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Efficiency in the highly market-segmented Chinese banking sector: A meta-frontier non-radial directional distance function approach

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ABSTRACT

In this paper, we apply the so-called meta-frontier non-radial directional distance function approach to a performance analysis of 143 Chinese banks over the period 2006–13. We find that relative to the group frontier in each market segment, the Big-5 Chinese banks display good efficiency. However, their low meta-technology ratios indicate that they are currently unable to make full use of their technological potential to achieve higher economic goals, such as cost-cutting and full profit-maximization. As befits their ownership structure, the joint stock commercial banks display the best technical efficiency. Further, the low efficiency scores and high meta-technology ratios demonstrate that the city commercial banks may serve as the primary implementation channels for local policies, particularly fixed investment. While only at the start-up stage in China, foreign banks display the highest meta-technology ratios, suggesting they possess generally better operating environments. Finally, we find Chinese banks generally exhibit a stable and increasing level of technical efficiency over the sample period, save a very small decline during the 2008 global financial crisis, whereas cost and profit efficiency exhibit significant volatility.

JEL classification:

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D24
G21

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Meta-frontier analysis
Non-radial directional distance function
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1. Introduction

Following more than three decades of sustained economic growth, China is now the world's second-largest economy after the US, with the Chinese economy now thoroughly integrated with most other global economies. However, China's financial system remains arguably unsound, and certainly less well developed than are those in the developed world. This is a double-edged sword. On the one hand, China will be unable to maintain stable and sustainable growth without a sound financial system. On the other, following the recent global financial crisis (GFC), it is now widely realized that the banking unsoundness arising from, say, liquidity problems or bank inefficiency in other countries, can trigger financial instability elsewhere through systemic risk or economic interdependence.

The GFC has indeed endowed many banks with fewer resources, resulting in a widespread call for them to become more efficient on the premise that efficiency matters for stability as well as economic growth and development. Indeed, while stability is critical, it is largely contingent on efficiency (Schaeck et al., 2006), such that banks that are more efficient are less likely to become problematic (Wheelock and Wilson 2000). Efficient banks will also perform their key financial intermediation function in a least costly way, thereby fostering economic growth and development. In particular, recent analysis suggests that an inefficient banking sector combined with poor financial infrastructure may already be restraining financial and economic growth and development in China (Berger et al., 2009).

Consequently, China's financial system, especially the banking sector, has attracted increasing attention from practitioners and academics alike both inside and outside China. Among the very large number of existing studies on bank efficiency, few have considered Chinese banks and therefore able to draw appropriate implications of these studies for domestic industry practice and bank policy. As an example, using a sample of 38 banks over the period 1994–2003, Berger et al. (2009) suggested that while most foreign banks in China had relatively high cost and profit efficiencies, the Big-5 state-owned banks were among the least-profit efficient banks because of their poor revenue performance and high levels of nonperforming loans. In another study based on a somewhat larger sample of 88 banks from 1996 to 2006, Berger et al. (2010) found that the foreign ownership of banks in China brought with it more advanced monitoring and managerial expertise, and was often

associated with better networks, partnerships, and even direct or indirect affiliation with international conglomerates.

In a similar vein, Ariff and Can (2008) concluded that joint-stock banks in China were both more cost- and profit-efficient than were their state-owned counterparts, while Kumbhakar and Wang (2007) found that private ownership in Chinese joint-equity banks improved technical efficiency. Elsewhere, Jiang et al. (2009), using a sample of Chinese commercial banks over the period 1995–2005, suggested that joint stock and state-owned banks in China were both relatively efficient, and that foreign banks were consistently least efficient. Finally, Fu and Heffernan (2009) argued that the relative efficiency (RE) hypothesis appeared to prevail over the structure-conduct-performance (SCP) hypothesis in the Chinese banking sector, implying that larger banks were generally more efficient.

Unfortunately, despite this emerging body of research we remain relatively uniformed about the performance of the world's second-largest banking sector with in excess of USD 1.2 trillion in assets in registered banks. We attribute this in part to the historical degree of segmentation in the Chinese banking sector. First, under a reform schedule from the 1990s until 2006, the Chinese banking sector underwent a fast-moving process of commercialization and capitalization. In particular, during this time, the five largest stated-owned banks converted to commercial banks through a partially privatization process, including taking on minority foreign ownership, and ultimately, listing on the Shanghai and Hong Kong stock exchanges.

Second, in order to meet the criteria of Basel II, particularly those relating to capitalization, by 2005 the Chinese government had successively injected more than RMB 315 billion (USD 38 billion) of additional capital into the Big-5 banks and off-loaded about RMB 2.5 trillion (USD 0.3 trillion) in nonperforming loans (NPL) from their asset portfolios. Third, in line with the agreement governing China's entry into the World Trade Organization (WTO) in 2001, China's banking sector was granted a five-year period of grace, after which foreign banks were permitted to register as fully operating commercial banks, thereby competing with China's domestic commercial banks, particularly in resident deposit-taking in the local currency. In this sense, foreign and domestic banks in China first commenced something approximating full retail competition in 2006. By 2006, the Big-5 banks, along with 13 joint-stock commercial banks, 115 city banks, 54 rural banks and 12 foreign banks, comprised the banking sector in China. However, the continuing high degree of market

segmentation, combined with a general lack of transparency, continues to make the Chinese banking sector a “black box” in terms of its overall performance.

The purpose of this paper is to throw light on the recent performance of the Chinese banking sector in the following respects. First, in light of the strong market segmentation in the Chinese banking sector, we apply the so-called meta-frontier analysis approach to the performance analysis of Chinese banks. Given that many frontier analysis techniques draw on the performance of a decision-making unit (DMU) (here, a bank) relative to benchmark performers, the common frontier requires strict environmental homogeneity for all DMUs under consideration. That is, banks should have a common production frontier. However, Chinese banks in different market segments are subject to quite different productive environments because of variation in regulations, market conditions, and clientele. For example, city commercial banks (CCBs) mainly operate only in their home city or just one or two neighboring cities; foreign banks (FBs) only establish themselves in a few metropolitan cities; and rural commercial banks (RCBs) typically restrict their businesses to rural areas.

In addition, most of the large state-controlled banks operate at different levels of control, with the Big-5 and some joint stock commercial banks (JSCBs) controlled at the state level and CCBs and RCBs at the city level. The implication is that differences in operating environment entail dissimilar feasible efficiency frontiers. To address this, we use meta-frontier efficiency techniques to construct a unique group frontier for each market segment in addition to a common frontier i.e. a meta-frontier. This enables a more realistic insight into bank performance. Second, asset quality in Chinese banks has been long been a concern. Given that the state-controlled banks arguably lack power over loan qualities, the sheer volume of potential problem loans in Chinese banks is an ongoing problem. Bearing this in mind, we apply a non-radial directional distance function approach, where loan quality in the form of nonperforming loans (NPL) serves as one of the outputs. In this approach, a better performing bank is one that that can both maximize loans and/or income while minimizing NPL.

Third, we examine the efficiency of 143 banks operating in China over the period of 2006–13, accounting for some 96% of all banking assets in China. We compare the efficiency of the Big-5 banks, JSCBs, CCBs, RCBs and FBs. Fortunately, the sample period includes the GFC, thus we can examine performance trends in Chinese banks before, during and after the most

recent financial crisis. Lastly, we employ a bootstrap truncated model, which enables further detailed investigation of the firm-level determinants of Chinese bank efficiency.

Our results reveals that relative to the group frontier for each segment, the Big-5 banks exhibit good performance in terms of cost and profit efficiency, while the JSCBs display the best performance in terms of technical efficiency. However, the low meta-frontier ratio for the Big-5 may indicate that they have more restricted conditions such that they are unable to make full use of their technological potential to achieve higher-order economic goals, such as cost-cutting and optimal profit-maximization.

At the other end of the spectrum, the worst performers are the CCBs in terms of efficiency scores. Largely owned by city governments or local authorities, the CCBs often serve as the major implementation channels of local government policy, particularly in fixed investment. At the same time, the CCBs attempt to dominate selected local markets, especially in small business finance, and for which they receive some market protection via local government policy. Elsewhere, the FBs do not exhibit good management efficiency, evidencing that they remain immature in the Chinese market following their recent entry in 2007. Therefore, their banking business awaits further expansion in terms of both the types of business and the operating locations in which they compete in China. However, their high meta-technology ratios reveal that the FBs have generally the best bank-operating environment, which they derive from better management, superior market discipline, and developed corporate cultures. Finally, over time, the technical efficiency of Chinese banks displays an upward trend, with only a very slight setback during the 2008 GFC. However, cost and profit efficiency fluctuates markedly.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the Chinese banking sector. Sections 3 and 4 discuss the methodology and data. Section 5 presents the empirical results. Section 6 concludes.

2. An overview of the Chinese banking sector

Prior to 1978, a single bank, the People's Bank of China (PBOC), dominated the Chinese banking sector. Following a series of fundamental economic and financial reforms after 1978, we can categorize the evolution of the Chinese banking system into four main periods.

1978–1984

During this period, the single-bank system dominated by the PBOC transformed into an effectively two-tier banking system (Jiang et al., 2009). Commercial banking operations were detached from the PBOC, resulting in it emerging as China's financial sector regulatory and supervisory authority. The commercial banking operations of the PBOC were then distributed among four specialized state-owned banks: the Agricultural Bank of China (ABC), the China Construction Bank (CCOB), the Industrial and Commercial Bank of China (ICBC), the Bank of China (BOC), which ultimately became the Big-4 banks.

1984–2001

Motivated by the transition from policy-oriented to market-oriented banks, the Chinese government cautiously converted the two-tier banking system into a multiple-tier system. First, three policy-related banks were established to finance major government projects (e.g. infrastructure). However, the asset quality of the four state-owned banks deteriorated significantly, as these banks made many of their loans to state-owned enterprises (SOEs) and government projects, which had little incentive to repay. To ameliorate this problem, in 1994 the government established the three policy banks to take over the policy-lending activities of the Big-4 banks, funded mainly through the issue of state bonds and loans by the PBOC. In addition, the Ministry of Finance issued RMB 270 billion (USD 32.6 billion) of 30-year government special bonds to recapitalize the Big-4 banks in 1998 (Berger, 2010).

Second, during this time, the hitherto exclusively state-owned bank ownership structure gradually converted into a state-controlled ownership structure. In 1986, the first domestic joint-equity bank, the China Bank of Communications (CBOC), was established. Together with the original Big-4, these state-control dominated banks became today's Big-5. In 1995, the Central Bank Law of China confirmed PBOC as the central bank, and officially defined the other state-owned banks as 'commercial banks' thus directed them more towards commercial business. In line with the law, another 12 national JSCBs were established.

Third, with the implementation of the Commercial Bank Law, urban and rural credit cooperatives started to merge and form city and rural commercial banks. Local governments, local enterprises, and households variously own the CCBs, which offer commercial banking services (intermediary, settlements, money transfers, etc.) to city-based small and medium sized enterprises and residents, although they also have been trying to attract larger firms headquartered in their respective cities, and which would normally do business with a state bank. RCBs operate much like their urban counterparts but in rural areas.

Finally, in 1982, the central bank lifted the restriction on foreign banks operating representative offices in China and they were permitted to open branches in the Special Economic Zones (SEZ). Since 1994, FBs were allowed to operate in 23 cities based on individual applications, and permitted to do business with Chinese enterprises by taking deposits and making loans in local currency in the Shanghai Pudong New Zone in 1996. The total assets of FBs in China reached nearly RMB 272 billion (USD 32,844 million) by 1999, however, during much of the 1990s, foreign banks were prohibited from conducting any consumer banking in local currency with mainland residents. Regulatory permission for foreign investors to hold minority stakes in domestic banks was forthcoming more slowly. The first case was in 1996, when the Asian Development Bank (ADB) bought a 1.9% stake in China Everbright Bank (a national majority state-owned commercial bank) (Berger, 2010). However, further foreign acquisitions of the shares of domestic banks were generally cautious and minor throughout this period.

2001–2006.

Following China's entry into the WTO in 2001, the Chinese government further accelerated and deepened its banking reforms in order to promote the competitiveness of the Chinese domestic banks in light of the entry of foreign banks from 2006 onwards under the rules and obligations set by the WTO. In 2003, the China Banking Regulatory Commission (CBRC) was established, taking on the role of banking supervisory authority from the PBOC. The PBOC is now only responsible for overall financial stability and systemic liquidity. After this, the State Council (SC) officially announced acceptance of the principle of private ownership. In 2005, the CBRC adopted three new tools to strengthen the monitoring of bank NPLs, namely, peer group comparison, assessing the deviation of the accuracy of loan classifications and tracking the migration of loans from different categories.

In terms of capital adequacy, the 8 percent minimum capital adequacy ratio, as defined in Basel I, was introduced, with a minimum of 4 percent total capital. All banks were required to meet these ratios by 2007. Moreover, bank regulation has adopted a risk-based framework, with guidelines for credit, market and operational risk. In addition, a CAMEL15-type risk assessment system has been introduced with quantitative and qualitative criteria for capital, asset quality, management competence, liquidity, and profitability. For asset quality, the five-tier loan classification system was made compulsory for all banks by the end of 2005. In the same vein, full provisioning of NPLs was introduced by the end of 2008.

To comply with asset quality requirements for supervising purposes and capitalization, an injection of the equivalent of USD 33 billion in RMB into the Big-4, was made in 1999–2000, combined with the transfer of NPLs from the large banks to four newly created Asset Management Companies (AMC) for the equivalent of USD 170 billion. This was followed in December 2003 with USD 22.5 billion of capital injections into the China Construction Bank (CCOB) and the Bank of China (BOC). In 2004, the equivalent of USD 15.6 and 18.1 billion in NPLs were respectively auctioned by the CCOB and BOC to the AMCs, while in 2005, USD 15 billion was injected into the Industrial Commercial Bank (ICBC) (Garcia-Herrero et al., 2006).

In December 2005, the first Chinese bank with a foreign minority stake, China Bohai Bank, was established. The Bank of Communications was the first to take this route in June 2005 when it raised more than US $2 billion in an IPO in Hong Kong. Subsequently, three of the Big-4 banks had floated on the Shanghai and Hong Kong stock markets by 2006 (the fourth similarly listed in 2010). Starting in 2000, the controls on foreign currency lending rates and large-value foreign currency deposit rates began to be removed. As for domestic currency transactions, a corridor was established in 1996 for RMB loans, which was gradually widened until the upper limit was lifted in October 2004. In October 2004, the lower limit, but not the upper limit, on the interest rate for all RMB deposits was lifted.

A crucial milestone in the financial liberalization process was the conclusion of the negotiations for China's accession to the WTO in late 2001. The commitments agreed to under WTO implied the full opening up of the Chinese banking system to foreign affiliates by the end of 2006. At the beginning, foreign banks were only allowed to carry out foreign-currency transactions. As a second step, foreign banks were authorized to permitted offer local currency services to foreign enterprises and individuals. In 2003, the wholesale market in domestic currency was opened to foreign competition for a large number of provinces. Finally, from the end of 2006 onwards, foreign banks were able to offer all banking services in local currency in all provinces, even to individual households.

2006 onwards

Up to 2007, China made remarkable progress in banking reform with far-reaching economic and financial implications. The segmented commercial banking sector formed, now comprising the Big-5 banks, JSCBs, CCBs, RCBs, and FBs, along with urban and rural credit cooperatives, finance, trust and investment, and financial leasing companies and postal

savings institutions, etc. For the major commercial banks, the NPL ratio fell significantly from about 30% in 1999 to 10.5% in 2005, down to 6.7% by 2007.

Following the joint-stock conversions of the largest four state-owned banks, the ABC listed on both the Shanghai and Hong Kong exchanges, with different categories of shareholders including foreign banks, with all of the Big-5 now ostensibly operating as commercial banks. After their conversion to joint-stock companies, the banks have diversified their financial services to include corporate and personal financial services. Even, the Big-5 banks are investing overseas. However, the Big-5 share of banking sector assets declined from 58% in 2003 to 47% in 2011. The second-largest group of banks in China consists of the 12 JSCBs. Their share, measured in terms of banking sector assets, increased from about 11% to over 16% between 2003 and 2011 (mostly at the expense of the Big-4).

By 2009, local governments owned 18.5% of the shares of CCBs, with most shares held by other Chinese banks or corporations and foreign banks, and a small amount by bank employees and private investors. According to the CBRC's 2010 annual report, the CCBs in China accounted for some 11% of the total assets in the banking sector. As of the end of 2011, there were 349 village and township banks, 85 rural commercial banks, 223 rural cooperative banks, and 2,646 rural credit cooperatives in China. By and large, the various rural financial institutions provide services to China's large but relatively declining rural population.

According to the CBRC's 2011 annual report, 37 wholly foreign-owned banks, plus two foreign joint-venture banks and one wholly foreign-owned finance companies, had incorporated in China by the end of 2010 with a combined total of 270 branches or subsidiaries. In addition, 90 foreign banks had chosen to open branches in China. As a result, 360 separate foreign banking establishments were operating in China by the end of 2010 in 45 cities and 27 provinces across the country. The combined assets of these institutions was valued at RMB 1.74 trillion (approximately $274 billion), or 1.83% of total banking assets in China (Martin, 2012).

The Chinese banking system was arguably resilient with respect to the direct financial effects of the 2007 GFC, in large part because it focused on the strongly growing domestic market with little exposure to overseas wholesale funding markets. In response to the sharp downturn in external demand, the Chinese authorities implemented substantial economic stimulus through a rapid expansion in bank credit, largely directed at government infrastructure projects. The increase in bank credit in 2009 was equivalent to about 30 percent of GDP. The

sizeable amount of government mandated lending is likely to have slowed the ongoing commercialization of the Chinese banks, and have added to their credit risks (Martin, 2012).

However, the Chinese government did not slow the pace of reform during and after the GFC. In 2007, the PBOC has announced a number of additional measures, such as eliminating the upper limit on RMB loans for credit cooperatives and abolishing the existing lower limit on lending rates for all institutions. The PBOC also intends to eliminate the upper limit for all RMB deposits and liberalize interest rates on remaining foreign currency deposits at some future time. In the current setting, the liberalization of the ceiling on the lending rate and of the floor on the deposit rate implies no limit as to how large the spread between the lending and deposit rate, but is clear on how small it can be, i.e. the difference between the reference lending and deposit rates.

The commitments agreed to under the WTO have implied the full opening up of the Chinese banking system to foreign affiliates since the end of 2006. Although the WTO commitments do not deal directly with the foreign acquisition of a stake from a Chinese bank, the Chinese authorities have increased the limit on the bank foreign ownership from 15 to 20 percent of the total capital for a single investor, and 25 percent for all investors, although the latter not for listed banks. This reflects the general perception that the banking system needs fresh capital and highly qualified bank management.

Despite substantial reforms, including major restructuring of ownership claims, a number of challenges remain for the Chinese banking sector. For example, foreign ownership remains relatively small, as so does foreign involvement in governance. The banking system remains dominated by largely state-owned enterprises, and bank lending continues to be driven by the availability of funds, not borrower quality. Chinese banks also continue to be largely constrained by government intervention at different levels and subject to substantial political influence. Last, China’s banks are compelled to meet contradictory goals of supporting employment while reforming themselves into modern commercial banks (Bailey et al., 2011).

3. Theoretical Framework

3.1 Meta- and group-frontiers

Assume that there are j=1,...,N banks and that each bank uses input vector $x \in \Re_+^M$ to jointly produce outputs vector $y \in \Re_+^S$ and undesirable outputs $b \in \Re_+^J$. Here the multi-output production technology with undesirable output can be expressed as

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\}, \tag{1}$$

where T is often assumed to satisfy the standard axioms of production theory (Färe and Grosskopf, 2005). For instance, inactivity is always possible, and finite amounts of inputs can produce only finite amounts of outputs. In addition, we often assume inputs and desirable outputs are strongly or freely disposable. For a reasonable model of joint-production technologies, as described in Färe et al. (1989), we need to impose weak disposability and null-jointness assumptions on T. We express the two assumptions as follows:

(i) If $(x, y, b) \in T$ and $0 \le \theta \le 1$, then $(x, \theta y, \theta b) \in T$;

(ii) If $(x, y, b) \in T$ and b=0, then y=0.

The weak-disposability assumption implies that reducing undesirable outputs, such as NPLs, in a bank are costly in terms of the proportional reduction in total loans. The null-jointness assumption states that NPLs are not avoidable in bank loans and that the only feasible way to remove NPLs is to cease loans.

After specifying the bank joint-production technology T, it is possible to use parametric techniques or nonparametric data envelopment analysis (DEA) to construct the bank production technology. In this paper, we employ a nonparametric DEA piecewise linear production frontier to construct the bank joint production technology. Then we can express T for N generators exhibiting constant returns to scale (CRS) as

$$\begin{aligned} T = \{(x, y, b) \; : & \sum_{n=1}^{N} z_n x_{mn} \le x_m, m = 1, \ldots, M, \\ & \sum_{n=1}^{N} z_n y_{sn} \ge y_s, s = 1, \ldots, S, \\ & \sum_{n=1}^{N} z_n b_{jn} = b_j, j = 1, \ldots, J, \\ & z_n \ge 0, n = 1, \cdots, N. \} \end{aligned} \tag{2}$$

3.2 Generalized directional distance functions

The directional distance function, developed by Chambers et al. (1996), is a relatively new method for performance measurement. According to Fukuyama and Weber (2009), the conventional directional distance function as a radial measure of efficiency (inefficiency) may overestimate efficiency when there are non-zero slacks. The literature mostly supports non-radial measures of efficiency for measuring bank efficiency because of their several advantages (e.g. Fukuyama and Weber, 2009, Barros et al., 2012). For this reason, Barros et al. (2012) and Zhou et al. (2012) provide a formal definition of the non-radial directional distance function, which is a generalized form of basic directional distance function. Following Zhou et al. (2012), we define the generalized directional distance function as follows:

$$\vec{D}(x,y,b;g) = \sup\{\mathbf{w}^T\boldsymbol{\beta} : \big((x,y,b) + g \cdot diag(\boldsymbol{\beta})\big) \in T\} \tag{3}$$

where $\mathbf{w} = (w_m^x, w_s^y, w_j^b)^T$ denotes a normalized weight vector relevant to numbers of inputs and output, $g = (-g_x, g_y, -g_b)$ is an explicit directional vector, and $\beta = (\beta_m^x, \beta_s^y, \beta_j^b)^T \geq 0$ denotes the vector of scaling factors. We compute the value of $\vec{D}(x,y,b;g)$ by solving the following DEA-type model:

$$\begin{aligned}
\vec{D}(x,y,b;g) = \max\ & w_m^x\beta_m^x + w_s^y\beta_s^y + w_j^b\beta_j^b \\
\text{s.t.}\ & \sum_{n=1}^{N} z_n x_{mn} \leq x_m - \beta_m^x g_{xm}, m = 1,\ldots,M, \\
& \sum_{n=1}^{N} z_n y_{sn} \geq y_s + \beta_s^y g_{ys}, s = 1,\ldots S, \\
& \sum_{n=1}^{N} z_n b_{jn} = b_j - \beta_j^b g_{bj}, j = 1,\ldots J, \\
& z_n \geq 0, n = 1,2,\cdots,N \\
& \beta_m^x,\ \beta_s^y, \beta_j^b \geq 0
\end{aligned} \tag{4}$$

We may set the directional vector g in different ways based on specific bank goals. If $\vec{D}\ (x,y,b;g) = 0$, then the bank to be evaluated is located on the frontier of best practices in the direction of g.

The overall technical efficiency (TE) for the bank is the average efficiency of each factor. Suppose that β_x^*, β_y^*, and β_b^* represent the optimal solutions to Equation (4), then the TE can be formulated as:

$$TE = 1 - \vec{D}(x, y, b; g) = 1 - \left[\frac{1}{M + S + J} (\sum_{m=1}^{M} \beta_{xm}^{*} + \sum_{s=1}^{S} \beta_{ys}^{*} + \sum_{j=1}^{J} \beta_{bj}^{*}) \right]. \quad (5)$$

3.3 Meta-frontier generalized directional distance function

We now combine the concept of meta-frontier production technologies in O'Donnell et al. (2008) with that of the generalized distance function to develop our meta-frontier generalized directional distance function and investigate the group heterogeneity of bank joint-production in China. For this, we define the group- and meta-frontier technologies.

Suppose that H groups show some technological heterogeneity, such that human resources, management knowhow, and other specific constraints may prevent banks in some groups from accessing the management technologies in other groups. Following Battese et al. (2004) and O'Donnell et al. (2008), we define the group-frontier technology of group h as $T_h = \{(x, y, b) : x \text{ can produce } (y, b)\}$, h=1,2,…H. Assume that T_h is specified as the nonparametric joint production technology described in equation (3). Then we define the generalized directional distance function for group h as

$$\overset{\sqcup}{D}^{g}(x, y, b; g) = \sup\{\mathbf{w}^T \boldsymbol{\beta} \ : \big((x, y, b) + g \cdot diag(\boldsymbol{\beta})\big) \in T_h\}, h = 1,2...H \quad (9)$$

Unlike a group-frontier technology, we can construct a meta-frontier technology from all observations for all groups by enveloping all group-frontier technologies. Therefore, we can consider the following definition: $T_m = \{T_1 \cup T_2 \cup ... \cup T_H\}$. Here we formulate a generalized function based on a meta-frontier technology as follows:

$$\overset{\sqcup}{D}^{m}(K, L, F, E, C; g) = \sup\{\mathbf{w}^T \boldsymbol{\beta} : \big((x, y, b) + g \cdot diag(\boldsymbol{\beta})\big) \in T_m\} \quad (10)$$

In equation (9), we calculate $\overset{\sqcup}{D}^{g}(\cdot)$ by solving model (4) with use the of input and output data from group h. Suppose N_h observations for group h. We compute $\overset{\sqcup}{D}^{m}(\cdot)$ by solving the following:

$$
\begin{aligned}
\vec{D}^m(x,y,b;g) = \max\ & w_m^x \beta_m^x + w_s^y \beta_s^y + w_j^b \beta_j^b \\
\text{s.t.} & \sum_{h=1}^{H}\sum_{n_h=1}^{N_h} z_n^h x_{mn} \le x_m - \beta_m^x g_{xm}, m = 1,\ldots,M, \\
& \sum_{h=1}^{H}\sum_{n_h=1}^{N_h} z_n^h y_{sn} \ge y_s + \beta_s^y g_{ys}, s = 1,\ldots S, \\
& \sum_{h=1}^{H}\sum_{n_h=1}^{N_h} z_n^h b_{jn} = b_j - \beta_j^b g_{bj}, j = 1,\ldots J, \\
& z_n^h \ge 0, n_h = 1,2,\cdots,N_h, h = 1,\ldots H, \\
& \beta_m^x,\ \beta_s^y, \beta_j^b \ge 0.
\end{aligned} \tag{11}
$$

where z_n^h represents the intensity variables for constructing the meta-frontier technologies. Equation (11) indicates that we need data on all the banks to construct the meta-frontier. The meta-frontier joint-production technologies cover all group-frontier technologies. After solving equations (9) and (10), we obtain the optimal solutions for all variables under group- and meta-frontier technologies, respectively.

O'Donnell et al. (2008) point out that we can decompose the technical efficiency from meta-frontier technologies (*MTE*) into within-group technical efficiency (*GTE*) and the meta-technology ratio (*MTR*). *GTE* measures the relative efficiency of observations under specific group-frontier technologies, whereas *MTR*, also referred to as the technology gap ratio, measures how close a group-frontier technology is to a meta-frontier technology. O'Donnell et al. (2008) show that *MTE* does not exceed *GTE*, such that *MTR* is no greater than unity. The higher value the *MTR*, the closer the group-frontier technology is to the meta-frontier technology. An *MTR* value equal to unity implies no gap between the two technologies, that is, a complete overlap between the group- and meta-technologies.

<FIGURE 1 HERE>

Following O'Donnell et al. (2008), we decompose *MTE* into within-group technical efficiency (GEC) and a meta-technology ratio (MTR) index, respectively. Here we consider a simple example in Figure 1 to illustrate the decomposition of *MTE*. Suppose that the input is *x* and the output is *y* and that the bank under analysis belong to two heterogeneous groups. We compute two group frontiers, *XX'* and *YY'*. Based on a specific bank *a* operating at *XX'*, its performances under the group frontier *GTE* and the MTE according to M are formulated as:

$$GTE = \frac{y_2 - y_1}{x_2 - x_1}, \quad MTE = \frac{y_3 - y_1}{x_3 - x_1} \tag{12}$$

Therefore, *MTRT* captures the gap between the group frontier and the meta-frontier as: if $y_2=y_3$ and $x_2=x_3$ which means no technology gap, then the MTR=1.

$$MTR = \frac{MTE}{GTE} = \left[\frac{y_3 - y_1}{y_2 - y_1}\right] * \left[\frac{x_2 - x_1}{x_3 - x_1}\right] \tag{13}$$

Drawing on the intermediation approach to bank efficiency estimation, we develop three input–output specification models to examine the efficiency of Chinese banks, as shown in Table 1. In Model A, the inputs are personnel expenses (PEX), total deposits (DEP) and physical capital (FIX), and the outputs are total loans (LOA) (including loans, advances, and other receivables), non-interest income (NON) and the non-performing loan ratio (NPL) (the ratio of non-performing loans to total loans). We use Model B to investigate cost efficiency when incorporating input prices, with input prices proxied by personnel expenses divided by total assets (PLB), interest expenses divided by total deposits (PDP), and operating expenses less labour expenses divided by fixed assets (PPC). The outputs are normalized total loans (LOA), non-interest income (NON) and the non-performing loan ratio (NPL). Finally, we use Model C to examine the profit efficiency of the banks, where the additional outputs are the normalized pre-tax profits (PRO) and the non-performing loan ratio (NPL), and the inputs are the same as Model B .

<TABLE 1 HERE>

3.4 Bootstrap truncated regression

In early research in this area, Tobit regression was typical in the second-stage regressions used to examine the determinants of DEA efficiency analysis. However, more recently, bootstrap truncated regression has proposed. One disadvantage with Tobit and OLS regression is that the efficiency scores obtained through empirical DEA computation and not observed directly. Thus, OLS models (including the Tobit model), which assume independently distributed error terms, are invalid. In addition, empirical estimates of the efficiency frontier draw on only a select sample of banks, which eliminates some efficiency production possibilities not observed in the sample. Further, the two-stage regression model depends on explanatory variables that not directly observed but estimated in the first stage. This implies that the error term is correlated with the second-stage explanatory variables.

To overcome these disadvantages, the truncated bootstrap regression approach of Simar and Wilson (2007) enables consistent inferences within models, explaining efficiency scores while simultaneously producing standard errors and their confidence intervals. The truncated bootstrap model is as follows:

$$\phi^{\wedge} = z_i \beta + \varepsilon_i \tag{14}$$

Our aim is to recognize the relationship between MTE scores $\phi^{\wedge}$ and explanatory variables z_i , which refer to the vector of parameters with some statistical noise ε_i in Equation (14). Previous studies have suggested some estimation procedures based on the OLS or Tobit model. However, because of the biased estimation as mentioned above, our approach follows the following steps:

1. Calculate the MTE score $\phi^{\wedge}$ for each bank by using the meta-frontier distance approach model according to (11).
2. Conduct the truncated regression of $\phi^{\wedge}$ and z_i by using the maximum likelihood function to estimate $\beta^{\wedge}$ and $\sigma_{\varepsilon}^{\wedge}$ of β and σ_{ε}, respectively.
3. Repeat the following steps *B* times (*B* = 2000) to obtain a set of bootstrap estimates $\{\hat{\phi}^{*}_{i,b}, b = 1,...B\}$:
   a. Draw ε_i from the N (0, $\hat{\sigma}^2$) distribution with left truncation at (1- $\beta^{\wedge} z_i$);
   b. Calculate $\phi_i^* = z_i \beta^{\wedge} + \varepsilon_i$;
   c. Generate a pseudo data set (x_i^* y_i^*), where $x_i^* = x_i$ and $y_i^* = y_i \, \phi_i^{\wedge} / \phi_i^*$;
   d. Substitute a new meta-frontier estimate θ_i^* with the set of pseudo data (x_i^* y_i^*)
4. For each DMU, calculate the bias-corrected estimate $\phi^{\wedge\wedge}{}_i = \phi^{\wedge}{}_i - bia^{\wedge}s_i$, where $bia^{\wedge}s_i$ is the bootstrap estimator of bias defined as $bia^{\wedge}s_i = 1/B \sum_{b=1}^{B} \phi^{\wedge *}{}_{i,b} - \phi^{\wedge}{}_i$.
5. Conduct the truncated regression of $\phi^{\wedge\wedge}{}_i$ on z_i to obtain the estimates ($\beta^{\wedge\wedge}$, $\sigma^{\wedge\wedge}$) of (β , σ).
6. Repeat the following three steps *B2 (B2=2000)* times to obtain a set of bootstrap estimates $\{\beta_b^{\wedge\wedge *}, \sigma^{\wedge\wedge *}, b = 1,...B2\}$:

a. For i=1,…,n, ε_i is drawn from N (0, $\sigma^{\wedge\wedge}$) with left truncation at (1- $\beta^{\wedge\wedge} z_i$);

b. For i=1,…,n, execute $\phi^{**} = \beta^{\wedge\wedge} z_i + \varepsilon_i$;

c. Again, conduct the truncated regression of $\phi^{**}{}_i$ on z_i to obtain the estimates of ($\beta^{\wedge\wedge *}$, $\sigma^{\wedge\wedge *}$).

See Simar and Wilson (2007) for the estimation algorithm. Some researchers have conducted empirical analyses to verify that in the two-stage DEA model, truncated bootstrap regression can provide robust results than the Tobit model and result in smaller standard errors and less variance.

3.4 Correlates with bank efficiency

The firm-specific variables in Table 2 include intangible assets (INT), debt to equity ratio (DER), the ratio of cash and dues from banks to assets (CASH), the ratio of loans to deposit (LDR), the net interest margins (NETI), the ratio of investment in marketable securities to loans (INV) and the capital adequacy ratio (CAR). Intangible assets (INT) (in logarithms) represent the accounting value of goodwill, patents, copyrights, trademarks, formulae, organizational costs, customer lists, franchises and licenses, purchased servicing rights, and capitalized value of software development, advertising costs and servicing rights. We interpret an intangible asset as an indicator of future growth opportunities (Ozkan, 2001). Thus, we expect a bank with substantial intangible investments to be more efficient. Though a number of studies examine the value relevance of intangible assets (Oliveira et al., 2010; Dahmash et al., 2009), there has been previously no attention to the role of intangible assets as a determinant of bank efficiency.

A higher debt to equity ratio (DER) may reduce agency costs through pressure to generate cash flow to pay interest expenses and through the threat of liquidation, which can cause personal losses to managers' salaries, reputations, etc. In this respect, DER may positively affect bank efficiency. Conversely, further increases in DER may incur significant agency costs, because a relatively high DER makes bankruptcy or financial distress more likely because of risk shifting or a reduced effort to control risk (Berger and Patti, 2006). In this case, DER has a negative effect on bank efficiency. The ratio of cash and dues from banks to assets (CASH) represents liquidity risk. We expect CASH to affect bank efficiency negatively due to opportunity cost of holding liquid assets (Kwan, 2003). The ratio of loans to deposit (LDR) represents insolvency risk. LDR reflects a bank's ability to covert deposits

to loans (Dietsch and Lozano-Vivas, 2000), and thus exerts a positive influence on efficiency.

We justify net interest margins (NETI) as follows. Over the past few decades, interest margins on loans have declined significantly and banks have become more involved in non-loan services, such as fund managements, financial planning, and insurance services to improve their bottom line. In addition, the ratio of investment in marketable securities to loans (INV) is positively associated with efficiency because investment securities are more efficient than loans in generating revenues. Finally, we specify the capital adequacy ratio (CAR) as a measure of regulatory compliance.

4. *Data*

We investigate the efficiency of Chinese banks over the period 2006 to 2013, which as discussed earlier, is the fourth period in the long history of Chinese banking reforms. During this time, all the major banks had completed transition in their ownership structure and most city or rural commercial banks had transformed from other financial institutions into banks. In this sense, we minimize the likelihood of bias in our estimates in terms of the violation of homogeneity. The sample is an unbalanced panel comprising 143 Chinese banks over 8 years, with 682 bank-year observations for the Big-5 banks, 11 JSCBs, 85 CCBs and 24 RCBs. The data is from the China Stock Market Accounting Research database (CSMAR) and Bankscope. Table 2 provides summary statistics for the variables.

5. Results and Discussion

5.1 Efficiency estimates

We base the estimates of the meta-frontier non-radial directional distance function (MNDDF) models on the CRS free-oriented slack-based DEA models given by Eq. 11. In the analysis, we use GTE, GCE and GPE to refer to the DEA estimates of Models A, B and C relative to the group frontiers; MTE, MCE, and MPE to the DEA estimates of Models A, B and C relative to the meta-frontiers, respectively; and TER, CER, and PER to the DEA estimates of the meta-technology ratio.

<TABLE 3 HERE>

To investigate whether there are statistically significant differences between the group- and meta-frontiers, we apply a Kruskal–Wallis test to the differences in the efficiency scores

between the five bank segments. As shown in Table 3, all the null hypotheses are rejected at the 1% level, evidencing that the banks in the different segments are operating under the different boundaries of restricted technology sets, where the restrictions can derive from the differences in business environments such as regulations, restrictions, policies and/or business markets, etc. In other words, the segments lead to the different technological frontiers to which the performance of the sample banks is to measured relative.

<TABLE 4 HERE>

Table 4 provides descriptive statistics for the estimates for all the selected banks across the five segments. For example, in the first segment, we calculate the technical efficiency scores (GTE) of the Big-5 banks with respect to the group frontier to vary between 0.713 and 1.000 over the 8-year period, with an average of 0.916 and a standard deviation of 0.097. The cost efficiency scores (GCE) for the same segment range between 0.628 and 1.000, with an average GCE of 0.918, while the profit efficiency scores lie between 0.417 and 1.000 with an average GPE of 0.726. This means that given their business environment, the Big-5 banks are approximately 91.6% efficient in minimizing inputs and bad outputs i.e. non-performing loans, and maximizing good outputs i.e. loans and non-interest income. When we consider input prices or/and profits, the efficiency levels are 91.8% and 72.6%, respectively. In other words, the existing business environment allows for an 8.4%, 8.2%, and 27.4% improvement management in minimizing inputs or costs and bad outputs and maximizing good outputs or profits.

As shown in the upper panel in Table 4, relative to the group frontier in each segment, the Big-5 banks exhibit the best performance in GCE and GPE, whereas, the JSCBs have the best performance in GTE with average GTE scores of 93.8%. The good performance of the Big-5 in terms of GCE and GPE may well result from the well-organized business operating systems in these very large banks, while the better performance of JSCBs in TE may reflect the ownership advantages of the joint-stock firms in terms of governance, which is consistent with Jiang et al. (2009).

The worst performers in terms of efficiency are the CCBs, with average scores of 63.4%, 49.4%, and 32.8% for GTE, GCE and GPE, respectively. On one hand, Chinese local governments normally use CCBs as the major channels for implementation of their policies, particularly those related to fixed investment. On the other hand, CCBs attempt to dominate local financial markets, particularly retail finance, deriving protection from competition from

local governments. The low level of efficiency relative to the group frontiers suggests that the CCBs have greater management potential to improve under the local banking environment.

With respect to the FBs, relative to their boundaries in the restricted technology sets, they do not exhibit good performance in their management efficiency. We interpret this in two ways. First, FBs largely remain at the startup/emerging growth stage of banking operations in China. Therefore, their banking business awaits further expansion in terms of both the types of business and operating locations in China. Second, there is a great potential for FBs to expand their banking business in China given the boundaries of the technology sets, as indicated by the meta-technology ratio.

As discussed, the meta-technological ratio measures the gap between the group (here, segment) frontiers and the meta-frontier. The second panel in Table 4 reveals that FBs with the highest levels of technology at 98.1% display the smallest gap between the group frontier and the meta-frontier. That is, the FBs have the best environment for banking business, which they could derive from their better management, greater market discipline, and/or established corporate cultures (Berger et al., 2009). There is no doubt that the opening-up of banking markets starting from the end of 2006 under WTO entry agreements greatly improved the performance potential of FBs in China's banking markets. However, as in the first panel, FBs still have room to realize this potential in China. In the meantime, CCBs have the highest levels of meta-technology ratio in Models B and C, which means that depending on their sizes, the CCBs can realize high levels of saving costs and/or maximizing profits when operating locally. As discussed, they also benefit from the protection of local governments in local financial markets.

Interestingly, the Big-5 have the lowest meta-frontier ratios, which indicates that the advanced technology they possess is not readily able to be fully converted into economic advantages like cost-saving and profit-maximizing. In other words, the Big-5 banks appear to have more restricted conditions. These restricted conditions may derive from the regulations, policies or the functions they carry out. As discussed in Section 2, the Big-5 have long undertaken the functions of implementing government fiscal policy. Therefore, it is unsurprising that the focus of the Big-5 departs from the conventional business goals of profit maximization and cost minimization, as reflected in their low meta-technology ratios (MR). The low MR levels of the Big-5 also provide good evidence that the Chinese banking sector is far from fully competitive.

In the second panel in Table 4, all groups and models have the maximum value of one, except the Big-5 with a maximum value of 0.55 for Model C (the RCBs have a maximum value of 0.76 for Model A. This means that, over the sample period of 2006–13, there must have been at least one year when the combination of inputs and outputs placed one bank (i.e. a Big-5 bank or a rural commercial bank) on their respective group frontier, but well below the meta-frontier.

Finally, we provide the efficiency scores relative to the meta-frontier, which is the product of the efficiency scores relative to the group frontiers and the meta-technology ratios, in the third panel of Table 4. When business environment is ignored, that is, all banks in the five segments are measured against a common technological frontier i.e. the meta-frontier, all efficiency scores are lower than are those relative to the group frontiers. For example, the average efficiency score of the Big-5 is 86.8%, which is much lower than the 91.6% in the first panel. The difference arises from the meta-technology ratios in the second panel. In a similar vein, the RCBs exhibits low levels of efficiency relative to the meta-frontier, which is largely attributable to the large technological gap between the group frontier and meta-frontier. We interpret this as being the result of the very tough restrictions imposed on the banking business of the RCBs.

<FIGURE 2 HERE>

Figure 2 depicts the efficiency trends for the selected banks relative to the meta-frontier over the sample period. As shown, technical efficiency exhibits a stable and increasing trend over the period except for a very slight fall during the GFC in 2008. By comparison, bank costs and profits exhibit significant fluctuation over the period, especially during the GFC. Another turning point in the efficiency trend is after 2010, when the cost and profit efficiency curves present a declining trend, but the technical efficiency trend remains stable. In 2009, and as a way to mitigate the effects of the GFC, the Chinese government released a stimulus package worth RMB 4 trillion channeled through the banks, resulting in a large increase in Chinese bank loans in 2009. Figure 2 illustrates this well. However, the stimulus package worsened asset (loan) quality and risk, thus the Chinese government and regulators turned attention to these risks and were putting in place measures and policies to prevent a surge in NPLs as well as limiting lending to the real estate sector and other industries with excess capacity since 2010. Therefore, we can see a turning point from 2010 onwards. Another interpretation of the turning point arises from the requirements of Basel II for Chinese banks starting in 2011, as

also indicated by the trends in the meta-technology ratios (KPMG, 2012). As depicted in Figure 3, the average gap between the group (segment) frontier and the meta-frontier varied over the period, with defined turning points in 2008 and 2011.

<FIGURE 3 HERE>

Figure 4 plots the trends in the meta-frontier efficiency and meta-technology ratios of the five segments. As shown, the GFC and Chinese government policies greatly affect the FBs in their profit performance, with the group profit frontier increasing significantly over the sample period, that is, the gap between the group frontier and meta-frontier have considerably narrowed, reflecting the progressive opening of the Chinese banking sector to foreign competition. Another good-performing segment are the JSCBs in Model B, which we interpret as reflecting the advantages in ownership structure under the better-regulated banking environments in place since 2012 with the implementation of Basel II.

<FIGURE 4 HERE>

5.2 Firm-level determinants of efficiency

In the second stage, following suggestions by Simar and Wilson (2007), we employ a bootstrap truncated regression model to analyze the firm-level factors behind the various measures of bank performance. As we pooled the bank data to find the firm-level determinants of bank efficiency, we specify the efficiency scores relative to meta-frontier as the dependent variables. As a simple test of the potential for multicollinearity, we use a correlation matrix, as shown in Table 5. As the maximum correlation coefficient is only about 0.5, we believe multicollinearity is not a significant concern.

<TABLE 5 HERE>

Table 6 provides the maximum likelihood estimates. As shown, an increase in the capital adequacy ratio (CAR) improves technical, cost and profit efficiency. This finding is consistent with the notion that banks will be less likely to incur loans losses and are better placed in attracting deposits in a banking sector with a high capital adequacy requirement (Kasman and Yildirim, 2006; Grigorian and Manole, 2006). Intangible assets (INT) have a significant and positive effect on technical efficiency, indicating that it may actually be a proxy for advanced technology or management techniques, which can improve the technical efficiency of the banks. Financial leverage (DER) is significantly and positively associated with technical and cost efficiency, but has no significant effects on profit efficiency. The

positive effect on technical and cost efficiency of DER is consistent with the benefit of debt tax shields. This is also in line with the agency cost hypothesis, which implicitly indicates a positive relationship between DER and efficiency (Margaritis and Psillaki, 2007). In a similar vein, the loan to deposit ratio (LDR) also shows a significant and positive effects on TE. As expected, the ability to convert deposits into loans is in line with improved efficiency of banks. This result is consistent with a number of studies (e.g., Barros, et al., 2007; Valverde et al., 2007).

<TABLE 6 HERE>

As an indicator of liquidity risk, the ratio of cash and dues from banks to assets (CASH) exhibits a negative effect on TE but a positive effect on CE and PE. The negative effects of CASH on TE are due to the opportunity cost of holding liquid assets (Kwan, 2003). The positive effects of CASH on CE and PE are then perhaps because liquid assets makes bankruptcy or financial distress less likely due to liquidity risk and thus improves bank revenues. Interest margins (NETI), as expected, have positive effects on PE, but negative effects on TE. Given the net interest income is an indicator of market competition, the negative effects of NETI provide some evidence that increasing competition in Chinese banking sector can help improve bank efficiency. Thus, banks may still depend on lending services to achieve significant improvements in cost and profit efficiencies despite the fact loans are generally more costly than securities.

6. Concluding Remarks

The purpose of this analysis was to examine Chinese bank performance, as measured by technical, cost and profit efficiency, across a wide variety of banks and a relatively long sample period. First, taking account of the heterogeneity arising from the high degree of market segmentation in Chinese banking sector, we applied the so-called meta-frontier analysis approach to the analysis of the performance of Chinese banks. Given that the frontier analysis techniques draw on the distance of the performance of assumed relatively homogeneous banks to better performing banks, the meta-frontier analysis approach makes efficiency comparisons across subgroups of banks operating in different market segments. Under this approach, a common meta-frontier and group frontiers are the boundary of an unrestricted technology set and the boundaries of restricted technology sets, respectively, and the so-called meta-technology ratio measures the distance between the group frontier and the

meta-frontier.

Second, given that state-dominated banks arguably lack control on loan qualities, we applied a non-radial directional distance function approach, where loan quality (as measured by non-performing loans) serve as one output. In this approach, a better performer is a bank that can maximize loans and/or incomes, but minimize NPLs. Third, we specified three models to examine the performance of Chinese banks over the period post-2006 which include both GFC and post-GFC periods. Finally, we employed a bootstrap truncated model to investigate the effects of risk management on bank efficiency, including liquidity, credit, and insolvency risk, etc.

Our results revealed significant differences in the group frontiers between the different segments. We found that relative to the group frontier in each segment, the Big-5 banks exhibited the best performance in GCE and GPE, whereas the joint stock commercial banks displayed the best performance in GTE. We argued the good performance of the Big-5 in terms of GCE and GPE might have benefited from the well-organized business operating systems of these very large banks, whereas the better performance of the JSCBs in TE may reflect the ownership advantages of joint stock firms in terms of governance. However, the low levels of the meta-frontier ratio for the Big-5 may indicate that they have more restricted conditions where they are unable to make full use of their technological potentials to achieve higher economic goals such as cost cutting and profit maximization. These restricted conditions may also derive from the additional regulations, policies, or functions they bear. The low MR levels of the Big-5 evidence that the Chinese banking sector is far from fully competitive.

At the other end of the spectrum, the worst performers are the city commercial banks largely owned by city governments or their authorities in terms of efficiency scores. This can be a benefit for the banks in that the local governments use the CCBs as a conduit for the implementation of local public policy. The CCBs also benefit from the protection given by the local governments from non-local banks. Therefore, the CCBs have the highest meta-technology ratios in terms of cost and profit efficiency.

The foreign banks (FBs) did not display good performance in their management efficiency, which indicates that FBs remain at a startup/early growth stage of banking operation in China. Therefore, their banking business model awaits further expansion in terms of both the types of business and the operating locations in China. However, the high meta-technology ratios

for the FBs reveals that they have the best banking business environment, we argue derives from their better management, greater market discipline, and/or developed corporate cultures. Finally, the rural commercial banks (RCBs) exhibit low levels of efficiency over the period, which is largely attributable to the large technological gaps between their group frontier and meta-frontier. We interpret this as resulting from the very tough government regulations imposed on their banking business.

Over the sample period of 2006–13, the technical efficiency of the Chinese banks exhibit a stable and increasing trend, except for a very slight and not unexpected decline during the 2008 GFC. By comparison, bank costs and profits fluctuate widely, particularly after the GFC. With respect to the firm-level determinants of bank efficiency, the estimates of a bootstrap truncated regression model reveals that the capital adequacy ratio (CAR), financial leverage (DER), intangible assets (INT), and the loan to deposit ratio (LDR) have a significant and positive effect on technical efficiency. In contrast, the ratio of cash and dues from banks to assets (CASH) and interest margins (NETI) exert negative effects on technical efficiency. In addition, CAR, CASH, and DER are positively associated with the cost efficiency, while CAR, CASH, and NETI are positively associated with profit efficiency.

References

Aigner, D., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production models. Journal of Econometrics 6, 21–37.

Ariff, M., Can,L., 2008. Cost and profit efficiency of Chinese banks: A non-parametric analysis. China Economic Review 19(2), 260–273.

Bailey, W., Huang, W., Yang, Z., 2011. Bank loans with Chinese characteristics: Some evidence on inside debt in a state-controlled banking system, Journal of Financial and Quantitative Analysis 46(6), 1795–1830.

Barros, C.P., Ferreira, C., and Williams, J., 2007. Analysing the determinants of performance of best and worst European banks: a mixed logit approach. Journal of Banking and Finance 31, 2189–2203.

Barros, C.P., Managi, S., Matousek, R., 2012. The technical efficiency of the Japanese banks: non-radial directional performance measurement with undesirable outputs. Omega 40, 1–8.

Battese, G.E., Rao, D.S.P., O'Donnell, C.J., 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. Journal of Productivity Analysis 21, 91–103.

Berger, A. N., Hasan, I., Zhou, M., 2010. The effects of focus versus diversification on bank performance: Evidence from Chinese banks, Journal of Banking and Finance 34, 1417–1435.

Berger, A. N., Hasan, I., Zhou, M., 2009. Bank ownership and efficiency in China: What will happen in the world largest nation?, Journal of Banking and Finance 33, 113–130.

Berger, A.A., Patti, E.B.D., 2006. Capital structure and firm performance: A new approach to testing agency theory and an application to the banking industry. Journal of Banking and Finance 30, 1065–1102.

García-Herrero, A. Gavilá, S. and Santabárbara, D. 2009. What explains the low profitability of Chinese banks? Journal of Banking and Finance 33 (11). 2080–2092.

Chambers, R.G., Chung,Y.,F., & Färe,R., 1996. Benefit and distance functions. .Journal of Economic Theory 70,407–419.

Dahmash, F., Durand, R., & Watson, J. (2009). The value relevance of reliability of reported goodwill and identifiable intangible assets. British Accounting Review 41, 120–137.

Dietsch, M., Lozano-Vivas, A., 2000. How the environment determines banking efficiency: a comparison between French and Spanish industries. Journal of Banking and Finance 24, 985–1004.

Färe R, Grosskopf S, Noh D-W, Weber W (2005) Characteristics of a polluting technology: theory

and practice. Journal of Econometrics, 126(2):469–492.

Färe, R., Grosskopf, S., Lovell, C.A.K., & Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Review of Economics and Statistics 71,90–98.

Fu, X., and Heffernan S., 2009. The effects of reform on China's bank structure and performance, Journal of Banking and Finance 33, 39–52.

Fukuyama, H., Weber, W.L., 2009. A directional slacks-based measure of technical efficiency. Socio-Economic Planning Sciences 43, 274–287.

Grigorian, D, V., & Manole, V. 2006. Determinants of Commercial Bank Performance in Transition: An Application of Data Envelopment Analysis, Comparative Economic Studies, Palgrave Macmillan, 48(3), 497–522.

Jiang, C., Yao, S., Zhang, Z., 2009. The effects of governance changes on bank efficiency in China: A stochastic distance function approach, China Economic Review 20, 717–731.

Kasman A., Yildirim, C., 2006. Cost and profit efficiencies in transition banking: the case of new EU members. Applied Economics 38,1079–1090.

Kumbhakar, S.C., Wang, D., 2007. Economic reforms, efficiency, and productivity in Chinese banking, Journal of Regulatory Economics 32, 105–129.

Kwan, S.H., 2003. The x-efficiency of commercial banks in Hong Kong. Journal of Banking and Finance, 30, 1127–1147.

Margaritis, D., Psillaki, M., 2007. Capital structure and firm efficiency. Journal of Business Finance and Accounting 34, 1447–1469.

Martin, M. (2012). China's banking system: Issues for congress. Congressional Research Service, 20.

O'Donnell, C.J., Prasada Rao, D.S., Battese, G.E., 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empirical Economics 34, 231–255.

Oliveira, L., Rodrigues, L.L., Craig, R., 2010. Intangible assets and value relevance: evidence from the Portuguese stock exchange. The British Accounting Review 42, 241–252.

Ozkan, A., 2001. Determinants of capital structure and adjustment to long run target: evidence from UK company panel data. Journal of Business Finance and Accounting 28, 175–198.

Schaeck, K., Martin, C., Simon, W., 2006. Are competitive banking systems more stable? Journal of Money, Credit and Banking 41(4), 711–734.

Simar, L. and Wilson. P.W. (2007). Estimation and inference in two-stage semi-parametric models of production processes. Journal of Econometrics, 136: 31–64.

Valverde, S.C., Humphrey, D.B., Paso, R.L.D., 2007. Do cross-country differences in bank efficiency support a policy of "national champions"? Journal of Banking and Finance 31, 2173–2188.

Wheelock, D. C., Wilson, P. W., 2000. Why do banks disappear? The determinants of U. S. bank failures and acquisitions, The Review of Economics and Statistics 82, 127–138.

Zhou, P., Ang, B.W., Wang, H., 2012. Energy and CO2 emission performance in electricity generation: a non-radial directional distance function approach. European Journal of Operational Research 221,625–635.

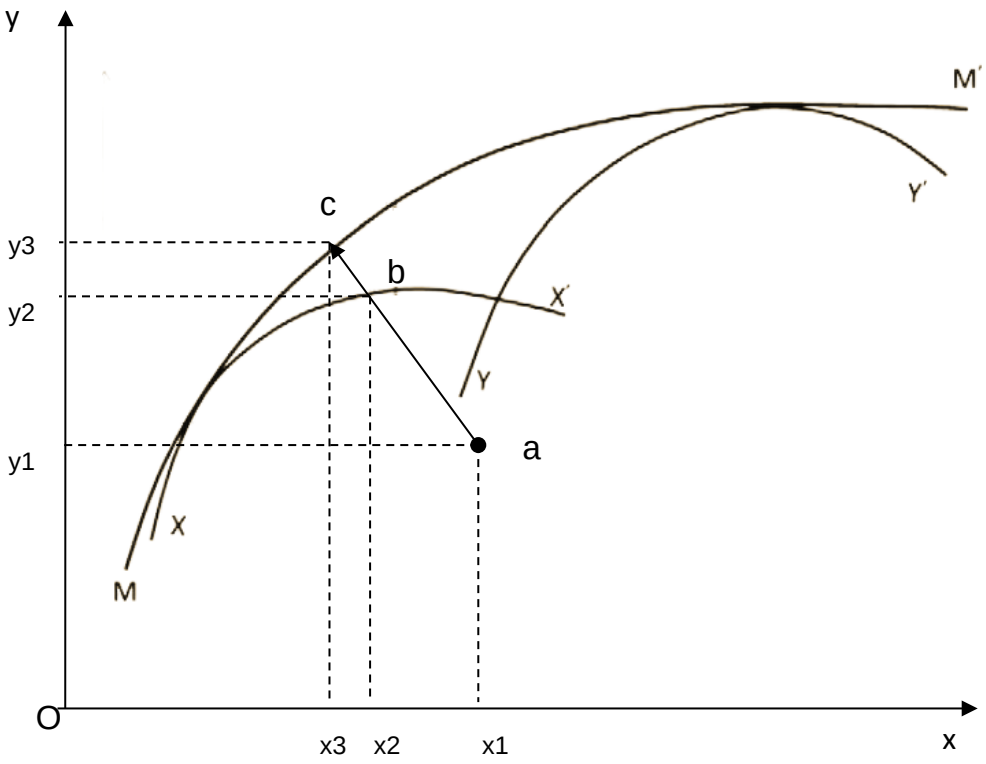

Fig. 1: A theoretical meta-frontier

Table 1 Model specification

	Model A	Model B	Model C
Inputs	Personnel expenses (PEX)	Personnel expenses divided by total assets (PLB)	Personnel expenses divided by total assets (PLB)
	Total deposits (DEP)	Interest expenses divided by total deposits (PDP)	Interest expenses divided by total deposits (PDP)
	Physical capital (FIX)	Operating expenses less labor expenses divided by fixed assets (PPC)	Operating expenses less labor expenses divided by fixed assets (PPC)
Outputs	Total loans (LOA)	Total loans normalized by equity (LOA)	Pre-tax profits (PRE) normalized by equity
	Non-interest income (NON)	Non-interest income normalized by equity (NON)	Non-performing loans to total loans ratio (NPL)
	Non-performing loans to total loans ratio (NPL)	Non-performing loans to total loans ratio (NPL)	

Table 2 Variable definitions and statistics

Variable	Definition	Mean	Min.	Max.
AST	Total assets (RMB bil.)	711.218	2.464	18917.752
EQC	Total equity (RMB bil.)	43.719	0.195	1278.463
TC	Total costs (RMB bil.)	22.899	0.043	577.786
P	Profits (RMB mil.)	10345.424	–57.386	338537.000
PEX	PERSONNEL EXPENSES (RMB mil.)	1598.142	0.009	47697.000
DEP	Total deposits (RMB bil.)	543.064	0.133	14620.825
FIX	Fixed assets (RMB bil.)	5.574	0.001	158.968
PLB	Personnel price (%)	2.779	0.001	22.232
PPC	Physical capital price (%)	300.816	0.809	3562.606
PDP	Deposit price(%)	2.607	0.188	28.800
LOA	Loans (RMB bil.)	360.886	0.015	9922.374
NII	Non-interest income (RMB mil.)	4078.043	–93.548	137628.000
CIT	Equals one if the bank is city commercial bank; zero otherwise	0.611	0	1
RUR	Equals one if the bank is rural commercial bank; zero otherwise	0.152	0	1
FOR	Equals one if the bank is foreign bank; zero otherwise	0.079	0	1
LST	Equals one if the bank is listed; zero otherwise	0.164	0	1
NAT	Equals one if the bank is national; zero otherwise	0.157	0	1
INT	Intangible assets (logarithm)	15.691	0.001	24.004
NPL	Non-performing loans/total loans	0.014	0.000	0.226
LDR	Loans/deposits	0.652	0.082	3.946
DER	Debt/equity	14.725	1.368	55.738
CASH	Cash and dues from banks/total assets	0.165	0.000	0.424
NETI	Net margin (net interest income/revenue) (%)	0.526	0.198	0.954
INV	Investments/total loans	0.016	0.000	0.708
CAR	Capital adequacy	0.143	0.012	0.667

Table 3 Kruskal–Wallis tests of efficiency differences

	Null hypothesis (Ho)	Chi-Square	p-value
Technical efficiency with respect to the meta-frontier			
MTE	MTE (group1=…group5)	276.39	0.000
MCE	MCE (group1=…group5)	14.17	0.007
MPE	MPE (group1=…group5)	16.04	0.003
Technical efficiency with respect to the group frontiers			
GTE	MTE (group1=…group5)	387.19	0.000
GCE	MCE (group1=…group5)	275.69	0.000
GPE	MPE (group1=…group5)	452.28	0.000

Table 4 Efficiencies by group

Segment	Model	Mean	SD	Min.	Max.
Technical efficiency with group frontiers					
Big-5	A	0.916	0.097	0.713	1.000
	B	0.918	0.111	0.628	1.000
	C	0.726	0.171	0.417	1.000
JSCB	A	0.938	0.073	0.518	1.000
	B	0.662	0.217	0.288	1.000
	C	0.560	0.201	0.100	1.000
CCB	A	0.634	0.216	0.189	1.000
	B	0.494	0.233	0.164	1.000
	C	0.328	0.221	0.093	1.000
RCB	A	0.849	0.128	0.536	1.000
	B	0.753	0.216	0.241	1.000
	C	0.459	0.283	0.021	1.000
FB	A	0.821	0.194	0.378	1.000
	B	0.697	0.271	0.122	1.000
	C	0.549	0.349	0.150	1.000
Meta-technology ratio					
Big-5	A	0.948	0.046	0.783	1.000
	B	0.480	0.120	0.345	1.000
	C	0.372	0.084	0.195	0.550
JSCB	A	0.889	0.133	0.352	1.000
	B	0.824	0.294	0.386	1.000
	C	0.446	0.134	0.288	1.000
CCB	A	0.700	0.128	0.460	1.000
	B	0.924	0.380	0.271	1.000
	C	0.955	0.077	0.327	1.000
RCB	A	0.434	0.137	0.201	0.760
	B	0.553	0.214	0.143	1.000
	C	0.564	0.118	0.319	1.000
FB	A	0.981	0.031	0.840	1.000
	B	0.753	0.424	0.166	1.000
	C	0.722	0.249	0.251	1.000
Technical efficiency with respect to the meta-frontier					
Big-5	A	0.868	0.106	0.700	1.000
	B	0.441	0.128	0.313	1.000
	C	0.264	0.074	0.156	0.550
JSCB	A	0.835	0.145	0.330	1.000
	B	0.535	0.215	0.183	1.000
	C	0.259	0.177	0.035	1.000
CCB	A	0.450	0.200	0.130	1.000
	B	0.456	0.235	0.054	1.000
	C	0.313	0.210	0.038	1.000
RCB	A	0.376	0.151	0.140	0.760
	B	0.412	0.189	0.104	1.000
	C	0.254	0.169	0.014	1.000
FB	A	0.805	0.194	0.370	1.000
	B	0.498	0.308	0.064	1.000
	C	0.411	0.319	0.041	1.000

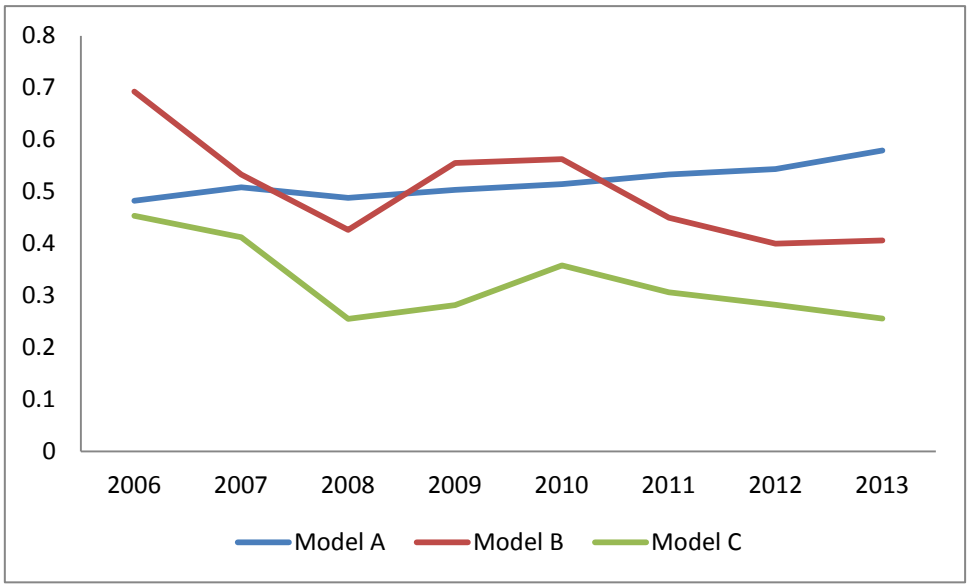

Fig. 2 Efficiency trends relative to the meta-frontier by model

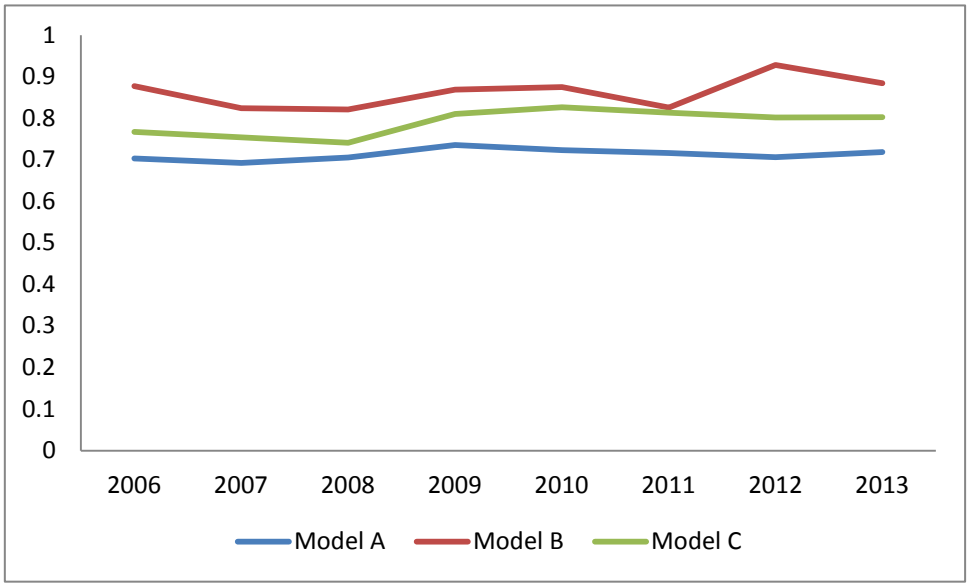

Fig. 3 Meta-technology ratios over time by model

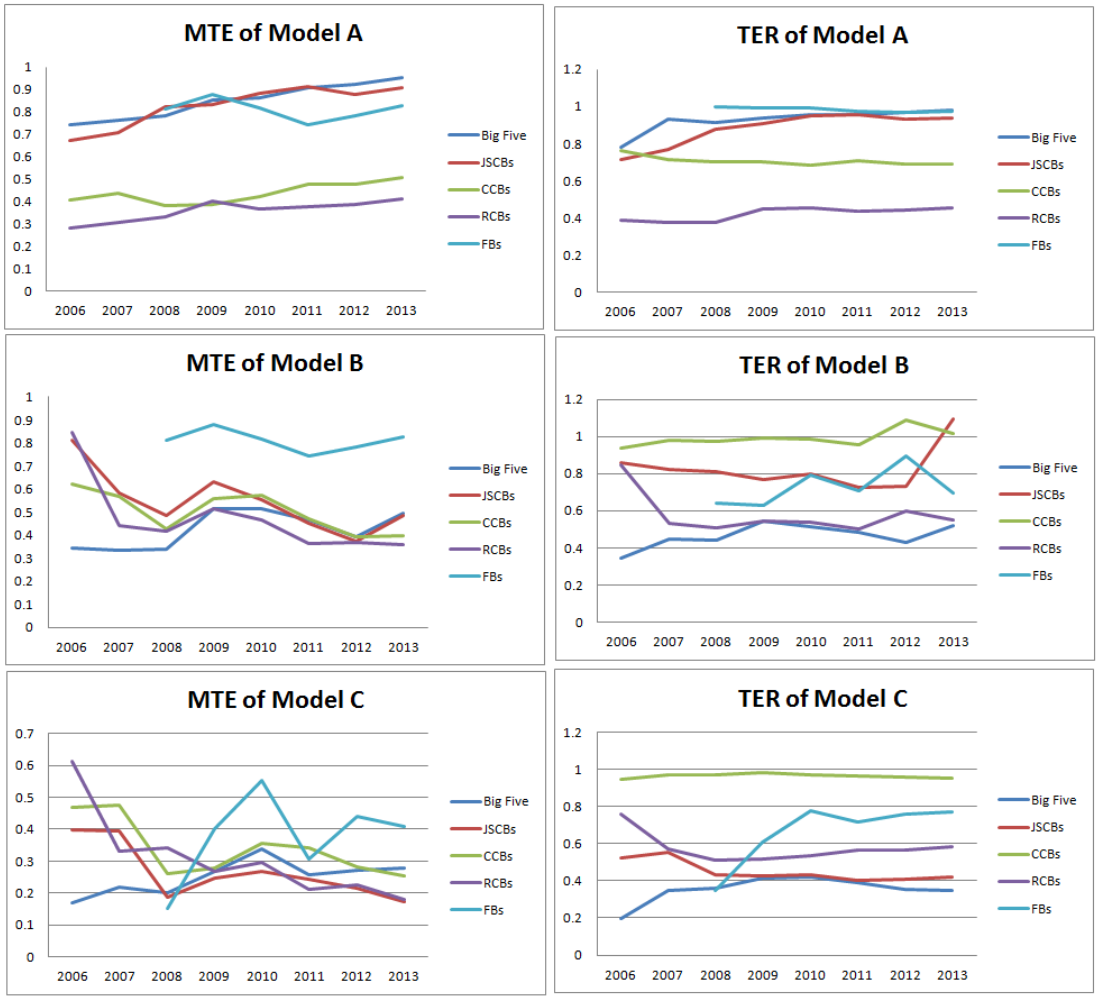

Fig. 4 Trends in efficiency and meta-technology ratios by model

Table 5 Correlations between controllable firm factors

	CASH	NETIN	INV	INT	DER	LDR	CAR
CASH	1						
NETIN	0.2614	1					
INV	–0.2025	–0.0281	1				
INT	0.0489	–0.0407	–0.1048	1			
DER	0.0123	–0.2041	–0.1703	0.0839	1		
LDR	–0.22	0.0938	–0.0687	–0.0151	–0.1748	1	
CAR	–0.1628	0.1066	0.5881	–0.1865	–0.5309	0.1329	1

Table 6 Firm-level efficiency determinants

Variables	Coefficient	Boot. SD	z-statistic	p-value
Dependent variable MTE				
CAR	0.928***	0.138	6.729	<0.001
CASH	–0.751***	0.228	–3.296	0.001
DER	0.013***	0.002	7.192	<0.001
INT	0.005***	0.002	2.722	0.007
LDR	0.914***	0.077	11.889	<0.001
NETI	–0.665***	0.098	–6.796	<0.001
Obs.	1,690			
Log-likelihood	160.705***			
Dependent variable MCE				
CAR	0.163*	0.084	1.940	0.052
CASH	0.586***	0.157	3.729	<0.001
DER	0.017***	0.001	12.998	<0.001
INT	0.001	0.001	–0.250	0.803
LDR	0.043	0.029	1.491	0.136
NETI	0.066	0.063	1.055	0.291
Obs.	1,690			
Log-likelihood	243.697***			
Dependent variable MPE				
CAR	0.247*	0.127	1.947	0.052
CASH	0.464**	0.230	2.024	0.043
DER	0.001	0.002	0.381	0.703
INT	–0.001	0.002	–0.610	0.542
LDR	–0.058	0.050	–1.156	0.248
NETI	0.269***	0.097	2.770	0.006
Obs.	1,690			
Log-likelihood	276.738***			