studying transitioning economies in central and eastern Europe. For example, Piesse and Thirtle (2000) even find negative return for energy in a production function for light manufacturing industry during early transitions in Hungary. They rationalize this result as a consequence of wasting cheap energy.

The pattern of extremely low capital efficiency and low energy efficiency are not typically observed in a competitive market. But it is observed in this study, and has been reported in previous studies in China or other transitioning economies such as central and east Europe. It seems to be a pattern linked to transitioning economies. It is reasonable to postulate that the allocative inefficiency observed here is more likely to be a result of institutional reasons rather than firm-specific reasons such as management defects. However, this conclusion is only speculative, since this study does not separate the distortionary effects of all these factors. This suggests the need for future research.
4.1.2 Technical efficiency

Based on their technical efficiencies, the manufacturing sectors can be roughly divided into three groups. The high efficiency group includes chemicals, food, machinery and rubber. The low efficiency group includes electricity, petroleum and other industries. The remaining sectors, mining, metals, nonmetals, textile and timber, fall in-between.

Energy sectors, such as the electricity and petroleum industry, are historically less open to foreign capital compared to other industries and heavily regulated by government. The petroleum industry, for example, is dominated by three major groups and is closely regulated by the State Development Planning Commission and the State Economic and Trade Commission (Sepulchre 2004; Lam 2005). State enterprises also dominate the electricity industry. These state enterprises are vertical integrated, controlling all transmission and distribution networks and 90% of power generation. Although the energy sector has been open to foreign capital since the early 1990s, foreign direct investment in the energy sector is still low. Foreign investment is held back by institutional barriers, such as the risks associated with industry restructuring and time-consuming approval procedures (Lam 2005). Therefore, it is not surprising that electricity and petroleum sectors are in the lowest efficiency group in this study. Lack of competition and heavy government regulation may both contribute to the low efficiency. The machinery industry, on the other hand, has been open to foreign investment since the 1980s. FDI from developing countries in Asia was concentrated on the machinery sector to use China’s cheap labor and mainly target export. These FDI firms are relatively small and engaging in fierce competition with one another. Therefore, it is more likely for enterprises in the machinery industry to have better performance.

The explanations above are only speculative. To better understand the technical efficiency difference across sectors, the correlation coefficient between the technical efficiency and capital share or foreign capital intensity is calculated. It is found that a positive correlation
exists between foreign capital intensity and technical efficiency, while no significant correlation exists between capital share and technical efficiency. This finding is consistent with the previous studies showing that FDI have positive effect on local productivity (Liu and Wang 2003).

However, the analysis here is not enough to develop a causal relationship between the two. This also asks for future research.

4.2 Policy implications

Strong evidence of allocative inefficiency suggests that more reforms are needed for either completing the enterprise transformation, or improving enterprise management. Most importantly, institutional reforms are needed for improving the efficient use of capital and energy. The technical efficiency comparison indicates that energy sectors are within the lowest efficiency group. This suggests that further reforms are needed in these industries to introduce more competition. The positive correlation between the technical efficiency and FDI implies that openness and competition are associated with the performance of an industry. In this sense, WTO accession would have a positive effect on the overall performance for industrial sectors since the accession agreement requires more openness to FDI.
Chapter 5

Conclusion
5.1 Summary of empirical findings

In this study, I examine the overall allocative efficiency and industry-specific technical efficiency in Chinese manufacturing industry. A dataset for large- and medium-sized enterprises in Chinese manufacturing industries from 1999 to 2004 is analyzed. The results show evidence of allocative inefficiency existing in Chinese manufacturing industries, suggesting firms’ behavior deviates significantly from cost minimization. Capital and energy are over-used and labor is underused compared to the use of materials. The overall allocative efficiency is approximately 0.67. Technical efficiencies vary dramatically across industries. Based on their technical efficiency, the 12 industries under study can be roughly divided into three groups. The high efficiency group includes chemicals, food, machinery and rubber. The low efficiency group includes electricity, petroleum and other industries. Mining, metals, nonmetals, textiles and timber fall in-between. Multiple reasons may lead to the allocative inefficiency, such as incomplete transformation, distortions from regulation, and managerial defects. A simple correlation coefficient is calculated to investigate the relationship between technical efficiency and capital measures of the industry. It is found that foreign capital intensity is highly correlated with technical efficiency in the industry, while capital share has little correlation with technical efficiency.

5.2 Suggestions for future studies

This study is restricted by limited number of observations for each industry and the complication of computations due to the nonlinear form of the estimated equations. Estimation for individual industry sector is not possible. Once more data are available, applying the shadow price approach to individual sector should provide more insight.
In addition, this study can not identify factors causing allocative inefficiency. In particular, it can not determine whether the inefficient input allocation is caused by non-profit seeking objectives of the state enterprises, government regulation, or poor management. Futures research looking into the nature of allocative inefficiency is needed.

Although the technical efficiency estimates for different manufacturing sectors provide information on their overall performances, this study does not examine extensively the factors leading to the differences in technical efficiency across sectors. Further, although a positive correlation between technical efficiency and FDI is found, this study does not answer the question of which one is the cause. All of these questions are left to future research.
References:


