Financial Innovation

RESEARCH

Open Access

# Evaluating the resource management and profitability efficiencies of US commercial banks from a dynamic network perspective

Qian Long Kweh[1], Wen-Min Lu[2*], Kaoru Tone[3] and Hsian-Ming Liu[4]

*Correspondence:
wenmin.lu@gmail.com

[1] School of Management, Canadian University Dubai, City Walk – Al Wasl, Dubai, United Arab Emirates
[2] Department of International Business Administration, Chinese Culture University, No. 55, Hwa-Kang Road, Shilin District, Taipei 114, Taiwan
[3] National Graduate Institute for Policy Studies, 7-22-1 Roppongi, Minato-Ku, Tokyo 106-8677, Japan
[4] Department of Financial Management, National Defense University, No. 70, Sec. 2, Zhongyang North Rd., Beitou 247964, Taiwan

## Abstract

The central concept of strategic benchmarking is resource management efficiency, which ultimately results in profitability. However, little is known about performance measurement from resource-based perspectives. This study uses the data envelopment analysis (DEA) model with a dynamic network structure to measure the resource management and profitability efficiencies of 287 US commercial banks from 2010 to 2020. Furthermore, we provide frontier projections and incorporate five variables, namely capital adequacy, asset quality, management quality, earning ability, and liquidity (i.e., the CAMEL ratings). The results revealed that the room for improvement in bank performance is 55.4%. In addition, we found that the CAMEL ratings of efficient banks are generally higher than those of inefficient banks, and management quality, earnings quality, and liquidity ratios positively contribute to bank performance. Moreover, big banks are generally more efficient than small banks. Overall, this study continues the current heated debate on performance measurement in the banking industry, with a particular focus on the DEA application to answer the fundamental question of why resource management efficiency reflects benchmark firms and provides insights into how efficient management of CAMEL ratings would help in improving their performance.

**Keywords:** Performance evaluation, Dynamic network data envelopment analysis, CAMEL ratings, Resource management efficiency, Profitability efficiency

## Introduction

Banks are financial institutions that mobilize financial resources through their intermediation role for productive investment, trade, and other economic activities. One of the causes of banks' poor profitability is the mismanagement of resources. Therefore, resource underutilization is a problem where a large bank cannot convert its vast resources into financial outcomes compared with some of its peers with limited resources. Evaluating resource management and profitability efficiencies is useful for bank managers in making resource management policies. When bank managers overcome resource mismanagement, they can maximize their profitability. Therefore, identifying banks that can serve as benchmarks for other competitors is vital in the new borderless business world. Single-dimensional performance measures such as corporate financial returns, which are most commonly employed in strategic management studies (Chen et al. 2013a), are subject to interpretation (Feroz et al. 2003).

In terms of long-term decision-making, an assessment of bank performance with data envelopment analysis (DEA)[1] may be a more relevant measure than a financial ratio. DEA can handle multiple inputs (resources) and outputs (financial outcomes) to calculate efficiency. Furthermore, it can determine possible sources of inefficiency in resource management. Owing to the advantages of DEA, its application in identifying the top performers in the banking industry and their efficiency in transforming resources into profitability are beneficial because it allows performance evaluation from a multidimensional perspective (Bagozzi and Phillips 1982; Chakravarthy 1986) as resource management and profitability efficiencies create competitive advantages. Moreover, it allows scholars to impartially determine the leading benchmarks and reasons underlying the differences between firms. Considering the merits of applying DEA as a measurement tool in strategic benchmarking (Chen et al. 2013a; Delmas et al. 2007; Delmas and Tokat 2005; Majumdar 1998; Schefczyk 1993), this study argues that DEA is relevant because it reflects the relative competency in resource utilization in banks.

Existing studies generally apply conventional DEA models but cannot provide a reliable strategic benchmarking of dynamic network performance in the banking industry. Conventional DEA techniques directly assign input- or output-oriented models that may lack objectivity in terms of reflecting the real input or output conditions for each decision-making unit (DMU). Similar to the two-stage production model used in this study, assigning input- or output-oriented models without being subjective is difficult. Thus, instead of radial measures, nonradial measures, which directly address the input excesses and output shortfalls of the DMUs, should be employed to achieve realistic results. Moreover, input or output indicator selection for efficiency analysis purposes can be subjective (Luo et al. 2012; Ouenniche and Carrales 2018), depending on the research objectives.

Although prior studies (An et al. 2015, 2021; Henriques et al. 2020; Tan et al. 2021; Wang et al. 2014a, 2014b) have applied a two-stage network DEA model to assess the efficiency of commercial banks, forerunners (Avkiran 2015; Fukuyama and Weber 2013; Zha et al. 2016) suggested that employing a DEA model with a dynamic network structure to measure firm performance in the banking industry leads to informative results. Unlike the study by Chao et al. (2015), which also applied a DEA model with a dynamic network structure, this study examines the dynamic network performance of the US banking industry from a resource-based perspective. Therefore, from a long-term network operational performance perspective, this study presents a new approach for assessing bank performance from the facets of resource management and profitability efficiencies. As the dynamic network-DEA (DN-DEA) approach is closely related to the use of input–output, cross-stages, and cross-periods variables when evaluating efficiency, this study develops a framework to evaluate two types of bank efficiencies—resource management and profitability efficiencies—by investigating the efficient uses

[1] DEA is a linear programming methodology for measuring the relative efficiency of decision-making units that transform multiple inputs into multiple outputs (Charnes et al. 1978).

of not only resources (e.g., staff), other expenses to generate intermediate outcomes (e.g., deposits and investments) and interest and noninterest incomes but also carryover inputs (e.g., bank premises and equity) and outputs (e.g., total debts and nonperforming assets) over a long period.

The results reveal that the sample banks have approximately 55.4% of room for improving their efficiency. Although the capital adequacy, asset quality, management quality, earning ability, and liquidity ratings (CAMEL ratings) of efficient banks are generally higher than those of inefficient banks, our regression results reveal that management quality, earnings quality, and liquidity ratios (capital adequacy and asset quality ratios) are positively (negatively) and significantly related to bank performance. Moreover, on average, the overall and divisional efficiencies of big banks are greater than those of small banks. In summary, the impact of dynamic effect and carryovers on overall bank efficiency is highlighted.

This study provides at least three contributions. First, it employs a DN-DEA, namely the dynamic network slack-based measure (DNSBM) model (Tone and Tsutsui 2014)—which comprises dynamic slack-based measure (DSBM) (Tone and Tsutsui 2010) and network slack-based measure (NSBM) (Tone and Tsutsui 2009)—to assess the relative efficiency of US banks. We propose a two-stage evaluation model via the network structure between two successive periods through the dynamic structure using the DNSBM model. The time effect is considered in most DEA models; however, a consideration of dynamic carryover accounting items that are accumulated and carried over from one term to another is lacking. The key to the success of a bank may be the number of bank premises and equity level, both of which are the carryover inputs in this study.

Second, this study supports the DEA results with the CAMEL[2] ratings to determine the top performers in the US banking industry. In particular, we find that the scores of the CAMEL ratings, especially the management quality, earnings quality, and liquidity ratios, of banks that are efficient in utilizing their resources are higher than those of inefficient banks.

Third, this study provides a frontier projection analysis. As this study employs DN-DEA model with dynamic variables in determining the best-performing DMUs, the insight derived from the analysis is helpful for bank managers to fully understand the strategic decision-making for resource management, which can ultimately create competitive advantages, making such businesses sustainable in the current competitive and dynamic business environment. Notably, resource utilization issues are addressed within the resource-based paradigm by using the DEA approach. Furthermore, this study compares the efficiencies of big and small banks.

The remainder of the paper is structured as follows. In "Literature review" section, we review studies on DEA applications in the banking industry. In "Research design" section, we present the research design of this study, and in "Empirical findings" section, we report and discuss the findings. In the final section, we discuss the conclusions and present some recommendations for future research.

[2] The CAMEL rating system is the primary rating mechanism in the United States to supervise banks. CAMEL denotes the five critical dimensions relating to bank operation and performance: capital adequacy, asset quality, management quality, earning ability, and liquidity.

## Literature review

### Non-DEA methods of measuring bank performance

In today's dynamic global economy, strategic benchmarking has become a crucial factor for banks to attain and sustain competitive advantages. In its broadest sense, the term *strategic benchmarking* is used to refer to performance measurement (Chakravarthy 1986). However, strategic benchmarking in the banking industry is challenging, owing to the diversity in operating scope and the complexity of operation-related data. Various studies have employed numerous approaches to assess bank performance, including financial ratio indicators, regression approach, and frontier efficiency analysis (Berger et al. 1993; Paradi et al. 2011a, b). The regression approach is a refined method for evaluating bank performance. Management can identify major determinants of performance by selecting input and output performance variables to construct an appropriate regression model, estimate the expected performance of a given proposal, compare actual and expected values, and adopt appropriate actions. However, these two approaches have inherent limitations in evaluating bank performance. Using financial indicators, constructing representative overall performance indices for comparison and identifying benchmarking policies are difficult. The regression approach also requires a large sample size with the assumption of a normal distribution, and a specific function is applied to express the relationships between analytical variables.

Therefore, these approaches are ineffective in analyzing bank performance when multiple input and multiple output (MIMO) systems are employed. In summary, employing financial indicators provides only a one-sided performance evaluation, and the obtained information addresses only specific operational aspects. Meanwhile, regression approach estimators yield mean-based results rather than precise ones, thereby providing insufficient information for evaluating performance directly.

### Traditional methods for measuring bank performance

Given the limitations of traditional methods, the appropriate method for assessing bank performance is the frontier efficiency method (Chen et al. 2013a), wherein bank performance can be assessed by identifying its resource efficiency relative to the efficiency frontier of top-performing banks. The major advantage of this method is that it can analyze MIMO systems without being affected by the sample size or the function settings among analytical variables. Based on the settings of the frontier and inefficiencies and assumptions of random errors (Bauer et al. 1998; Paradi et al. 2011a, b), the frontier efficiency method is employed using various approaches, including DEA, distribution-free, free disposal hull, stochastic frontier, and thick frontier approaches. Among them, the DEA approach is considered the most robust frontier efficiency method for evaluating bank performance as it can efficiently assess the relationships between MIMO systems. Moreover, it estimates the efficiency frontier by using actual data without requiring specific settings of the functional form and random error, thereby obviating the bias in bank performance measures (Berger and Humphrey 1997).

The most notable study in which DEA models were applied to analyze bank performance was conducted by Sherman and Gold (1985), which utilized the CCR model (Charnes et al. 1978) to compare operating efficiencies among 14 branches of a savings bank. DEA is widely applied to conduct an appropriate efficiency evaluation of various banking issues or examine the effects of notable banking topics on bank efficiency, including bank ownership, corporate events, regulatory reform and liberalization initiatives, and environmental factors. Furthermore, conventional DEA models were employed to assess bank performance in the surveys conducted by Berger and Humphrey (1997) and Fethi and Pasiouras (2010).

Therefore, the management of a bank can employ the DEA approach to identify strategic benchmarking and managerial actions in a complex operating environment (Bauer et al. 1998). The extant literature on performance measurement in the banking industry reveals that there is a heated debate on the application of DEA. From 1985 to 2010, 323 DEA application studies in the banking industry were published in the Web of Science database (Liu et al. 2013b), which implies that research on strategic benchmarking using DEA will continue to grow (Liu et al. 2013a).

### Network or DN-DEA for measuring bank performance

This study identifies four mainly explored areas—conventional, two-stage, network, and DN-DEA models—and presents the effectiveness of these DEA approaches in determining the efficiency of banks in managing resources and generating profits to obtain a holistic view of the DEA application in the banking industry. However, the drawback of employing conventional DEA models is that the transformation process of converting the inputted resources into outputted products is not explicitly modeled (Färe and Grosskopf 2000). Moreover, the simple transformation structure of conventional DEA models may not have sufficient capacity to depict the complexity of bank operations.

Therefore, the transformation process can be further decomposed into several subprocesses or substages to examine bank performance in detail. In these subprocesses or substages, the outputs of the first stage become the inputs to the second stage. The outputs of the first stage are referred to as intermediate measures or products. The study by Seiford and Zhu (1999) was the first to use a two-stage production model to examine the marketability and profitability efficiencies of US commercial banks. Zhu (2000) employed the same performance measure model to study the performance of Fortune 500 companies. Henriques et al. (2020) reviewed the literature on the application of two-stage DEA in the banking industry and concluded that two-stage DEA models have several controversies, including the technique used in the second stage and the possible influence of nondiscretionary variables on efficiency.

However, according to Tone and Tsutsui (2009), the drawback of the conventional DEA and two-stage models is the lack of consideration for intermediate measures or inner linking activities. This limitation can be overcome by using the network DEA model. Several advanced DEA models with a network structure have been developed to address the drawback of the lack of consideration of the internal structure of DMUs, e.g., Kao (2009); Tone and Tsutsui (2009); Cook et al. (2010); Cook et al. (2010); Chen et al. (2013b).

Finally, the latest theoretical development of the DEA methodology, dynamic DEA, and DN-DEA integrates the measurement of intertemporal efficiency change with network structure. Several methods, including window analysis and the Malmquist productivity index, have been developed to measure changes in efficiency over time. However, these models focus on separate periods independently and do not account for the effect of carryover activities between two consecutive terms (Tone and Tsutsui 2014). Tone and Tsutsui (2010) extended the concept of dynamic DEA in the slack-based measure (SBM) framework. Furthermore, Tone and Tsutsui (2014) combined their works on NSBM and DSBM to propose a DN-DEA model. This model can manage multiple divisions connected by links of network structures within each period and evaluate the overall efficiency over the entire observed period and the dynamic change in efficiency.

Following studies such as Chao et al. (2015), which also applied a DN-DEA model, this study examines the dynamic network performance of the US banking industry from a resource-based perspective.

## Research design

### Technical specification: DNSBM model

As depicted in Fig. 1, we divide the performance of banks into resource management and profitability efficiencies. We analyze the main resources that contribute to bank performance and evaluate the mechanism of the inner network production structure of banks. Although certain studies (e.g., Chen 2002; Nguyen 2018; Nguyen et al. 2016; Silva et al. 2017) compared DEA with stochastic frontier analysis (SFA) when measuring bank efficiency, SFA can only accommodate one output at a time. Moreover, the assumptions under the inefficiency term distribution must be imposed to decompose the error term. However, DEA uses linear programming to calculate an efficient deterministic frontier against which DMUs are compared in terms of their efficiencies in transforming multiple inputs into outputs. DEA can also open the black box of the complicated production process of banks with a network structure. However, the DEA approach, including window analysis or the Malmquist productivity index, neglects the effect of carryovers on changes in performance. Although these models consider the effects of time changes on performance, they only aim to obtain independent partial best solutions for different periods (Tone and Tsutsui 2010). The DN-DEA method employed in the present study can overcome the aforementioned problems in evaluating bank performance from the resource-based perspective. In particular, this study employs the DNSBM model (Tone and Tsutsui 2014) to evaluate bank performance over a long-term period.

SBM is a method for nonradial efficiency measurement that complies with the "unit invariant" assumption and can measure efficiency value by integrating differential variables from over-input and under-output. SBM is a suitable method when the input and output cannot be adjusted by their ratios. Performance is measured using three categories of orientation—input-oriented, output-oriented, and nonoriented efficiencies. In this study, we gauge the nonoriented efficiency of banks because we simultaneously consider the variances of input and output slacks. When combined with the dynamic effect and network structure, the DEA approach can handle multiple inputs and outputs from a long-term and divisional perspective.

In addition, Cook et al. (2010) indicated that the two-stage and network DEA models mainly differ in the assumption of intermediate measures. The two-stage DEA model establishes that the outputs of the first stage are the sole inputs to the second stage, whereby no other external inputs can be included in the second stage. Meanwhile, the

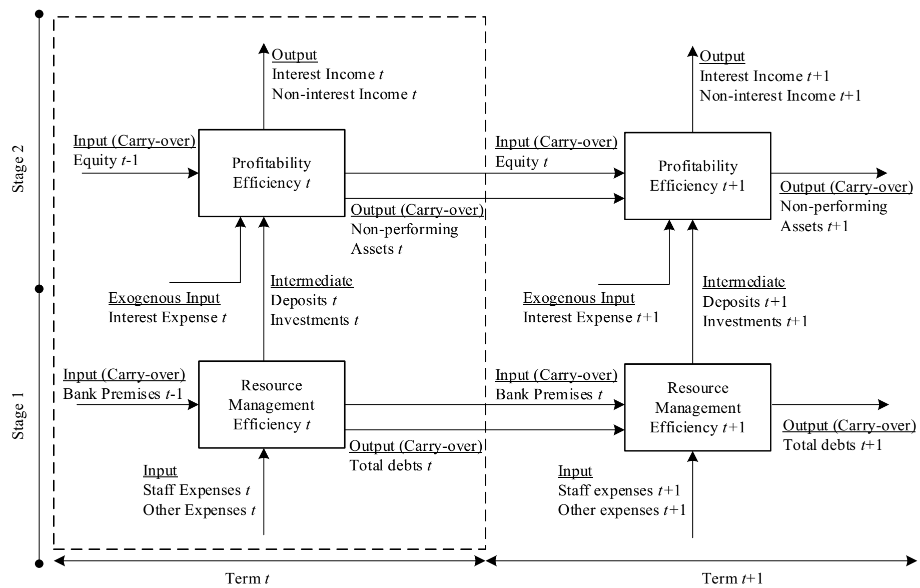


**Fig. 1** Dynamic network production processes of banks

network DEA model further relaxes this assumption and allows additional independent inputs along with intermediate measures in performance evaluation. Therefore, we include an exogenous input that is not an outcome of resource management—interest expense—when assessing the Stage 2 profitability efficiency.

Regarding the formulation of the DN-DEA method, the dynamic network production processes in Fig. 1 that deal with $n$ DMUs ($j$=1,..., $n$) consisting of $k$ stages ($k = 1, \ldots, K$) over $T$ periods ($t = 1, \ldots, T$) are considered. In each period, the DMUs use common $m_t^k$ inputs ($i = 1, \ldots, m_t^k$) in $k$ stages and $r_t^k$ outputs ($r = 1, \ldots, r_t^k$) in $k$ stages. Let $x_{iot}^k \left( i =, \ldots, m_t^k \right)$ and $y_{rot}^k \left( r = 1, \ldots, r_t^k \right)$ denote the observed input and output values of DMU $j$ in $k$ stages at period $t$, respectively. $z_{vjt}^{(k,h)} \left( v = 1, \ldots, V_t^{kh} \right)$ links intermediate products of DMU $j$ from stage $k$ to $h$ in period $t$, where $V_t^{kh}$ is the number of items in links from $k$ to $h$ (e.g., deposits and investments). $C_{pjt}^{k,(t-1,t)} \left( j = 1, \ldots, n; p = 1, \ldots, C_{free}^k; k = 1, \ldots, K; t = 1, \ldots, T \right)$ is the carryover of bank $j$ at stage $k$ from period $t-1$ to $t$, where $C_{free}^k$ is the number of items in the free carryover from stage $k$(e.g., bank premises and equity). This study employs the notion $C_{qot}^{k,bad} (q = 1, \ldots, C_{bad}^k; t = 1, \ldots, T; k = 1, \ldots, K)$ for denoting undesirable carryover link[3] values to identify them by period ($t$), DMU ($j$), stages ($k$), and item ($i$). $C_{bad}^k$ is the number of bad links (e.g., nonperforming assets and total debts). These values are all observed values up to period $T$. This study expresses $DMU_o (o = 1, ..., n)$ by using these expressions for production.

Let $\Lambda_o^*, s_{iot}^{k-}, s_{rot}^{k+}, s_{vot}^{(k,h)}$ and $s_{qo,bad}^{(t-1,t)^-}$ denote the overall efficiency during period $T$, excess input, output shortfall, slacks and free in sign, and excess undesirable carryover, respectively. The objective function is an extension of the nonoriented SBM model (Tone 2001)

[3] In Tone and Tsutsui (2010), the term *bad link* denotes inputted carryover, which is restricted to be not greater than the observed one.

and deals with excesses in input resources, outputs, and undesirable links. The numerator and denominator are the average input efficiency and inverse of the average output efficiency, respectively. This study defines the nonoriented overall efficiency as a ratio that ranges from 0 to 1 and becomes 1 when all slacks are 0. The objective function value is also unit invariant.

$$\Lambda_o^* = Min \frac{\frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{K} w_t^k \left[1 - \frac{1}{\left(m_t^k + C_{bad}^k\right)}\left(\sum_{i=1}^{m_t^k}\frac{s_{iot}^{k-}}{x_{iot}^k} + \sum_{q=1}^{C_{bad}^k}\frac{s_{qo,bad}^{(t-1,t)-}}{C_{qo,bad}^{k,(t-1,t)}}\right)\right]}{\frac{1}{T}\sum_{t=1}^{T}\sum_{k=1}^{K} w_t^k \left[1 + \frac{1}{r_t^k}\left(\sum_{r=1}^{r_t^k}\frac{s_{rot}^{k+}}{y_{rot}^k}\right)\right]} \tag{1}$$

s.t.

$$x_{iot}^k = \sum_{j=1}^{n} x_{ijt}^k \lambda_{jt}^k + s_{iot}^{k-} (i = 1, \ldots, m_t^k; \quad t = 1, \ldots, T; \quad k = 1, \ldots, K), \tag{3}$$

$$y_{rot}^k = \sum_{j=1}^{n} y_{rjt}^k \lambda_{jt}^k - s_{rot}^{k+} (r = 1, \ldots, r_t^k; \quad t = 1, \ldots, T; \quad k = 1, \ldots, K), \tag{3}$$

$$\sum_{j=1}^{n} \lambda_{jt}^k = 1 \, (t = 1, \ldots, T; \quad k = 1, \ldots, K), \tag{4}$$

$$\sum_{j=1}^{n} z_{vjt}^{(k,h)} \lambda_{jt}^h = \sum_{j=1}^{n} z_{vjt}^{(k,h)} \lambda_{jt}^k, \quad \forall (k,h)(v = 1, \ldots, V_t^{kh}; \quad t = 1, \ldots, T), \tag{5}$$

$$z_{vot}^{(k,h)} = \sum_{j=1}^{n} z_{vjt}^{(k,h)} \lambda_{jt}^k + s_{vot}^{(k,h)}, \quad \forall (k,h)(v = 1, \ldots, V_t^{kh}; \quad t = 1, \ldots, T), \tag{6}$$

$$\sum_{j=1}^{n} C_{pj,free}^{k,(t-1,t)} \lambda_{jt-1}^k = \sum_{j=1}^{n} C_{pj,free}^{k,(t-1,t)} \lambda_{jt}^k, \quad (p = 1, \ldots, C_{free}^k; \quad t = 1, \ldots, T; \quad k = 1, \ldots, K) \tag{7}$$

$$C_{po,free}^{k,(t-1,t)} = \sum_{j=1}^{n} C_{pj,free}^{k,(t-1,t)} \lambda_{jt}^k + s_{po,free}^{(t-1,t)}, \, (p = 1, \ldots, C_{free}^k; \quad t = 1, \ldots, \quad T; \, k = 1, \ldots, K) \tag{8}$$

$$\sum_{j=1}^{n} C_{qj,bad}^{k,(t-1,t)} \lambda_{jt-1}^k = \sum_{j=1}^{n} C_{qj,bad}^{k,(t-1,t)} \lambda_{jt}^k, \, (q = 1, \ldots, C_{bad}^k; \quad t = 1, \ldots, T; \quad k = 1, \ldots, K) \tag{9}$$

$$C_{qo,bad}^{k,(t-1,t)} = \sum_{j=1}^{n} C_{qj,bad}^{k,(t-1,t)} \lambda_{jt}^k + s_{qo,bad}^{(t-1,t)-}, \, (q = 1, \ldots, C_{bad}^k; \quad t = 1, \ldots, T; \quad k = 1, \ldots, K) \tag{10}$$

$\lambda_{jt}^k, s_{iot}^{k-}, s_{rot}^{k+}, s_{qot,bad}^{(t-1,t)-} \geq 0$, $s_{vot}^{(k,h)} \in$ free in sign, $\sum_{t=1}^{T} W^t = 1, \sum_{k=1}^{K} w^k = 1$, $W^t \geq 0 (\forall t), w^k \geq (\forall k) 0$.

$W^t (t = 1, \ldots, T)$ is the weight of period $t$, and $w^k (k = 1, \ldots, K)$ is the weight of stage $k$. This study adopts equal weight. Equations (2) and (3) are the input and output constraints, respectively. Equation (4) suggests the assumption of variable returns to scale.[4]

[4] This study performs DEA efficiency analysis under each assumption and compares the derived efficiency scores to choose between constant returns to scale and VRS (Avkiran 2001). An untabulated t-test shows a significant difference between two groups of efficiency scores. The results verify that assuming VRS for the assessment in this study is safe.

Furthermore, Eqs. (5) and (6) suggest that the linking activities are freely determined while maintaining continuity between inputs and outputs. This case can determine whether the current link flow is appropriate in the light of other DMUs, that is, the link flow may increase or decrease in the optimal solution of the linear programs.

Equations (7) and (8) indicate that the current link flow corresponds to carryovers that the DMUs can freely handle. The value of such flow can be increased or decreased from the observed one. Deviation from the current value is not directly reflected in the efficiency evaluation. However, the continuity condition between the two periods explained below has an indirect effect on the efficiency score, and its value can be increased or decreased from the observed one. Moreover, Eqs. (9) and (10) indicate that the current link flow corresponds to an undesirable carryover. In our model, undesirable carryovers are treated as inputs, and their values should not be greater than the observed ones. The comparative excess carryovers in this category are accounted as inefficiency.

Equations (2)–(10) denote the production possibility set for the objective $DMU_o(o = 1, \ldots, n)$. The following is obtained by accounting for Eqs. (2)–(10) in an optimum solution of Eq. (1):

$$\left\{\begin{array}{l} \lambda_{jk}^{t*}, j = 1, ..., n;\ s_{iot}^{k-*}, i = 1, ..., m_t^k; s_{rot}^{k+*}, r = 1, ..., r_t^k;\ s_{vot}^{(k,h)^*}, v = 1, ..., V_t^{kh};\\ s_{po,free}^{(t,t+1)}, p = 1, ..., C_{free}^k;\ s_{qo,bad}^{(t,t+1)^{-*}}, q = 1, ..., C_{bad}^k;\ t = 1, ..., T; k = 1, ..., K \end{array}\right\}$$

If the optimal solution for Eq. (1) satisfies $\Lambda_o^* = 1$, then the target $DMU_o$ is called nonoriented overall efficiency. In Eq. (11), if all optimal solutions satisfy $\rho_{ot}^* = 1$, then $DMU_o$ is called nonoriented term efficiency for term $T$. This scenario implies that the optimal slacks for term $t$ in Eq. (11) are all 0.

$$\rho_{ot}^* = \frac{\sum_{k=1}^{K} w_t^k \left[1 - \frac{1}{m_t^k + C_{bad}^k}\left(\sum_{i=1}^{m_t^k} \frac{s_{iot}^{k-*}}{x_{iot}^k} + \sum_{q=1}^{C_{bad}^k} \frac{s_{qo,bad}^{(t-1,t)^{-*}}}{C_{qo,bad}^{k,(t-1,t)}}\right)\right]}{\sum_{k=1}^{K} w_t^k \left[1 + \frac{1}{r_t^k}\left(\sum_{r=1}^{r_t^k} \frac{s_{rot}^{k+*}}{y_{rot}^k}\right)\right]}, \quad t = 1, \ldots, T \tag{11}$$

Division efficiency ($\rho_o^{k*}$) is defined by

$$\rho_o^{k*} = \frac{\sum_{t=1}^{T} W^t \left[1 - \frac{1}{m_t^k + C_{bad}^k}\left(\sum_{i=1}^{m_t^k} \frac{s_{iot}^{k-*}}{x_{iot}^k} + \sum_{q=1}^{C_{bad}^k} \frac{s_{qo,bad}^{(t-1,t)^{-*}}}{C_{qo,bad}^{k,(t-1,t)}}\right)\right]}{\sum_{t=1}^{T} W^t \left[1 + \frac{1}{r_t^k}\left(\sum_{r=1}^{r_t^k} \frac{s_{rot}^{k+*}}{y_{rot}^k}\right)\right]}, \quad k = 1, \ldots, K. \tag{12}$$

Finally, term-divisional efficiency ($\rho_{ot}^{k*}$) is defined by

$$\rho_{ot}^{k*} = \frac{\left[1 - \frac{1}{m_t^k + C_{bad}^k}\left(\sum_{i=1}^{m_t^k} \frac{s_{iot}^{k-*}}{x_{iot}^k} + \sum_{q=1}^{C_{bad}^k} \frac{s_{qo,bad}^{(t-1,t)^{-*}}}{C_{qo,bad}^{k,(t-1,t)}}\right)\right]}{\left[1 + \frac{1}{r_t^k}\left(\sum_{r=1}^{r_t^k} \frac{s_{rot}^{k+*}}{y_{rot}^k}\right)\right]}, \quad k = 1, \ldots, K; \quad t = 1, \ldots, T. \tag{13}$$

In Eq. (13), if all optimal solutions satisfy $\rho_{ot}^{k*} = 1$, then the target $DMU_o$ is called nonoriented term efficient with divisions $k$ at term $T$. This scenario implies that the optimal slacks with divisions $k$ at term $t$ in Eq. (13) are all 0.

**Production processes of banks in a dynamic and network structure**

Bank managers strive to develop rigorous and strategic decision-making processes. Bank managers should also assess various indicators for evaluating bank performance to ensure reliable strategic benchmarking (Chakravarthy 1986; Cooper et al. 2004). The DEA approach, which is widely used to measure firm-level resource management efficiency from a multidimensional perspective, should be employed. As previously discussed, DEA is a linear programming technique used to evaluate the relative efficiency of banks by simultaneously considering multiple inputs and outputs (Cooper et al. 2006). This nonparametric method allows for the identification of a "production frontier" as the basis for an efficiency evaluation from a resource-based perspective, in which banks that meet efficiency benchmarks can serve as references for inefficient banks. This can make inefficient banks assess and improve their resource management to improve their efficiency.

Cooper et al. (2004) analyzed various DEA approaches over the years and the basic ones include the CCR (Charnes et al. 1978) and BCC model (Banker et al. 1984). In this study, we apply the concept of network DEA (Kao 2009; Tone and Tsutsui 2009) as the basis for production process development in banks to understand the relationships between inner economic activities. This model can simultaneously evaluate the overall and divisional efficiencies. It does not consider inner activities as a "black box." This study considers the effects of time on performance. In particular, we add carryovers spanning several periods to evaluate dynamic performance by applying the concept of dynamic DEA (Tone and Tsutsui 2010).

As the banking industry is dynamic, we employ the DNSBM model developed by Tone and Tsutsui (2014) rather than the conventional DEA models to evaluate the dynamic network performance of US commercial banks over a long-term period. This model is superior to conventional DEA models in two main aspects. First, the network structure (Tone and Tsutsui 2009) can measure managerial efficiency in resource management and the inner linking activities between resource management and profitability efficiencies. Second, it considers the period effect by incorporating the influence of carryovers[5] on changes in corporate performance across several periods (Tone and Tsutsui 2010). In summary, bank managers should focus on improving their resource management and profitability efficiencies over long-term periods. Therefore, we propose the following dynamic network production processes for US commercial banks.Fig. 1 depicts the dynamic network production processes of banks. The first-stage process—resource management efficiency—is intended to assess the relative efficiency of banks in managing their resources. Likewise, the second-stage node—profitability efficiency—is proposed to evaluate the relative efficiency of banks in producing competitive advantages.

[5] Carryovers are known as permanent accounts in accounting studies. This type of account has a balance that is accumulated and brought from one period to another (e.g., from period $t$ to period $t+1$) on the balance sheet (Weygandt, Kimmel, and Keiso 2010). From a longitudinal view of banking operations, account balances, including bank premises and capitals, are long-term carryovers used by banks to ensure sustainable performance.

Similar to previous studies (e.g., Matthews 2013; Sun and Chang 2011), we consider two inputs ($m_t^k$ inputs), namely staff expenses and other expenses; two carryovers ($C_{free}^k$ for free carryover input and $C_{qot}^{k,bad}$ for undesirable carryover output), namely bank premises (an input) and total debts (an output); and two outputs ($r_t^k$ outputs), namely interest and noninterest incomes, in the intermediation approach. In between the two stages, we have two intermediates ($V_t^{kh}$ intermediates), namely deposits and investments (the inner linking accounts), which are products of the first stage and act as inputs to the second stage. In particular, banks utilize their resources, including staff, expenses, and bank premises, to collect deposits first and generate investments, with total debts being an undesirable item. That is, this first stage of resource management efficiency is consistent with the resource utilization stage in the study by Kweh et al. (2021). Regarding the second stage, that is, profitability efficiency, we estimate how efficiently the two intermediates—deposits and investments—are transformed into interest and noninterest incomes. Moreover, we add one exogenous input (interest expense) and two carryovers—equity (an input) and nonperforming assets (an output)—to evaluate the second-stage efficiency. These carryovers help address the dynamism and stiff competition in the banking sector. Overall, the inclusion of undesirable items in the efficiency evaluation model provides further insights into bank efficiencies. Readers can refer to Appendix 1 for abbreviations of technical terms and their expositions.

### Data collection

The data used in this study are extracted from the BankScope database for the fiscal years of 2010–2020. In this study, we limit our sample to banks with North American Industry Classification System code 522,110 (i.e., commercial banks that primarily engage in accepting demand and other deposits and providing commercial, industrial, and consumer loans). In addition, we require banks to have existed since 2010 and continued their operations until at least 2020. Following the exclusion of banks with incomplete data, 287 commercial banks (DMUs) were used for the analysis.

Table 1 presents the summary statistics of the inputs, intermediates, carryovers, and outputs used in the DEA analysis. The large values of standard deviations for all variables suggest that a large variation exists in the sample banks. The untabulated results reveal that the mean values of all variables fluctuated over the 2010–2020 sample period. Accordingly, this study investigates the efficiency of banks in managing their resources to achieve profitability. The application of DEA, which is a relative measure of efficiency from a multidimensional perspective, allows us to reasonably estimate the resource management and profitability efficiencies of banks with different sizes and levels of resources and income.

We test the following to further validate the DEA model and dataset used in this study. The first condition states that the number of DMUs should be at least twice the sum of the inputs, intermediates, carryovers, and outputs used in each technology set or stage (Golany and Roll 1989). In the first stage, we have six indicators. However, we employ five indicators in the second stage of the DEA analysis. The analysis of the 287 sample banks validates the developed DEA model. The second condition requires that the variables used should have "isotonic" relationships, whereby the correlations between inputs and outputs should be positive and significant. The untabulated

**Table 1** Summary statistics of DEA variables

| Variable | Mean | St. Dev | Minimum | Maximum |
|---|---|---|---|---|
| *Input* | | | | |
| Staff expenses | 870.07 | 3,659.49 | 1.38 | 36,965.00 |
| Other expenses | 2,731.11 | 10,690.63 | 3.58 | 135,517.00 |
| *Exogenous input* | | | | |
| Interest expense | 772.99 | 3,165.31 | 0.35 | 38,964.41 |
| *Carryover (Free)* | | | | |
| Bank premises$_{t-1}$ | 584.68 | 2,373.79 | 0.72 | 38,448.22 |
| Equity$_{t-1}$ | 6,880.71 | 27,264.38 | 2.16 | 279,354.00 |
| *Carryover (Undesirable Output)* | | | | |
| Total debts | 12,889.18 | 58,353.59 | 0.25 | 753,752.00 |
| Nonperforming assets | 710.07 | 3,670.56 | 0.03 | 57,392.29 |
| *Intermediate* | | | | |
| Deposits | 50,527.99 | 186,327.08 | 62.38 | 2,144,257.00 |
| Investments | 12,537.51 | 54,536.31 | 4.11 | 750,634.00 |
| *Output* | | | | |
| Interest income | 1,608.23 | 5,969.08 | 2.04 | 57,245.00 |
| Noninterest income | 1,180.48 | 5,350.36 | 0.05 | 64,980.00 |

The variables are measured in millions of US dollars. Staff expenses are the total compensation paid. Other expenses include noninterest expenses such as selling and administrative expenses. Interest expenses are interests paid and payable on any borrowings or debt. Bank premises are the property, plant, and equipment. Equity is the difference between a bank's assets and its liabilities. Total debts are amounts due of borrowed money. Nonperforming assets are loans or advances that are in default or in arrears. Deposits are money placed into a deposit account at a bank. Investments are money that a bank receives from customers and invests in a variety of assets. Interest income is the money that a bank earns from lending its funds. Noninterest income is income that are generated by noninterest related activities such as fees and commissions

correlation results indicate that abundant inputs generate abundant outputs, justifying the inclusion of the aforementioned variables in the DEA model.

We also calculate the five CAMEL variables using financial information obtained from the database and not from the rating score from US bank supervisory authorities, which is consistent with the study by Wang et al. (2013). That is, this study calculates the following five financial variables, which are key financial ratios that can reflect bank operations and performance from a different perspective:

*Capital adequacy ratio* (C): This variable reflects a bank's ability to manage risk exposure to absorb unforeseen losses. We expect a positive result for the measure, that is, the ratio of total equities to total assets.

*Asset quality ratio* (A): This ratio reveals the quality of the loan portfolio, the use of nonperforming loan ratios, and the provision for loan loss reserve. The higher the value of this variable is, the lower the asset quality rating is. In this study, we measure this variable as the ratio of nonperforming loans to total equities.

*Management quality ratio* (M): The capability of the management of a bank to manage risks and ensure efficient operation and compliance is represented by this ratio, which is measured as the ratio of noninterest expense to total assets. A deficient management would have a high value of this ratio.

*Earning ability ratio* (E): This variable measures the profitability of a bank, where a high value indicates that a bank has a high ability to generate earnings. We measure this variable as the ratio of net income to total assets.

*Liquidity ratio* (L): This variable refers to the availability of assets of a bank that can be readily converted into cash to fulfill its obligations. Consistent with Wang et al. (2013), we measure this variable as the ratio of total cash and receivables to total assets. A bank with access to adequate fund sources is recognized as having a strong liquidity level; therefore, a high value of this ratio is preferable.

## Empirical findings

### DEA analysis

Table 2 presents the overall efficiency scores for the 287 US commercial banks. Few banks achieved overall efficiency over the sample period (2010–2020). Overall, the average efficiency score is 0.446, and only four banks are efficient with an efficiency score of 1. The mean efficiency score implies that the room for improvement in the overall performance, that is, the production processes of benchmark banks, is approximately 55.4% for inefficient banks. The number of banks with overall efficiency over the sample period varies, with a maximum of seven banks being efficient in a year.

The DNSBM model can also be used to evaluate the dynamic changes in divisional efficiency. Table 2 presents the resource management and profitability efficiency scores. Resource management efficiency (mean = 0.689) is the main factor driving overall efficiency (profitability efficiency mean = 0.437). This finding is indirectly consistent with the focus of this study, that is, strategic benchmarking from the resource-based perspective. Differences exist between banks in terms of resource management; therefore, banks should first focus on various profitable investments while sustaining and improving their resource utilization pattern to gain competitive advantages, which can ultimately improve overall efficiency. Comparing the number of efficient banks in both stages is also valuable. However, a comparison of the two sets of results indicates that several banks are efficient in terms of resource management efficiency but not in profitability.

**Table 2** Efficiency scores for the 287 US commercial banks

| Year | Overall efficiency | | Resource management efficiency | | Profitability efficiency | |
|---|---|---|---|---|---|---|
| | Mean | No. of efficient banks | Mean | No. of efficient banks | Mean | No. of efficient banks |
| 2010 | 0.405 | 5 | 0.703 | 29 | 0.341 | 14 |
| 2011 | 0.442 | 7 | 0.721 | 24 | 0.376 | 20 |
| 2012 | 0.451 | 7 | 0.716 | 20 | 0.396 | 29 |
| 2013 | 0.457 | 6 | 0.701 | 19 | 0.398 | 22 |
| 2014 | 0.475 | 6 | 0.708 | 26 | 0.428 | 20 |
| 2015 | 0.503 | 5 | 0.715 | 22 | 0.460 | 24 |
| 2016 | 0.518 | 4 | 0.696 | 16 | 0.482 | 24 |
| 2017 | 0.500 | 5 | 0.670 | 15 | 0.464 | 26 |
| 2018 | 0.484 | 6 | 0.657 | 19 | 0.453 | 26 |
| 2019 | 0.530 | 6 | 0.639 | 16 | 0.512 | 25 |
| 2020 | 0.517 | 7 | 0.653 | 21 | 0.497 | 25 |
| Overall | 0.446 | 4 | 0.689 | 15 | 0.437 | 6 |

In summary, the current assessment of resource management and profitability efficiencies of US commercial banks helps to gain insight into the resource-based perspective. Although these findings are insightful, they only provide an approximate scope for improvement but do not reveal areas that require improvement. Therefore, we discuss the frontier projection analysis in the following section.

### Frontier projections

As previously noted, only four banks achieve overall efficiency, and the remaining banks have approximately 55.4% room for improvement to become efficient. However, the areas that bank managers should address for efficiency improvement to be sustainable are unclear. We conduct a frontier projection analysis in Panel A of Table 3 to provide a clear direction in strategic benchmarking from the resource-based perspective to help bank managers resolve the aforementioned problem. This analysis provides some information on the potential areas of improvement in inefficient banks. In particular, we provide indications of reductions in specific input amounts and additions required in specific output amounts, which can marginally contribute to efficiency. The results presented in Panel B of Table 3 imply that while reductions (additions) are required for input (output) amounts, the top four efficient banks (their average overall efficiency is 1.000) are transforming more resources into more outcomes than their inefficient counterparts, that is, the bottom four (their average overall efficiency is 0.156).

The results of the frontier projection analysis are presented in Table 3. To manage their resources, on average, US commercial banks that were inefficient in 2020 should reduce their staff expenses, other expenses, and bank premises by 18.7%, 27.2%, and 18.7%, respectively. Moreover, 35.9% of total debts should be reduced. Regarding the slack of output variables in the first stage, the sample banks should have been operating with 16.9% (141.9%) more deposits (investments). In terms of achieving profitability efficiency, they should consider reducing the amounts of interest expenses and nonperforming assets while increasing their equity alongside the aforementioned deposits and investments. The results also imply that the sample banks could have done better with a high percentage of interest and noninterest incomes.

In addition, we find that the percentages of the frontier projections fluctuate across the sample period for all inputs and outputs. The banks should pay attention to their total debts and nonperforming assets. Another overutilized resource is bank premises. These results provide crucial insights into strategic benchmarking from a long-term resource utilization perspective, whereby bank managers should consider carryovers and inner linking activities to examine bank performance.

### Discussion—CAMEL ratings and bank size

Prior studies on solving multiple-criteria decision-making problems (Kou et al. 2021; Yu et al. 2021; Zhang et al. 2021) suggest looking into a hybrid framework for performance evaluation. In the banking industry, previous studies have also emphasized the importance of CAMEL ratings. Efficient banks are predicted to have CAMEL rating scores that are higher than those of inefficient banks. We classify the sample banks into two groups and assign a value of 1 for a bank with an efficiency score greater than the median value of the overall efficiency and 0 otherwise. The untabulated results indicate

**Table 3** Benchmarking analysis

| Year | First stage | | | | First/Second stage | | Second stage | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Input | | Carryover (Input) | Carryover (Undesirable) | Intermediate | | Exogenous input | Carryover (Input) | Carryover (Undesirable) | Output | |
| | Staff expenses | Other expenses | Bank premises | Total debts | Deposits | Investments | Interest expenses | Equity | Nonperforming assets | Interest income | Noninterest income |
| *Panel A: Frontier projections for reduction in inputs and addition in outputs by year and percentage (%)* | | | | | | | | | | | |
| 2010 | −36.8 | −48.2 | −6.6 | −29.9 | 11.4 | 76.1 | −30.2 | 44.2 | −50.6 | 19.5 | 273.3 |
| 2011 | −49.5 | −32.2 | 8.7 | −28.4 | −9.7 | 73.9 | −16.9 | 28.7 | −26.4 | 67.4 | 649.4 |
| 2012 | −20.1 | −22.8 | −23.9 | −24.3 | 22.3 | 92.3 | −37.8 | 36.9 | −35.3 | 27.1 | 351.6 |
| 2013 | −20.7 | −20.3 | −20.3 | −30.4 | 28.3 | 80.4 | −41.7 | 40.8 | −34.1 | 36.5 | 337.8 |
| 2014 | −19.0 | −20.4 | −23.6 | −32.2 | 28.7 | 86.5 | −40.7 | 40.0 | −33.9 | 47.9 | 342.4 |
| 2015 | −19.1 | −21.6 | −19.5 | −34.5 | 30.1 | 71.0 | −38.6 | 39.6 | −29.5 | 38.9 | 322.2 |
| 2016 | −24.0 | −23.9 | −24.3 | −37.7 | 15.1 | 84.9 | −34.5 | 25.7 | −37.1 | 18.5 | 249.0 |
| 2017 | −24.2 | −21.7 | −28.4 | −41.6 | 16.8 | 90.4 | −32.0 | 23.6 | −42.2 | 19.2 | 278.4 |
| 2018 | −26.1 | −25.0 | −28.0 | −41.1 | 9.8 | 114.3 | −35.3 | 18.2 | −39.7 | 19.9 | 287.7 |
| 2019 | −24.1 | −25.3 | −21.2 | −42.5 | 8.7 | 114.6 | −35.1 | 19.5 | −43.7 | 21.5 | 248.5 |
| 2020 | −18.7 | −27.2 | −18.7 | −35.9 | 16.9 | 141.9 | −39.9 | 7.5 | −45.3 | 13.8 | 306.3 |
| *Panel B: Comparison between bank efficiency in transforming resources to generate profitability (the variables are measured in millions of US dollars)* | | | | | | | | | | | |
| Top 4 | 19,946.66 | 49,026.07 | 9,234.25 | 252,923.84 | 871,277.73 | 248,305.95 | 8,261.75 | 128,205.95 | 6,904.00 | 28,103.14 | 31,370.30 |
| Bottom 4 | 88.65 | 298.74 | 118.66 | 1,811.22 | 7,329.40 | 1,905.77 | 111.15 | 1,238.27 | 102.87 | 294.43 | 27.45 |

**Table 4** Regression analysis (n = 3,289)

| Variable | Coefficient | Standard Error | t-statistic | Prob |
|---|---|---|---|---|
| Intercept | 0.395 | 0.0226 | 17.5403 | < 0.001 |
| Capital adequacy ratio (C) | − 0.499 | 0.1681 | − 2.9715 | 0.003 |
| Asset quality ratio (A) | − 2.252 | 0.3989 | − 5.6474 | < 0.001 |
| Management quality ratio (M) | 2.371 | 0.4030 | 5.8838 | < 0.001 |
| Earnings ability ratio (E) | 3.270 | 0.6641 | 4.9241 | < 0.001 |
| Liquidity ratio (L) | 1.028 | 0.0807 | 12.7253 | < 0.001 |
| Adjusted R-squared | 0.086 | | | |
| F-statistic | 62.564*** | | | |

This table reports the ordinary least square results with dependent variable being overall efficiency and explanatory variables as the CAMEL ratings. The standard errors are derived after adjusting according to White heteroskedasticity-consistent standard errors & covariance. That is, $OE_{it} = \beta_1 + \beta_2 C_{it} + \beta_3 A_{it} + \beta_4 M_{it} + \beta_5 E_{it} + \beta_6 L_{it} + \beta_6 \varepsilon_{it}$ where *i* represents bank, *t* represents time, and $\varepsilon$ is the error term

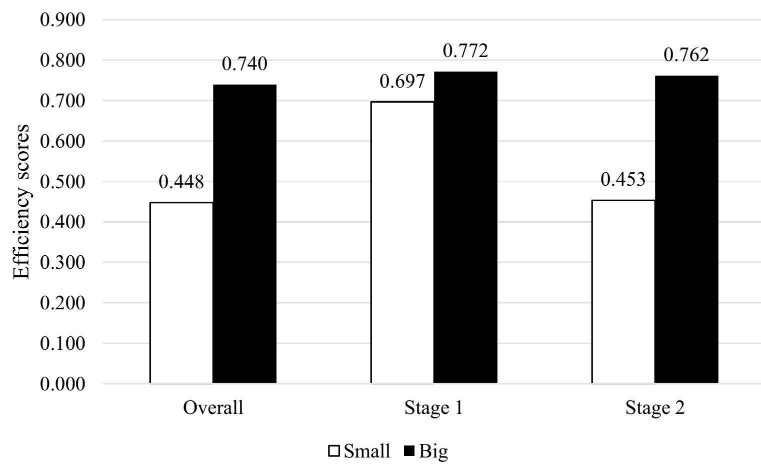


**Fig. 2** Comparisons of efficiency scores between big and small banks

that several efficient banks have slightly higher capital adequacy (0.102 vs. 0.101), earning ability (0.008 vs. 0.007), liquidity (0.061 vs. 0.045), and management quality ratios (0.029 vs. 0.027) but lower asset quality ratios (0.012 vs. 0.014) than slightly efficient banks. These results are generally consistent with prior studies such as the study by Barr et al. (2002). In particular, relatively efficient banks have a low value of asset quality ratio, that is, their asset quality rating is not as favorable as that of the relatively inefficient banks owing to the high level of nonperforming loans. A possible explanation for this is that they have large loan portfolios, resulting in low asset quality. In Table 4, further analysis of the regression of the overall efficiency on the CAMEL ratings indicates that the capital adequacy (coefficient = − 0.499, p = 0.003), asset quality (coefficient = − 2.252, p < 0.001), liquidity (coefficient = 1.028, p < 0.001), management quality (coefficient = 2.371, p < 0.001), earning ability (coefficient = 3.270, p < 0.001), and liquidity ratios (coefficient = 1.028, p < 0.001) are significantly related to overall efficiency.

Moreover, the important role of the DEA is to help a DMU find the best benchmark. When analyzing all banks together, it is not realistic for a small bank to become a very large bank overnight, especially if a small bank's benchmark is a very large bank. Therefore, we split the sample banks into banks with large and small bank premises for further analysis. Big (small) banks are those having bank premises more (less) than the overall mean bank premises of the sample banks. The results in Fig. 2 indicate that big banks are generally more efficient than small banks (0.740 vs. 0.448). Consistent with the aforementioned results, their respective overall efficiencies are attributable to their resource management efficiencies. In addition, our untabulated results reveal that big banks have lower capital adequacy (0.091 vs. 0.1037), asset quality (0.009 vs. 0.014), and management quality ratios (0.023 vs. 0.028) but higher liquidity ratio (0.074 vs.0.050) than small banks. Their earnings ability ratio is similar at 0.008.

These results suggest that banks should improve their resource management efficiency, which has become their internal strength in the aftermath of the 2007–2009 global financial crisis. Banks should also efficiently manage their undesirable total debts and nonperforming assets. Banks can gain competitive advantages that would ultimately increase profitability efficiency and sustainability by efficiently utilizing resources. Moreover, it may be difficult for them to immediately manage their long-term assets such as bank premises. Having equity for operations may also improve their performance. Thus, considering carryover items in strategic benchmarking is imperative because it allows bank managers to assess the overall bank performance over a long-term period. Furthermore, banks should effectively manage their CAMEL ratings, especially the management quality, earnings quality, and liquidity ratios, all of which positively contribute to bank efficiency.

## Conclusion

The empirical evidence from this study suggests that the sample banks encounter various challenges because only four of them are efficient, with approximately 51.2% room for improvement. Moreover, the relative efficiency of the sample banks has been decreasing since the 2008 global financial crisis. Therefore, to be profitable, banks must efficiently manage their resources. Inputted carryover items, such as bank premises, emerge as the main input that bank managers should focus on to manage and determine bank performance. The results also reveal that the performance of the sample banks has been fluctuating since 2010 after the global financial crisis, with contributions mainly from their resource management efficiency. According to the frontier projection analysis, inefficient banks should reduce their bank premises. Thus, adjustments can be made on any idle or underutilized bank premises to increase profitable investments. This observation implies the possibility that an efficient bank may have CAMEL rating scores higher than those of relatively inefficient peer-benchmarked banks. Furthermore, this study finds that efficient banks generally have CAMEL ratings higher than those of inefficient banks.

This study is novel as it is different from prior studies in terms of the inclusion of inputted (bank premises and equity) and undesirable carryovers (total debts and nonperforming assets), unlike prior studies. Both have been overlooked in the efficiency evaluation of banks as indicators of dynamic effects over a long period. As measuring bank efficiency is a complicated process in which the results can be exposed to subjective judgment, this study proposes a DEA efficiency framework to estimate the dynamic network production processes of banks. This study is designed to measure the performance of US commercial banks over a long-term period. As DEA is a practical methodology for strategic benchmarking, we employ a DN-DEA model, i.e., the DNSBM model

(Tone and Tsutsui 2014), to evaluate resource management and profitability efficiencies. We address resource utilization issues within the resource-based paradigm and perform a frontier projection analysis. The results can serve as a reference for bank managers in managing their input resources. The CAMEL rating scores and bank sizes provide further comprehension of the performance of the sample US commercial banks from 2010 to 2020.

Although this study measures the performance of US commercial banks with intermediates, it lacks a ranking analysis. Therefore, further research into the ranking of the relative efficiency of the banks is warranted in determining top-performing banks. Researchers may consider using the network-based ranking approach proposed by Liu et al. (2009) or an innovative two-stage ranking method (Wang et al. 2021). Moreover, future studies may include undesirable intermediate outputs such as carbon emissions (Li et al. 2021) when more data become available. As not many banks are regarded as efficient, future studies can also consider examining banks with individual efficiency as a case study. This study discusses the efficiencies of the sample banks on average but not on an individual basis. Moreover, the crucial role of the DEA is to help a DMU find the best benchmark. Therefore, future studies may apply metafrontier DN-DEA method to simultaneously evaluate and better distinguish banks of different sizes in a DEA analysis or consider the notion of extended facet production possibility set to determine the closest benchmark (Zhu et al. 2022).

## Appendix 1: Abbreviations of technical terms and their expositions

| Variables | Expositions |
|---|---|
| DEA | Data envelopment analysis |
| DMU | Decision-making unit |
| DN-DEA | DEA model with a dynamic and network structure |
| DNSBM | dynamic network slack–based measure |
| NSBM | network slack-based measure |
| CAMEL | capital adequacy (C), asset quality (A), management quality (M), earning ability (E), and liquidity (L) |
| MIMO | multiple input and multiple output |

**Acknowledgements**
Nil.

**Author contributions**
QL, conceptualization; writing—original draft; writing—review & editing; formal data analysis. WM, methodology and framework; project administration. KT, methodology and framework. HM, writing—original draft. All authors read and approved the final manuscript.

**Funding**
Funding was provided by Ministry of Science and Technology (Grant No. MOST 107-2410-H-034-056-MY3).

**Availability of data and materials**
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

## Declarations

### Competing interests
The authors declare that they have no competing interests.

Received: 11 March 2021 Accepted: 10 July 2023
Published online: 03 January 2024

### References
An Q, Chen H, Wu J, Liang L (2015) Measuring slacks-based efficiency for commercial banks in China by using a two-stage DEA model with undesirable output. Ann Oper Res 235(1):13–35. https://doi.org/10.1007/s10479-015-1987-1
An Q, Wu Q, Zhou X, Chen X (2021) Closest target setting for two-stage network system: an application to the commercial banks in China. Expert Syst Appl 175:114799
Avkiran NK (2001) Investigating technical and scale efficiencies of Australian Universities through data envelopment analysis. Socioecon Plann Sci 35(1):57–80. https://doi.org/10.1016/S0038-0121(00)00010-0
Avkiran NK (2015) An illustration of dynamic network DEA in commercial banking including robustness tests. OMEGA Int J Manag Sci 55:141–150. https://doi.org/10.1016/j.omega.2014.07.002
Bagozzi RP, Phillips LW (1982) Representing and testing organizational theories: a holistic construal. Adm Sci Q 27(3):459–489
Banker RD, Charnes A, Cooper WW (1984) Some models for the estimation of technical and scale inefficiencies in data envelopment analysis. Manag Sci 30(9):1078–1092
Barr RS, Killgo KA, Siems TF, Zimmel S (2002) Evaluating the productive efficiency and performance of US commercial banks. Manag Financ 28(8):3–25. https://doi.org/10.1108/03074350210767988
Bauer PW, Berger AN, Ferrier GD, Humphrey DB (1998) Consistency conditions for regulatory analysis of financial institutions: a comparison of frontier efficiency methods. J Econ Bus 50(2):85–114
Berger AN, Humphrey DB (1997) Efficiency of financial institutions: International survey and directions for future research. Eur J Oper Res 98(2):175–212
Berger AN, Hancock D, Humphrey DB (1993) Bank efficiency derived from the profit function. J Bank Finance 17(2):317–347
Chakravarthy BS (1986) Measuring strategic performance. Strateg Manag J 7(5):437–458
Chao C-M, Yu M-M, Wu H-N (2015) An application of the dynamic network DEA model: the case of banks in Taiwan. Emerg Mark Financ Trade 51(sup1):S133–S151
Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429–444
Chen T-Y (2002) A comparison of chance-constrained DEA and stochastic frontier analysis: bank efficiency in Taiwan. J Oper Res Soc 53(5):492–500
Chen CM, Delmas MA, Lieberman MB (2013a) Production frontier methodologies and efficiency as a performance measure in strategic management research. Strateg Manag J. https://doi.org/10.1002/smj.2199
Chen Y, Cook WD, Kao C, Zhu J (2013b) Network DEA pitfalls: divisional efficiency and frontier projection under general network structures. Eur J Oper Res 226(3):507–515
Cook WD, Liang L, Zhu J (2010) Measuring performance of two-stage network structures by DEA: a review and future perspective. OMEGA Int J Manag Sci 38(6):423–430
Cooper WW, Seiford LM, Zhu J (2004) Handbook on data envelopment analysis. Kluwer, UK
Cooper WW, Seiford LM, Tone K (2006) Introduction to data envelopment analysis and its uses: with DEA-solver software and references. Springer, USA
Delmas M, Tokat Y (2005) Deregulation, governance structures, and efficiency: the U.S. electric utility sector. Strateg Manag J 26(5):441–460. https://doi.org/10.1002/smj.456
Delmas M, Russo MV, Montes-Sancho MJ (2007) Deregulation and environmental differentiation in the electric utility industry. Strateg Manag J 28(2):189–209. https://doi.org/10.1002/smj.578
Färe R, Grosskopf S (2000) Network dea. Socioecon Plann Sci 34(1):35–49
Feroz EH, Kim S, Raab RL (2003) Financial statement analysis: a data envelopment analysis approach. J Oper Res Soc 54(1):48–58
Fethi MD, Pasiouras F (2010) Assessing bank efficiency and performance with operational research and artificial intelligence techniques: a survey. Eur J Oper Res 204(2):189–198
Fukuyama H, Weber WL (2013) A dynamic network DEA model with an application to Japanese Shinkin banks. Efficiency and productivity growth: modelling in the financial services industry, pp 193–213
Golany B, Roll Y (1989) An application procedure for DEA. OMEGA Int J Manag Sci 17(3):237–250
Henriques IC, Sobreiro VA, Kimura H, Mariano EB (2020) Two-stage DEA in banks: terminological controversies and future directions. Expert Syst Appl 161:113632
Kao C (2009) Efficiency decomposition in network data envelopment analysis: a relational model. Eur J Oper Res 192(3):949–962
Kou G, Akdeniz ÖO, Dinçer H, Yüksel SJFI (2021) Fintech investments in European banks: a hybrid IT2 fuzzy multidimensional decision-making approach, vol 7(no 1), pp 1–28
Kweh QL, Lu W-M, Tone K, Nourani M (2021) Risk-adjusted banks' resource-utilization and investment efficiencies: does intellectual capital matter? J Intellect Capital. https://doi.org/10.1108/JIC-03-2020-0106
Li Y, Xue H, Lin L, Li F, Liang L, Kou G (2021) Provincial production and pollution treatment performance in China based on a two-stage eco-inefficiency approach with undesirable intermediate outputs. J Clean Prod 331:130016
Liu JS, Lu W-M, Yang C, Chuang M (2009) A network-based approach for increasing discrimination in data envelopment analysis. J Oper Res Soc 60(11):1502–1510

Liu JS, Lu LYY, Lu W-M, Lin BJY (2013a) Data envelopment analysis 1978–2010: a citation-based literature survey. OMEGA Int J Manag Sci 41(1):3–15. https://doi.org/10.1016/j.omega.2010.12.006
Liu JS, Lu LYY, Lu W-M, Lin BJY (2013b) A survey of DEA applications. OMEGA Int J Manag Sci 41(5):893–902
Luo Y, Bi G, Liang L (2012) Input/output indicator selection for DEA efficiency evaluation: an empirical study of Chinese commercial banks. Expert Syst Appl 39(1):1118–1123
Majumdar SK (1998) On the utilization of resources: perspectives from the US telecommunications industry. Strateg Manag J 19(9):809–831
Matthews K (2013) Risk management and managerial efficiency in Chinese banks: a network DEA framework. OMEGA Int J Manag Sci 41(2):207–215. https://doi.org/10.1016/j.omega.2012.06.003
Nguyen TLA (2018) Diversification and bank efficiency in six ASEAN countries. Glob Financ J 37:57–78
Nguyen TPT, Nghiem SH, Roca E, Sharma P (2016) Bank reforms and efficiency in Vietnamese banks: evidence based on SFA and DEA. Appl Econ 48(30):2822–2835
Ouenniche J, Carrales S (2018) Assessing efficiency profiles of UK commercial banks: a DEA analysis with regression-based feedback. Ann Oper Res 266:551–587
Paradi JC, Rouatt S, Zhu H (2011a) Two-stage evaluation of bank branch efficiency using data envelopment analysis. OMEGA Int J Manag Sci 39(1):99–109
Paradi JC, Yang Z, Zhu H (2011b) Assessing bank and bank branch performance. In: Handbook on data envelopment analysis. Springer, pp 315–361
Schefczyk M (1993) Operational performance of airlines: an extension of traditional measurement paradigms. Strateg Manag J 14(4):301–317
Seiford LM, Zhu J (1999) Profitability and marketability of the top 55 US commercial banks. Manag Sci 45(9):1270–1288
Sherman HD, Gold F (1985) Bank branch operating efficiency: evaluation with data envelopment analysis. J Bank Finance 9(2):297–315
Silva TC, Tabak BM, Cajueiro DO, Dias MVB (2017) A comparison of DEA and SFA using micro-and macro-level perspectives: efficiency of Chinese local banks. Phys A Stat Mech Appl 469:216–223
Sun L, Chang T-P (2011) A comprehensive analysis of the effects of risk measures on bank efficiency: Evidence from emerging Asian countries. J Bank Finance 35(7):1727–1735. https://doi.org/10.1016/j.jbankfin.2010.11.017
Tan Y, Wanke P, Antunes J, Emrouznejad A (2021) Unveiling endogeneity between competition and efficiency in Chinese banks: a two-stage network DEA and regression analysis. Ann Oper Res 306(1–2):131–171
Tone K (2001) A slacks-based measure of efficiency in data envelopment analysis. Eur J Oper Res 130(3):498–509
Tone K, Tsutsui M (2009) Network DEA: a slacks-based measure approach. Eur J Oper Res 197(1):243–252. https://doi.org/10.1016/j.ejor.2008.05.027
Tone K, Tsutsui M (2010) Dynamic DEA: a slacks-based measure approach. OMEGA Int J Manag Sci 38(3):145–156
Tone K, Tsutsui M (2014) Dynamic DEA with network structure: a slacks-based measure approach. OMEGA Int J Manag Sci 42(1):124–131. https://doi.org/10.1016/j.omega.2013.04.002
Wang W-K, Lu W-M, Wang Y-H (2013) The relationship between bank performance and intellectual capital in East Asia. Qual Quant 47(2):1041–1062
Wang K, Huang W, Wu J, Liu Y-N (2014a) Efficiency measures of the Chinese commercial banking system using an additive two-stage DEA. Omega 44:5–20. https://doi.org/10.1016/j.omega.2013.09.005
Wang K, Huang W, Wu J, Liu Y-N (2014b) Efficiency measures of the Chinese commercial banking system using an additive two-stage DEA. OMEGA Int J Manag Sci 44:5–20
Wang H, Peng Y, Kou G (2021) A two-stage ranking method to minimize ordinal violation for pairwise comparisons. Appl Soft Comput 106:107287. https://doi.org/10.1016/j.asoc.2021.107287
Weygandt JJ, Kimmel PD, Keiso DE (2010) Financial accounting: IFRS. Wiley, Taiwan
Yu D, Kou G, Xu Z, Shi S (2021) Analysis of collaboration evolution in AHP research: 1982–2018, vol 20(no 1), pp 7–36
Zha Y, Liang N, Wu M, Bian Y (2016) Efficiency evaluation of banks in China: a dynamic two-stage slacks-based measure approach. Omega 60:60–72. https://doi.org/10.1016/j.omega.2014.12.008
Zhang J, Kou G, Peng Y, Zhang YJIS (2021) Estimating priorities from relative deviations in pairwise comparison matrices. Inf Sci 552:310–327
Zhu J (2000) Multi-factor performance measure model with an application to Fortune 500 companies. Eur J Oper Res 123(1):105–124
Zhu Q, Aparicio J, Li F, Wu J, Kou G (2022) Determining closest targets on the extended facet production possibility set in data envelopment analysis: modeling and computational aspects. Eur J Oper Res 296(3):927–939

## Publisher's Note