Multi-Directional Meta-Frontier DEA Model for Total Factor Productivity Growth in the Chinese Banking Sector: A Disaggregation Approach

Ning ZHU\textsuperscript{1}, Tomas BALEŽENTIS\textsuperscript{2,*}, Zhiqian YU\textsuperscript{3}, Wenjie WU\textsuperscript{4}

\textsuperscript{1}School of Economics and Commerce, South China University of Technology, No. 382, Outer Ring East Road, Higher Education Mega Center, Guangzhou, 510006, Guangdong Province, China

\textsuperscript{2}Lithuanian Institute of Agrarian Economics, A. Vivulskio Str. 4A-13, 03220 Vilnius, Lithuania

\textsuperscript{3}School of Economics and Statistics, Guangzhou University, No. 230, Wai Huan Xi Road, High Education Mega Center, Guangzhou, 510006, Guangdong Province, China

\textsuperscript{4}College of Economics, Jinan University, No. 601, West of Huangpu Avenue, Guangzhou, 510632, Guangdong Province, China

e-mail: ningzhu@scut.edu.cn, tomas@lai.lt, yzq_8866@hotmail.com, caswwj@foxmail.com

Received: March 2019; accepted: November 2019

Abstract. Departing from conventional TFP index without variable-specific analysis, this paper applies a novel Malmquist productivity index on the basis of the multi-directional efficiency analysis to investigate not only the overall total factor productivity growth, but also the variable-specific productivity growth in the Chinese banking sector. Moreover, considering heterogeneous types of banks, the metafrontier framework is taken into account. It is found that the total factor productivity tended to decline in the Chinese banking during 2005–2015 with technological change being the main source of regress. The large state-owned commercial banks performed better than the small-medium commercial banks in terms of total factor productivity growth.

Key words: data envelopment analysis, total factor productivity, multi-directional efficiency analysis, metafrontier, Chinese banking.

1. Introduction

Due to the constant decline in labour force and capital investment in China since 2007, as well as the fact that the global economic growth has been in downturn, the so-called “China’s New Normal Economy” has experienced a serious impact both at domestically and abroad. Indeed, apart from traditional factor inputs, like labour and capital aspects, the total factor productivity (TFP) becomes a critical component which probably improves efficiency gains and technological progress to promote economic growth in China. An efficient financial market is indispensable to stimulate economy (Goldsmit, 1969; Gurly and Shaw, 1960; King and Levine, 1993). As the banking sector dominating the Chinese
financial market, the banking TFP is a particularly effective benchmark to evaluate and improve the overall TFP in China.

The measures of efficiency and productivity change can be applied to gauge the performance of the banking sector (Coelli et al., 2005; Belas et al., 2018; Chovancova et al., 2019; Radojicic et al., 2018; Wang et al., 2018; Zeng and Xiao, 2018; Zeng et al., 2019). In general, there are two types of TFP indices, where one is direct, e.g. Laspeyres, Paasche, Fisher and Törnqvist indices, whereas the other is indirect, e.g. Malmquist and Hicks-Moorsteen productivity indices. Currently, the indirect TFP index is widely-used in various fields, and O’Donnell (2012) provides a detailed introduction and a comparison. Furthermore, a rich body of research on the banking TFP growth using various TFP indices has been published in international academic journals over the past decades (e.g. Berg et al., 1992; Grifell-Tatjé and Lovell, 1997; Casu et al., 2004; Park and Weber, 2006; Koutsomanoli-Filippaki et al., 2012; Casu et al., 2013; Kumar Sharma and Dalip, 2014; Fujii et al., 2014; Degl’Innocenti et al., 2017; Kevork et al., 2017), and there are series of studies on the TFP growth of the Chinese banking sector as well (e.g. Kumbhakar and Wang, 2007; Matthews et al., 2009; Matthews and Zhang, 2010; Chang et al., 2012; Zhu et al., 2015, 2018). However, most of the aforementioned research focuses only on the overall banking TFP growth, not allowing for variable-specific analysis. Therefore, the current paper identifies a gap, with respect to not only the overall level, but also the variable-specific productivity change of the TFP growth. In terms of the variable-specific productivity change, we choose a new disaggregation approach on the basis of the multidirectional efficiency analysis (MEA) framework by Asmild et al. (2003) instead of the conventional aggregative Russell framework which requires a specification of an objective function. Therefore, a novel TFP index based on MEA approach is applied to explore the source of the TFP growth in the Chinese banking sector.

Furthermore, due to heterogeneous environment which needs different intermediation technologies and managerial choices which affect the ability to attain the optimum benchmark in banking sector (Koeter and Poghosyan, 2009), regarding various types of Chinese banks including, for example, large stated-owned commercial banks (LSCBs) which are usually called the Big Four, and small-medium commercial banks (SMCBs) which involve joint stock commercial banks and city commercial banks, we specifically incorporate the MEA-based TFP index into a metafrontier framework.

The rest is arranged as follows: Section 2 reviews literature, Section 3 introduces methodology, Section 4 issues data used, Section 5 is empirical analysis, and Section 6 provides a conclusion.

2. Literature Review

Usually, the non-parametric data envelopment analysis (DEA) and the parametric stochastic frontier analysis (SFA) are the two most popular approaches to measure the TFP growth, but the conventional approach does not allow for variable-specific analysis without an arbitrary choice of weighting scheme (Asmild et al., 2016), so we will review
literature on the variable-specific analysis, particularly the MEA approach, apart from the empirical analysis of the TFP growth in the Chinese banking sector. Moreover, the development of the metafrontier approach in the TFP growth is reviewed as well.

2.1. Overall TFP Growth of Chinese Banks

There have been series of studies investigating the TFP growth in the Chinese banking sector. However, most of them focused on the overall level of the TFP growth and its components.

Kumbhakar and Wang (2007), using the stochastic frontier analysis, presented that the average TFP growth in the Chinese banking sector was positive. In detail, pure efficiency changes did not affect the TFP growth significantly, and the TFP growth of state-owned commercial banks were mostly benefited in positive scale effect, while that of joint stock commercial banks were combined with both positive scale effect and technological progress.

Sufian (2009) used a Malmquist productivity index, taking off-balance sheet into account, to measure the TFP growth of the Chinese banking sector, and it was found that the whole banking sector had low TFP growth, where state-owned commercial banks and city commercial banks had poor technological change, but benefited in scale efficiency change, while joint stock commercial banks were poor in pure technical efficiency change.

Matthews et al. (2009) used a conventional Malmquist productivity index with a smooth bootstrap approach to study the TFP growth of the Chinese banking sector from 1997–2006, and they specifically accounted for non-performing loans which has been a critical factor affecting performance of the Chinese banking sector. Furthermore, Matthews and Zhang (2010) evaluated the TFP growth of the Chinese banks during the period 1998–2007. They determined 5 types of models with different variables according to production and intermediation approaches, and, while investigating the source of the TFP growth, it was found that efficiency gains were driven by cost reduction, while technological progress was promoted by non-interesting income.

Zhu et al. (2015) applied a DEA-based Luenberger productivity indicator to investigate the TFP growth of 25 Chinese banks over the period 2004–2010. It was found that the overall Chinese banking sector performed well, where the change of return to scale in technology was the main driving force during the period studied, and pure technical efficiency change and pure technological change both were not significant, but the scale efficiency change had a negative effect to TFP.

Zhu et al. (2018) used a non-radial, biennial Luenberger productivity indicator to evaluate the TFP growth of the Chinese banking sector during the period of 2004–2012. The overall Chinese banking sector operated with an average growth rate of 5.4%, where technological progress of the Chinese banking sector dominated during the earlier period, and efficiency gains surpassed technological progress during the later period.

2.2. Variable-Specific Productivity Change Measurement

Conventional TFP index, like the most widely applied Malmquist productivity index, usually concerns only the overall level, but ignores the contribution of individual factor.
In respect of solving the problem, there have been several appropriate approaches to obtain the variable-specific productivity change, like Russell index (Färe and Lovell, 1978), Zieschang index (Zieschang, 1984), slack-based measures (Tone, 2001), among others. Regarding the applications in the banking TFP field, two representative empirical studies include Chang et al. (2012) and Fujii et al. (2014). Chang et al. (2012) incorporated an input slack-based productivity framework into Luenberger productivity indicator, and investigated the source of the TFP growth by disaggregating to individual input productivity contribution. It was found that the technological change was the driving force to promote the TFP growth. Regarding contribution to input productivity change, capital investment was the major source of the TFP growth in the Chinese banking sector. Fujii et al. (2014) applied a weighted Russell directional distance model to measure the TFP change with non-performing loans. It is found that the TFP growth has not improved significantly over the period 2004–2011, where non-performing loans have a positive effect to the TFP growth during the earlier period, but there is a different pattern in non-performing loans after 2008. Moreover, labour force, loans and fixed assets contribute to positive TFP growth, whereas deposits are negative.

However, Asmild et al. (2016) argued the main drawback of these aforementioned disaggregation approaches is that they require a specification of an objective function which involves an arbitrary aggregation of the variable-specific efficiency score. Therefore, a novel MEA-Malmquist productivity index which deals with the problem of specification of an objective function in conventional disaggregation approaches is utilized in the current paper. The MEA approach was originally proposed by Bogetoft and Hougaard (1999), and further developed by Asmild et al. (2003). It is widely applied in various fields, such as transportation (Holvd et al., 2004), banking (Asmild and Matthews, 2012; Zhu et al., 2019), and many others. MEA is directly designed to obtain specific-variable efficiency scores, and it is in that sense a natural choice for specific-variable TFP growth.

2.3. Metafrontier Approach in TFP Growth

Due to different external factors, like environment, resources, and opportunity, the technology of various firms, indeed, may be heterogeneous. However, conventional studies on performance evaluation assumed that all DMUs have a homogeneous technology, namely there exists only one technological frontier for all DMUs. Therefore, Hayami (1969) initially proposed the conception of metaproduction, while Hayami and Ruttan (1970) then provided a clearer interpretation of metaproduction conception.

With exception of the SFA-based metafrontier approach introduced by Battese and Rao (2002) and Battese et al. (2004), the DEA-based metafrontier approach on the basis of distance function was developed by O’Donnell et al. (2008). Subsequently, plenty of banking efficiency research using DEA-based metafrontier approach became popular (e.g. Kontolaimou and Tsekouras, 2010; Chiu et al., 2016).

Apart from the efficiency aspect, O’Donnell et al. (2008) further extended the concept of metafrontier to the domain measuring the TFP growth. Afterwards, Oh and

3. Methodology

We treat each bank as a decision making unit (DMU) and then construct the best practice frontier with the technology with undesirable outputs. Assuming there exist K DMUs, and each DMU uses N inputs \( X = (x_1, \ldots, x_N) \in R_N^+ \) to jointly produce M desirable outputs \( Y = (y_1, \ldots, y_M) \in R_M^+ \) and L undesirable outputs \( B = (b_1, \ldots, b_L) \in R_L^+ \). Therefore, the combination of inputs and outputs in period \( t = 1, \ldots, T \) is \( (x_{k,t}, y_{k,t}, b_{k,t}) \). Its corresponding output sets satisfy the byproduct axiom (null-jointness), the assumption of the compact set, and the jointly weak disposability (weak disposability of undesirable outputs and strong disposability of desirable outputs and inputs).

3.1. MEA-Malmquist Productivity Index and Its Disaggregation

The MEA-Malmquist productivity index (MEA-MPI) introduced by Asmild et al. (2016) is developed on the basis of the MEA approach initially by Bogetoft and Hougaard (1999) and Asmild et al. (2003). With respect to the MEA, it gains endogenous project directions of inputs and outputs, respectively, based on local single production objective, and further gains endogenous direction vectors based on global dominant set. In Eq. (1), with exception of the \( n \)-th input in the set \( N \), where \( n \in N \), the rest including \( (N - 1) \) inputs \( x \) removing the \( n \)-th, \( M \) desirable outputs \( y \), and \( L \) undesirable outputs \( b \), are fixed. It is also interpretable according to Eqs. (2)–(3), respectively.
\[ x_{k'n}^t(x, y, b) = \min_{\theta_{k'n}} \theta_{k'n}, \]
\[ \text{s.t. } \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \leq \theta_{k'n}, \quad n = 1, \ldots, N, \]
\[ \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \leq x_{k'n(-n)}^t, \quad -n = N \backslash \{n\}, \]
\[ \sum_{k=1}^{K} \lambda_k^t y_{km}^t \geq y_{k'm}^t, \quad m = 1, \ldots, M, \]
\[ \sum_{k=1}^{K} \lambda_k^t b_{kl}^t = b_{k'l}^t, \quad l = 1, \ldots, L, \]
\[ \lambda_k^t \geq 0, \quad k = 1, \ldots, K, \]
\[ (1) \]

\[ y_{k'm}^t(x, y, b) = \max_{\psi_{k'm}} \psi_{k'm}, \]
\[ \text{s.t. } \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \leq x_{k'n}^t, \quad n = 1, \ldots, N, \]
\[ \sum_{k=1}^{K} \lambda_k^t y_{km}^t \geq \psi_{k'm}, \quad m = 1, \ldots, M, \]
\[ \sum_{k=1}^{K} \lambda_k^t y_{km}^t \geq y_{k'(-m)}^t, \quad -m = M \backslash \{m\}, \]
\[ \sum_{k=1}^{K} \lambda_k^t b_{kl}^t = b_{k'l}, \quad l = 1, \ldots, L, \]
\[ \lambda_k^t \geq 0, \quad k = 1, \ldots, K, \]
\[ (2) \]

\[ b_{k'l}^t(x, y, b) = \min_{\eta_{k'l}} \eta_{k'l}, \]
\[ \text{s.t. } \sum_{k=1}^{K} \lambda_k^t x_{kn}^t \leq x_{k'n}^t, \quad n = 1, \ldots, N, \]
\[ \sum_{k=1}^{K} \lambda_k^t y_{km}^t \geq y_{k'm}, \quad m = 1, \ldots, M, \]
\[ \sum_{k=1}^{K} \lambda_k^t b_{kl}^t = \eta_{k'l}, \quad l = 1, \ldots, L, \]
\[ \sum_{k=1}^{K} \lambda_k^t b_{kl}^t = b_{k'(-l)}^t, \quad -l = L \backslash \{l\}, \]
\[ \lambda_k^t \geq 0, \quad k = 1, \ldots, K. \]
\[ (3) \]

According to Eqs. (1)–(3), it maximizes the potential inputs contraction and the potential outputs expansion, and it can calculate the endogenous direction vector for individual
input and output in Eq. (4).

\[
\begin{align*}
\mathbb{M}^{\text{MEA}}_x &= (x'_{k1} - \theta'_{k1}, \ldots, x'_{kN} - \theta'_{kN}) \\
\mathbb{M}^{\text{MEA}}_y &= (\psi'_{k1} - y'_{k1}, \ldots, \psi'_{kM} - y'_{kM}) \\
\mathbb{M}^{\text{MEA}}_b &= (b'_{k1} - \eta'_{k1}, \ldots, b'_{kL} - \eta'_{kL}).
\end{align*}
\] (4)

Afterwards, the direction vector \((\mathbb{M}^{\text{MEA}}_x, \mathbb{M}^{\text{MEA}}_y, \mathbb{M}^{\text{MEA}}_b)\) is put into the conventional DEA-based directional distance function by Chambers et al. (1996) in Eq. (5).

\[
\vec{D}(x, y, b) = \max \beta, \\
\text{s.t.} \sum_{k=1}^{K} \lambda'_k x'_{kn} \leq x'_{k'n} - \beta \mathbb{M}^{\text{MEA}}_x, \quad n = 1, \ldots, N, \\
\sum_{k=1}^{K} \lambda'_k y'_{km} \geq y'_{k'm} + \beta \mathbb{M}^{\text{MEA}}_y, \quad m = 1, \ldots, M, \\
\sum_{k=1}^{K} \lambda'_k b'_{kl} = b'_{k'l} - \beta \mathbb{M}^{\text{MEA}}_b, \quad l = 1, \ldots, L, \\
\lambda'_k \geq 0. \quad k = 1, \ldots, K.
\] (5)

With regard to the ideal reference point \((\theta'_{k1}, \ldots, \theta'_{kN}, \psi'_{k1}, \ldots, \psi'_{kM}, \eta'_{k1}, \ldots, \eta'_{kL})\) and the solution of Eq. (5), \(\beta\), determining the benchmark selection for each individual variable, one can calculate the variable-specific efficiency score at time period \(t\) for input \(n\), output \(m\), and undesirable output \(l\) as

\[
e'_{x'k'n} = \frac{x'_{k'n} - \beta'_k (x'_{k'n} - \theta'_{k'n})}{x'_{k'n}},
\] (6)

\[
e'_{y'km} = \frac{y'_{km} - \beta'_k (\psi'_{k} - y'_{km})}{y'_{km}},
\] (7)

\[
e'_{b'kl} = \frac{b'_{k'l} - \beta'_k (b'_{k'l} - \eta'_{k'l})}{b'_{k'l}}.
\] (8)

Due to advantages of the non-radial and non-oriented slack-based measure (SBM) by Tone (2001) which considers both desirable and undesirable outputs to an underlying objective of maximizing virtual outcomes (Avkiran, 2011), the overall efficiency score is measured as:

\[
e'_k = \frac{1}{\frac{1}{N} \left( \frac{\beta'_k (x'_{k'n} - \theta'_{k'n})}{x'_{k'n}} \right)} \left( \frac{1}{\frac{1}{M+L} \left( \frac{\beta'_k (\psi'_{k'm} - y'_{k'm})}{y'_{k'm}} + \frac{\beta'_k (b'_{k'l} - \eta'_{k'l})}{b'_{k'l}} \right)} \right).
\] (9)

On the basis of the aforementioned efficiency measure, we can further construct the overall MEA-Malmquist productivity index and its decomposition including efficiency
change (EC) and technology change (TC) in Eqs. (10)–(12).

\[
MPI = \left[ \frac{e_{k,t+1}^{t+1,t+1}}{e_{k,t}^{t+1}} \right]^{\frac{1}{2}},
\]

(10)

\[
EC = \left( \frac{e_{k,t+1}^{t+1,t+1}}{e_{k,t}^{t+1}} \right),
\]

(11)

\[
TC = \left[ \frac{e_{k,t+1}^{t+1,t+1}}{e_{k,t}^{t+1,t+1}} \right]^{\frac{1}{2}}.
\]

(12)

Analogously, the variable-specific productivity measures are obtained by plugging the efficiency scores from Eqs. (6)–(8) in Eqs. (10)–(12).

### 3.2. Metafrontier Framework

In general, the metafrontier MEA-Malmquist productivity index (MMPI) implying potential production frontier can be decomposed into metafrontier efficiency change (MEC) and metafrontier technological change (MTC) as well as conventional MPI decomposition in Eq. (13).

\[
MMPI = MEC \times MTC.
\]

(13)

Analogously, the groupfrontier MEA-Malmquist productivity index (GMPI) implying actual production frontier can be decomposed into group efficiency change (GEC) and group technological change (GTC) in Eq. (14).

\[
GMPI = GEC \times GTC.
\]

(14)

The productivity growth gap (PGG) measures the gap between metafrontier and group frontier technology in Eq. (15), where the efficiency change gap (ECG) implies the gap between MEC and GEC to capture the pure catch-up gap change which is identical to the pure technological catch-up (PTCU) in Chen and Yang (2011), while the technological change gap (TCG) implies the change of frontier-shift between the group-frontier and the metafrontier that captures the innovation gap change which is similar to the frontier catch-up (FCU) component in Chen and Yang (2011). Therefore, \( ECG > (\text{or} <) 1 \) means a shrinkage (increase) of the technological gap in terms of pure catch-up, whereas \( TCG > (\text{or} <) 1 \) means the group frontier shift is faster (slower) than the metafrontier shift, indicating the reduction (increase) of innovation gap.

\[
PGG = \frac{MMPI}{GMPI} = \frac{MEC \times MTC}{GEC \times GTC} = \left( \frac{MEC}{GEC} \right) \times \left( \frac{MTC}{GTC} \right) = ECG \times TCG.
\]

(15)
Consequently, the \( \text{MMPI} \) is decomposed as Eq. (16) by rearranging Eqs. (13)--(15).

\[
\text{MMPI} = \frac{\text{GMPI} \times \text{MMPI}}{\text{GMPI}} = \text{GMPI} \times \text{PGG} = \text{GEC} \times \text{GTC} \times \text{ECG} \times \text{TCG}.
\] (16)

4. Data Used

There are 176 observations covering 16 main Chinese commercial banks during the period 2005–2015. According to bank characteristics, particularly involving ownership, the whole sample is divided into two groups, namely the large state-owned commercial banks (LSCBs) and the small-medium commercial banks (SMCBs). The LSCBs include 4 state-owned commercial banks commonly known as the Big Four,\(^1\) while the SMCBs include 9 joint stock commercial banks and 3 city commercial banks. All data source from the Bankscope database, and price is constant in 2004.

Berger and Humphrey (1997) introduced two main approaches to choose appropriate input and output variables in banking performance measures, including the production approach which interprets banks as primarily producing services for account holders and the intermediation approach which interprets banks as primarily intermediating funds between savers and investors. However, Berger and Humphrey (1997) further argued that neither of the two approaches could fully capture the dual roles of financial institutions. Recently, a profit-oriented approach by Drake \textit{et al.} (2006) became a more welcome variable selection in evaluating banking performance, due to the fact that both the decreasing cost and the increasing revenue are considered simultaneously which can be more appropriate in capturing the diversity of strategic responses by banks in the face of dynamic changes in competitive and environmental conditions (e.g. Drake \textit{et al.}, 2006; Pasiouras, 2008; Fethi and Pasiouras, 2010; Avkiran, 2011; Zhu \textit{et al.}, 2015, 2019). A typical profit-oriented approach treats cost component, like interest expense and non-interest expense as input variable, while treats revenue component, like interest income and non-interesting income, as output variable.

Finally, the selected variables are as follows:

Inputs:
- Interest expenses (IE);
- Non-interest expenses (NIE).

Desirable outputs:
- Interest income (II);
- Non-interest income (NII).

Undesirable output:
- Non-performing loans (NPLs).

\(^1\)Although the Bank of Communications changed to be a SOCB in 2006 due to financial restructuring, it is, actually, not a “pure” SOCB like the Big Four, and thus here classifies it as a JSCB conventionally.
Table 1 presents the descriptive statistics of the sample. It is straightforwardly found that, firstly, absolute gaps among various resources of the LSCBs and the SMCBs are obvious, where LSCBs are with the largest share, but SMCBs maintain a faster growth; secondly, NII has the fastest growth rate in all variables for two types of banks, where the rates of SMCBs (40%) obviously surpass that of LSCBs (21%); thirdly, LSCBs have the largest magnitude of positive effect in reducing NPLs (−5%) than the SMCBs (8%).

5. Empirical Analysis

5.1. Overall TFP Growth

Table 2 presents the overall TFP growth in the Chinese banking sector during the period 2005–2015. It is found that the mean of $\text{MMPI}$ is 0.9606 implying the Chinese banking TFP has a decline by 4% on average each year approximately. Actually, during the earlier period 2005–2008, the $\text{MMPI}$ shows a serious slope, while after 2008 the $\text{MMPI}$ has a potential upward trend, although the values are still below 1. With regard to the decomposition, the mean of $\text{GEC}$ has a positive growth by 1%, but that of $\text{GTC}$ has a negative
growth by 3.6%, while those of ECG and TCG are not significant. It is obvious that GTC, whose growth rates are below 1 during all the studied period, is the main source to reduce the overall banking TFP growth, particularly the GTC during 2006–2007 drops to the bottom at 88.37%. A potential explanation is that, with regard to the banking sector, there are usually two ways to affect technological change, namely physical technology and policy impact, respectively. As a matter of fact, the former, such as advanced network communication equipment, has been updated so timely in the Chinese banking sector that it should have a positive effect to technological progress. Consequently, the technological regress should be ascribed to policy impact. Indeed, in order to adapt to the economic slowdown before 2008, tight monetary policy and strict capital regulations slowed loan growth rate, and it thus shows a drop in technological change during 2005–2008 (Cai and Guo, 2009). Additionally, there is a remarked drop in GTC from 0.9755 to 0.9261 during 2008–2010 which probably sources from the impact of global financial crisis since 2008. Subsequently, series of appropriate national and local policies were issued to improve technological change of the Chinese banking sector after 2010. The GEC mostly maintains a positive growth, which is largely due to effective financial reform in the Chinese banking sector since 2003. However, the contributions of ECG and TCG are limited which presents that the gaps between metafrontier and groupfrontier on both efficiency change and technological change are small, and it is corresponding with results of some existing research (e.g. Asmild and Matthews, 2012; Wang et al., 2014; Zhu et al., 2015).

Furthermore, comparing the TFP growth in two types of banks, LSCBs and SMCBs, in Fig. 1, it is found that LSCBs outperformed SMCBs in MMPI slightly, which mainly attributes to systematic financial reform in LSCBs, involving stripped of non-performing loans, financial reorganization, and listing in market with assistance of government, since 2003. Indeed, both LSCBs and SMCBs show a rising trend as time passed. The fluctuations of GEC and GTC in both LSCBs and SMCBs are significant, where SMCBs perform better in GEC, and LSCBs outperform SMCBs in GTC. As a matter of fact, SMCBs are more sensitive to impacts of monetary policy and capital regulations than LSCBs, because, unlike LSCBs undertaking more social responsibility (Iannotta et al., 2013), SMCBs prefer to pursue profit maximization within market orientation, rather than policy orientation. Therefore, it causes lower GTC in SMCBs than LSCBs. However, due to more flexible market-oriented mechanism, SMCBs surpass LSCBs in GEC.

The changes of ECG and TCG in SMCBs are nearly flat, while change of ECG in LSCBs has a slight downtrend, and that of TCG in LSCBs has a slight uptrend. It implies that LSCBs has a slower growth rate in efficiency gains than overall sample banks, whereas it has a faster growth rate in technological progress than overall ones, which are corresponding with aforementioned GEC and GTC, respectively.

5.2. Variable-Specific Productivity Growth

Figure 2 presents the changes of variable-specific productivity growth and its decomposition during the period 2005–2015. As a whole, IE, NIE, and II in all decomposition fluctuate insignificantly, because they are traditional banking businesses with a stable growth. However, both NPL and NIE have greater fluctuations.
With regards to MMPI, IE, NIE, and II operated similarly, and they outperform NPL and NII markedly before 2008. However, both NPL and NII show an upward trend, and even NPL has been ahead of all other factors since 2012. Considering why NPL and NII fell behind other factors before 2008, the former mainly attributes to partly imperfect financial environment and partly global financial crisis. Afterward, the completion of financial reform, particularly LSCBs’ reform, reduced NPL substantially. The later NII is a renewed banking business because traditional II has occupied most banking business in the Chinese banking sector before. After fully opening to the world since 2007, the Chinese banking sector begun to closely concern and rapidly develop NII businesses competing with domestic and foreign banks.
Fig. 2. Changes of MMPI and its decomposition of individual variable.

Investigating changes of GEC and GTC, NPL and NII surpass others in GEC, whereas both are below others in GTC. Indeed, the GECs of both NPL and NII have improved due to effective financial reform, and another potential factor driving the NII growth positively is, recently, the supply side reform which encourages the Chinese banking sector to improve financial services and increase financial innovations, so the NII is among the best in GEC during 2013–2015. However, several factors, like macroeconomic regulation and credit policy, may undermine GTC, and consequently it causes overall MMPI of NPL and NII at the bottom as well. With regards to ECG and TCG, it is obvious that NPL is a critical component to change the gaps of efficiency change and technological changes in the Chinese banking sector during the earlier studied period.
Figure 3 describes individual variable-specific productivity growth involving LSCBs and SMCBs, respectively. It is obvious that, as a whole, LSCBs outperform SMCBs in reducing NIE and increasing II and NII, while SMCBs do better in reducing IE and NPL. Regarding individual variable-specific productivity growth, SMCBs are better than LSCBs in GEC for each variable, but the gaps between them are small, while LSCBs surpass SMCBs in GTC significantly, particularly in NII (6%) and NPL (4%). The ECG and TCG between LSCBs and SMCBs are similar, with the exception of NPL (6.7%) in TCG that the groupfrontier of NPL in SMCBs moves towards metafrontier faster than that in LSCBs. A possible explanation is that, due to stronger risk of the management level in SMCBs which operate within market mechanism, SMCBs are more motivated to reduce NPLs, and pay more attention to improve asset quality.
Table 3
Innovator banking groups in technological change.

<table>
<thead>
<tr>
<th>Year</th>
<th>Overall</th>
<th>IE</th>
<th>NIE</th>
<th>NPL</th>
<th>II</th>
<th>NII</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LSCB</td>
<td>SMCB</td>
<td>LSCB</td>
<td>SMCB</td>
<td>LSCB</td>
<td>SMCB</td>
</tr>
<tr>
<td>05/06</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>06/07</td>
<td>1</td>
<td>5</td>
<td>2</td>
<td>5</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>07/08</td>
<td>2</td>
<td>5</td>
<td>2</td>
<td>6</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>08/09</td>
<td>2</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>09/10</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>10/11</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>11/12</td>
<td>1</td>
<td>3</td>
<td>0</td>
<td>3</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>12/13</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>13/14</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>4</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>14/15</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>4</td>
</tr>
</tbody>
</table>

5.3. **Innovator Banks**

The technological change implies what happens to the production frontier, but not whether the bank has contributed to a shift in the production frontier (Färe et al., 1994). In order to provide evidence as to which banks are the “innovators”, we aim to check whether that bank actually causes the production frontier to shift (e.g. Färe et al., 1994; Oh, 2010; Fujii et al., 2014). The following Eqs. (17)–(19) give three conditions to identify this issue, where Eq. (17) implies that the production frontier moves towards producing more desirable outputs and less undesirable outputs and using less inputs, Eq. (18) implies that it is not possible to produce outputs at the $t+1$ period using inputs at the $t+1$ period with technology at $t$ period, namely the technology progress has been generated, and Eq. (19) implies that the innovator should be on the production frontier.

\[
TE^{t+1} > 1,
\]

\[
D^t(x^t+1, y^t+1, b^{t+1}) > 1,
\]

\[
D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}) = 1.
\]

Table 3 shows the number of innovator banks in both overall and variable-specific technological changes over the studied period. It is found that, generally, the proportion of LSCBs as innovators is higher during the earlier period (2007–2011), whereas it has a down trend since 2011, particularly in 2015. Particularly, compared with other variable-specific technological changes, there are less innovator banks in NPL in both LSCBs and SMCBs. It implies that there is still a lot of space to improve the reducing of NPL, because there are more opportunities to generate technological innovations in reducing NPL than that in the other factor. Besides, another important factor, NII, has relatively less innovators as well.

Investigating individual banks, it is found that the Bank of China is an outstanding innovator within the overall technological progress in LSCBs, whereas the China Construction Bank plays as the innovator mostly within variable-specific technological progress in
LSCBs. Regarding the SMCBs, the China Merchant of China, the Industrial Bank, and the Bank of Beijing have the most opportunities to be the innovators in both overall and variable-specific technological progress.

5.4. Comparison

Furthermore, it is meaningful to make a comparison between current MEA-MPI and conventional MPI. In Table 4, it is obvious that the trend of the TFP growth in both MEA-MPI and MPI is similar, where the overall TFP growth, the MMPI, has a negative effect, and technological regression is the main source slowing the TFP growth in MEA-MPI as well. However, regarding the exact value of the individual component of the TFP growth, it is found that, as the whole, the MPI would overestimate the TFP growth approximately, where the mean of MMPI in MEA-MPI is lower than that in MPI by $-2.13\%$ significantly at 1% level, and it is analogous to GTC by $-2.41\%$ significantly at 1% level as well. A possible explanation is that the MEA-MPI takes potential productivity into overall evaluation, whereas the MPI only considers past productivity (Asmild et al., 2016).

6. Conclusion

We attempted to explore the source of the TFP growth in the Chinese banking sector when China’s economic growth has slowed down since 2007. Apart from the conventional TFP index which does not allow for specific-variable analysis, like the most widely used MPI, the novel MEA-MPI is applied to investigate both overall and variable-specific productivity growth in the Chinese banking sector. It is found that the overall TFP growth in the Chinese banking sector is negative by 4% on average, but it shows a potential uptrend during the later studied period. These results may have been impacted by infeasibilities, among other reasons. Efficiency gains is the main driving force to promote the TFP growth of the Chinese banking sector, whereas the technological change has a negative contribution. Comparing two types of banks, the gap of productivity change between LSCBs and SMCBs is narrowing, where LSCBs and SMCBs do better in GTC and GEC, respectively. Furthermore, NPL and NII are two main sources impacting the TFP growth in the Chinese banking sector, and the technological change is the main gap between LSCBs and SMCBs.
according to their individual variable-specific productivity change. Last but not least, SM-CBs play as innovator banks to shift the production frontier more than LSCBs as a whole. A comparison between MEA-MPI and conventional MPI implies that the conventional MPI probably overestimates the TFP growth. Further research could address economic transformations in the banking sector (Kaminskyi and Versal, 2018) as contextual factors. Song et al. (2020) presented a production-based approach to measure progress towards the green economy which could also be adapted for the banking sector.

Funding

The authors gratefully acknowledge financial supports from the National Social Science Foundation of China (19CJY061), the National Natural Science Foundation of China (71703040), the Humanities and Social Research Project of Ministry of Education of China (17YJC790215, 17JZD013, 18YJC790207), the Natural Science Foundation of Guangdong Province (2018A0303130230), and the Fundamental Research Funds for the Central Universities (2019MS079).

References


N. Zhu obtained his PhD in economics from Jinan University, China, in 2016. He visited the University of Copenhagen, Denmark, during 2014–2016. He is a distinguished research fellow at School of Economics and Commerce, South China University of Technology, China. His research interests include efficiency and productivity analysis, banking management.

T. Baležentis is a research professor at Lithuanian Institute of Agrarian Economics and a professor at Vilnius University (Lithuania). He holds PhD degrees from Vilnius University and University of Copenhagen. Dr. Baležentis has published over 120 papers in SSCI/SCI journals. The research activities of Dr. Baležentis span over multi-criteria decision making, agricultural economics, energy economics, and managerial economics. He has published in *European Journal of Operational Research, Decision Sciences, Fuzzy Sets and Systems, Energy Economics, Energy Policy* and *Resource and Environmental Economics*.

Z. Yu obtained her PhD in economics from Jinan University, China, in 2014. She visited Business School of Copenhagen, Denmark, during 2012–2013. She is currently an associate professor at School of Economics and Statistics, Guangzhou University, China. Her research interests include efficiency and productivity analysis, public economics.

W. Wu obtained his PhD in economic geography from London School of Economics and Political Science, the UK, in 2013. He is currently a professor at College of Economics, Jinan University, China. His research interests include urban development, spatial economics.