CONTEMPORARY ECONOMIC POLICY

WHAT CAUSES THE EFFICIENCY AND THE TECHNOLOGY GAP UNDER DIFFERENT OWNERSHIP STRUCTURES IN THE CHINESE BANKING INDUSTRY?

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This paper estimates and compares the cost efficiency of the Chinese banking industry among different ownership types for the period 2003–2014, using the stochastic metafrontier model. We find that foreign banks have the lowest cost frontier, while state-owned commercial banks undertake the least sophisticated technology. Moreover, the results of the upward trend in the technology gap ratio (TGR) and in metafrontier cost efficiency support that a more open financial market is able to enhance banking efficiency. As for the role of environmental conditions, off-balance sheet items, non-performing loans, and financial market structure significantly impact the TGRs of different bank types. (*JEL* C51, G21, D24)

I. INTRODUCTION

Many academic researchers have looked into the issue of whether deregulation, globalization, and various financial innovations—which are frequently accompanied by increasing competition, operating risk, and global risk—influence bank performance. How to correctly measure and compare bank efficiency is therefore pivotal and worth a more thorough investigation. Since 1979, China's financial authorities have adopted a sequence of major reforms to address the institutional, political, and organizational problems faced by the banking industry and to meet international banking standards. The reforms also attempt to deal with encroaching risk and competition (Dong et al. 2014a; Dong, Hamilton, and Tippett 2014b; Hou, Wang, and Li 2015; Jiang, Yao, and Feng 2013; Tang and Floros 2013). These structural reforms have pushed the banking sector toward commercialization, modernization, privatization, and universalization and allowed multiple categories of bank ownership structure to arise for operating in separate market segments.

According to the 2015 annual report of the China Banking Regulatory Commission (CBRC), Chinese banks are mainly classified into three policy banks (PBs), five state-owned commercial banks (SOCBs), 12 joint stock commercial banks (JSCBs), and 133 city commercial banks (CCBs). China's accession to the World Trade Organization (WTO) in 2001 accelerated the opening up process of its financial system (Hou, Wang, and Zhang 2014; Jiang, Yao, and

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ABBREVIATIONS

CBRC: China Banking Regulatory Commission
CCBs: City Commercial Banks
CE: Cost Efficiency
DEA: Data Envelopment Analysis
ETA: Equity to Total Assets Ratio
HHI: Herfindahl–Hirshmann Index
JSCBs: Joint Stock Commercial Banks
LP: Linear Programming
LR: Likelihood-Ratio
MCE: Metafrontier Cost Efficiency
ML: Maximum Likelihood
NPL: Non-Performing Loans
OBS: Off-Balance Sheet Items
PBs: Policy Banks
ROA: Return on Assets
SFA: Stochastic Frontier Approach
SMF: Stochastic Metafrontier
SOCBs: State-Owned Commercial Banks
TGR: Technology Gap Ratio
WTO: World Trade Organization

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Feng 2013). After a 5-year transitional period (2001–2006), its banking sector became fully exposed to foreign bank competition. By the end of 2015, 37 locally incorporated foreign banks from 15 countries and regions had set up 306 branches, and 153 banks from 46 countries and regions had established 174 representative offices in China (CBRC, 2015). Chinese banks are now facing keen competition not only from domestic markets, but also from abroad. Bank managers are realizing that it is better to adopt the best technologies in order to lower production costs and to gain excess profit. An important research question is whether the structural reforms and the increasing foreign participation in China's domestic banking market have helped promote bank efficiencies.

China's unique regulatory environment might cause a very distinct connection between market competition and bank efficiency, making it particularly suitable for comparing the efficiency scores among different ownership structures. On the one hand, the banks' productive performance and their ownership type are endogenously related due to self-selection.[1] Banks with different ownership structures may be confronted by various economic, financial, political, or geographical operation constraints (Huang and Fu 2013). For example, although SOCBs have been partially privatized, the ultimate voting control remains with the state, which exerts substantial influence over their lending practices (Dong et al. 2014a). The city commercial banks in China are the main providers of banking services within a particular administrative region. Compared to other types of banks, city commercial banks appear to adopt different production technologies, leading to heterogeneous cost structures, in order to be viable in markets with increasing competition. On the other hand, the differentials of innovation patterns between the ownership clusters may be based on determining productive performance. For example, the governance mechanism of foreign banks is capable of transforming innovation competencies and capabilities, including their well-developed banking system, management skill, advanced technology, and access to lower cost funds, into productive performance (Huang and Fu 2013; Fang, Hasan, and Marton 2011). This paper thus provides new insights of cost efficiency from the angle of the newly developed stochastic metafrontier (SMF) cost function, using data collected from Chinese banks spanning 2003–2014. These banks are categorized into four forms (groups): SOCBs, JSCBs, CCBs, and foreign banks.

By carrying out efficiency comparisons among banks, many previous studies rely on estimating either a common frontier or individual group frontiers. The former implicitly assumes that banks from different groups have access to the same technology, but this assumption tends to be strong and implausible. Although the estimation of individual group frontiers relaxes the assumption that all banks in different groups share the same technology, the so-derived efficiency scores are not comparable, due to the fact that those group frontiers represent distinct technologies. This motivates Battese, Rao, and O'Donnell (2004) to propose a mixed two-step approach to find the metafrontier production function that allows for efficiency comparisons among different groups.[2] Their two-step procedure combines the conventional stochastic frontier approach (SFA) in the first step, estimating the group-specific frontiers, with the mathematical programming technique in the second step, estimating the metafrontier production function. The two steps involve the use of two distinct approaches: econometric and nonparametric programming approaches. A potential limitation of the programming technique is that the parameter estimates lack statistical properties, as linear (or quadratic) programming is in essence deterministic, such that its estimates are typically confounded with random shocks.

To fill this gap in the literature, the current paper employs the newly developed approach by Huang, Huang, and Liu (2014) to estimate and compare the metafrontier cost efficiencies of Chinese banks for different forms of ownership structures.[3] The major difference between the stochastic metafrontier approach and the mixed

1. This mechanism has been introduced in an integrated framework of R&D investments, productive performance, and exporting orientation (Aw, Roberts, and Xu 2011; Cassiman, Golovko, and Martínez-Ros 2010; Gkypali and Tsekouras 2015; Máñez, Rochina-Barrachina, and Sanchis-Llopis 2015). Following this vein, banks' productive performance and their ownership structure are endogenously related, and therefore the sample banks are classified by ownership regimes.

2. Their approach has been widely applied by, for example, O'Donnell, Rao, and Battese (2008), Bos and Schmiedel (2007), Chen (2012), Chen and Yang (2011), Huang, Chiang, and Chen (2011b), Huang and Fu (2013), Jiang and Sharp (2015), and Lee and Huang (2016), to mention a few.

3. Recently, the new metafrontier model, developed by Huang, Huang, and Liu (2014), has been used by, for example, Chang, Huang, and Kuo (2015), Huang, Chiang, and Tsai (2015), and Lee and Huang (2017).

two-step approach lies in the second step, where the new approach suggests using SFA, rather than linear or quadratic programming techniques, to estimate the metafrontier. In this manner, both the parameter estimates and their standard errors can be estimated, which allows for conducting statistical inferences. In addition, the technology gap ratio (TGR) can be further specified as a set of environmental variables to describe the effects of the exogenous variables, which are faced by banks of different ownership types, on TGRs. Under the above framework, this paper is capable of comparing the efficiency scores among Chinese banks of different groups against the unique benchmark, that is, the metafrontier cost function.

In summary, the present study makes a number of contributions to the literature. First, it compares the performance in the banking industry among different ownership structures, enriching the literature from the perspective of transitional economies. Second, our data cover the period 2003–2014, which includes the last round of China's banking reform aimed at increasing the competitiveness of financial institutions after entering the WTO. Third and finally, with regards to the econometric modeling framework, the stochastic metafrontier approach is capable of assessing the source of managerial abilities and the choice of production technologies through the specification of bank-specific and ownership-specific environmental variables.

The rest of the paper is organized as follows. Section II briefly reviews the previous literature specific to the measurement of banks' efficiency in China's banking industry. Section III formulates the stochastic metafrontier cost function and outlines its estimation procedure. Section IV describes the data source and variable definitions. Section V performs an empirical study. The last section concludes the paper.

II. LITERATURE REVIEW

Previous studies on efficiency measurement have mainly concentrated on financial sectors in the United States and Western European countries, for example, Maudos et al. (2002), Jonas and King (2008), Weill (2009), and Degl'Innocenti et al. (2017). The performance of banks in emerging economies has drawn relatively less attention by academic researchers (Chang et al. 2012; Dong, Girardone, and Kuo 2017; Zhang et al. 2013). Far too little focus has been paid to the efficiency of financial institutions in Asian transition economies. In the case of China, its banking industry faces quite a different regulatory environment from those of other transitional or emerging economies. This exceptional regulatory environment is expected to cause very distinct managerial strategies used by bank managers of different ownership types, making its banking sector particularly suitable for characterizing and comparing efficiency among different ownership structures.

Research works on the relationship between bank ownership and efficiency in China are rare. Those limited numbers of studies generally focus on three types of banks: SOCBs, JSCBs, and CCBs. Yao et al. (2007) compile panel data of 22 Chinese commercial banks and estimate the measure of efficiency covering 1995–2001, finding that state-owned banks are less efficient than their private counterparts. Berger, Hasan, and Zhou (2009) claim that the extant literature ignores the factor of a changing production environment, such as the number of state-owned banks decreasing in China, while the number of foreign banks are increasing. After analyzing the efficiency of Chinese banks over 1994–2003, they conclude that state-owned banks, particularly the Big Four, are by far the least efficient, while foreign banks are the most efficient. Jiang, Yao, and Feng (2013) examine the static effect of ownership and the dynamic effect of privatization on Chinese bank performance in the period 1995–2010. Evidence shows that private intermediaries, such as JSCBs and CCBs, significantly outperform SOCBs.

Chen, Skuly, and Brown (2005) utilize the method of data envelopment analysis (DEA) to compute the cost, technical, and allocative efficiencies of 43 Chinese banks for the period 1993–2000 and uncover that large state-owned banks and small joint-equity banks are more efficient than medium-sized joint-equity banks. Fu and Hefferman (2009) use SFA to assess the cost efficiency of China's banking sector over the period 1985–2002 and find that JSCBs perform better than SOCBs. Yin, Yang, and Mehran (2013) also employ SFA to investigate the technical efficiency of Chinese banks over 1999–2010 and conclude that banks with majority state ownership (Top Five) and foreign-funded banks are less efficient than joint-stock banks and regional banks. Huang, Lin, and Chen (2017) generalize network DEA to copula-based network SFA, which allows firms to produce outputs through multistage processes. Their empirical exercise uses data from China's banking industry over the period 2002–2015 and divides the entire production process into two stages. Evidence is found that JSCBs have higher technical efficiency in both production stages compared to the other types of banks.

All of the aforementioned works that involve cross-group comparisons of efficiency count on either estimating a common frontier or individual group frontiers. As mentioned previously, the common frontier approach implicitly assumes that all forms of banks studied undertake homogeneous technology, which is inconsistent with reality and possibly leads to biased parameter estimates and efficiency scores. Consequently, the derived empirical outcomes provide little guidance to bank managers on whether or not to take steps to improve their managerial abilities. The individual frontiers approach suffers from the problem of incomparability arising from heterogeneous benchmarks for banks from different groups. The current paper attempts to solve the foregoing difficulties under the framework of the stochastic metafrontier cost function, instead of the stochastic metafrontier production function of Huang, Huang, and Liu (2014). The estimation of a cost frontier is likely to be preferable to a production frontier, since the cost frontier can take into account the cases of multiple outputs and quasi-fixed inputs. More importantly, the cost frontier has the underlying assumption of cost minimization that appears to be an appropriate objective pursued by China's banking industry, because it is getting more and more competitive, although highly regulated, and it has demand-driven financial outputs.

Kounetas, Mourtos, and Tsekouras (2009) and Kontolaimou et al. (2012) further apply non-parametric data envelopment analysis and propose an analytical framework that decomposes the efficiency difference into input- and output-invariant components. The proposed decomposition allows the comparison of two firms not only with respect to overall technical efficiency, but also in terms of input and output sizes. Analogously, Atkinson and Cornwell (1993, 1994a, 1994b) also propose an analytical approach that models technical efficiency using both output- and input-orientated measures, whereas the standard error-components (stochastic frontier) method merely models non-cost minimizing behavior with a function of input-specific disturbances that come from the input demand or share equations. However, the form of inefficiency in the input-oriented model is less clear. Therefore, the present study chooses the cost function to describe the underlying technology in an input-oriented fashion.

III. METHODOLOGY

A. *Stochastic Metafrontier Cost Function and Technology Gaps*

The underlying metafrontier cost function for all groups in the t^{th} period is defined as $f_t^M\left(X_{jit}\right)$, $j=1, \ldots, J$, which envelops all group-specific cost frontiers. Since group j's cost frontier must be larger than or equal to $f_t^M\left(X_{jit}\right)$ by definition, their relationship is expressed as:

$$(1) \qquad f_t^j\left(X_{jit}\right) = f_t^M\left(X_{jit}\right) e^{U_{jit}^M}, \qquad \forall j, i, t.$$

Here, $U_{jit}^M \geq 0$. The ratio of the metafrontier to group j's frontier is defined as the technology gap ratio (TGR):

$$(2) \qquad \mathrm{TGR}_{it}^j = \frac{f_t^M\left(X_{jit}\right)}{f_t^j\left(X_{jit}\right)} = e^{-U_{jit}^M} \leq 1.$$

Measure TGR evaluates the deviation of the potential cost defined by the metafrontier cost function from the group-specific cost frontier. This measure reflects how advanced is the production technology adopted by the group, which may depend on economic and non-economic factors. Thus, it is allowed to vary across firms and groups and over time. The larger the TGR value is, the more advanced technology the group undertakes, and so the group cost frontier is closer to the meta-cost frontier.

For a given output level Y_{jit}, the difference between a bank's actual cost C_{jit} and the metafrontier $f_t^M\left(X_{jit}\right)$ can be decomposed into three components:

$$(3) \qquad f_t^M\left(X_{jit}\right) / C_{jit} = \mathrm{TGR}_{it}^j \times \mathrm{CE}_{it}^j \times e^{-v_{jit}}.$$

It is noteworthy that although both the technology gap ratio TGR_{it}^j and the firm's cost efficiency CE_{it}^j are bounded between zero and one, the metafrontier $f_t^M\left(X_{jit}\right)$ does not necessarily envelop all banks' observed cost C_{jit}. The unrestricted ratio in Equation (3) distinguishes the metafrontier modeling by using the stochastic cost frontier analysis from DEA. After accounting for the random noise component, the decomposition can be expressed alternatively as:

$$(4) \qquad \mathrm{MCE}_{jit} = \frac{f_t^M\left(X_{jit}\right) e^{v_{jit}^M}}{C_{jit}} = \mathrm{TGR}_{it}^j \times \mathrm{CE}_{it}^j.$$

Here, MCE_{jit} is defined as the bank's cost efficiency with respect to the meta-cost frontier. Equation (4) states that MCE can be decomposed into TGR and CE.

B. Estimation Procedure

The two-step mixed procedure suggests using SFA to estimate the group-specific stochastic frontier by maximum likelihood (ML) in the first step. To estimate the metafrontier function of Equation (1) in the second step, Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) suggest the use of mathematical programming techniques that are deterministic and susceptible to the effects of random shocks. This present research extends the stochastic metafrontier production function of Huang, Huang, and Liu (2014) to the stochastic metafrontier cost function, which has to be estimated by ML, rather than programming techniques. This new modeling permits one to associate TGR with a set of environmental variables, since TGR is treated as if the inefficiency term is like U_{jit}, while programming techniques fail to do so.

Given the estimated group-specific frontiers $\hat{f}_t^j\left(X_{jit}\right)$ for all $j=1, \ldots, J$ groups from the first step, the estimation error (V_{jit}^M) of the group-specific frontier is then:

$$\ln\hat{f}_t^j\left(X_{jit}\right) - \ln f_t^j\left(X_{jit}\right) = V_{jit}^M. \tag{5}$$

Substituting the unobserved group-specific frontiers $f_t^j\left(X_{jit}\right) = \ln\hat{f}_t^j\left(X_{jit}\right) - V_{jit}^M$ into the left-hand side of Equation (1), we obtain:

$$\ln\hat{f}_t^j\left(X_{jit}\right) = \ln f_t^M\left(X_{jit}\right) + U_{jit}^M + V_{jit}^M, \quad \forall\ i, t, j = 1, 2, .., J. \tag{6}$$

Equation (6) looks like the conventional stochastic frontier regression and is therefore called the SMF regression. It has to be estimated by ML.

Following Battese and Coelli (1995), U_{jit}^M can be further related to a set of environmental variables. Note that the variance of V_{jit}^M is not constant, because it contains the residual. This problem of heteroskedasticity will result in an inconsistent estimated covariance matrix of the parameter estimates in Equation (6). Thus, the log-likelihood function is referred to as the log quasi-likelihood function. The quasi-maximum likelihood parameter estimates are consistent, but their corresponding standard errors are not and can be corrected by the "sandwich" estimator (see White 1982; Johnston and DiNardo 1997; Huang, Huang, and Liu 2014 for details).

The above two-step stochastic frontier approach ensures that the metafrontier cost function lies underneath group-specific cost frontiers. TGR can be calculated by the following conditional expectation:

$$TGR_{it}^j = E\left(e^{-U_{jit}^M}\,\middle|\,V_{jit}^M + U_{jit}^M\right) \le 1. \tag{7}$$

Note that TGR (U_{jit}^M) is a function of environmental variables to be described shortly.

C. Econometric Model

Let $W=(W_1, \ldots, W_N)'$ be an N-vector of input prices and $Y=(Y_1, \ldots, Y_M)'$ be an M-vector of output quantities. Both group-specific cost frontier and metafrontier cost function are specified in the standard translog form, along with a time trend, to capture potential technical progress—namely:

$$\begin{aligned}\ln f_t^j\left(X_{it}\right) &= a_0 + \sum_{m=1}^{M} a_m \ln\left(Y_{mit}\right) + \sum_{n=2}^{N} \beta_n \ln\left(W_{nit}\right) + \varphi_1 T \\ &+ \frac{1}{2}\left[\sum_{m=1}^{M}\sum_{k=1}^{M} \delta_{mk} \ln Y_{mit} \ln Y_{kit} + \sum_{n=1}^{N}\sum_{h=1}^{N} \gamma_{nh} \ln W_{nit} \ln W_{hit} + \varphi_{11} T^2\right] \\ &+ \sum_{m=1}^{M}\sum_{n=1}^{N} \rho_{mn} \ln Y_{mit} \ln W_{nit} \\ &+ \sum_{m=1}^{M} \psi_m \ln Y_{mit} T + \sum_{n=1}^{N} \theta_n \ln W_{nit} T + \varepsilon.\end{aligned} \tag{8}$$

Here, X_{jit} contains the time trend (T), all logged values of Y and W, and their squared and cross-product terms. Notations α, β, φ, δ, γ, ρ, ψ, and θ are unknown technology parameters to be estimated.

The composed error of $\varepsilon = v + U$ consists of a two-sided error term of $v \sim N\left(0, \sigma_v^2\right)$ and a one-sided error $U \ge 0$ that reflects a bank's cost inefficiency. Following Battese and Coelli (1995), we associate this inefficiency term with an array of environmental variables, that is,

$$U_{it} = \tau'\Omega_{it} + u_{it} \ge 0, \tag{9}$$

TABLE 1
Summary of Variable Definitions and Data Sources

Variable	Definition	Source
Input and output		
Total loans (y_1)	Short-term and long-term loans	Bankscope
Other earning assets (y_2)	Other earning assets, including government bonds, corporate securities, and other investments	Bankscope
Non-interest revenue (y_3)	Fee and commission income and other income	Bankscope
Labor (x_1)	Total assets (net of fixed assets)	Bankscope
Physical capital (x_2)	Total fixed assets	Bankscope
Borrowed funds (x_3)	Deposits and borrowed money	Bankscope
Price of labor (w_1)	Total personnel expenses/total assets	Bankscope
Price of physical capital (w_2)	Other operating expenses/total fixed assets	Bankscope
Price of borrowed funds (w_3)	Total interest expenses/total funding	Bankscope
Micro-environmental variables		
Equity to asset ratio	Ratio of a bank's equity capital to total assets	Bankscope
Average return on assets	Average ROA of all banks per annum	Bankscope
Macro-environmental variables		
Off-balance sheet items	Off-balance sheet items	Bankscope
Non-performing loan	Loan loss reserves	Bankscope
HHI	Herfindahl–Hirshmann index	Bankscope

where Ω_{it} denotes a collection of environmental variables, τ is the corresponding coefficient, and $u_{it} \sim N\left(0, \sigma_u^2\right)$. Equation (9) implies that u_{it} is a truncated normal random variable, since $-\tau'\Omega_{it} \leq u_{it} \leq \infty$. It is noteworthy that we shall use different sets of environmental variables for the group-specific and metafrontier cost functions in the two steps.

IV. DATA DESCRIPTION

A. Variable Definitions

We compile all input and output variables for Chinese banks from the accounting statements provided by the BankScope database. The sample contains a total of 114 Chinese commercial banks, including SOCBs, JSCBs, CCBs, and foreign banks, spanning 2003 to 2014. The data are scrutinized carefully in order to avoid potential inconsistency, missing values, and outliers. We have removed several banks reporting extreme values in the variables of main interest. The final unbalanced panel data have 536 bank-year observations. The aggregated book values of their total assets account for more than 85% of the respective industry-wide values in 2014. Hence, the given sample is well representative of China's overall banking industry.

We define input and output variables based upon the intermediation approach that has been widely applied by numerous researchers to assess bank efficiency. The three inputs are labor (x_1), physical capital (x_2), and borrowed funds (x_3), which are employed to manufacture three outputs: total loans (y_1), other earning assets (y_2), and non-interest revenue (y_3). The price of labor (w_1) is calculated as the ratio of personnel expenses to total assets net of fixed assets.[4] The price of physical capital (w_2) is measured by the ratio of other operating expenses to fixed assets. The price of borrowed funds (w_3) is defined as the ratio of total interest expenses to all deposits and borrowed money.[5] Total costs equal the sum of the above three expenses. All of the inputs and outputs are expressed in thousands of real U.S. dollars deflated by the consumer price index with base year 2000. Table 1 presents the definitions of all variables used.

Table 2 summarizes the descriptive statistics for all variables and the distribution of banks across different groups of ownership structures. These statistics show that input quantities and

4. Since there are quite a few missing values on the number of employees, the item of total assets net of fixed assets is used as a proxy for the number of employees. This choice is also done by Altunbaş et al. (2000), Altunbaş, Evans, and Molyneux (2001), Weill (2004), and Fries and Taci (2005).

5. In the framework of cost frontier, it is essential to fulfill the assumption of the cost function that firms face exogenous input prices in competitive factor markets. In the case of China, although the assumption of perfectly competitive market may be doubtful in the past, we must argue that our setting is unlikely to be subject to the endogeneity problem, because China's financial market is highly regulated. Thus, the input prices may still be exogenously determined by the government. In addition, our selection is not isolated, as Berger, Hasan, and Zhou (2009), Liu et al. (2012), Hou, Wang, and Li (2015), and Huang, Lin, and Chen (2017) also use these input prices.

TABLE 2
Summary Statistics for Different Groups of Ownership Structures

	SOCBs	JSCBs	CCBs	Foreign Banks
Number of banks	5	12	66	31
Number of observations	56	88	253	139
Outputs				
Loans	657,076,803	115,936,487	11,015,655	4,911,024
	(436,732,664)	(98,731,546)	(15,195,044)	(5,381,752)
Investments	445,141,931	90,882,438	11,657,994	4,139,472
	(242,581,552)	(79,136,124)	(15,615,665)	(4,954,668)
Non-interest revenue	7,865,726	1,320,868	93,710	75,398
	(6,834,041)	(1,705,127)	(131,656)	(96,427)
Inputs				
Labor (total assets net of fixed assets)	1,286,996,751	236,043,164	26,857,841	10,580,372
	(842,595,950)	(203,661,713)	(35,194,141)	(11,888,654)
Physical capital	13,474,023	1,230,577	189,135	41,141
	(7,617,358)	(1,053,137)	(213,504)	(105,437)
Borrowed funds	1,163,681,670	214,488,995	24,348,620	8,983,067
	(737,766,942)	(182,436,966)	(31,954,069)	(10,137,947)
Input prices				
Price of labor	0.0054	0.0051	0.0051	0.0076
	(0.0010)	(0.0012)	(0.0020)	(0.0031)
Price of physical capital	0.4443	0.9466	0.8353	5.0038
	(0.0746)	(0.4568)	(0.6892)	(6.4501)
Price of funds	0.0171	0.0239	0.0238	0.0208
	(0.0038)	(0.0083)	(0.0082)	(0.0098)
Total cost	33,918,930	7,616,230	860,264	323,808
	(22,938,584)	(7,014,846)	(1,133,147)	(366,680)
Micro-environmental variables				
Equity to total assets ratio (%)	5.0802	5.1648	7.1311	16.6584
	(4.2513)	(1.3661)	(3.5084)	(13.6229)
Average return on assets (%)	0.9401	0.9807	1.0240	1.0056
	(0.1363)	(0.1196)	(0.0862)	(0.1034)
Macro-environmental variables				
Off-balance sheet items	200,605,947	65,440,270	4,727,827	2,320,751
	(126,214,611)	(64,425,342)	(5,865,818)	(3,601,572)
Non-performing loan	23,122,178	2,670,235	286,444	54,927
	(20,147,846)	(2,341,739)	(416,647)	(62,125)
Herfindahl−Hirshmann index	1,617	1,379	1,125	1,198
	(620)	(481)	(251)	(314)

Notes: All inputs and outputs are expressed in thousands of real U.S. dollars with base year 2000. Standard deviations are in parentheses.

prices and output levels fluctuate substantially among different forms of ownership, implying that banks with different ownership structures might operate under dissimilar production technologies, thus hindering any direct comparison of their performance among different ownership structures. This justifies the use of the stochastic metafrontier model that enables the calculation of comparable technical efficiencies for firms running under heterogeneous technologies.

B. Environmental Variables

The empirical analysis is executed by a two-step procedure, where the effects of environmental factors on cost efficiency and technology gaps can be considered. We divide the environmental variables into bank-specific and ownership-specific variables to highlight the different atmospheres encountered by the sample banks. The former types of variables are used in the first-step estimation of the group frontiers in Equation (1), which influences managerial abilities, while the latter types of variables are utilized in the second-step estimation of the metafrontier in Equation (6), which characterizes the environment affecting the choice of production technologies. Following Allen and Rai (1996), Dietsch and Lozano-Vivas (2000), Lozano-Vivas, Pastor, and Hasan (2001), Lozano-Vivas, Pastor, and Pastor (2002), Huang et al. (2011a), Huang, Huang, and Liu (2014), Huang, Chiang, and Tsai (2015), and Lee and Huang (2016, 2017), we identify two bank-specific environmental variables: equity to total assets ratio (ETA) and average return on assets (ROA). We also compile three ownership-specific environmental variables that may be correlated with TGR: off-balance sheet items (OBS), non-performing loans (NPL), and the Herfindahl–Hirshmann index (HHI).

The variable ETA serves as a proxy for banks' risk-taking behaviors. A bank with a lower equity level implies that its managers tend to have a higher risk-taking attitude and are willing to conduct greater leverage (Lee and Huang 2017). Conversely, a risk-averse manager tends to trade off earnings for reducing insolvency risk (Moon and Hughes 1997). It is often claimed that a well-capitalized bank is more efficient (Mester 1993; Berger and Mester 1997; Lozano-Vivas, Pastor, and Pastor 2002; Huang et al. 2011a; Lee and Huang 2016, 2017). Hence, the relationship between ETA and inefficiency is expected to be negative. The variable ROA represents a bank's profitability, which is intimately affected by the industry's competitive condition. To avoid possible endogeneity, the average return on assets in each year is calculated and used in the second step. It is often recognized in the literature that the higher the profitability ratio is, the more efficient the bank will be (Berger 1993; Allen and Rai 1996; Huang et al. 2011a; Lozano-Vivas, Pastor, and Pastor 2002; Lee and Huang 2016, 2017), implying that the average ROA is negatively associated with inefficiency.

From the managerial perspective, it is also important to know what really matters for the technology gap under different ownership. In this regard, one salient feature of our method is that the technology gap ratio can be linked with ownership-specific environmental variables. Off-balance sheet (OBS) items, usually accompanied by relatively high risks, refer to credits, loan commitments, securitization, and derivatives, which are not reported on the balance sheet. There is a growing trend that banking services have shifted from traditional on-balance sheet activities to non-traditional off-balance sheet activities (Goddard, Molyneux, and Wilson 2001; Hou, Wang, and Li 2015; Lozano-Vivas and Pasiouras 2010). Banks with a higher level of off-balance sheet business usually operate under advanced technology, leading OBS to be negatively related to TGRs. The variable NPL is used as an indicator of loan quality. Banks with a lower amount of non-performing loans usually set up a sound process on the decision of loan granting and hence function under a sophisticated technology, indicating that NPLs are negatively correlated with TGRs. The variable HHI acts as a proxy for market competition and is defined as the sum of squared market shares (multiplied by 100) over all banks under consideration in terms of total assets. It ranges from 0 to 10,000. According to the quiet life hypothesis, banks running in a highly concentrated market are apt to be inefficient, due to the lack of competition (Hicks 1935). However, a higher value of HHI corresponds to a market consisting of fewer firms that are likely to build larger-scale production with more advanced technologies to seize the market. The higher the HHI value is, the more advanced technology the bank undertakes, and so its group frontier is inclined to be closer to the metafrontier. Thus, the effect of HHI on TGR is ambiguous, depending on which of the above two forces dominates.

V. EMPIRICAL RESULTS

A. *Parameter Estimates*

We exploit software FRONTIER 4.1 to estimate cost frontiers for each group and the metafrontier cost function. Tables 3 and 4 present the parameter estimates for each ownership type, that is, SOCBs, JSCBs, CCBs, and foreign banks. More than one half of the parameter estimates in each group frontier reach statistical significance at least at the 10% level. Coefficient estimates of the chosen environmental variables are shown at the bottom panel. As expected, ETA is negatively associated with cost inefficiency for all sample groups, implying that the higher ETA is, the more efficient the bank will be. This result is consistent with many previous works, for example, Mester (1993), Berger and Mester (1997), Lozano-Vivas, Pastor, and Pastor (2002), Huang et al. (2011a), Lee and Huang (2016, 2017), and verifies that well-capitalized banks tend to be more efficient than undercapitalized ones. With some exceptions, the coefficient of ROA is found to be significantly negative, showing that high cost efficiency is associated with high profitability in these ownership groups. This outcome is also congruent with, for example, Berger (1993), Allen and Rai (1996), Huang et al. (2011a), Lozano-Vivas, Pastor, and Pastor (2002), and Lee and Huang (2016, 2017).

Before estimating the metafrontier, it is important to test the null hypothesis (H_0) that the sample banks from different ownership structures adopt the same technology. If the hypothesis is not rejected by the data, then all banks of different groups share the same technology, implying that the estimation of the metafrontier is not

TABLE 3
Parameter Estimates for Different Ownership Structures

Independent Variables	SOCBs		JSCBs	
	Coefficient	S.E.	Coefficient	S.E.
Constant	57.576***	0.998	4.481	5.687
$\ln y1$	−1.112	0.757	−0.651	0.930
$\ln y2$	−2.916***	0.758	0.943	0.674
$\ln y3$	−1.022	0.841	1.224**	0.553
$\ln w2$	−0.607**	0.242	−1.136	0.835
$\ln w3$	−3.125***	0.376	−0.325	0.782
$\ln y1 \times \ln y1$	0.380**	0.160	0.392***	0.117
$\ln y2 \times \ln y2$	0.506***	0.109	0.274**	0.128
$\ln y3 \times \ln y3$	0.200**	0.083	−0.041	0.041
$\ln y1 \times \ln y2$	−0.257**	0.122	−0.359***	0.103
$\ln y1 \times \ln y3$	0.034	0.086	−0.040	0.056
$\ln y2 \times \ln y3$	−0.140	0.094	0.061	0.049
$\ln w2 \times \ln w2$	0.539***	0.160	−0.072	0.084
$\ln w3 \times \ln w3$	1.131***	0.260	0.392***	0.070
$\ln w2 \times \ln w3$	−0.023	0.143	−0.066	0.069
$\ln y1 \times \ln w2$	−0.205	0.178	0.212***	0.071
$\ln y1 \times \ln w3$	−0.133	0.152	0.139**	0.064
$\ln y2 \times \ln w2$	0.109	0.118	0.016	0.067
$\ln y2 \times \ln w3$	0.121	0.129	−0.032	0.060
$\ln y3 \times \ln w2$	0.020	0.115	−0.206***	0.042
$\ln y3 \times \ln w3$	0.231*	0.120	−0.067**	0.031
$t \times \ln y1$	−0.028	0.017	−0.024*	0.014
$t \times \ln y2$	−0.028	0.026	0.017	0.014
$t \times \ln y3$	−0.030	0.021	0.016**	0.007
$t \times \ln w2$	0.004	0.024	0.034**	0.015
$t \times \ln w3$	−0.119***	0.024	−0.036***	0.012
t	1.466***	0.180	−0.189	0.174
t^2	0.030***	0.005	−4.30E-04	0.004
Constant	−0.187***	0.010	0.806**	0.369
ETA	−0.008***	0.002	−0.111***	0.009
ROA	0.249***	0.008	−0.690*	0.370
$\sigma_u^2 + \sigma_v^2$	0.001***	9.62E-05	0.014***	2.30E-04
$\sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$	0.927***	0.169	0.956***	0.012
Log-likelihood	130.538		168.347	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

necessary. Referring to the operation in Battese, Rao, and O'Donnell (2004), a likelihood-ratio (LR) test is carried out here. The LR tests are widely used with maximum likelihood techniques (Chen, Huang, and Yang 2009; Huang, Chen, and Yang 2010; Lee and Huang 2016, 2017; Liu et al. 2012). With an LR test, we estimate a restricted model and unrestricted model and use a chi-square statistic to test whether the differences between the two are statistically significant. The LR statistic is defined by $\lambda = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} \sim x^2(m)$. The value of the log-likelihood function for the stochastic cost frontier derived by pooling the data for all sample groups ($L(H_0)$), which assumes that those banks from different groups undertake the same technology, is equal to 500.12, shown at the bottom line of the first column in Table 5. The sum of the values of the log-likelihood functions for the four cost frontiers ($L(H_1)$) is equal to 745.27, which assumes that the sample banks from different groups adopt heterogeneous technology. The degrees of freedom for the chi-square distribution involved equal 99, which is the difference between the number of parameters estimated under H_1 and H_0, respectively. Since the LR test statistic of 490.31 exceeds the corresponding critical value even at the 1% level, the hypothesis is decisively rejected. We claim that the sample banks from different groups are indeed operating under different technologies, which justifies the estimation of the metafrontier.

Columns 3 to 4 and 5 to 6 of Table 5 summarize the second-step estimates from the linear programming (LP) technique and the stochastic metafrontier technique, respectively.[6] Although

6. We do not show the estimation results from the quadratic programming technique, due to the fact that the results are quite similar to those from the LP model.

TABLE 4
Parameter Estimates for Different Ownership Structures

Independent Variables	CCBs		Foreign Banks	
	Coefficient	S.E.	Coefficient	S.E.
Constant	4.349***	1.022	1.987*	1.081
ln$y$1	0.227	0.195	0.192	0.194
ln$y$2	0.080	0.181	0.634***	0.242
ln$y$3	0.285**	0.122	0.231	0.147
ln$w$2	0.239	0.165	−0.417**	0.193
ln$w$3	0.858***	0.196	0.321*	0.168
$\ln y1 \times \ln y1$	0.261***	0.031	0.258***	0.025
$\ln y2 \times \ln y2$	0.223***	0.025	0.250***	0.063
$\ln y3 \times \ln y3$	0.007	0.006	−0.010	0.017
$\ln y1 \times \ln y2$	−0.206***	0.022	−0.243***	0.036
$\ln y1 \times \ln y3$	−0.027**	0.012	−0.018	0.017
$\ln y2 \times \ln y3$	−0.004	0.009	0.013	0.029
$\ln w2 \times \ln w2$	−0.028*	0.016	0.026	0.018
$\ln w3 \times \ln w3$	0.206***	0.027	0.241***	0.028
$\ln w2 \times \ln w3$	0.013	0.020	−0.030	0.018
$\ln y1 \times \ln w2$	−0.038***	0.015	0.033	0.023
$\ln y1 \times \ln w3$	−0.001	0.019	−0.013	0.021
$\ln y2 \times \ln w2$	0.027*	0.014	−0.026	0.028
$\ln y2 \times \ln w3$	−0.041**	0.020	0.058**	0.027
$\ln y3 \times \ln w2$	0.004	0.007	−0.002	0.012
$\ln y3 \times \ln w3$	0.014	0.012	−0.044**	0.018
$t \times \ln y1$	−0.009	0.005	0.017*	0.009
$t \times \ln y2$	0.006	0.005	−0.031**	0.013
$t \times \ln y3$	0.008***	0.003	−0.001	0.006
$t \times \ln w2$	0.002	0.004	0.020***	0.006
$t \times \ln w3$	0.001	0.007	−0.003	0.010
t	0.118**	0.048	0.188**	0.089
t^2	−0.018***	0.002	−0.008	0.005
Constant	0.435*	0.223	2.664***	0.960
ETA	−0.032***	0.008	0.013	0.008
ROA	−0.436*	0.229	−4.139***	0.861
$\sigma_u^2 + \sigma_v^2$	0.032***	0.004	0.070**	0.030
$\sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$	0.950***	0.007	0.932***	0.031
Log-likelihood	303.651		142.733	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

the parameter estimates from the LP technique differ slightly versus the corresponding estimates from the stochastic metafrontier, the former estimates are found to have larger variation. All of the macro-level environmental factors have significant influences on TGRs. As expected, the coefficient estimate of OBS is significantly negative, meaning that active off-balance sheet businesses may encourage banks to undertake innovative production technology, prompting the group-specific frontier to be closer to the metafrontier. The coefficient estimate of NPL is significantly positive, suggesting that banks with a higher amount of NPLs tend to adopt inferior technology such that their TGR values are inclined to be lower. In particular, those banks may fail to have a well-established administrative procedure ensuring that each loan application is processed under stipulated rules and impersonal criteria. Similarly, the significantly positive coefficient of HHI displays that banks within a more concentrated atmosphere potentially accept financial innovations in a tardy manner, due possibly to there being no market competition. Tsekouras and Daskalopoulou (2006) argue that the debate regarding the relationship between firm efficiency and market concentration is still inconclusive due to the variables used and the analytical framework employed to examine this relationship. Although the differential efficiency hypothesis (Demsetz 1973) posits a positive relationship, it is far from holding uniform explanatory power. In our analysis, the quiet-life hypothesis may be able to explain this situation, but is related to the adoption of production technology, rather than technical efficiency.

TABLE 5

Parameter Estimates for Common Frontier and Metafrontier

Independent Variables	Common Frontier		Metafrontier (LP)		Stochastic Metafrontier	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.D.
Constant	1.131	0.739	−1.973	1.915	−0.158	0.503
$\ln y1$	0.327***	0.121	0.819**	0.370	0.382***	0.096
$\ln y2$	0.929***	0.104	0.807***	0.275	0.966***	0.090
$\ln y3$	−0.147**	0.073	−0.318	0.229	−0.158**	0.063
$\ln w2$	−0.202**	0.099	0.026	0.242	−0.184***	0.068
$\ln w3$	0.268***	0.083	0.226	0.240	0.431***	0.076
$\ln y1 \times \ln y1$	0.237***	0.014	0.162***	0.046	0.236***	0.012
$\ln y2 \times \ln y2$	0.172***	0.018	0.073	0.055	0.172***	0.013
$\ln y3 \times \ln y3$	3.30E-04	0.006	−0.036*	0.020	0.011*	0.006
$\ln y1 \times \ln y2$	−0.218***	0.015	−0.159***	0.045	−0.218***	0.011
$\ln y1 \times \ln y3$	−0.009	0.007	−0.001	0.024	−0.011*	0.006
$\ln y2 \times \ln y3$	0.019**	0.008	0.053**	0.020	0.015**	0.007
$\ln w2 \times \ln w2$	−0.002	0.008	−0.020	0.020	−0.013**	0.006
$\ln w3 \times \ln w3$	0.217***	0.013	0.199***	0.038	0.233***	0.012
$\ln w2 \times \ln w3$	−0.011	0.007	−0.053**	0.022	−0.024**	0.007
$\ln y1 \times \ln w2$	0.003	0.010	−0.029	0.028	−0.008	0.009
$\ln y1 \times \ln w3$	−0.022**	0.010	0.004	0.029	−0.017*	0.009
$\ln y2 \times \ln w2$	0.007	0.009	0.028	0.023	0.019**	0.008
$\ln y2 \times \ln w3$	0.048***	0.010	0.062**	0.031	0.033***	0.010
$\ln y3 \times \ln w2$	0.002	0.005	0.002	0.013	0.002	0.004
$\ln y3 \times \ln w3$	−0.025***	0.007	−0.052***	0.017	−0.020***	0.008
$t \times \ln y1$	0.004	0.004	−0.011	0.011	0.008**	0.004
$t \times \ln y2$	−0.005	0.004	0.016	0.011	−0.009***	0.003
$t \times \ln y3$	0.001	0.002	−0.006	0.005	0.001	0.002
$t \times \ln w2$	0.004	0.002	0.014**	0.007	0.008***	0.002
$t \times \ln w3$	0.003	0.003	2.77E-04	0.008	0.004	0.003
t	0.001	0.027	0.075	0.067	0.104***	0.027
t^2	−0.001	0.001	−0.018***	0.004	−0.013***	0.001
Constant	0.101	0.117	–	–	−0.962***	0.282
ETA	−0.020***	0.003	–	–	–	–
ROA	−0.552***	0.161	–	–	–	–
ln OBS	–	–	–	–	−0.035***	0.009
ln NPL	–	–	–	–	0.066***	0.011
HHI	–	–	–	–	3.60E-04***	7.81E-05
$\sigma_u^2 + \sigma_v^2$	0.061***	0.010	–	–	0.006***	1.04E-04
$\sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$	0.922***	0.012	–	–	0.638***	0.053
Log-likelihood	500.116				790.801	

Notes: The standard errors of stochastic metafrontier are computed by the sandwich-form. The standard errors of the linear programming (LP) are obtained by bootstrapping.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

B. Measures of Cost Efficiency and Technology Gaps

Table 6 summarizes the descriptive statistics of the TGR, CE, and MCE measures for all ownership structures. Recall that the scores of CE are not comparable among different groups. The overall average of CE is equal to 0.942 with a standard deviation of 0.060. The average values (standard deviations) of CE vary from roughly 0.927 (0.059) for CCBs to 0.969 (0.036) for JSCBs. A representative city commercial bank can save around 7.3% of its current production cost for the given output levels, provided it is producing on the efficient cost frontier. In contrast, the potential cost an average joint stock commercial bank can save is merely 3.1%, whose actual cost lies quite close to the group frontier for a given bundle of outputs.

It is important to note that the mean values (standard deviations) of the TGR in all ownership structures, derived from the LP method, are less (greater) than those from the SMF method, leading to lower average MCE values. The programming method underestimates banks' TGR and MCE, but overestimates their standard deviations. The findings are in accordance with previous studies.[7] This may be attributed

7. See Berger and Humphrey (1997) for a comprehensive survey.

TABLE 6
Summary Statistics of Various Efficiency Scores

	Metafrontier (LP)				Stochastic Metafrontier (SMF)			
	Mean	**Min**	**Max**	**S.D.**	**Mean**	**Min**	**Max**	**S.D.**
Technology gap ratio (TGR)								
SOCBs	0.8023	0.4501	0.9711	0.1401	0.8825	0.5330	0.9842	0.1347
JSCBs	0.9026	0.6083	1.0000	0.0864	0.9547	0.6837	0.9908	0.0724
CCBs	0.8848	0.6260	1.0000	0.0747	0.9843	0.8546	0.9933	0.0149
Foreign banks	0.9344	0.6388	1.0000	0.0721	0.9885	0.9563	0.9943	0.0060
All banks	0.8919	0.4501	1.0000	0.0925	0.9699	0.5330	0.9943	0.0621
Group-specific cost efficiency (CE)								
SOCBs	0.9671	0.8083	0.9956	0.0343	0.9671	0.8083	0.9956	0.0343
JSCBs	0.9691	0.7146	0.9933	0.0360	0.9691	0.7146	0.9933	0.0360
CCBs	0.9267	0.4939	0.9893	0.0588	0.9267	0.4939	0.9893	0.0588
Foreign banks	0.9439	0.4251	0.9866	0.0727	0.9439	0.4251	0.9866	0.0727
All banks	0.9423	0.4251	0.9956	0.0602	0.9423	0.4251	0.9956	0.0602
Metafrontier cost efficiency (MCE)								
SOCBs	0.7750	0.4464	0.9545	0.1338	0.8531	0.4968	0.9705	0.1318
JSCBs	0.8761	0.4672	0.9878	0.0980	0.9266	0.5461	0.9821	0.0889
CCBs	0.8207	0.3402	0.9652	0.0905	0.9124	0.4665	0.9760	0.0619
Foreign banks	0.8815	0.4251	0.9833	0.0941	0.9332	0.4109	0.9802	0.0735
All banks	0.8408	0.3402	0.9878	0.1040	0.9139	0.4109	0.9821	0.0824

to the fact that the estimated efficiency scores from the programming technique are easy to be confounded with noise, as pointed out by, for example, Berger and Mester (1997), O'Donnell and Coelli (2005), and Huang, Huang, and Liu (2014).

According to the SMF model, the TGR average values (standard deviations) range from 0.883 (0.135) for SOCBs to 0.989 (0.006) for foreign banks, leading to an overall mean value of 0.970 (0.062). The average TGRs of these groups do not fall far apart, except for SOCBs. This can be ascribable to the financial reforms and the opening up process in China, because these liberalization policies have sped up financial innovations and stimulated market competition and technological progress.

The state-owned commercial banks are found to assume the least sophisticated technology, since their cost frontier deviates farthest from the metafrontier, as opposed to the remaining three groups' frontiers. In contrast, foreign banks take the best technology, whose cost frontier is the nearest to the metafrontier. SOCBs are obliged to finance government projects or state-owned enterprises (SOEs), which contribute high social returns at the expense of little profits due to their divergence from the market mechanism and imposition by certain government intervention (Clarke, Cull, and Shirley 2005; Dong et al. 2014a). In addition, soft budget constraints that cause excessive risk-taking and the misallocation of resources result in inferior technology (Sheshinski and Lopez-Calva 2003). Since most foreign banks come from developed countries with advanced financial systems, these banks operate under better technology (Huang and Fu 2013). Another possible reason is related to knowledge spillovers. Kontolaimou and Tsekouras (2010) argue extensively on the role of absorptive capacity and strategic orientation on the productive efficiency of banking firms when ownership type is adopted as the technology heterogeneity factor. Given that foreign banks have high absorptive capacity and intra-type strategic orientation, the technology they adopt is more advanced.

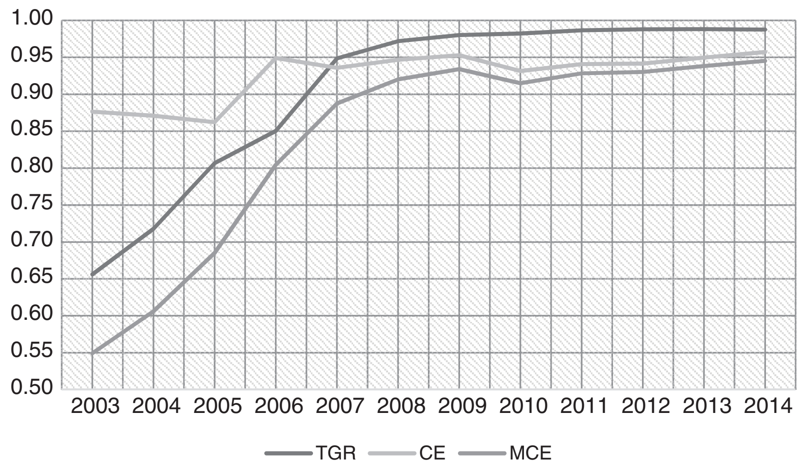
We now compare the performance of various ownership structures, on the basis of MCE that is measured against the metafrontier cost function. The average values of MCE across the four groups range between 0.853 and 0.933, with an overall mean value of 0.914. Foreign banks are the most efficient, while SOCBs are the least efficient.[8] The forgoing is in line with many previous studies, such as Yao et al. (2007), Berger, Hasan, and Zhou (2009), Lin and Zhang (2009), and Jiang, Yao, and Feng (2013). To verify whether

8. It is also interesting to note that the standard deviation of SOCBs is much larger than that of foreign banks. This variation can be attributed to the influence of the Agricultural Bank of China (ABC). The ABC is known as having low efficiency with acknowledged non-performing loans and questionable management practices (Chang et al. 2012; Dobson and Kashyap 2006; Foo and Witkowska 2014; Hou, Wang, and Zhang 2014). It is seen that the three efficiency scores of ABC, that is, TGR, CE, and MCE, are lower than those of other SOCBs, along with having the largest standard deviations. We thank a referee for pointing this out.

TABLE 7
Summary Statistics of Various Efficiency Scores over Time from SMF

	CE		TGR		MCE	
Period	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
2003	0.876	0.192	0.656	0.166	0.549	0.048
2004	0.871	0.198	0.718	0.121	0.606	0.095
2005	0.862	0.154	0.807	0.093	0.685	0.080
2006	0.949	0.053	0.850	0.071	0.804	0.042
2007	0.936	0.069	0.948	0.031	0.888	0.070
2008	0.947	0.085	0.972	0.026	0.920	0.087
2009	0.953	0.042	0.980	0.010	0.934	0.044
2010	0.931	0.058	0.982	0.011	0.915	0.057
2011	0.941	0.044	0.987	0.005	0.928	0.045
2012	0.942	0.044	0.988	0.003	0.930	0.044
2013	0.950	0.032	0.988	0.005	0.938	0.032
2014	0.957	0.026	0.988	0.006	0.945	0.024
2003–2006	0.895	0.146	0.779	0.126	0.687	0.116
2007–2010	0.941	0.064	0.975	0.022	0.918	0.065
2011–2014	0.948	0.037	0.988	0.005	0.936	0.037
Average	0.942	0.060	0.970	0.062	0.914	0.082

FIGURE 1
Trends in CE, TGR, and MCE Based on the Stochastic Metafrontier Method



the differences between these mean efficiency scores across the four ownership structures reach statistical significance, we calculate the paired *t* statistics. These statistics are rejected at the 1% level. One can conclude that the mean scores of MCE across the four groups are not equal to one another.

C. Trends of Various Efficiency Measures

The crucial issue is whether the enforcement of financial reforms and the opening up process in China raise bank efficiencies. To shed light on this issue, Table 7 reports the average values of CE, TGR, and MCE over the sample period, and Figure 1 draws these trends. To better understand the processes of financial reforms, we also summarize China's banking reforms in Table 8. The mean CE values demonstrate a gradual downward trend from 0.876 to 0.862 in the period 2003–2005, which may be attributed to the creation of the China Banking Regulatory Commission aimed at improving the bank monitoring system in a 5-year transitional period. After 2005, there is a strong upward trend from 0.862 to 0.949, except for two declines in 2007

TABLE 8
Summary of Financial Reforms in the Chinese Banking Industry

Time	Event Description
December 2001	China joined the World Trade Organization and accelerated its financial reforms and the opening up process of its financial system to be aligned with the WTO.
April 2003	The China Banking Regulatory Commission was established to oversee reform and regulation of the banking sector, allowing PBC to focus on monetary policy.
December 2003	The government injected US$45 billion into Bank of China (BOC) and China Construction Bank Corporation (CCBC)
September 2004	The revised version of the *Rules for Implementing the Regulation of the People's Republic of China Governing Foreign-funded Financial Institutions* took effect to relax restrictions placed on foreign banks, interest rates and RMB business.
April 2005	The government injected US$15 billion into Industrial and Commercial Bank of China (ICBC)
October 2005	The government started to enforce the financial reforms by getting the large state-owned commercial banks in shape for initial public offerings and listing. China Construction Bank was the first to issue an IPO among the Big Four.
January 2007	The government has started to allowed foreign banks to conduct local-currency business without restrictions. Domestic banks have had to compete with foreign banks without government protection.
October 2008	The government injected US$19 billion into Agricultural Bank of China (ABC).
July 2010	All large state-owned commercial banks have undergone initial public offering (IPO) in various markets to become share-holding commercial banking corporations.

and 2010, corresponding to the subprime crisis and European debt crisis.

Measure MCE exposes a strong upward trend over the entire sample period, except in 2010. Although this upward trend weakens after the European debt crisis, this rising trend still suggests that a more opened-up financial market is able to nurture managerial abilities in the long run. The reason that MCE is slightly resistant to the financial crises in 2007 and 2010 can be explained by the ongoing banking reforms and fiscal stimulus package worth about US$586 billion that were pushed through the banking system (Jiang, Yao, and Feng 2013). Another probability relates to the credit boom during the financial crisis. The stimulus policy of the China government promoted a credit boom and increased profits under a controlled interest rate margin (Wang and Feng 2014). Finally, the mean TGR values have a similar trend as MCEs, which exhibit a strong growing trend from 0.656 to 0.948 during 2003–2007 and then turn to a gradually ascending trend from 0.972 to 0.988 during 2008–2014. After China joined the WTO in 2001, it undertook a series of fundamental reforms and transformation aimed at improving the monitoring system and increasing competitiveness. Table 8 summarizes these reforms. These financial reforms and the opening up process in China appear to benefit the sample banks in terms of technology progress.

Furthermore, Casu, Ferrari, and Zhao (2013) present an interesting assessment of the effects of regulatory reforms on efficiency change in the case of Indian banks. By specifying a dummy variable to capture the period before and after reregulation, they find that financial reforms benefit the banking sector, but their effects are not uniformly distributed across different ownership types. Our paper takes a different route in assessing the impacts of financial reforms through dividing the entire period into three sub-periods: 2003–2006 (transitional period), 2007–2010 (completely open period), and 2011–2014 (post-reform period). The results confirm our previous arguments that the opening up process not only improves the efficiency, but also lets banks operate under advanced technology.[9]

An interesting question immediately arises: Which element of MCE, that is, either CE or TGR, is the main determinant of MCE? Figure 1 displays that the average CE scores exceed those of TGR before 2007, and the reverse is true after 2008. This denotes that the chief source of inefficiency comes from inferior technology adopted by the sample banks before the subprime crisis, while managerial inabilities are the major cause of inefficiency after the crisis. Recall that the implementation of Chinese financial reforms in the past decade has intensified the competitive conditions in the financial market. The policy appears to be successful in improving banks'

9. We also conduct an extension analysis with respect to β-convergence and σ-convergence according to the methodology employed by Casu et al. (2016). Evidence shows that banks in China not only are moving progressively toward higher efficiency, but also toward the use of more advance technology. For the sake of brevity, these estimates are not shown, but are available from the authors upon request.

efficiency, resulting primarily from the catching-up in financial technology. Facing a more competitive environment, Chinese banks attempt to learn modern technology to lower their production costs.

VI. CONCLUSION

This paper compares the cost efficiencies of Chinese banks for different types of ownership structures, using the new stochastic metafrontier cost function, for the period 2003–2014. Differing from Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008), we formulate the stochastic metafrontier cost function to gauge the sample banks' TGR in the context of SFA, instead of mathematical programming. SFA has two advantages. First, the regression coefficients have statistical properties, allowing one to make statistical inferences. Second, TGR can be further specified as a function of exogenous variables that reflect environmental differences met by different banks in distinct groups. This helps one to appropriately calculate comparable cost efficiencies for banks operating under different technologies.

We classify the sample banks into four forms: SOCBs, JSCBs, CCBs, and foreign banks. Our empirical results show that both TGR and metafrontier cost efficiency are underestimated by programming techniques. Under the desirable stochastic metafrontier model, the average TGRs in these ownership structures are quite close to one another, with the exception of SOCBs. Both TGR and MCE exhibit upward trends from 2003 to 2014, which are consistent with the easing of government intervention and increasing market competition. These policies foster an environment inducing banks to adopt superior technology, which offsets the slightly downward trend of CE. Loss-incurring banks, arising from the adoption of inferior technology, would be compelled to exit the market.

According to MCE, evidence is found that foreign banks are the most efficient, while SOCBs are the least efficient. It is suggested that SOCBs exercise prudential lending practices and modernize their financial technology to catch up with foreign banks from developed countries. The entry of foreign banks not only injects loanable funds, but also introduces superior managerial skills and technology. One may infer that expanding the share of foreign ownership in domestic banks could also bring forth efficiency gains. As to the effect of environmental conditions, we obtain that off-balance sheet items (OBS), non-performing loans (NPLs), and financial market structure are crucial determinants of the technology gap between the group cost frontier and the metafrontier for banks.

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