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總要素投入生產力成長、技術進步
及效率變動之研究

Total-factor Input Productivity Growth, Technical Progress,
and Efficiency Change
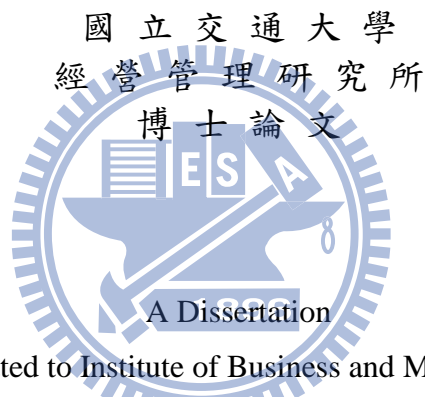
研 究 生：張子溥

指導教授：胡均立　教授

中 華 民 國 九十九 年 十 月

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摘　　　　要

　　傳統部分要素生產力指數忽略要素間互補或替代關係，也忽略了技術變動的影響；然而總要素生產力指數無法計算個別投入要素的生產力變動情況。因此，本論文提出「總要素投入生產力」指數，旨在總要素架構下計算單一投入要素之生產力變動。「總要素投入生產力」指數是以Luenberger生產力指數的觀念為基礎，並利用一般化方向距離函數加以修正，能夠在總要素架構中探討單一要素的生產力變動情形。該指數同時能夠拆解出要素使用效率以及技術之跨期變化程度，藉此提供更深入之分析。

　　本論文將總要素投入生產力指數應用於能源議題與銀行議題上。首先在能源議題應用部分，本論文探討中國大陸各省的總要素能源生產力變動。研究結果發現，中國大陸整體在2000~2004年間的總要素能源生產力呈現負成長。根據進一步拆解，發現該生產力負成長乃是導因於技術衰退所致，儘管整體相對效率有小幅提升。本論文同時也嘗試找出影響總要素能源生產力變動的因素；研究發現經濟發展狀況、產業結構與能源使用結構皆會影響總要素能源生產力指數的高低。

　　第二個應用是分析中國大陸銀行業總要素生產力的主要來源。本論文提出總要素投入生產力指數的延伸模型，藉此模型可得總要素生產力變動等於個別總要素投入生產力變動之平均。本論文將中國大陸銀行業總要素生產力分解為資金、資本和員工三種投入生產力。研究結果發現中國大陸銀行業在2005~2009年期間的總要素生產力呈現成長趨勢，且該成長主要是來自於資本使用的生產力提升。另外一方面，總要素生產力成長也

可歸因於技術之進步，尤其是資本使用的技術進步貢獻最大。

　　透過上述兩個應用，顯示本論文提出之總要素投入生產力不但能夠解決傳統生產力指標之不足，也可提供更深入的探討與分析。

關鍵詞：總要素投入生產力、效率變動、技術變動、方向距離函數、銀行、能源。

Total-factor Input Productivity Growth, Technical Progress, and Efficiency Change

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ABSTRACT

Traditional productivity measures neglect the substitution or complement effects among all factors and do not distinguish between the contribution due to technical change and changes in efficiency. The total-factor productivity index, such as Malmquist and Luenberger productivity indices, may not evaluate single factor productivity change under a total-factor framework. Therefore, this dissertation introduces a total-factor input productivity index (TIPI), based on the Luenberger productivity index, to calculate one particular input productivity change with a total-factor concern. This proposed index can be also decomposed into change in relative efficiency and shift in technology.

This dissertation further applies the TIPI to investigate energy- and banking-related issues. With respect to the application of the energy issue, this dissertation analyzes the total-factor energy productivity change of regions in mainland China. This result shows that total-factor energy productivity presents negative growth in mainland China during 2000-2004. This energy productivity decline is mainly attributable to negative technical growth even though the relative efficiency improves. The investigation herein also explores the determinants of total-factor energy productivity change and finds that regions' development status, industrial structure, and energy mix affect energy productivity growth.

The second application investigates the sources of total-factor productivity change in Chinese banks. This dissertation proposes an extended TIPI model and then shows that the total-factor productivity change is equal to the arithmetic mean of the productivity changes of all inputs. Such an application decomposes the total-factor productivity change into fund, capital, and labor productivity changes of mainland China banks. This result indicates that the banking industry there presents positive total-factor productivity growth during 2005-2009. It is found that this total-factor productivity growth is mainly driven by capital usage productivity improvement. Moreover, the total-factor productivity growth can be attributed to technical progress, especially for capital usage technology. These two applications show that the total-factor input productivity index has advantages over traditional productivity measures and total-factor productivity indices.

Keywords: Total-factor input productivity; Efficiency change; Technical change; Directional distance function; Banking; Energy
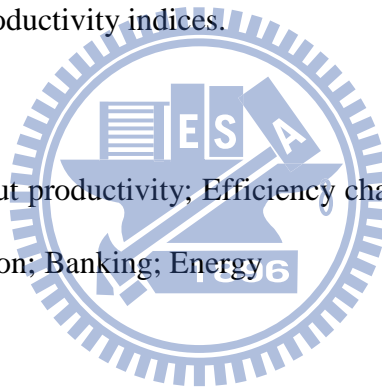
誌謝

　　就在本論文完成的同時，我的博士求學生涯將在此畫上句點，並向下一段人生旅途邁進。回顧過去四年多的日子，一路上受到相當多的幫助，因此我要在這裡向所有老師、朋友們致上最誠摯的謝意：

　　本論文得以順利完成，最要感謝指導教授胡均立老師的悉心指導。承蒙恩師　胡均立教授從六年前碩士班以來一路地協助，不僅僅在學術研究之路上的啟蒙與指導，對於未來人生規劃也給予學生許多寶貴的建議。這一切令學生銘感於心，也期待未來在學術研究過程中能持續與恩師相互合作。

　　感謝研究指導委員會的丁承老師與周雨田老師，兩位老師從論文計畫書到學位口試期間提供不少建議以及指正，使得本論文更為充實與完整。感謝林師模老師、林進財老師、邱永和老師以及黃宗煌老師在學位論文口試給予學生相當多有用的意見，除了針對研究內容的不足之處提出建議之外，也指出不少未來進一步研究的看法。未來學生若能繼續在學術上發光發熱，更要感謝各位老師的指教。

　　在博士班作研究的日子，或許有時會有倦怠的時候，還好有許多學長姐、同學可以分擔解憂、相互打氣。在此特別謝謝志良學長、秀瑩學姐、郁玫、世緯、疆平在最後這一段日子的協助。此外，讀書累的時候，打排球是最好的休閒，謝謝四年來所有參與過交大經管排球隊的學弟妹們，大家齊心協力幫所上爭取到四座獎盃，也帶給我許多歡樂的時光。再者，謝謝幾位大學死黨的一路相挺。

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<div style="text-align: right">

張子溥　　謹致

交通大學經營管理研究所

中華民國九十九年十月十五日

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1. INTRODUCTION

1.1 Motivation and purpose

Productivity, defined as the ratio of output that is produced to the input that is used, is a measure of output from a production process, per unit of input. There are many well-known productivity measures in a variety of research fields - for example, labor productivity in factories, energy productivity in power stations, and land productivity (yield) in farming - however, these traditional measures are what is known as partial measures of productivity. Coelli et al. (1998) argue that these partial productivity measures provide a misleading conclusion if considered in isolation, because the partial productivity measures neglect the substitution or complement effects among all inputs. Hence, recent research studies in the productivity and efficiency fields consider a total factor productivity measure which involves all factors of production.

There are two famous total factor productivity indices used to study how the productivity of all inputs changes: One is the Malmquist productivity index and the other is the Luenberger productivity index. These two indices are greatly applied in different areas, such as energy and environment (e.g., Hu et al., 2005; Wei et al., 2007), the financial sector (e.g., Casu et al., 2004; Worthington, 1999), the agricultural sector (e.g., Mao and Koo, 1997; Umetsu et al., 2003), and national productivity (e.g., Chang and Luh, 2000; Yörük and Zaim, 2005), etc. Unfortunately, the Malmquist productivity index and Luenberger productivity index cannot deal with the productivity change of a single factor under total factor framework, meaning that those indices are unavailable if we want to investigate the productivity change of one particular factor among all input factors. Therefore, this thesis tries to overcome the disadvantage of a total factor productivity index and introduce an advanced approach to measure single factor productivity change under a total-factor framework.

The main purpose of this thesis is to construct a new index, the so-called total-factor input productivity index (TIPI), to evaluate one particular input productivity change with a total-factor framework. Hence, the contribution of this thesis is to modify the disadvantages of traditional partial productivity measures and total factor productivity indices. The proposed index can then be widely applied to varied research issues. For example, we can compute the productivity growth of energy input with a total-factor (involving labor and capital inputs) concerned. Moreover, the productivity of an employee (also considering funds and capital inputs) can be evaluated when researching banking issues. Chapters 3 and 4 respectively offer two applications in energy and banking issues.

Before discussing the proposed methods any further, the following sub-sections present the advantages of this proposed index and the research flows. Subsection 1.2 gives a graphic example to illustrate the idea of a total-factor input productivity index. Sub-section 1.3 briefly describes the theoretical concept of the proposed index.
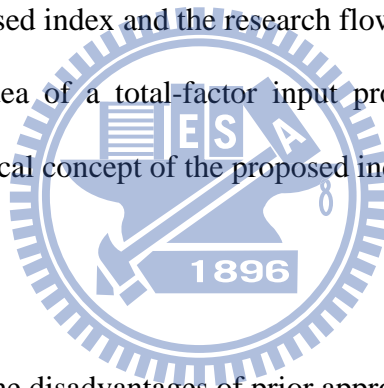
1.2 A graphic example of the disadvantages of prior approaches

As mentioned above, a traditional productivity index neglects the substitution or complement effect between all inputs, implying that the output is produced solely by the particular input. It may hence easily underestimate or overestimate the rate of productivity growth. There is another drawback to using a traditional productivity index, i.e. it does not distinguish the contribution due to technical change and changes in efficiency. In other words, the traditional indicator assumes the technology is always consistent year after year. However, the productivity will improve, because of technical progress (Coelli et al., 1998). Hence, this thesis uses Figure 1 to illustrate the comparison between a traditional productivity index and the proposed new index using an example of energy productivity.
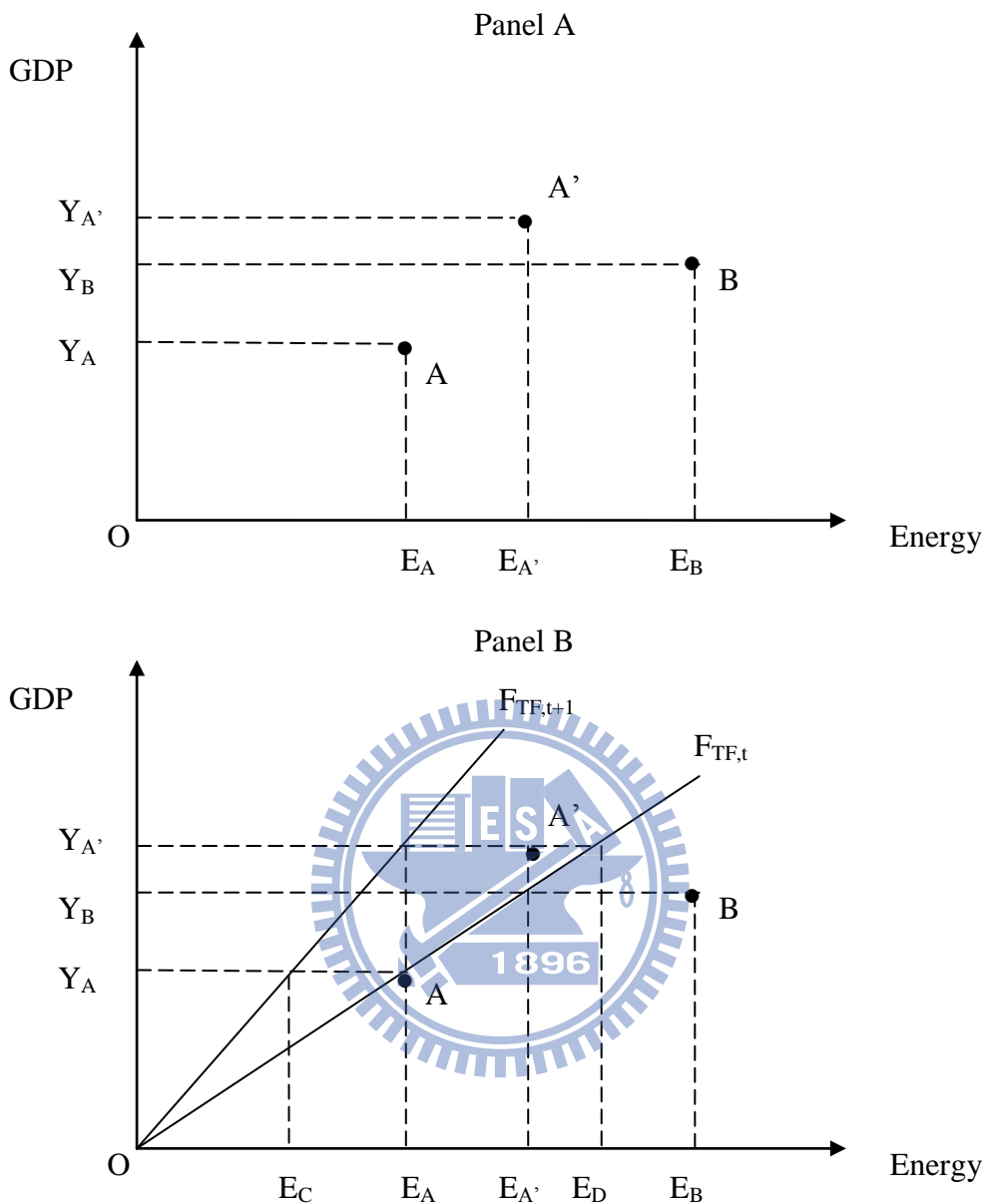
Panel A

Panel B

Figure 1.1 The graphic conception of traditional productivity, TFEE, and TIPI

Panel A of Figure 1 sketches the concept of a traditional energy productivity indicator. If two objects operate at points A and B, then their traditional energy productivity equals Y_A/E_A and Y_B/E_B, respectively.   In this example, the energy productivity of point A is higher than point B.   When we consider that one object has increased its energy productivity from one year to the next (from point A to point A'), the improvement of energy productivity is

equal to $(Y_{A'}/E_{A'} - Y_A/E_A)^1$.

Hu and Wang (2006) propose an indicator, the so-called the total-factor energy efficiency (TFEE), under a total-factor framework to compare the relative energy efficiency among regions in mainland China. They provide a measure to compare the efficiency of energy use under a total-factor framework during the same year (i.e. points A and B). I use Panel B of Figure 1 to demonstrate their ideas and consider a special case assuming the production frontier for energy use shows linearity in multi-factor framework. TFEE is a relative index that computes a ratio of minimum (target) input level to actual level for each object at each particular year. The two production frontiers, $F_{TF,t}$ and $F_{TF,t+1}$, refer to the best practice using the minimum energy to produce the same amount of output under a total-factor framework at years t and $t+1$, so that this example assumes technical growth. According to the definition, the TFEE of points A and B respectively equals E_A/E_A (=1) and $E_{A'}/E_B$ (<1), indicating a higher efficiency if an object operates at point A.

TFEE cannot completely depict the productivity improvement due to the technical change. As shown in Panel B of Figure 1, if one object improves its energy productivity from one year to the next (from point A to point A'), then the TFEE framework only computes the total-factor energy efficiency change ($E_A/E_{A'} - 1$), while not measuring the frontier shift effect at all. Therefore, the proposed total-factor input productivity tries to extend the static TFEE to a dynamic indicator and is expected to overcome all the drawbacks discussed earlier.

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[1] In this article, any change is based on differences rather than more traditional ratios. For more advantages about differences, see Boussemart et al. (2003).

1.3 The theoretical concept of proposed index

Hu and Wang (2006) propose the total-factor energy efficiency index defined as a ratio of the optimal-to-actual energy input, in order to compute the relative energy efficiency of each region in mainland China under a multifactor framework. As discussed above, the concept of TFEE considers the substitution and complement effects among energy and other inputs. Sequentially, Hu et al. (2006) apply the same concept in the water resource issue, but the methodology used by previous studies only focuses on computing relative energy efficiency among objects in each year such that it lacks insights with longitudinal data. Therefore, this thesis proposes an innovative method to deal with dynamic productivity changes.

To study the particular input productivity changes under a total factor framework, this thesis introduces a total-factor input productivity index that integrates the concept of the TFEE index with the Luenberger productivity index to measure the change of total-factor input productivity. The Luenberger productivity index introduced by Chambers et al. (1996), as a difference of the directional distance function, measures whether total factor productivity changes from the base period to the next period. As shown by Luenberger (1992) and Chambers et al. (1998), the directional distance function provides a flexible method to calculate both input contractions and output expansions. According to the flexibility of the directional distance function, some researchers have considered that the Luenberger productivity index is more appropriate than the well-known Malmquist productivity index (Boussemart et al., 2003; Managi, 2003). Moreover, Chambers et al. (1996) illustrates that the Luenberger productivity index can be decomposed into efficiency and technical changes.

This thesis applies a non-parametric programming method, commonly known as the data envelopment analysis (DEA) approach, to compute the total-factor input productivity change. Additionally, the proposed index can be decomposed into two components: One is the

change in relative efficiency, indicating that an object is getting closer to or farther from its annual frontier (catch-up effect or fall-behind effect).　　The other is a shift in the technology level of a particular input use, showing the shift in the production frontier under the total-factor framework.

Comparing to traditional parametric methods (such as the Cobb-Douglas function and translog production function), the advantage of using the DEA method is it avoids model misspecification (Boussemart et al., 2003; Wei et al., 2007).　　Moreover, the DEA-Luenberger index easily computes total-factor productivity change, efficiency change, and technical change.　　Since the DEA-Luenberger index cannot analyze the change in single factor productivity under total factor concern, the total-factor input productivity index is introduced herein to deal with this issue.
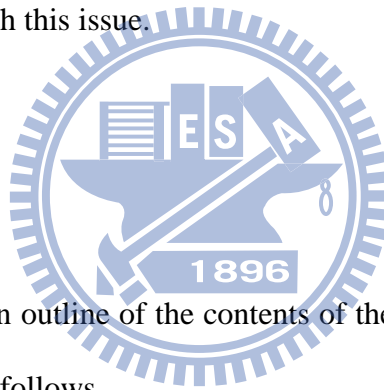
1.4 Outlines of chapters

This section provides an outline of the contents of the subsequent chapters in this thesis. The outline of chapters is as follows.

Chapter 2 Methodology:　　This chapter demonstrates how to construct the total-factor input productivity index in detail.　　The methods used, including DEA, directional distance function, and related linear programming problem, are presented here.　　Additionally, the steps to calculate the total-factor input productivity index are also described.

Chapter 3 Application in energy issue:　　This chapter applies the proposed index to research on an energy topic.　　An empirical study of total-factor energy productivity growth of China is executed.　　This empirical application further decomposes the total-factor energy productivity growth of each province into total-factor energy efficiency change and total-factor energy technical change.　　It provides a more detailed investigation of the energy

use performances of each province.

Chapter 4 Application in banking: This thesis also presents an application in the financial sector, i.e. the total-factor input productivity growth of mainland China banks. This application shows the total-factor input productivity of each input (such as funds, capital, and employees) in order to investigate the advantages or disadvantage of all researched banks.

Chapter 5 Concluding remarks: This chapter provides the conclusions and summarizes the advanced total-factor input productivity index of this thesis.
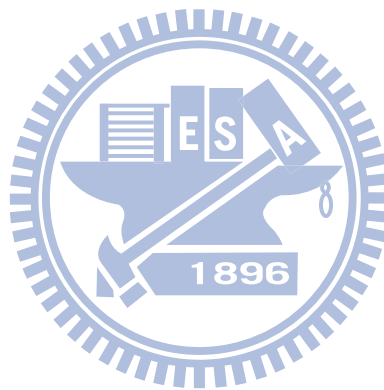
2. METHODOLOGY

In the case of productivity growth, the Luenberger productivity index is a convenient method to overcome the drawbacks of TFEE: We first assumed that the production technology $\mathbf{F}^t$ models the transformation of multiple inputs, $\mathbf{x}^t \in R_+^M$, into multiple outputs, $\mathbf{y}^t \in R_+^S$, for each time period t, where:

$$\mathbf{F}^t = \{(\mathbf{x}^t, \mathbf{y}^t) : \mathbf{x}^t \text{ can produce } \mathbf{y}^t\}. \tag{2.1}$$

The computation of the Luenberger productivity index relies on directional distance functions. Following Chambers et al. (1998), the directional distance functions could be defined at *t* as:

$$\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) = \max\{\beta \in \Re : (\mathbf{x}^t - \beta \mathbf{g}_x, \mathbf{y}^t + \beta \mathbf{g}_y) \in \mathbf{F}^t\}. \tag{2.2}$$

where $(\mathbf{g}_x, \mathbf{g}_y)$ is a nonzero vector in $R_+^M \times R_+^S$. Thus, this function is defined by simultaneously contracting inputs while expanding outputs. One notices that $\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) \geq 0$, and $\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) = 0$ if and only if $(\mathbf{x}^t, \mathbf{y}^t)$ is on the production frontier. Therefore, the Luenberger productivity index would be measure as follows:

$$\begin{aligned} L(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{x}^t, \mathbf{y}^t) = \frac{1}{2}\Big[&\left(\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})\right) \\ &+ \left(\vec{D}_{(t+1)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})\right)\Big], \end{aligned} \tag{2.3}$$

if the Luenberger productivity index is less than, equal to, or greater than zero, then it respectively stand for productivity regress, no change, or progress between period *t* and *t*+1.

Luenberger productivity index is a multi-factor productivity index and can calculate the total-factor productivity change of research objects. However, the commonly used Luenberger productivity index, which assumes a special case with proportional distance function, cannot deal with single factor productivity change under total-factor framework. Therefore, this thesis introduces a total-factor input productivity index which applies a

generalized directional distance function proposed by Färe and Grosskopf (2010) and an optimal-to-actual input ratio under total-factor framework to substitute all the components of Luenberger productivity index.

The proposed total-factor input productivity index (hereafter, TIPI) combines the features of Luenberger productivity index with the concept of total-factor energy efficiency proposed by Hu and Wang (2006). For the ideas of calculating TIPI, the first step is to compute the efficient level of particular input. In other words, it is important to find out the actual slack of input of each object. This paper derives the actual slack of objective input from directional distance function, a flexible tool to account for both efficient inputs and outputs when measuring efficiency. However, most literature considers a special case, assuming the directional vector ($\mathbf{g}_x$, $\mathbf{g}_y$) is equal to ($\mathbf{x}$, $\mathbf{y}$), to contract input and expand output variables by an equal scale (Chambers et al., 1996; Chambers et al., 1998; Boussemart et al., 2003). It is a convenient approach but cannot obtain exact input or output slacks. Fortunately, Färe and Grosskopf (2010) introduce a generalized directional distance function and use linear programming method to acquire how many excess inputs have been employed and how many too few outputs have been produced. We illustrate the approach of Färe and Grosskopf (2010) and the relationship with the ideas of TFEE as the following:

We first define some mathematical notations. Assume that there are M inputs and S outputs for each of N objects in each time period of T. The ith input and rth output variable of the jth object is represented by x_{ij}^t and y_{rj}^t in time t, respectively. Moreover, Färe and Grosskopf (2010) propose the vectors

$$e_l = (0, \cdots, 0, 1, 0, \cdots, 0), \quad l = 1, ..., m+s. \tag{2.4}$$

where the 1 is in the lth place of the vector. Therefore, the generalized directional distance functions for the observation o in time t can be state as following linear programming problems:

$$\max \ \beta_1 + \cdots + \beta_M + \gamma_1 + \cdots + \gamma_S$$

$$\text{s.t.} \ \sum_{j=1}^{N} \lambda_j x_{ij}^t \le x_{io}^t - \beta_i e_i, \ \ i = 1, \ldots, M,$$

$$\sum_{j=1}^{N} \lambda_j y_{rj}^t \ge y_{ro}^t + \gamma_r e_r, \ \ r = 1, \ldots, S, \tag{2.5}$$

$$\lambda_j \ge 0, \beta_i \ge, \gamma_r \ge 0,$$

$$j = 1, \ldots, N; \ i = 1, \ldots, M; \ r = 1, \ldots, S.$$

where λ_j is the intensity variable that serves to form a convex combination of observed inputs and outputs. As shown in equation (2.5), the products $\beta_i e_i$ and $\gamma_r e_r$ can be interpreted as the input and output slacks, respectively. It is noteworthy that the true slacks are based on the constant return to scale assumption, indicating the efficient level of inputs and outputs for achieving the overall technical efficiency.

Although this advanced approach would easily obtain the actual slacks of each type of input and output variables, it has difficulty applying this generalized directional distance function to derive the Luenberger productivity index. Since the e_l has a value of one for each input and output, implying that e_l plays the role of the units of data, β_i (γ_r) would be the number of units of each type of input (output) that can be contracted (expanded). Concerning the widespread variation of each input and output among regions, the Luenberger productivity index would present a meaningless and incomparable result if we directly use the 'number' of slacks.

For dealing with the above-mentioned problem, the concept of TFEE, an optimal-to-actual ratio under total-factor framework, is applied in this thesis. Then we define $\vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t)$ as the ratio of slack to original objective input, indicating the distance from the frontier for efficient using at t. Accordingly, $TFEE_t^t$ is equal to $(1 - \vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t))$ as shown in the first line of equation (2.6). Other three distance functions can be substituted by TFEE in the same consideration. The computation of $\vec{D}_{i(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ is exactly like equation (2.5), where $t+1$ is substituted for t. However, there would confront an infeasible

linear programming problem when computing the two intertemporal directional distance function, i.e., $\vec{D}_{i(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ and $\vec{D}_{i(t+1)}(\mathbf{x}^t, \mathbf{y}^t)$. It is because that the production possibilities frontier constructed from observations in period t may not contain an observation from period $t + 1$ (and vice versa). Therefore, we employ three-year windows data following the approach of Färe et al. (2001) to calculate two intertemporal directional distance functions. Finally, the index of energy productivity change under total-factor framework, TIPI, will be completely constructed by equations (2.6) and (2.7).

$$TFEE_t^t = \frac{\text{Target input under technology in } t}{\text{Actual input in } t} = 1 - \vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t)$$

$$TFEE_t^{t+1} = \frac{\text{Target input under technology in } t+1}{\text{Actual input in } t} = 1 - \vec{D}_{i(t+1)}(\mathbf{x}^t, \mathbf{y}^t)$$

$$TFEE_{t+1}^{t+1} = \frac{\text{Target input under technology in } t+1}{\text{Actual input in } t+1} = 1 - \vec{D}_{i(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$$

$$TFEE_{t+1}^t = \frac{\text{Target einput under technology in } t}{\text{Actual input in } t+1} = 1 - \vec{D}_{i(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}). \tag{2.6}$$

Therefore,

$$
\begin{aligned}
TIPI_i &= \frac{1}{2}\Big[\big(\vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{i(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})\big) \\
&\quad + \big(\vec{D}_{i(t+1)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{i(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})\big)\Big] \\
&= \Big[TFEE_{t+1}^{t+1} - TFEE_t^t\Big] \\
&\quad + \frac{1}{2}\Big[\big(TFEE_{t+1}^t - TFEE_{t+1}^{t+1}\big) + \big(TFEE_t^t - TFEE_t^{t+1}\big)\Big]. \tag{2.7}
\end{aligned}
$$

Note that if the value of TIPI is less than, equal to, or greater than zero, then it indicates total-factor energy productivity regress, no change, or progress from period t to $t+1$.

However, TIPI is only an aggregate index which might be oversimplified or over-aggregated. In other words, although TIPI computes the average of total-factor input productivity change, it does not indicate the sources of change directly. Thus, a more deeply

study in the components of TIPI is necessary. According to Boussemart et al. (2003), TIPI can be decomposed into two components: total-factor energy efficiency change and total-factor energy technical change. The former component measured the change in relative energy efficiency and the later measured the shift in the technology of energy use. In equation (2.7), the first difference (outside the bracket) represents total-factor input efficiency changes and the second difference captures total-factor input technical changes.

Considering the example in Panel B of Figure 1 again, the total-factor energy productivity change by equation (2.7) from point A to point A' is equal to

$$\left(\frac{E_A}{E_{A'}} - \frac{E_A}{E_A} \right) + \frac{1}{2} \left[\left(\frac{E_D}{E_{A'}} - \frac{E_A}{E_{A'}} \right) + \left(\frac{E_A}{E_A} - \frac{E_C}{E_A} \right) \right]. \tag{2.8}$$

Accordingly, the first difference shows a negative total-factor input efficiency change and the second difference presents a positive total-factor input technical change.
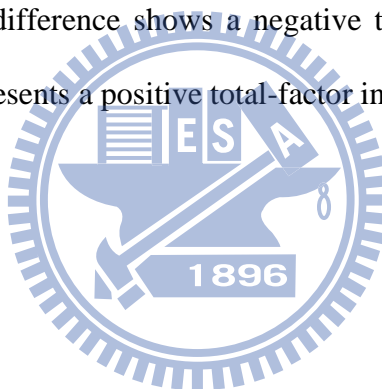
3. APPLICATION ON AN ENERGY ISSUE: AN EMPIRICAL STUDY OF CHINA

3.1 Application background

In the course of economic development, energy use provides the embodied and disembodied technical progress and productivity growth (Berndt, 1990; Narayan and Wong, 2009). In fact, several studies have found positive relationships between energy consumption and economic growth (Abosedra et al., 2009; Narayan et al., 2010). However, energy use is also a major source of greenhouse gas causing environmental problems (Herring, 1999; Miketa and Mulder, 2005; Jinke et al., 2008; Sari and Soytas, 2009). Under the concern of economic growth and environmental pressure, the study of energy use, such as energy efficiency, energy intensity, and energy productivity, has become a significant research issue over the past several decades.

The energy issue is more important in mainland China, as the economy has grown aggressively in the past two decades, and China is now the second largest energy-consuming economy in the world behind the United States. In 2004, China consumed primary energy over 59 quadrillion Btu, which accounted for 13.3% of the world (EIA, 2006). Moreover, Crompton and Wu (2005) forecast that the total energy consumption in mainland China shall increase at an annual growth rate of 3.8% from 2003 to 2010. Along with this progressive demand for energy, the assessment of energy use should be taken into consideration under China's energy policy. Due to the above concern, the Chinese government has been actively shifting its economic development mode and reforming the economic structure since China's Agenda 21 was adopted in 1993. The 10th Five-Year Plan carried out in 2001 also emphasizes improving energy efficiency and conservation. For example, energy consumption per 10,000 RMB yuan GDP in 1990 prices should be reduced to 2.2 tons of standard coal; energy conservation should be accumulated to 340 million tons of standard

coal; and the annual energy conservation ratio shall reach 4.5% by 2005. Whether or not these energy policies actually improve regional energy efficiency in mainland China remains to be examined by empirical research.

There are two well-known indicators used to study how energy inputs are efficiently used: One is energy intensity which measures the amount of energy consumption for every economic output produced in the economy, and the other is energy efficiency (or energy productivity) defined as economic output divided by energy input (Berndt, 1990; Patterson, 1996; Han et al., 2007; Nel and van Zyl, 2010). Notice that each represents identical measures from different perspectives, but we only focus on the application of the later (energy productivity) in this paper. The conventional energy efficiency index is actually the partial-factor energy productivity in which energy is the single input while substitution or complement among energy and other inputs (e.g., labor and capital stock) are neglected. Some researchers suggest that only using partial-factor energy productivity to evaluate energy consumption may obtain a plausible result (Han et al., 2007; Hu and Wang, 2006). For example, the energy efficiency index may increase solely when energy is substituted by labor, instead of any underlying improvement in technical energy efficiency (Patterson, 1996).

Hu and Wang (2006) propose a new indicator, so-called the total-factor energy efficiency (TFEE) index defined as a ratio of the optimal-to-actual energy input, in order to compute the relative energy efficiency of each region in mainland China under a multifactor framework. Meanwhile, they conclude that the commonly used energy efficiency index overestimates the benefit from energy consumption because of significant substitution effects among inputs. Wei et al. (2009) later extend the work of Hu and Wang (2006) to explain what factors cause the variation in the cross-regional TFEE. Moreover, Hu and Kao (2007) and Honma and Hu (2008) also apply the concept of TFEE to investigate related issues in APEC economies and Japan's regions, respectively. However, the methodology used by previous studies only

focuses on computing relative energy efficiency among objects in each year such that it lacks insights with longitudinal data. Therefore, an innovative method will be proposed in this article to deal with dynamic energy productivity changes.

The main purpose of this application is to evaluate the energy productivity change of regions in mainland China with a total-factor framework during 2000-2004. In order to study the energy productivity changes, this paper introduces a total-factor energy productivity index (TFEPI) which integrates the concept of the TFEE index with the Luenberger productivity index to measure the change of total-factor energy productivity. Note that the terms, energy efficiency and energy productivity, are used interchangeably in traditional literature, while they are clearly distinguished in this paper. The term energy productivity in this study is similar to the well-known definition as a ratio of the output (GDP) to energy inputs. Nevertheless, energy efficiency is defined as using less energy input to produce the same amount output under a production frontier representing the current technology to use energy.

Hence, this study applies a non-parametric programming method, commonly known as the data envelopment analysis (DEA) approach, to compute the total-factor energy productivity change. Additionally, TFEPI can be decomposed into two components: One is the change in relative energy efficiency, indicating that an object is getting closer to or farther from its annual frontier (catch-up effect or fall-behind effect). The other is shift in the technology level of energy use, showing the shift in the production frontier under the total-factor framework. The improvement of energy technology may be because of many aspects, such as changing energy mix, innovating and diffusing energy-saving technologies, and upgrading production process and equipments (Miketa and Mulder, 2005; Ni and Johansson, 2004).

The remainder of this chapter is organized as follows. Section 3.2 interprets data

sources and variables' descriptions.   Section 3.3 presents and discusses empirical results in the case of mainland China.   Finally, section 3.4 summaries this chapter.

3.2 Total-factor energy productivity index

The ratio of GDP to energy consumption is one of the most popular indicators to measure energy efficiency due mainly to its simplicity and intuitive (Ang, 2006).   However, the TFEPI introduced in this study provides two advantages: first, traditional energy efficiency indicator only takes account of energy as single input.   This indicator may easily overestimate the real change in energy productivity when energy is substituted for other inputs.   Second, traditional indicator disregards the technology level of energy use.   In other words, the traditional indicator assumes the technology is always consistent year after year.   In fact, the productivity would improve because of technical progress (Coelli et al., 1998).

Therefore, this paper introduces a total-factor energy productivity index which applies a generalized directional distance function proposed by Färe and Grosskopf (2010) and an optimal-to-actual input ratio under total-factor framework (TFEE) to substitute all the components of Luenberger productivity index.   Following the methodology in chapter 2, we denote $\vec{D}_{E(t)}(\mathbf{x}^t, \mathbf{y}^t)$ as the distance from the frontier for energy using at t, which can be also interpreted as the ratio of the total slack to an energy input.   Additionally, because the four components in equation (6) consist of two measurements within the same time period and two for intertemporal comparison, those four input-oriented distance functions would be replaced by the ratio of target energy input and actual energy input under technologies in different periods:

$$TFEE_t^t = \frac{\text{Target energy input under technology in } t}{\text{Actual energy input in } t} = 1 - \vec{D}_{E(t)}(\mathbf{x}^t, \mathbf{y}^t)$$

$$TFEE_t^{t+1} = \frac{\text{Target energy input under technology in } t+1}{\text{Actual energy input in } t} = 1 - \vec{D}_{E(t+1)}(\mathbf{x}^t, \mathbf{y}^t)$$

$$TFEE_{t+1}^{t+1} = \frac{\text{Target energy input under technology in } t+1}{\text{Actual energy input in } t+1} = 1 - \vec{D}_{E(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$$

$$TFEE_{t+1}^{t} = \frac{\text{Target energy input under technology in } t}{\text{Actual energy input in } t+1} = 1 - \vec{D}_{E(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}). \tag{3.1}$$

Therefore,

$$TFEPI = \left[TFEE_{t+1}^{t+1} - TFEE_t^t \right] \\ + \frac{1}{2} \left[\left(TFEE_{t+1}^t - TFEE_{t+1}^{t+1} \right) + \left(TFEE_t^t - TFEE_t^{t+1} \right) \right]. \tag{3.2}$$

Note that if the value of TFEPI is less than, equal to, or greater than zero, then it indicates total-factor energy productivity regress, no change, or progress from period t to $t+1$.

3.3 Data and variables' descriptions

This study appends the panel dataset of Hu and Wang (2006) and analyzes 29 provincial level data from 2000 to 2004. According to the notion of Dan (2007) and *National Western Development Strategy*, the 29 provinces are divided to three major areas: the east (the provinces of Shandong, Hebei, Liaoning, Jiangsu, Zhejiang, Fujiang, Guandong, Guanxi, and Hainan, and the three municipalities of Beijing, Tianjing, and Shanghai), central (the provinces of Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, and Hunan), and west (the provinces of Inner Mongolia, Sichuan, Guizhou, Yunnan, Shaanxi, Ganxu, Qinghai, Ningxia, and Xinjiang). Since the capital stock data of Chongqing are hard to calculate, this municipality is combined with Sichuan province in this research. We also do not take account Tibet, because the energy input data of Tibet are not available for this research.

In our multiple inputs and outputs model, labor, capital stock, energy consumption, and total sown area of farm crops are the four inputs, while real GDP is the single output. Regional energy consumption data are collected from the *China Energy Statistical Yearbook*.

The energy datasets include the conventional energy consumption－mainly coal, petroleum, and natural gas.   Data of GDP, labor employment, and total sown area of farm crops are all collected from the *China Statistical Yearbook*.   This research uses the total sown area of farm crop data as a proxy of biomass energy, which is one of the main sources for non-commercial energy use in mainland China's rural area (Hu and Wang, 2006).   However, data of regional capital stock are not available in any statistical yearbooks of China.   Li (2003) uses capital formation to construct provincial capital stock datasets for the period 1984-1998.   We extend capital stock data calculated by the authors according to the formula (Li, 2003):

Capital stock in the current year = Capital stock (previous year)

+ Capital formation (current year)

- Capital depreciation (current year).   (3.3)

All monetary inputs and outputs such as the GDP and capital stock are transformed into 2000 prices with GDP deflators.

The units of real GDP, labor, real capital, farm area, and energy consumption are billions of US$, millions of people, billions of US$, 1000 ha, and tons of standard coal equivalent (tce), respectively.   Table 1 provides the descriptive statistics of inputs and output variables. The average real GDP of 29 regions in mainland China is 357.3 billion RMB and the standard deviation of GDP is 273.7 billion RMB.   Among 29 regions in this research, Guangdong has the highest GDP output (1.03 trillion RMB), or about forty times that of Ningxia (29.0 billion RMB).   This information reveals a great disparity of economic performance among the regions in mainland China.   Other variables appear to have the same pattern with the GDP result.   Table 3.1 also shows a correlation matrix, whereby all inputs have positive correlation coefficients with the output, implying that all inputs satisfy the isotonicity property with output for the DEA model.

Table 3.1
Summary statistics of input and output variables (2000-2004)

Variables	Mean	S. D.	Correlation Matrix				
Inputs							
Capital Stocks (1 billion RMB)	1,396.28	1,050.96	1.00				
Labor (1 million persons)	22.27	15.47	0.50	1.00			
Energy Consumption (tce)	6,204.17	3,841.46	0.79	0.69	1.00		
Total sown area of farm crops (1,000 ha)	5,320.23	3,624.06	0.27	0.85	0.57	1.00	
Output							
Gross Domestic Product (1 billion RMB)	357.28	273.74	0.86	0.71	0.83	0.48	1.00

Note: (1) All monetary units are at the 2000 price level. (2) tce : metric tons of standard coal equivalent.
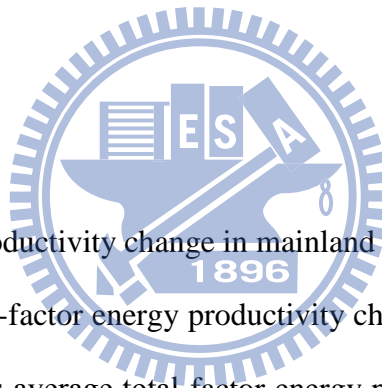
3.4 Results and discussion

3.4.1 Total-factor energy productivity change in mainland China

Table 3.2 presents total-factor energy productivity change for regions in mainland China during 2000-2004.   China's average total-factor energy productivity change from the period 2000 to 2004 is negative (-0.014), implying that the total-factor energy productivity was decreasing by 1.4% annually since 2000, especially from the period 2001 to 2002 (-3.2%). However, the traditional energy productivity index reveals that China's energy productivity change was only decreasing 0.5% annually during the research period as calculated from *China Energy Statistical Yearbook*.   The comparative result shows that the traditional energy productivity index might overestimate the energy productivity change if energy is taken as the single input.   One possible explanation is that the substitution among inputs to produce the output is significant.   For example, the partial labor productivity (GDP-to-labor ratio) in mainland China shows an increase of about 10% annually during 2000-2004.   In addition, if

the same process is applied to compute the labor productivity under the total-factor framework, then the total-factor labor productivity improves 0.06% annually. Hence, the partial energy productivity would overestimate when other inputs become more productive and substitute energy input.

Table 3.2

Total-factor energy productivity changes by region

Region		01/00	02/01	03/02	04/03	Average	Cumulative
Beijing	E	0.048	0.040	0.007	-0.029	0.016	0.066
Tianjin	E	0.022	0.026	0.038	-0.028	0.014	0.057
Hebei	E	-0.002	-0.026	-0.026	0.000	-0.013	-0.053
Liaoning	E	0.012	0.020	-0.007	-0.034	-0.002	-0.009
Shanghai	E	0.000	-0.024	0.000	0.000	-0.006	-0.024
Jiangsu	E	0.014	-0.008	0.000	0.000	0.001	0.006
Zhejiang	E	0.072	-0.103	0.031	0.009	0.002	0.000
Fujian	E	0.000	0.000	0.000	0.000	0.000	0.000
Shandong	E	0.150	-0.240	-0.019	0.009	-0.025	-0.135
Guangdong	E	-0.020	0.000	-0.007	0.000	-0.007	-0.027
Guangxi	E	0.030	-0.074	-0.046	-0.026	-0.029	-0.115
Hainan	E	-0.021	-0.075	-0.067	0.001	-0.041	-0.155
Shanxi	C	-0.030	-0.015	0.009	0.019	-0.004	-0.018
Jilin	C	0.019	-0.046	-0.030	0.012	-0.011	-0.046
Heilongjiang	C	0.035	0.032	-0.018	0.013	0.016	0.063
Anhui	C	-0.008	0.004	0.021	0.029	0.011	0.046
Jiangxi	C	0.091	-0.124	-0.047	0.041	-0.010	-0.051
Henan	C	0.005	-0.026	-0.046	-0.025	-0.023	-0.090
Hubei	C	0.053	-0.054	-0.071	-0.043	-0.029	-0.115
Hunan	C	-0.107	-0.122	-0.234	-0.085	-0.137	-0.450
Inner Mongolia	W	-0.032	-0.012	-0.025	-0.034	-0.026	-0.099
Sichuan	W	-0.025	0.020	-0.070	-0.018	-0.024	-0.093
Guizhou	W	0.001	0.011	-0.031	-0.005	-0.006	-0.024
Yunnan	W	0.004	-0.071	-0.013	-0.015	-0.023	-0.092
Shaanxi	W	-0.066	-0.036	-0.001	-0.003	-0.026	-0.103
Gansu	W	0.026	-0.016	-0.013	0.008	0.001	0.004
Qinghai	W	0.006	0.008	0.003	-0.041	-0.006	-0.024
Ningxia	W	-0.003	-0.003	-0.055	-0.003	-0.016	-0.063
Xinjiang	W	-0.004	-0.011	-0.001	-0.024	-0.010	-0.039
Average		0.009	-0.032	-0.025	-0.009	-0.014	-0.056

In regards to the total-factor energy productivity change of regions level, seven of twenty-nine regions (Beijing, Tianjin, Jiangsu, Zhejiang, Heilongjiang, Anhui, and Qinghai) enhance their total-factor energy productivity. Beijing has the highest total-factor energy

productivity growth in mainland China, whereby its total-factor energy productivity cumulatively improves about 6.6% since 2000. Heilongjiang, with a 1.6% improvement annually in total-factor energy productivity, is the second best performer among twenty-nine regions. However, six regions see a sharp decline in their total-factor energy productivity of more than 10% since 2000: Shandong, Guangxi, Hainan, Hubei, Hunan, and Shaanxi. Among them, Hunan presents the worst performance by decreasing 13.7% annually on average during 2000-2004. In the first period (2000-2001), sixteen regions have positive total-factor energy productivity growth, especially for Shandong with a 15% improvement. However, the number of regions improving their total-factor energy productivity shows a significant decline in 2001-2003. Only eight and six regions increase their total-factor energy productivity in the second and third periods, respectively.

The TFEPI represents an arresting pattern among the three major areas in mainland China. Figure 3.1 shows the TFEPI of three areas in each period and Figure 3.2 shows the cumulative total-factor energy productivity change of three areas in each year. As Figure 3.1 shows, only the TFEPI of the east and central areas is positive in the first period, implying that all areas almost present negative growth of total-factor energy productivity in the research period. The east area is the best performer among the three areas, especially showing a increasing of the total-factor energy productivity (2.5%) in the first period. The highest TFEPI of the east area is 0.025 and the lowest is -0.036. The east area's average TFEPI is -0.005, illustrating that the total-factor energy productivity of the east area decreases by 0.5% annually during the period 2000-2004. However, the central area has the lowest average TFEPI at -0.023, although the TFEPI of central area improves 0.7% in 2001-2002. Moreover, the TFEPI of the west area reveals a similar pattern to the central area, presenting a deep drop in TFEPI from 2002 to 2003.

Figure 3.2 depicts the cumulative change of total-factor energy productivity of the three

major areas (we assume initial total-factor energy productivity equals to unity in 2000).   The result is consistent with Figure 3.1 that total-factor energy productivity of all areas provides a progressive decline trend during the research period.   The east area's total-factor energy productivity slightly decreased about 2.2% since 2000, while the total-factor energy productivity of central and west areas dramatically decreased over 9.1% and 6.4%, respectively.   It is noteworthy that the east area has the highest level of per capita income and the highest level of energy productivity growth.   As opposed to the east area, the west has the lowest level of per capita income and energy productivity growth.   The results do not represent the convergence of energy productivity in mainland China, suggesting that areas with relatively low economic growth cannot catch up to advanced areas.
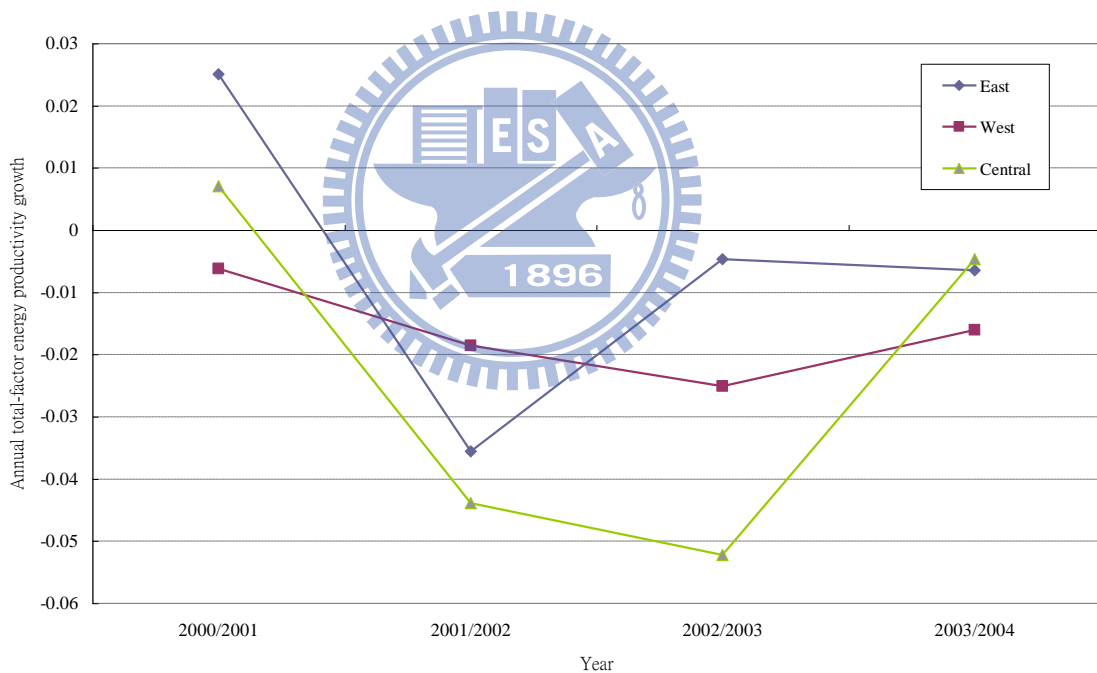
Figure 3.1 Annual total-factor energy productivity growth among three major areas
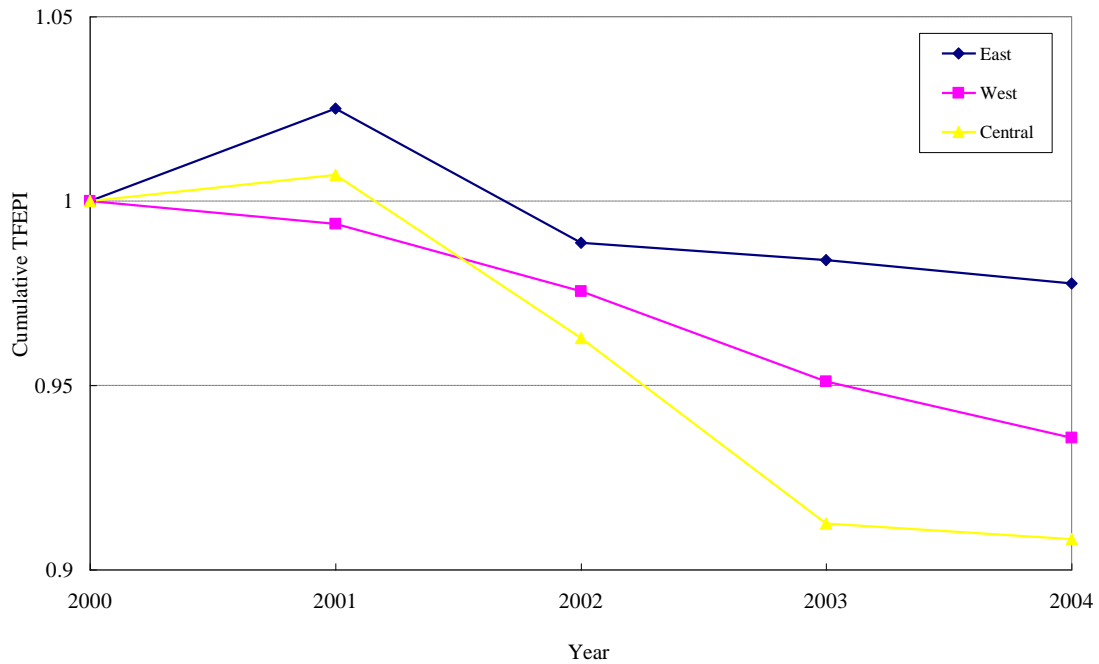
Figure 3.2 Cumulated total-factor energy productivity change among three major areas

These TFEPI results for regions and areas in mainland China are consistent with the arguments of Lin (1998) who finds different local emphases in implementing energy policy for Agenda 21. For instance, the richer coastal regions emphasize reforming traditional production and consumption patterns and adopting environmental friendly energy technologies, while the poorer inland regions emphasize efficient use and conservation of energy (Lin, 1998).

3.4.2 Components of total-factor energy productivity growth

In order to examine what happens to the total-factor productivity of regions in mainland China, we first decompose the TFEPI into its two components – total-factor energy efficiency change and technical change by equation (2.7). Total-factor energy efficiency (TFEE) change indicates the change of relative efficiency for consuming the energy input among 29 regions. Table 3.3 lists the calculation results of total-factor energy efficiency change. The results of Table 3.3 show that the whole country's average total-factor energy efficiency

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change is 0.006 during 2000-2004. This reveals that the total-factor energy efficiency of China improves about 0.6% per year and presents a slight catch-up effect such that the gap between all regions in mainland China has progressively diminished since 2000. However, there is a downward plunge of total-factor energy efficiency during the period 2001-2003. The yearly total-factor energy efficiency change is about -0.6% in the period 2001-2002.

Table 3.3 also presents the results of total-factor energy efficiency change for regions level. The total-factor energy efficiency changes in three regions (Shanghai, Fujian, and Guangdong) are equal to zero in each period, meaning that these regions' capacities for using energy to generate economic output are the best performer all the time. Stated another way, these regions still perform on the production frontier throughout the periods. However, the catch-up effect does not exist for all regions. Over half of 29 regions possess relative energy efficiency improvement - that is, their energy consumption efficiency catches up to the production frontier. The total-factor energy efficiency of Beijing, Tianjin, Heilongjiang, and Anhui rapidly increases to more than 3% annually on average, especially that of Heilongjiang (3.9%). There are also two regions (i.e., Inner Mongolia, Hunan) confronting a marked efficiency decline with over 1% annual change, especially for Hunan (-6.3%). It is worth noting that the above results only focus on the change of TFEE. We simultaneously consider the regions' TFEE and TFEE change for further analysis. For example, in 2004, although Heilongjiang has the fastest growth rate of TFEE, its TFEE score (0.674) is lower than the score of Hunan (0.746) whose growth rate is the worst among 29 regions. Additionally, there are four regions (i.e., Guizhou, Gansu, Qinghai, and Xinjiang) in the west area that improved their TFEE, but the TFEE of all of them are still below the country's average TFEE in 2004. This indicates that some regions try to catch up to the frontier, while the inequality of total-factor energy efficiency exists in mainland China.

Table 3.3

Annual total-factor energy efficiency changes by region

Region		01/00	02/01	03/02	04/03	Average
Beijing	E	0.062	0.067	0.022	-0.026	0.031
Tianjin	E	0.037	0.054	0.056	-0.022	0.031
Hebei	E	0.010	-0.003	-0.004	0.021	0.006
Liaoning	E	0.022	0.042	0.016	-0.014	0.016
Shanghai	E	0.000	0.000	0.000	0.000	0.000
Jiangsu	E	0.025	0.000	0.000	0.000	0.006
Zhejiang	E	0.092	-0.070	0.050	0.022	0.024
Fujian	E	0.000	0.000	0.000	0.000	0.000
Shandong	E	0.171	-0.209	0.013	0.039	0.003
Guangdong	E	0.000	0.000	0.000	0.000	0.000
Guangxi	E	0.048	-0.040	-0.013	0.003	-0.001
Hainan	E	0.000	-0.031	-0.025	0.039	-0.004
Shanxi	C	-0.025	-0.005	0.019	0.029	0.004
Jilin	C	0.030	-0.025	-0.010	0.032	0.007
Heilongjiang	C	0.048	0.060	0.011	0.039	0.039
Anhui	C	0.006	0.033	0.052	0.059	0.037
Jiangxi	C	0.111	-0.087	-0.012	0.075	0.022
Henan	C	0.020	0.003	-0.018	0.000	0.001
Hubei	C	0.070	-0.022	-0.041	-0.018	-0.003
Hunan	C	0.000	0.000	-0.198	-0.056	-0.063
Inner Mongolia	W	-0.023	0.004	-0.009	-0.021	-0.012
Sichuan	W	-0.012	0.049	-0.043	0.005	0.000
Guizhou	W	0.007	0.022	-0.020	0.005	0.003
Yunnan	W	0.017	-0.047	0.011	0.006	-0.003
Shaanxi	W	-0.053	-0.012	0.024	0.020	-0.006
Gansu	W	0.034	0.000	0.003	0.023	0.015
Qinghai	W	0.014	0.023	0.019	-0.028	0.007
Ningxia	W	0.002	0.008	-0.046	0.004	-0.008
Xinjiang	W	0.005	0.008	0.018	-0.007	0.006
Average		0.025	-0.006	-0.004	0.008	0.006

The second component of TFEPI is total-factor energy technical change, representing the shift in the technology of energy use during one period. As shown in Table 3.4, the whole country's average total-factor energy technical change is -0.020, indicating that the technology of using energy in mainland China regresses significantly by 2.0% per year during the research period 2000-2004. A possible reason for the result may be the proportion of low-efficiency source of energy (such as coal) continues to increase in mainland China during

the 2000-2004 periods (Ni and Johansson, 2004). None of the four yearly periods shows a positive technical growth, while a rapid drop occurs in 2001-2002 of up to -2.6%. Considering Tables 3.2, 3.3, and 3.4, we derive a conclusion: The total-factor energy productivity of China has dropped 5.6%, decreasing by 1.4% annually on average since 2000. However, this energy productivity decline is mainly attributable to negative technical growth and not relative efficiency change.

Table 3.4

Annual total-factor energy technical changes by region

Region		00/01	01/02	02/03	03/04	Average
Beijing	E	-0.014	-0.027	-0.015	-0.003	-0.015
Tianjin	E	-0.015	-0.029	-0.018	-0.007	-0.017
Hebei	E	-0.012	-0.023	-0.023	-0.020	-0.019
Liaoning	E	-0.010	-0.021	-0.023	-0.019	-0.018
Shanghai	E	0.000	-0.024	0.000	0.000	-0.006
Jiangsu	E	-0.011	-0.008	0.000	0.000	-0.005
Zhejiang	E	-0.020	-0.033	-0.019	-0.014	-0.022
Fujian	E	0.000	0.000	0.000	0.000	0.000
Shandong	E	-0.021	-0.031	-0.032	-0.029	-0.028
Guangdong	E	-0.020	0.000	-0.007	0.000	-0.007
Guangxi	E	-0.018	-0.034	-0.033	-0.029	-0.029
Hainan	E	-0.021	-0.044	-0.042	-0.038	-0.036
Shanxi	C	-0.005	-0.009	-0.010	-0.010	-0.009
Jilin	C	-0.012	-0.022	-0.021	-0.019	-0.018
Heilongjiang	C	-0.013	-0.028	-0.028	-0.026	-0.024
Anhui	C	-0.014	-0.029	-0.031	-0.029	-0.026
Jiangxi	C	-0.020	-0.036	-0.035	-0.034	-0.031
Henan	C	-0.015	-0.030	-0.029	-0.025	-0.024
Hubei	C	-0.017	-0.032	-0.030	-0.025	-0.026
Hunan	C	-0.107	-0.122	-0.036	-0.029	-0.074
Inner Mongolia	W	-0.008	-0.017	-0.016	-0.013	-0.013
Sichuan	W	-0.014	-0.029	-0.027	-0.024	-0.023
Guizhou	W	-0.005	-0.012	-0.011	-0.009	-0.009
Yunnan	W	-0.013	-0.023	-0.024	-0.021	-0.020
Shaanxi	W	-0.012	-0.024	-0.025	-0.022	-0.021
Gansu	W	-0.008	-0.016	-0.016	-0.015	-0.014
Qinghai	W	-0.007	-0.015	-0.016	-0.013	-0.013
Ningxia	W	-0.005	-0.010	-0.008	-0.007	-0.008
Xinjiang	W	-0.009	-0.019	-0.019	-0.016	-0.016
Average		-0.015	-0.026	-0.020	-0.017	-0.020

Table 3.4 also reports regional total-factor energy technical change in each period. Accordingly, only one region (Fujian) has a non-negative total-factor energy technical change over the entire period, showing that the total-factor energy technical change of Fujian is unchanged during the period 2000-2003. This also illustrates no shift in the frontier of energy usage technology in mainland China over the research periods. Conversely, the total-factor energy technical changes of Hainan, Jiangxi, and Hunan decrease most rapidly to more than 3% annually. Moreover, Heilongjiang, one of China's old industrial bases, has an average total-factor energy technical change with -2.4%. The total-factor energy technical change of the other two old industrial base regions, Liaoning and Jilin, are -1.8% and -1.8% annually on average, respectively. It reveals that the major problem of China's old industrial bases is technology regression and not being under efficient energy usage.

3.4.3 Determinants of TFEPI

As mentioned above, the total-factor energy productivity of China presents a negative growth trend in which only seven regions enhance their total-factor energy productivity among twenty-nine regions in the period 2000-2004. Therefore, three sets of factors affecting the regional TFEPI scores are explored: The first set contains state variables, including area, the ratio of FDI to GDP, human capital, and GDP per capita. Yang (2002) considers that China's regional development strategies since the reforms directly drive the widening spatial development gap. The east area consisting of coastal regions and special economic zones has received preferential resource allocations and attracted foreign direct investment since early 1980. This region-biased policy may cause technology, skilled labor, and investment inequality among the regions. FDI is a possible factor affecting regional energy productivity growth. Fisher-Vanden et al. (2006) consider that technological innovation can be imported from abroad, especially for developing country such as mainland

China. The energy productivity may increase due to the human capital accumulation which helps input more skilled labor into the production process. Here the ratio of annual university graduates to population is used as an index of human capital, according to Fleisher and Chen (1997). GDP per capita would measure the region's development status. This factor can also analyze cross-region convergence of total-factor energy productivity and examine whether the advantage of backwardness exists.

The second set is region's industry structural change. Wei et al. (2007) and Fisher-Vanden et al. (2004) mention that industry structural change can cause a great influence on energy efficiency. For example, a shift from an energy-intensive sector, such as a secondary industry to a tertiary industry, increases energy efficiency. We adopt the proportion change of GDP contributed by primary, secondary, and tertiary industries to characterize a region's industry structure.

The third set is the change in energy mix. Miketa and Mulder (2005) point out that the change in energy mix is an important source of energy productivity growth. Moreover, natural gas and electricity are more efficient and energy-saving sources than coal and oil. Hence, the change in share of coal, oil, natural gas, and electricity is used to characterize a region's energy mix.

In this analysis, pooled OLS and random-effects regression is used to estimate the determinants of TFEPI in Model 1 and Model 2, respectively. As the note of Table 3.5 explains, the F, LM, and Hausman tests reveal that the random-effects regression is more appropriate for the comprehensive model (Model 2).[2] Table 3.5 offers the estimation results. According to the results of regression, this paper has the following findings: First, the east area has a better TFEPI and the west area has a significantly lower TFEPI. Second, regions with a higher previous GDP per capita that represent that higher development have better

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[2] This thesis uses year dummies to capture the year effects in Model 2.

TFEPI performances. These two findings indicate that the total-factor energy productivity among regions in mainland China is diverse from 2000 to 2004. Third, FDI ratio and human capital reveal slight positive effects on energy productivity growth as they are solely considered, while the effects disappear if these factors are taken with others in Model 2. It indicates that FDI investment and human capital do not have directly effect on energy productivity growth. Four, the result also shows that increasing the proportion of GDP generated by the secondary industry deteriorates the total-factor energy productivity of the region. Finally, the result shows that the energy mix has significant effect on TFEPI, which is similar to the work of Miketa and Mulder (2005). Actually, the total-factor energy productivity would increase substantially as raising the share of electricity use. It is concluded that advancing the technology of energy consumption and adjusting industry structure and energy mix are vital matters for the regions in mainland China to raise their energy productivity.
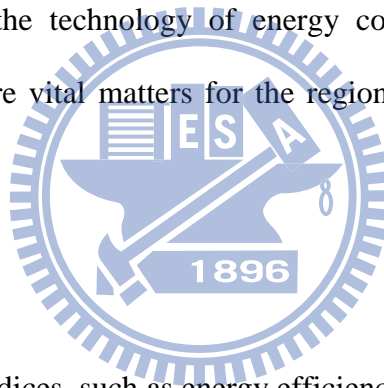
3.5 Summary

Conventional energy indices, such as energy efficiency and energy intensity, can be used to evaluate how energy inputs are efficiently utilized. However, these indicators neglect the substitution among energy consumption and other factors so that the results obtained from conventional energy indicators overestimate or underestimate the actual state. This paper proposes the total-factor energy productivity index (TFEPI) to assess energy productivity growth for regions in mainland China. TFEPI constructs a multiple-input framework that avoids single-input bias since energy is not the only input to produce economic output. The DEA approach based on the Luenberger index and relative TFEE is applied to conduct a total-factor energy productivity index in this study. The TFEPI proposed in this paper is a dynamic indictor to measure the total-factor energy productivity growth by getting rid of the

Table 3.5

Estimation results of effects of regional characteristics on TFEPI

| | Dependent Variable: TFEPI | |
	Model 1	Model 2
Constant	0.012　(0.009)	0.001　(0.017)
West	-0.011*　(0.006)	-0.002　(0.015)
Central	-0.018　(0.020)	-0.009　(0.017)
Time trend	-0.005**(0.002)	
Lagged GDP per capita		0.201**(0.101)
Lagged FDI		-0.001　(0.003)
Lagged human capital		0.006　(0.087)
Growth of primary industry		-0.131　(0.098)
Growth of secondary industry		-0.165***(0.069)
Growth of tertiary industry		-0.406　(0.312)
Growth of coal share		0.001　(0.001)
Growth of oil share		0.001　(0.001)
Growth of natural gas share		0.002　(0.002)
Growth of electricity share		0.064***(0.06)
Number of observations	116	116
Adjusted R-square	0.035	0.562

Note: (1) Numbers in parentheses are standard errors.
(2) *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.
(3) Model 1: F test (p-value=0.16); LM test (p-value=0.36); Hausman test (p-value=0.99)
(4) Model 2: F test (p-value<0.01); LM test (p-value<0.01); Hausman test (p-value=0.89)

substitution and complement effects among all inputs.　It helps provide more insights about efficiency changes as well as technology changes in energy use.

This paper reports the results of an empirical study of regional productivity growth in mainland China.　Accordingly, China's average total-factor energy productivity was decreasing by 1.4% per year during 2000-2004, especially in the period 2001-2002 (-3.2%). However, the traditional energy productivity index reveals that China's energy productivity change was only decreasing 0.5% annually during the research period.　This comparative result shows that the traditional energy productivity index overestimates the energy productivity change if energy is taken as the single input.　At the regional level, seven of twenty-night regions enhance their total-factor energy productivity.　The TFEPI not only evaluates total-factor energy productivity change, but also appraises change in relative energy

efficiency (catching up effect) and shift in the technology of energy use (innovation effect) by decomposing TFEPI. The finding from a change in relative energy efficiency shows that the whole country's average total-factor energy efficiency improves about 0.6% per year and two periods (2001-2003) present negative growth. This indicates that the relative energy efficiency gap between all regions has gradually condensed since 2000. Nevertheless, the results of total-factor energy technical change illustrate that the technology of use energy declines progressively at 2.0% per year during 2000-2004. Over the five years, none of all regions in mainland China shows a positive total-factor energy technical change. We conclude that energy productivity decline in mainland China is attributable to negative technical growth and not relative efficiency change.

What causes regional total-factor productivity inequality and decline in mainland China are important issues in future work. In the present study we only examine the effect of a region's development status, economic structure, and energy mix on total-factor energy productivity change, but these effects cannot completely explain the situation of energy productivity in mainland China. Some research studies based on cross-country or cross-region studies suggest that relative energy price may be the key determinants of energy productivity growth (Miketa and Mulder, 2005; Fisher-Vanden et al., 2004). For example, the oil price shows a discrepancy between regions in mainland China, because local governments still have some authority to set the selling price. Hence, the difference in pricing among regions could result in some regions with higher prices (such as Shanghai) having an incentive to improve energy productivity, recommending that additional research focus on the components of the total-factor energy productivity index to draw more precise conclusions about specific effects on energy productivity growth among regions in mainland China. Moreover, it may be of interest for future studies to discuss the contribution of each input variables toward total factor productivity growth. Hence, additional research would

usefully extend the present TFEPI to investigate how the productivity of other input variables change.

4. APPLICATION OF A BANKING ISSUE: AN EMPIRICAL STUDY OF BANKS IN MAINLAND CHINA

4.1 Application background

In the past three decades, China's banking system has reformed gradually and gained remarkable successes in many respects.   The total assets of the banking industry are at over RMB 60 trillion, or 300 times that in 1978.   In November 2009 the capital adequacy ratio and the provision coverage of the banking industry were over 10% and 150%, respectively. With respect to bank soundness, Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), and Bank of China (BOC) are the three largest listed banks in the world.   Moreover, the financial reforms have made efficiency and productivity improvements in the banking sector (Chen et al., 2005; Matthews et al., 2009).

This paper aims to investigate the total-factor productivity (TFP) changes and to disaggregate the sources of productivity change in China's banking industry from 2005 to 2009.   China's 'Big Four' state-owned banks (SOBs) have been partially privatized to take on minority foreign ownership since 2005.   However, the academic literature related to bank productivity mainly focuses on U.S. and European banks, using the Malmquist productivity index and Luenberger productivity index approaches.

One of the first studies to investigate productivity change in the banking industry is Berg et al. (1992), who employee the Malmquist index for productivity growth and find the source of productivity growth is efficiency improvement in Norway's banks during the years 1980-89.   Other evidence indicates that productivity growth is mainly driven by technical change in the U.S. (Alam, 2001; Mukherjee et al., 2001) and European banks (e.g., Casu et al., 2004; Koutsomanoli-Filippaki et al., 2009; Barros et al., 2010) by applying the Malmquist index or Luenberger index.

Few research studies have taken a look at the productivity growth of Chinese banks. Kumbhakar and Wang (2007) use the input distance function to analyze the efficiency and TFP change of 14 Chinese banks during 1993-2002. They suggest that joint-stock banks (JSBs) are more efficient and gain a higher TFP growth rate than SOBs. Matthews et al. (2009) apply the Malmquist index with a bootstrap method to evaluate the productivity change for 14 Chinese banks from 1997 to 2006. They indicate that JSBs generally show a better performance than SOBs, while there is no productivity growth for the SOBs since technological progress is offset by efficiency regression.

In summary, it is found that prior literature adopts the Malmquist productivity index or Luenberger productivity index to investigate the change of TFP, efficiency change, and technical change. Unfortunately, these two indices are aggregative indices and cannot deal with the productivity change of a single factor under a total-factor framework, meaning insights may be lacking if we want to investigate the productivity change of one particular factor among all input factors (such as labor, capital, and fund inputs). This paper tries to overcome the disadvantage of the total-factor productivity index and introduces an index to measure the productivity change of an individual factor under a total-factor framework.

The proposed index, the so-called total-factor input productivity index (TIPI), uses a Färe-Lovell efficiency measure to extend the traditional Luenberger productivity index and finds out the strongly efficient vector for each input. This index then can be decomposed into total-factor input efficiency change and total-factor input technical change, meaning that we can discuss the sources of individual input productivity. Furthermore, we will show that the TFP change is the average of the productivity change of individual input.

The remainder of this chapter is organized as follows. Section 4.2 describes an extended model. Section 4.3 interprets the data sources and variables' descriptions. Section 4.4 provides the empirical results.

4.2 Extended model

This application extends the model introduced in Chapter 2.　I illustrate the approach of extended TIPI as follows:　Assume there are M inputs and S outputs for each N objects in each time period of T.　The ith input and rth output variable of the jth object are represented by x_{ij}^t and y_{rj}^t in time t, respectively.　Briec (2000) introduces a Färe-Lovell efficiency measure that has the advantage to select a strong efficient vector onto the frontier.　Therefore, the input-oriented directional distance functions for the observation o in time t can be stated as the following linear programming problems:

$$\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t) = \max \ \frac{1}{M}(\beta_1 + \cdots + \beta_M)$$

$$\text{s.t.} \ \sum_{j=1}^{N} \lambda_j x_{ij}^t \leq x_{io}^t (1 - \beta_i), \ \ i = 1, ..., M,$$

$$\sum_{j=1}^{N} \lambda_j y_{rj}^t \geq y_{ro}^t, \ \ r = 1, ..., S, \quad \quad (4.1)$$

$$\lambda_j \geq 0, \beta_i \geq 0,$$

$$j = 1, ..., N; \ i = 1, ..., M; \ r = 1, ..., S.$$

where λ_j is the intensity variable that serves to form a convex combination of observed inputs and outputs.　It is noteworthy that the Färe-Lovell efficiency measure is based on the constant return to scale assumption, indicating the efficient level of inputs and outputs for achieving overall technical efficiency.

The other three distance functions in equation (2.3) can be calculated straightforward according to equation (4.1).　The computation of $\vec{D}_{(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ is exactly like equation (4.1), where $t+1$ is substituted for t.　A similar approach is adopted for two intertemporal directional distance functions, i.e., $\vec{D}_{(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ and $\vec{D}_{(t+1)}(\mathbf{x}^t, \mathbf{y}^t)$.　It is noted that these two intertemporal directional distance functions need not be greater than or equal to zero. Therefore, the Luenberger productivity index for total factors can be computed based on

equations (2.3) and (4.1).

With respect to TIPI, we further define β_i obtained from equation (4.1) as $\vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t)$, meaning that $\vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t)$ is the distance function for the ith input variable at t under a total-factor framework. Accordingly, the TIPI for the ith input can be measured as follows:

$$
\begin{aligned}
TIPI_i = \frac{1}{2}\Big[&\left(\vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{i(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}) \right) \\
&+ \left(\vec{D}_{i(t+1)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{i(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}) \right) \Big],
\end{aligned}
\tag{4.2}
$$

Note that if the value of TIPI is less than, equal to, or greater than zero, then it indicates the productivity of the ith input regresses, does not change, or progresses from period t to $t+1$.

TIPI is only an aggregate index that might be oversimplified or over-aggregated. In other words, although TIPI computes the total-factor input productivity change, it does not indicate the sources of change directly. Thus, a more deep study on the components of TIPI is necessary. Based on the traditional Luenberger productivity index, TIPI can be further decomposed into two components: efficiency change (EFFCH) and technical change (TECHCH). The former component measures the change in relative efficiency and the latter measures the shift in the technology of the ith input used:

$$
EFFCH_i = \vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{i(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})
\tag{4.3}
$$

$$
TECHCH_i = \frac{1}{2}\Big[\vec{D}_{i(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}) - \vec{D}_{i(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}) + \vec{D}_{i(t+1)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t) \Big]
\tag{4.4}
$$

Because $\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t)$ is equal to the arithmetic mean of the distance functions of all inputs, we decompose the TFP change into the productivity change of individual input as:

$$
\begin{aligned}
TFPCH &= \frac{1}{M}\big[TIPI_1 + TIPI_2 + \cdots + TIPI_M \big] \\
&= \frac{1}{M}\big[EFFCH_1 + \cdots + EFFCH_M \big] + \frac{1}{M}\big[TECHCH_1 + \cdots + TECHCH_M \big] \\
&= EFFCH + TECHCH
\end{aligned}
\tag{4.5}
$$

Equation (4.5) indicates that the TFP change is the arithmetic mean of the change of

individual input productivity, and the efficiency change and technical change of individual input can be aggregated as the total-factor efficiency change and technical change, respectively.

4.3 Data and variables' descriptions

The literature typically applies two approaches to evaluate bank efficiency and productivity. One is the intermediation approach, which is based on the main function of the bank as a financial intermediary. Another is the production approach, which views banks as the producers of financial services. Under the intermediation approach, this article specifies two outputs and three inputs to investigate the total-factor input productivity change of banks. The output variables encompass total loans (*TL*) and other earning assets (*OEA*).[3] These output variables are commonly adopted in previous literature, such as Berger et al. (2009) and Bonin et al. (2005). It is noteworthy that the quality of loans (e.g., non-performing loans or problem loans) has received more emphasis in recent studies. Therefore, loan loss reserves are subtracted from total loans in order to ensure that this output is of comparable quality. With respect to input variables, labor (employees), physical capital, and funds are the conventional inputs in previous research (Altunbas et al., 2001; Beccalli et al., 2006). Funds (*F*) define total deposits and short-term funding; capital (*C*) measures total fixed assets; labor (*L*) is the total number of bank employees.

This application collects a balanced panel data covering 2005-2009 from 21 Chinese commercial banks, including the Big Four state-owned banks, national shareholding commercial banks, and major city commercial banks in mainland China. All financial data,

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[3] Other earning assets include (1) loans and advances to banks, (2) trading securities and at FV through income, (3) derivatives, (4) available for sale securities, (5) held to maturity securities, (6) at-equity investments in

such as the items of balance sheets and income statements, are taken from Bankscope database, a comprehensive resource of international banking institutions.   Unfortunately, the information on the numbers of employees for each Chinese bank is quite incomplete in the database.   Therefore, this variable is complemented through each bank's annual report.

All nominal prices are transferred using the GDP deflator with 2009 as the base year. Table 4.1 summarizes the output and input data of our sample from 2005 to 2009.   It is noteworthy that the high standard deviations of all variables indicate that the Big Four state-owned banks dominate China's bank industry.   The correlations between each pair of input-output variables are highly positive, which is consistent with economic intuition and production theory.

Table 4.1
Descriptive statistics for output and input variables (2005-2009)

Variable	Description	Mean	S.D.
TL - million RMB	Total loans excluding loan loss reserves	975,807	1,346,472
OEA - million RMB	Total other earning assets	899,962	1,384,179
F (Funds) - million RMB	Total deposits & short-term funding	1,777,375	2,568,205
C (Capital) - million RMB	Total fixed assets	19,458	30,733
L (Labor) - person	Numbers of employees	76,176	135,012

Sources: Bankscope database and each bank's annual report.

4.4 Empirical results

This section first illustrates the total-factor productivity growth, individual input productivity change, and the decomposition of productivity change at the industry level.   It then presents and discusses the empirical results at the firm level.

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associates, (7) other securities, (8) investment in property, (9) insurance assets, and (10) other earning assets.

4.3.1 Productivity analysis at the industry level

Figure 4.1 shows the annual total-factor productivity growth and productivity changes of three inputs from 2005 to 2009. The average annual TFP growth rate is 3.79% and the TFP cumulatively grows by 15.81%, indicating an upward trend for Chinese banks. All sub-periods present a positive TFP growth rate except the period of 2007-2008 (-1.24%). One reasonable explanation is that the global financial crisis impacted quite negatively the international banking sector, and even Chinese banks could not escape from it in 2008.
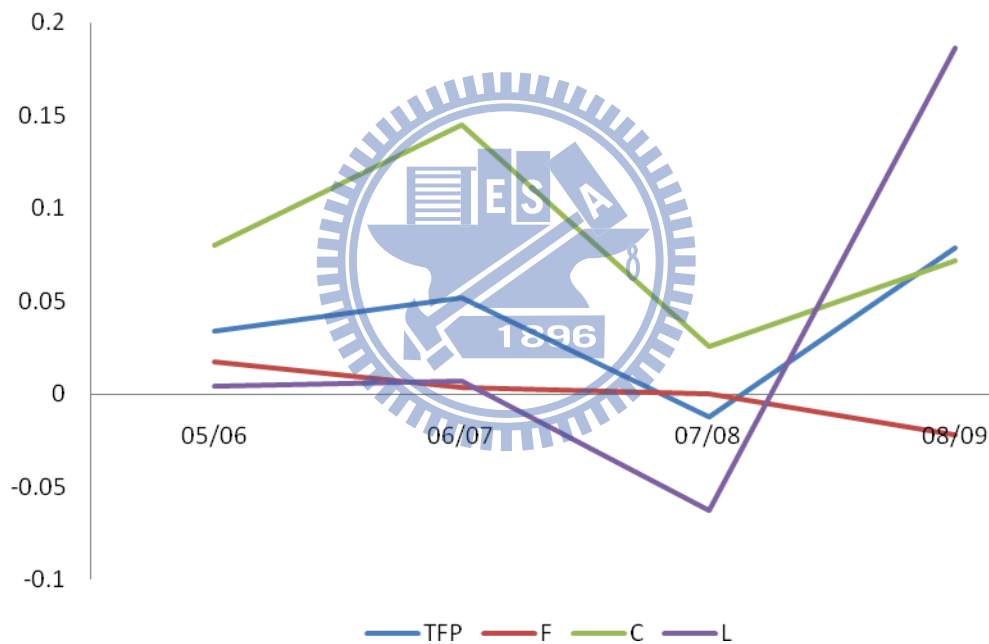
Figure 4.1 Annual change of TFP and total-factor input productivity

Figure 4.1 indicates the productivity change of three inputs under a total-factor framework. During 2005-2007, three inputs have positive productivity change, especially for capital used. Capital and fund productivity improve 2.56% and 0.02% from 2007 to 2008, respectively. Although labor productivity of Chinese banks decreases 6.30% from 2007 to 2008, it outstandingly improves 18.6% in the last sub-period. In summary, capital, labor, and fund productivity cumulatively change 36.00%, 12.32%, and -0.22% over the

research period, respectively.　We conclude that TFP's improvement is mainly contributed by capital management and human resource reinforcement in China's bank industry.

With respect to the source of TFP growth, the literature mostly decomposes TFP into technical change and efficiency change.　Hence, this paper illustrates these two components in Figure 4.2.　Figure 4.2 sketches the cumulative growth of TFP, technical change, and efficiency change during 2005-2009.　Accordingly, there is a strictly increasing trend of technical change, meaning that the production frontier substantially shifts upward.　However, there is no catch-up effect in the bank industry since the change in relative efficiency totally decreases 3.84% from 2005 to 2009.　This indicates that inefficient banks are getting farther from the annual frontier in China's banking sector.
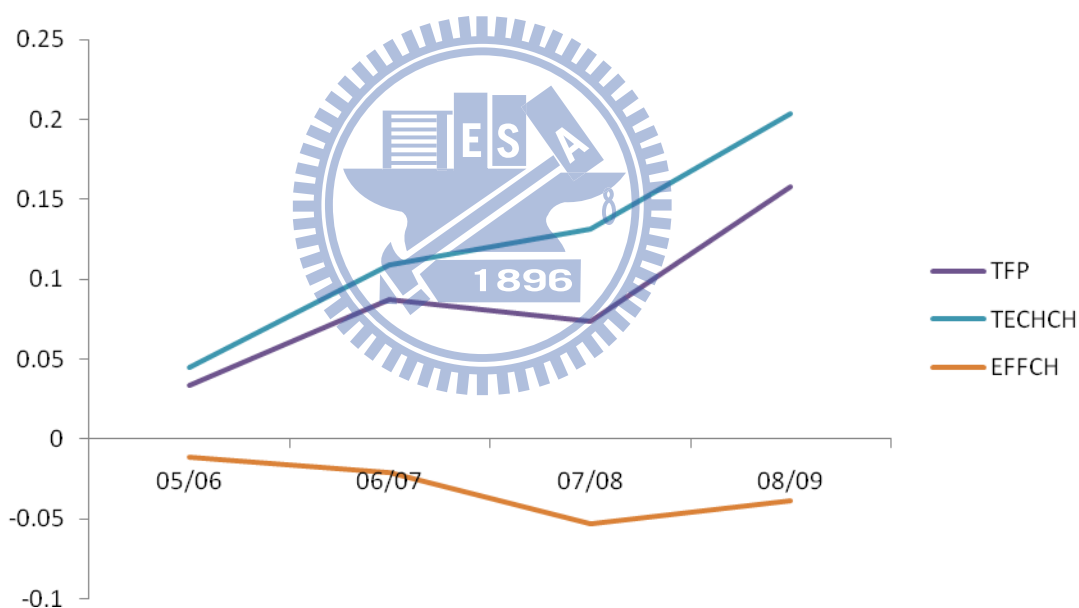
Figure 4.2 Cumulative changes of TFP and its components

As mentioned above, the TFP drops during 2007-2008.　Figure 4.2 shows that a plunge in efficiency change results in a decline for TFP in this period.　In other words, technical progress is swamped by average efficiency losses from 2007 to 2008.　Hence, we summarize that the TFP gains are principally driven by technical progress.　In general, this result is consistent with previous findings in Kumbhakar and Wang (2007) and Matthews et al. (2009).

Aside from the two components (i.e., technical progress and efficiency change) of TFP, we further decompose the productivity growth of individual inputs into those two components. The upside of Table 4.2 provides the annually technical change of three inputs under a total-factor framework in each sub-period. The technology of capital used gains the highest growth rate with 11.40% annually, while that of labor resource improves 3.18% on average. However, the technology of funds used slightly regresses with a rate of 0.33% annually. Hence, we consider that the technical progress of capital usage is the main source of the total-factor technology shift.

Table 4.2

Annually technical changes and efficiency changes of three inputs

| Period | Technical Change | | | |
	Total-factor	Fund	Capital	Labor
2005/2006	0.0446	0.0194	0.0914	0.0230
2006/2007	0.0619	-0.0008	0.1866	-0.0003
2007/2008	0.0199	0.0009	0.1245	-0.0656
2008/2009	0.0636	-0.0329	0.0536	0.1703
Average	0.0475	-0.0033	0.1140	0.0318

| Period | Efficiency Change | | | |
	Total-factor	Fund	Capital	Labor
2005/2006	-0.0109	-0.0022	-0.0114	-0.0191
2006/2007	-0.0101	0.0039	-0.0414	0.0071
2007/2008	-0.0324	-0.0007	-0.0989	0.0026
2008/2009	0.0149	0.0106	0.0185	0.0158
Average	-0.0096	0.0029	-0.0333	0.0016

The lower panel of Table 4.2 lists the annual efficiency change of three inputs under a total-factor framework in each sub-period. This result shows that fund and labor inputs both present positive efficiency changes on average, although these changes are relatively small. It also implies that the gaps in the relative efficiency of those two inputs gradually narrow among Chinese banks. Nevertheless, the average efficiency of capital input decreases year by year from 2005 to 2008, indicating that there is no catch-up effect for capital management

in China's bank industry. Only for the last period does one see that efficiency improvement of TFP results from all inputs' efficiency enhancement.

4.3.2 Productivity analysis at the firm level

This subsection compares the productivity growth, including TFP and three inputs, among 21 Chinese banks. Table 4.3 lists the productivity change of TFP and three inputs as well as the decomposition of each productivity indicator. From the viewpoint of TFP change, five banks are 'innovators', meaning that these banks construct the efficiency frontier each year and cause the frontier to shift. However, if we further investigate individual input productivity, only Bank of Beijing (#2) is an innovator that shifts the frontiers of all inputs, especially for the technical progress of capital use.

According to Table 4.3, one bank (Bank of China) shows a negative growth of TFP (-0.84%) among 21 Chinese banks. The decline of TFP results from its efficiency regress (9.68%), though its technical change is positive (8.84%) during 2005-2009. Furthermore, the total-factor input productivity changes of Bank of China decrease about 0.12% to 1.72% for three inputs. This result shows that the drops of inputs' productivity can be attributed to the efficiency changes of capital (-15.12%) and labor (-13.49%) usage.

Aside the six banks discussed above, other banks tend to fall into one of three categories based on Table 4.3. The first group indicates that the total-factor productivity growth is mainly driven by efficiency improvement. These banks include China CITIC Bank (#8) and Evergrowing Bank (#14). Nevertheless, it is worth noting that the major sources of efficiency improvement of China CITIC Bank and Evergrowing Bank are capital efficiency (11.60%) and labor efficiency (14.62%), respectively.

The second group includes Agricultural Bank of China (#1), Bank of Communications (#4), Guangdong Development Bank (#15), and ICBC (#17). All of these banks have the

Table 4.3

Productivity growth, technical progress, and efficiency change of TFP and individual input

Bank	Total-Factor			Fund			Capital			Labor		
	TFPCH	TECHCH	EFFCH	FPCH	TECHCH	EFFCH	CPCH	TECHCH	EFFCH	LPCH	TECHCH	EFFCH
Bank #1	0.0045	0.0040	0.0005	-0.0085	-0.0198	0.0112	0.0135	0.0475	-0.0340	0.0086	-0.0158	0.0244
Bank #2	0.1103	0.1103	0.0000	0.0081	0.0081	0.0000	0.2014	0.2014	0.0000	0.1215	0.1215	0.0000
Bank #3	-0.0084	0.0884	-0.0968	-0.0067	-0.0025	-0.0042	-0.0012	0.1500	-0.1512	-0.0172	0.1177	-0.1349
Bank #4	0.0468	0.0268	0.0200	0.0027	0.0086	-0.0059	0.0291	0.0486	-0.0195	0.1087	0.0232	0.0856
Bank #5	0.0436	0.0436	0.0000	-0.0072	-0.0072	0.0000	0.0822	0.0822	0.0000	0.0556	0.0556	0.0000
Bank #6	0.0212	0.0442	-0.0230	0.0008	0.0032	-0.0024	0.0535	0.0590	-0.0055	0.0094	0.0704	-0.0610
Bank #7	0.0153	0.0702	-0.0549	0.0057	0.0057	0.0000	0.0158	0.1268	-0.1110	0.0244	0.0781	-0.0537
Bank #8	0.0683	0.0168	0.0515	-0.0078	-0.0103	0.0025	0.1707	0.0547	0.1160	0.0418	0.0059	0.0359
Bank #9	0.0202	0.0537	-0.0336	0.0034	0.0060	-0.0026	0.0266	0.1157	-0.0891	0.0305	0.0395	-0.0089
Bank #10	0.0068	0.0511	-0.0443	0.0078	0.0058	0.0021	0.0344	0.1563	-0.1219	-0.0220	-0.0089	-0.0132
Bank #11	0.0238	0.0752	-0.0514	0.0005	0.0038	-0.0034	0.0722	0.1677	-0.0955	-0.0014	0.0540	-0.0554
Bank #12	0.0135	0.0135	0.0000	-0.0260	-0.0260	0.0000	0.1121	0.1121	0.0000	-0.0455	-0.0455	0.0000
Bank #13	0.0299	0.0299	0.0000	0.0104	0.0104	0.0000	0.1241	0.1241	0.0000	-0.0448	-0.0448	0.0000
Bank #14	0.0892	0.0079	0.0813	-0.0033	-0.0134	0.0101	0.0957	0.0080	0.0878	0.1753	0.0290	0.1462
Bank #15	0.0739	0.0505	0.0233	0.0466	0.0053	0.0414	0.0828	0.1286	-0.0458	0.0922	0.0177	0.0745
Bank #16	0.0322	0.0489	-0.0167	-0.0083	-0.0059	-0.0024	0.0575	0.1010	-0.0435	0.0474	0.0516	-0.0042
Bank #17	0.0466	0.0343	0.0123	0.0067	0.0029	0.0038	0.0950	0.0759	0.0190	0.0381	0.0240	0.0141
Bank #18	0.0382	0.0687	-0.0305	0.0109	0.0109	0.0000	0.0861	0.1248	-0.0387	0.0176	0.0703	-0.0527
Bank #19	0.0389	0.0391	-0.0001	-0.0487	-0.0487	0.0000	0.1106	0.1110	-0.0004	0.0550	0.0550	0.0000
Bank #20	0.0030	0.0425	-0.0394	0.0171	0.0067	0.0104	-0.0315	0.1343	-0.1658	0.0235	-0.0136	0.0371
Bank #21	0.0781	0.0781	0.0000	-0.0138	-0.0138	0.0000	0.2649	0.2649	0.0000	-0.0167	-0.0167	0.0000

Note: Banks #1-#21 are Agricultural Bank of China (1), Bank of Beijing Co. Ltd. (2), Bank of China Limited (3), Bank of Communications Co. Ltd. (4), Bank of Nanjing (5), Bank of Ningbo (6), Bank of Shanghai (7), China CITIC Bank Corporation Limited (8), China Construction Bank Corporation (9), China Everbright Bank Co. Ltd. (10), China Merchants Bank Co. Ltd. (11), China Minsheng Banking Corporation (12), China Zheshang Bank Co. Ltd. (13), Evergrowing Bank Co. Ltd. (14), Guangdong Development Bank (15), Hua Xia Bank (16), Industrial & Commercial Bank of China (17), Industrial Bank Co. Ltd. (18), Shanghai Pudong Development Bank (19), Shanghai Rural Commercial Bank (20), and Shenzhen Development Bank Co. Ltd. (21), respectively.

characteristics that the TFP growth is mainly driven by the technical progress. However, there are some differences between those banks when we further analyze total-factor input productivity of individual input. For examples, ICBC is the only one in which all input productivity changes are positive and the components (technical change and efficiency change) of three input productivities are also positive. Agricultural Bank of China presents a slight technical improvement (0.40% per year) of TFP, while this progress is caused by the technological progress of capital usage, and not the other two inputs.

The last group containing nine banks presents that the technological gains transcend the efficiency regressions and results in TFP growth. From the view of individual input, the sources of TFP growth are capital productivity improvement and the technical progress of capital use for those banks. It confirms that the TIPI proposed by this paper is necessary in order to investigate the source of TFP in more detail.

### 4.3.3 Further analysis of productivity and efficiency

The previous subsection illustrates the results of the total-factor inputs' productivity growth and their decompositions. However, it is noteworthy to simultaneously consider banks' static efficiency level and dynamic productivity change. Therefore, the following analysis focuses on banks' relative efficiency and productivity change in order to obtain more insights about each bank's advantages and disadvantages.

First of all, this paper uses the industry's mean efficiency score and productivity change rate to construct an efficiency-productivity matrix for each input variable.[4] Banks at the first (right upper) quadrant present a better relative efficiency and higher productivity growth rate, indicating these banks have the strength (or advantage) of particular inputs. Banks at the second (left upper) quadrant present better efficiency, but a lower productivity growth rate.

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[4] The particular input efficiency of a bank can be calculated by $(1 - \vec{D}_{i(t)}(\mathbf{x}^t, \mathbf{y}^t))$.

We consider that these banks will confront a threat for using particular inputs, because their productivity growth rates are slower than the industry's average. Although banks at the second quadrant have better efficiency, they may be caught by rapid-growth banks. In addition, banks are weak in certain inputs when they locate on the third (left lower) quadrant. Following our consideration, banks at the fourth (right lower) quadrant gain an opportunity of certain inputs for challenging more efficient banks in the future.

Panel A of Figure 4.3 shows the overall technical efficiency and total-factor productivity change of each Chinese bank. There are six banks located on the first quadrant, including five efficient banks (i.e., Bank of Beijing, Bank of Nanjing, Industrial Bank, Shanghai Pudong Development Bank, and Shenzhen Development Bank). Among these banks, Bank of Beijing has the highest TFP growth rate of 11.03% per year. Relative to the industry's average, however, six banks locate on the fourth quadrant, meaning those banks are relatively inefficient and have a lower TFP growth rate. Accordingly, Bank of China is the only one that presents an annual negative TFP growth and the other two banks of the Big Four, i.e. Agricultural Bank of China and China Construction Bank Corporation, have a similar pattern to Bank of China.
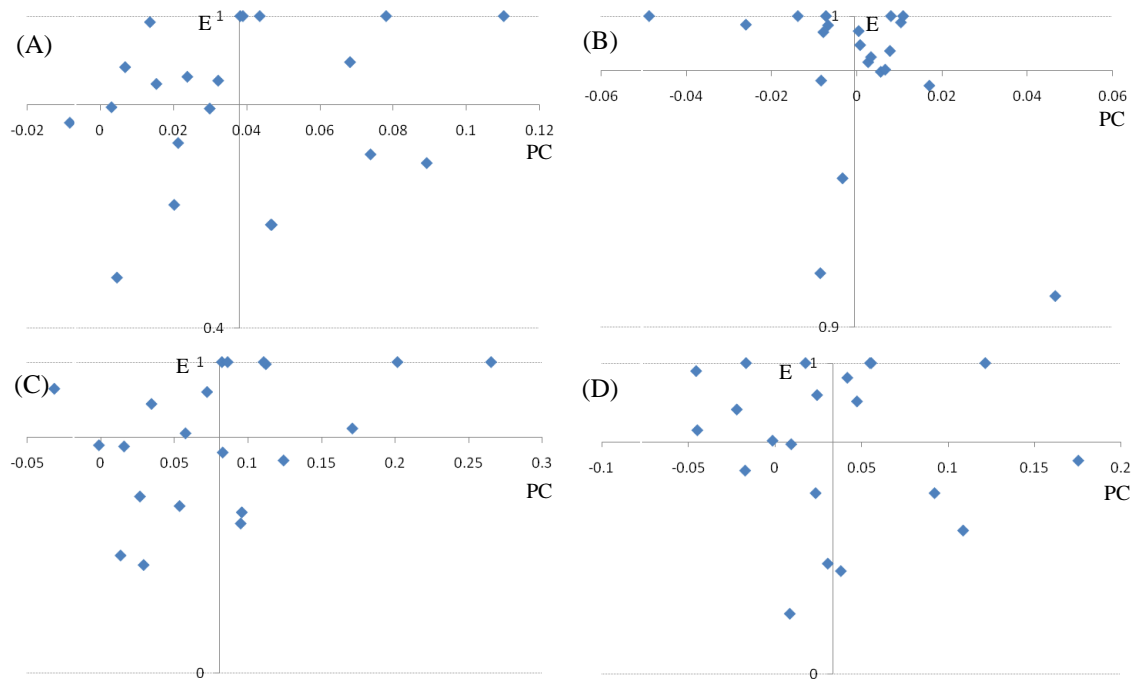
Note: The horizontal and vertical axis are productivity change (PC) and efficiency score (E), respectively. Panels (A)-(D) show the matrices for total factor, fund input, capital input, and labor input, respectively.

Figure 4.3 The efficiency-productivity matrices of TFP and individual input

Panels B, C, and D of Figure 4.3 show the efficiency-productivity matrices of fund, capital, and labor inputs for each bank, respectively. The matrix of fund input (Panel B) shows that the mean of fund effectiveness is close to one, meaning that all banks almost use this input efficiently. Although only three banks are at the fourth quadrant, the fund productivity of nine banks regresses over the research periods. It is noteworthy that three efficient banks (Bank of Nanjing, Shanghai Pudong Development Bank, and Shenzhen Development Bank) present a recession of fund productivity, suggesting that they should pay more attention to this problem.

With respect to the matrix of capital input (Panel C), the patterns of capital input and Panel A are alike since the improvement of capital productivity is the main source of TFP change in mainland China. Shenzhen Development Bank is one of seven banks locating on the first quadrant and has the highest capital productivity increase rate (26.49% annually) among those banks. Furthermore, ICBC is the only one of the Big Four that lies in the

fourth quadrant (i.e., low efficiency but high productivity enhancement), indicating capital usage is a potential advantage for ICBC relative to others.

Finally, Panel D of Figure 4.3 provides the labor efficiency-productivity matrix. It shows that improvement in the labor productivity of eight banks is higher than the industry's average. Accordingly, Evergrowing Bank has the highest growth rate of 17.53%, though its efficiency level is lower than the average, suggesting that Evergrowing Bank may gain strength in labor input in the future. Six banks decrease their labor productivity and most of them (five banks) lie in the second quadrant. This means that these five banks will lose the advantage of labor productivity in the future if they do not take notice of this warning.

We further gather the results of Figure 6 and represent the state of individual banks in Table 4.4, which help us to find the advantages and disadvantages of each bank more clearly. For example, Bank of Beijing (#2) is efficient in the usage of all inputs and has relatively higher productivity improvements in all inputs, indicating that this bank has the advantages of three resource inputs over other banks. Agricultural Bank of China (#1), however, presents entirely different patterns of three inputs compared to Bank of Beijing, i.e. Agricultural Bank of China has no advantages of any input. Furthermore, the results of the efficiency-productivity matrices of Bank of Nanjing (#5) and China CITIC Bank (#8) are identical, showing strength gains in capital and labor use, but have warnings of fund use.

Except for Agricultural Bank of China, the other banks of the Big Four also represent distinguishing features of total-factor inputs' productivity. For instance, Bank of China (#3) and China Construction Bank (#9) are both poor in efficiency as well as productivity growth of capital and labor inputs, while China Construction Bank has advanced capacity for fund use. Moreover, ICBC (#17) not only stands at an advantage for fund use, but gains potential opportunities for other inputs.

Table 4.4

The advantages and disadvantages of each bank

Bank	Fund input	Capital input	Labor input	TFP
Bank #1	III	III	III	III
Bank #2	I	I	I	I
Bank #3	II	III	III	III
Bank #4	I	III	IV	IV
Bank #5	II	I	I	I
Bank #6	I	III	III	III
Bank #7	IV	III	II	II
Bank #8	II	I	I	I
Bank #9	I	III	III	III
Bank #10	I	II	II	II
Bank #11	I	II	II	II
Bank #12	II	I	II	II
Bank #13	I	IV	II	III
Bank #14	III	IV	IV	IV
Bank #15	IV	IV	IV	IV
Bank #16	III	II	I	II
Bank #17	I	IV	IV	IV
Bank #18	I	I	II	I
Bank #19	II	I	I	I
Bank #20	IV	II	III	III
Bank #21	II	I	II	I

Note: Bank #1-#21 are Agricultural Bank of China (1), Bank of Beijing Co. Ltd. (2), Bank of China Limited (3), Bank of Communications Co. Ltd. (4), Bank of Nanjing (5), Bank of Ningbo (6), Bank of Shanghai (7), China CITIC Bank Corporation Limited (8), China Construction Bank Corporation (9), China Everbright Bank Co. Ltd. (10), China Merchants Bank Co. Ltd. (11), China Minsheng Banking Corporation (12), China Zheshang Bank Co. Ltd. (13), Evergrowing Bank Co. Ltd. (14), Guangdong Development Bank (15), Hua Xia Bank (16), Industrial & Commercial Bank of China (17), Industrial Bank Co. Ltd. (18), Shanghai Pudong Development Bank (19), Shanghai Rural Commercial Bank (20), and Shenzhen Development Bank Co. Ltd. (21), respectively.

5. CONCLUSIONS

This thesis proposes a total-factor input productivity index to compute one particular factor productivity change under the total-factor framework. This proposed index tries to overcome the disadvantages of a traditional productivity index, such as energy productivity, labor productivity, and land productivity: first, a traditional productivity index neglects the substitution or complement effects among all inputs; second, a traditional indicator disregards the technology level of factor use.   In addition, the total-factor input productivity index also modifies the well-known total factor productivity index, the Luenberger productivity index that cannot deal with single factor productivity change under a total-factor framework.

This thesis accomplishes two distinct research studies to show that the total-factor input productivity index can be applied among a broad field. The first study is an application of energy productivity in mainland China.   This case investigates the total-factor energy productivity change of regions in mainland China.   The components of total-factor energy productivity change (i.e. efficiency change and technical change) are also presented.   The results indicate that energy productivity in mainland China declines over the research period and the main problem of energy use there is attributable to negative technical growth.

The second study is an application on banks in mainland China.   This application tries to investigate the source of TFP growth as well as the productivity change of each input factor (i.e. labor, capital, and fund).   The results indicate that the TFP growth is mainly driven by the technical progress in China's banking industry.   If I further analyze the TIPI of Chinese banks, it is found that the source of technical progress is attributed to the technological gain of capital usage.   In addition, this application uses efficiency-productivity matrices to realize what are the advantages and disadvantages in a Chinese bank.

This thesis provides a new decomposition approach that decomposes TFP growth into

the change of individual input productivity. Prior literature mainly decomposes TFP growth into efficiency change and technical change. In fact, there are alternative ways to decompose the same TFP measures under a VRS assumption (e.g., Chang and Luh, 2000). Thus, I suggest that the proposed TIPI can be further decomposed into detailed components (such as scale efficiency change of individual input and Input bias index) if following works extend this index with a VRS technology assumption.

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