Risk-Adjusted Dynamic Efficiency and Productivity Growth in Emerging Market Banking: Evidence from Vietnam's Two-Stage Operations

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Abstract: - This study examines the dynamic efficiency and productivity trajectories of 20 Vietnamese listed banks from 2017 to 2023, a period characterized by significant regulatory shifts and economic volatility. We develop a two-stage Dynamic Network Data Envelopment Analysis (DNDEA) model with a slacks-based measure (SBM) to decompose the banking value chain into resource-generation and income-generation phases. A pivotal contribution of this research is the explicit treatment of non-performing loans (NPLs) as undesirable carry-over variables, thereby capturing the intertemporal persistence of credit risk. Our empirical results reveal significant heterogeneity: while overall efficiency is primarily hindered by resource-generation slacks (overuse of labor and equity), the income-generation phase exhibits relative resilience. Utilizing the Cumulative Malmquist Productivity Index, we identify divergent trajectories among banks, distinguishing "Consistent Benchmarks" that maintain robust stability from "Volatile" performers sensitive to macroeconomic shocks. These findings offer critical insights for macroprudential oversight, suggesting that regulators must monitor structural, stage-specific inefficiencies to safeguard financial stability in emerging markets.

Key-Words: - dynamic network DEA; bank efficiency; non-performing loans; carry-over; heterogeneity; productivity growth; emerging markets, Vietnam.

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1 Introduction

In an emerging economy like Vietnam, the banking sector serves as a crucial financial intermediary and a fundamental driver of systemic stability and growth [1]. As Vietnam deepens its global integration, the industry has become indispensable in facilitating domestic investment and trade. Between 2017 and 2023, the sector underwent profound transformations characterized by aggressive asset expansion and structural regulatory reforms—most notably the implementation of Basel II standards—aimed at strengthening capital adequacy and enhancing risk transparency [2]. However, the unprecedented shocks of the COVID-19 pandemic interrupted this growth, testing the sector's resilience and exposing latent vulnerabilities in bank balance sheets [3]. These volatile shifts have reshaped the landscape into a complex environment where traditional static performance metrics—which often treat banks as opaque "black boxes"—are no longer sufficient for evaluating institutional health [4].

To address these limitations, this study adopts a two-stage Dynamic Network Data Envelopment

Analysis (DNDEA) model, which effectively "opens the black box" by integrating internal operational linkages with the temporal dimension of banking activities [5], [6]. While DNDEA has been applied in developed markets [7], [8], [9], its implementation in Vietnam's unique and rapidly evolving banking sector remains underexplored. By capturing the long-term impact of decisions across multiple periods—specifically modeling non-performing loans (NPLs) as intertemporal carry-overs—this approach provides a more realistic understanding of efficiency [10], [11]. Unlike traditional static models that fail to capture complex, multi-stage internal decision-making processes, our DNDEA framework distinguishes short-term operational performance from long-term dynamic efficiency by explicitly incorporating intertemporal carry-overs.

This research makes three key contributions. Methodologically, this study applies a two-stage DNDEA framework to evaluate the dynamic operational efficiency of Vietnamese commercial banks while explicitly incorporating undesirable outputs and intertemporal carry-overs. Empirically, it provides novel insights by identifying the resource generation stage as the primary operational bottleneck and revealing a significant divergence between static efficiency levels and dynamic productivity growth. Practically, the findings offer a diagnostic roadmap for bank managers to optimize resource allocation and for policymakers to develop nuanced, risk-sensitive supervisory strategies aligned with the institutional realities of Vietnam's financial ecosystem.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the two-stage DNDEA model, variable specification, and the Cumulative Malmquist Productivity Index. Section 4 reports and discusses the empirical results. Finally, Section 5 concludes the paper with the main findings and implications.

2 Literature Review

The measurement of productive efficiency using non-parametric methods originates from [12], whose seminal work laid the conceptual foundation for DEA, later operationalized by [13]. Since its inception, DEA has been extensively applied in the banking sector, evolving from simple radial models to more sophisticated frameworks that provide nuanced insights into the production process [14]. This methodological progression reflects a clear trajectory: from early "black-box" models that ignored internal processes to advanced approaches that capture inter-stage linkages, intertemporal dependencies, and risk-related outputs.

A fundamental criticism of early DEA applications was their treatment of banks as homogeneous entities, abstracting from the complex internal mechanisms of financial intermediation [15]. Such models offered limited diagnostic power, as they could not identify the specific stages where inefficiencies originated. To address this limitation, the Network DEA (NDEA) framework was developed [5], enabling the decomposition of banking activity into interconnected stages. The two-stage model became particularly influential, typically separating the resource generation function from the income-generating function [16], [17], [18]. This enables analysts to determine whether performance shortfalls originate from deposit mobilization or from inefficiencies in transforming mobilized resources into profitable assets. [19] Further integrated super-efficiency and undesirable outputs into NDEA models to better capture bank efficiency under regulatory constraints, while [20] utilized a DNDEA to model stage interactions and time-based carry-overs in Taiwan's financial sector. Furthermore, studies on U.S. banks have demonstrated that DNDEA frameworks better reflect intertemporal efficiency and internal resource flows [9]. While NDEA provided a more realistic representation, its static nature limited its ability to account for the intertemporal consequences of decisions. The development of DNDEA addressed this by introducing "carry-over" variables that explicitly link consecutive periods [6]. The DNDEA framework has been successfully applied to assess bank efficiency across diverse economic contexts, including the U.S. [9], Japan [7], and the MENA region [21].

The explicit incorporation of risk and undesirable outputs further enhances the realism of DNDEA models. A notable example is [7], who modeled non-performing loans (NPLs) as both an undesirable output of the current lending process and as an undesirable input constraining future operations. This is consistent with recent studies emphasizing the importance of explicitly incorporating NPLs into banking efficiency analysis [10], underscoring the necessity of multi-stage dynamic frameworks.

Regulatory requirements also shape banking operations. In Vietnam, capital adequacy regulations influence banks' resource allocation and risk management during restructuring [2], providing an important institutional background for efficiency analysis. These mandates act as binding conditions that not only dictate capital structure but also indirectly influence the ability to optimize resource allocation across stages. By acknowledging these institutional boundaries, this study provides a holistic view of efficiency that transcends mere technical calculation, bridging the gap between operational performance and regulatory compliance.

The analysis traces the evolution of efficiency measurement from the original DEA model [13] to advanced methods such as the non-radial slacks-based measure (SBM) approach [22], which directly addresses input excesses and output shortfalls. The DNDEA framework comprehensively integrates internal structure and temporal relationships of banking operations. While previous studies have applied DEA variants to the banking sector globally, as well as specialized applications like inverse DEA during the COVID-19 pandemic [3] and models incorporating nonperforming loans [10], research in the Vietnamese emerging economy remains largely unexplored. Traditional DEA models, such as those employed by [23] and [1], assess cost and technical efficiency but treat banks as single-stage units, failing to capture internal operations. Another study, [4] utilizes the Malmquist index to measure productivity changes over time, demonstrating that technological progress and efficiency shifts significantly influence bank efficiency. Although previous empirical studies have examined profitability and liquidity in Vietnamese listed commercial banks [24], the application of the DNDEA framework itself fills a notable methodological and empirical void in the existing literature.

Against the backdrop of the Vietnamese banking sector's structural transformation and volatility from 2017 to 2023, this study addresses the aforementioned methodological void by presenting the first comprehensive DNDEA assessment of 20 listed commercial banks. By synthesizing structural decomposition [5] with intertemporal efficiency tracking [6], this research provides a robust analytical lens for resource optimization and risk-sensitive supervision, extending the efficiency frontier to an emerging market context.

3 Research Design and Methodology

3.1 The Two-stage Dynamic Network SBM Model

This study employs a two-stage Dynamic Network DEA model based on the non-radial SBM approach [22]. The model evaluates stage-wise efficiency over multiple periods by incorporating intermediate links, undesirable outputs, and intertemporal carry-over variables [6]. Equal weights are assigned to all stages and periods, following common practice to ensure balanced evaluation without introducing subjective weighting assumptions [25], [26].

The model evaluates a set of N decision-making units (DMUs). Let j = 1,…, N (DMUs/banks); t = 1,…, T (terms/years); k = 1,2 (divisions/stages).
For division k at time t, let
$x_{jkt} \in \mathbb{R}_+^{m_k}$ (inputs),
$y_{jkt} \in \mathbb{R}_+^{s_k}$ (desirable outputs)
$b_{jkt} \in \mathbb{R}_+^{u_k}$ (undesirable outputs),
$z_{jt} \in \mathbb{R}_+^{q}$ (within-term links from stage 1 to stage 2)
Inter-term carryovers at time t:

$c_{jt} \in \mathbb{R}_+^{l}$ (bad carryovers; e.g., NPLs).

The DMU under evaluation is indexed by o ($1 \leq o \leq N$). Variables:
$\lambda_{jkt} \geq 0$: intensity for DMU j at division k at time t (j = 1,…, N; k = 1,2; t = 1,…, T)
$s^x_{ikt} \geq 0$, $s^y_{rkt} \geq 0$, $s^b_{pkt} \geq 0$: slacks for inputs, desirable outputs, and undesirable outputs, respectively (i = 1,…,m_k; r = 1,…,s_k; p = 1,…,u_k).
$s^{z+}_{mt}, s^{z-}_{mt} \geq 0$: link imbalance slacks (m = 1,…,q).
$s^{c+}_{ct}, s^{c-}_{ct} \geq 0$: excess bad-carryover on the output side and input side, respectively (c = 1,…, l)

We apply equal weights across all terms and stages: $w_t = \frac{1}{T}$, $v_1 = v_2 = \frac{1}{2}$. Define $\Gamma_k = m_k + u_k$

A value of $\rho^\star = 1$ indicates zero slacks in all terms or stages; $\rho^\star < 1$ implies inefficiency.
Stage-wise production (for all t and k).

$$\sum_{j=1}^{N} \lambda_{jkt}\, x_{ijkt} \leq x_{iokt} - s^x_{ikt},\ \ i = 1, \dots, m_k,$$
$$\sum_{j=1}^{N} \lambda_{jkt}\, y_{rjkt} \geq y_{rokt} + s^y_{rkt},\ r = 1, \dots, s_k,$$
$$\sum_{j=1}^{N} \lambda_{jkt}\, b_{pjkt} \leq b_{pokt} - s^b_{pkt}, p = 1, \dots, u_k,$$
$$\sum_{j=1}^{N} \lambda_{jkt} = 1$$

The corresponding production possibility set (PPS) for stage k in period t is defined as:

$$\mathcal{P}_t^k = \left\{ (x, y, b) \;\middle|\; \begin{array}{r} x \ge \sum_{j=1}^N \lambda_{jkt}\, x_{jkt}, \\ y \le \sum_{j=1}^N \lambda_{jkt}\, y_{jkt}, \\ b \ge \sum_{j=1}^N \lambda_{jkt}\, b_{jkt}, \\ \sum_{j=1}^N \lambda_{jkt} = 1, \\ \lambda_{jkt} \ge 0, j = 1, \ldots, N \end{array} \right\}$$

This production possibility set serves as the feasible technology against which the operational efficiency of each bank is evaluated.

The intermediate-link balance condition is (for each component $m = 1, \ldots, q$, all t).

$$\sum_{j=1}^{N} \lambda_{j,1,t}\; z_{mjt} + s_{mt}^{z+} \;=\; \sum_{j=1}^{N} \lambda_{j,2,t}\; z_{mjt} + s_{mt}^{z-}$$

The undesirable carry-over continuity constraints are (for $c = 1, \ldots, l$ and $t = 1, \ldots, T-1$):

$$\sum_{j=1}^{N} \lambda_{j,2,t} C_{cj,t} - S_{ct}^{c+} = \sum_{j=1}^{N} \lambda_{j,1,t+1} C_{cj,t+1} + S_{c,t+1}^{c-}$$

Nonnegativity.

$$\lambda_{jkt} \ge 0, \quad s_{ikt}^{x}, s_{rkt}^{y}, s_{pkt}^{b}, s_{mt}^{z+}, s_{mt}^{z-}, s_{ct}^{c+}, s_{ct}^{c-} \;\ge\; 0.$$

All intensity and slack variables are non-negative.

The non-oriented risk-adjusted DNDEA–SBM objective is defined as Eq. (1) (Appendix)

Here, W_t is the period weight, and v_k is the stage weight. This study uses equal weights, namely

$$W_t = \frac{1}{T} \qquad v_1 = v_2 = \frac{1}{2}$$

A value of $\rho_o = 1$ indicates that all slacks are zero and the bank is dynamically efficient, whereas $\rho_o < 1$ indicates inefficiency caused by input excesses, undesirable outputs, or undesirable carry-overs. Eq. (1) jointly evaluates the efficiencies of the two interconnected banking stages through intermediate financial links and intertemporal carry-over variables. The two-stage network structure identifies stage-specific sources of inefficiency, while modeling non-performing loans (NPLs) as undesirable carry-overs captures the persistent impact of credit risk on future banking performance.

Although Eq. (1) is fractional, it can be solved as a linear programming problem through the standard Charnes–Cooper transformation. Let us define a scaling scalar variable $\tau > 0$:

$$\tau = \frac{1}{\Gamma}$$

where Γ is explicitly defined by setting the denominator of the objective function to 1 (via multiplication by τ):

$$\Gamma = \sum_{t=1}^{T} W_t \sum_{k=1}^{2} v_k \left[1 + \frac{1}{s_k} \sum_{r=1}^{s_k} \frac{s_{rkt}^{y}}{y_{rokt}} \right] > 0$$

The transformed variables are defined linearly as:

$$\hat{\lambda}_{jkt} = \tau \lambda_{jkt}, \qquad \forall_{j,k,t}$$
$$\hat{s}_{ikt}^{x} = \tau s_{ikt}^{x},\ \hat{s}_{rkt}^{y} = \tau s_{rkt}^{y},\ \hat{s}_{pkt}^{b} = \tau s_{pkt}^{b}, \quad \forall_{j,r,p,k,t}$$
$$\hat{s}_{mt}^{z+} = \tau s_{mt}^{z+},\ \hat{s}_{mt}^{z-} = \tau s_{mt}^{z-}, \quad \forall_{m,t}$$
$$\hat{s}_{ct}^{c+} = \tau s_{ct}^{c+},\ \hat{s}_{ct}^{c-} = \tau s_{ct}^{c-}, \quad \forall_{c,t}$$

This transformation changes only the computational form of the model and does not alter the production technology, VRS convexity, network links, or carry-over continuity conditions.

3.2 Mathematical Properties of the Proposed DNDEA–SBM Model

3.2.1 Boundedness of the Efficiency Measure

The following mathematical properties are established based on the dynamic SBM framework proposed by [6] and the theoretical properties of SBM developed by [22]. These properties are important because they establish the validity of the efficiency measure under the variable returns-to-scale (VRS) production technology. The following results do not alter the original DNDEA–SBM formulation but establish several theoretical properties of the proposed model.

Theorem 1

Assume that the production possibility set under the VRS technology is non-empty and feasible. Then the dynamic efficiency score obtained from the DNDEA–SBM model satisfies $0 < \rho \le 1$.

Furthermore, $\rho = 1$ if and only if all slacks included in the objective function are equal to zero.

Proof. Since all slack variables are non-negative, input, undesirable-output, and carry-over slacks decrease the numerator of Eq. (1), whereas desirable-output slacks increase its denominator. Hence, $\rho \le 1$. When all slacks are zero, the numerator and denominator are both equal to one, yielding $\rho = 1$. Otherwise, at least one positive slack implies $\rho < 1$. Therefore, $0 < \rho \le 1$, with equality if and only if all slacks included in the objective function are zero.

3.2.2 Structural Properties under VRS

To establish the mathematical properties of the proposed model, we analyze the production possibility set (PPS) and the objective function of the proposed non-oriented DNSBM model. Let $\mathcal{P}_{VRS}$ denote the feasible production possibility set generated by the stage-wise production, network-link, and carry-over continuity constraints.

Theorem 2

The production possibility set $\mathcal{P}_{VRS}$ defined by the stage-wise constraints, intermediate link balance conditions, and intertemporal carry-over continuity constraints is a closed and convex set. The set is obtained by combining the stage-wise production possibility sets (PPS).

Proof. Let $(\mathrm{X}^1, \mathrm{Y}^1, \mathrm{B}^1, \mathrm{Z}^1, \mathrm{C}^1)$ and $(\mathrm{X}^2, \mathrm{Y}^2, \mathrm{B}^2, \mathrm{Z}^2, \mathrm{C}^2)$ be two distinct feasible operational vectors in $\mathcal{P}_{VRS}$, corresponding to intensity vectors $\lambda^{k,t,1}$ and $\lambda^{k,t,2}$, respectively. For any scalar $\alpha \in [0,1]$, consider the convex combination $\lambda^{k,t,\alpha} = \alpha\lambda^{k,t,1} + (1-\alpha)\lambda^{k,t,2}$. Since the stage-wise production envelope, intermediate links, and intertemporal continuity requirements are formulated as systems of linear inequalities and equalities, the linearity of the constraints guarantees that:

$$\sum_{j=1}^{N} \lambda_{jkt}^{\alpha}\, x_{ijkt} = \alpha \sum_{j=1}^{N} \lambda_{jkt}^{1}\, x_{ijkt} + (1 - \alpha) \sum_{j=1}^{N} \lambda_{jkt}^{2}\, x_{ijkt}$$

Furthermore, the VRS convex hull requirement satisfies

$$\sum_{j=1}^{N} \lambda_{jkt}^{\alpha} = \alpha(1) + (1-\alpha)(1) = 1$$

Therefore, $\mathcal{P}_{VRS}$ constitutes a closed convex polyhedral production possibility set under the VRS technology.

3.2.3 Effect of Undesirable Carry-over Variables

Theorem 3

Suppose that all contemporaneous inputs, intermediate products, and desirable outputs remain unchanged. If the undesirable carry-over variable increases between two consecutive periods, $c_{t+1} > c_t$, then the attainable dynamic production frontier weakly contracts, and the corresponding dynamic efficiency score cannot increase.

Proof. Because undesirable carry-over variables link consecutive production periods through intertemporal continuity constraints, an increase in bad carry-overs tightens the feasible production set by requiring more resources to absorb accumulated credit risk. Consequently, $\mathcal{P}_{VRS}$ (ct+1)⊆ $\mathcal{P}_{VRS}$ (ct) where $\mathcal{P}_{VRS}(.)$ denotes the production possibility set (PPS), implying $\rho_{t+1} \leq \rho_t$. Hence, an increase in accumulated non-performing loans cannot improve dynamic efficiency.

3.2.4 Computational Properties of the Linearized Model

The DNDEA–SBM model in Eq. (1) is formulated as a linear fractional programming problem [22] and is transformed into an equivalent linear programming (LP) model using the Charnes–Cooper transformation [27]. The transformation introduces a normalization variable and rescales the decision variables while preserving the feasible region and the optimal efficiency score.

For a dataset containing N banks, one LP model is solved for each evaluated bank; thus, the total number of optimization problems is $N_{\mathrm{LP}} = N$. The size of each LP grows linearly with the number of stages, periods, variables, and associated constraints. Because the transformed formulation is a standard LP problem, it can be solved efficiently using established polynomial-time LP algorithms [28], ensuring computational tractability for multi-period banking datasets. Therefore, the proposed DNDEA–SBM framework remains computationally tractable for multi-period banking datasets.

3.3 Measuring Long-term Productivity: The Cumulative Malmquist Index

While the DNDEA model evaluates efficiency at different points in time, productivity change is measured using the Cumulative Malmquist Productivity Index (CmltMPI). The conventional Malmquist Productivity Index (MPI), introduced by [29], measures productivity change between adjacent periods and can be computed using DEA distance functions, including the non-radial SBM model [30]. However, the standard MPI does not satisfy the circularity test and is sensitive to short-term fluctuations [31]. Therefore, this study adopts the CmltMPI, which builds on global and fixed-base index concepts [32], [33] to provide a more stable measure of long-term productivity change.

The CmltMPI index from the base period 0 to period k is calculated as the product of the sequential adjacent-period Malmquist indices:

$$\mathrm{CmltMPI}_{0\to k} = \prod_{t=1}^{k} M\,(x^t, y^t, x^{t-1}, y^{t-1})$$

where $M(x^t, y^t, x^{t-1}, y^{t-1})$ is the standard Malmquist index between period $t-1$ and t, defined as:

$$M(x^t, y^t, x^{t-1}, y^{t-1}) = \left[\frac{D^{t-1}(x^t, y^t)}{D^{t-1}(x^{t-1}, y^{t-1})} \times \frac{D^t(x^t, y^t)}{D^t(x^{t-1}, y^{t-1})}\right]^{\frac{1}{2}}$$

A value of the CmltMPI index greater than 1 indicates cumulative productivity growth; a value less than 1 indicates a cumulative decline, and a value equal to 1 signifies no change relative to the base period.

3.4 Empirical Setting: Variables, Data Sources, and Bank Classification

Banking mapping (two-stage):
Stage 1 (resource generation): $\mathbf{x}_{\cdot,1,t} =$ {labor, fixed assets, equity}; links $\mathbf{z}_{\cdot,t} =$ {deposits, loans}.
Stage 2 (income generation): desirable outputs $\mathbf{y}_{\cdot,2,t} =$ { interest income, non-interest income }; undesirable output $\mathbf{b}_{\cdot,2,t} =$ {NPLs (same-term)}.
Carryovers: bad $\mathbf{c}_t =$ {NPLs}.

NPLs are modeled as undesirable carry-over variables to capture the persistent impact of credit risk on long-term banking efficiency. Unlike static DEA models that treat credit risk only as a contemporaneous undesirable output, this specification recognizes that NPLs continue to consume capital and managerial resources across multiple periods, thereby constraining future production possibilities [7], [8], [10]. The conceptual structure of the two-stage DNDEA model is illustrated in Figure 1 (Appendix).

Variable selection follows the intermediation approach, which views banks as financial intermediaries that transform liabilities into income-generating assets [34]. To better represent internal banking operations, this study adopts a two-stage network structure consistent with the SBV reporting framework under Circular 41/2016/TT-NHNN (Basel II) [35]. Labor costs, fixed assets, and equity are used as inputs; customer deposits and loans are specified as intermediate products [6], [36]; interest and non-interest income are treated as desirable outputs [24]; and NPLs are incorporated as undesirable carry-over variables [6], [7], [9]. Detailed variable definitions are reported in Table 1 (Appendix).

The dataset consists of a balanced panel of 20 commercial banks listed on the Ho Chi Minh Stock Exchange (HSX) and Hanoi Stock Exchange (HNX) during 2017–2023. Financial data were collected from audited annual financial statements and annual reports to guarantee accuracy and consistency.

4 Empirical Results and Discussion

Table 2 (Appendix) reports the descriptive statistics of the variables employed in the DNDEA model based on 140 bank-year observations (20 listed commercial banks over the period 2017–2023). Customer deposits and customer loans exhibit the largest variability, reflecting substantial differences in bank size across the Vietnamese banking sector. Equity capital displays considerable dispersion, suggesting heterogeneous capital structures and risk management practices among banks. Meanwhile, the descriptive statistics confirm sufficient variation in all input, intermediate, output, and carry-over variables, supporting the suitability of the DEA framework for efficiency analysis.

4.1 Dynamic Efficiency: Heterogeneity, Benchmarking, and Divergent Trends

Figure 2 (Appendix) illustrates the temporal evolution of efficiency scores for the sampled banks. From 2017 to 2023, the sector maintained an average overall efficiency of 0.8932, indicating that Vietnamese listed banks generally operate near the efficiency frontier. However, a detailed analysis reveals that efficiency peaked in 2018 before gradually declining, reflecting macroeconomic headwinds and systemic pressures intensified by the global pandemic. A pivotal finding is the persistent efficiency gap between the two operational stages: Stage 1 (Resource Generation) remained consistently lower than Stage 2 (Income Generation). A paired-samples t-test was conducted to compare the technical efficiency of Stage 1 and Stage 2 across the 140 bank-year observations. The results indicate that the mean efficiency of Stage 2 ($M = 0.9223$) is significantly higher than that of Stage 1 ($M = 0.8641$), with a mean difference of -0.0582 ($t = -3.465$, $df = 139$, $p = 0.001$). This suggests that the primary source of technical inefficiency lies not in income transformation but in a systemic bottleneck during the mobilization and optimization of core operational inputs. These results imply that while banks exhibit resilience in revenue generation, they face structural challenges in addressing resource-generation slacks, particularly amid evolving capital requirements. To verify the robustness of the stage-wise efficiency comparison, a Wilcoxon signed-rank test was additionally performed. The results of Table 4 (Appendix) confirmed a statistically significant difference between Stage 1 and Stage 2 efficiency ($Z = -3.283$, $p = 0.001$), which is fully consistent with the paired-samples t-test. Therefore, both parametric and non-parametric tests support the conclusion that the resource generation stage is significantly less efficient than the income generation stage.

These industry-wide trends mask considerable variation among individual banks. As shown in Table 3 (Appendix), banks are classified into four strategic categories based on average performance—a pattern typical in banking systems linked to differences in scale and risk management approaches [37], [38]. The "Consistent Benchmark" group (e.g., VCB, BID) represents the sector's leading edge with perfect efficiency scores. Conversely, the "Improver" group (e.g., HDB, MSB) demonstrates successful progress, whereas the "Volatile" group reflects an unstable operational model, and the "Laggard" group (e.g., SHB, EIB) faces ongoing structural difficulties.

Our empirical results consistently identify Stage 1 as the primary structural bottleneck, characterized by significant slacks in labor and equity utilization. These inefficiencies may be partially attributed to rigorous capital adequacy requirements imposed during the 2017–2023 restructuring period. As discussed by [2], regulatory mandates force banks to maintain higher equity buffers, which, while strengthening systemic stability, can lead to the "overuse of equity" slacks identified in our analysis. This suggests that the measured technical inefficiency is not merely a reflection of poor managerial practice, but an endogenous response to the binding regulatory environment. Consequently, banks appear to prioritize compliance and risk-mitigation over immediate input optimization—a strategic trade-off frequently overlooked by traditional static "black-box" models.

To further elucidate this heterogeneity, Figure 3 (Appendix) illustrates the efficiency trajectories of representative banks. VCB demonstrates steady consistency near the frontier, while MSB exhibits a remarkable ascent, converging toward benchmark levels. In contrast, TCB displays a U-shaped recovery following period-specific shocks, while SHB shows persistent underperformance. A cross-case synthesis confirms that Stage 1 serves as the primary structural bottleneck for lower-performing institutions. This aligns with global empirical evidence suggesting that resource mobilization efficiency is a critical determinant of long-term banking competitiveness [9], [39]. Ultimately, these results reinforce that optimizing efficiency in the Vietnamese banking sector depends on calibrating core operational processes and input management, rather than focusing solely on the subsequent profitability stage.

4.2 Long-term Productivity: Trajectories and Macro-financial Implications

A notable discovery is the dynamic evolution within the "Volatile" category. For instance, TCB recorded the greatest overall productivity growth, indicating that its phases of lower efficiency were likely investment periods aimed at strategic transformations. Conversely, some "Consistent Benchmark" banks like BAB and NVB show a cumulative drop in productivity. This phenomenon, where firms operating at peak efficiency experience stagnant productivity growth, is a recognized challenge in productivity analysis, as the Malmquist index captures shifts that static efficiency measures often miss, [31], [40] . Research in other emerging banking markets similarly confirms that the most efficient banks do not always achieve the highest productivity improvements [41]. These findings support a sophisticated perspective that differentiates between operational efficiency and dynamic productivity growth [42].

Figure 4 (Appendix) illustrates the cumulative productivity trajectories of VCB, MSB, TCB, and SHB, validating the quantitative findings in Table 5 (Appendix). TCB demonstrates the most aggressive cumulative growth (CmltMPI = 3.07), a trend likely driven by its pioneering digital transformation and focus on high-yield retail lending. In contrast, VCB maintains a highly stable trajectory (CmltMPI = 2.90), reflecting the conservative risk-return profile typical of state-owned commercial banks. This visualization underscores a critical finding: static efficiency levels (Table 3, Appendix) and productivity dynamics (Figure 4, Appendix) do not always align. A bank may maintain high static efficiency yet experience stagnant productivity if it fails to advance its technological frontier.

Notably, banks classified as 'Laggards' in static efficiency, such as SHB, exhibit high CmltMPI values (1.6944). This suggests that while these banks operate below the efficiency frontier at a given snapshot, they are undergoing rapid technological catch-up. This 'convergence effect' indicates that laggard banks are effectively leveraging dynamic adjustments—such as digital transformation or credit risk restructuring—to accelerate productivity growth, even if their cumulative resource utilization remains sub-optimal compared to the 'Leaders' group.

To connect individual bank narratives with the broader macroeconomic context, Figure 5 (Appendix) presents the sector-wide annual

CmltMPI, broken down by operational stage. During the 2018–2019 pre-pandemic period, strong productivity growth was primarily driven by Stage 2 (Income Generation), indicating that banks effectively leveraged a high-interest-margin environment. However, the 2020 decline in CmltMPI across both stages underscores a synchronized operational paralysis caused by the COVID-19 pandemic, during which capital mobilization and lending activities were severely restricted. Interestingly, the 2022 recovery was driven by Stage 1 (Resource Generation), marking a strategic shift toward cost optimization and liability restructuring as banks adapted to post-pandemic liquidity constraints. This divergence underscores that external shocks do not affect the banking value chain uniformly. Our findings align with the scholarly consensus that systemic crises reshape industry frontiers [42], while further contributing by identifying that resilience in Stage 1 often serves as a prerequisite for broader sector recovery in emerging markets.

One-way ANOVA revealed a statistically significant difference in Stage 1 cumulative productivity across the four strategic groups ($F = 7.007$, $p = 0.003$), whereas no significant differences were observed for Overall CmltMPI ($F = 1.193$, $p = 0.344$) or Stage 2 CmltMPI ($F = 0.365$, $p = 0.779$) (Table 6, Appendix). Because the assumption of homogeneity of variances was violated for Stage 1 (Levene's $p = 0.004$), Games–Howell post-hoc comparisons were performed. Although no individual pairwise comparison remained statistically significant after adjustment, the omnibus ANOVA indicates that heterogeneity in cumulative productivity is primarily associated with the resource generation stage rather than the income generation stage.

5 Conclusion

Between 2017 and 2023, the Vietnamese banking sector underwent rapid transformation driven by Basel II implementation [35] and economic growth, interrupted by the systemic shocks of the COVID-19 pandemic. This study utilized a two-stage DNDEA model to evaluate 20 listed banks, treating NPLs as undesirable carry-over variables to capture the intertemporal persistence of credit risk.

Empirical results indicate that inefficiency predominantly originates in the resource generation stage, identifying a structural bottleneck in core input management. Furthermore, the Cumulative Malmquist Productivity Index reveals a decoupling between static efficiency and dynamic progress, highlighting distinct strategic patterns ranging from "stable stagnation" to "dynamic transformation." Specifically, excessive utilization of labor and equity capital emerges as the primary driver of technical inefficiency, a finding that warrants strategic attention.

These findings carry significant implications. For bank executives, optimizing core input allocation is a strategic imperative for sustainable profitability, particularly given the critical impact of liquidity management on profit generation [24]. For regulators, our dynamic measures support a transition toward risk-based, stage-specific supervision, enabling macroprudential frameworks that more effectively address credit risk accumulation across economic cycles. By disentangling the banking value chain, this research underscores that long-term resilience in emerging economies requires a synchronized focus on both structural efficiency and risk-adjusted growth [43].

While this study offers a robust methodological framework, it is subject to certain limitations. The scope is confined to the listed commercial banks, which may not fully represent the broader sector, including non-listed and foreign institutions. Furthermore, the model does not explicitly incorporate external macroeconomic shocks, such as GDP fluctuations or interest rate volatility. Future research could enhance these findings by expanding the sample size, integrating macroeconomic control variables, and testing the model’s robustness through alternative input-output configurations.

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APPENDIX

Equation 1: Two-Stage Dynamic Network SBM Objective Function

$$\rho_o = \min \frac{\sum_{t=1}^{T} W_t \sum_{k=1}^{2} v_k \left[1 - \frac{1}{m_k+u_k}\left(\sum_{i=1}^{m_k} \frac{s_{ikt}^{x}}{x_{iokt}} + \sum_{p=1}^{u_k} \frac{s_{pkt}^{b}}{b_{pokt}}\right) - \frac{1}{l}\sum_{r=1}^{l} \frac{s_{rt}^{c+}}{c_{rot}}\right]}{\sum_{t=1}^{T} W_t \sum_{k=1}^{2} v_k \left[1 + \frac{1}{s_k}\sum_{r=1}^{s_k} \frac{s_{rkt}^{y}}{y_{rokt}}\right]}.$$

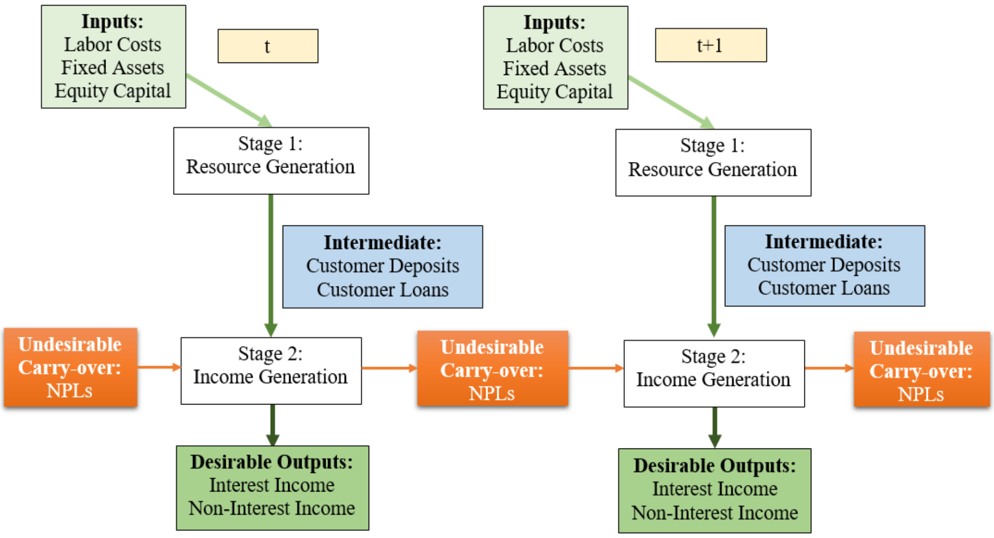

Fig. 1: The two-stage dynamic network DEA framework with undesirable NPL carry-overs
Source: created by the authors

Table 1. Variables definition and role in the network model

Category	Variable Name(Code)	Definition and Measurement
Stage 1 Inputs	Labor Costs (I_LAB)	Encompasses all employee salaries, benefits, and social insurance costs. Recorded as "Personnel Expenses" in the Income Statement.
	Fixed Assets (I_FIX)	The book value of physical fixed assets, represented as "Tangible Fixed Assets" on the Balance Sheet.
	Equity Capital (I_CAP)	The book value of total equity, represented by the "Total Equity" figure on the Balance Sheet.
Intermediate Links	Customer Deposits (L_{DEP})	Money raised from individuals and organizations, recorded as "Customer Deposits" on the Balance Sheet.
	Customer Loans (L_{LOA})	The total value of loans given to customers, represented as "Loans to Customers" on the Balance Sheet.
Stage 2 Outputs	Interest Income (O_{INI})	Revenue generated from lending operations, recorded as "Interest and Similar Income" on the Income Statement.
	Non-Interest Income (O_{NII})	Revenue from non-lending activities, calculated as the total of non-interest income items reported on the Income Statement.
Carry-overs	Non-Performing Loans (NPLs)	The total amount of substandard (Group 3), doubtful (Group 4), and loss (Group 5) loans, as determined from the notes to the financial statements.

Source: created by the authors

Table 2. Descriptive Statistics

Variable	Mean	SD	Min	Max
Labor Cost (I_LAB)	3,981.88	3,253.50	367.12	14,478.08
Fixed Assets (I_FIX)	3,400.36	3,406.18	250.77	11,436.53
Equity Capital (I_CAP)	22,618.83	17,997.56	2,980.57	103,331.78
Customer Deposits (L_DEP)	331,757.33	362,915.70	39,860.58	1,704,690.19
Customer Loans (L_LOA)	316,774.24	349,679.11	31,751.34	1,737,195.82
Interest Income (O_INI)	32,123.81	29,782.84	3,939.41	152,761.32
Non-interest Income (O_NII)	8,494.75	8,110.50	231.95	31,061.96
Non-performing Loans (NPL)	5,112.37	5,526.05	351.61	28,427.85

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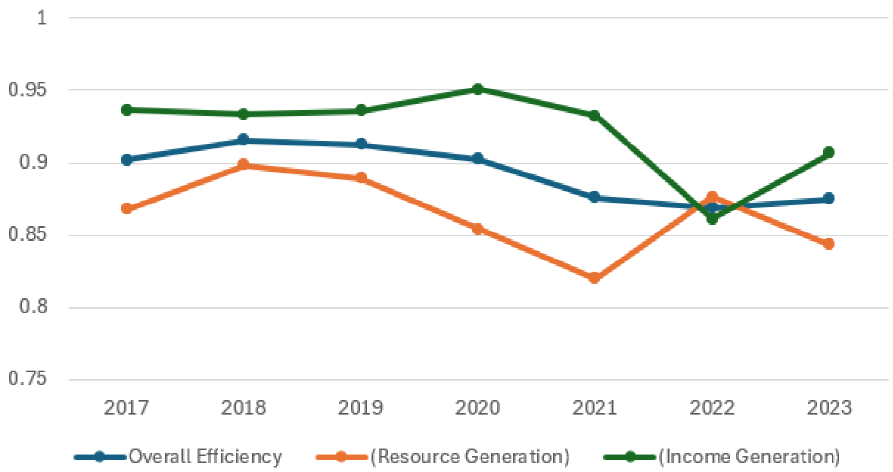

Fig. 2: Annual Efficiency Trends by Stage (2017–2023)

Source: created by the authors

Table 3. Mean Efficiency Scores, Rankings, and Strategic Classification (2017–2023)

Rank	Bank	Strategic Group	Overall Eff.	Stage 1 Eff.	Stage 2 Eff.
1	BAB	Consistent Benchmark	1.0000	1.0000	1.0000
1	BID	Consistent Benchmark	1.0000	1.0000	1.0000
1	CTG	Consistent Benchmark	1.0000	1.0000	1.0000
1	NVB	Consistent Benchmark	1.0000	1.0000	1.0000
1	VCB	Consistent Benchmark	1.0000	1.0000	1.0000
1	VPB	Consistent Benchmark	1.0000	1.0000	1.0000
7	VIB	Improver	0.9849	0.9719	0.9978
8	HDB	Improver	0.9615	0.9230	1.0000
9	NAB	Volatile	0.9556	1.0000	0.9112
10	MSB	Improver	0.9549	0.9461	0.9637
11	TPB	Volatile	0.9515	0.9228	0.9801
12	STB	Volatile	0.9374	0.9021	0.9726
13	TCB	Volatile	0.8932	0.7864	1.0000
14	LPB	Volatile	0.8557	0.7927	0.9188
15	ACB	Laggard	0.8505	0.7011	1.0000
16	MBB	Volatile	0.8145	0.6867	0.9423
17	OCB	Volatile	0.7235	0.7686	0.6785
18	SSB	Laggard	0.7072	0.7213	0.6931
19	EIB	Laggard	0.6469	0.4027	0.8911
20	SHB	Laggard	0.6264	0.7562	0.4965
		Average	0.8932	0.8641	0.9223

Note: The bank abbreviations correspond to the following institutions: ACB: Asia Commercial Joint Stock Bank; BAB: Bac A Commercial Joint Stock Bank; BID: Joint Stock Commercial Bank for Investment and Development of Vietnam; CTG: Vietnam Joint Stock Bank for Industry and Trade (VietinBank); EIB: Vietnam Export Import Commercial Joint Stock Bank (Eximbank); HDB: Ho Chi Minh City Development Joint Stock Commercial Bank; LPB: LPBank (formerly Lien Viet Post Joint Stock Commercial Bank);

Rank	Bank	Strategic Group	Overall Eff.	Stage 1 Eff.	Stage 2 Eff.
MBB: Military Commercial Joint Stock Bank; MSB: Vietnam Maritime Commercial Joint Stock Bank; NAB: Nam A Commercial Joint Stock Bank; NVB: National Citizen Commercial Joint Stock Bank; OCB: Orient Commercial Joint Stock Bank; SHB: Saigon - Hanoi Commercial Joint Stock Bank; SSB: Southeast Asia Commercial Joint Stock Bank (SeABank); STB: Sai Gon Thuong Tin Commercial Joint Stock Bank (Sacombank); TCB: Vietnam Technological and Commercial Joint Stock Bank (Techcombank); TPB: Tien Phong Commercial Joint Stock Bank; VCB: Joint Stock Commercial Bank for Foreign Trade of Vietnam (Vietcombank); VIB: Vietnam International Commercial Joint Stock Bank; VPB: Vietnam Prosperity Joint Stock Commercial Bank.					

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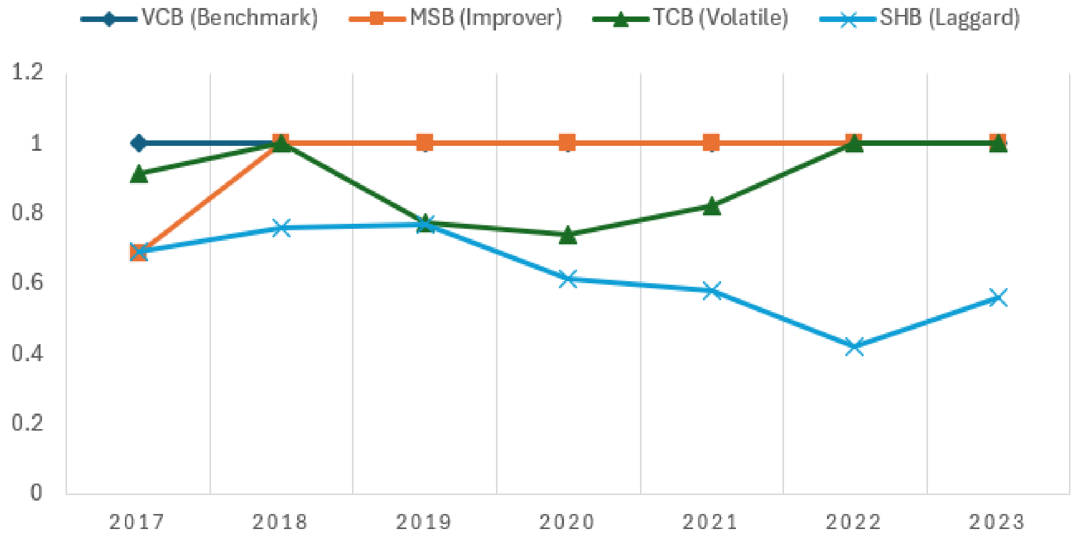

Fig. 3: Intertemporal Efficiency Trajectories for Selected Representative Banks (2017–2023)
Source: created by the authors

Table 4. Statistical validation of stage-wise technical efficiency differences

Test	Stage 1 Mean	Stage 2 Mean	Test Statistic	p-value	Decision
Paired-samples t-test	0.8641	0.9223	t = -3.465	0.001***	Significant
Wilcoxon signed-rank test	–	–	Z = -3.283	0.001***	Significant

Note: *** $p < 0.01$; the complete balanced panel of 140 bank-year observations.

Source: created by the authors

Table 5. Rankings Based on the Cumulative Malmquist Productivity Index (2017–2023)

Eff. Rank	Bank	Strategic Group	MPI Rank	Overall CmltMPI	Stage 1 CmltMPI	Stage 2 CmltMPI
1	BAB	Consistent Benchmark	15	0.9402	1.0000	0.8840
1	BID	Consistent Benchmark	9	1.3592	1.0000	1.8473
1	CTG	Consistent Benchmark	10	1.3201	1.0000	1.7426
1	NVB	Consistent Benchmark	16	0.9254	1.0000	0.8564
1	VCB	Consistent Benchmark	2	2.8977	1.0000	8.3965
1	VPB	Consistent Benchmark	5	1.5830	1.0000	2.5058
7	VIB	Improver	13	0.9773	1.2450	0.7671
8	HDB	Improver	6	1.5681	1.8629	1.3199
9	NAB	Volatile	14	0.9554	1.0000	0.9128
10	MSB	Improver	11	1.1738	1.6052	0.8584
11	TPB	Volatile	19	0.6130	0.7541	0.4983
12	STB	Volatile	12	1.1549	0.7602	1.7545
13	TCB	Volatile	1	3.0710	1.2109	7.7885
14	LPB	Volatile	17	0.7213	0.6390	0.8143
15	ACB	Laggard	8	1.3941	0.5278	3.6822
16	MBB	Volatile	3	2.6282	1.2596	5.4840

Eff. Rank	Bank	Strategic Group	MPI Rank	Overall CmltMPI	Stage 1 CmltMPI	Stage 2 CmltMPI
17	OCB	Volatile	20	0.5685	0.7339	0.4403
18	SSB	Laggard	18	0.6637	0.6812	0.6466
19	EIB	Laggard	7	1.5119	1.1637	1.9642
20	SHB	Laggard	4	1.6944	1.0096	2.8437

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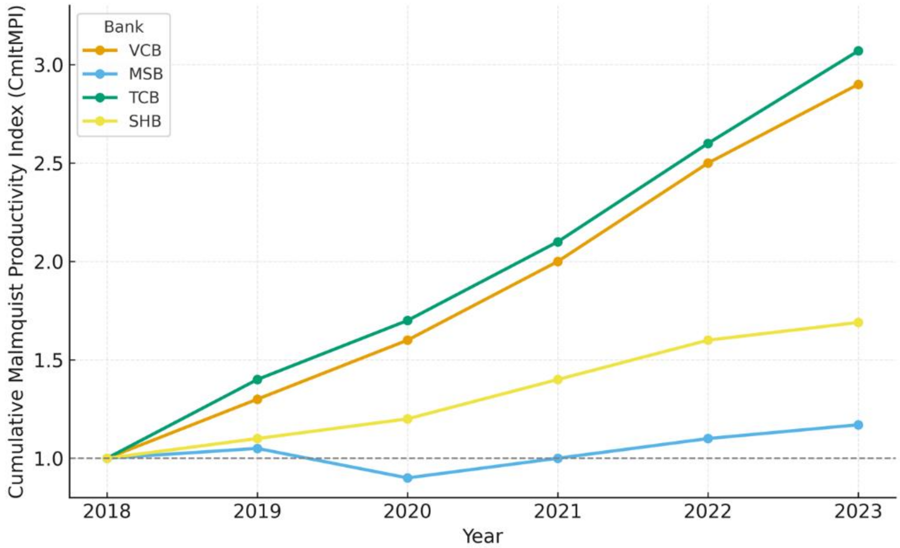

Fig. 4: Cumulative Productivity Growth by Strategic Group (2018–2023)

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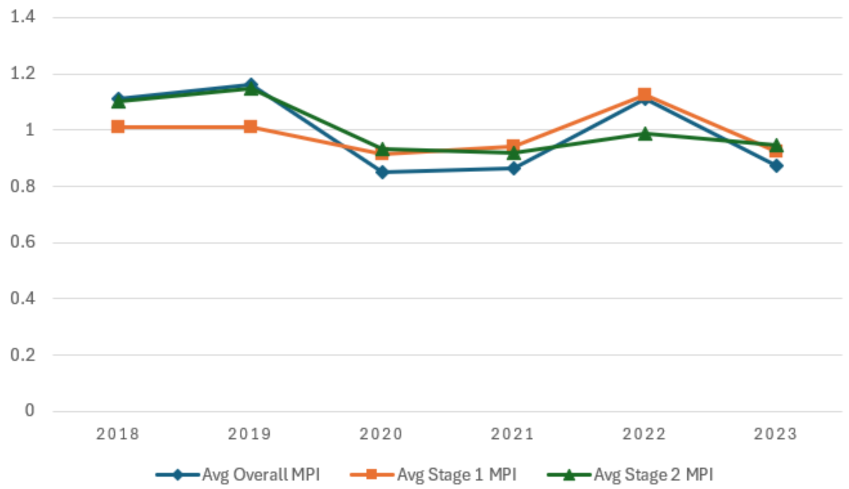

Fig. 5: Decomposition of Sector-Wide Average Annual MPI (2018–2023)

Source: created by the authors

Table 6. Comparison of cumulative productivity across strategic groups

Variable	Benchmark Mean	Improver Mean	Volatile Mean	Laggard Mean	F	p-value
Overall CmltMPI	1.0225	1.0597	0.9965	0.9900	1.193	0.344
Stage 1 CmltMPI	1.0000	1.5821	0.9102	0.8089	7.007	0.003**
Stage 2 CmltMPI	2.7054	0.9752	2.5053	2.4020	0.365	0.779

Source: created by the authors