Annals of Operations Research
https://doi.org/10.1007/s10479-024-06023-3

ORIGINAL RESEARCH

An MCDA composite index of bank stability using CAMELS ratios and shannon entropy

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Received: 13 April 2023 / Accepted: 22 April 2024

Abstract

This study uses the multi-criteria decision-analysis (MCDA) approach to construct a composite performance index (CPI) directly from the CAMELS financial ratios. The CPI has several promising characteristics, such as (i) being an absolute measure of performance that allows for adding or removing data without affecting the existing scores; (ii) employing CAMELS ratios directly in its calculation without the need for normalization or imputation of positive values; (iii) employing the dynamic weighting system of data envelopment analysis (DEA); (iv) providing more robust insights on the Vietnamese banking system under the Shannon entropy approach; and (v) can be an alternative measure of bank stability, compared to the CAMELS ratings and z-scores. Based on a rich dataset of 45 Vietnamese banks spanning from 2002 to 2020, our findings suggest that the proposed CPI could offer an overall view consistent with other approaches for measuring banking sector performance and stability and identifying specific strengths and weaknesses of banks.

Keywords Composite performance index · Multi-criteria decision-analysis (MCDA) · Data envelopment analysis · CAMELS · Shannon entropy · Vietnamese banks

JEL codes G21 · G32

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Published online: 09 May 2024

1 Introduction

Bank stability and performance are fundamental to the financial system's health, as the soundness of the banking sector has far-reaching effects on the entire financial industry and the broader economy (Ngo & Le, 2019; Ben Lahouel et al., 2022). A stable banking system is essential for promoting economic growth, stability, and the effective operation of payment and settlement systems (Adrian & Shin, 2008). Market analysts from institutions such as banks, accounting, and securities firms commonly use financial ratio analysis (RA) as a standard tool to examine performance at all levels (Barnes, 1987; Paradi & Zhu, 2013). Regulators also employ financial ratios to monitor the operations of banks (Avkiran, 2011), while investors rely on them as references in making their decisions. Since ratios have a single-dimension characteristic, they only reflect the relationship between the numerator and denominator and fail to reflect the multidimensional nature of firms' activities. There are also problems with using a large number of ratios, making the implicit assumption of constant returns to scale, and not setting targets for improvement for inefficient banks based on ratios (Paradi & Zhu, 2013).

There has been an increased use of frontier analysis approaches, such as stochastic frontier analysis (SFA) and data envelopment analysis (DEA), to evaluate efficiency and performance in the banking industry due to their superiority over standard financial ratios (Bauer et al., 1998). Of the two, DEA is particularly suitable for studying the banking industry with complex input-output settings and a limited number of observations, as it does not require an *a priori* functional form (Emrouznejad & Yang, 2018; Hammami et al., 2022). Thanassoulis et al. (1996) suggested that DEA and RA should not be seen as alternatives but as complementary approaches in performance evaluation.

Studies that attempt to incorporate RA with DEA often adopt a two-stage approach. In the first stage, DEA is used to determine the efficiency/performance of the banks under investigation. In the second stage, the DEA scores are related to the ratios to explore the connection between banks with different DEA scores and their financial information. Sherman and Gold (1985) were among the first to apply the two-stage DEA approach in their study of 14 bank branches. They used a simple integration technique, examining the DEA score and two operating ratios (non-personnel operating expense per transaction and transactions processed per full-time equivalent employee) in parallel. The results suggested that DEA provided insights into bank branch performance that were not evident from RA alone (Sherman & Gold, 1985). Subsequent studies, such as that by Yeh (1996), used principal factor analysis to associate twelve ratios divided into four groups (capital adequacy, profitability, asset utilization, and liquidity) with DEA scores. Pasiouras (2008) later proposed using regression in the second stage. In his study of a cross-country sample of 715 banks from 95 countries in 2003, he found that the CAMELS ratios positively and significantly influenced the banks' performance. This two-stage DEA approach has gained popularity in recent years, with Henriques et al. (2020) identifying up to 91 relevant publications in Web of Science, ScienceDirect, and Scopus for 2003–2018. A simple search on Google Scholar using the keywords "two-stage DEA" AND "bank" returned about 4,700 results as of 14 February 2023. For more information on this approach, please refer to Henriques et al. (2020).

The major problem with the two-stage DEA approach is that it treats the ratios as exogenous, assuming they are not influenced by the efficiency score itself, when in reality, they may be endogenous, driven by factors reflected in the efficiency score.[1] As a result, one should incorporate the ratios directly into the DEA models. However, mixing ratios and volume values in DEA estimation can introduce biases (Dyson et al., 2001), and thus an all-ratio DEA model should be utilized. Halkos and Salamouris (2004) were the first to adopt this approach and used the ratios as the outputs, while a dummy variable was used as the input for all banks involved. The assumption is that inputs should be similar and equal for all banks operating in the same market, and the focus is on how banks manage their outputs. Therefore, all ratios used as outputs should be desirable, meaning that higher values indicate better performance, such as return on assets, return on equity, and net interest margin (Halkos & Salamouris, 2004; Le, 2018).

Avkiran (2011) argued that desirable ratios could be used as outputs of DEA models, while undesirable ratios (e.g., impaired loans over net interest income or impaired loans over equity) and the reciprocal of desirable ratios (e.g., reciprocal of capital adequacy ratio or reciprocal of dividends per share) can be used as DEA inputs. The selection of input and output ratios is based on the degree of direct managerial control and the ratio's position in the production process (Avkiran, 2011). Wong et al. (2014), Horváthová and Mokrišová (2018), and Ngo and Le (2019) have extended this approach. However, these studies only yield relative efficiency scores rather than absolute efficiency scores, which are meaningful only within the research sample and cannot be used to compare performance between samples.[2] Additionally, modifying the data in the sample requires recalculating the DEA models every time, making adding or removing data from the sample impossible.

Another approach in the all-ratio DEA methodology is to combine the individual ratios (or components/dimensions) into a composite measurement or index (Cherchye et al., 2007; OECD, 2008; Aouni et al., 2014). One way to combine financial ratios into a composite index in the banking sector is by following the CAMELS rating system. CAMELS is an acronym for the six components of bank safety and soundness: Capital adequacy, Asset quality, Management quality, Earnings ability, Liquidity, and Sensitivity to market risks (FDIC, 1996). It was originally developed by U.S. federal regulators for evaluating a bank's financial health based on each component and provides a composite rating to assess their overall health, financial status, and management (Cole & Gunther, 1998). However, there are issues with the CAMELS approach, such as variable identification, discriminatory power, and accuracy in its calculation, which may explain why the use of CAMELS ratings in research studies has been limited (DeYoung et al., 2001; Männasoo & Mayes, 2009). More details on these problems can be found in Sect. 3.3 below.

In a nutshell, (financial) ratio analysis has the advantage of being simple and thus popular with regulators or market analysts, but it is single-dimensional and has weak discriminatory power. In contrast, the two-stage DEA approach can provide a multidimensional evaluation of banks' stability and performance, but it treats financial ratios as exogenous factors rather

[1] Although the bootstrap DEA (Simar & Wilson, 2007) can account for such ratios as endogenous variables, we do not consider it as a (traditional) two-stage DEA model because it is a loop of DEA and regression thousands of times. For more details, please refer to Simar and Wilson (2007) and Simar and Wilson (2011), among others.

[2] DEA measures the efficiency of a certain decision-making-unit (DMU) relative to other DMUs in the sample assuming that a common frontier exists in the sample (Charnes et al., 1978). Comparison between samples employing different frontiers is therefore impossible. This issue also applies to other relative measurements derived from stochastic frontier analysis (SFA), thick frontier approach (TFA), distribution-free approach (DFA), and free disposal hull (FDH)– see more in Berger and Humphrey (1997).

than endogenous ones. The all-ratio DEA approach considers the endogenous characteristics of the ratios. Still, its results are relative measures, meaning that adding or removing data from the sample is not possible. The CAMELS-based composite index approach can be seen as an all-ratio DEA approach to measure banking stability. However, it still faces challenges in variable identification, discriminatory power, and accuracy. It is noted that the basic principle of constructing a composite index is to assign appropriate weights to its components, and DEA can be used as a multi-criteria decision analysis (MCDA) tool to determine the optimal weights for each CAMELS ratios/components (Paradi & Zhu, 2013; Emrouznejad & Yang, 2018; Lu et al., 2021).In this paper, a DEA-like MCDA technique is proposed to construct a composite performance index (CPI) that provides an absolute measurement (such that adding or removing data does not affect the index) of the multidimensional stability of banks (or firms, in general).

This paper makes several contributions to the literature. Firstly, to the best of our knowledge, this is the first study to extend the DEA approach to measure the absolute performance (or stability) of a set of banks, as opposed to their relative performance in traditional DEA models. Secondly, since the CPI is constructed from the CAMELS ratios, it can be used to assess the financial stability of banks. Thirdly, to enhance the robustness of the CPI results from different weight restriction settings, they are further aggregated using the Shannon entropy approach, providing more robust insights into the stability of the banks. These three contributions are of practical importance, as they can offer valuable insights to bank managers in their decision-making process. Fourthly, this study is also the first to examine the absolute performance of the Vietnamese banking sector, using data from 2002 to 2021, representing the longest data series on Vietnamese banks. Despite the growing number of studies on the efficiency and performance of Vietnamese banks (e.g., Ngo & Tripe, 2017; Mateus & Hoang, 2021; Le et al., 2022a), none of them have addressed this issue before.

Our CPI is consistent with other indicators of financial stability, such as the CAMELS ratings or z-score (Boyd et al., 1993). We observed that Vietnamese banks had a high average CPI score of 22.43 at the beginning of the 2006–2015 period, which could be attributed to the booming financial markets in Vietnam in 2006. However, their performance declined to 16.08 in 2021, marking a decrease of nearly 30%. Moreover, the CPI scores for 2006–2008 were significantly higher than those for 2009–2010, suggesting that the Global Financial Crisis of 2007/2008 negatively impacted Vietnamese banks. At the individual bank level, the CPI revealed that, on average, the Joint-Stock Commercial Banks (JSCBs) outperformed the State-Owned Commercial Banks (SOCBs), consistent with previous research on ownership and efficiency (La Porta et al., 2002; Bonin et al., 2005; Berger et al., 2010; Jiang et al., 2013). Our findings also highlight that the comparative strength of Vietnamese banks lies in their liquidity and capital adequacy, while their weaknesses were associated with income and risk management. Therefore, addressing these issues should be a focus for Vietnamese banks to enhance their performance and stability in the future.

The remainder of this paper is constructed as follows. Section 2 discusses bank stability and the CAMELS framework. Section 3 explains the methodology and introduces the data on the Vietnamese banking sector. Section 4 discusses the results of the CPI of Vietnamese banks and compares the results of the CAMELS ratings and z-score. Section 5 offers some conclusions and future directions.

2 Bank stability and the CAMELS framework

Bank stability refers to the ability of banks to withstand financial shocks and maintain the normal functioning of the financial system (Adrian & Shin, 2008). It is crucial for various aspects, including financial stability, public confidence, economic growth, risk management, and regulatory compliance. Firstly, banks play a critical role in the economy by mobilizing savings and allocating credit to individuals and businesses, making a stable banking system essential for the overall financial stability of a country (Ngo, 2012). A sound banking system enables banks to handle economic shocks such as financial crises or recessions more effectively. Secondly, bank stability affects public confidence in the banking system and, by extension, the financial system of a country. If people lose trust in banks, they may withdraw their deposits, leading to bank runs and potentially causing a collapse of the banking system. A stable banking system helps maintain public confidence in the financial system (Thakor, 2014). Thirdly, a sound banking system is crucial for economic growth as banks facilitate growth by providing credit to individuals and businesses. During both good and bad times, a stable banking system ensures that credit is available, enabling companies to invest and grow, creating jobs and driving economic growth (Rosengard & Huynh, 2009; Mirza et al., 2015). Fourthly, a stable banking system requires that banks have effective risk management practices in place to manage risks and ensure they do not pose a threat to their stability (Ben Lahouel et al., 2022). Sound risk management practices help banks navigate uncertainties and mitigate potential adverse impacts on their stability. Finally, a stable banking system adheres to regulations, which helps prevent fraud, misconduct, and other forms of financial malpractice (Vives, 2016). Without a sound banking system, an economy can suffer from economic instability, leading to negative impacts on businesses, individuals, and the overall economy (Adrian & Shin, 2008). Therefore, ensuring bank stability is crucial for the smooth functioning of the financial system and the overall health of an economy.

The global financial crisis of 2008 brought the issue of banking stability to the forefront of economic discourse (Hesse & Čihák, 2007; IMF, 2010; Chortareas et al., 2012), giving rise to a revisit of the CAMELS framework. The crisis demonstrated the need for stronger regulation and supervision of the banking sector, as well as the importance of maintaining banking stability (Vives, 2016). Regulation refers to the legal framework that governs the activities of banks, while supervision refers to the ongoing monitoring of banks by regulatory authorities. The role of regulation and supervision is to ensure that banks comply with sound banking practices, such as maintaining adequate capital and liquidity, and to prevent the buildup of systemic risk in the financial sector. Evidence shows that an effective regulation and supervision system can help promote bank stability (Chortareas et al., 2012; Hsieh & Lee, 2020).

Capital adequacy, which refers to the funds a bank holds in reserve to cover potential losses (FDIC, 1996), is a crucial component that can be monitored to enhance bank stability. Adequate capitalization acts as a buffer for banks, enabling them to absorb losses and ensuring the financial system's stability during crises (Mahdi & Boujelbene Abbes, 2018; Nguyen et al., 2022a). This, in turn, fosters greater confidence among depositors and stakeholders, reducing the risk of bank runs or bankruptcy (Thakor, 2014). However, it is important to note that holding more capital may also entail costs for banks (Dagher et al., 2016).

The second component of CAMELS is Asset Quality, which is measured by the creditworthiness and risk associated with a bank's assets, including loans and investments. The quality of a bank's assets directly impacts its financial performance and ability to absorb losses. Banks with high-quality assets are less likely to experience loan losses, thereby contributing to the financial system's stability. On the contrary, banks with low-quality assets are more vulnerable to financial shocks and have a higher likelihood of failure, which poses a risk to the stability of the banking system (Mirza et al., 2015; Prima Sakti & Mohamad, 2018; Kallel & Triki, 2022).

The third component is Management quality. A strong management team with expertise in strategic planning, risk management, and sound governance practices can effectively guide a bank in navigating potential risks and making informed decisions, thereby contributing to a stable financial system (Bertrand & Schoar, 2003; Ben Lahouel et al., 2022). Conversely, banks with poor management quality may engage in risky practices and make detrimental decisions, posing risks not only to themselves but also to the broader financial system (Abor et al., 2019; Adam et al., 2021).

Earnings ability refers to a bank's capacity to consistently generate stable and sufficient profits to meet its obligations and maintain its financial health. A bank with a strong earnings ability is better positioned to withstand economic shocks and sustain its financial stability over time (Sufian, 2009; Ngo & Tripe, 2017). For instance, Hafeez et al. (2022) found a positive relationship between bank profitability and stability, confirming the argument of Xu et al. (2019) that a higher earnings ability helps mitigate systemic and idiosyncratic risks for the bank. Moreover, it is argued that earnings ability can also impact the capital adequacy and liquidity of the bank (Berger, 1995; Xu et al., 2019), which, in turn, influences the overall stability of the bank.

Liquidity is another essential aspect of bank stability. It refers to a bank's ability to meet its obligations as they come due (FDIC, 1996), which is important for the survival and long-term stability of the bank. A lack of liquidity can lead to a bank run, where depositors withdraw their funds all at once, resulting in a shortage of funds and a potential bank collapse. Therefore, banks must maintain adequate liquidity to ensure they can meet the demands of their depositors and other creditors. Extensive research on liquidity, liquidity management, and liquidity risk consistently agrees that liquidity can help prevent bank runs and maintain the financial system's stability (e.g., Ben Salah Mahdi & Boujelbene Abbes, 2018; Hsieh & Lee, 2020; Ben Lahouel et al., 2022).

The last component of the CAMELS framework is Sensitivity to market risk, which was added to the framework in the late 1990s to better capture a bank's exposure to market risk, which can impact the bank's stability and overall financial health (FDIC, 1996). This component was added to provide a clearer indication of the FDIC's supervisory concerns regarding the growing recognition of the importance of market risk in banking and the need to effectively manage this risk to ensure the stability and resilience of the banking sector. To do that, the Sensitivity to market risk component evaluates a bank's ability to manage its exposure to various market risks, such as interest rate changes, foreign exchange rate changes, and changes in the value of financial instruments (Ben Lahouel et al., 2022). There is a substantial body of literature showing that these market risks can have negative impacts on banks' operations and performance, thereby hindering bank stability (e.g., Ben Salah Mahdi & Boujelbene Abbes, 2018; Abor et al., 2019; Djebali & Zaghdoudi, 2020; Adam et al., 2021). In the current world, there is increasing recognition that climate-related risks should also be considered in this component (UNEPFI, 2018, 2021; Campiglio et al., 2022). Nevertheless, diversification of a bank's activities has been shown to be a potential solution to reduce sensitivity to market risk, as demonstrated in studies by Berger et al. (2010), Curi et al. (2015), and Ben Lahouel et al. (2022).

Overall, bank stability is crucial for any country to maintain and achieve economic development. Using the CAMELS framework is an easy way to assess the stability of a bank or the entire banking sector in a country. However, using an independent financial ratio of a specific component of the CAMELS framework and an aggregated CAMELS score pose problems. The former has been discussed in the Introduction section, while the latter will be explained in Sect. 3.3 below. Therefore, this paper proposes a novel composite index that combines the strengths of DEA, CAMELS, and Shannon entropy approaches to overcome these issues. The following section elaborates on its methodological characteristics.

3 Methodology

3.1 Data envelopment analysis (DEA) as an MCDA technique

MCDA is a method used to aggregate multiple objective functions or measures in which a goal is set for such measurements. In Data Envelopment Analysis, the objective of a set of Decision Making Units (DMUs), such as banks, is to maximize their productive efficiency while considering their constrained multiple inputs and outputs (Charnes et al., 1978). Such MCDA model for multiple inputs/outputs maximization can be stated as follows.

$$EF_{j_0} = \max_{u,v} \frac{\sum_{r=1}^{m} u_r y_{rj_0}}{\sum_{i=1}^{k} v_i x_{ij_0}} \tag{1}$$

$$\begin{aligned} &subject\,to \\ &\qquad \frac{\sum_{r}^{m} u_r y_{rj}}{\sum_{i}^{k} v_i x_{ij}} \leqslant 1, \forall j \\ &\qquad u_r, v_i \geqslant \varepsilon, \forall i, r \end{aligned}$$

where EF_{j_0} is the goal to be maximized for DMU j_0 ($j=1,2,.,n$), v_i and u_r are the optimal weights assigned to the relevant inputs x_i ($i=1,2,.,k$) and outputs y_r ($r=1,2,.,m$) of this DMU, and ε is a non-Archimedean value designed to enforce positivity on the weights.

Equation (1) shows that one needs data for both inputs and outputs of the DMUs. To construct a DEA-like composite index from financial ratios, previous studies either categorize those ratios into inputs and outputs (Avkiran, 2011; Avkiran & Cai, 2014; Ben Lahouel et al., 2022), or use all ratios as outputs and an additional dummy variable as an input (Lovell, 1995; Halkos & Salamouris, 2004; Cherchye et al., 2008; Kao et al., 2008). More importantly, the first constraint of Eq. (1) implies that the optimal weights v_i and u_r of the examined DMU j_0 also need to satisfy the goals for all other sample DMUs. As such, when a DMU is included or removed from the sample, this constraint requires Eq. (1) to be recalculated for the whole sample.[3] In the next section, we explain how the maximized goal is

[3] If the removed DMU(s) does/do not lie on the frontier, then no re-calculation is needed. However, if the removed DMU(s) is/are the efficient ones, or for the case of adding in new DMU(s), re-calculation is essential.

calculated independently as an absolute performance measurement in our CPI approach and, thus, overcome this problem.

3.2 The composite performance index (CPI) using Shannon Entropy

The CPI approach constructs its goal to evaluate the absolute performance of banks directly from their financial ratios. Since those ratios were selected based on the CAMELS rating system (and their availability), the CPI can also reflect the banks' financial stability. Specifically, Capital adequacy is proxied by Equity capital to total assets (ETA), whereas a higher level of ETA is likely to reduce financial distress (Canbas et al., 2005; Brewer & Jackson, 2006; Männasoo & Mayes, 2009). Asset quality is proxied by Nonperforming loans to total loans (NPLRATIO): a lower level of problem loans will be related to a more stable bank (Gonzalez-Hermosillo, 1999; Li et al., 2009; Le & Ngo, 2020). Management quality can be proxied by Return on assets (ROA) because profitability should be positively correlated with management performance (DeYoung et al., 2001; Männasoo & Mayes, 2009; Zhao et al., 2021). Earnings ability is reflected in Net interest margin (NIM), where a higher NIM indicates good yields on loans, lower costs, effective use of earning assets, and a sensible mix of funding (Chortareas et al., 2012; Ngo & Le, 2019; Ben Lahouel et al., 2022). Liquidity is proxied by Liquid assets over total assets (LTA), given that a high level of liquid assets would indicate that the bank was likely to be more stable (Mahdi & Boujelbene Abbes, 2018; Hsieh & Lee, 2020). Lastly, Sensitivity to market risk is proxied by the Absolute value of the cumulative 1-year repricing gaps over total assets (GTA), as there is an argument that banks strategically price consumer deposits as a function of their interest rate risk exposure target, such that changes in GTA reflect deviations from that target (Brewer & Jackson, 2006). Therefore, a higher value of GTA indicates that the bank is more affected by changes in interest rates (Abor et al., 2019; Adam et al., 2021; Gomez et al., 2021). Because NPLRATIO and GTA have negative relationships with bank performance, they were treated as undesirable ratios (Halkos & Salamouris, 2004; Avkiran, 2011) and transformed into their reciprocals.[4] For instance, Scheel (2001) and Ramanathan (2006) argued that pollution such as CO_2 and NO_x are the output of economic development; however, creating more of them is not desirable. Our situation for NPLRATIO and GTA is the same: they are the products of banking activities but not desirable. Since the relationship between those undesirable ratios and their reciprocal is negative, it makes the relationship between the reciprocals and bank performance positive. In this sense, the reciprocals of NPLRATIO and GTA are desirable ratios of bank performance and can be treated similarly to LTA or ROA.

Consequently, a DEA-like goal programming problem in which the weights of the ratios are assigned by the data itself, rather than *a priori* weights, is constructed to compute the CPI of a certain bank in a certain year:

$$CPI_t^n = max \sum_i k_{it} X_{it}^n \tag{2}$$

[4] This technique is also applied, for example, by Lovell et al. (1995), and called 'reciprocal multiplicative'. Because our model is not constrained like a DEA model, we do not believe that this distorts our results.

$$\text{subject to}$$
$$\sum k_{it} = 1 \text{ (all weights add up to 1 for each it combination)},$$
$$\alpha \leqslant k_{it} \leqslant \beta \text{ (weight restriction)}.$$

where CPI_t^n represents the composite performance index of bank *n* in year *t*; X_{it}^n is the (transformed, if necessary) CAMELS ratio *i* of bank *n* in year t; and k_{it} is the weight of ratio *Xi* of bank *n* in year *t*. As such, a higher CPI value indicates a higher bank performance, with 100 points being the highest attainable value.

The weight restriction constraint in Eq. (2) is to secure that each variable at least plays some role in the composite index because zero weights may not be consistent with the management view, i.e., one could not expect the weight assigned to NPLRATIO to be zero and ignore it from the CPI, but not too high so that it dominates the other variables (Allen et al., 1997). This kind of restriction is commonly found in the "benefit of doubt" (BOD) approach (e.g., Cooper et al., 2009; Rogge, 2018; Niroomand et al., 2019). The BOD is similar to our Eq. (2) but it also has a constraint requiring all composite indices to be no greater than 1 (see, for example, Constraint 5a of Cherchye et al., 2007; or Eq. (5) in Rogge, 2018). In this sense, it closely follows the traditional DEA approach and thus, the relative measurement issue regarding Eq. (1) still holds as a limitation of the BOD. More importantly, this constraint also requires the weights to be small enough so that the indices can be smaller than unity and thus, BOD results (i.e., implying a small lower bound for weight restriction) get closer to DEA results (i.e., no weight restriction).

To improve the robustness of the CPI, we employ several weight restriction settings and combine the results following the Shannon Entropy approach (Shannon, 1948; Huynh et al., 2022). Such an idea of combining different scores or indices derived from different weight settings is similar to the cross-efficiency (Sexton et al., 1986) or geometric BOD (Van Puyenbroeck & Rogge, 2017) approaches in the DEA literature. According to Şahin (2021), the Shannon Entropy can provide reliable (combined) results in cases where the response (in our situation, the CPI under a certain weighting system) may not be accurate. Kumar et al. (2021) further argued that it can also determine the importance of every response without any *a priori* assumptions to derive the best (combined) index. In this sense, Karagiannis and Karagiannis (2020) also pointed out that the use of Shannon Entropy in constructing composite indicators allows for higher discriminatory power in examining each response (or CPI). Specifically, the Shannon Entropy's algorithm for such a combination is as follows.

Step 1. Construct the CPI matrix for *n* bank-observations under *k* settings of weight restriction. The data is pooled across time, so the subscript t has been omitted from the following Eq.

$$E = \begin{bmatrix} CPI_{11} & CPI_{12} & \cdots & CPI_{1k} \\ CPI_{21} & CPI_{22} & \cdots & CPI_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ CPI_{n1} & CPI_{n2} & \cdots & CPI_{nk} \end{bmatrix} \tag{3}$$

Step 2. Normalize matrix E by setting

$$\widehat{E}_{ij} = \frac{E_{ij}}{\sum_{i=1}^{n} E_{ij}}, i = 1,.,n, j = 1,.,k \tag{4}$$

Step 3. Compute the Shannon entropy value for the normalized matrix $\widehat{E}$ using

$$e_j = -\frac{1}{\ln n}\sum_{j=1}^{n} \widehat{E}_{ij}\ln\widehat{E}_{ij} \tag{5}$$

Step 4. Set $d_j = 1 - e_j$. The degree of importance for each bank under all weight restriction settings can then be assessed via the weight

$$\omega_j = \frac{d_j}{\sum_{j=1}^{k} d_j} \tag{6}$$

Step 5. Consequently, the comprehensive performance index for each bank is

$$\overline{CPI}_j = \sum_{j=1}^{k} \omega_j E_{ij} \tag{7}$$

Our comprehensive performance index $\overline{CPI}$ constructed in Eq. (2)–(7) has some advantages. First, by removing the constraint for the relationship of efficiencies within the sample (comparing Eq. (2) and Eq. (1), the CPI thus becomes an absolute measure of performance rather than a relative one. For instance, one may notice that if they follow the DEA approach as in Eq. (1), a DMU may have an efficiency score of 0.9 if there are 20 DMUs involved; however, if there are 21 DMUs then the efficiency score may change to 0.8 or even 1.0. In this sense, the DEA efficiency score is a relative measure. Our CPI, however, is argued to be an absolute measure because if a DMU has a CPI of 15, then no matter how the data is changed, it will still be at 15. Second, it also helps overcome the problem of negative values in traditional DEA models because the CPI does not need to reflect the proportional relationship of the radial expanded or contracted inputs and outputs as in DEA (Portela & Thanassoulis, 2010). Moreover, since there is no need for data normalization as with other composite indices (OECD, 2008), combined with the first advantage of being an absolute measurement, it is possible to include new data or exclude (outlier) data from our sample without affecting the CPI results for the rest of the sample.[5] Thirdly, by aggregating different settings of weight restriction, the final Shannon's $\overline{CPI}$ measurement is more robust and can provide more information than the CPI itself. In our analysis, four weight restriction settings are employed in the estimation of Eq. (2): the fixed and equal weights for all CAMELS ratios (i.e., $k_{it} = 0.1667$), the free weights of traditional DEA (i.e., $0 \le k_{it} \le 1$), the non-zero weights (i.e., $0.05 \le k_{it} \le 1$), and the non-zero non-dominant weights (i.e., $0.05 \le k_{it} \le 0.49$). As we have tried with other weight settings and found that the results do not change much, we only used these four basic settings in our Shannon's $\overline{CPI}$. The relevant results and discussions in the following sections are based on this measurement.

[5] For example, with our sample of 45 Vietnamese banks for the periods of 2002–2020, the CPI will not be affected if we examine only 20 banks in the 2010–2015 periods, or if we extend the study to 50 banks from 1990 to 2020 when more data is available.

3.3 The robustness of the CPI: comparison with other measures

According to Eq. (2), it is obvious that the CPI is correlated with the (component) financial ratios X_{it}^{m}. Therefore, it is reasonable that the CPI is strongly correlated with other DEA-like approaches (Halkos & Salamouris, 2004; Avkiran, 2011; Ben Lahouel et al., 2022); we thus do not report them here due to the space-saving reason. Here, we are more interested in the CPI as an absolute measure of bank stability, and we thus use the CAMELS ratings and the z-score for comparison purposes.

According to the FDIC (1996), when using the CAMELS rating system, banks are rated on a 1 to 5 scale in each category or dimension, varying from fundamentally strong to fundamentally weak. Consequently, a composite rating (the CAMELS ratings) is defined, also using a scale from 1 to 5, where banks that are sound in every dimension (generally rated 1 or 2) belong to composite 1, and banks that are extremely unsafe or unsound (generally rated as category 5) belong to composite 5 (Board of Governors of the Federal Reserve System, 1990; FDIC, 1996). Following Grier (2007) and Koch and MacDonald (2010), we construct the CAMELS component (and composite) ratings for our sample banks using data on our six ratios (ETA, NPLRATIO, ROA, NIM, LTA, and GTA) as in Table 1 below.

Several weaknesses of the CAMELS composite ratings are revealed as follows. First, these ratings can be subjective since they depend on the judgment of the bank's examiners on the overall performance of the bank (Brockett et al., 1997). Second, the discriminatory power of this composite rating scheme is not strong as it is difficult to differentiate banks within a composite. Third, the double scaling method could lead to double bias in the calculation of the final score: the first bias may occur when the original CAMELS ratio data are converted into CAMELS ratings (from 1 to 5), and the second happens when those CAMELS ratings are converted into the CAMELS composite ratings.[6] We argue that while the CPI is still consistent with the CAMELS ratings (with a negative relationship), it is superior to the latter because (i) it is directly computed from the bank's financial information and thus, (ii) it is not affected by bank examiners' prejudices (conscious or otherwise) and (iii) there are no composition or double scaling issues.

Another common measure for the bank's soundness (and thus its performance) is the z-score. For a certain bank and year, it is defined as the ratio of the sum of capital over assets

Table 1 The CAMELS rating scheme

Rating	ETA	NPLRATIO	ROA	NIM	LTA	GTA
1	>7	<0.5	>2.0	>5.0	>25	<10
2	6–7	0.5–1.0	1.5–2.0	4.0–5.0	22.5–25	10–15
3	5–6	1.0–1.5	1.0–1.5	3.0–4.0	20–22.5	15–20
4	4–5	1.5–2.0	0.5–1.0	2.0–3.0	17.5–20	20–25
5	<4	>2.0	<0.5	<2.0	<17.5	>25

Source Based on Grier (2007) and Koch and MacDonald (2010)

Notes ETA: Equity capital to total assets, NPLRATIO: Nonperforming loans to total loans, ROA: Return on assets, NIM: Net interest margin, LTA: Liquid assets over total assets, GTA: Absolute value of the cumulative 1–year repricing gaps over total assets. ETA, ROA, NIM, and LTA have a positive relationship with bank stability, while NPLRATIO and GTA are the opposite

[6] The composite rating is initially the average of the individual component rating (Board of Governors of the Federal Reserve System, 1990), and it thus follows the average fixed weights approach.

and return on assets to the sample's standard deviation of the return on assets (Prima Sakti & Mohamad, 2018; Hafeez et al., 2022). Thus, using our data, we have:

$$z_t^m = \frac{ETA_t^m + ROA_t^m}{\sigma^m} \tag{8}$$

where z_t^m represents the z-score of bank m in year t and σ^m is the standard deviation of all *ROAs* of bank *m* over all *t* periods. Since the z-score has a negative relationship with the bank's insolvency, we expect to see a positive correlation between the CPI_t^m and z_t^m.

4 Empirical analysis

4.1 Data on Vietnamese banks (2002–2020)

The Vietnamese banking sector has undergone significant changes and growth since the country transitioned to a market-oriented economy in the late 1980s. Before this period, the banking system was centralized and dominated by a single state-owned bank, the State Bank of Vietnam. In the early 1990s, the government introduced a series of reforms aimed at modernizing the banking sector and attracting foreign investments, including the establishment of both state-owned commercial banks (SOCBs) and joint-stock commercial banks (JSCBs), the creation of a legal framework for banking operations, and the introduction of more market-based interest rates (Oh, 1999; Ngo, 2012). The Vietnamese banking sector has recently experienced rapid growth, with total assets reaching US$738 billion in October 2022 (SBV, 2023). However, the industry has faced several challenges over the years, including high levels of bad debts, the lack of adequate risk management practices, liquidity, the challenges related to technology and cybersecurity, and the competition and efficiency issues of the SOCBs (Le et al., 2020, 2022a; Nguyen et al., 2020). For instance, Hoang et al. (2021) reported that Vietnamese banks faced a high volatility in bank stability during 2013–2019. Such a situation is confirmed in Nguyen et al., 2022b), (2023), among others. In response, the Vietnamese government has implemented measures to address these issues, such as establishing a debt trading market and introducing debt restructuring programs, requiring banks to comply with international risk management standards and to establish risk management committees, providing liquidity support to banks, and increasing the use of market-based interest rates (SBV, 2020, 2021). It is, therefore, important to examine the stability of the Vietnamese banking system.

Our data is collected from the Vietnamese Banking Database (Le et al., 2022b) as an unbalanced panel data of 45 Vietnamese banks from 2002 to 2020, totaling 567 bank-year observations. These banks, on average, accounted for more than 95% of total domestic deposits for the banking system for the period examined (Le et al., 2022b), making them a suitable sample for our study. To the best of our knowledge, this is the largest database utilized in the Vietnamese banking efficiency literature. The list of the sampled banks is presented in Table 2, while Table 3 shows the descriptive statistics for our CAMELS variables (original values but not reciprocals). One can see that the average Vietnamese bank follows Basel's requirements (BIS, 2011) to have strong capital adequacy, moderate asset quality, high profitability, and high liquidity; however, it is also highly sensitive to market risks.

Table 2 Sample banks for the study

No.	Bank	Bank Code	Type	No.	Bank	Bank Code	Type
1	An Binh Commercial Joint Stock Bank	ABB	JSCB	24	Nam A Commercial Joint Stock Bank	NAB	JSCB
2	Asia Commercial Joint Stock Bank	ACB	JSCB	25	National Citizen Bank	NCB	JSCB
3	Vietnam Bank for Agriculture and Rural Development	AGB	SOCB	26	Ocean Commercial One Member Limited Liability Bank	OB	JSCB
4	Joint Stock Commercial Bank for Investment and Development of Vietnam	BIDV	SOCB	27	Orient Commercial Joint Stock Bank	OCB	JSCB
5	BacA Joint Stock Commercial Bank	BAB	JSCB	28	Petrolimex Group Commercial Joint Stock Bank	PGB	JSCB
6	Bao Viet Joint Stock Commercial Bank	BVB	JSCB	29	Southern Commercial Joint Stock Bank	PNB	JSCB
7	Construction Bank (former name: Trustbank)	CB	JSCB	30	Vietnam Public Joint Stock Commercial Bank	PVB	JSCB
8	Vietnam Joint Stock Commercial Bank of Industry and Trade	CTG	SOCB	31	Saigon Commercial Bank	SCB	JSCB
9	DongA Joint Stock Commercial Bank	DAB	JSCB	32	South East Asia Joint Stock Commercial Bank	SEAB	JSCB
10	Vietnam Export Import Commercial Joint Stock Bank	EIB	JSCB	33	Saigon Bank for Industry & Trade	SGB	JSCB
11	First Joint Stock Commercial Bank	FCB	JSCB	34	Saigon– Hanoi Commercial Joint Stock Bank	SHB	JSCB
12	Great Asia Commercial Joint Stock Bank	GAB	JSCB	35	Saigon Thuong Tin Commercial Joint Stock Bank	STB	JSCB
13	Global Petro Commercial Joint Stock Bank	GPB	JSCB	36	Viet Nam Technological and Commercial Joint Stock Bank	TCB	JSCB
14	Hanoi Building Commercial Joint Stock Bank	HBB	JSCB	37	VietNam Tin Nghia Commercial Joint Stock Bank	TNB	JSCB
15	Ho Chi Minh City Development Joint Stock Commercial Bank	HDB	JSCB	38	TienPhong Commercial Joint Stock Bank	TPB	JSCB
16	HSBC Bank (Vietnam) Limited	HSBC	JSCB	39	Viet A Joint Stock Commercial Bank	VAB	JSCB
17	Indovina Bank Ltd.	IVB	JSCB	40	Vietnam Bank for Social Policies	VBSP	SOCB
18	Kienlong Commercial Joint Stock Bank	KLB	JSCB	41	Joint Stock Commercial Bank for Foreign Trade of Vietnam	VCB	SOCB
19	Lien Viet Post Joint Stock Commercial Bank	LVB	JSCB	42	Viet Capital Commercial Joint Stock Bank	VCPB	JSCB
20	Military Commercial Joint Stock Bank	MB	JSCB	43	Vietnam International Commercial Joint Stock Bank	VIB	JSCB
21	Vietnam Maritime Commercial Joint Stock Bank	MSB	JSCB	44	Vietnam Commercial Joint Stock Bank for Private Enterprise	VPB	JSCB

Table 2 (continued)

No.	Bank	Bank Code	Type	No.	Bank	Bank Code	Type
22	Mekong Development Joint Stock Commercial Bank	MDB	JSCB	45	Western Commercial Joint Stock Bank	WEB	JSCB
23	Mekong Housing Bank	MHB	JSCB				

Notes SOCB: State Owned Commercial Bank; JSCB: Joint Stock Commercial Bank

Table 3 Descriptive statistics of the original CAMELS variables (2002–2020)

	ETA	NPLRATIO	ROA	NIM	LTA	GTA
Full sample (N=567)						
Mean	11.37	1.13	1.26	9.16	41.94	35.38
Standard Deviation	8.28	2.66	1.14	18.73	15.92	20.88
Minimum	0.10	0.03	–5.51	–0.94	1.87	0.13
Maximum	66.08	54.60	8.10	158.58	86.19	86.73
Bank groups (mean value)						
SOCBs (N=87)	6.98	0.89	0.80	12.00	29.43	45.64
JSCBs (N=480)	12.17	1.17	1.35	8.10	44.20	33.53

Notes ETA: Equity capital to total assets, NPLRATIO: Nonperforming loans to total loans, ROA: Return on assets, NIM: Net interest margin, LTA: Liquid assets over total assets, GTA: Absolute value of the cumulative 1-year repricing gaps over total assets, SOCBs: State-owned commercial banks, and JSCBs: Joint-stock commercial banks. ETA, ROA, NIM, and LTA have a positive relationship with bank stability, while NPLRATIO and GTA are the opposite

A closer look at individual CAMELS ratios reveals a more detailed picture of the Vietnamese banking sector over time. For instance, Fig. 1 shows that after 2010, there was a deterioration in the industry's stability: NIM was stable, ETA, LTA, and ROA were decreasing, while GTA was increasing. Notably, the NPLRATIO fell from around 2.5 per cent (2004–2009) down to less than 1.0 per cent (2010 onward), showing the effectiveness of the government's efforts in controlling bad debts in the system (Ngo & Tripe, 2017; Le et al., 2022a). However, this improvement was not enough to strengthen the entire banking sector, leading to the concern that Vietnamese banks might focus too much on their nonperforming loans but not on other issues. The following section shows that, by using the CPI, we can examine this situation in more detail.

4.2 Performance of Vietnamese banks: results from the CPI

As discussed previously, the CPI provides a multidimensional measure of the stability of Vietnamese banks rather than the individual aspects (e.g., ETA or NIM). Figure 2 shows that during 2002–2020, Vietnamese banks experienced three major periods. The first one observed a decline in the average CPI from 24.76 in 2002 to 18.74 in 2005. This is consistent with the findings of Ngo (2012) and Vo and Nguyen (2018) and also in line with the performance of the VN-Index of the country's stock market (Rosengard & Huynh, 2009). To deal with this situation, the Vietnamese government decided in 2006 to restructure its financial system, with the main purpose being to (i) privatize the state-owned commercial banks and (ii) develop the stock market (Vo & Nguyen, 2018). It led to the second period of 2006–2015 with an increasing trend in the CPI, reaching a peak of 27.97 points in 2015. As discussed

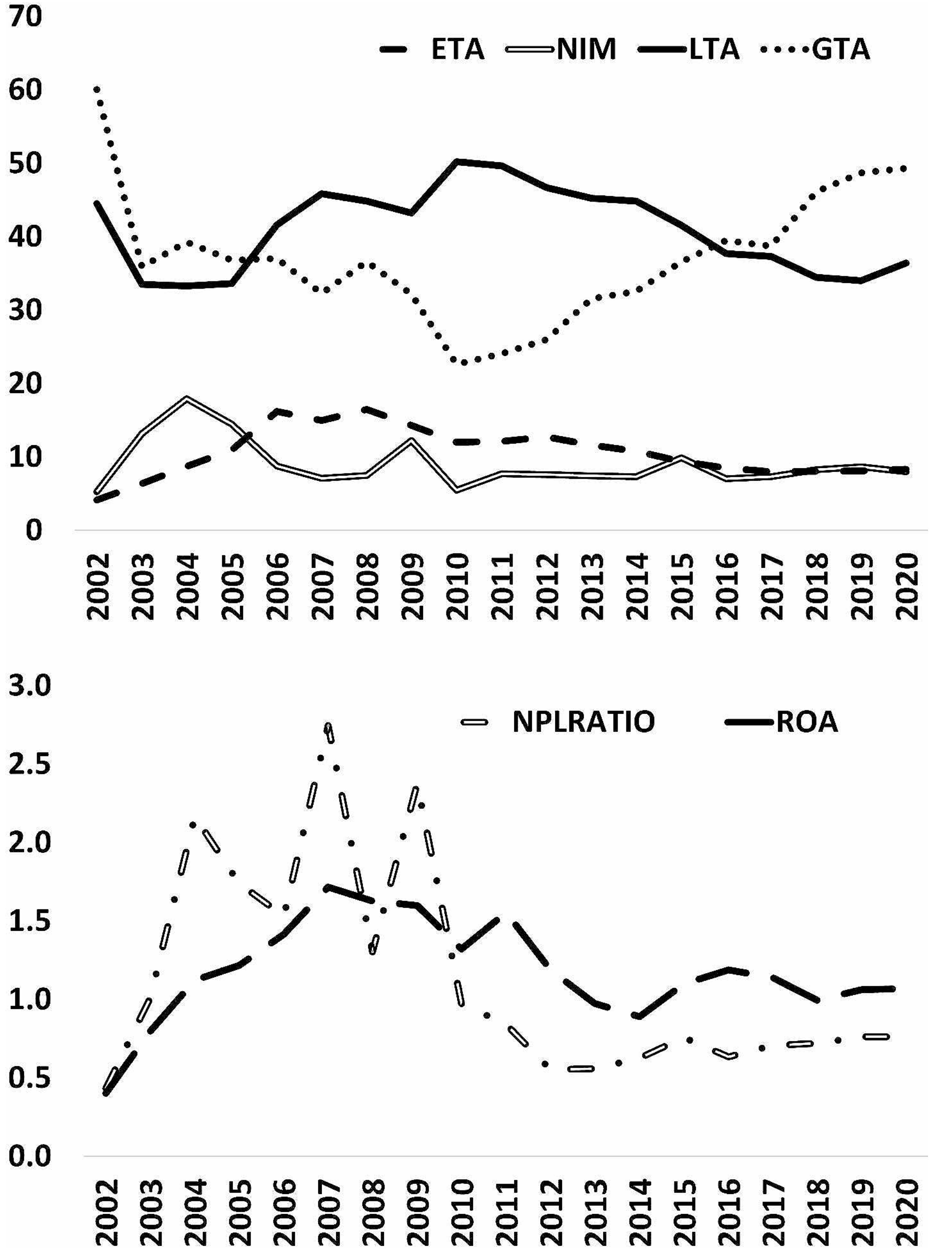

Fig. 1 The CAMELS ratios of Vietnamese banks (2002–2020). *Note* ETA: Equity capital to total assets, NPLRATIO: Nonperforming loans to total loans, ROA: Return on assets, NIM: Net interest margin, LTA: Liquid assets over total assets, GTA: Absolute value of the cumulative 1-year repricing gaps over total assets. ETA, ROA, NIM, and LTA have a positive relationship with bank stability, while NPLRATIO and GTA are the opposite

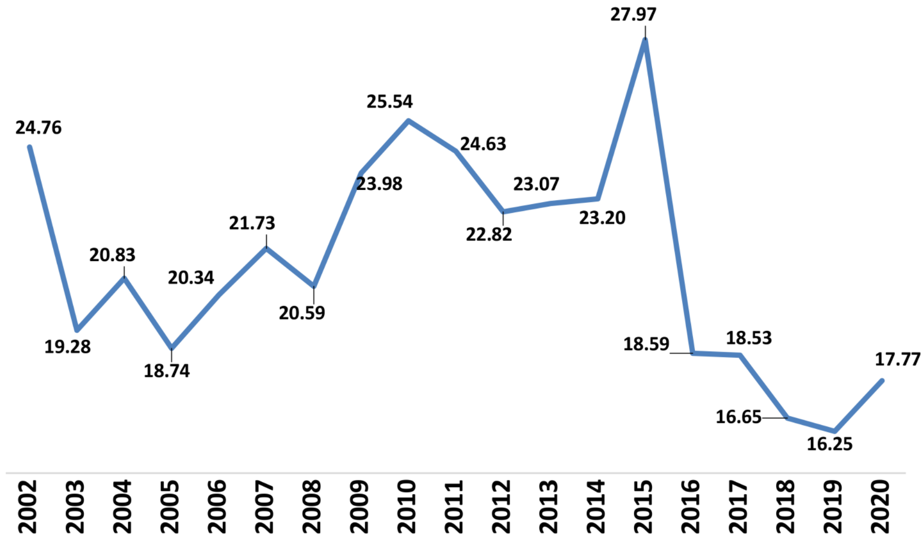

Fig. 2 Trend of the average values of the CPI over time

by Vo and Nguyen (2018), however, the improvement in performance of banks was mainly driven by the booming stock market, in which banks were strong players (Mateus & Hoang, 2021). Such development is not sustainable; the third period of post-2015 shows a sharp decrease in the CPI to the bottom point of 16.25 in 2019. A recovery sign can be seen in 2020. However, with the recent COVID–19 pandemic (SBV, 2021; FitchRatings, 2022), Vietnamese banks may suffer another round of poorer performance.

At the individual bank level, the CPI shows that, on average, the joint-stock commercial banks (JSCBs) are more financially stable than state-owned commercial banks (SOCBs), consistent with prior evidence on banking sectors in developing countries (La Porta et al., 2002; Bonin et al., 2005; Berger et al., 2010; Jiang et al., 2013). Specifically, three of the five SOCBs (i.e., 60%) in the Vietnamese banking system are among the group of the least stable banks: CTG, BIDV, and AGB (see Fig. 3). This is clearer when looking at the CAMELS ratios of the two bank groups, where SOCBs have lower ETA, ROA, and LTA but higher GTA than JSCBs (see Table 3). The two aspects in which SOCBs outperformed JSCBs are NPLRATIO and NIM, indicating that SOCBs may be better at lending activities. As discussed earlier by Le (2017); Le et al. (2022a), SOCBs can exhibit economies of scale thanks to their large size and branch networks to attract more customers.

Furthermore, the calculation of the CPI, as in Eq. (2), implies that higher weights are dynamically assigned to the ratios on which the bank has advantages. By examining the frequency and values of the weights across different weight restriction settings (see Sect. 2.2 above), we can see that the (comparative) strength of Vietnamese banks relies on liquidity (LTA) and capital adequacy (ETA), as they were assigned the highest and second-highest weights, respectively, except for the equal weight setting. In contrast, their weakness associates with ROA, GTA, and NPLRATIO (see Table 4). In other words, during the 2002–2020 period, the Vietnamese banking sector had strengthened its equity capital and (liquidity) assets but focused less on management quality and risk management. This helps explain the

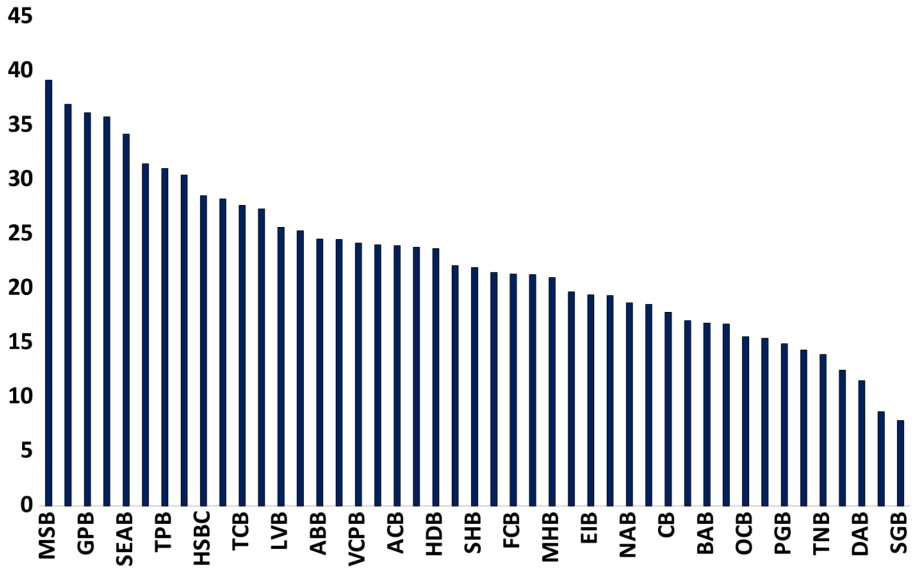

Fig. 3 Average CPI scores of individual banks (2002–2020). *Note* The five SOCBs in the system are AGB, BIDV, CTG, VBSP, and VCB

Table 4 Frequency of optimal weights assigned to CAMELS ratios in the CPI (%)

	ETA	NPLRATIO	ROA	NIM	LTA	GTA
Model 1	2.65	0.00	0.00	5.11	92.24	0.00
Model 2	35.77	1.41	1.00	14.25	46.57	1.00
Model 3	16.67	16.67	16.67	16.67	16.67	16.67
Model 4	6.73	5.00	5.00	8.70	69.57	5.00
AverageALL	**15.45**	**5.77**	**5.67**	**11.18**	**56.26**	**5.67**
AverageCPI	**15.05**	**2.14**	**2.00**	**9.36**	**69.46**	**2.00**

Note Model 1 uses the free weights of traditional DEA (i.e., $0 \leq k_{it} \leq 1$), Model 2 uses the non-zero weights (i.e., $0.05 \leq k_{it} \leq 1$), Model 3 applies the fixed and equal weights (i.e., $k_{it} = 0.1667$), and Model 4 applies the non-zero non-dominant weights (i.e., $0.05 \leq k_{it} \leq 0.49$) for all CAMELS ratios. AverageALL accounts for all four models, while AverageCPI only accounts for the three Models 1, 2 and 4

level of bad debts of Vietnamese banks, which led to the establishment of the Vietnamese Asset Management Company (or "bad bank") in 2013 as well as the restructuring of the whole banking sector in Vietnam in the post-2011 period (Du & Sim, 2016; Ngo & Tripe, 2017). Our findings further suggest that Vietnamese banks should target those issues in the future to improve their performance and financial stability.

4.3 Robustness testing

We first report the correlations between the Shannon CPI and its components, i.e., the four settings of weight restriction mentioned in Sect. 3.2 above. Specifically, Table 5 shows that all CPI measures are highly correlated, in which the Shannon's CPI strongly associates with

Table 5 Spearman's ranking correlation between the Shannon's CPI and its components

Shannon's CPI				
0.950	Model 1			
(0.000)				
0.811	0.924	Model 2		
(0.000)	(0.000)			
0.662	0.834	0.954	Model 3	
(0.000)	(0.000)	(0.000)		
0.938	0.999	0.937	0.855	Model 4
(0.000)	(0.000)	(0.000)	(0.000)	

Note Model 1 uses the free weights of traditional DEA (i.e., $0 \le k_{it} \le 1$), Model 2 uses the non-zero weights (i.e., $0.05 \le k_{it} \le 1$), Model 3 applies the fixed and equal weights (i.e., $k_{it} = 0.1667$), and Model 4 applies the non-zero non-dominant weights (i.e., $0.05 \le k_{it} \le 0.49$) for all CAMELS ratios

Table 6 Spearman's ranking correlation between the CPI, CAMELS ratings and z-score

	CPI	CAMELS	z-score
CPI	1.000 (0.000)		
CAMELS	–0.374 (0.000)	1.000 (0.000)	
z-score	0.451 (0.032)	–0.212 (0.000)	1.000 (0.000)

Notes Model 1 uses the free weights of traditional DEA (i.e., $0 \le k_{it} \le 1$), Model 2 uses the non-zero weights (i.e., $0.05 \le k_{it} \le 1$), Model 3 applies the fixed and equal weights (i.e., $k_{it} = 0.1667$), and Model 4 applies the non-zero non-dominant weights (i.e., $0.05 \le k_{it} \le 0.49$) for all CAMELS ratios

the traditional DEA approach (i.e., Model 1) via a Spearman's coefficient of 0.945 and also strong/moderate associates with the other three models.

As discussed, we also compute the CAMELS ratings and z-scores for the sampled banks and compare them to the CPIs. We expect a positive relationship between CPIs and z-scores, while there should be a negative association between CPIs and the CAMELS ratings. Table 6 reports Spearman's ranking correlation between the three measures.

The results from Table 6 are consistent with the literature where the CAMELS ratings and z-scores show a negative relationship, indicating that banks with higher CAMELS ratings tend to be less stable (Ben Lahouel et al., 2022; Hafeez et al., 2022). It also shows that the CPI is consistent with the other two measures (all are significant at 1%), indicating that the CPI could be used as a measure of bank stability, an alternative to the CAMELS ratings and z-scores. We, therefore, argue that the CPI can be used for future bankruptcy or survival analyses.

5 Conclusions

We have recently seen extensive use of techniques such as stochastic frontier analysis (SFA) and data envelopment analysis (DEA) in the performance evaluation of banking and financial institutions (Avkiran & Cai, 2014; Hammami et al., 2022; Kallel & Triki, 2022);

although traditional ratio analysis (RA), especially ones based on the CAMELS rating system (Adam et al., 2021; Ben Lahouel et al., 2022), still shows its usefulness in measuring bank performance and stability. Each approach has its pros and cons, and the integration of several methods has the potential to combine advantages while minimizing weaknesses.

Specifically, RA is simple, popular, and has predictive ability, but it fails to capture the multidimensional performance of the firms/banks (Paradi & Zhu, 2013). Other studies based on both DEA and RA (Halkos & Salamouris, 2004; Avkiran, 2011; Ben Lahouel et al., 2022) can examine the multidimensional perspective but are limited to the relative measurement of DEA, such that adding or removing data to the sample requires the measures to be recalculated. In this paper, we employed an MCDA technique to create an absolute measure of (Shannon's entropy) composite performance index (CPI) that can still evaluate the multidimensional performance and stability of Vietnamese banks (2002–2020). The use of rich data allows us to examine the financial stability of the Vietnamese banking sector over time for individual banks and different bank groups. Specifically, the CPI suggests that Vietnamese banks had experienced three major periods regarding their stability: a decline period (2002–2005), a recovery and improvement period (2006–2015), and a sharp decreasing period (2016–2019) with a slight hope in 2020, although COVID–19 may ruin it. More importantly, we found that the JSCBs are more financially stable than the SOCBs, consistent with prior evidence on banking sectors in developing countries. Our findings also help explain the strengths and weaknesses of Vietnamese banks during those periods, suggesting that to improve their performance and stability, banks in Vietnam should pay more attention to management quality, asset quality, and risk management. Our results are robust and consistent with the CAMELS ratings and z-scores; thus, the CPI could be used to measure bank stability in future bankruptcy or survival analyses.

Our CPI has several promising characteristics of (i) being an absolute measure of performance that allows for adding or removing data without affecting the existing scores; (ii) employing CAMELS ratios directly in its calculation without the need for normalization or imputation of positive values; (iii) employing the dynamic weighting system of DEA goal programming; (iv) providing more robust insights on the Vietnamese banking system under the Shannon entropy approach; and (v) can be an alternative measure of bank stability. It is, however, possible to extend our research to more weight settings such as cross-efficiency (Sexton et al., 1986), geometric BOD (Van Puyenbroeck & Rogge, 2017), or common sets of weights (Hammami et al., 2022). Other research directions may include more data and variables, examine the impacts of important events such as COVID-19, or apply other entropies such as Boltzmann-Gibbs (Dragulescu & Yakovenko, 2000) or Rényi (Aczél, 2006).

Funding Open Access funding enabled and organized by CAUL and its Member Institutions

Declarations

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest The authors declare no conflict of interest.

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