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Article

The relation between efficiency of credit operation and non-performing loans—An application of network DEA model with undesirable outputs

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Abstract: To evaluate the efficiency of decision-making units, researchers continually develop models simulating the production process of organizations. This study formulates a network model integrating undesirable outputs to measure the efficiency of Vietnam's banking industry. Employing methodologies from the data envelopment analysis (DEA) approach, the efficiency scores for these banks are subsequently computed and comparatively analyzed. The empirical results indicate that the incorporation of undesirable output variables in the efficiency evaluation model leads to significantly lower efficiency scores compared to the conventional DEA model. In practical terms, the study unveils a deterioration in the efficiency of banking operations in Vietnam during the post-Covid era, primarily attributed to deficiencies in credit risk management. These findings contribute to heightening awareness among bank managers regarding the pivotal importance of credit management activities.

Keywords: data envelopment analysis; undesirable outputs; credit operation; non-performing loans

1. Introduction

Data envelopment analysis (DEA) has long evolved into an effective tool for scholars in evaluating the operational efficiency of decision-making units (DMUs). In this framework, the presence of both desirable and undesirable output-input variables is plausible (Halkos and Petrou, 2019). For instance, the quantity of defective products constitutes an unanticipated output variable, and the objective is consistently to minimize this parameter to enhance overall efficiency. Conversely, within an industrial production process, factors such as waste or pollution are also deemed undesirable outcomes (Scheel, 2001). The reduction of these variables is demonstrably conducive to heightened system efficiency. Conventional DEA models presuppose the augmentation of output variables, and the reduction of inputs as means to enhance efficiency or approach the efficient frontier (Charnes et al., 1978). However, if undesirable outputs are treated as input variables in an effort to diminish them, the computational outcomes of the DEA model may fail to accurately mirror the intricacies of the actual production process.

Similarly, this phenomenon also exists in financial markets, especially banking industry. Banks function as intermediary institutions, assuming a critical role in shaping the dynamics of a financial system. Fundamentally, the credit activities undertaken by banks constitute the foundational operations that dictate the viability of these institutions. Despite a transition towards non-interest income services, the share of this operation in the total income remains substantial for banks. Nevertheless, within the context of credit expansion, a frequent undesirable outcome is the escalation of non-performing loans (NPLs). This variable functions as an indicator representing the quality of the bank's assets, forecasting signs of potential bankruptcy and, consequently, impacting the organization's capability to operate stably and effectively (Partovi and Matousek, 2019). This underscores the necessity for effective management of NPLs within the banking sector (Takahashi and Vasconcelos, 2024). In terms of mission and significance, this task is assessed to be on par with credit expansion. Consequently, the weight assigned to this undesirable output is also equivalent to that of the desirable outputs, such as revenue or income. The assessment of credit operation's efficiency under the integration of non-performing loans, therefore, is pivotal in comprehending the importance of NPL management activities.

While several studies are ambiguous concerning whether or not researchers should control for problem loans in efficiency estimation (for instance Berger and DeYoung (1997), the prevailing consensus among the majority of research indicates their substantial contribution to bank inefficiencies (Partovi and Matousek, 2019; Takahashi and Vasconcelos, 2024). Within contemporary literature, non-performing loans (NPLs) have been classified either as a controlled variable (Fries and Taci, 2005; Podpiera and Weill, 2008) or as an undesirable output (Fukuyama and Matousek, 2017; Fukuyama and Weber, 2015; Kumbhakar and Horncastle, 2015). These studies uniformly furnish evidence corroborating the role of NPLs in exacerbating bank inefficiency. Berger and DeYoung (1997) posit that the principal limitation of investigations addressing the impact of NPLs lies in their assumption that NPLs constitute a controlled variable rather than an undesirable output, directly impinging upon the production process. Consequently, in the context of this study, NPLs will be construed as an undesirable output when estimating efficiency scores.

This study examines the Vietnamese banking sector as its primary focus. As a developing nation in the midst of ongoing financial system restructuring, the banking industry in Vietnam has confronted various challenges in recent years (Dang et al., 2023). Especially, the escalating NPL ratio, alongside scandals related to capital mobilization through bonds, has substantially eroded the reputation of the industry. This research, therefore, raises concerns about the relationship between NPL and the credit operation's efficiency of the Vietnamese banking sector, with broader implications for other developing countries at large.

This study contributes to the literature of both operational research and banking efficiency perspectives. Firstly, it extends the application of undesirable DEA model to a network production process which better illustrates Vietnam banking's operation. Secondly, through the result of the study, the negative correlation between NPL and banking efficiency is confirmed and some managerial suggestions, therefore, can be drawn.

The rest of this paper is structured as follows. In the second section, we introduce the derivation of the network DEA with undesirable outputs. The third section elucidates variables selection and data collection. The fourth section presents empirical results. Subsequently, in the final section conclusion and some implications are provided.

2. Network DEA model with undesirable outputs

Establishing a framework to delineate the operational process of DMUs holds paramount significance in assessing efficiency through the employment of the DEA model. Researchers, conventionally, suggest that banks utilize inputs such as labor, assets, deposits, and loans to generate outputs, encompassing bank income inclusive of both interest and non-interest income (Berger and Humphrey, 1997; Staub et al., 2010). Nevertheless, recent scholarly inquiries into the operational dynamics of the banking industry have underscored a contentious discourse surrounding the intricacies of this endeavor. A pivotal point of contention revolves around the classification of deposits as either input or output variables (Hunter and Timme, 1995). The emergence of DEA network models has, to some extent, ameliorated these disputes by bifurcating banking operations into two distinct phases: capital formation, leading to the accrual of deposits, and capital utilization, resulting in the provision of loans and investments (Holod and Lewis, 2011). This delineation serves to elucidate the distinct roles of these variables with greater clarity.

Building upon the foundational principles of the network DEA model, this research delves into an examination the credit operations of Vietnam's banking sector. Within this framework, credit operations are delineated into two primary stages: credit extension and credit management. In this process, banks utilize input variables, primarily deposits, to provide loans to their clientele. These loans serve as the principal revenue stream for banks, manifested through interest income, albeit accompanied by an inherent challenge of non-performing loans. This structure inherently embodies a two-stage network structure.

The two-stage network structure is presented as in **Figure 1**. Throughout this section, we assume that there is a set of n equivalent DMUs, that is $DMU = \{DMU_j; j = 1, 2, \dots, n\}$, needed to appraise the performance.

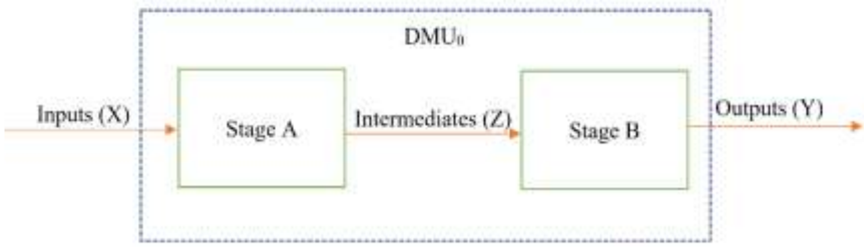


Figure 1. General two-stage network DEA model.

2.1. Solving the network DEA model

Suppose that a specific DMU$_j$ has I inputs, R outputs, and D intermediates. The set of variables that contribute to the production process can be denoted as $X_j = \{x_{1j}, x_{2j}, \dots, x_{Ij}\}$, $Y_j = \{y_{1j}, y_{2j}, \dots, y_{Rj}\}$, and $Z_j = \{z_{1j}, z_{2j}, \dots, y_{Dj}\}$, respectively.

To compute the overall efficiency of this model, we first assume that there is no connection between the two stages. According to the conventional DEA model (Charnes et al., 1978), the efficiency of each stage can be defined as $\theta_0^{A*} = \frac{\sum_{d=1}^{D} \eta_d z_{d0}}{\sum_{i=1}^{I} v_i x_{i0}}$, and $\theta_0^{B*} = \frac{\sum_{d=1}^{D} u_r y_{r0}}{\sum_{i=1}^{I} \widetilde{\eta_d} z_{d0}}$. Note that $u_r, v_i, \eta_d, \widetilde{\eta_d}$ are non-negative multipliers which reflect the relative importance of corresponding variable.

Researchers have long debated the relationship between stages in the network DEA model. To address this issue, two perspectives have been raised: the noncooperative and centralized approaches (Liang et al., 2006, 2008). The non-cooperative network DEA assumes the existence of a 'leader-follower nexus' among the stages. In other words, if we consider that stage A is more important than stage B (stage A is the leader), the efficiency of stage A is calculated first. Then, stage B's efficiency is computed with a constraint that stage A's efficiency is fixed. Although this approach appears effective when there is obvious evidence about the role of stages, it does not reflect real-world situations. An alternative approach to gauging the efficiency of a two-stage network may be derived from a centralized perspective. Within this perspective, discerning an optimal set of weight values for the intermediate measures emerges as pivotal in maximizing the overall efficiency of the system. Concretely, this centralized model can be articulated by imposing $\eta_d = \widetilde{\eta_d}$ in the program to estimate the efficiency of stages A and B distinctly. The efficiencies of both stages are consequently concurrently ascertained. Typically, the optimization model seeks to maximize the mean values of θ_0^A and θ_0^B, giving rise to nonlinear programming predicaments. However, it is imperative to underscore that, owing to $\eta_d = \widetilde{\eta_d}$, $\theta_0^A * \theta_0^B$ can be transformed as $\frac{\sum_{r=1}^{R} u_r y_{r0}}{\sum_{i=1}^{I} v_i x_{i0}}$. Consequently, rather than pursuing the maximization of the mean values of θ_0^A and θ_0^B, we are compelled to address the following program.

$$\theta_0^{AB(\text{centralized})} = \text{Max}(\theta_0^A * \theta_0^B) = \frac{\sum_{r=1}^{R} u_r y_{r0}}{\sum_{i=1}^{I} v_i x_{i0}} \quad (1)$$
$$s.t.\, \theta_j^A \leq 1; \theta_j^B \leq 1; \eta_d = \widetilde{\eta_d}$$

This model can be linearized as

$$\begin{aligned} &\theta_0^{AB(\text{centralized})} = \text{Max} \sum_{r=1}^{R} u_r y_{r0} \\ &s.t. \sum_{r=1}^{R} u_r y_{rj} \leq \sum_{d=1}^{D} \eta_d z_{d0}\ \forall j \\ &\sum_{d=1}^{D} \eta_d z_{d0} \leq \sum_{i=1}^{I} v_i x_{ij}\ \forall j \\ &\sum_{i=1}^{I} v_i x_{i0} = 1 \\ &v_i, \eta_d, u_r \geq \varepsilon; \end{aligned} \quad (2)$$

Suppose this model results in a unique efficiency score for the network system, we can compute the efficiency of stage A and stage B as following $\theta_0^{A(\text{centralized})} = \frac{\sum_{d=1}^{D} \eta_d^* z_{d0}}{\sum_{i=1}^{I} v_i^* x_{i0}}$ and $\theta_0^{B(\text{centralized})} = \frac{\sum_{r=1}^{R} u_r^* y_{r0}}{\sum_{i=1}^{I} \eta_d^* z_{d0}}$, wherein * denotes the optimal solutions obtained from model Equation (2).

2.2. Undesirable outputs

The desirable (good) and undesirable (negative) outputs are symbolized as y_{rj}^g

and y_{rj}^{b}, respectively. In this context, our objective is to augment y_{rj}^{g} while diminishing y_{rj}^{b} to optimize efficiency. Nevertheless, in the conventional output-oriented DEA model, augmentation is applied simultaneously for both y_{rj}^{g} and y_{rj}^{b} to enhance overall efficiency. To amplify the desirable outputs and diminish the undesirable outputs, the following steps can be undertaken. First, the undesirable outputs are multiplied by -1, followed by the identification of appropriate multipliers v_i to ensure the transformation of all undesirable outputs into positive values. Consequently, $\bar{y}_{rj}^{b} = -y_{rj}^{b} + v_r > 0$. This can be achieved by $v_r = \max_j\{y_{rj}^{b}\} + 1$ (Zhu, 2014).

Theoretically, we could treat undesirable outputs as inputs; however, this conceptualization does not faithfully capture the intricacies of the production process. An alternative approach involves implementing a straightforward transformation on the undesirable outputs (e.g., $1/y_{rj}^{b}$), subsequently employing the adjusted variables as outputs. The methodology adopted in this study pragmatically employs a monotonic linear transformation. The utilization of a linear transformation, given its capacity to preserve convexity, establishes it as a judicious choice for the DEA model.

The target efficiency for a DMU to reach is

$$\begin{cases} \hat{x}_{i0} = x_{i0} - s_i^{-^*} \\ \hat{y}^{g}{}_{r0} = h^* y_{r0}^{g} + s_i^{+^*} \\ \hat{y}^{b}{}_{r0} = v_r - (h^* \bar{y}_{r0}^{g} + s_r^{+^*}) \end{cases}$$

3. Variable selection and data collection

3.1. Variable selection

Figure 2 depicts the model outlining the general credit operations of banks, an extension derived from the work of (Fukuyama and Matousek, 2017; Holod and Lewis, 2011; Sealey Jr. and Lindley, 1977). In accordance with this conceptual framework, banks employ pivotal resources of production, including labor expenses and fixed assets, in the process of products generation. Furthermore, the credit operations encompass distinctive input components, which are interest expenses and deposits. These inputs are paramount in shaping the efficiency paradigm of credit operations.

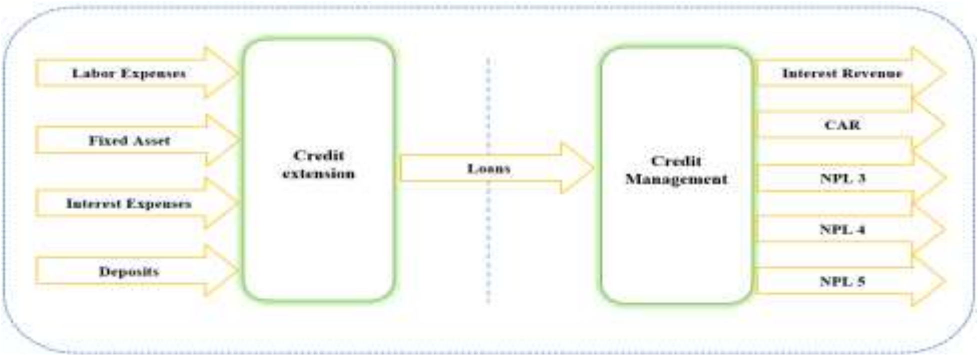


Figure 2. The banking's credit operation.

Subsequently, these constituent factors undergo amalgamation to engender a pivotal financial product, namely loans. The final outcome of this operational sequence manifests as interest revenue, emblematic of the yield from the financial process. In addition, as a precautionary measure for the protection of depositors, the Bank for International Settlements (BIS) stipulates that banks adhere to a Capital Adequacy Ratio (CAR) in alignment with progressively rigorous criteria. This ratio functions as a quantifiable indicator of a bank's accessible capital, delineated as a percentage relative to the bank's credit risk. This metric serves as an evaluative tool for the bank's capacity to absorb financial losses, standardizing its ability to settle obligations, manage credit risks, and sustain effective operations. A bank boasting a favorable CAR is inherently better positioned to absorb potential losses, thereby mitigating the risk of default and financial detriment to depositors.

Last but not least, an integral aspect of this process involves an undesirable outcome—non-performing loans (NPLs). This output constitutes banking credit that may experience delayed repayment or face potential default by the borrowers. As stipulated in Article 10 of Circular 11/2021/TT-NHNN, commercial bank loans are systematically classified into five groups, with loans falling within groups 3–5 (overdue for 91 days or more) being officially designated as NPLs.

3.2. Data collection

Table 1 presents a summary of descriptive statistics of the selected variables. The research encompasses a total of 10 variables, inclusive of 4 inputs, 1 intermediate, and 5 outputs. The data pertaining to these variables predominantly comprise secondary data extracted from the annual reports and financial statements of the selected banks. The research sample is comprised of 17 publicly listed banks on both the Hanoi and Ho Chi Minh City Stock Exchanges, spanning the years from 2018 to 2021.

Table 1. Variables' descriptive statistic.

Variables		**Sources of the data**	**Mean**	**Median**	**Min**	**Max**	**St.D.**
Inputs	Labor expenses	Annual reports	4,129,082	3,236,162	394,130	11,428,468	3,051,006
	Fixed assets	Balance sheets	3,860,970	2,748,688	300,052	11,114,537	3,461,197
	Interest expenses	Income statements	17,040,136	11,194,263	2,196,765	64,890,703	15,387,874
	Deposits	Balance sheets	339,712,349	207,682,050	29,206,157	1,380,397,799	350,308,970
Intermediates	Loans	Balance sheets	323,696,051	215,837,420	29,471,994	1,354,632,643	332,359,185
Outputs	Interest revenue	Income statements	31,675,284	24,419,864	3,171,636	101,007,908	26,655,109
	CAR	Annual reports	11.18	10.88	8.35	16.62	1.92
	NPL 3	Note to the financial statements	1,159,359	517,854	23,123	7,095,731	1,646,938
	NPL 4		961,525	574,218	7448	7,535,242	1,304,189
	NPL 5		2,516,489	1,387,797	169,912	16,525,054	2,933,139

Note: the unit of CAR is %, other variables are in million Vietnam dong.

The statistical analysis reveals pronounced disparities in the operational scale among banks within the Vietnamese banking system. For example, an examination of the variable representing employee expenses, the mean value (4.129 trillion) being higher than the median (3.236 trillion) suggests that there are some extremely high values pulling the average to the right. This is indicative of a slightly right-skewed distribution. It implies that few banks offer employees very high salaries, which can influence the average but have less impact on the median. Furthermore, the standard deviation for this variable reaches 3.051 trillion, encompassing a large range from a minimum value of 394 billion to a maximum of 11.428 trillion. Other variables such as fixed assets, deposits, loans, and interest expenses exhibit a somewhat analogous distribution pattern. This descriptive statistical analysis shows that the vast majority of the sample are small-scale banks, while large-scale banks only account for a small amount but have a significant difference in scale. This may suggest that while the banking sector in Vietnam is predominantly composed of smaller institutions, the few large banks wield significant influence and likely have a considerable impact on the overall financial landscape of the country.

Upon scrutinizing the variables pertaining to NPLs, a notable revelation emerges—the prevalence of group 5 NPLs, indicative of a potential capital loss, constitutes the most substantial portion among the diverse loan groups. The average value for this category reaches a noteworthy 2.516 trillion dong. Concurrently, a considerable disparity exists between the bank with the highest NPLs in group 5 (BID-2020) and the one with the lowest (KLB-2018). It is crucial to emphasize, however, that this divergence may stem from dissimilarities in scale rather than necessarily implying disparities in the management of NPLs.

4. Empirical results

The efficiency of the two stages, namely credit extension and credit management, among Vietnamese commercial banks in the year 2021, are elucidated in **Table 2**. We use the codes of banks in the DMU column for abbreviation purpose. The third column encapsulates the overall efficiency scores of the network system computed from model Equation (2). The last two columns represent the efficiency decomposition of credit extension and credit management stages, as illustrated in **Figure 2**.

Table 2. The credit operation's efficiency of Vietnamese banking.

No.	DMU	Overall efficiency	Credit extension	Credit management	No.	DMU	Overall efficiency	Credit extension	Credit management
1	ACB	0.454	0.903	0.503	9	MBB	0.527	0.936	0.563
2	BAB	0.651	0.935	0.696	10	SHB	0.464	1.000	0.464
3	BID	0.385	1.000	0.385	11	STB	0.345	0.828	0.416
4	CTG	0.385	1.000	0.385	12	TCB	0.550	1.000	0.550
5	EIB	0.423	0.770	0.550	13	TPB	0.611	0.861	0.710
6	HDB	0.597	0.842	0.709	14	VCB	0.386	1.000	0.386
7	KLB	0.607	0.607	1.000	15	VIB	0.575	1.000	0.575
8	LPB	0.546	0.976	0.559	16	VPB	0.746	1.000	0.746

Note: the result in this table was estimated thanks to the help of Lingo 19—an optimization programing software.

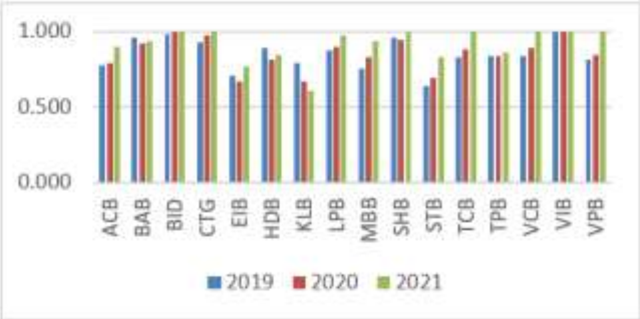
It becomes apparent that the majority of banks exhibit commendable performance in the initial stage of—credit extension. In fact, a significant number of commercial banks in Vietnam manage to achieve the maximum credit growth permitted within the regulatory confines set by the State Bank. The credit extension phase poses minimal challenges for most banks in Vietnam, a characteristic often observed in developing economies where there is a consistently high demand for capital. According to the calculation results for this stage, 7 out of 16 banks attain maximum efficiency, and 11 out of 16 banks garner high efficiency scores, surpassing the threshold of 0.9. Even the bank with the lowest efficiency score, KLB, still achieves a respectable score of 0.6. Overall, the average efficiency score for banks in the first stage stands at 0.92, accompanied by a low standard deviation of 0.11.

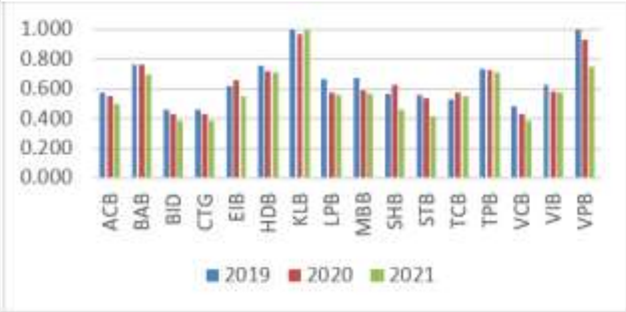
In contrast, the credit management stage reveals a notably disparate distribution of efficiency scores across banks. More specifically, the average efficiency score is 0.57, with a standard deviation of 0.17. KLB emerges as the bank with the highest efficiency score in this stage, whereas BID records the lowest score at 0.39. Significantly, three out of the Big Four in the banking industry, namely BID, CTG, and VCB, exhibit the lowest efficiency scores, hovering around 0.39. Conversely, smaller-scale banks like KLB, while potentially facing challenges in lending, demonstrate prowess in credit management. Among large-capitalization banks, only VPB achieves a commendable high efficiency score.

Figure 3 delineates the efficiency of the banking credit system over years. Upon initial inspection, it is evident that VPB emerges as the most efficient bank within the credit system, succeeded by KLB. The industry's lowest efficiency is associated with STB, consistently registering efficiency scores not surpassing 0.4 points. Overall, the efficiency of credit operations across Vietnamese banks exhibited a declining trend over the years, potentially reaching its nadir in 2022. It can be asserted that the timeframe spanning 2019 to 2021 underscores notable challenges within the sphere of banking credit activities.

Figure 3. The efficiency of Vietnam banking's credit operation.

An intriguing observation arises when scrutinizing the efficiency of the credit extension stage, revealing a trend suggestive of enhanced efficiency. As depicted in **Figure 4a**, a noticeable uptrend in the efficiency of this activity is evident for most banks over the period 2019–2021, with the exceptions of BAB, HDB, and KLB, which experienced a marginal decline. Consequently, it can be asserted that Vietnamese banks encounter no substantial impediments in credit extension operations.





(a) **(b)**

Figure 4. (a) the efficiency of credit extension; **(b)** credit management.

To examine the impact of the NPLs variable on the banks' efficiency scores, we can decompose the contribution of the output variables within the operational process. Consequently, the contribution level of output variables to operational efficiency is ascertained according to the formula $u_r y_{r0} / \sum_{r=1}^{R}(u_r y_{r0})$. The computational results reveal that the primary output of credit operation—interest revenue contributes the most to the efficiency score, accounting for approximately 90.62%. An intriguing observation is that the weight of the Capital Adequacy Ratio (CAR) variable is notably smaller than the cumulative weight of the NPLs variables (3.57% compared to 6.99%). However, upon subdividing NPLs into debt groups, the most significant impact on efficiency emanates from group 3 (overdue debts from 91 to 180), with a weight of 4.84%. Conversely, the bad debt group, which entails the potential loss of capital, exerts only a minimal influence on efficiency, accounting for only 0.86%. This outcome suggests that credit risk management outweighs credit risk provisioning in terms of importance. Consequently, bank administrators should prioritize actual management activities pertaining to bad debt rather than relying solely on historical data for provisioning purposes.

Based on the foregoing analysis, we can reiterate that the challenges encountered in banking credit operation predominantly originate from credit risk management operations. As illustrated in **Figure 4b**, it is apparent that a substantial decline in efficiency characterizes the credit management stage for the majority of banks. The escalation of non-performing loans within the banking sector, witnessing a rise from 4.218 trillion in 2018 to 5.469 trillion in 2021, marking a notable 27.73% increase, serves as a poignant indicator of a deterioration in the efficiency of credit management. Particularly noteworthy is the consistently lower level of efficiency maintained by State-owned commercial banks (including BID, CTG, and VCB). VPB emerges prominently as the bank undergoing the most significant reduction in this domain, experiencing a decrease of up to 0.25 efficiency points from 2019 to 2021.

The 2023 annual report of the State Bank of Vietnam elucidates several primary catalysts contributing to the burgeoning phenomenon of escalating non-performing loans. The economic situation, both domestically and internationally, is characterized by volatility, underscored by the deepening complexity of conflicts such as the Russia-Ukraine dispute and escalating tensions in the Middle East. These geopolitical tumults have precipitated disruptions in the global supply chain, engendering an elevated risk of inflation and exerting deleterious effects on economies across the globe, including

Vietnam. Furthermore, Vietnam's principal trading partners are confronted with myriad potential recessionary threats, particularly in the aftermath of recent incidents involving several banks in the United States. The management of bad debt by financial institutions confronts multifarious challenges within the intricate fabric of the post-Covid-19 economic landscape. The pervasive gloom pervading the real estate market further compounds the intricacies associated with the management of collateral assets. Moreover, the extant legal framework pertaining to the restructuring of credit institutions and the resolution of bad debts remains incomplete, thereby impeding efficacious remediation efforts. Concurrently, the dearth of policies incentivizing the participation of both domestic and foreign investors in the sphere of collateral management and bad debt trading exacerbates the prevailing predicament.

This trajectory intimates that financial institutions are encountering hurdles in proficiently overseeing their credit portfolios, thereby culminating in a heightened frequency of loans failing to be repaid as initially envisaged. Such a surge in non-performing assets carries profound ramifications for the fiscal robustness and resilience of the banking sphere, potentially prompting the implementation of remedial measures aimed at fortifying credit risk management protocols and augmenting the scrutiny applied to loan quality assessments.

In order to discern the distinctions between the proposed model in this paper and the conventional DEA model (excluding undesirable outputs), the study conducted efficiency computations using an alternative model that omits three undesirable outputs (NPLs). Subsequently, the efficiency scores derived from the two models underwent a comparative analysis utilizing a non-parametric Mann-Whitney U-Test, wherein the null hypothesis (H0) posited no difference between the two models. The test results revealed a z-value of −4.761, significantly exceeding the critical value of 1.96 in absolute value. This unequivocally indicates that employing the network DEA model with undesirable outputs consistently results in lower efficiency scores compared to the model that does not incorporate these "bad" outcomes. The integration of such variables into the model evidently provides a more accurate reflection of real-world operations and exerts a negative impact on the efficiency of various activities, including banking credit operations.

5. Conclusion

This research inherited and derived a network DEA model incorporating undesirable outputs to assess the efficiency of banking operations in Vietnam. The incorporation of undesirable outputs within the DEA model contributes to a more veracious evaluation of the real production of DMUs. Within the banking sector, the nexus between NPLs and the efficiency of credit activities becomes more conspicuous. The assessment of banking industry efficiency, incorporating the undesirable outputs—NPLs, carries heightened significance and analytical value.

The outcomes of the empirical analysis conducted in this study reveal an overarching diminishing trend in the efficiency of Vietnamese banks in the period 2019–2021. This descent is indicative of the challenges confronting not only the banking sector but also the economy of Vietnam in the post-COVID-19 era. Decomposing the efficiency scores exposes that the challenges confronting banks predominantly emanate from deficiencies in credit management activities rather than in the credit extension stage. This trait is emblematic of developing nations. It implies to banking executives the imperative and paramount importance of credit quality management, superseding a singular focus on the quantitative expansion of credit, as has historically been emphasized.

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