Chapter 5
Pitching DEA Against SFA in the Context of Chinese Domestic Versus Foreign Banks

Necmi Kemal Avkiran and Yushu (Elizabeth) Zhu

Abstract The primary motivation is to show how the efficient frontier methods data envelopment analysis (DEA) and stochastic frontier analysis (SFA) can be used synergistically. As part of the illustration, we directly compare locally incorporated foreign banks with Chinese domestic banks. Both DEA and SFA reveal that foreign banks are *less* efficient. DEA shows the main source of inefficiency for foreign banks as managing *interest income*, whereas domestic banks are inefficient in managing *non-interest income* and *interest expense*. SFA reveals contextual variables such as interbank ratio, loan-to-deposit ratio and cost-to-income ratio are significant in explaining inefficiency. The correspondence of rankings based on DEA vs. SFA is positive and moderate in strength but efficiency estimates do not belong to the same distribution. Using DEA and SFA side-by-side can encourage more rigorous and in-depth bank efficiency studies where each method's limitation can be overcome by the other.

Keywords Technical efficiency • Scale efficiency • Data Envelopment Analysis • Stochastic frontier analysis • Single-output Translog function • Multi-output Translog distance function • Cobb-Douglas function • Robustness testing • Chinese banks • Efficiency spillovers • Profitability • Potential improvements • Efficiency contribution measure

5.1 Introduction

The *primary motivation* of this chapter is to compare and contrast the well-established efficient frontier methods data envelopment analysis (DEA) and stochastic frontier analysis (SFA) in generating efficiency estimates. In efficient frontier literature on banking, the choice between DEA and SFA is often based on authors' preferences and the complementary nature of these methods makes a final compelling argument in favor of one or the other difficult. We set out to

N.K. Avkiran (✉) • Y. Zhu
UQ Business School, The University of Queensland, Brisbane 4072, QLD, Australia
e-mail: n.avkiran@business.uq.edu.au; e.zhu@business.uq.edu.au

S.-N. Hwang et al. (eds.), *Handbook of Operations Analytics Using Data Envelopment Analysis*, International Series in Operations Research & Management Science 239, DOI 10.1007/978-1-4899-7705-2_5

explore whether DEA and SFA can be used in a synergistic manner to allay various research design concerns such as potential distortion of results by measurement error or mis-specification of assumed functional relationships. The research design includes various robustness tests such as sensitivity of results to majority state-owned large banks, and stability of results to modelled outputs and functional specification.

Briefly, DEA is a peer benchmarking method used in comparing performance of organizations of similar operations and identifying relative inefficiencies that may detract from performance. As a non-parametric efficient frontier method, DEA calculates a comparative ratio of weighted outputs to weighted inputs that defines performance—reported as a relative efficiency estimate. On the other hand, SFA is a parametric efficiency measurement method that explains the variation in organizational performance in terms of managerial efficiency, operating environment and statistical noise. SFA efficiency estimates are based on parameter values of regression. In Sect. 5.3, further details on DEA and SFA and formal definitions are provided, including a discussion of how firm-specific factors (i.e. contextual variables) can be used to explain inefficiency.

The primary motivation of this chapter is executed in the context of how foreign banks in China perform when compared against domestic banks as well as each other in the post-2007 period. Between 2002 and 2006, China further opened up its domestic financial markets to foreign financial institutions through various reforms that expanded the scope of business in foreign exchange and renminbi (RMB). Business engaged in by domestic and locally incorporated foreign banks (hereon, foreign banks) include such activities as receiving deposits from the general public; granting loans of short, medium or long term; handling negotiable instruments; trading bonds; issuing letters of credit and guarantees; handling domestic and foreign settlements; issuing bank cards; interbank lending, etc., all effective as of 11 December 2006.[1] That is, foreign banks are allowed to conduct the same types of RMB business as their domestic counterparts and have essentially been granted equal status as of December 2006 (Xu 2011). Consequently, as of 2007, foreign banks have been in competition with domestic banks, and these two cohorts can be analyzed together in benchmarking studies to enable a more direct comparison. Recent examples of applications of DEA to Chinese banking data include Chen et al. (2005), Ariff and Can (2008), Hu et al. (2008), Yao et al. (2008), Avkiran and Morita (2010) and Avkiran (2011). Others who have used SFA instead include Fu and Heffernan (2007) and Jiang et al. (2009). Luo et al. (2011) use DEA as well as SFA in a study of Chinese domestic banks only.

[1] See 'Regulations of the People's Republic of China on Administration of Foreign-funded Banks' (CBRC 2006). The same regulations also apply to the banking institutions established on Chinese mainland by financial institutions originating from the Hong Kong Special Administrative Region, the Macao Special Administrative Region, or Taiwan. For example, in our sample, Hang Seng bank (China) Ltd, and CITIC Ka Wah Bank (China) Ltd with home groups from the Hong Kong Special Administrative Region are treated as foreign banks rather than Chinese domestic banks (see Article 72).

Key findings of this study for the period 2008–2010 show foreign banks to be generally less efficient compared to domestic banks based on DEA as well as SFA. An examination of the sources of inefficiency reveals management of *interest income* as an area in need of closer examination by foreign banks. On the other hand, domestic bank operations appear to be primarily inefficient in managing *non-interest income* and *interest expense*. Other findings suggest that contextual variables such as interbank ratio, loan-to-deposit ratio and cost-to-income ratio are significant in explaining inefficiency. However, significance tests show that efficiency estimates from these different methods do not belong to the same distribution. Furthermore, lower SFA efficiency estimates are better in separating the more efficient domestic banks from foreign banks. Under SFA, single-output Translog functional form emerges as a better specification compared to the Cobb-Douglas specification or the two-output Translog distance function. Overall, intuitive findings from bank performance analysis pave the way for use of DEA and SFA side-by-side without the researcher having to justify one method at the expense of the other. We expect such an inclusive approach to bring stronger rigor to applications of frontier methods in banking and encourage more in-depth studies.

The rest of the chapter is organized as follows. Section 5.2 begins by briefly discussing the Chinese banking sector. It continues to further discuss efficiency spillovers that bring foreign and domestic banks closer and details the performance models used for estimating bank efficiency including firm-specific factors. Section 5.3 describes the data, followed by a discussion of DEA and SFA methods that includes formulations. Section 5.4 reports results and analyses based on DEA and SFA and corresponding robustness tests, ending with a comparison of DEA versus SFA efficiency estimates. Section 5.5 concludes the chapter with a summary of main findings and managerial implications.

5.2 Conceptual Framework

5.2.1 Chinese Banking Sector

The Chinese banking sector has been offering a wider range of products and services as a result of the ongoing deregulation which gained momentum since China joined the World Trade Organization in December 2001. Main examples of successful listings among the Chinese domestic banks include the Agricultural Bank of China Ltd., Bank of China Ltd., Bank of Communications Ltd., China Construction Bank Corp., and Industrial and Commercial Bank of China Ltd. These majority state-owned commercial banks keep a large branch network throughout China, and thus, hold a greater share of the retail banking market. Other domestic banks include joint-stock commercial banks with minority state or government ownership, city commercial banks, rural commercial banks, and wholly state-owned banks known as policy banks. The China Banking Regulatory Commission (CBRC)—established in 2003—is the main entity responsible for monitoring implementation of regulations and reforms, and the People's Bank of China is the central bank. A more extensive historical background to the development of the Chinese banking sector can be read in Berger et al. (2009) and in Asmild and Matthews (2012).

Foreign banks in China have a history of slow entry—representative offices being allowed for the first time in 1979—followed by branches a few years later in special economic zones. It was not until 1996 that foreign banks—under individual licenses—were permitted to engage in business with local enterprises by accepting deposits and writing loans in renminbi. Lin (2011) maintains that the predominant form of foreign bank entry into China is *green field* investment where new branches are established from ground up, rather than the *brown field* approach that requires taking over or building on an existing branch. Green field investments are likely to be more expensive because such an exercise would include recruiting and training staff while working on building reputation. Furthermore, such costs would have to be allocated across multiple periods, and at least during the initial years of operation, cost control is likely to be treated as of secondary importance because the focus would be on expanding market share.

The basic motivation of policy makers and regulators for encouraging foreign bank presence revolves around anticipated enhancement of structure and competitive efficiency of a country's banking system. For example, foreign banks are often credited with contributing to improvement of domestic banking through efficiency spillovers. Spillovers may take the form of emulation of innovative products and services of foreign banks by domestic banks as seen in personal banking, and relocation of talent from foreign to domestic banks (see Deng et al. 2011 and Xu 2011). *Such spillovers bring foreign and domestic bank operations closer*, *thus enabling benchmarking against a common frontier*. Nevertheless, foreign banks are still in a stage of growth as they open more branches and employ more people. According to PricewaterhouseCoopers (2012, p. 21) "They are yet to benefit from increases in operational efficiency and economies of scale". It is this expectation of substantial differences in performance that further encourages this chapter to pitch DEA against SFA in the context of measuring the operational or technical efficiency of foreign and domestic banks.

The initial anticipated finding based on the comment by PricewaterhouseCoopers (2012) is more efficient domestic banks for the period 2008–2010, which can be explained by the progress made by the domestic banks since the early days of foreign ownership (see preceding discussion on efficiency spillovers). Yet, an earlier study by Berger et al. (2009) based on SFA efficiency estimates of thirty-eight Chinese banks across 1994–2003 state that, on average, in developing nations foreign banks are usually *more efficient* than or at least as efficient as private domestic banks, and more efficient than state-owned banks. In contrast, Lensink et al. (2008) who use SFA on a much larger sample of 2095 banks across 105 countries (1998–2003) report a general finding of *less efficient* foreign banks. Therefore, in the presence of these potentially conflicting findings, we compare and contrast our chosen non-parametric and parametric methods with a view to using one method as a robustness test for the other.

5.2.2 Modeling Performance to Estimate Bank Efficiency

There is no consensus on how to model bank performance, particularly in the context of evaluating technical efficiency. A recent study of major DEA applications in banking literature in top journals across 2004–2009 concludes, ". . .there is no clear agreement amongst the selection of inputs and outputs beyond the general observance of the intermediation approach to bank behavior" (Avkiran 2011, p. 326). The traditional intermediation executed by banks as part of their regular operations include incurring *interest expense* and *non-interest expense* to generate deposits (bank liabilities) and writing loans (bank assets) to generate *interest income*, as well as generating *non-interest income* from service fees and sales commissions. Hence, in this performance benchmarking exercise where we pitch DEA against SFA, the objective of banks is considered as implementing this intermediation process efficiently in order to operate profitably. Since we are looking at two main expense categories and two main revenue categories as the potential key variables, we are in fact proposing to measure profitability when we treat them as inputs and outputs, respectively.

One of the basic operations of banks is to make profits by selling liabilities with one set of features (e.g. liquidity, risk, size and return) and using the proceeds to buy assets with a different set of features. For example, term deposit accounts (liabilities) held in the name of a number of individuals can provide the underlying funds needed to write a mortgage loan (asset). In fact, there is no need to look at different types of assets and liabilities and sacrifice discrimination unless the purpose is to comment on specific products/services, and the researcher has a very large sample. Therefore, the performance modeling in this study begins with a parsimonious set of two discretionary key inputs and one output (where we collapse interest income and non-interest income into *total income*) designed to generate a technical efficiency estimate for each bank. In the second stage, we model all four key variables without aggregation and note whether findings on comparing DEA and SFA are still similar when dimensionality rises. Yao et al. (2008), Jiang et al. (2009) and Avkiran (2011) use similar variables involving Chinese banks. Others who have also used these variables with banks from other countries include Miller and Noulas (1996), Bhattacharyya et al. (1997), Brockett et al. (1997), Leightner and Lovell (1998), and Sturm and Williams (2004).

5.2.3 Contextual Variables

According to Banker and Natarajan (2008), OLS or Tobit regression can be used in order to understand the impact of various factors or contextual variables on DEA efficiency estimates. On the other hand, McDonald (2009) concludes that while Tobit may not be appropriate in this context, OLS is a consistent estimator when used in second stage DEA efficiency analyses (see Greene 2012 regarding Tobit regression and the further discussion at the end of Sect. 5.3.2 of this chapter). In SFA, firm-specific factors or contextual variables are incorporated into the regression equation. For example, we can explore the relationship between efficiency and a selection of key traditional financial performance ratios. Potential candidates include cost-to-income as an overall efficiency ratio used by industry analysts; impaired loans-to-gross loans (or, non-performing loans ratio, NPL) as a measure of credit or asset quality; and interbank ratio as a measure of liquidity (ratio of due from banks to due to banks).[2]

Historically, domestic banks have shown limited appetite for efficient operations or lending purely based on risk-return analysis because of their closer ties with governments. For example, in the past many politically directed lending decisions have contributed to high non-performing loans, although such practices may gradually be in decline—at least as evidenced by substantially lower non-performing loans (e.g., according to the China Banking Regulatory Commission, in 2005 the NPL ratio was 4.2 %, whereas by 2009—midway through this study—it had fallen to 1.58 %).[3] Similarly, because of domestic banks' larger branch networks and more captive customer base—where workers' wages are deposited—such banks have a larger deposits base although this does not necessarily imply a larger interbank ratio if lending to other banks is limited.

Another financial ratio of potential interest is the loan-to-deposit. This ratio can also be used as a firm-specific factor to acknowledge the impact of regulation on efficiency. For example, the loan-to-deposit ratio is decreed not to exceed 75 % for all banks operating in China, yet the foreign banks appear to be handicapped by a smaller branch network in raising deposits, with flow-on limitations on lending (the grace period for meeting the 75 % threshold ended in December 2011). Another related confounding factor is the practice by the regulators of accepting only one branch application at a time. All else the same, these conditions are likely to make efficient revenue generation more difficult because lower deposit raising capacity is expected to limit revenue generation from traditional lending activities. Thus, this study also investigates whether regulation of the loan-to-deposit ratio is likely to have an impact on the efficiency estimates. Summing up, we explore to what extent

---

[2] The interbank ratio is the ratio of funds lent to other banks divided by funds borrowed from other banks. A ratio greater than 1 indicates that the bank is a net lender in the interbank market and is therefore more liquid.

[3] http://www.cbrc.gov.cn/EngdocView.do?docID=B22DBFC5175C4AC0AC7926AD7AFEEE27.

a small selection of key traditional financial ratios (firm-specific factors or contextual variables) are likely to play a significant role in explaining inefficiency.

5.3 Data and Method

5.3.1 Data

This study spans 2008–2010 in an effort to measure the performance of banks in China against their peers and excludes the three wholly state-owned policy banks the Agricultural Development Bank of China, the China Development Bank and the China Exim Bank. Remaining commercial banks with varying degrees of state ownership are included based on panel data availability across the variables of interest. Essentially, 2008 marks the first reporting period that captures the operations for foreign banks when they are considered as offering a range of products and services similar to domestic banks (data were collected in late 2012 and early 2013 but data for 2011 were mostly unavailable). The 3-year study period is also appropriate for the common efficient frontier constructed with the pooled data. The primary data source was Wharton's Research Data Services.

After accounting for missing data, we were left with 16 foreign banks and 37 domestic banks that consistently had data across all the variables for the 3-year study period (see Table 5.1). The sample represents about 75 % of the market as measured by bank assets. We were also able to collect data for this sample for the firm-specific factors of cost-to-income ratio, impaired loans-to-gross loans, interbank ratio and loan-to-deposit ratio. Overall, the data collection effort produces a sample of 159 bank-year observations in a balanced panel data set, and enables setting up an efficient frontier common across 3 years. In this sample, four of the Big Six foreign banks and eight countries and domestic commercial banks are well represented (see Table 5.1).

Descriptive statistics and correlations between performance variables and firm-specific factors are shown in Table 5.2. All of the firm-specific factors are correlated at low levels with the performance variables, and all of the NPL and interbank ratio correlations are statistically insignificant. The extensive testing in Banker and Natarajan (2008, p. 56) demonstrates that two-stage methods become unreliable in explaining the impact of contextual variables (i.e. firm-specific factors) when such variables are highly correlated with performance variables; the correlations in the second half of Table 5.2 are all low and mostly insignificant.

Once the foreign and domestic banks are benchmarked against the common frontier, it is easier to compare how these different cohorts perform against each other. This approach is appropriate as long as the panel data do not cover too many years because it assumes no substantial changes in the production technology during the study period. Various applications of the common frontier in banking can be found in Dietsch and Lozano-Vivas (2000), Hasan and Marton (2003),

Table 5.1 Banks in the study (53 banks, or 159 bank-years across 2008–2010)

	Sorted by home country	
Foreign banks in China (N = 16)	Crédit Agricole CIB (China)	France
	Société Générale (China)	France
	CITIC Ka Wah Bank (China)[a]	Hong Kong
	Hang Seng Bank (China)[b]	Hong Kong
	Nanyang Commercial Bank (China)	Hong Kong
	Bank of Tokyo Mitsubishi UFJ (China)	Japan
	Mizuho Corporate Bank (China)	Japan
	Hana Bank (China)	Korea
	Woori Bank (China)	Korea
	Bank International Ningbo	Singapore
	United Overseas Bank (China)	Singapore
	Fubon Bank (Hong Kong)	Taiwan
	HSBC Bank (China)[b]	United Kingdom
	Royal Bank of Scotland (China)	United Kingdom
	Standard Chartered Bank (China)[b]	United Kingdom
	Citibank (China)[b]	United States of America
Chinese domestic banks (N = 37)	*Sorted alphabetically*	
	Agricultural Bank of China	China Merchants Bank
	Bank of Beijing	China Minsheng Banking
	Bank of China	China Zheshang Bank
	Bank of Communications	Chong Hing Bank
	Bank of Dongguan	Fudian Bank
	Bank of Fuxin	Fujian Haixia Bank
	Bank of Guangzhou	Guangzhou Rural Commercial Bank
	Bank of Hangzhou	Hankou Bank
	Bank of Jilin	Harbin Bank
	Bank of Nanjing	Huaxia Bank
	Bank of Ningbo	Huishang Bank
	Bank of Qingdao	Industrial and Commercial Bank of China
	Bank of Shanghai	Industrial Bank
	Bank of Wenzhou	Nanchong City Commercial Bank
	Beijing Rural Commercial Bank	Shanghai Pudong Development Bank
	China CITIC Bank	Shanghai Rural Commercial Bank
	China Construction Bank	Shengjing Bank
	China Everbright Bank	Shenzhen Development Bank[c]
	China Guangfa Bank	

[a]This bank's new name is CITIC Bank International (China) Ltd.
[b]Belongs to the group of Big Six foreign banks
[c]This bank's new name is Ping An Bank Co Ltd.

Table 5.2 Descriptive statistics on performance data adjusted for GDPD and firm-specific factors ($N = 159$)[a]

	Mean	Median	SD[b]	CV[c]	Minimum	Maximum	Skewness
Interest expense[d]	2184.12	257.75	4914.24	2.25	0.28	23,581.23	3.00
Non-interest expense	1617.06	203.77	3806.12	2.35	5.16	16,422.91	3.00
Interest income	5689.89	669.63	13,237.00	2.33	4.73	65,203.36	3.07
Non-interest income	821.65	64.10	2203.35	2.68	0.00	10,348.24	3.32
Total income	6511.53	770.21	15,369.30	2.36	8.65	75,497.37	3.07
Impaired loans-to-gross loans (or, NPL)[e]	1.77	1.02	4.45	2.52	0.05	38.22	7.38
Interbank ratio	350.84	191.09	671.87	1.92	15.16	7280.19	7.69
Loan-to-deposit ratio	65.62	62.63	20.70	0.32	25.91	209.82	3.21
Cost-to-income ratio	49.26	41.41	30.65	0.62	23.06	350.83	6.70
Correlation matrix	Interest expense	Non-interest expense	Interest Income	Non-interest income	Total income[f]		
Impaired loans-to-gross loans (or, NPL)[e]	−0.013 (0.869)	−0.012 (0.876)	−0.014 (0.862)	−0.012 (0.885)	−0.014 (0.864)		
Interbank ratio	−0.058 (0.464)	−0.046 (0.561)	−0.052 (0.514)	−0.045 (0.575)	−0.051 (0.521)		
Loan-to-deposit ratio	−0.182 (0.022)	−0.172 (0.030)	−0.177 (0.026)	−0.161 (0.043)	−0.175 (0.027)		
Cost-to-income ratio	−0.180 (0.023)	−0.164 (0.038)	−0.177 (0.026)	−0.154 (0.053)	−0.174 (0.028)		

[a]The Gross Domestic Product Deflator (GDPD) used in this study is considered technically more accurate than the Consumer Price Index (CPI). GDPD is not based on a fixed basket of goods and services; that is, the basket is allowed to change with people's consumption and investment patterns. Thus, new expenditure patterns are allowed to show up in the deflator as people respond to changing prices. Annual GDPD for the study years were: 7.8 % (2008), −0.6 % (2009) and 6.7 % (2010) Data were not winsorized because of the relatively small sample of banks with complete data on variables of interest. For example, the minimum of 0.00 reported for non-interest income is actually .000001 and belongs to Bank of Guangzhou in 2009. Similarly, the maximum of 7280.19 reported for interbank ratio belongs to Royal Bank of Scotland (China) in 2010

[b]*SD* standard deviation

[c]*CV* coefficient of variation (SD/Mean)

[d]All the financial items are in USD million

[e]Significance levels are in brackets

[f]Sum of interest income and non-interest income

Avkiran (2009) and Chortareas et al. (2013). Next, we proceed to outline the principles of DEA and SFA—the two efficient frontier methods at the heart of this study—where the primary motivation of the chapter calls for close attention to designing tests in a comparable manner.

5.3.2 Data Envelopment Analysis (DEA)

Before providing a formal definition of the DEA model used, we begin with an intuitive introduction to this non-parametric method. DEA informs the user whether performance can be improved relative to observed benchmark performance in a peer group. Under standard DEA, the relative efficiency estimate (a scalar value) is expressed as a number between 0 and 1, where a decision-making unit (DMU) with an estimate of less than 1 is considered inefficient. Benchmark units on the efficient frontier determine the potential improvements or projections for the various inefficient units not on the frontier. DEA follows the condition of Pareto optimality for efficient operations, where a DMU or a production unit is not efficient if an output can be raised without raising any of the inputs and without lowering any other output. Similarly, a DMU is not efficient if an input can be lowered without decreasing any of the outputs and without increasing any other input (Charnes et al. 1981).

Key strengths of DEA include the property that no preconceived functional structure is imposed on the data in determining the efficient units. That is, DEA does not assume a particular production technology common to all DMUs. This means a unit's efficiency can be assessed based on other observed performance by benchmarking similar organizations that are better at executing various processes. As an efficient frontier method, DEA identifies the inefficiency in a particular DMU by comparing it to efficient DMUs, rather than trying to associate a DMU's performance with statistical averages that may not be applicable to that DMU. Another strength of DEA is its ability to handle related multiple inputs and multiple outputs in producing a scalar estimate. That is, the optimization process embedded in the linear program behind DEA accounts for the trade-off between multiple variables before reporting a single efficiency estimate for a unit. As Gelade and Gilbert (2003) underline, individual ratios looking at different aspects of an organization's effectiveness cannot depict a full picture because ratios are unlikely to be independent. Alongside the various strengths already mentioned, standard DEA's main limitation is the assumption that data are free of measurement error, thus making DEA more sensitive than stochastic methods to the presence of measurement error. That is, DEA is often considered deterministic where the method assumes random variations cancel out one another (for an opposite argument where DEA is set up as a stochastic frontier estimation method, see Banker and Natarajan 2008).

Historically, DEA literature has been dominated by radial models that can be traced to publication of the seminal article, Charnes et al. (1978). In this study, we use the output-oriented, variable returns-to-scale version of radial DEA (often abbreviated as BCC after Banker et al. 1984). Output-orientation is used because we are primarily interested in identifying overall revenue generating inefficiencies, i.e. measuring to what extent banks are maximizing their revenues for given levels of expenses. Next we briefly provide a formal definition of radial DEA (Coelli et al. 2005, Cooper et al. 2007, 2011 provide authoritative expositions of DEA with extensive detail).

Efficiency can be defined as the ratio of weighted sum of outputs to weighted sum of inputs. Efficiency of a DMU, h_o, assuming controllable inputs and constant returns-to-scale, can thus be written as

$$
\begin{aligned}
h_o &= \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\
\text{where } s &= \text{number of outputs} \\
u_r &= \text{weight of output } r \\
y_{ro} &= \text{amount of output } r \text{ produced by the observed DMU} \\
m &= \text{number of inputs} \\
v_i &= \text{weight of input } i \\
x_{io} &= \text{amount of input } i \text{ used by the observed DMU}
\end{aligned}
\tag{5.1}
$$

While outputs and inputs can be measured and entered in this equation without standardization, determining a common set of weights can be problematic. DMUs may well value outputs and inputs quite differently. This potential problem was addressed through optimization in the CCR model by Charnes et al. (1978) by allowing a DMU to adopt a set of weights that will maximize its efficiency ratio without the same ratio for other DMUs exceeding 1. Introduction of this constraint converts the productivity ratio into a measure of *relative* efficiency. Thus, we re-write (5.1) in the form of a fractional programming problem:

$$
\begin{aligned}
&\max \ h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\
&\text{subject to} \\
&\qquad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \ \text{ for each DMU in the sample} \\
&\text{where } \mathrm{j} = 1, \ldots, \mathrm{n} \ \text{(number of DMUs).}
\end{aligned}
\tag{5.2}
$$

Equation (5.2) represents the *ratio form* DEA. However, (5.2) has an infinite number of solutions. To avoid this problem, we convert (5.2) to the more familiar components of a linear programming problem. In (5.3), known as the *multiplier form*, we set the denominator to a constant and maximize the numerator.

$$\begin{aligned} &\max && h_o = \sum_{r=1}^{s} u_r y_{ro} \\ &\text{subject to} && \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \\ &&& \sum_{i=1}^{m} v_i x_{io} = 1 \\ &&& u_r, v_i \geq \varepsilon \succ 0 \end{aligned} \tag{5.3}$$

In order to prevent an output or an input being mathematically omitted in calculation of efficiency, the smallest values weights u and v are permitted to have are non-zero small positive numbers (ε). Equation (5.3) represents constant returns-to-scale with controllable inputs. It is a primal linear programming problem that models *input contraction* (i.e. input-oriented). The output-oriented CCR model is represented by (5.4):

$$\begin{aligned} &\min && h_o = \sum_{i=1}^{m} v_i x_{io} \\ &\text{subject to} && \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0 \\ &&& \sum_{r=1}^{s} u_r y_{ro} = 1 \\ &&& u_r, v_i \geq \varepsilon \succ 0 \end{aligned} \tag{5.4}$$

The BCC model used in this study to measure pure technical efficiency is derived by introducing a convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$ into (5.4), thus ensuring that an inefficient DMU is benchmarked against DMUs of similar size.

The radial models defined above generate bounded efficiency estimates. As such, Tobit regression of firm-specific factors on DEA efficiency estimates can be regarded appropriate in explaining their impact because estimates are bounded or censored (Grosskopf 1996). However, given the doubts raised by McDonald (2009) about using Tobit in second stage DEA efficiency analyses, we focus on OLS regression and compare findings to Tobit regression. According to Banker and Natarajan (2008), particularly when there is no direct production correspondence between inputs and outputs, DEA may have an advantage over parametric methods where efficiency estimates are generated in the first stage and inefficiencies are explained in the second stage by introducing contextual variables via regression (see Simar and Wilson 2011 for a *caveat emptor* on two-stage DEA).

5.3.3 Stochastic Frontier Analysis (SFA)

Aigner et al. (1977) and Meeusen and van den Broeck (1977) devised Stochastic Frontier Analysis (SFA) independently, and SFA is often regarded as the parametric equivalent of DEA. SFA is a type of regression in which the asymmetric (non-negative) managerial inefficiency effects can be separated from the symmetric error term component, i.e. statistical noise. Examples of statistical noise include errors in measuring variables in the model, or omitted variables; instances of managerial inefficiency include inadequately trained personnel.

We consider the well-established Cobb-Douglas and Translog (Transcendental Logarithmic) functions. Translog is a generalization of the Cobb-Douglas function and includes second order input terms; Translog is a flexible functional form that allows partial elasticities of substitution between inputs to vary. To bring confidence to the choice of functional specification, we initially investigate both options and perform a likelihood ratio (LR) test to compare the fit of the two functional specifications. Based on the LR test results (see second last paragraph in Sect. 5.4.3.1), we find that the Translog function is more appropriate. An additional argument as to why Cobb-Douglas would be inappropriate in a competitive industry such as banking is the non-concave Cobb-Douglas output dimensions (Klein 1953, p. 227).

In the core SFA analysis using the Translog function with pooled data, the sum of outputs *interest income* and *non-interest income* (i.e. total income) becomes the dependent variable. The input variables and the firm-specific factors that may impact efficiency are the same as those used in DEA. The general equation using the Translog function with two inputs is as follows:

$$\begin{aligned} \text{Production function: } ln(y_i) &= \beta_0 + \beta_1(\ln x_{1,i}) + \beta_2 \ln(x_{2,i}) + \frac{1}{2}\beta_3(\ln x_{1,i})^{\mathbf{2}} \\ &\quad + \frac{1}{2}\beta_4(\ln x_{2,i})^2 + \beta_5 \ln x_{1,i} {*} \ln x_{2,i} - z_i\delta + W_i + v_i \\ \text{Inefficiency function: } E[\mu_i] &= z_i\delta \qquad u_i \sim N^+\left(\mu_i, \sigma_u^2\right) \end{aligned} \tag{5.5}$$

where $ln(y_i)$, is the natural logarithm of the output *total income*, $\ln(x_{1i})$, $\ln(x_{2i})$, are the logarithm of the inputs *interest expense* and *non-interest expense*, respectively, followed by three variables which are the second order of the input variables and their interaction term. The Translog function provides a broader format to describe the relationship between the output and input levels than the Cobb-Douglas function because the output variable may be correlated with higher order input variables—a relationship not considered in a Cobb-Douglas function; Cobb-Douglas also makes the simplistic assumption that all production units have the same elasticities. v_i is the two-sided i.i.d. error term. u_i is the inefficiency term comprised of two parts where W_i is defined by the truncation of the normal distribution with zero mean and the variance of σ^2, and $z_i\delta$ is the mean of inefficiencies modeled as a linear function of the firm-specific factors.

Altogether, there are five variables in the inefficiency equation (including the foreign bank dummy variable) to explain bank inefficiencies by firm characteristics—discussed earlier under the heading of firm-specific factors. In summary, we expect to observe that the output production of total income can be explained by the input variables of *interest expense* and *non-interest expense* and their second order approximations. The inefficiency function allows us to test the association between inefficiencies and bank characteristics. While in the single-output Translog function the two outputs are aggregated into one output as *total income*, it is also possible to test the two-output case. Therefore, later in the chapter we explore the two-input two-output extended model which has greater dimensionality.

A distance function can handle the case of multiple outputs (see Coelli and Perelman 1999, 2000). The output distance function (Shephard 1970) is defined on the output set $P(x)$ as follows:

$$D_O(x, y) = \min\{\theta : (y/\theta) \in P(x)\} \tag{5.6}$$

where θ is the scalar distance, and $D_O(x, y)$ is non-decreasing, positively linearly homogenous and convex in y and decreasing in x (Lovell et al. 1994). The above output distance function can be represented in Translog form:

$$\begin{aligned} \ln D_{Oi} = \alpha_0 + \sum_{m=1}^{M}\alpha_m lny_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\alpha_{mn} lny_{mi} lny_{ni} + \sum_{k=1}^{K}\beta_k lnx_{ki} \\ + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M}\gamma_{km} lnx_{ki} lny_{mi} \end{aligned} \tag{5.7}$$

where $i = 1, 2, \ldots, N$, denotes bank-years in the data set. We choose the output of *interest income* as the Mth output, y_{Mi}, and derive the multiple-output Translog distance function for SFA:

$$\begin{aligned} -lny_{Mi} = \alpha_0 + \sum_{m=1}^{M-1}\alpha_m lny^*_{mi} + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1}\alpha_{mn} lny^*_{mi} lny^*_{ni} + \sum_{k=1}^{K}\beta_k lnx_{ki} \\ + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K}\beta_{kl} lnx_{ki} lnx_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M-1}\gamma_{km} lnx_{ki} lny^*_{mi} + v_i - u_i \end{aligned} \tag{5.8}$$

where $y^*_{mi} = y_{mi}/y_M, y^*_{ni} = y_{ni}/y_M$.

The SFA regression does not require specification of the direction of impact of firm-specific factors and these can be observed from the signs of the emerging parameters. Neither is it essential to assume a functional form although it is common practice. SFA enables hypothesis testing and estimation of standard errors using maximum-likelihood methods (Coelli et al. 1998). Similar to the studies by Jiang et al. (2009) and Deng et al. (2011) on Chinese bank efficiency, this study also relies on the one-step approach proposed in Battese and Coelli (1995) where non-negative technical inefficiencies are a function of firm-specific factors (contextual variables). Banker and Natarajan (2008) also consider appropriate for the parametric approach a one-step procedure that jointly estimates inefficiency and the impact of contextual variables; further support for the one-step procedure can be found in Wang and Schmidt (2002) who provide evidence based on Monte Carlo testing. Inefficiencies are independently distributed as truncations of normal distribution with constant variance but mean values that are a linear function of the observed variables. We use FRONTIER 4.1 (by Tim Coelli) to estimate the parameters of SFA regressions.

SFA efficiency estimates based on regression are not highly sensitive to large data changes—a potential advantage over DEA when substantial measurement errors are suspected. Fries and Taci (2005) claim SFA to be more appropriate in situations where measurement errors are more likely—such as transition economies. On the other hand, SFA may be inappropriate if the structural form assumed or the distributional assumptions made for random errors or inefficiencies are not representative of the organizations studied. For example, Luo and Donthu (2005) report that management prefer DEA and regard it as a more reliable frontier method.

In summary, DEA and SFA both have some key assumptions that may become the main weaknesses of these methods. That is, standard DEA assumes no measurement error, whereas SFA studies commonly assume a particular structure which may not be appropriate for the whole sample. Thus, this study compares and contrasts results from both methods in an analysis where an industry best-practice frontier is determined under each approach. We unfold the comparison in two stages where we initially use a single output (core model) but later move to a two-output benchmarking model (extended model)—assuming variable returns-to-scale in acknowledgement of the nature of the sample (see the next section for formal tests of scale inefficiency).

5.4 Results and Analysis

5.4.1 Testing for Scale Inefficiency Using DEA

In general, assuming variable-returns-to-scale would acknowledge the often different scale of operations anticipated among banks operating across China. A quick look at the minima and maxima in Table 5.2 suggests the presence of substantial differences in the scale of operations. Therefore, we explore this issue through the radial DEA formulations of CCR (Charnes et al. 1978) and BCC (Banker et al. 1984) which permit calculation—rather than inference—of scale inefficiencies, i.e. scale efficiency equals the ratio of CCR to BCC efficiency estimates. We compute rank correlations between output-oriented CCR and BCC estimates (two inputs and two outputs) and measure statistical differences. Spearman's rho 0.7340 between CCR and BCC estimates are significant at the 0.000 level. However, when we test for statistical differences between radial CCR and BCC efficiency estimates, Mann-Whitney *U* test rejects the null at the 0.000 significance level.

The above finding suggests there are significant differences between efficiency estimates that assume constant returns-to-scale vs. variable returns-to-scale, i.e. there is substantial scale inefficiency despite a statistically significant rank correlation. We quantify such differences by computing scale efficiencies. While the mean scale efficiency is reasonably high at 0.9029, there is a wide range of estimates (0.3350–1.0000) that are substantially skewed at −2.35. When we rank the bank-years on descending scale efficiency, we find that the last fourteen places are occupied by foreign banks with Société Générale (China) representing the bottom two bank-years (ranked results are available from the authors). The overall conclusion is one of substantial scale inefficiency at least in some of the banks, but to a greater extent with the foreign banks when mean scale efficiency estimates are compared across the two cohorts (domestic 0.9357 vs. foreign 0.8269). Thus, we conclude that using the variable returns-to-scale specification is better in order to rule out any impact of scale inefficiency in the overall analysis; this choice is also in line with Translog SFA (see last paragraph in Sect. 5.4.3.1), thus enabling a meaningful comparison between DEA and SFA.

5.4.2 Main DEA Results

5.4.2.1 Core Model (Single-Output BCC-O)

The analysis begins with the radial, output-oriented BCC which assumes variable returns-to-scale. In order to facilitate a more systematic comparison between DEA and SFA, we begin with a simple *core model* comprised of one output (total income) and two inputs (interest expense and non-interest expense). Instead of simply listing ranked 159 bank-years obtained from DEA, we provide a summary of the information extracted (the ranked list is available from the authors). Results indicate a wide range of efficiency estimates (0.4867–1.0000). Mean efficiency estimates (foreign 0.7900, domestic 0.8672) and mean ranks (foreign 95, domestic 72) point to a *less efficient* foreign bank cohort. Mann-Whitney *U* test for foreign versus domestic banks efficiency estimates rejects the null that the estimates come from the same distribution at the 0.004 level. The three most frequently referenced or emulated efficient bank-years by DEA algorithm in determining the relative efficiency estimates for others in the sample are: 77 times for Huishang Bank 2010 (domestic), 63 times for Bank International Ningbo 2008 (foreign) and 46 times for Bank of Beijing 2008 (domestic)—highlighting the dominance of domestic banks.

Next, following the example set by Banker and Natarajan (2008) and McDonald (2009), we report OLS regression of firm-specific factors on the core performance model DEA efficiency estimates, which suggests, all else the same, a 1 percentage point drop in the loan-to-deposit or cost-to-income ratios could lead to a 0.0708 percentage point and 0.2159 percentage point rise in overall bank efficiency significant at the 0.0459 and 0.0017 levels, respectively, where the residuals are distributed normally (Tobit regression results are very similar to OLS and available from the authors). These relationships are robust to various additional tests such as logging variables or removing outliers.[4]

An additional robustness test of the sample involves removing the five majority state-owned large banks from the data set of the core model (i.e. 15 bank-year data points) and checking the difference between the two cohorts' efficiency estimates. Mean efficiency estimates (foreign 0.7900, domestic 0.8676) are almost identical to those of the full sample—indicating little if any distortion caused by the large majority state-owned banks. Once again, Mann-Whitney *U* test on foreign versus domestic banks rejects the null that the estimates come from the same distribution at the 0.004 level for the core model. Similarly, when we regress firm-specific factors on efficiency estimates from the reduced sample, the same factors emerge as statistically significant in explaining efficiency with almost identical coefficients and significance levels (available from the authors).

5.4.2.2 Extended Model (Two-Output BCC-O)

The extended model takes advantage of two outputs (i.e. interest income and non-interest income that were summed to create total income under the core model), and the same two inputs. The extended model approach is designed to explore whether similar findings can be observed in the presence of increased dimensionality. Once again, results indicate a wide range of efficiency estimates (0.5444–1.0000). Mean efficiency estimates (foreign 0.8258, domestic 0.9156) and mean ranks (foreign 94, domestic 70) still point to a *less efficient* foreign bank cohort. Mann-Whitney *U* test rejects the null that the estimates come from the same distribution at the 0.002 level. The three most frequently emulated efficient bank-years are: 56 times for Nanchong City Commercial Bank 2010 (domestic), 55 times for Bank of Beijing 2009 (domestic) and 55 times for Bank of Jilin 2010 (domestic)—once again highlighting the dominant domestic banks where Bank of Beijing perseveres across both models. OLS regression of firm-specific factors on the extended model DEA efficiency estimates reveal similar results to that of the core model where a 1 percentage point drop in the loan-to-deposit or cost-to-income ratios could lead to a 13.5167 percentage points and 0.1168 percentage point rise in overall bank efficiency significant at the 0.0001 and 0.0498 levels, respectively (Tobit regression results are very similar to OLS and available from the authors). Once again, tests of robustness reveal that the above relationships hold after removal of outliers or logging of variables.

[4] SFA is even less sensitive to the presence of any outliers because it estimates the efficient frontier by fitting a regression line to the production possibilities set, rather than relying on extreme performers to define the frontier.

The additional robustness test of removing the five majority state-owned large banks from the data set results in mean estimates almost identical to those of the full sample. Mann-Whitney *U* test on foreign versus domestic banks rejects the null that the estimates come from the same distribution at the 0.006 level for the extended model. Regressing firm-specific factors on efficiency estimates shows the same factors as statistically significant in explaining efficiency with almost identical coefficients and significance levels (details available from the authors). In short, we have no reason to believe that including the majority state-owned banks in either the core or the extended model are distorting our main findings.

5.4.2.2.1 Overall Potential Improvements Identified by DEA Using the Extended Model

Figure 5.1 summarizes the overall potential improvements identified by DEA using the extended model, i.e. radial inefficiencies or under-produced outputs, as well as slacks or over-utilized inputs. In the full sample of 159 bank-years, most of the inefficiencies are embedded in non-interest income—which suggests that some banks are falling substantially behind their peers in generating income from less traditional banking activities. The second largest source of inefficiency is interest expense and this can be construed as a reflection of the regulated interest rates in China. The second pie-chart also identifies non-interest income, followed by interest expense, as the main sources of inefficiency among domestic banks. Finally, the third pie-chart points to interest income as the major source of inefficiency among foreign banks. This observation can be interpreted as an outcome of their limited branch networks and the general position of domestic banks across China as favored institutions, in particular, with regards to government or state related loans. As intuitively expected, compared to foreign banks the extent of inefficiencies embedded in interest expense is much greater with domestic banks because of their operations' emphasis on handling deposits.

In summary, the pie-charts indicate that the main source of inefficiency among the foreign banks is interest income, whereas the domestic banks appear to be mostly inefficient in managing their non-interest incomes and interest expenses. The inefficiencies seen with foreign banks are a reflection of limited access such institutions have to potential borrowers. At the same time, the inefficiency embedded in non-interest income of domestic banks highlights the potential for growth as such banks become more skilled in providing less traditional banking services. Similarly, as market deregulation unfolds at a steady pace, inefficiencies in interest expenses are also likely to lessen.

5.4.2.2.2 Assessing the Marginal Role of the Output Variables in DEA: Efficiency Contribution Measures (ECM) for the Extended Model

We implement the method outlined in Pastor et al. (2002) on the extended model using the full sample, i.e. N = 159. The approach calls for making an *inefficient*

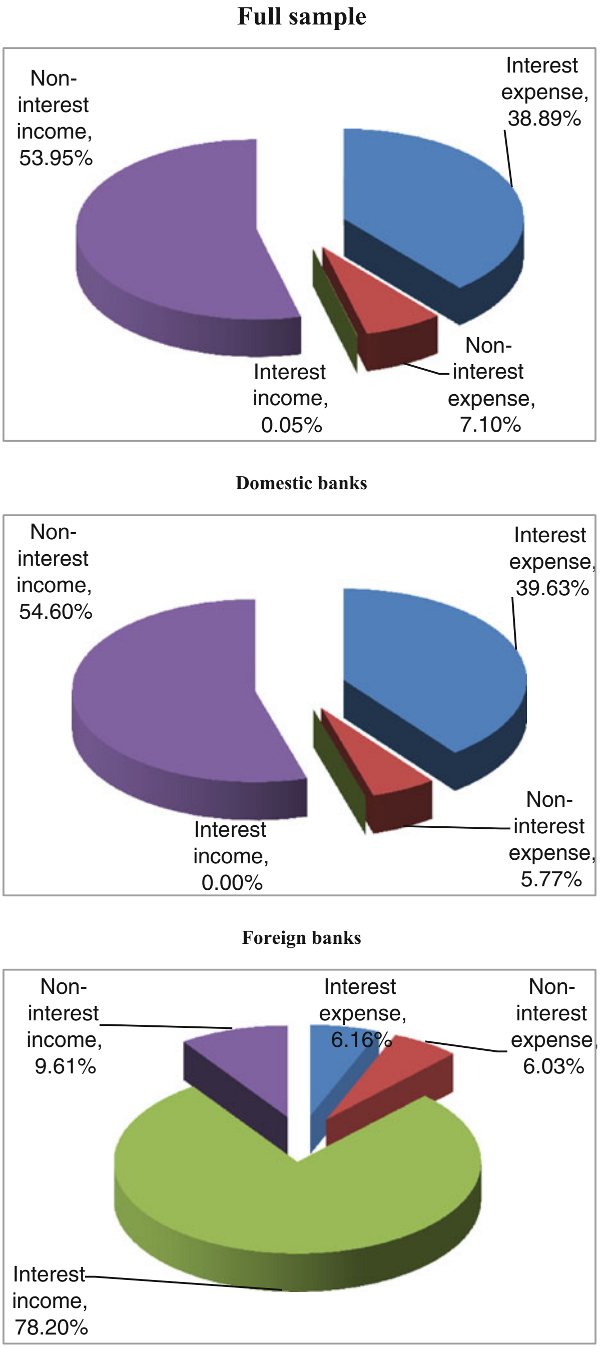

Fig. 5.1 Potential improvements identified by output-oriented DEA for the variables in the extended model with two outputs and two inputs

DMU *efficient* by increasing actual output levels to their projected levels determined by the efficient frontier, and re-running output-oriented DEA without the variable under scrutiny (i.e. the candidate). Calculation of ECM for each of the two candidates follows the steps outlined below:

1. The initial DEA with the full-complement of variables identifies the projected output levels for the inefficient DMUs.
2. Actual output levels for inefficient DMUs are replaced by projections, i.e. virtual DMUs are created.
3. DEA is repeated without the candidate output variable but in the presence of virtual DMUs.
4. The ratio of the efficiency estimate from the reduced model to the estimate from the original full-complement model yields ECM or ρ_o.
5. If $\rho_o = 1$, then the candidate has no marginal effect on the observed DMUs' efficiencies. Alternatively, if $\rho_o > 1$, then the candidate variable has some effect.

Pastor et al. (2002) develop a non-parametric statistical test to evaluate the significance of ECM. From the full set of ECM (ρ) values generated using the sample, a random sample of ρ values are drawn. If a candidate is not relevant, efficiency estimates are unlikely to be affected by its presence. This means corresponding random ρ values are also unlikely to be high. This idea is formalized by introducing two parameters, namely, $\bar{\rho}$ $(\bar{\rho} \succ 1)$ representing tolerance for changes in efficiency estimates due to the candidate, and $p_o(0 < p_o < 1)$ representing the proportion of units with efficiency changes that exceed the tolerance. Hence, the marginal impact of a candidate on efficiency estimates would be deemed statistically significant when $P[\Gamma \succ \bar{\rho}] \succ p_o$ where Γ is the random ρ. For example, if $p_o = 0.20$ and $\bar{\rho} = 1.15$, the above relationship would indicate the candidate as relevant if more than 20 % of the DMUs had associated efficiency change greater than 15 % when the variable is omitted. Using Monte Carlo experiments, Pastor et al. (2002) report that parameters of $p_o = 0.15$ and $\bar{\rho} = 1.1$ provide a good performance of the significance test. We adopt these parameters to evaluate the significance of ECM scores for candidate variables. Results indicate that when *interest income* is treated as the candidate, 3.77 % of the DMUs have ECM above 1.1. Alternatively, when *non-interest income* is the candidate, a significant 44.03 % (i.e. greater than 15 %) of the DMUs have ECM greater than 1.1, i.e. non-interest income plays a greater role in efficiency evaluation or discriminating between the DMUs. This finding ties in well with the insight previously gained from Figure 5.1 where the largest potential improvement (inefficiency) across the full sample was indicated for non-interest income.

5.4.3 SFA Results

5.4.3.1 Core Model (Single-Output Translog Function)

We start with the Translog function SFA and report the results in Table 5.3 using the dependent variable of *total income* (the logarithm of the sum of interest income

Table 5.3 SFA parameters for the core model with one output[a]

		Sample robustness test
	Translog function (N = 159) (5.1)	Translog function without large majority state-owned banks (N = 144) (5.2)
Dependent variable: Total income		
Production function[b]		
Intercept[c]	1.664***(0.000)	1.641***(0.000)
Interest expense	0.322***(0.000)	0.310***(0.000)
Non-interest expense	0.628***(0.000)	0.648***(0.000)
0.5 * Interest expense squared	0.129***(0.000)	0.126***(0.000)
0.5 * Non-interest expense squared	0.087*(0.047)	0.077(0.051)
Interest expense × Non-interest expense	−0.105**(0.004)	−0.099***(0.001)
Inefficiency function (firm-specific factors)		
Impaired loans-to-gross loans (asset quality)[d]	−0.211(0.179)	−0.232(0.189)
Interbank ratio (liquidity)	0.002*(0.019)	0.002**(0.01)
Loan-to-deposit ratio (regulation)	0.076**(0.004)	0.072*(0.038)
Cost-to-income ratio (overall efficiency)	0.535***(0.000)	0.534***(0.000)
Foreign bank dummy	0.116***(0.000)	0.115***(0.000)
Sigma-squared $(\sigma_u^2 + \sigma_v^2)$	0.005***(0.000)	0.005***(0.000)
Gamma $\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}\right)$	0.999***(0.000)	0.999***(0.000)
Log likelihood	199.649	179.678
LR test of the one-sided error	273.147	253.730
Mean efficiency estimate	0.7168	0.7113

[a]SFA model assumes a truncated normal distribution of inefficiencies. *P*-values are in parentheses
[b]All the variables take logarithm values in the production functions
[c]***Significant at 0.1 %; **significant at 1 %; *significant at 5 %
[d]Also known as the non-performing loans ratio (NPL)

and non-interest income). The Translog function is well-specified because all the input variables are highly significant. A positive relationship between the output variable and the first order of two input variables (the logarithm of *interest expense* and the logarithm of *non-interest expense*) suggests that total income rises with an increase in different expense components that are part of the intermediation process undertaken by banks. The second order approximation input variables are also shown to be significant (with one exception under robustness testing) and the magnitudes of the coefficient estimates are non-negligible which indicates the second order approximation is also significantly related to the output variable.

Next, we focus on the inefficiency function results detailed in column 1 of Table 5.3 and the statistically significant coefficients therein. The estimated coefficients in the inefficiency function reveal how firm-specific factors impact on bank technical efficiency. For example, the positive coefficient for cost-to-income ratio is consistent with the expectation that higher costs would be found in less efficient operations (a relationship already observed under the regression of firm-specific factors on DEA efficiency estimates). This is a highly anticipated finding and brings further confidence to the analysis because the cost-to-income ratio is the banking industry's standard overall efficiency ratio. A positive coefficient for interbank ratio (the liquidity measure) is also consistent with conventional wisdom. That is, a higher interbank ratio suggests that a bank having difficulty in converting deposits to commercial or consumer loans would lend to other banks in the wholesale market instead, thus enjoying narrower interest margins in the process. This reduction in margins manifests itself as inefficiency in generating income. Similarly, the positive loan-to-deposit ratio signals that regulation handicaps banks' ability to generate income as this ratio approaches the 75 % threshold (see Sect. 5.2.3). On the other hand, the positive and significant coefficient of the foreign bank dummy variable brings confidence to the overall finding already reported using DEA that foreign banks are less efficient than domestic banks.

Finally, the insignificant coefficient for the impaired loans-to-gross loans ratio indicates that non-performing loans in Chinese banking are well managed and do not impact on efficiencies in generating income. This is a reflection of the high-growth Chinese economy where authorities regard non-performing loans as an acceptable price to pay for growth; in fact, there is a thriving market where NPL are removed from bank books through purchases made by asset management companies originally established by government in 1999.

Other parameters reported include the gamma value, $\gamma = \frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}$, that is, the variance of the normal distribution scaled by the sum of the variance of the normal distribution and variance of the two-sided disturbance term. In theory, the gamma value can range between 0 and 1, where a higher value indicates inefficiencies playing a greater role in the total residual terms. The high gamma values (0.999) across both samples imply negligible noise; this insight also brings more confidence to DEA reported earlier as the presence of high levels of noise in data can potentially distort DEA efficiency estimates—highlighting how the two methods can complement each other. Coupled with mostly statistically significant production and inefficiency function variables, results indicate that the presence of inefficiency is non-negligible and dominate the variance of the total residual terms; therefore, the two-sided noise v_i has little impact on total variance. The null hypothesizing the absence of inefficiency is rejected at the 0.001 level of significance with a log likelihood ratio of 199.6 along with the high LR test of the one-sided error at 273.1. These observations indicate that the model is well specified and significant at the equation level.

Focusing on the efficiency estimates for all bank-years using the Translog function, once again, instead of listing the ranked 159 bank-years obtained from

SFA (core model), we summarize our key observations (the ranked list is available from the authors). Results indicate a wide range of efficiency estimates (0.1516–0.9706). Examining the two cohorts' mean efficiency estimates (foreign 0.5818, domestic 0.7752) and mean ranks (foreign 127, domestic 60) indicates that SFA also estimates the foreign bank cohort to be less efficient but in a more discriminating manner than DEA. Independent samples *t*-test and Mann-Whitney *U* test on foreign versus domestic bank efficiency estimates both reject the null that the estimates come from the same distribution at the 0.0001 level. The top performing three bank-years in the sample in descending order are all domestic banks represented by the Bank of Guangzhou (2008, 2010), and Huishan Bank (2010) and there is a very clear congregation of domestic bank-years in the top half of the sample sorted by descending SFA efficiency estimates. A comparison of SFA and DEA is offered in Sect. 5.4.4.

We continue by implementing the same sample robustness test previously undertaken with DEA. That is, we exclude the five majority state-owned large banks to see whether the results of our core SFA test will vary. We find that leaving out the 15 bank-years (five banks for three consecutive years) does not change the main results (see results in column two of Table 5.3). The input variables of interest expense and non-interest expense are still significantly positively correlated with the output variable of total income, foreign banks remain less efficient, and the associations originally observed in the inefficiency equation are retained.

We also test the Cobb-Douglas function first mentioned in Sect. 5.3.3. To determine which functional form fits the data better, other factors such as the dependent variable and firm-specific factors are kept the same. The Cobb-Douglas is a special case of the Translog function where all the coefficients of the second order terms are restricted to be 0, i.e. $\beta_3 = \beta_4 = \beta_5 = 0$ in (5.5). Hence, Cobb-Douglas imposes more stringent assumptions on data than the Translog function. In choosing between Cobb-Douglas and Translog specifications, such restrictions are tested using the likelihood ratio test (LR test) with the null hypothesis that Cobb-Douglas is nested in Translog. The null is strongly rejected at the level of 0.001 with the LR ratio of 141.94, thus adding another formal argument in favor of the Translog function first visited in paragraph 2 of Sect. 5.3.3.

In DEA, we have already established that the appropriate assumption on the elasticity of scale is variable returns-to-scale (VRS). In the spirit of ensuring DEA and SFA analyses are comparable, we need to establish that VRS also holds in SFA. Hence, the null hypothesis of constant returns-to-scale (CRS) in Translog SFA is tested. The returns-to-scale can be estimated as the sum of interest expense and non-interest expense coefficients (see Sect. 8.4 in Coelli et al. 2005). The assumption of CRS is equivalent to the null hypotheses that the first order coefficients add up to 1 and rows and columns of the matrix of the second order coefficients sum up to zero. In order to test the restrictions *jointly*, we employ the Wald test. The unreported results (available from the authors) show that the null hypothesis of CRS is strongly rejected at the level of 0.000 with the Chi(3)-square value of 424.72. Hence, we are confident that efficiency estimates from DEA and SFA are based on the same assumption of variable returns-to-scale.

5.4.3.2 Extended Model (Two-Output Translog Function)

Column 1 of Table 5.4 presents the two-output Translog function results on the full sample of 159 bank-years. Nine regressors of output and input items are used in the right hand side of the Translog function and their signs vary. Interpreting the coefficients of these regressors is difficult at best where inputs and outputs interact with each other; thus, normally emphasis is placed on efficiency estimates.

We next turn to the inefficiency function results in Table 5.4 with two outputs. The observed signs correspond to the findings using the single-output Translog function and results suggest the higher cost-to-income ratio is associated with less efficiency and foreign banks are less efficient than domestic banks. However, the other three firm-specific variables are shown to be unrelated to bank technical inefficiencies. We also test the robustness of the two-output model using a smaller sample of 144 bank-years in which the five large majority state-owned banks are removed. The sample robustness test results reported in column 2 of Table 5.4 are quantitatively similar to that of column 1 with the exception of an insignificant gamma. The gamma value is an important measure of the presence of inefficiencies and the robustness test suggests the component of inefficiency is now negligible in relation to the total residual terms—a most unlikely scenario given what we already know about the sample. The above observations suggest that the single-output Translog function provides a better fit for our data than the two-output model.

5.4.4 Comparing DEA and SFA Results

We now return to the primary motivation of this study. Theory points out that DEA efficiency estimates are expected to be greater than SFA efficiency estimates because DEA efficiency estimates are upwardly biased in comparison to the unobserved true efficiency estimates, in particular with small samples (Badin et al. 2014). On the other hand, SFA may provide more consistent estimates. Descriptive statistics in Table 5.5 on the full sample indicate that the mean and median DEA efficiency estimates are higher than SFA efficiency estimates. We run a series of statistical tests to further compare DEA efficiency estimates with those generated by SFA. For the core model, Spearman's *rho* 0.590 significant at the 0.01 level indicates that the correspondence of rankings between the two methods is moderate rather than high; for the extended model, the rank correlation is 0.538 also significant at the 0.01 level. These correlations compare favorably to the Spearman's *rho* of 0.480 (significant at the 0.10 level) reported by Luo et al. (2011) on a sample of Chinese commercial banks across 1999–2008. More importantly, Mann-Whitney *U* test rejects the null that the estimates come from the same distribution at the 0.05 level for both the core and extended models—highlighting the different distributions of efficiency estimates created by a non-parametric versus parametric efficient frontier method. In summary, DEA

Table 5.4 SFA parameters for the extended model with two outputs

		Sample robustness test
	Translog function (N = 159) (1)	Translog functionwithout large majority state-owned banks (N = 144) (2)
Dependent variable: Log(*Interest income*)		
Production function		
Intercept[a]	1.252*** (0.000)	1.318 ***(0.000)
Log(Non-interest income/Interest income)	0.125**(0.005)	0.120***(0.001)
Log(Interest expense)	−0.431** (0.000)	−0.381***(0.000)
Log(Non-interest expense)	−0.528*** (0.000)	−0.550***(0.000)
Log(Interest expense) * Log (Non-interest expense)	0.128**(0.004)	0.095*(0.024)
0.5Log(Interest expense) * Log (Non-interest income/Interest income)	−0.072* (0.036)	−0.060*(0.042)
0.5Log(Non-interest expense) * Log (Non-interest income/Interest income)	0.054(0.171)	0.046(0.169)
0.5Log(Interest expense) * Log(Inter-est expense)	−0.159*** (0.000)	−0.129***(0.000)
0.5Log(Non-interest expense) * Log (Non-interest expense)	−0.104(0.052)	−0.073(0.165)
0.5Log(Non-interest income) * Log (Non-interest income)	0.004(0.123)	0.005*(0.014)
Inefficiency function (firm-specific factors)		
Impaired loans-to-gross loans (asset quality)[b]	−0.082(0.633)	−0.179(0.236)
Interbank ratio (liquidity)	0.002(0.208)	0.002(0.062)
Loan-to-deposit ratio (regulation)	0.002(0.957)	0.005(0.906)
Cost-to-income ratio (overall efficiency)	0.511*** (0.000)	0.495***(0.000)
Foreign bank dummy	0.172*** (0.000)	0.181***(0.000)
Sigma-squared $(\sigma_u^2 + \sigma_v^2)$	0.006*** (0.000)	0.006***(0.000)
Gamma $\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}\right)$	0.999*** (0.000)	0.014 (0.997)
Log likelihood	183.265	165.891
Mean efficiency estimate	0.7475	0.7414

[a]***Significant at 0.1 %; **significant at 1 %; *significant at 5 %
[b]Also known as the non-performing loans ratio (NPL)

Table 5.5 Descriptive statistics on DEA and SFA efficiency estimates (N = 159)

	DEA, core model (single-output BCC-O)[a]	SFA, core model (single-output Translog function)	DEA, extended model (two-output BCC-O)	SFA, extended model (two-output Translog function)
Mean	0.8439	0.7168	0.8885	0.7475
Median	0.8520	0.7426	0.9129	0.7790
Standard deviation	0.1157	0.1275	0.1112	0.1382
Coefficient of variation[b]	0.1371	0.1779	0.1251	0.1849
Maximum	1.0000	0.9706	1.0000	0.9997
Minimum	0.4867	0.1516	0.5444	0.1692
Skewness	−0.6064	−0.9699	−1.0550	−0.7566
Kurtosis	−0.0055	2.2913	0.5435	1.2988
Number of efficient bank-years	17	n/a	29	n/a

[a]Core model has one output; extended model has two outputs. BCC-O; Banker, Charnes and Cooper radial DEA, output-oriented
[b]Ratio of standard deviation to mean

and SFA efficiency estimates that use Chinese data from 2008 to 2010 are statistically different.

Similarly, a visual examination of the distribution of bank-years across the unreported sample sorted on SFA efficiency estimates reveals a stronger congregation of foreign banks in the bottom half of the table compared to the DEA's sorted sample (available from the authors). In fact, under SFA the more efficient bank-years are almost entirely populated by domestic banks. The more noticeable congregation of domestic versus foreign banks in the sorted SFA sample suggests that SFA efficiency estimates are more discriminating. The non-parametric Kolmogorov-Smirnov test (K-S test) can also be used as a formal test to establish whether the efficiency estimates from SFA and DEA differ significantly. The null hypothesis of 'no difference' or 'same distribution' is rejected for efficiency estimates from both the single-output and two-output performance models at a *D-statistic* of 0.4717 (0.000) and 0.5157 (0.000), respectively; the K-S test also reports that the efficiency estimates are unlikely to be normally or log normally distributed.[5]

[5] The higher number of efficient bank-years under DEA with the extended model reflects the impact of greater dimensionality when a second output is introduced; the impact of increased dimensionality is equally easily discernible when core model means and medians are compared against those from the extended model (see Table 5.5). Clearly, there is a loss of discrimination as dimensionality rises for a given sample size – better known as the curse of dimensionality.

We extend the comparison by examining the bank-years common to the fourth (top 25 %) and first (bottom 25 %) quartiles across DEA and SFA with the aim of observing the degree of agreement between these methods at the two extremes when results are ranked (N = 159). Twenty-two of the forty bank-years found in the fourth quartile in the single-output Translog SFA are also found in DEA, and 24 are found in the first quartile—a rather poor correspondence confirming the distributional test reported earlier in this section. Similarly, 19 of the bank-years found in the fourth quartile in SFA based on the two-output Translog function are found in DEA, and 23 are found in the first quartile. A closer look at the membership of the top ten bank-years ranked in the single-output Translog SFA finds only four corresponding to those identified as efficient under DEA; the same approach yields a correspondence of five bank-years when the two-output Translog function results are compared to DEA—once again highlighting the distributional differences between parametric and non-nonparametric results.

The above observations highlight the risks involved in exclusively relying on DEA or SFA for ranking purposes. Does the researcher have to favor one method over the other? The answer can be found in time-series forecasting literature which suggests that a single set of efficiency estimates can be constructed by taking the geometric means of the estimates to emerge from DEA and SFA (Coelli and Perelman 1999). It has been argued that taking simple average of estimates from multiple methods can reduce bias by averaging out individual biases (Palm and Zellner 1992).

5.5 Concluding Remarks

The primary motivation of this study is to compare and contrast the popular DEA and SFA methods in a bank benchmarking exercise and explore the possibility of using these rival methods in a complementary manner. This motivation is actioned in the context of how foreign banks in China perform when compared against domestic banks.

It is worth summarizing the complementarity between DEA and SFA. In particular, when the non-parametric and parametric methods lead to the same key findings as seen in this chapter, researchers can rely on DEA to identify the main potential improvements (see Fig. 5.1), while SFA can be relied upon to directly explain the role of firm-specific factors on inefficiency (see Table 5.3). On the other hand, when DEA and SFA produce significantly different rankings, then the researcher may consider other ranking approaches, e.g. constructing geometric means based on efficiency estimates from DEA and SFA before ranking. In situations where measurement error cannot be reliably assessed, SFA can act as a test of robustness for DEA. Similarly, when the functional structure assumed by SFA may not apply equally across the sample, DEA can become the test of robustness for SFA. Interestingly, sample robustness testing suggests that the presence of large majority state-owned commercial banks do not distort the main findings. Furthermore, at least in the case of Chinese banking data, the single-output

Translog function estimated by SFA is a better fitting functional specification than the Cobb-Douglas or the two-output Translog functions.

According to DEA, in general, foreign banks are less efficient than domestic banks. A break-down of the sources of inefficiency in the modeled performance variables point to management of interest income among the foreign banks as a key area for potential improvement, whereas the domestic banks appear to suffer mainly from inefficiencies in managing non-interest income and interest expense. The inefficiencies identified in this study with foreign bank operations can be construed as a consequence of limited access they have to potential depositors and borrowers. Similarly, the inefficiency found in generation of non-interest income by domestic banks points to the potential for expansion as domestic banks become more adept in less traditional banking services. These are intuitive findings based on what we know about Chinese bank regulation and well-accepted strengths and weaknesses of foreign versus domestic bank operations.

SFA reports similar yet more discriminating results to that of DEA regarding the less efficient foreign banks. Parameters of the inefficiency function in SFA reveal mostly anticipated relationships. For example, the liquidity measure, regulation measure, and the industry ratio for overall efficiency show a significant but negative impact on total income. Overall, results point to the use of parsimonious benchmarking models and a Translog function as appropriate choices for discriminating among performance of banks.

DEA and SFA efficiency estimates based on the study's performance modeling are significantly correlated but they do not belong to the same distribution. Overall, the intuitive findings from these methods from opposing camps indicate that efficiency estimates are not simply manifestations of specific assumptions that underlie DEA or SFA, thus bringing confidence to using either method or both in benchmarking bank performance. That is, similar to the conclusion reached by Weill (2004) for European banking, we also conclude that neither method can be categorically identified as the most suitable for Chinese banking.

The two methods illustrated in this study can be used by regulators for checking against in-house performance evaluation systems and identifying those banks that may need closer scrutiny. For regulatory purposes, the comparison of the two efficient frontier techniques can be further expanded by following the six consistency conditions identified by Bauer et al. (1998). Revealed potential improvements can also be used by bank management who may be interested in developing a better understanding of their weaknesses and strengths against their industry peers. Other compelling reasons to undertake multivariate benchmarking can be found within the framework of Basel III expected to be fully implemented by 2019. Given the greater awareness of the interconnectedness of the global financial system since the global financial crisis of 2007–2009, comparisons with peers are likely to be more important than simply mechanically checking a list of regulatory boxes for a given institution. For example, two ratios proposed within the Basel III framework, namely, the 30-day liquidity coverage ratio (LCR), and the net stable funding ratio (NSFR), deserve special attention and can be included in future benchmarking exercises when data become available.

Acknowledgements We wish to extend our sincere thanks to Chris O'Donnell and Valentin Zelenyuk for their guidance on SFA, Mette Asmild for general comments, Keay-shen See for his unwavering assistance in data collection (others include Jay Shen, Danielle Chang and Jimmy Leung), and Martin Cvelbar for his prompt service on all matters related to the use of library services. We also appreciate the pre-submission critical reading of the chapter by Tom Smith, Terry Walter, Barry Oliver and Ghon Rhee, as well as the suggestions made by the workshop participants at the Griffith University and the World Finance Conference.

References

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function 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*, 260–273.

Asmild, M., & Matthews, K. (2012). Multi-directional efficiency analysis of efficiency patterns in Chinese banks 1997–2008. *European Journal of Operational Research, 219*, 434–441.

Avkiran, N. K. (2009). Removing the impact of environment with units-invariant efficient frontier analysis: An illustrative case study with intertemporal panel data. *Omega—International Journal of Management Science, 37*, 535–544.

Avkiran, N. K. (2011). Association of DEA super-efficiency estimates with financial ratios: Investigating the case for Chinese banks. *Omega—International Journal of Management Science, 39*, 323–334.

Avkiran, N. K., & Morita, H. (2010). Benchmarking firm performance from a multiple-stakeholder perspective with an application to Chinese banking. *Omega—International Journal of Management Science, 38*, 501–508.

Badin, L., Daraio, C., & Simar, L. (2014). Explaining inefficiency in nonparametric production models: The state of the art. *Annals of Operations Research, 214*, 5–30.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1078–1092.

Banker, R. D., & Natarajan, R. (2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations Research, 56*(1), 48–58.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*, 325–332.

Bauer, P. W., Berger, A. N., Ferrier, G. D., & Humphrey, D. B. (1998). Consistency conditions for regulatory analysis of financial institutions: A comparison of frontier efficiency methods. *Journal of Economics and Business, 50*, 85–114.

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

Bhattacharyya, A., Lovell, C. A. K., & Sahay, P. (1997). The impact of liberalization on the productive efficiency of Indian commercial banks. *European Journal of Operational Research, 98*, 332–345.

Brockett, P. L., Charnes, A., Cooper, W. W., Huang, Z. M., & Sun, D. B. (1997). Data transformations in DEA cone ratio envelopment approaches for monitoring bank performances. *European Journal of Operational Research, 98*, 250–268.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*, 429–444.

Charnes, A., Cooper, W. W., & Rhodes, E. (1981). Evaluating program and managerial efficiency—An application of data envelopment analysis to program follow through. *Management Science, 27*, 668–697.

Chen, X. G., Skully, M., & Brown, K. (2005). Banking efficiency in China: Application of DEA to pre- and post-deregulation eras: 1993–2000. *China Economic Review, 16*, 229–245.

China Banking Regulatory Commission. (2006). *Regulations of the People's Republic of China on Administration of Foreign-funded Banks*. Retrieved from http://www.cbrc.gov.cn/EngdocView.do?docID=20080116D0F770B46656D8DAFF4313B4992E4E00

Chortareas, G. E., Girardone, C., & Ventouri, A. (2013). Financial freedom and bank efficiency: Evidence from the European Union. *Journal of Banking & Finance, 37*, 1223–1231.

Coelli, T., & Perelman, S. (1999). A comparison of parametric and non-parametric distance functions: With application to European railways. *European Journal of Operational Research, 117*(2), 326–339.

Coelli, T., & Perelman, S. (2000). Technical efficiency of European railways: A distance function approach. *Applied Economics, 32*, 1967–1976.

Coelli, T. J., Prasada, R. D. S., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). New York: Springer.

Coelli, T. J., Prasada, R. D. S., & Battese, G. E. (1998). *An introduction to efficiency and productivity analysis*. Boston: Kluwer Academic Publishers.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-Solver software* (2nd ed.). New York: Springer.

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). *Handbook on data envelopment analysis* (2nd ed.). Norwell, MA: Kluwer Academic Publishers.

Deng, Z., Guo, H., & Kong, G. (2011). Efficiency spillovers of foreign direct investment in the Chinese banking system. *Global Economic Review, 40*, 179–191.

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

Fries, S., & Taci, A. (2005). Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. *Journal of Banking & Finance, 29*, 55–81.

Fu, X., & Heffernan, S. (2007). Cost X-efficiency in China's banking sector. *China Economic Review, 18*, 35–53.

Gelade, G., & Gilbert, P. (2003). Work climate and organizational effectiveness: The application of data envelopment analysis in organizational research. *Organizational Research Methods, 6*, 482–501.

Greene, W. H. (2012). *Econometric analysis*. Boston: Prentice Hall.

Grosskopf, S. (1996). Statistical inference and nonparametric efficiency: A selective survey. *Journal of Productivity Analysis, 7*, 161–176.

Hasan, I., & Marton, K. (2003). Development and efficiency of the banking sector in a transitional economy: Hungarian experience. *Journal of Banking & Finance, 27*, 2249–2271.

Hu, J.-L., Su, Y.-Y., & Chen, C.-P. (2008). Efficiency of nationwide banks in China. *The Journal of American Academy of Business, 13*(2), 84–90.

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

Klein, L. R. (1953). *A textbook of econometrics*. New York: Row Peterson.

Leightner, J. E., & Lovell, C. A. K. (1998). The impact of financial liberalization on the performance of Thai banks. *Journal of Economics and Business, 50*, 115–131.

Lensink, R., Meesters, A., & Naaborg, I. (2008). Bank efficiency and foreign ownership: Do good institutions matter? *Journal of Banking & Finance, 32*, 834–844.

Lin, H. D. (2011). Foreign bank entry and firms' access to bank credit: Evidence from China. *Journal of Banking & Finance, 35*, 1000–1010.

Lovell, C. A. K., Richardson, S., Travers, P., & Wood, L. L. (1994). Resources and functioning: A new view of inequality in Australia. In W. Eichhorn (Ed.), *Models and measurement of welfare and inequality*. Berlin: Springer.

Luo, X. M., & Donthu, N. (2005). Assessing advertising media spending inefficiencies in generating sales. *Journal of Business Research, 58*, 28–36.

Luo, D., Yao, S. J., Chen, J., & Wang, J. L. (2011). World financial crisis and efficiency of Chinese commercial banks. *The World Economy, 34*, 805–825.

McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses. *European Journal of Operational Research, 197*, 792–798.

Meeusen, W., & van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18*, 435–445.

Miller, S. M., & Noulas, A. G. (1996). The technical efficiency of large bank production. *Journal of Banking & Finance, 20*, 495–509.

Palm, F. C., & Zellner, A. (1992). To combine or not to combine? Issues of combining forecasts. *Journal of Forecasting, 11*, 687–701.

Pastor, J. T., Ruiz, J. L., & Sivent, I. (2002). A statistical test for nested radial DEA models. *Operations Research, 50*(4), 728–735.

PricewaterhouseCoopers. (2012). Foreign banks in China.

Shephard, R. W. (1970). *Theory of cost and production functions*. Princeton: Princeton University Press.

Simar, L., & Wilson, P. W. (2011). Two-stage DEA: Caveat emptor. *Journal of Productivity Analysis, 36*, 205–218.

Sturm, J. E., & Williams, B. (2004). Foreign bank entry, deregulation and bank efficiency: Lessons from the Australian experience. *Journal of Banking & Finance, 28*, 1775–1799.

Wang, H. J., & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis, 18*, 129–144.

Weill, L. (2004). Measuring cost efficiency in European banking: A comparison of frontier techniques. *Journal of Productivity Analysis, 21*, 133–152.

Xu, Y. (2011). Towards a more accurate measure of foreign bank entry and its impact on domestic banking performance: The case of China. *Journal of Banking & Finance, 35*, 886–901.

Yao, S. J., Han, Z. W., & Feng, G. F. (2008). Ownership reform, foreign competition and efficiency of Chinese Commercial Banks: A non-parametric approach. *The World Economy, 31*, 1310–1326.