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# The sources of bank productivity growth in China during 2002–2009: A disaggregation view

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ABSTRACT

This study investigates the sources of bank productivity growth in China over the period 2002–2009. In order to perform this research, we propose an advanced index – input slack-based productivity index (ISP) – a model that disaggregates total factor productivity growth into each input productivity change. Funds, capital, and employees are chosen as the inputs, whereas loans and other earning assets are outputs in this study. Our results show that technological gains transcend the efficiency regressions and result in total factor productivity growth. More specifically, technical progress in capital productivity reveals the dominant force behind the total factor technical change and productivity improvement. In addition, this paper uses these disaggregation terms to find out the competitive advantages and disadvantages of input usages for each Chinese bank. These findings indicate that the ISP index provides more insights than traditional total factor productivity indices.



## 1. Introduction

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 over RMB 60 trillion, or 300 times that in 1978.[1] In November 2009 the capital adequacy ratio and the provision coverage of the banking industry were over 10% and 150%, respectively. Chinese banks in recent years have raised their importance in the world banking system. For example, Industrial and Commercial Bank of China, China Construction Bank, Agricultural Bank of China, and Bank of China are four of the largest 10 banks in the world. Moreover, financial reforms have made efficiency and productivity improvements in the banking sector (Chen et al., 2005; Matthews et al., 2009).

This paper investigates the total factor productivity (TFP) changes and disaggregates the sources of productivity change in China's banking industry from 2002 to 2009. This research period is meaningful for Chinese banks, because China has entered the World Trade Organization (WTO) in December 2001. In addition, 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 US 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 employ the Malmquist index for productivity growth and find that the source of productivity growth is efficiency improvement in Norway's banks during 1980–1989. Other evidence indicates that productivity growth is mainly driven by technical change for the American (Alam, 2001; Mukherjee et al., 2001), European, and Japanese banks (e.g., Casu et al., 2004; Koutsomanoli-Filippaki et al., 2009; Barros et al., 2010; Assaf et al., 2011) by applying the Malmquist index or Luenberger index. However, only a few research studies have taken a look at the productivity growth of Chinese banks, such as Kumbhakar and Wang (2007), Matthews et al. (2009) and Matthews and Zhang (2010). These studies generally conclude that a positive TFP growth is dominantly driven by technical progress in China's banking industry and the TFP growth rate of joint-stock banks (JSBs) is higher than SOBs.

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[1] RMB stands for Renminbi, the Chinese currency.

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In summary, prior literature adopts the Malmquist productivity index (MPI) or Luenberger productivity index (LPI) to investigate the change of TFP, efficiency change, and technical change. Unfortunately, these two indices are aggregative and do not simultaneously deal with the TFP growth and 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 herein, the so-called input slack-based productivity index (ISP), uses a Färe–Lovell efficiency measure to extend the traditional Luenberger productivity index and finds the strongly efficient vector for each input. This index then can be decomposed into particular input efficiency change and input technical change, meaning that we can discuss the sources of individual input productivity. Furthermore, we show that the TFP change is the average of the productivity change of an individual input. It is meaningful that we can explore the sources of each bank's TFP growth, efficiency change, and technical progress.

The remainder of this paper is organized as follows. Section 2 reviews financial reform in China's banking industry and the literature on efficiency and productivity improvements of Chinese banks. Section 3 illustrates our proposed total factor input productivity index. Section 4 interprets the data sources and variables' descriptions. Section 5 provides the empirical results and Section 6 concludes this paper.

## 2. Literature review

### 2.1. Financial reform in China's banking industry

China is both a developing country and a transitional market economy. Financial reform and development there reflect the influence of both these contexts. Referring to the environment with different regulations and competition, the China Banking Regulatory Commission (CBRC) divides the financial reform of the banking industry into three stages. We briefly introduce these three stages of financial reform process since 1978 (for more details, see Kumbhakar and Wang, 2007; Berger et al., 2009, 2010; Lin and Zhang, 2009).

#### 2.1.1. First stage of financial reform (1978–1993)

Before financial reform, China's financial system took on a mono-bank model (i.e. People's Bank of China, PBOC). During 1978–1993, the financial system began the first round of financial reform aimed at restructuring the operations of its banking system. To expand the banking system, four wholly state-owned specialized banks, commonly called the 'Big Four', were founded and provided loans to state-owned enterprises (SOEs) in specific sectors. Bank of China, Agricultural Bank of China, and China Construction Bank were founded in 1979, and Industrial and Commercial Bank of China was established in 1984. Sequentially, the Big Four were allowed to enter and compete in all sectors in 1985.

#### 2.1.2. Second stage of financial reform (1994–2002)

During the 1990s, the asset quality of the Big Four worsened significantly as they accumulated a great amount of non-performing loans (NPLs). This difficulty was attributed to these banks making large volume policy loans to the SOEs, which only played a social role rather than for profit maximization. To alleviate this problem, the Chinese government launched the second round of financial reform in 1994. Accordingly, the government set up three major instruments for strengthening the balance sheets and the competitiveness of SOBs as follows.

First, to decrease the massive NPLs in China's financial system, the government established three policy banks to take over the policy-lending activities from the SOBs in 1994. The government also initialed four asset management companies (AMCs) to absorb the existing pool of NPLs in 1998. These AMCs bought the NPLs of the SOBs with a sum of 1.4 trillion RMB at face values (roughly 20% of their outstanding loans).

Second, in May 1995 the government enacted the 'Commercial Banks Law of the People's Republic of China' to construct a legal commercial banking system. The SOBs now could move more toward being a commercial business and profit-driven. Additionally, the government encouraged the entry of both new domestic commercial banks and foreign banks by relaxing the entry barriers. In the mid-1990s, 10 joint-stock banks (JSBs) and over 100 city commercial banks (CCBs) were established in the banking system.

Third, new accounting principles, which are consistent with the basic ideas of the International Accounting Standards, were adopted in July 1993. After the Asian financial crisis, China's central bank recognized the importance of risk management in the banking sector and adopted a new risk management system with five-tier classifications of loans in 1998.

#### 2.1.3. Third stage of financial reform (2003–present)

In 2003, three important policies were implemented in line with the third stage of financial reform. First, the China Banking Regulatory Commission (CBRC) was established to realize better governing of Chinese banking institutions. Second, CBRC promoted foreign share purchases, regulating that foreigners could own up to 25% of any domestic bank and ownership from any one single foreign investor was allowed at between 5% and 20%. Third, the State Council provided US$45 billion of foreign exchange reserves to Bank of China and China Construction Bank in order to reinforce their capital structures.

Up until now, many state-owned banks, joint-stock banks, and city commercial banks have brought in foreign strategic investors after 2003. For example, in October 2005, Royal Bank of Scotland announced a US$3.1 billion investment which gave the British bank control of just under a 10% in Bank of China. Further investments were made by Swiss bank UBS and Singapore government-led Temasek, which also promised to subscribe to an additional US$500 million worth of shares during Bank of China's initial public offering (IPO).

Aside from financial restructuring and foreign strategic investments, China's government encouraged banks to list on stock exchanges in order to improve their governance and external monitoring. For instance, to date, all of the Big Four banks have successfully issued IPOs inside and outside China. Table 1 summarizes some information on the IPOs of the Big Four. It shows that China Construction Bank was the first to issue an IPO among the Big Four, whereas Bank of China was the first to take this route on the local market – the Shanghai Stock Exchange. Moreover, the Agricultural Bank of China completed the world's largest IPO at a total of US$22.1 billion.

The step of China's financial reforms is ongoing. The capital adequacy ratios of all Chinese banking institutions were for the first time over 8% on average in 2007 and over 10% in 2009. Furthermore, China Development Bank Corporation was established in 2008, indicating that reform in policy banks had also made significant progress.

### 2.2. Evolution of efficiency and productivity improvements of Chinese banks

After an introduction on China's financial reform, this subsection further reviews existing research studies that investigate efficiency and productivity issues to see whether the reform would

**Table 1**
Information on the IPOs of the Big Four state-owned banks.

| Bank | Value of IPO | Stock exchange | Date |
|---|---|---|---|
| China Construction Bank | \$8 billion<br>\$7.6 billion | Hong Kong Exchange<br>Shanghai Stock Exchange | October 2005<br>September 2007 |
| Bank of China | \$11.2 billion<br>\$2.5 billion | Hong Kong Exchange<br>Shanghai Stock Exchange | Jun 2006<br>July 2006 |
| Industrial & Commercial Bank of China | \$16 billion<br>\$5.9 billion | Hong Kong Exchange<br>Shanghai Stock Exchange | October 2006<br>October 2006 |
| Agricultural Bank of China | \$11.98 billion<br>\$10.12 billion | Hong Kong Exchange<br>Shanghai Stock Exchange | July 2010<br>July 2010 |

*Note*: The value of IPO is exchanged from local currency to US dollars. The value of the IPO includes exercised over-allotment options.

benefit China's banking industry. We also survey studies providing an international comparison of bank efficiency or productivity growth.

Chen et al. (2005) examine the cost, technical, and allocative efficiencies of 43 Chinese banks during 1993–2000. Their results indicate that bank efficiency levels have improved since the financial deregulation of 1995. However, Fu and Heffernan (2009) use a cost frontier model to evaluate the effect of bank structure reform in China for the period 1985–2002 and obtain a contrary result to Chen et al. (2005), i.e. bank efficiency declines significantly after 1993. They also show that SOBs are less efficient than JSBs, which is echoed by Berger et al. (2009, 2010) and Lin and Zhang (2009). Accordingly, Berger et al. (2009) suggest that minority foreign ownership of the Big Four significantly enhance their performance.

Barros et al. (2011) investigate the technical efficiency of major Chinese banks over the period 1998–2008, finding an efficiency improvement of Chinese banks, especially after China entered the WTO. However, this paper shows that the effects of bank size and ownership on efficiency do not matter. Sun and Chang (2011) study the relationship between risk measures and bank efficiency in eight emerging Asian countries from 2002 to 2008. Based on their results, Chinese banks present relatively higher cost efficiency than those in other emerging Asian countries, except India. In addition, a clear upward trend of the average efficiency level of Chinese banks is noted in their research.

With respect to the emphasis of our study, few studies in the literature investigate 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 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.

Matthews and Zhang (2010) extend earlier research to measure the productivity of Chinese commercial banks for the period 1997–2007. They present that, in general, city commercial banks gain positive TFP growth, while the growths of SOBs and JSBs are neutral. Chen and Yang (2011) adopt a metafrontier Malmquist productivity index and conduct a cross-country comparison of bank productivity in China and Taiwan from 1993 to 2007, showing a positive TFP growth for these banks while the growth rate in China is less than Taiwan. They also indicate that China's banking industry gains positive technical progress, but a deterioration of efficiency change.

To sum up, existing research studies in general suggest that bank productivity has benefited from the financial reform, while the conclusions about bank efficiency are mixed. However, the literature on Chinese bank productivity is still insufficient. To our best knowledge, there are no studies emphasizing the relationship between TFP and each input factor's productivity growth. Therefore, our paper tries to fill this gap by introducing an input slack-based productivity index.

## 3. Methodology

With respect to productivity growth, the Luenberger productivity index is a convenient method to compute total factor productivity change. We first assume that 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:

$$\mathbf{F}^t = \{(\mathbf{x}^t, \mathbf{y}^t) : \mathbf{x}^t \text{ can produce } \mathbf{y}^t\}. \tag{1}$$

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

$$\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) = \max\{\beta \in \Re : (\mathbf{x}^t - \beta\mathbf{g}_x, \mathbf{y}^t + \beta\mathbf{g}_y) \in \mathbf{F}^t\}, \tag{2}$$

where $(\mathbf{g}_x, \mathbf{g}_y)$ is a non-zero vector in $R_+^M \times R_+^S$. Therefore, this function is defined by contracting inputs and expanding outputs simultaneously. One notices that $\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) \geqslant 0$, 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 is measured as follows:

$$L(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{x}^t, \mathbf{y}^t) = \frac{1}{2}\Big[(\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})) + (\vec{D}_{(t+1)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}))\Big]. \tag{3}$$

If the Luenberger productivity index is less than, equal to, or greater than zero, then it respectively stands for productivity regress, no change, or progress between periods $t$ and $t + 1$.

The Luenberger productivity index is actually a multi-factor productivity index that calculates the total factor productivity change of research objects. However, the commonly used Luenberger productivity index, assuming a special case with a proportional distance function, cannot deal with a single factor productivity change under total factor framework. Therefore, this paper introduces an input slack-based productivity index (hereafter, ISP) that applies input-oriented directional distance functions and a Färe–Lovell efficiency measure to extend the Luenberger productivity index. The proposed ISP thus not only calculates the total factor productivity change, but also the productivity change of an individual input under the total factor concern simultaneously.

We illustrate the approach of the proposed ISP index as follows. Assume there are M inputs and S outputs for each N objects in each time period of T. The $i$th input and $r$th output variable of the $j$th 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 (Kerstens et al., 2011). Therefore, the input-oriented directional distance functions for observation $o$ in time $t$ are stated as the following linear programming problems:

$$\vec{D}_{(t)}(\mathbf{x}^t,\mathbf{y}^t) = \max \frac{1}{M}(\beta_1 + \cdots + \beta_M)$$
$$\text{s.t.} \sum_{j=1}^{N} \lambda_j x_{ij}^t \leqslant x_{io}^t(1-\beta_i),$$
$$\sum_{j=1}^{N} \lambda_j y_{rj}^t \geqslant y_{ro}^t,$$
$$\lambda_j \geqslant 0, \beta_i \geqslant 0,$$
$$j = 1,\ldots,N; i = 1,\ldots,M; r = 1,\ldots,S. \tag{4}$$

Here, $\lambda_j$ is an $n \times 1$ vector of positively intensity variables that serves to form a convex combination of observed inputs and outputs. Moreover, $\beta_i$ is a scalar that indicates the proportional contraction of the $i$th input in order to catch up to the efficient level. Hence, if all the slack variables are zero, i.e. $\beta_1 = \beta_2 = \ldots = \beta_M = 0$, then the observation $o$ is on the strongly efficient frontier (Kerstens et al., 2011). 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 Eq. (3) can be calculated straightforward according to Eq. (4). The computation of $\vec{D}_{(t+1)}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})$ is exactly like Eq. (4), where $t+1$ is substituted for $t$. A similar approach is adopted for two intertemporal directional distance functions: $\vec{D}_{(t)}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})$ 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 Eqs. (3) and (4).

With respect to ISP, we further define $\beta_i$ obtained from Eq. (4) 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 $i$th input variable at $t$ under a total factor framework. Accordingly, the ISP for the $i$th input is measured as follows:

$$ISP_i = \frac{1}{2}\left[(\vec{D}_{i(t)}(\mathbf{x}^t,\mathbf{y}^t) - \vec{D}_{i(t)}(\mathbf{x}^{t+1},\mathbf{y}^{t+1})) + (\vec{D}_{i(t+1)}(\mathbf{x}^t,\mathbf{y}^t) - \vec{D}_{i(t+1)}(\mathbf{x}^{t+1},\mathbf{y}^{t+1}))\right]. \tag{5}$$

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

ISP is only an aggregate index that might be oversimplified or over-aggregated. In other words, although ISP computes the total factor input productivity change, it does not indicate the sources of change directly. Thus, a deeper study on the components of ISP is necessary. Based on the traditional Luenberger productivity index, ISP 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 $i$th input:

$$EFFCH_i = \vec{D}_{i(t)}(\mathbf{x}^t,\mathbf{y}^t) - \vec{D}_{i(t+1)}(\mathbf{x}^{t+1},\mathbf{y}^{t+1}), \tag{6}$$

$$TECHCH_i = \frac{1}{2}\left[\vec{D}_{i(t+1)}(\mathbf{x}^{t+1},\mathbf{y}^{t+1}) - \vec{D}_{i(t)}(\mathbf{x}^{t+1},\mathbf{y}^{t+1}) + \vec{D}_{i(t+1)}(\mathbf{x}^t,\mathbf{y}^t) - \vec{D}_{i(t)}(\mathbf{x}^t,\mathbf{y}^t)\right]. \tag{7}$$

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:

$$\begin{aligned} TFPCH &= EFFCH + TECHCH \\ &= \frac{1}{M}[EFFCH_1 + \cdots + EFFCH_M] + \frac{1}{M}[TECHCH_1 + \cdots + TECHCH_M] \\ &= \frac{1}{M}[ISP_1 + ISP_2 + \cdots + ISP_M]. \end{aligned} \tag{8}$$

Eq. (8) indicates that the TFP change is the arithmetic mean of the change of individual input productivity. Moreover, the efficiency change and technical change of individual input can be aggregated as the total factor efficiency change and technical change, respectively.

Eq. (8) is the main contribution of this paper. The first formula of Eq. (8), mostly used in previous research, indicates the TFP change can be decomposed into total factor efficiency change and technical change, respectively. The other two formulae, first proposed in this paper, provide information about what factor is the driving force of TFP change. Using a disaggregation view, it will be useful and fruitful as we are interested in the sources of TFP – that is, to explore which input factor mainly contributes the highest productivity growth in any productivity research.

## 4. 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 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*). 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 (e.g., Lensink et al., 2008). 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 paper collects a balanced panel data covering 2002–2009 from 19 Chinese commercial banks. The sample banks include the Big Four state-owned banks, 10 national joint-stock commercial banks, and five major city commercial banks in China. These 19 banks own about 65% of total assets in China's whole banking sector, meaning that our sample banks are strongly representative to investigate the TFP growth of Chinese banks. As mentioned above, China has experienced some epochal events during this research period. First, China jointed the WTO such that foreign entry has had a limited impact on the local banking industry. Second, state-owned banks have been partially privatized to take on minority foreign ownership since 2005. Finally, the global financial crisis struck China's financial sector and banking industry in 2008.

All financial data, such as items from balance sheets and income statements, are taken from the Bankscope database, a comprehensive resource of international banking institutions. All nominal prices are transformed using the GDP deflator with 2009 as the base year. Unfortunately, information on the number of employees for each Chinese bank is quite incomplete in this database. Therefore, this variable is complemented through each bank's annual report.

Panel A of Table 2 summarizes the output and input data of our sample from 2002 to 2009. The high standard deviations of all variables are quite noteworthy, indicating that the structure of Chinese banking industry evolves differently in bank size and operation scale. We also show these descriptive statistics based on the groups of banks in panel B, which clearly demonstrates that the Big Four state-owned banks dominate China's bank industry. For example, the average total loans of SOBs in excess of 3 million RMB are about 7 and 40 times the total loans of JSBs and CCBs in

**Table 2**
Descriptive statistics for output and input variables (2002–2009). *Source*: Bankscope database and each bank's annual report.

Panel A: Variables' definitions and descriptive statistics (million RMB except labor)

| Variable | Description | Mean | S.D. |
|---|---|---|---|
| TL | Total loans excluding loan loss reserves | 958,422 | 1,300,145 |
| OEA | Total other earning assets | 796,736 | 1,225,890 |
| F | Funds – Total deposits & short-term funding | 1,690,653 | 2,394,361 |
| C | Capital – Total fixed assets | 21,589 | 32,422 |
| L | Labor – Number of employees | 83,319 | 143,942 |

Panel B: Descriptive statistics (in average by bank groups)

| Groups | TL | OEA | *F* | *C* | *L* |
|---|---|---|---|---|---|
| SOB | 3,284,697 | 2,861,273 | 5,927,574 | 80,959 | 347,020 |
| JSB | 468,471 | 328,012 | 765,767 | 7954 | 18,030 |
| CCB | 77,305 | 82,553 | 150,887 | 1364 | 2934 |

*Note*: All nominal prices are transferred using the GDP deflator with 2009 as the base year. SOB, JSB, and CCB are state-owned banks, joint-stock banks, and city commercial banks, respectively.

the sample period, respectively. All other variables present similar patterns of differences among the three groups of banks.[2] Moreover, the correlations between each pair of input–output variables (not present) are highly positive, which is consistent with economic intuition and the production theory.

## 5. 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 group and firm levels.

### 5.1. Productivity analysis at the industry level

Fig. 1 shows the annual total factor productivity growth and productivity changes of three inputs from 2002 to 2009. The average annual TFP growth rate is 3.85% and the TFP cumulatively grows by 29.84%, indicating an upward trend for Chinese banks. All sub-periods present a positive TFP growth rate except the period of 2007–2008 (−1.46%). 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.

Fig. 1 also indicates the productivity change of three inputs under a total factor framework. During 2004–2007, three inputs present a positive productivity change, especially for capital used. Capital and fund productivity improve 2.57% and 0.03% from 2007 to 2008, respectively. Although the labor productivity of Chinese banks decreases 7.00% from 2007 to 2008, it outstandingly improves 19.28% in the last sub-period. There is an interesting finding that Chinese banks have experienced a decline in the growth rate of fund productivity. It shows that the fund productivity growth rate starts from 3.33% in 2003, gradually falls to 0.08% in 2007, and finally decreases to −2.53% in 2009. The more likely explanation rests in that the usage of funding is quite competitive and has confronted a predicament.

In summary, capital, labor, and fund productivity cumulatively change 56.09%, 24.55%, and 9.81% over the research period, respectively. We conclude that TFP's improvement mainly attributes to capital management and human resource reinforcement in China's bank industry.

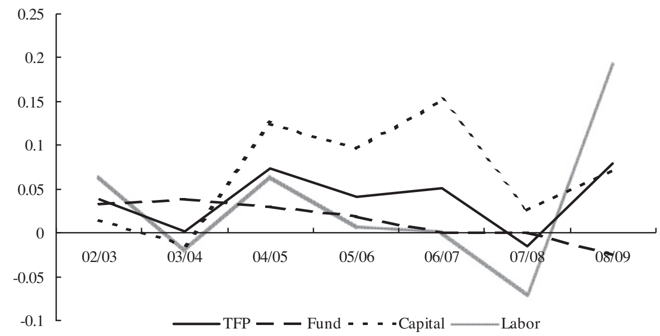


**Fig. 1.** Annual change of TFP and total factor input productivity indices.

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 Fig. 2. Fig. 2 sketches the cumulative growth of TFP, technical change, and efficiency change during 2002–2009. Accordingly, there is a strictly increasing trend of technical change with an average of 5.03% per year, meaning that the production frontier substantially shifts upward. However, there is no catch-up effect in the bank industry, because the change in relative efficiency totally decreases 8.08% from 2002 to 2009. This indicates that inefficient banks are getting farther from the annual frontier in China's banking sector.

As mentioned above, the TFP drops during 2007–2008. Fig. 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 3 provides the annual technical change of three inputs under a total factor framework in each sub-period. The technology of capital used achieves the highest growth rate with 9.22% annually, followed by labor resource progression (4.40%) and fund usage improvement (1.47%). However, the most improvements of fund usage occurred before 2005, meaning that the technology of funds used presents a sharp decline in recent years. Hence, we consider that the technical progress of capital usage is the main source of the total factor technology shift.

The lower panel of Table 3 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 negative 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 become broader among Chinese banks. Furthermore, the efficiency change of capital input decreases year by year with an average of 2.5% from 2002 to 2009, 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 in TFP results from all inputs' efficiency enhancement.

### 5.2. Productivity analysis at the group level

This sub-section analyzes the sources of productivity growth of three groups (i.e., state-owned banks, joint-stock banks, and city commercial banks) of Chinese banks. Fig. 3 illustrates the cumula-

[2] The sample banks make up three groups of banks and reveal obvious differences among these groups. Battese et al. (2004) argue that firms in different groups may have different technologies. They propose a metafrontier production function model to calculate comparable technical efficiencies for firms operating under different technologies. However, our paper does not follow the concept of metafrontier, because we are interested in the frontier of China's bank industry as a whole.

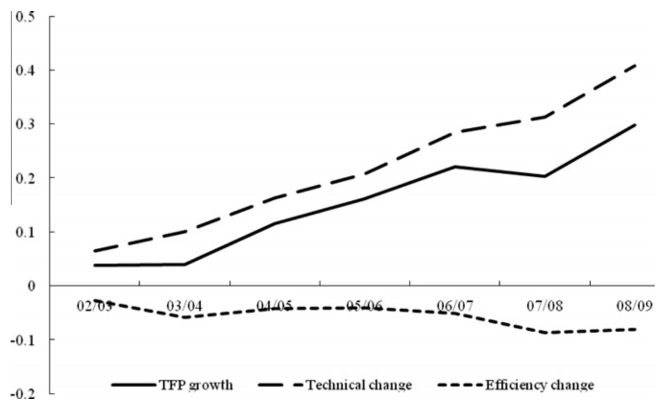


**Fig. 2.** Cumulative changes of TFP and its components.

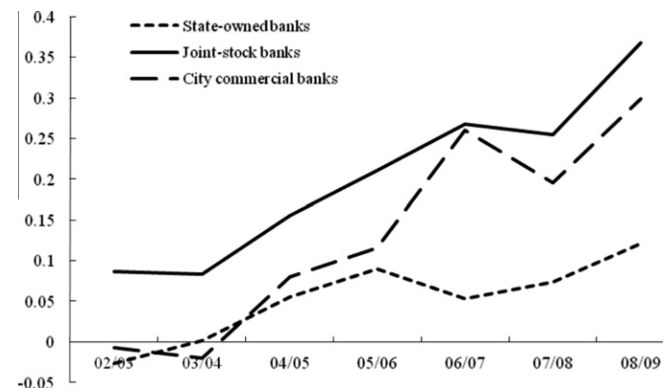


**Fig. 3.** Cumulative TFP growths of the three bank groups.

**Table 3**
Annually technical changes and efficiency changes of three inputs.

| Period | Total factor | Fund | Capital | Labor |
|---|---|---|---|---|
| *Technical change* | | | | |
| 2002/2003 | 0.0649 | 0.0483 | 0.0219 | 0.1244 |
| 2003/2004 | 0.0336 | 0.0340 | 0.0337 | 0.0332 |
| 2004/2005 | 0.0562 | 0.0349 | 0.1307 | 0.0031 |
| 2005/2006 | 0.0388 | 0.0196 | 0.0765 | 0.0205 |
| 2006/2007 | 0.0632 | −0.0013 | 0.1909 | 0.0002 |
| 2007/2008 | 0.0223 | 0.0008 | 0.1232 | 0.0571 |
| 2008/2009 | 0.0729 | −0.0332 | 0.0683 | 0.1835 |
| Average | 0.0503 | 0.0147 | 0.0922 | 0.0440 |
| *Efficiency change* | | | | |
| 2002/2003 | −0.0270 | −0.0150 | −0.0070 | −0.0591 |
| 2003/2004 | −0.0320 | 0.0042 | −0.0474 | −0.0527 |
| 2004/2005 | 0.0169 | −0.0050 | −0.0064 | 0.0622 |
| 2005/2006 | 0.0018 | −0.0010 | 0.0201 | −0.0136 |
| 2006/2007 | −0.0117 | 0.0021 | −0.0391 | 0.0019 |
| 2007/2008 | −0.0369 | −0.0005 | −0.0975 | −0.0129 |
| 2008/2009 | 0.0065 | 0.0079 | 0.0023 | 0.0093 |
| Average | −0.0118 | −0.0011 | −0.0250 | −0.0093 |

tive TFP change of each group from 2002 to 2009. It shows that joint-stock banks have the highest cumulative productivity growth (36.76% over the research period), followed by city commercial banks with a total of 29.92%. The Big Four state-owned banks present the lowest growth rate of 1.70% annually and a total of 12.13% during 2002–2009. Our results are consistent with Kumbhakar and Wang (2007) and Matthews et al. (2009) who find joint-stock banks have better productivity growth than state-owned banks. Moreover, the patterns of JSBs and CCBs are quite similar after 2004, showing a drop in TFP during the recent financial crisis. We interpret this to mean that JSBs and CCBs have introduced foreign strategic investors much more than SOBs. Therefore, JSBs and CCBs would be more impressionable if the global financial environment encounters great difficulties.

This paper further disaggregates the TFP growth of each group into three input productivity changes and illustrates the results in Fig. 4. As shown in Fig. 4, SOBs with the lowest TFP growth present annual growth rates of 1.59%, 1.90%, and 1.61% for fund, capital, and labor productivity, respectively. In contrast, the highest TFP growth of JSBs is mainly driven by capital productivity improvement with an average of 9.23%. The sources of CCBs' TFP change benefit from capital and labor productivity enhancements as the both growth rates are over 5% annually. Again, Fig. 4 represents that capital productivity mainly contributes to the TFP change of Chinese banks, while fund productivity has the least effect on TFP.

In order to gain a better realization of the sources behind each input productivity growth of the three bank groups, we also report

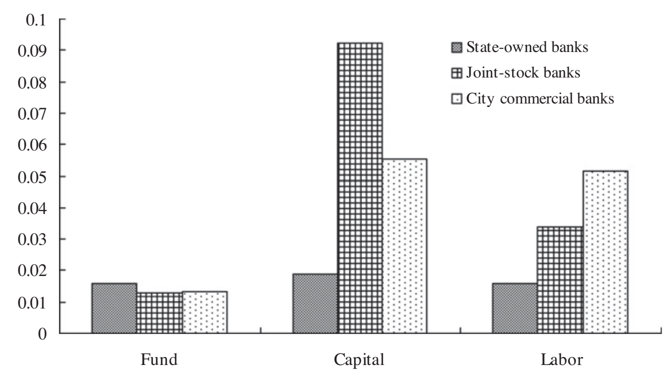


**Fig. 4.** Annual growth rate of individual input productivity (by bank groups).

the contributions from technical change and efficiency to each input productivity growth. Table 4 lists the shares of contributions of those two components in percentage terms. At first blush, all bank groups have a similar result, presenting that technology progress is the dominant force behind each input productivity growth during the research period.

In fact, SOBs and CCBs gain input productivity growth from technology improvements, while all of their efficiency changes represent negative contributions, especially for stated-owned banks. For example, the capital productivity growth of SOBs, which is the major source of their TFP growth, is driven by technical change (the contribution is 336.61%). In contrast, efficiency change is calculated to be −4.50% annually, accounting for −236.61% of the capital productivity growth of SOBs. This indicates that most benefits from strong technology progress are offset by efficiency regression.

JSBs, the highest TFP growth group, show a little different result from SOBs and CCBs in Table 4. JSBs experience faster fund and capital productivity growths that are driven by technical enhancements, but regressed by efficiency changes. With respect to labor productivity, they are the only one group gaining productivity growth from both technical change (78.43%) and efficiency change (21.57%).

### *5.3. Productivity analysis at the firm level*

This subsection compares productivity growth, including TFP and the three inputs, among 19 Chinese banks. Table 5 lists the productivity change of TFP and the three inputs as well as the decompositions 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

**Table 4**
The contribution (%) to three input productivity changes.

| Groups | Fund productivity | | Capital productivity | | Labor productivity | |
|---|---|---|---|---|---|---|
| | TECHCH | EFFCH | TECHCH | EFFCH | TECHCH | EFFCH |
| SOB | 101.64 | −1.64 | 336.61 | −236.61 | 331.24 | −231.24 |
| JSB | 110.08 | −10.08 | 115.00 | −15.00 | 78.43 | 21.57 |
| CCB | 108.75 | −8.75 | 156.55 | −56.55 | 139.03 | −39.03 |

*Note*: TECHCH and EFFCH are denoted as the technical change and efficiency change of particular input, respectively. SOB, JSB, and CCB are state-owned banks, joint-stock banks, and city commercial banks, respectively.

frontier to shift. Among these innovators, Bank of Beijing has experienced the fastest growth rate of TFP change with an average of 8.12%, followed by Shenzhen Development Bank (7.04%), and Bank of Nanjing (4.04%).

If we further investigate individual input productivity indices, only Bank of Beijing and Bank of Nanjing are innovators that shift the frontiers of all three inputs. More specifically, for Bank of Beijing, the main force of TFP growth is technical progress of labor usage with an average of 12.28%. Nevertheless, the driving force of productivity for Bank of Nanjing is technical improvement of capital usage with an average of 20.60%. It is interesting that although China Minsheng Banking Corporation is an innovator as we only consider the viewpoint of total factor, its fund productivity and labor productivity gradually decline over the research period.

According to Table 5, one bank – Agricultural Bank of China – shows a negative average growth of TFP (−1.91%) among 19 Chinese banks. The decline of TFP results from its efficiency drop (6.56%), though its technical change is positive (4.65%) during 2002–2009. Furthermore, the total factor input productivity changes of Agricultural Bank of China decrease about 2.49% and 4.32% for capital and labor productivity, respectively. This result shows that the drops of inputs' productivity can be attributed to the efficiency changes of capital (−9.11%) and labor (−10.57%) usage.

Aside from the six banks discussed above, other banks tend to fall into one of two categories based on Table 5. The first group includes Bank of Communications, China Construction Bank, and Industrial Bank. All of these banks have the characteristic that TFP growth is mainly driven by technical progress. It is worth noting that there are some differences between those banks when we further analyze the total factor input productivity of each input. For example, China Construction Bank and Industrial Bank are banks in which all input productivity changes are positive and the components (technical change and efficiency change) of three input productivities are also positive (or no change). Bank of Communications presents moderate technical progress and efficiency improvement of 2.52% and 1.65% annually, respectively. The dominant force behind its TFP growth is increasing labor productivity, especially strong efficiency change (5.93% per year).

The second group containing 10 banks presents that the technological gains transcend the efficiency regressions and results in TFP growth. From the view of individual input, except for Guangdong Development Bank, the banks' sources of TFP growth are capital productivity improvement and the technical progress of capital use. Additionally, Guangdong Development Bank gains TFP growth from labor productivity change and technical change of labor usage. These findings confirm that the TIPI proposed by this paper is necessary in order to investigate the source of TFP in more detail.

### 5.4. 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 a productivity–efficiency matrix for each input variable.[3] Chinese banks can now be classed into one of the following four categories: Banks in the first category (labeled as H/H) present a higher productivity growth rate and better relative efficiency, indicating these banks have strength (or advantage) of particular inputs. Banks in the second category (labeled as L/H) present a better efficiency, but a lower productivity growth rate. We consider that these banks will confront a threat from using particular inputs, because their productivity growth rates are slower than the industry's average. Although banks in the second category have better efficiency, they may be caught up by rapidly growing banks. In addition, banks are weak in certain inputs when they locate in the third category (labeled as L/L), presenting a slower productivity growth and lower efficiency. Following our consideration, banks, in the fourth category (labeled as H/L), with lower efficiency but higher productivity growth gain an opportunity of certain inputs to challenge more efficient banks in the future.

According to the definitions mentioned above, Table 6 shows the calculation and classification results. We next discuss some major findings as follows. The last column of Table 6 presents the classification based on the overall technical efficiency and total factor productivity change of each Chinese bank. There are seven banks located in the 'H/H' group, including all innovators except China Minsheng Banking Corporation. Relative to the industry's average, however, five banks are in the 'L/L' group, meaning those banks are relatively inefficient and have a lower TFP growth rate. These banks include three of the Big Four state-owned banks. Only China Construction Bank presents a relatively higher productivity growth.

Second, with respect to fund input (the second column of Table 6), the average fund effectiveness is close to one (98.70%), meaning that all banks almost use this input efficiently. It is noteworthy that four efficient banks, i.e. Bank of Nanjing, China Minsheng Banking Corporation, Hua Xia Bank, and Shenzhen Development Bank, present relatively low fund productivity, suggesting that they should pay more attention to this problem.

Third, the result of capital input (the third column of Table 6) presents a phenomenon that the stronger is getting stronger and the weaker is getting weaker. It shows that most banks are classed as the 'H/H' or 'L/L' group, and only three banks do not locate in these two groups, indicating that the better performers still gain faster capital productivity growth. Fourth, the fourth column provides the result of the labor productivity–efficiency matrix. It shows that improvement in the labor productivity of eight banks is higher than the industry's average. However, three banks decrease their labor productivity and two of them lie in the 'L/H'

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

**Table 5**
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 |
| Agricultural Bank of China | −0.0191 | 0.0465 | −0.0656 | 0.0107 | 0.0107 | 0.0000 | −0.0249 | 0.0662 | −0.0911 | −0.0432 | 0.0625 | −0.1057 |
| Bank of Beijing | 0.0812 | 0.0812 | 0.0000 | 0.0234 | 0.0234 | 0.0000 | 0.0974 | 0.0974 | 0.0000 | 0.1228 | 0.1228 | 0.0000 |
| Bank of China | 0.0163 | 0.0572 | −0.0409 | 0.0023 | 0.0047 | −0.0024 | 0.0255 | 0.0926 | −0.0670 | 0.0212 | 0.0743 | −0.0532 |
| Bank of Chongqing | 0.0107 | 0.0596 | −0.0489 | −0.0042 | 0.0002 | −0.0044 | 0.0288 | 0.0968 | −0.0680 | 0.0075 | 0.0817 | −0.0742 |
| Bank of Communications | 0.0417 | 0.0252 | 0.0165 | 0.0156 | 0.0190 | −0.0034 | 0.0178 | 0.0241 | −0.0063 | 0.0918 | 0.0325 | 0.0593 |
| Bank of Nanjing | 0.0404 | 0.0404 | 0.0000 | 0.0106 | 0.0106 | 0.0000 | 0.0483 | 0.0483 | 0.0000 | 0.0624 | 0.0624 | 0.0000 |
| Bank of Ningbo | 0.0352 | 0.0425 | −0.0073 | 0.0186 | 0.0199 | −0.0014 | 0.0446 | 0.0699 | −0.0253 | 0.0424 | 0.0376 | 0.0048 |
| Bank of Shanghai | 0.0324 | 0.0638 | −0.0314 | 0.0179 | 0.0179 | 0.0000 | 0.0579 | 0.1214 | −0.0634 | 0.0215 | 0.0522 | −0.0307 |
| China CITIC Bank | 0.0390 | 0.0390 | 0.0000 | 0.0153 | 0.0153 | 0.0000 | 0.0772 | 0.0772 | 0.0000 | 0.0244 | 0.0244 | 0.0000 |
| China Construction Bank | 0.0449 | 0.0346 | 0.0103 | 0.0322 | 0.0309 | 0.0014 | 0.0558 | 0.0395 | 0.0163 | 0.0468 | 0.0335 | 0.0132 |
| China Everbright Bank | 0.0366 | 0.0611 | −0.0245 | 0.0263 | 0.0263 | 0.0000 | 0.0680 | 0.1310 | −0.0630 | 0.0155 | 0.0260 | −0.0104 |
| China Merchants Bank | 0.0351 | 0.0645 | −0.0294 | 0.0126 | 0.0146 | −0.0019 | 0.0756 | 0.1302 | −0.0546 | 0.0170 | 0.0486 | −0.0316 |
| China Minsheng Banking Corporation | 0.0199 | 0.0199 | 0.0000 | −0.0009 | −0.0009 | 0.0000 | 0.1063 | 0.1063 | 0.0000 | −0.0458 | −0.0458 | 0.0000 |
| Guangdong Development Bank | 0.0450 | 0.0546 | −0.0096 | 0.0213 | 0.0274 | −0.0060 | 0.0396 | 0.0804 | −0.0409 | 0.0741 | 0.0561 | 0.0180 |
| Hua Xia Bank | 0.0387 | 0.0386 | 0.0000 | −0.0032 | −0.0014 | −0.0018 | 0.0896 | 0.0877 | 0.0019 | 0.0296 | 0.0296 | 0.0000 |
| Industrial & Commercial Bank of China | 0.0258 | 0.0395 | −0.0137 | 0.0183 | 0.0183 | 0.0000 | 0.0196 | 0.0576 | −0.0380 | 0.0395 | 0.0426 | −0.0031 |
| Industrial Bank | 0.0835 | 0.0624 | 0.0211 | 0.0328 | 0.0328 | 0.0000 | 0.1330 | 0.1076 | 0.0255 | 0.0847 | 0.0469 | 0.0378 |
| Shanghai Pudong Development Bank | 0.0540 | 0.0544 | −0.0003 | −0.0018 | −0.0018 | 0.0000 | 0.1099 | 0.1109 | −0.0010 | 0.0540 | 0.0540 | 0.0000 |
| Shenzhen Development Bank | 0.0704 | 0.0704 | 0.0000 | 0.0121 | 0.0121 | 0.0000 | 0.2060 | 0.2060 | 0.0000 | −0.0068 | −0.0068 | 0.0000 |

*Note*: TFPCH is total factor productivity change; FPCH is fund productivity change; CPCH is capital productivity change; LPCH is labor productivity change. TECHCH and EFFCH are denoted as the technical change and efficiency change of total factor or a particular input, respectively.

**Table 6**
The advantages and disadvantages of each bank.

| Bank | Fund | Capital | Labor | TFP |
|---|---|---|---|---|
| Agricultural Bank of China | L/L | L/L | L/L | L/L |
| Bank of Beijing | H/H | H/H | H/H | H/H |
| Bank of China | L/H | L/L | L/L | L/L |
| Bank of Chongqing | L/L | L/L | L/L | L/L |
| Bank of Communications | H/L | L/L | H/L | H/L |
| Bank of Nanjing | L/H | L/H | H/H | H/H |
| Bank of Ningbo | H/H | L/L | H/L | L/L |
| Bank of Shanghai | H/H | L/H | L/H | H/L |
| China CITIC Bank | H/H | H/H | L/H | H/H |
| China Construction Bank | H/L | L/L | L/L | H/L |
| China Everbright Bank | H/H | H/H | L/H | L/H |
| China Merchants Bank | L/H | H/H | L/H | L/H |
| China Minsheng Banking Corporation | L/H | H/H | L/H | L/H |
| Guangdong Development Bank | H/L | L/L | H/L | H/L |
| Hua Xia Bank | L/H | H/L | L/H | H/H |
| Industrial & Commercial Bank of China | H/L | L/L | H/L | L/L |
| Industrial Bank | H/H | H/H | H/H | H/H |
| Shanghai Pudong Development Bank | L/H | H/H | H/H | H/H |
| Shenzhen Development Bank | L/H | H/H | L/H | H/H |
| *Industry average* | | | | |
| Productivity growth | 0.0137 | 0.0672 | 0.0347 | 0.0385 |
| Efficiency score (%) | 98.70 | 76.40 | 74.21 | 83.10 |

*Note*: H/H–high productivity growth and efficiency level; H/L–high productivity growth but efficiency level; L/L–low productivity growth and efficiency level; L/H–low productivity growth but high efficiency level.

group. This means that these banks will lose the advantage of labor productivity in the future if they do not take notice of this warning.

In summary, Table 6 helps us to find out the advantages and disadvantages of each bank more clearly. For example, Bank of Beijing 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, however, presents entirely different patterns of three inputs compared to Bank of Beijing, i.e. Agricultural Bank of China has no advantage from any input. Furthermore, the results of China Merchants Bank and China Minsheng Banking Corporation are identical, showing strength gains in capital use, but issue warnings in fund and labor use.

Except for Agricultural Bank of China, the other Big Four banks also represent distinguishing features of total factor inputs' productivity. For instance, Bank of China and China Construction Bank are both poor in efficiency as well as productivity growth for capital and labor inputs, while China Construction Bank has advanced capacity for fund use. Industrial & Commercial Bank of China not only stands out with an advantage in fund use, but gains potential opportunities from labor input.

**Table 7**
Comparison the TFP change between ISP index and Luenberger index.

| Period | TFPCH from ISP index | TFPCH from Luenberger index | Differences |
|---|---|---|---|
| 2002/2003 | 0.0378 | 0.0282 | 0.0096 |
| 2003/2004 | 0.0017 | 0.0047 | −0.0031 |
| 2004/2005 | 0.0732 | 0.0274 | 0.0457 |
| 2005/2006 | 0.0407 | 0.0369 | 0.0037 |
| 2006/2007 | 0.0516 | 0.0402 | 0.0114 |
| 2007/2008 | −0.0147 | 0.0091 | −0.0238 |
| 2008/2009 | 0.0794 | 0.0122 | 0.0672 |

*Note*: TFPCH is total factor productivity change. The Luenberger index is calculated through the proportional input-oriented directional distance functions model.

### *5.5. Comparison with conventional methods*

The ISP index first proposed in this paper allows for simultaneously discussing the changes of TFP and each input productivity. We believe that this measure can provide more insights than the commonly-used TFP indices (i.e. LPI and MPI). Hence, this section further compares the results obtained from the ISP index with some conventional methods.[4]

With respect to bank TFP growth, this paper first compares the TFP growth rates computed by the ISP index with a commonly-

[4] We thank the referee's constructive comment.

**Table 8**
Correlation between the growth rates obtained from ISP and conventional methods.

| Period | Spearman rank correlation coefficients | | | |
|---|---|---|---|---|
| | Total factor | Fund | Capital | Labor |
| 2002/2003 | 0.8158** | 0.3914 | 0.8100** | 0.6807** |
| 2003/2004 | 0.8667** | 0.7053** | 0.7322** | 0.6099** |
| 2004/2005 | 0.8246** | 0.6035** | 0.9123** | 0.8109** |
| 2005/2006 | 0.6439** | 0.8281** | 0.8544** | 0.8351** |
| 2006/2007 | 0.7070** | 0.9434** | 0.6912** | 0.4930* |
| 2007/2008 | 0.7649** | 0.8239** | 0.5842** | 0.8404** |
| 2008/2009 | 0.3316 | 0.0220 | 0.3789 | 0.3491 |

*Note*: For alternative methods, three input productivity changes are calculated through partial factor productivity index, i.e. using a one input and two outputs model for each input.
* Significance at 0.05 level.
** Significance at 0.01 level.

used LPI that is based on the proportional input-oriented directional distance functions. Table 7 lists the TFP growth rates and the difference between the two models. As can be seen, the TFP growth rates calculated by the ISP index for each sub-period range between −1.47% and 7.94%, whereas the growth rates obtained from the traditional LPI are between 0.47% and 4.02%. In addition, the mean differences in the TFP growth rates range between 0.31% and 6.72% in absolute value. We can see that the TFP growth rates obtained from the ISP index are more volatile than those obtained from the traditional LPI. One possible explanation is that, relatively to the ISP index, the traditional LPI underestimates the potential gains/losses in input reduction (Kerstens et al., 2011).[5]

We next turn to compare the input productivity growth rates obtained from the ISP index with the partial factor productivity index that calculates single input productivity growth using a one input (one of funds, capital, and labor input) and two outputs model. Table 8 reports the Spearman rank correlation coefficients of each comparison. For example, the second column of Table 8, listing the correlation between fund productivity obtained from the ISP index and partial factor productivity index, shows that all the rank correlation coefficients are positive ranging from 0.0220 to 0.9434. In general, the computed ranks of bank productivity growths are roughly consistent among two methods. However, for the period 2008–2009, the rank correlation of fund productivity growth rates between the ISP index and the partial factor productivity index is positive (0.0220), but quite near zero and insignificant. This suggests that the partial factor productivity index neglecting the substitutability or complementarity between all inputs may obtain a doubtful result. Similar conclusions about capital and labor productivity changes can be seen in Table 8. Therefore, we consider that the ISP index can simultaneously derive TFP growth and input productivity changes, providing more insights than traditional productivity indices.

## 6. Conclusions

This paper investigates the sources of productivity growth for 19 Chinese banks during the period 2002–2009. Because employees, funds, and capital are the main resources (inputs) within a bank's operation, this study also analyzes the productivity changes of these inputs. Unfortunately, commonly-used productivity measures, i.e., Luenberger and Malmquist productivity indices, are aggregated indices that do not understand the productivity changes of each input factor directly. Therefore, this paper proposes an advanced measure – input slack-based productivity index (ISP) – which combines the feature of the Färe–Lovell efficiency measure into the Luenberger productivity index, to deal with our research topic.

The proposed ISP index has two advantages over traditional indices. First, ISP rapidly calculates total factor productivity growth and decomposes TFP growth into the productivity changes of each input. Second, ISP measures TFP growth as the arithmetic mean of each input's productivity change. Thus, we find out the major forces behind TFP growth.

The empirical findings are briefly summarized as follows. First, from the viewpoint of China's whole banking industry, our results present that the industry gains total factor productivity growth with a total of 29.84% over the research period. It is found that the main force behind TFP growth is attributed to technology progress with a total of 40.84%. More specifically, our ISP index shows that the technical improvement of capital productivity is the major source of Chinese banks' TFP growth. Second, with respect to the bank group level, joint-stock banks reveal the highest TFP growth rate, followed by city commercial banks and state-owned banks. Again, the TFP growth of joint-stock banks is mainly driven by capital productivity enhancement. Third, comparing to other Chinese banks, Bank of Beijing gains the highest TFP growth rate with an average of 8.12% annually. Bank of Beijing also presents relatively higher growth rates and efficiency levels in all input usages, especially for labor input.

This advanced index herein can accordingly provide more useful insights than traditional productivity indices. We consider that the ISP index cannot only be used to examine banking issues, but also be applied to other research topics that target the disaggregation terms of TFP growth. We do suggest that the ISP index can be improved and extended through some aspects of future research. For example, this paper does not analyze what determinants affect the fluctuations of those disaggregation terms of TFP and input productivity growths, which should be an interesting topic for any following works. Technically, the ISP index proposed in this study is structured based on the concept of constant-to-scale (CRS). More fascinating decomposition terms can be accomplished if future studies extend the ISP index to a variable return to scale assumption.

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[5] This paper also follows Barros et al. (2012) and adds NPL as the undesirable output in the model. However, we do not compare this model with our proposed index herein, because the results are inconsistent with existing literature. For example, if we add NPL to the model, one of the Big Four becomes an efficient bank that is opposite to the findings of Berger et al. (2009, 2010) and Lin and Zhang (2009). One potential explanation is that the discrimination of this method might worsen due to our small number of banks.

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