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Association of DEA super-efficiency estimates with financial ratios: Investigating the case for Chinese banks

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ABSTRACT

The great majority of applications of the popular frontier technique data envelopment analysis (DEA) do not test for the association of efficiency estimates with key performance indicators used by industry observers. Nevertheless, identifying efficiency estimates' associations with commonly accepted financial measures of performance could guide benchmarking activities, pricing decisions, and regulatory monitoring. Thus, the current paper investigates to what extent bank DEA super-efficiency estimates are associated with key financial ratios. A low correlation may present an opportunity to address inefficiencies that were not obvious in financial ratio analysis, thus enabling an update of inferences drawn from ratios. Regressing ratios on efficiency estimates may also help predict financial ratios. Where an input–output specification is comprised of key financial ratios, DEA can also be used to objectively identify benchmarks for ratio analysis based on actual observed data collected from peers. Nine super-efficiency DEA formulations across two profitability models are systematically tested. The slacks-based measure of DEA with a parsimonious profitability efficiency model emerges as the most significant combination explaining the variation in the two industry ratios, *post-tax profit/average total assets* and *return on average equity*.

1. Introduction

According to Ahmad et al. [1, p. 8], "The most commonly used indicators of bank performance or efficiency are the accounting ratios and efficiency scores obtained from various frontier efficiency approaches". Some of the earliest applications of data envelopment analysis (DEA), arguably the most widely used frontier efficiency technique first popularized by Charnes et al. [2], are in the banking sector (e.g., see [3–5]). According to the Web of Science database,[1] there are more than one-hundred and seventy articles that combine DEA and banking. As a result, DEA is a well-established relative efficiency analysis technique in banking. Yet, the great majority of applications of DEA in banking literature do not test for the association of computed efficiency estimates with key performance indicators widely used by industry observers. The current paper investigates to what extent estimates from bank efficiency models, that is, from a selection of input–output specifications based on recent literature are associated with key performance indicators such as financial ratios when tested through various DEA formulations. While efficiency analyses can be used together with key performance indicators in a complementary manner [6], to the best of the author's knowledge, no one has *systematically* tested the association between efficiency and key financial ratios.[2]

Insights gained from the current study can bridge efficiency and financial ratio analyses of bank performance, where various industry observers including regulators are more familiar with ratios, thus better informing decision-makers and future researchers alike. For example, a low correlation may present an opportunity to address production inefficiencies that were not obvious in financial ratio analysis, thus enabling an update of inferences drawn from ratios. Significant regression coefficients may also help predict financial ratios through efficiency estimates. Equally important, where an input–output specification in DEA is based on key financial ratios, such an analysis can be used to objectively identify benchmarks for ratios based on actual observed data collected from peers. Benchmarks thus identified can contribute to within-industry ratio analysis.

The empirical analysis in the current study focuses on China, where the Chinese banking sector is a newcomer to the field of DEA publications. Notwithstanding Chinese journals, there are only a handful of DEA studies based on Chinese banks published in

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[1] http://thomsonreuters.com/products_services/science/science_products/scholarly_research_analysis/research_discovery/web_of_science

[2] Elyasiani et al. [22] report a limited study using only one input–output specification and price data.

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international journals (see [7–11]). Furthermore, as a result of the ongoing deregulation which gained momentum since China joined the World Trade Organization in 2001, Chinese banks are currently offering a wider range of products and services.[3] There is also a substantial effort by foreign banks locally incorporating, as well as major domestic banks listing on stock exchanges. As a result, the ongoing liberalization of the Chinese banking sector is attracting the interest of researchers in what may well be recorded in history as the main economy to have led the world out of the recent global financial crisis (GFC). According to Laurenceson and Qin [10, p. 59], "The need for China's banks to improve their efficiency is mounting now that they are operating in an increasingly competitive and liberalized banking environment."

Therefore, this is a particularly appropriate point in time to pause and critically reflect on existing multivariate relative efficiency modeling that uses the popular frontier technique of DEA. As Chinese banks come under increasing scrutiny by the international banking and investment community, as well as their domestic capital markets, identifying efficiency estimates' associations with commonly accepted financial measures of performance could guide benchmarking activities, pricing decisions and regulatory monitoring. Findings of the current study indicate mostly low correlations, suggesting an inadequacy in ratios' ability to represent multivariate production inefficiencies. Nevertheless, the ratios of *post-tax profits to average total assets* and *return on average equity* are significantly associated with efficiency estimates, where the former ratio has the stronger relationship. Findings also indicate poor credit quality with Chinese banks. The non-radial DEA formulation that has gained popularity in recent times, namely, super-efficiency slacks-based measure, dominates all other formulations in terms of generating estimates that are correlated with ratios. The paper also illustrates how DEA can be used to address the long-recognized problem of objectively selecting financial ratio benchmarks.

The remainder of the paper is organized as follows. Section 2 begins with an introduction to DEA, followed by an exposition of the conceptual framework built around the paper's motivation and anticipated associations between ratios and relative profit efficiency. Methodology is detailed in Section 3 with explanations of input–output specifications and data used. Section 4 discusses the findings from various empirical tests, while Section 5 offers some concluding remarks.

2. Conceptual framework

2.1. Data envelopment analysis (DEA)

DEA is an efficient frontier technique that computes a comparative ratio of weighted outputs to weighted inputs for each decision-making unit (DMU) using linear programming. The linear program scales the relative efficiency estimate between 0 and 1, thus enabling easy comparison, where 1 represents an efficient operation relative to others in the sample, and a DMU with a score less than 1 is defined as inefficient. At the heart of this concept lies the condition of Pareto optimality for efficient production. Pareto optimality states that a DMU is not efficient if it is possible to raise an output without raising any of the inputs and without lowering any other output; similarly, a DMU is not efficient if it is possible to lower an input without decreasing any of the outputs and without increasing any other input [12].

In linear programs without weight restrictions, a DMU has complete freedom to select weights that are most favorable for its assessment, thus maximizing its efficiency score. Under input-orientation, the objective is to estimate how much the inputs can fall while maintaining existing levels of outputs. Alternatively, under output-orientation, the objective is to expand outputs for given levels of inputs. Basic principles of DEA formulation dictate that for any input, the reference unit must consume proportionately no more of the resource than does the unit under consideration. Similarly, for any output, the reference unit must produce no less than the unit evaluated.

DEA's ability to capture the interaction among multiple inputs and multiple outputs in a scalar value, that is, in a single number, is its distinct advantage over traditional ratio analysis. DEA also has the advantage of not assuming a particular distribution for data. That is, DEA does not pre-specify a production technology. The importance of the latter is that a DMU's efficiency is based on actual observed performance within the sample. The key limitation of DEA is the assumption of data being free of measurement error. Thus, DEA is more sensitive to the presence of measurement error than parametric techniques. The reader not familiar with DEA can refer to Cooper et al. [13] for a more in-depth exposition. Avkiran and Rowlands [14] provide a comparison of DEA against its main parametric counterpart, stochastic frontier analysis, and show how to address measurement error if its presence is suspected.

Traditional DEA suffers from tied ranks because the efficient DMUs in a sample share the same score of 1. Where the sample size is small, discrimination can become problematic. Andersen and Peterson [15] solved this problem under the name of super-efficiency, where their approach removes censoring of scores above 1. That is, the researcher is able to distinguish among the efficient units in the sample and rank them. While in some cases it is possible to encounter identical super-efficiency scores, a separate stream of DEA literature has addressed this under the heading of *infeasibility* (see [16], and the relevant literature therein). Super-efficiency also helps in generating more meaningful correlations and measures of central tendency in an empirical application with multiple efficient units where such units would otherwise share the same score of 1. The current study uses a set of super-efficiency DEA formulations as part of systematically testing for associations between efficiency estimates and financial ratios.

All else the same, the author's preferred DEA formulation among widely available and accepted formulations is variable returns-to-scale, non-oriented, non-radial super-efficiency slacks-based measure (see SBM by Tone [17,18]). In literature reporting DEA applications, SBM has slowly become the preferred non-radial model in the first decade of the twenty-first century. Assuming variable-returns-to-scale acknowledges the often different scale of operations found in business units and permits translation invariance. The choice of non-orientation and non-radial modeling further enhances the relevance of frontier efficiency studies to the world of business. For example, non-orientation ensures the analysis simultaneously captures slacks on the cost and revenue sides of the profitability equation as the linear program minimizes inputs (such as expenses), and maximizes outputs (such as revenues). Similarly, use of non-radial modeling acknowledges the generally non-proportional nature of slacks in organizations where production relationships call for different proportions of reduction in inputs and rise in outputs.

2.2. To associate or not to associate?

DEA studies that neglect an exploration of associations between efficiency and financial ratios do so for a number of

[3] Ironically, the historically slow adoption in China of sophisticated investment securities, such as collateralized debt obligations, insulated Chinese banks from the full impact of the recent global financial crisis.

reasons. One reason is the common motivation for undertaking DEA, namely, DEA's ability to simultaneously capture the interactions among multiple inputs and multiple outputs. That is, DEA takes a broader view of performance measurement and this is considered its distinct advantage over traditional ratio analysis which normally relies on two variables in a ratio. Yeh [19, p. 980] succinctly explains the principal shortcomings of traditional ratio analysis as, "…each single ratio must be compared with a benchmark ratio one at a time while one assumes that other factors are fixed and the benchmarks chosen are suitable for comparison."

Application of DEA in banking normally starts with a bank behavior model used to conceptualize the production possibilities, such as the production, intermediation and value-added approaches,[4] thus enabling managerial insight to potential operational or financial improvements. On the other hand, focusing solely on individual key performance indicators can limit inferences that can be drawn, or it can bias the analysis because of a missing multi-dimensional perspective required to capture the complex operations of modern corporations. Hence, most DEA studies do not concern themselves with ratio analysis which they regard as less sophisticated. Nevertheless, many market analysts continue to use financial ratios grouped under various categories such as strength and soundness, credit quality, profitability, etc., to price assets or to make investment recommendations (see [20]). Regulators also use financial ratios to monitor the performance of banks.

Another argument for not testing associations makes the point that firms that appear profitable in their peer group are not necessarily efficient in applying resources to generate various outputs. That is, DEA may identify resource inefficiencies that are preventing a firm from reaching its full profit potential, whereas financial ratios on profitability may indicate the same firm to be a high performer against a subjectively chosen industry benchmark. According to Sherman and Zhu [21, p. 302], "…studies of benchmarking practices with DEA have identified numerous sources of inefficiency in some of the most profitable firms…" The few researchers who have tested for the correlation between bank profitability and DEA scores sometimes report insignificant correlations (see [21,10]),[5] and at other times report significant correlations (see [22,23]). Thus, the nature of this association, that is, its direction, magnitude and statistical significance, cannot be taken for granted, and there is a need to explore the association of relative efficiency with different categories of financial ratios in an effort to bridge the gap between academia and business world.

In summary, despite the above-discussed reasons why DEA researchers may overlook an investigation of the association between efficiency and ratio analysis, the latter remains popular with industry observers. Therefore, this paper maintains that there is value in exploring the nature of such associations. Where the association is weak, a preliminary implication is a potential to rid the bank of production inefficiencies and re-interpret financial ratios. Similarly, where the association is strong, efficiency estimates can be used to predict the much sought after financial ratios (see [24]). In the current study, the author anticipates discovering varying efficiency estimates when different input–output specifications and mathematical models are applied to Chinese banking data.

2.3. Financial ratios and anticipated associations with estimates of relative profitability efficiency

Profitability efficiency measured in the current study uses an approach where inputs represented by expenses are minimized and outputs represented by revenues are maximized (variables are detailed in Section 3.1). Table 1 shows a selection of key financial ratios widely accepted in the finance sector and adopted for the current study from a recent publication by Avkiran and Morita [25]. Anticipated signs of the associations with profitability efficiency are indicated in the second column. For example, a higher capital adequacy ratio (CAR) often leads to lower financial risk, and thus, lower borrowing costs for a bank (i.e., helps control the cost side of the profitability equation). Therefore, all else the same, a positive association is expected between relative profitability efficiency and CAR. It is more difficult to predict a sign of association for growth rate of assets (GRA) since this would depend on the mix of assets as well as pricing, although a positive association is likely assuming a bank's asset liability management is handled competently. Anticipated associations for the rest of the financial ratios are self-explanatory with regard to profitability efficiency.

The last column in Table 1 designates each financial ratio as either a potential input or an output depending on the degree of direct managerial control and its position in the production process. For example, CAR ratio is often a target set by board of directors in response to regulatory requirements and organizational risk tolerance (i.e., partly discretionary and critical to how safe a bank will be perceived). Remembering the earlier argument that a greater CAR ratio would normally be considered desirable as it lowers borrowing costs, the reciprocal of CAR is proposed as a potential input variable in bank relative efficiency modeling. Translation to a reciprocal acknowledges that DEA's linear program minimizes inputs.[6] Designating CAR as a potential input recognizes the flow-on effect this key soundness ratio would have in a bank's operations.

Similarly, growth rate of assets (GRA) and dividends per share (DPS) are also designated as potential inputs that are likely to enhance profitability efficiency (thus, the use of reciprocals). GRA (not only loans but fixed assets as well) is an important input that empowers the rest of the bank to enhance financial outcomes such as profits. DPS is also a key input to how profitable a bank's investors would consider its operations because dividends enter share price calculations. On the other hand, the credit quality ratios (and, in particular, the impaired loans therein) are the result of risk management decisions taken by the organization at various levels, and thus, are also designated as inputs. The remaining key financial ratios, that is, GREPS, ROAE, PTP/ATA, IM and PE in Table 1, are normally *outcomes* of a series of complex decisions on such matters as appetite for risk, targeted markets, pricing, asset mix, efficient utilization of organizational resources, and perceived quality of management. This approach to designating inputs and outputs leads to a balanced specification with six inputs and five outputs which can help identify financial ratio benchmarks using DEA for a peer group such as Chinese commercial banks. Nevertheless, the last column in Table 1 ought to be considered as illustrative rather than definitive in designating ratios as either an input or an output.

[4] See Avkiran [48] for a more detailed discussion of bank behavior models.

[5] Glawischnig and Sommersguter-Reichmann [49] find a low correspondence between rankings of alternative investments based on DEA and the modified Sharpe ratio. Similarly, Thanassoulis et al. [6] report very low but positive correlations between rankings based on DEA and performance indicators on perinatal care.

[6] As kindly pointed out by one of the reviewers, use of the reciprocal of CAR as an input variable means that, in the unlikely case of a bank funded wholly by equity, that bank is likely to appear as being very economical in use of this input and would also get a boost to the output ratio of net interest income to average total assets, thus appearing efficient. In the current sample, there is no evidence to support the concern about the use of the reciprocal of CAR because when it is omitted, the efficient frontier remains stable (results available upon request).

Table 1
Key financial ratios and anticipated associations with relative profit efficiency.

Key financial ratios[a]	Anticipated association with profit efficiency (±)	Potential input (*I*) or output (*O*)
Strength and soundness: total capital ratio (i.e., capital adequacy ratio or CAR)	+	*I* (*reciprocal*)
Growth: growth rate of assets (GRA)[b]	+	*I* (*reciprocal*)
Growth: growth rate of earnings per share (GREPS)[c]	+	*O*
Credit quality: impaired loans/net interest income (ILNII)	−	*I*
Credit quality: impaired loans/total assets (ILTA)	−	*I*
Credit quality: impaired loans/equity (ILE)	−	*I*
Profitability: return on average equity (ROAE)	+	*O*
Profitability: post-tax profit/average total assets (PTP/ATA)	+	*O*
Profitability: net interest income/average total assets (i.e., interest margin or IM)	+	*O*
Valuation: dividends per share (DPS)	+	*I* (*reciprocal*)
Valuation: price/earnings ratio as average of high and low (i.e., price to earnings ratio or PE)	+	*O*

The broken horizontal lines indicate groupings of ratios.

[a] Whenever appropriate, terminology reflects that used in the database OSIRIS by Bureau van Dijk Electronic Publishing.
[b] Total assets at the end of current period over total assets at the end of previous period.
[c] EPS current period over EPS previous period.

2.4. *Overview of the relevant literature on banking applications of DEA*

Beginning with papers on Chinese banking published in international journals, the author identifies those that illustrate an application of DEA in bank performance measurement. This is followed by a wider database search in Web of Science with the following terms: "data envelopment analysis" AND "bank" (excluding conference proceedings). The search then focuses on the recent articles that report major applications of DEA and appear in the top two tiers *A** and *A* as defined by the Australian Business Deans Council (ABDC) journal rankings.[7] Methodology papers with limited numerical examples designed to demonstrate mathematical relationships rather than draw economic inferences are not of interest in the current paper. Similarly, studies that focus on a single component of banking such as online banking, or studies that report bank branch performance are also omitted.

Table A1 in the appendix summarizes thirteen papers that fit the above search criteria. These papers span Australia, China, Japan, India, Malaysia, New Zealand, Poland and the USA across 2004–2009. All the selected studies from outside China have input–output specifications based on the *intermediation approach* to bank behavior (also known as the asset approach after Sealey and Lindley [26]). However, the input–output specifications in the studies on Chinese banks are more difficult to clearly fit under any of the traditional bank behavior models. In terms of DEA mathematical modeling, technical efficiency using BCC dominates Table A1 despite the age of BCC and the recent period studied in the current paper.[8] The apparent preference for input-oriented BCC in extant literature identified in the current paper can be partly explained by translation invariance afforded to outputs (which may sometimes be negative numbers), and partly explained by the easy availability of BCC in free DEA software. Measures of non-radial inefficiencies are captured by SBM and RAM (range-adjusted measure), with the former emerging as the more popular approach in this category. Similarly, the traditional orientation of input minimization appears to be the preferred choice of modeling relative efficiency, although output maximization and non-oriented modeling are also represented in Table A1. Regarding association of efficiency with financial ratios, the majority do not report such tests, with the exception of Laurenceson and Qin [10] who find insignificant associations, and Sathye [23] and Havrylchyk [27] who report significant associations.

[7] http://www.abdc.edu.au/3.36.0.0.1.0.htm.
[8] BCC: Banker, Charnes and Cooper [50] on measurement of radial inefficiencies assuming variable returns-to-scale.

3. Methodology

3.1. *Determining input–output specifications*

In Table A1, there is no clear agreement amongst the selection of inputs and outputs beyond the general observance of the intermediation approach to bank behavior. Taking this observation on board, the current study adopts a popular interpretation of the intermediation approach, where a technical efficiency approach is followed with the motivation of capturing how successful a bank is in maximizing its profitability. The minimized inputs are, *interest expense* and *non-interest expense*, and the maximized outputs are *interest income* and *non-interest income*. These variables measure a bank's profitability efficiency because they are costs and revenues as per profit and loss statement. Others who have used these variables include Miller and Noulas [28], Bhattacharyya et al. [29], Brockett et al. [30], Leightner and Lovell [31], Avkiran [32,33], Sturm and Williams [34], Avkiran [35], and Avkiran and Thoraneenitiyan [36].

Use of the term *profitability maximization* in the current paper differs from other approaches where input costs and output prices may be incorporated. Reliable analysis of the Chinese banking sector will continue to be challenging until more consistent use of international financial reporting standards becomes commonplace (see [37]). Thus, the current study opts for an input–output specification that uses a technical efficiency approach in the absence of reliable pricing information, but still manages to serve the key managerial objective of maximizing profits by tapping into prices indirectly. In addition to the *two-input two-output* parsimonious specification outlined in the previous paragraph, the paper also tests an expanded version of this profitability model. That is, the author re-introduces into DEA the main profit and loss statement items that comprise each of the four core variables (see Table 2). Finally, a third input–output specification (see the *financial ratio model* in Table 2) is designed with the

Table 2
DEA input–output specifications on profitability and ratio benchmarking.

	Inputs	Outputs
Core profitability model (CPM)	Total interest expense[a]	Gross interest and dividend income[c]
	Total non-interest expenses[b]	Total non-interest operating income[d]
Expanded profitability model (EPM)	Interest expense on customer deposits[a]	Interest income on loans[c]
	Other interest expense[a]	Other interest income[c]
	Personnel expenses[b]	Net fees and commissions[d]
	Other operating expenses[b]	Other operating income[d]
Financial ratio model (FRM)	Reciprocal of capital adequacy ratio	Growth rate of earnings per share
(see the last column in Table 1)	Impaired loans/net interest income	Return on average equity
	Impaired loans/total assets	Post-tax profit/average total assets
	Impaired loans/equity	Net interest income/average total assets
	Reciprocal of dividends per share	Price to earnings ratio
	Reciprocal of growth rate of assets	

[a, b, c, d] The superscript letters indicate the connection of the expanded model to the core model. These items are from the income statement found in the OSIRIS database.

express purpose of objectively identifying peer benchmarks for key financial ratios first identified in Table 1.

3.2. Study setting, data and tests

Here, the paper continues the discussion started in the introduction on Chinese banking, which forms the backdrop to the empirical testing. Main examples of successful listings include the Agricultural Bank of China Ltd., Bank of China Ltd., China Construction Bank Corp., and Industrial and Commercial Bank of China Ltd. These state-owned commercial banks (SOCB) dominate the retail banking market. They command more than half the deposits from the retail banking market and maintain a large branch network throughout China. Other bank groups include thirteen joint-stock commercial banks (JSCB), thirteen city commercial banks (CiCB), two rural commercial banks (RCB), three government banks known as policy banks (PB), and twenty locally incorporated foreign banks (LIFB) (China Banking Association [38], KPMG [39], and PWC [40]). The thirty-two commercial banks in the SOCB, JSCB, CiCB, and RCB groups account for most of the retail banking business in China. The interested reader can refer to [9] for a historical account of development of the Chinese banking sector.

Non-performing loans (NPL) in the Chinese banking sector appears to have recently been brought under control. According to the China Banking Regulatory Commission, in the final quarter of 2007 which roughly coincides with the beginning of the most recent GFC, non-performing loans' share of total loans was 8.05% for the SOCB group, 2.15% for the JSCB, 3.04% for the CiCB, 3.97% for the RCB, and 0.46% for the LIFB. Excluding the foreign banks, the average NPL for the commercial banks is 4.3%. This is a more respectable figure compared to the unsustainable position of more than 20% only a few years ago (KPMG [39]).

It was possible to collect data on the input–output specifications identified in Table 2 from the OSIRIS and DataStream data bases as well as bank annual reports for the fiscal years ending December 2007 and 2008 for twenty-one publicly listed Chinese commercial banks. In 2007, the real annual growth rate in gross domestic product peaked at 12.08% for the 21st Century, where 2008 showed a decline in the growth rate to 9.13% due to the GFC.[9] With this background, the study sample includes three banks from the SOCB group, nine from the JSCB group, five from CiCB group, and four from the LIFB group, thus comprising a representative sample of commercial banking in China.

The resulting data set is comprised of balanced panel data on the publicly quoted Chinese commercial banks for 2007–2008 on the three input–output specifications shown in Table 2. Various DEA tests are applied to the core profitability (CPM) and expanded profitability (EPM) efficiency models. The author anticipates stronger associations between efficiency estimates and higher level financial ratios that carry more performance information, that is, ratios sourced from closer to net profits on the profit and loss statement (e.g., see ROAE and PTP/ATA in Table 1). Financial ratios for 2007 and 2008 are correlated with efficiency estimates from a common frontier based on panel data across 2007–2008. This approach serves two purposes, namely, raising the discriminatory power of DEA by doubling the sample size, and facilitating estimation of future financial ratios by using the efficiency information contained in the two most recent years. The financial ratio model (FRM) helps objectively determine peer-based benchmarks for key financial ratios.

4. Findings

4.1. Preliminaries

Nine super-efficiency DEA formulations are executed using the code found in the commercially available software DEA Solver Pro by Saitech (version 5). A rule-of-thumb cut-off used in identifying potential outliers suggests a unit may be an outlier if its super-efficiency score exceeds 3 (see [41]); the current study adopts a more conservative cut-off of 2. With the exception of the Chong Hing Bank under the SBCC-O DEA formulation and the CPM profitability model (3.87), all of the super-efficiency scores are well below 2 (available from the author). However, since the Chong Hing Bank is not indicated as a potential outlier in any of the other seventeen models, it is not removed from the sample.

Table 3 shows descriptive statistics on the various DEA formulations across the core profitability and expanded profitability models. In general, mean estimates are lower under CPM and among non-radial SBM formulations. The coefficient of variation and skewness are low in most cases. Overall, the substantially smaller number of efficient banks under CPM suggests better discrimination (less dimensionality) when a parsimonious efficiency model is used. Comparing the number of efficient banks across non-radial and radial formulations, that is, SBM versus CCR/BCC does not indicate substantially different discrimination. However, a similar comparison across constant returns-to-scale (CRS) versus variable returns-to-scale (VRS) confirms a well-established DEA principle that VRS requires a larger sample to discriminate, in the absence of which there is an inevitable loss of discrimination, in particular under CPM (see the last column in Table 3). In summary, the above observations based on descriptive statistics are in line with the well-known characteristics of DEA estimates and bring additional confidence to working with the data set on Chinese commercial banks.

[9] Source for GDP: http://www.tradingeconomics.com/Economics/GDP-Growth.aspx?Symbol=CNY.

Table 3
Descriptive statistics for efficiency estimates across different DEA formulations and input–output specifications ($N=42$).

Core profitability model (CPM)	Mean	Median	SD[a]	CV[b]	Minimum	Maximum	Skewness	# efficient banks
SSBM-C-NO[c]	0.5756	0.5325	0.2609	0.4534	0.0559	1.2155	0.8621	6
SSBM-V-NO	0.7913	0.8187	0.3098	0.3915	0.2765	1.3023	−0.1228	17
SSBM-C-I	0.8220	0.7982	0.1607	0.1955	0.5531	1.2241	0.4590	6
SSBM-V-I	0.9429	0.9654	0.1891	0.2005	0.5679	1.4877	0.1790	18
SSBM-C-O	0.5949	0.5430	0.2721	0.4574	0.0559	1.2954	0.8293	6
SSBM-V-O	0.8131	0.8728	0.3320	0.4084	0.2765	1.6362	0.2009	17
SCCR-I[d]	0.8737	0.8657	0.1788	0.2046	0.5797	1.4481	1.1676	6
SBCC-I[e]	0.9957	0.9746	0.2415	0.2425	0.5876	1.9754	1.6421	18
SBCC-O	1.0567	0.9772	0.5017	0.4748	0.5799	3.8744	4.5457	18
Expanded profitability model (EPM)								
SSBM-C-NO	0.7992	1.0206	0.3784	0.4735	0.0129	1.2813	−0.7929	26
SSBM-V-NO	0.8759	1.0371	0.3937	0.4495	0.0132	1.4363	−0.8868	29
SSBM-C-I	0.9931	1.0234	0.2052	0.2066	0.6172	1.4711	0.2131	26
SSBM-V-I	1.0487	1.0438	0.2157	0.2057	0.6541	1.6363	0.4726	29
SSBM-C-O	0.8168	1.0218	0.3753	0.4594	0.0136	1.3844	−0.7992	26
SSBM-V-O	0.8695	1.0178	0.3740	0.4302	0.0139	1.6296	−0.8626	29
SCCR-I	1.1012	1.0438	0.2657	0.2413	0.6856	1.9092	1.2137	26
SBCC-I	1.1852	1.0873	0.3279	0.2767	0.6909	2.2532	1.5624	29
SBCC-O	1.1248	1.0590	0.2732	0.2429	0.6861	2.1799	1.8875	29

The broken horizontal line on the left of the table separates non-radial from radial formulations.

[a] SD: standard deviation.
[b] CV: coefficient of variation (SD/mean).
[c] Slacks-based measure (SBM) for the core profitability model outlined in Table 2. In model acronyms, the first ‘S’ denotes super-efficiency; ‘V’ denotes variable returns-to-scale; ‘C’ denotes constant returns-to-scale; ‘I’ denotes input orientation; ‘O’ denotes output orientation; ‘NO’ denotes non-orientation.
[d] Charnes, Cooper and Rhodes model. SCCR-O model has been omitted from the set because it results in identical estimates to those obtained with SCCR-I.
[e] Banker, Charnes and Cooper model.

It is also noted that infeasibility was not a major problem in the current study, with only a small number of ties observed across VRS SBM and BCC under CPM and EPM models used to generate bivariate correlations. More importantly, there was no infeasibility under the FRM model where specific rankings are used to determine potential benchmark levels for key financial ratios. Nevertheless, papers that use super-efficiency DEA need to be mindful of the potential for infeasibility under variable returns-to-scale, where ranking is central to the study design. Where substantial incidences of infeasibility are observed, the solution offered in [16] may be employed to fine tune results.

4.2. Correlations between efficiency estimates and key financial ratios

Pearson correlations between efficiency estimates and key financial ratios (identified earlier in Table 1) appear in Table 4. Overall, magnitudes of the correlation coefficients are low and statistically insignificant, with the exceptions of the key profitability ratios *return on average equity* (ROAE) and *post-tax profits to average total assets* (PTP/ATA). These findings support the discussion in Section 2 of the current paper. That is, inefficiencies identified through DEA's relative multicriteria decision making approach are not adequately captured by financial ratios. While the core profitability model generally shows higher *absolute* mean correlations, the group average for absolute mean correlations across categories of ratios indicates credit quality as the main problem area for Chinese banks. This observation is supported by the levels of non-performing loans mentioned in Section 3.2. Association of the PTP/ATA ratio with efficiency estimates is statistically significant at the 5% level with 17 out of 18 efficiency models, and in all instances PTP/ATA's coefficients correspond to the anticipated sign in Table 1. The second strongest association is with ROAE, where once again, the observed signs correspond to the anticipated signs with only one exception.

While signs of the observed coefficients, in general, agree with what was anticipated, DPS and PE clearly do not conform (see Table 4). Regarding DPS, this could be explained by a policy of stable dividend payout common in banking (see [42]). Descriptive statistics on the data (available from the author) lend support to this contention where the coefficient of variation on DPS is a low 0.48 in 2007 and 2.24 in 2008 (an economically unstable year). Similarly, growth rate of assets is 25% in 2007 and only 16% in 2008, where the fall in the growth rate of assets and the rise in DPS variability reflect the impact of the GFC in 2008. Regarding the signs of coefficients for PE, this may be a reflection of the time lag between efficiency estimates that represent historical performance and market price of bank stock that accounts for expected future earnings.

The expected association between the credit quality ratios and efficiency was negative since profit efficient banks are likely to have less impaired assets. While the direction of this anticipated relationship is supported in Table 4, none of the correlations are statistically significant. The two lowest *absolute* mean correlations under CPM correspond to the credit quality ratios ILNII and ILTA, suggesting substantial inefficiencies regarding risk and asset management (and by implication, impaired asset levels) of the Chinese commercial banks (see Section 3.2 for the discussion of substantial levels of non-performing loans).

Returning to the profitability ratios ROAE and PTP/ATA, the latter offers the most promising association as a key financial ratio that captures the essence of both the profit and loss statement (in its numerator) and the balance sheet of a bank (in its denominator). Comparing results across the two profitability models, the *absolute* mean PTP/ATA correlation across DEA formulations under the CPM profitability model (0.553) is substantially greater than the mean correlation under the EPM model (0.403) (a similar pattern can be observed for ROAE). The two highest correlations for PTP/ATA and ROAE are with SSBM-C-I (non-radial, constant returns-to-scale, and input oriented) and SCCR-I (radial, constant returns-to-scale, and input oriented) DEA formulations under core profitability modeling (see Table 4). The absolute mean correlations across ratios

Table 4
Bivariate correlations between efficiency estimates and key financial ratios.

	Financial ratios with anticipated signs (see Table 1)											
	[CAR+]	[GRA+	GREPS+]	[ILNII-	ILTA-	ILE-]	[ROAE+	PTP/ATA+	IM+]	[DPS+	PE+]	*amcR*
	[Strength]	[Growth]		[Credit quality]			[Profitability]			[Valuation]		
Core profitability model (CPM)												
SSBM-C-NO[a]	0.012	−0.153	0.066	−0.152	−0.119	−0.157	0.280	0.604*	0.180	−0.119	−0.206	*0.186*
SSBM-V-NO	0.277	−0.267	0.027	−0.123	−0.083	−0.242	0.119	0.484*	0.139	−0.111	−0.301	*0.198*
SSBM-C-I	0.125	0.271	0.519*	−0.043	0.077	0.005	0.643*	0.791*	0.572*	−0.342*	−0.299	*0.335*
SSBM-V-I	0.220	0.014	0.288	−0.114	−0.055	−0.155	0.392*	0.587*	0.294	−0.229	−0.303	*0.241*
SSBM-C-O	0.014	−0.212	0.004	−0.157	−0.136	−0.176	0.247	0.572*	0.117	−0.107	−0.208	*0.177*
SSBM-V-O	0.239	−0.323*	−0.026	−0.125	−0.110	−0.257	0.083	0.440*	0.040	−0.115	−0.313*	*0.188*
SCCR-I[b]	0.076	0.131	0.407*	−0.056	0.046	−0.027	0.639*	0.774*	0.447*	−0.300	−0.288	*0.290*
SBCC-I[c]	0.199	−0.078	0.169	−0.177	−0.139	−0.194	0.398*	0.594*	0.150	−0.166	−0.220	*0.226*
SBCC-O	0.034	−0.168	−0.023	−0.044	−0.085	−0.128	−0.006	0.127	−0.118	−0.095	−0.173	*0.091*
amcDEA[d]	*0.133*	*0.180*	*0.170*	*0.110*	*0.094*	*0.149*	*0.312*	*0.553*	*0.229*	*0.176*	*0.257*	
Group average amcDEA	*0.133*	*0.175*		*0.118*			*0.365*			*0.217*		
Expanded profitability model (EPM)												
SSBM-C-NO	0.271	−0.057	0.148	−0.098	−0.059	−0.168	0.240	0.384*	0.088	−0.064	−0.164	*0.158*
SSBM-V-NO	0.312*	−0.103	0.089	−0.116	−0.080	−0.200	0.200	0.362*	0.066	−0.059	−0.180	*0.161*
SSBM-C-I	0.177	−0.077	0.132	−0.073	−0.051	−0.153	0.238	0.415*	0.066	−0.181	−0.273	*0.167*
SSBM-V-I	0.266	−0.157	0.079	−0.234	−0.214	−0.273	0.207	0.437*	−0.035	−0.145	−0.237	*0.208*
SSBM-C-O	0.264	−0.069	0.133	−0.095	−0.062	−0.164	0.228	0.368*	0.066	−0.068	−0.166	*0.153*
SSBM-V-O	0.231	−0.076	0.142	−0.088	−0.040	−0.161	0.288	0.435*	0.115	−0.106	−0.225	*0.173*
SCCR-I	0.124	−0.188	−0.009	−0.116	−0.136	−0.184	0.154	0.338*	−0.134	−0.161	−0.250	*0.163*
SBCC-I	0.169	−0.258	−0.045	−0.280	−0.290	−0.285	0.158	0.375*	−0.206	−0.098	−0.187	*0.214*
SBCC-O	0.030	−0.155	0.111	−0.113	−0.078	−0.139	0.346*	0.512*	0.033	−0.234	−0.328*	*0.189*
amcDEA	*0.205*	*0.127*	*0.099*	*0.135*	*0.112*	*0.192*	*0.229*	*0.403*	*0.090*	*0.124*	*0.223*	
Group average amcDEA	*0.205*	*0.113*		*0.146*			*0.241*			*0.174*		

[a] Slacks-based measure (SBM) for the core profitability model outlined in Table 2. In model acronyms, the first 'S' denotes super-efficiency; 'V' denotes variable returns-to-scale; 'C' denotes constant returns-to-scale; 'I' denotes input orientation; 'O' denotes output orientation; 'NO' denotes non-orientation.
[b] Charnes, Cooper and Rhodes model. SCCR-O model has been omitted from the set because it results in identical estimates to those obtained with SCCR-I.
[c] Banker, Charnes and Cooper model.
[d] amcDEA, absolute mean correlation across nine DEA formulations; Group average amcDEA, average for each of the five ratio groupings identified in square brackets; amcR, absolute mean correlation across eleven ratios.
* Statistically significant at 5% level.

shown in the last column in Table 4 lend further support to the dominance of the SSBM-C-I formulation.

A simple regression where PTP/ATA is the dependent variable and SSBM-C-I (CPM) estimate is the independent variable indicates an adjusted R^2 of 0.616, suggesting 61.6% of the variation in the key profitability ratio PTP/ATA can be explained by efficiency estimates. A multiple stepwise regression, where estimates from all of the eighteen efficiency models are entered, raises the adjusted R^2 to 66.4% with the combination of SSBM-C-I (CPM) and SBCC-O (EPM) estimates. Similarly, a simple regression with the profitability ratio ROAE and SSBM-C-I (CPM) reveals an adjusted R^2 of 39.9%. A follow-up multiple stepwise regression raises the adjusted R^2 to 45.1% with the combination of SSBM-C-I (CPM) and SSBM-V-NO (CPM) estimates. In summary, SSBM-C-I (CPM) emerges as the most significant efficiency model explaining the variation in the profitability ratios PTP/ATA and ROAE, suggesting that it can be used for predicting these two ratios for Chinese banking.

4.3. *Identifying benchmark levels within peer group performance for key financial ratios*

In determining benchmark levels of input ratios and output ratios indicated by the *financial ratio model* (FRM) outlined in Table 2, the super-efficient SBM (variable returns-to-scale, non-oriented) is used as part of a common frontier analysis that combines 2007 and 2008 data (see end of Section 2.1 for the initial arguments on justifying this choice). Non-orientation is a particularly important modeling feature where inputs are minimized and outputs are maximized simultaneously, thus enabling observation of what could be the benchmark low input levels and high output levels. Bank of Ningbo, a city commercial bank, emerges as the *global leader* of the peer group because it is emulated the most frequently by the inefficient banks in DEA analysis (20 times) and has the highest super-efficiency score (1.93). The second most frequently emulated bank, Hang Seng Bank, comes in at a distant 10 times (super-efficiency score, 1.34).

Table 5 reports the actual observed inputs (not projections) and the actual observed outputs for Bank of Ningbo and Hang Seng Bank. Numbers in Table 5 indicate the levels that may be used as benchmarks in comparing peer bank performance on financial ratios. For example, for Bank of Ningbo, the benchmark CAR suggested by DEA is an unusually high proportion of 21%, where the Basel Accord requires a minimum of 8% for banks that deal with international transactions.[10] In the post-GFC environment of increased regulatory appetite, signaling that a bank can be profitable while maintaining a high capital adequacy ratio would be a welcome message, in particular, for the regulatory bodies. Still on the inputs side of the profitability equation, a growth rate in assets of 33.54% is

[10] Bank of Ningbo does not have the highest value in the sample although its CAR is significantly above the sample mean and median values of 13.85 and 13.00, respectively.

Table 5
Benchmarks for key financial ratios (see FRM model in Table 2) set by the top two leaders.

Input ratios and actual observed levels			*Output ratios and actual observed levels*		
	Bank of Ningbo	Hang Seng		Bank of Ningbo	Hang Seng
Reciprocal of capital adequacy ratio (CAR)	4.7619 (0.2100)[a]	9.0909 (0.1100)	Growth rate of earnings per share (GREPS)	0.5047	0.5070
Impaired loans/net interest income (ILNII)	0.0631	0.0854	Return on average equity (ROAE)	0.1700	0.3900
Impaired loans/total assets (ILTA)	0.0017	0.0017	Post-tax profit/average total assets (PTP/ATA)	0.0144	0.0263
Impaired loans/equity (ILE)	0.0200	0.0200	Net interest income/average total assets (IM)	0.0312	0.0209
Reciprocal of dividends per share (DPS)	2.1501 (0.4651)[a]	1.5385 (0.6500)	Price to earnings ratio (PE)	57.6400	16.5300
Reciprocal of growth rate of assets (GRA)	2.9817 (0.3354)[a]	8.6965 (0.1150)			

[a] Reversed reciprocal value is in brackets for ease of interpreting.

suggested can sustain a more than 50% growth in earnings, a 17% return on average equity, and a price-to-earnings ratio of 57.64 on the outputs side. Such benchmarking information can be used for pricing stocks by placing the performance of a bank under examination in the context of the sector's achievable high performance levels. Nevertheless, for those inefficient banks intending to emulate Bank of Ningbo, the best approach would be to treat the set of feasible financial ratio benchmarks demonstrated as an opportunity for a more in-depth analysis at various organizational levels. Choosing only one benchmark, such as aiming to reach Bank of Ningbo's growth rate in earnings, without taking into account the other key ratios in the efficiency model would not make much economic sense. Neither would it make sense to ignore the exploratory nature of DEA.

Focusing on the second leader Hang Seng Bank, instead of the global leader Bank of Ningbo, presents more realistic figures likely to appeal to managers. For example, at a CAR of 11%, which is closer to CAR ratios found in practice, and with a credit quality similar to that of the global leader and a lower growth in assets, Hang Seng succeeds in generating a similar growth in earnings but significantly higher profits. Overall, Hang Seng's figures are more in line with what would be expected from a well-managed bank with sustainable operations. As such, it is more likely to be accepted as a benchmark organization to be emulated than Bank of Ningbo, where the latter may suffer from some incorrectly reported accounting figures. This exercise also highlights the need to avoid a mechanical acceptance of some DEA findings, in particular when DEA is a deterministic technique that assumes away any measurement error.

Re-iterating an important message, the variables in the FRM model are ratios commonly found in the finance sector, which mark the starting point for this paper's analysis as first shown in Table 1. Thus, looking at the bottom half of Table 2 where FRM is shown, we can quickly see that variables such as CAR and the three ratios based on impaired loans are of immediate interest to banking regulators. Similarly, variables such as 'dividends per share', 'growth rate of earnings per share', 'return on average equity', 'price to earnings ratio', and others are all ratios commonly used in stock pricing. Thus, the benchmark levels for these ratios observed from the implementation of FRM provide direction for regulatory/market decision-makers by allowing them insight to peer performance.

In summary, the above analysis based on the performance of the top two leaders in the sample identifies benchmark financial ratios where the multi-dimensional interaction among inputs and outputs are captured by DEA. This approach brings objectivity to the selection of benchmark ratios because it is based on actual observations from a peer group, rather than theoretical projections reliant on a pre-specified production function or measures of central tendency. However, given a common frontier constructed on two years' of data, these benchmarks ought to be treated as short-term benchmarks to be recalculated as new data become available each year.

4.3.1. A footnote to methodology used to identify the top leaders

Chen and Ali [43] maintain that DMUs ranked at the top of their peer group using output–input ratios are also DMUs that define the CCR or the BCC efficient frontier. This section tests the effectiveness of the various unweighted output–input ratios in determining the top leaders and other efficient DMUs found on the super-SBM frontier. There are thirty output–input ratios based on five outputs and six inputs (not counting additional ratios that can be constructed by adding inputs in the denominator). Once again, Bank of Ningbo, which has the highest efficiency estimate, emerges as the global leader with the maximum number of first three positions (i.e., 19). That is, Table 6 indicates that the Bank of Ningbo generates the maximum value across output–input ratios in nine cases, and the second and third highest values across ten additional output–input cases. Hang Seng Bank retains its second rank with seventeen cases in top three highest output–input ratio values (see total frequency of maxima). However, after Hang Seng Bank, the correspondence between super-SBM rankings and rankings based on output–input ratios is less obvious. Nevertheless, the total frequency of maxima column in Table 6 clearly shows that fourteen out of eighteen efficient DMUs defining the super-SBM frontier are well represented by high output–input ratios. In conclusion, while output–input ratio analysis may be effective in identifying the top leaders and thus potential benchmarks, it is not reliable for overall ranking as it fails to capture the interaction among multiple inputs and multiple outputs.

5. Concluding remarks and discussion

This study is motivated by the disparate measurement of bank performance through efficiency estimates often found in academic publications versus financial ratios frequently used by industry. Part of the motivation includes a desire to find synergies between these different approaches to performance measurement. With this in mind, the author sets out to explore the associations between efficiency estimates based on the non-parametric frontier technique DEA and key bank performance ratios. Resulting correlations are generally low, suggesting an inadequate representation of production inefficiencies in ratio analysis. However, two profitability ratios, namely, *post-tax profits to average total assets*, and *return on average equity*, emerge as significant in their association with efficiency estimates, with the former ratio exhibiting a stronger relationship. This finding raises the potential to use efficiency estimates to predict certain key financial ratios' future values. The non-radial DEA formulation SSBM-C-I dominates all other formulations in terms of generating estimates that are correlated with ratios, and the core profitability model with its parsimonious two inputs and two outputs provides discriminating estimates. The paper also demonstrates how DEA can be used to address the problem of objectively selecting ratio benchmarks for a group of firms. Such ratio benchmarks can be used for firm-level benchmarking, regulatory scrutiny, and stock pricing.

Table 6
Banks ranked on the super-SBM estimate (see FRM model in Table 2) and their corresponding performance on unweighted output–input ratios ($N=38$).

Bank[a]	SSBM score	Frequency of 'first maximum'[b]	Frequency of 'second maximum'[c]	Frequency of 'third maximum'[d]	Total frequency of maxima
Bank of Ningbo	*1.9322*	*9*	*5*	*5*	*19*
Hang Seng Bank	*1.3439*	*10*	*5*	*2*	*17*
08_BOC Hong Kong	1.3027	0	4	1	5
08_Bank of Beijing	1.1717	2	0	0	2
Industrial Bank	1.1089	0	1	5	6
China Merchants Bank	1.1060	0	1	1	2
08_Fubon Bank (Hong Kong)	1.0975	2	0	0	2
Bank of Nanjing	1.0923	1	4	0	5
China CITIC Bank	1.0738	2	1	0	3
Bank of East Asia	1.0574	0	0	0	0
08_Shanghai Pudong Development Bank	1.0537	2	2	0	4
Industrial and Commercial Bank of China	1.0420	1	0	0	1
08_Bank of Nanjing	1.0403	0	0	2	2
08_Hang Seng Bank	1.0366	0	2	1	3
08_Bank of Ningbo	1.0206	1	0	1	2
08_China Construction Bank	1.0146	0	0	0	0
Shenzhen Development Bank	1.0036	0	0	0	0
China Construction Bank	1.0018	0	0	0	0
BOC Hong Kong	0.9997	0	4	6	10
Wing Hang Bank	0.4291	0	0	2	2
Shanghai Pudong Development Bank	0.3642	0	0	1	1
China Minsheng Banking	0.3567	0	0	0	0
Bank of Beijing	0.3553	0	0	1	1
Bank of Communications	0.2940	0	0	0	0
Fubon Bank (Hong Kong)	0.2835	0	0	1	1
08_Industrial Bank	0.2590	0	0	0	0
Huaxia Bank	0.2055	0	0	0	0
08_China Merchants Bank	0.1793	0	0	0	0
08_Bank of Communications	0.1485	0	0	0	0
08_Huaxia Bank	0.1303	0	0	0	0
08_China Minsheng Banking	0.1210	0	0	0	0
Bank of China	0.1020	0	0	0	0
08_China CITIC Bank	0.0924	0	0	0	0
08_Industrial and Commercial Bank of China	0.0812	0	0	0	0
08_Bank of China	0.0524	0	0	0	0
Chong Hing Bank	0.0254	0	0	0	0
Dah Sing Banking Group	0.0116	0	0	0	0
08_Shenzhen Development Bank	0.0048	0	2	1	3

[a] _08 indicates 2008 data; otherwise, data belong to 2007.
[b] This is the incidence of observed maximum output–input ratio values owned by a bank.
[c] This is the incidence of observed maximum after the 'first maximum' value is removed.
[d] This is the incidence of observed maximum after the 'first maximum' and the 'second maximum' values are removed.

Finally, results also point to poor credit quality with Chinese banks for 2007–2008.

China is, once again, one of the fastest growing economies. As its domestic markets become more sophisticated and new infrastructure projects come on line, the rising economic activity is going to spur the Chinese banking sector. While China catches up with developed countries, its banks will offer more sophisticated products and services to their clients. As a result, this increasingly competitive and liberalized business environment will focus attention of managers on identifying inefficiencies as profit margins become tighter. Investigations such as the analysis illustrated in this study are likely to become commonplace over the next five years, particularly as China would probably have taken over from Japan as the second largest economy in the world by the time this article is read. Frontier efficiency analysis of banks through such techniques as DEA can guide governments on deregulation and market structure, help market analysts in pricing decisions, and improve managerial performance by separating the best from the worst performers. The partial performance ratios often found in the industry, while informative, cannot generate the broad comparisons delivered by DEA because they lack simultaneous optimization on multiple variables (see [44]).

The vexed question of optimal capital adequacy ratio merits further comment. One cannot help but wonder whether the most recent global financial crisis would have turned out differently had the bankers and their regulators paid more attention to some of the comments by, say, Miller [51]. According to Miller, as per M&M Proposition II, expected earnings per share would normally rise in response to leveraging but would fall short of fully compensating for additional risk that accompanies leverage. The Basel III Accord negotiations aimed at preventing a repeat of the 2007–2009 GFC may well yield an agreement by the time this article appears in print. Yet, at the time of drafting the paper, there appears to be a significant gap between regulatory authorities inclined to implement harsh capital adequacy requirements and banks understandably concerned about stifling business. As Miller pointed out fifteen years ago, one-size-fits-all approach to regulation cannot be a substitute for the fine adjustments that can be achieved via private deals made in the marketplace. Even when the hardship of the recent GFC is still fresh in our minds, there is little reason to think that capital requirements will continue to be anything other than a source of dispute between bankers and regulators.

Follow up to the current study may include testing the efficiency of Chinese banks on a frontier comprised of banks from other East Asian countries. Those Chinese banks that emerge as efficient on a national frontier may not perform as well when pitched against banks operating in other countries. For example, Sathye [23], who reports a data envelopment analysis of banks in the Asia-Pacific region, suggests that banks efficient at the national level may not be so in a cross-country analysis. The methodology illustrated in the context of banking can also be extended to other industries. It would be interesting to see if the same DEA formulations would dominate the results, thus testing the generalizability of the findings.

Appendix A

Highlights from international publications on banking applications of DEA are given in Table A1.

Table A1
Highlights from international publications on banking applications of DEA (in chronological order, 2004–2009)

Publication {ABDC journal ranking} (sample)	Analysis	Inputs	Outputs	Association of efficiency with key financial ratios
Studies on Chinese banks				
Chen et al. [7] {*B*} (43 Chinese banks over 1993–2000)	Technical efficiency using BCC; cost efficiency; allocative efficiency (input minimization using cross-sectional data and measuring radial inefficiencies)	Interest expenses; non-interest expenses; price of deposits; price of capital	Loans; deposits; non-interest income	None reported
Drake et al. [8] {*A*} (413 observations on banks in Hong Kong over 1995–2001)	Technical efficiency with profit focus using BCC and SBM (input minimization using cross-sectional data and measuring radial and non-radial inefficiencies)	Employee expenses; Other non-interest expenses; loan loss provisions	Net interest income; Net commission income; total other income	None reported
Cooper et al. [9] {*C*} (41 observations across Chinese commercial banks in Chongqing, 1996–2000)	Technical efficiency using RAM (non-oriented analysis using pooled data and measuring non-radial inefficiencies)	Labor cost; fixed assets; administrative and operating expenses	Total loans; investments in securities and other assets; interest income from loans and other business	None reported
Laurenceson and Qin [10] {*C*} (267 observations across Chinese commercial banks, 2001–2006)	Cost efficiency using BCC (input minimization using pooled data and measuring radial inefficiencies)	Same as Chen et al. [7]	Same as Chen et al. [7]	ROA (0.11)[a] ILR (−0.21) CR (0.16) CIR (−0.36)
Studies from the rest of the world				
Kao and Liu [24] {*A**} (24 Taiwanese commercial banks, year 2000)	Technical efficiency (input minimization using imprecise cross-sectional data and measuring radial inefficiencies)	Total deposits; interest expenses; non-interest expenses	Total loans; interest income; non-interest income	None reported
Sturm and Williams [34] {*A**} (unbalanced panel data across 1988–2001 on banks operating in Australia, excluding foreign bank branches)	Technical, scale and cost/ revenue efficiency using BCC (input minimization using cross-sectional data and measuring radial inefficiencies)	*Model 1* (technical/scale efficiency): (i) employees, (ii) deposits, (iii) equity capital. *Model 1a*: same as above. *Model 1b*: same as above. *Model 2* (cost/ revenue efficiency): (i) interest expenses, (ii) non-interest expenses.	*Model 1*: (i) loans, (ii) off-balance sheet items. *Model 1a*: (i) loans less housing loans, (ii) housing loans (iii) off-balance sheet items. *Model 1b*: (i) loans, (ii) investments, (iii) off-balance sheet items. *Model 2*: (i) net interest income, (ii) non-interest income.	None reported
Sathye [23] {*A*} (458 banks across 18 countries in the Asia-Pacific region, 2000)	Technical, pure technical and scale efficiency using BCC (input minimization using cross-sectional data measuring radial inefficiencies)	Deposits; financial capital	Loans; net interest income	Multiple regression analysis shows 'return on assets' is significantly positively related to technical efficiency
Havrylchyk [27] {*A**} (10–38 Polish banks across 1997–2001)	Cost, allocative, technical, pure technical and scale efficiency using BCC (input minimization using cross-sectional data and unbalanced panel data measuring radial inefficiencies)	Capital, labor, deposits and their prices	Loans; government bonds; off-balance sheet items	Loan loss provisions/loans (−0.41 AE)[b] Loan/total assets (−0.13 CE; −0.30 TE; 0.11 AE) variance of ROA (1.30 CE; 1.10 TE; 0.69 AE)
Ahmad et al. [1] {*A*} (annual observations on 32 Malaysian banks, 1994–1999)	Malmquist total factor productivity (input minimization using balanced panel data and measuring radial inefficiencies)	Deposits; fixed assets; interest expense	Bank loans; other earning assets	None reported
Ray [45] {*A*} (68–73 Indian banks over 1997–2003)	Technical and scale efficiency using BCC (output maximization using cross-sectional data measuring radial inefficiencies)	Borrowed funds; labor; physical capital; Equity	Credit; investments; other income	None reported

Table A1. (*continued*)

Al-Sharkas et al. [46] {*A*} (440 US bank mergers, 1986–2002)	Allocative efficiency, technical efficiency, pure technical efficiency, scale efficiency, overall cost efficiency (cross-sectional data measuring radial inefficiencies)	Purchased funds; core deposits; labor (and inputs prices of all the above)	Consumer loans; business loans; real estate loans; securities	None reported
Avkiran [35] {*A*} (15 Australian and New Zealand banks over 1996–2003)	Profit efficiency using super-SBM (non-oriented approach using balanced panel data and measuring non-radial inefficiencies off a common frontier)	Interest expense; non-interest expense	Interest income; non-interest income	None reported
Drake et al. [47] {*A*} (1109 Japanese bank observations, 1995–2002)	Pure technical efficiency using SBM (input minimization using balanced panel data and measuring non-radial inefficiencies)	*Intermediation approach*: total deposits; total operating expenses; total provisions *Profit/revenue approach*: total non-interest expenses; total other operating expenses; total provisions *Production approach*: total non-interest expenses; total other operating expenses; total provisions	*Intermediation approach*: total loans; total other earning assets; net commission, fee and trading income; total other operating income *Profit/revenue approach*: net interest income; net commission, fee and trading income; total other operating income *Production approach*: total loans; total other earning assets; net commission, fee and trading income; total other operating income; total deposits	None reported

In alphabetical order: ABDC, Australian Business Deans Council; AE, allocative efficiency; BCC, Banker, Charnes and Cooper; CIR, cost to income ratio; CR, capital ratio; ILR, impaired loan ratio; RAM, range-adjusted measure; ROA, return on assets; SBM, slacks-based measure; TE, technical efficiency.

[a] Bivariate correlations are in brackets.

[b] Tobit regression coefficients significant at 5% or better, and the corresponding type of efficiency, that is, the dependent variable, are in brackets.

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