Published by Yayasan Amerta Insan Unggul

DOI: 10.65246

p-ISSN 3063-9840 | e-ISSN 3063-8194

GoodWill Journal of Economics, Management, and Accounting

journal homepage: https://jurnal.amertainstitute.com/index.php/GoodWill/index



Clustering Bank Financial Performance: Persistence and Migration among Indonesian Listed Banks

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ARTICLE INFO

Keywords:
Bank Financial Performance; Cluster Analysis; K-Means Clustering; Financial Ratios; Cluster Migration

Publication History:
Received: 11 April 2026
Screening: 25 April 2026
Review: 9 May 2026
Revision requested: 18 July 2026
Revised: 13 August 2026
Accepted: 27 October 2026

ABSTRACT

Indonesian listed banks operate within the same financial system, yet their financial profiles can differ substantially and may evolve differently over time. This study identifies financial-performance clusters among Indonesian listed banks and examines whether banks remain within or migrate between these profiles. The analysis covers 47 banks listed on the Indonesia Stock Exchange during 2022–2025, resulting in 188 bank-year observations. Net profit margin (NPM), return on assets (ROA), and debt-to-equity ratio (DER) were standardized and analyzed using Ward's hierarchical clustering followed by K-Means clustering. Four distinct financial profiles were identified: a Severe-Loss Profile, a High-Profitability and Low-Leverage Profile, a High-Leverage Profile, and a Moderate-Profitability and Lower-Leverage Profile. Despite substantial cross-sectional heterogeneity, cluster membership was remarkably persistent over time. Of 141 possible annual bank transitions, 129 (91.5%) remained within the same cluster, while only 12 (8.5%) represented migration. At the bank level, 38 of 47 banks (80.9%) maintained the same financial profile throughout all three annual transitions, with only nine banks migrating at least once. These findings show that financial heterogeneity among Indonesian listed banks coexists with substantial temporal persistence. By extending financial-ratio clustering from static classification to longitudinal tracking, this study provides a simple framework for identifying both persistent financial profiles and changes in banks' relative financial positions.

1. Introduction

Banks operating within the same financial system can exhibit considerably different financial characteristics. Differences in profitability, asset utilization, funding structures, and business strategies may produce distinct financial profiles even among institutions exposed to similar regulatory and economic environments. Globally, understanding such heterogeneity is important because financial ratios provide information about banks' financial conditions and relative positions within the banking sector. In Indonesia, this issue is particularly relevant given the diversity of banks listed on the Indonesia Stock Exchange (IDX), ranging from large, established institutions to smaller and more recently transformed banks. Previous evidence from Indonesian banking indicates that internal financial characteristics play an important role in explaining differences in profitability (Khalifaturofi'ah & Ulum, 2022). Accordingly, examining multiple financial indicators simultaneously provides a basis for understanding how listed banks differ in their overall financial profiles.

Financial ratios offer a practical means of comparing bank performance, but examining individual ratios separately may not adequately capture the broader financial characteristics of each institution. A bank may demonstrate relatively strong profitability while maintaining a financial structure that differs substantially from those of its peers. This multidimensional nature of financial performance makes cluster analysis relevant because it groups institutions according to similarities across several indicators rather than relying on predetermined classifications. Cyree et al. (2020) demonstrated that financial statement information can be used to construct relatively homogeneous bank peer groups and that these groups can provide greater

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explanatory value than classifications based primarily on bank size. This approach provides a basis for identifying financial profiles that reflect combinations of profitability and leverage rather than differences in a single financial measure.

Cluster analysis has also been applied to the Indonesian banking sector. Nadhilah and Sudrajad (2022) used longitudinal clustering to identify business models among Indonesian Islamic banks, demonstrating that banking institutions can be grouped according to combinations of their underlying characteristics. More recently, Aditiya et al. (2026) applied K-Means clustering to 25 Indonesian banking issuers using return on assets (ROA), return on equity (ROE), and loan-to-deposit ratio (LDR) during 2022–2024. Their findings confirm that financial ratios can reveal distinct profiles among Indonesian listed banks. Nevertheless, identifying distinct groups does not necessarily explain whether the resulting classifications remain stable over time or whether individual banks move between groups as their financial conditions change.

Bank financial conditions may evolve from one period to another as earnings, assets, liabilities, and capital positions change. Consequently, a bank that resembles one group of peers in a particular year may exhibit characteristics more consistent with another group in a subsequent period. Ayadi et al. (2021) investigated this temporal dimension by identifying business-model clusters among more than 3,000 European banks and tracking their evolution between 2010 and 2017. Their findings indicate that banking profiles are generally persistent, although some banks migrate between groups over time. Related research also supports the relevance of examining changes in banking classifications rather than treating them as permanently fixed (Lucas et al., 2019). These studies establish the importance of considering both cross-sectional differences among banks and the temporal stability of their financial characteristics.

Despite this progress, evidence on the temporal persistence of financial-performance clusters remains limited in the context of Indonesian listed banks. Existing Indonesian studies have primarily focused on identifying banking clusters or business models, leaving the stability of financial-performance profiles and the migration of individual banks across clusters less explored. This gap concerns not only whether distinct financial groups can be identified but also whether banks consistently retain their relative positions or move between groups over consecutive years. Without longitudinal tracking, a cluster classification provides only a period-specific view and may not reveal the extent to which financial profiles persist or change. Therefore, examining cluster membership across multiple years offers a more comprehensive perspective on financial heterogeneity in the Indonesian listed banking sector.

To address this gap, this study examines the financial-performance clusters of Indonesian listed banks over the 2022–2025 period. The analysis covers 47 banks and produces a balanced dataset of 188 bank-year observations. Net profit margin (NPM), ROA, and the debt-to-equity ratio (DER) are used to represent profitability relative to revenue, profitability relative to assets, and financial leverage, respectively. These indicators capture complementary dimensions of financial performance and structure, enabling banks to be classified according to their combined characteristics. The observation period also allows each bank to be followed across three consecutive annual transitions: 2022–2023, 2023–2024, and 2024–2025. This design supports an assessment of both the differences among identified financial profiles and the persistence or migration of individual banks over time.

Accordingly, this study addresses three research questions: (1) What financial-performance clusters can be identified among Indonesian listed banks during 2022–2025? (2) How do the financial characteristics of the identified clusters differ? and (3) To what extent do individual banks remain in or migrate between financial-performance clusters over time? The study contributes to the literature by extending financial-ratio clustering from period-specific classification to longitudinal tracking, thereby integrating the identification of heterogeneous financial profiles with an assessment of their temporal persistence. Practically, the resulting framework can support comparative financial assessment by helping researchers, analysts, and other banking stakeholders distinguish persistent financial profiles from changes in banks' relative financial positions. The study's novelty lies in applying this longitudinal perspective to Indonesian listed banks using profitability and leverage

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indicators over the 2022–2025 period, providing evidence on the coexistence of financial heterogeneity and temporal persistence within the sector.

2. Literature Review

2.1. Conceptual and Theoretical Foundations

2.1.1. Financial Performance of Banks

Bank financial performance is multidimensional because profitability depends not only on the ability to generate earnings but also on the resources employed and the financial structure supporting banking activities. Internal financial characteristics contribute to differences in bank profitability alongside broader macroeconomic conditions (Adelopo et al., 2018). Accordingly, financial performance is better examined through complementary indicators than through a single financial measure.

This study uses net profit margin (NPM) and return on assets (ROA) to represent two dimensions of profitability. NPM relates net income to revenue, indicating the extent to which revenue is converted into final earnings. ROA relates net income to total assets and reflects profitability relative to the resources controlled by a bank. The asset-based perspective is particularly relevant to banking because assets constitute a central component of financial intermediation. ROA has also been widely employed in empirical analyses of Indonesian bank profitability (Budiman & Hersugondo, 2022).

The third indicator, the debt-to-equity ratio (DER), represents financial leverage by comparing liabilities with shareholders' equity. Unlike NPM and ROA, DER does not directly measure profitability but captures a different dimension of the financial structure underlying banking activities. The relationship between profitability and leverage is relevant to understanding bank behavior because leverage constraints can influence risk-taking and financial decisions (Martynova et al., 2020). Therefore, combining NPM, ROA, and DER provides three conceptually distinct perspectives: profitability relative to revenue, profitability relative to assets, and financial leverage.

In this study, the three ratios are calculated consistently from annual financial statement data obtained from the same data provider for all banks and observation years. Consistency is particularly important for NPM because banks may present and aggregate income components differently. Consequently, NPM is treated as a standardized revenue-based profitability indicator for comparative clustering rather than as a substitute for bank-specific regulatory performance measures. Together, the three indicators provide the conceptual basis for identifying financial profiles characterized by different combinations of profitability and leverage.

2.1.2. Financial Performance Clustering

Cluster analysis groups observations according to similarities in selected characteristics without requiring predetermined classifications. In financial analysis, this method enables institutions to be compared across multiple dimensions and classified according to patterns emerging from the data. It is particularly relevant when a single indicator cannot adequately represent the differences among institutions.

The application of clustering to banking is supported by the diversity of financial structures and strategic characteristics across institutions. Banks with similar sizes may exhibit different combinations of profitability, funding, and leverage. Cyree et al. (2020) demonstrated that clustering financial statement information could produce relatively homogeneous peer groups with greater explanatory value for several measures of bank performance and risk than conventional size-based classifications. This evidence supports the use of multidimensional financial characteristics to identify economically interpretable groups of banks.

Clustering also provides a basis for distinguishing financial profiles without imposing a predetermined ranking of performance. A group with relatively high profitability may have a different leverage structure from another group with moderate profitability and lower leverage. Consequently, the resulting clusters must be interpreted according to their empirical characteristics rather than automatically classified as superior or inferior. This principle underlies the present study's use of cluster centers to characterize the financial profiles of Indonesian listed banks.

2.2. Review of Empirical Studies

2.2.1. Clustering in Banking and Financial Performance

Previous empirical studies have demonstrated the usefulness of clustering for identifying

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heterogeneous banking structures. Lueg et al. (2019) applied cluster analysis to archival data from large European and U.S. banks and showed that quantitative indicators could distinguish recognizable banking business models. Similarly, Farnè and Vouldis (2021) identified distinct groups of euro-area banks with different performance and risk characteristics. These findings indicate that clustering can reveal meaningful differences among banks that may not be adequately captured by conventional classifications.

Research in Indonesia provides further support for applying clustering to banking data. Nadhilah and Sudrajad (2022) used longitudinal K-Means clustering to identify business models among Indonesian Islamic banks across multiple quarterly periods. Their research demonstrated that combinations of banking characteristics could generate meaningful groups and that these classifications could be examined over time.

More directly, Aditiya et al. (2026) applied K-Means clustering to 25 Indonesian listed banking issuers using ROA, return on equity (ROE), and the loan-to-deposit ratio (LDR) during 2022–2024. They identified three distinct groups, demonstrating that financial ratios can differentiate the profiles of Indonesian listed banks. Although this research establishes a relevant precedent, the present study employs a different combination of financial indicators, covers 47 banks, extends the observation period through 2025, and explicitly examines changes in individual banks' cluster membership.

2.2.2. Persistence and Migration of Financial Profiles

Beyond identifying differences among banks, previous studies have examined whether banking classifications remain stable over time. Ayadi et al. (2021) analyzed business-model clusters among more than 3,000 European banks across 32 countries during 2010–2017 and tracked individual banks' movements between groups. Their findings indicated that banking business models were generally persistent, although some banks changed their strategic orientation. Less profitable and riskier banks were also more likely to migrate between groups, suggesting that changes in cluster membership may reflect economically meaningful differences in financial conditions.

A complementary methodological perspective is provided by Custodio João et al. (2023), who developed a dynamic clustering model for multivariate panel data and applied it to 299 European banks between 2008 and 2018. Their approach allowed observations to transition between clusters over time. Approximately 3% of banks transitioned between groups per quarter on average, and profitability differences partly explained the probability of transition. Together, these findings support the view that bank classifications may be persistent without being permanent.

Lucas et al. (2019) examined quarterly data for 208 European banks between 2008 and 2015, identifying multiple banking components and investigating how their characteristics evolved over time. Their findings demonstrate that banking classifications can incorporate both persistent and time-varying features. Similarly, Zhao and Xu (2026) examined clustering dynamics among major U.S. banks around the Federal Reserve's 2022–2023 rate hikes and documented changes in cluster membership despite relatively limited changes in aggregate cluster sizes. These studies emphasize the importance of examining individual banks' trajectories rather than relying exclusively on classifications observed at a particular point in time.

Marques and Alves (2020) also distinguished between persistent and non-persistent banks in their analysis of European banking business models. Their work reinforces the relevance of temporal stability as a characteristic of banking classifications. Collectively, these studies suggest that clustering can be used not only to identify heterogeneous banking profiles but also to investigate the extent to which individual institutions retain or change their relative positions over time.

Nevertheless, the methods and contexts of these studies differ from the present research. Some examine business-model classifications, while others employ dynamic clustering frameworks that explicitly model transitions. The present study instead uses a common financial-performance clustering structure and describes annual changes in individual banks' membership. This approach is intended to provide a straightforward assessment of persistence and migration using annual financial data.

2.3 Identification of the Research Gap

The reviewed literature establishes two important findings. First, cluster analysis can identify

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meaningful heterogeneity among banking institutions based on financial ratios and other quantitative characteristics (Cyree et al., 2020; Farnè & Vouldis, 2021; Lueg et al., 2019). Second, banking classifications may remain stable or change over time, as demonstrated by studies examining the persistence and migration of banking business models (Ayadi et al., 2021; Custodio João et al., 2023; Lucas et al., 2019; Marques & Alves, 2020).

In Indonesia, previous studies have applied clustering to Islamic banking business models and the financial ratios of listed banking issuers (Aditiya et al., 2026; Nadhilah & Sudrajad, 2022). However, the temporal persistence of financial-performance clusters among Indonesian listed banks remains insufficiently explored. In particular, further evidence is needed on whether banks maintain their relative financial profiles across consecutive years or migrate between groups as their profitability and leverage characteristics change.

This gap is both contextual and methodological. Contextually, the Indonesian listed banking sector has not been examined in the present study through a longitudinal assessment of financial-performance clusters covering 2022–2025. Methodologically, identifying clusters alone does not establish whether the resulting profiles persist over time. Independently generated annual clusters may also be difficult to compare because their labels do not necessarily represent equivalent financial profiles across years.

To address these limitations, the present study combines hierarchical clustering using Ward's method with K-Means clustering on pooled annual observations. The resulting common cluster structure is then used to track individual banks across the 2022–2023, 2023–2024, and 2024–2025 transitions. This design enables a consistent descriptive assessment of cluster persistence and migration without attempting to estimate a dynamic latent-state model or establish causal determinants of migration.

The study's novelty lies in extending financial-ratio clustering from static classification to longitudinal tracking within the Indonesian listed banking sector. By examining profitability relative to revenue, profitability relative to assets, and leverage simultaneously, the research identifies distinct financial profiles and assesses whether these profiles remain stable across consecutive annual periods.

2.4 Development of the Conceptual Framework

The conceptual framework links three financial indicators to the identification and longitudinal assessment of financial-performance clusters among Indonesian listed banks. NPM represents profitability relative to revenue, ROA represents profitability relative to total assets, and DER represents financial leverage. These indicators are standardized and analyzed jointly to identify groups of bank-year observations with similar financial characteristics.

The framework follows two analytical stages. First, hierarchical clustering using Ward's method helps identify plausible cluster structures, which are subsequently examined using K-Means clustering. The final cluster centers are interpreted according to the observed combinations of profitability and leverage, rather than predetermined performance rankings. Second, the common cluster assignments are tracked across four annual observations for each bank to determine whether membership remains unchanged or moves to another cluster.

Cluster persistence refers to a bank remaining in the same cluster between consecutive years, whereas cluster migration refers to a change in cluster membership. Examining both outcomes makes it possible to distinguish cross-sectional financial heterogeneity from temporal changes in banks' relative financial positions. Consistent with the approaches discussed by Ayadi et al. (2021) and Custodio João et al. (2023), this study recognizes that banking classifications may exhibit both persistence and movement. However, the analysis remains descriptive and does not establish the causes or consequences of migration.

2.5 Hypotheses or Research Propositions

This study adopts an exploratory quantitative design focused on identifying financial-performance clusters and describing their temporal stability. It does not specify causal relationships between independent and dependent variables or test the determinants of cluster migration. Accordingly, research propositions are more appropriate than causal hypotheses.

Proposition 1: Financial heterogeneity. Indonesian listed banks exhibit distinct financial-performance profiles based on the combined characteristics of NPM, ROA, and DER.

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This proposition is grounded in previous banking studies demonstrating that clustering can identify heterogeneous financial structures and performance characteristics (Cyree et al., 2020; Farnè & Vouldis, 2021). It directs the analysis toward identifying and interpreting the financial characteristics of the resulting clusters rather than imposing predetermined categories.

Proposition 2: Temporal persistence and migration. The financial-performance clusters of Indonesian listed banks exhibit varying degrees of persistence and migration across consecutive annual periods.

This proposition reflects previous evidence that banking classifications can remain stable while individual institutions move between groups over time (Ayadi et al., 2021; Custodio João et al., 2023; Marques & Alves, 2020). It guides the longitudinal analysis of bank-level cluster assignments from 2022 through 2025, distinguishing banks that maintain their financial profiles from those that experience changes in their relative positions.

The two propositions align the conceptual framework with the research questions and analytical procedures. The first concerns the identification of distinct financial profiles, while the second concerns their temporal behavior. Both are examined descriptively through the observed cluster characteristics and annual transitions, without assuming that migration necessarily indicates improved or deteriorated performance.

3. Research Methods

3.1. Research Design

This study employs a quantitative exploratory design to identify financial-performance profiles among Indonesian listed banks and examine changes in cluster membership over time. The exploratory approach is appropriate because the study aims to identify groups of banks based on similarities in their financial characteristics rather than test predetermined causal relationships. The analysis combines hierarchical clustering and K-Means clustering to establish a common classification of financial profiles, followed by longitudinal tracking to assess cluster persistence and migration. This design enables the study to examine both cross-sectional heterogeneity and temporal changes in banks' relative financial positions.

3.2. Research Context and Setting

The research focuses on banking companies listed on the Indonesia Stock Exchange (IDX) and classified under the Banks sub-industry of the IDX Industrial Classification (IDX-IC). The observation period covers four consecutive financial years, from 2022 to 2025. This setting provides a basis for examining differences in financial performance among Indonesian listed banks and tracking changes in their cluster membership under a common classification structure. The four-year period allows three consecutive annual transitions to be evaluated: 2022–2023, 2023–2024, and 2024–2025.

3.3. Population and Sample / Research Participants

The study population consists of banking companies classified under the Banks sub-industry of the IDX-IC. The sample was selected using purposive sampling based on two criteria: (1) the bank had been listed before the beginning of the observation period, and (2) complete financial information was available for all four years from 2022 to 2025. These criteria ensured that the same institutions could be observed throughout the study period. The final sample comprised 47 banks, each observed annually over four years, resulting in a balanced dataset of 188 bank-year observations. The balanced structure was necessary for tracking individual banks' cluster membership across consecutive annual periods and calculating persistence and migration consistently.

3.4. Data Sources and Data Collection

This study uses secondary data obtained from annual financial statements through Yahoo Finance, retrieved using the yfinance Python library. The raw financial statement variables consist of net income, total revenue, total assets, total liabilities, and total shareholders' equity. The same financial statement fields and data source were applied consistently across all sampled banks and observation years. The data collection process involved compiling the required financial statement information for each bank from 2022 through 2025 and organizing the observations into a bank-year dataset. The resulting dataset was structured to ensure that each bank had four annual observations. This structure provided the basis for calculating financial ratios, standardizing the clustering variables, identifying financial-

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performance profiles, and tracking cluster membership over time.

3.5. Measurement of Variables and Research Instruments

The study uses three financial ratios as clustering variables: net profit margin (NPM), return on assets (ROA), and debt-to-equity ratio (DER). These indicators represent profitability relative to revenue, profitability relative to assets, and financial leverage, respectively. The ratios are calculated from the financial statement variables obtained through Yahoo Finance. The operational definitions and formulas are as follows:

Table 1. The Operational Definitions and Formulas

Variable	Operational definition	Formula
Net Profit Margin (NPM)	Profitability relative to revenue	Net Income / Total Revenue
Return on Assets (ROA)	Profitability relative to total assets	Net Income / Total Assets
Debt-to-Equity Ratio (DER)	Financial leverage relative to shareholders' equity	Total Liabilities / Total Shareholders' Equity

Source: Author processed

For NPM, total revenue refers to the standardized annual financial statement field provided by Yahoo Finance. This definition was applied consistently across all observations. Because banks may present and aggregate income components differently, NPM is treated as a standardized revenue-based profitability indicator for comparative clustering rather than as a substitute for bank-specific regulatory performance measures.

Before clustering, all three ratios were standardized into Z-scores because they have different distributions and numerical scales. Standardization transforms each variable to have a mean of zero and a standard deviation of one, preventing variables with greater numerical dispersion from disproportionately influencing the distance calculations used in clustering (Hair et al., 2019).

3.6. Data Analysis Techniques

The analysis was conducted in several stages, comprising preliminary data examination, determination of the number of clusters, K-Means clustering, cluster profiling, and longitudinal analysis of cluster persistence and migration.

Preliminary data examination. The dataset was examined for missing observations, duplicate bank-year records, and extreme values. Descriptive statistics were used to evaluate the distributions of NPM, ROA, and DER, while pairwise correlations were examined to assess the degree of overlap among the clustering variables. The three ratios were subsequently standardized into Z-scores before the clustering procedures.

Determination of the number of clusters. Hierarchical cluster analysis was first conducted using Ward's method and squared Euclidean distance on the standardized variables. Ward's method combines observations or groups while minimizing increases in within-cluster variance and is commonly used as an exploratory procedure for identifying an appropriate clustering structure (Hair et al., 2019). The agglomeration schedule and dendrogram were examined to identify plausible cluster solutions based on noticeable increases in the agglomeration coefficient and the separation of major groups.

The candidate solutions identified through hierarchical clustering were then examined using K-Means clustering. The final number of clusters was selected by considering the hierarchical evidence and the financial interpretability of the resulting groups rather than imposing a predetermined number of performance categories.

K-Means clustering and cluster profiling. K-Means clustering was performed in IBM SPSS Statistics using the standardized NPM, ROA, and DER values. All 188 bank-year observations were pooled into a single clustering procedure rather than clustered separately for each year. This approach established a common set of cluster centers for the entire 2022–2025 period, enabling consistent comparisons of cluster membership across years.

The K-Means algorithm iteratively assigned observations to the nearest cluster center and updated the centers until the allocation stabilized.

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The final cluster centers were examined to identify the financial characteristics distinguishing each group. Cluster labels were assigned after evaluating the relative levels of NPM, ROA, and DER within each cluster. Cluster sizes were also examined to identify highly unbalanced or very small groups that might represent unusual financial profiles. All bank-year cluster assignments generated by SPSS were retained for the subsequent longitudinal analysis.

Cluster persistence and migration analysis. The cluster assignments were reorganized at the individual-bank level so that each bank had four annual assignments corresponding to 2022, 2023, 2024, and 2025. Three consecutive annual transitions were examined: 2022–2023, 2023–2024, and 2024–2025. A bank was classified as persistent during a transition if it remained in the same cluster in both consecutive years. Migration was recorded when its cluster membership changed between those years.

Transition matrices were constructed for each annual interval to summarize movements between clusters. Overall transition-level persistence was calculated as the proportion of annual transitions in which banks remained in the same cluster, while the migration rate represented the proportion of transitions involving a change in cluster membership.

Individual bank-level persistence was assessed by examining each bank's cluster assignments across the three annual transitions. The individual persistence rate was calculated as:

$$Persistence\ Rate_i = \frac{Number\ of\ Unchanged\ Consecutive\ Transitions_i}{3} \times 100\%$$

Under this definition, a bank that remained in the same cluster throughout all four years had a persistence rate of 100%, whereas a bank that changed clusters in every consecutive period had a persistence rate of 0%. These measures were used descriptively to distinguish stable financial profiles, occasional migration, and repeated changes in cluster membership. The analysis describes changes in banks' relative financial positions and does not establish causal relationships.

3.7. Validity, Reliability, and Trustworthiness

The quality of the analysis was supported by consistent data collection and preparation procedures. The same financial statement fields and data source were applied across all banks and observation years to promote comparability. The dataset was examined for missing observations, duplicate bank-year records, and extreme values before the clustering procedures. Descriptive statistics and pairwise correlations were also examined to understand the distributions of the financial indicators and their potential overlap.

Standardizing NPM, ROA, and DER into Z-scores ensured that differences in numerical scales did not disproportionately influence the distance calculations. The use of Ward's hierarchical clustering to examine plausible cluster structures, followed by K-Means clustering and an assessment of cluster interpretability, provided a systematic basis for selecting the final classification. The use of pooled observations and common cluster centers further supported consistency when tracking individual banks across years.

These procedures support the comparability and interpretability of the resulting financial profiles. However, the study did not employ survey-based reliability tests or psychometric validity assessments because its variables were derived from secondary financial statement data rather than responses to a measurement instrument.

3.8 Ethical Considerations

The study uses secondary financial statement data and does not involve surveys, interviews, experiments, or direct participation by human subjects. The analysis focuses on financial characteristics and cluster membership among publicly listed banking institutions. Data were organized and analyzed for academic research purposes, with interpretations based on the selected financial indicators and the observed clustering results.

The study does not establish causal explanations for changes in cluster membership. Accordingly, the findings are interpreted as descriptive evidence of financial heterogeneity, persistence, and migration rather than as proof of the causes or consequences of changes in bank performance. The methodology provided does not specify a separate ethics approval procedure.

3.9 Research Procedure

The research was conducted through the following sequential stages:

a. Population identification and sample selection:

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Identify banks classified under the Banks sub-industry of the IDX-IC and select institutions listed before 2022 with complete financial information for 2022–2025.

b. Data collection: Retrieve annual financial statement data from Yahoo Finance using the yfinance Python library.
c. Data preparation: Compile the bank-year dataset, examine missing observations and duplicate records, assess extreme values, and calculate NPM, ROA, and DER.
d. Standardization: Convert the three financial ratios into Z-scores to ensure comparability in the clustering procedure.
e. Hierarchical clustering: Apply Ward's method with squared Euclidean distance and examine the agglomeration schedule and dendrogram to identify plausible cluster solutions.
f. K-Means clustering: Evaluate candidate solutions and select the final cluster structure based on the hierarchical evidence and the interpretability of the resulting financial profiles.
g. Cluster profiling: Examine cluster centers and cluster sizes to characterize the financial profiles according to profitability and leverage.
h. Longitudinal tracking: Organize the cluster assignments of each bank across 2022–2025 and construct transition matrices for the three consecutive annual periods.
i. Persistence and migration assessment: Calculate transition-level persistence and migration rates, assess individual bank-level persistence, and identify banks experiencing cluster migration.
j. Interpretation: Interpret the findings descriptively in terms of cross-sectional financial heterogeneity and changes in banks' relative financial positions over time.

3.10 Methodological Limitations

Several methodological limitations should be acknowledged. First, the analysis uses only three financial ratios—NPM, ROA, and DER—to characterize financial-performance profiles. Other dimensions of banking performance, including liquidity, asset quality, capital adequacy, and operational efficiency, are not incorporated into the clustering procedure. Consequently, the identified profiles represent selected dimensions of financial performance rather than a comprehensive assessment of overall bank condition.

Second, the observation period covers four years, from 2022 to 2025. Although this period allows three consecutive annual transitions to be examined, it provides a relatively short window for evaluating longer-term changes in banks' financial profiles.

Third, the clustering and migration procedures are descriptive. They identify similarities among bank-year observations and track changes in cluster membership but do not establish the determinants or consequences of migration. Changes in cluster membership should therefore be interpreted as changes in relative financial profiles within the common clustering structure, not as evidence of causal relationships. Future research could extend the observation period, incorporate additional banking-specific indicators, and examine factors associated with migration between financial-performance profiles.

4. Results and Discussion

4.1. Research Results

4.1.1. Sample Description and Descriptive Statistics

The analysis covered 188 bank-year observations from 47 Indonesian listed banks over the 2022–2025 period. Table 1 presents the descriptive statistics of the three financial indicators used in the clustering procedure.

Table 2. Descriptive Statistics of Financial Indicators

Variable	N	Minimum	Maximum	Mean	Std. Deviation
NPM	188	-4.5903	0.5306	0.0767	0.6634
ROA	188	-0.0762	0.0841	0.0089	0.0189
DER	188	0.0810	14.5214	4.7980	2.9331

The descriptive statistics indicate considerable heterogeneity among Indonesian listed banks. NPM exhibited the widest dispersion, ranging from -459.03% to 53.06%. ROA also varied substantially, from -7.62% to 8.41%, while DER ranged from 0.08 to 14.52 times. The negative extreme values of NPM and ROA were retained because examination of the underlying observations indicated that they

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represented actual financial conditions rather than data errors. Retaining these observations is particularly relevant in a clustering context because extreme financial conditions may represent economically meaningful profiles that would otherwise be obscured by arbitrary removal.

The correlation analysis further indicated that NPM and ROA were positively associated (r = 0.761), which is expected because both represent profitability from different perspectives. In contrast, DER showed little correlation with NPM (r = -0.019) and a relatively weak negative correlation with ROA (r = -0.132). Thus, although the two profitability measures contain related information, leverage contributes a substantially different dimension to the clustering structure. This multidimensionality is important because banks with comparable profitability do not necessarily operate with comparable levels of leverage.

4.1.2. Data Quality and Preliminary Analysis

The dataset was examined for missing observations, duplicate bank-year records, and extreme values before clustering. The negative extreme values of NPM and ROA were retained because examination of the underlying observations indicated that they represented actual financial conditions rather than data errors. The correlation results indicated that NPM and ROA were positively associated, whereas DER had relatively weak correlations with both profitability indicators. Before the clustering procedures, the three variables were standardized into Z-scores to ensure comparability across their different numerical scales.

4.1.3. Main Analytical Results

a. Determination of the Number of Clusters

Hierarchical clustering using Ward's method was first employed to identify plausible numbers of clusters. Inspection of the agglomeration schedule showed increasingly large increases in the coefficient toward the final stages. The coefficient increased from 171.066 at Stage 184 to 227.303 at Stage 185, followed by 335.118 at Stage 186 and 561.000 at the final stage. Together with the dendrogram, this pattern indicated that three- and four-cluster structures were plausible alternatives. Rather than selecting the final solution solely from the largest increase in the agglomeration coefficient, both alternatives were subsequently examined using K-Means clustering.

Table 3. Comparison of Candidate Cluster Solutions

Solution	Cluster Sizes	Characteristics of the Solution	Assessment
Three clusters	84, 100, 4	Separates four extreme-loss observations, while the remaining observations form two relatively broad groups	Interpretable, but provides limited differentiation among the remaining observations
Four clusters	4, 32, 55, 97	Retains the four extreme-loss observations as a distinct group and further differentiates the remaining observations according to profitability and leverage	Retained as the final solution

As shown in Table 3, both solutions consistently identified the same small group of four observations characterized by extreme losses. The principal difference concerned the remaining observations. Under the three-cluster solution, these observations were divided into two relatively broad groups. The four-cluster solution preserved the distinct extreme-loss group while providing an additional separation among the remaining observations based on their profitability and leverage characteristics. The four-cluster solution was therefore retained because it provided a more informative representation of the financial heterogeneity in the sample without eliminating the distinct extreme profile identified in both candidate solutions.

The retained solution is consistent with the broader use of financial-statement information to identify meaningful heterogeneity among banks. Cyree et al. (2020), for example, demonstrate that clustering financial statement variables can generate relatively homogeneous bank peer groups, while Aditiya et al. (2026) show that financial ratios can differentiate listed banking issuers in Indonesia. The

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present analysis extends this evidence by establishing a common four-cluster structure across the 2022–2025 period, which subsequently allows changes in individual banks' financial profiles to be tracked over time.

b. Financial Characteristics of the Four Clusters

Table 3 presents the financial characteristics of the final four-cluster solution using the original, unstandardized ratios to facilitate economic interpretation.

Table 4. Financial Characteristics of the Final Clusters

Cluster	n	Mean NPM	Mean ROA	Mean DER	Financial Profile
C1	4	-412.04%	-6.49%	5.47×	Severe-Loss Profile
C2	32	35.00%	3.32%	2.66×	High-Profitability, Low-Leverage Profile
C3	55	21.31%	1.01%	8.24×	High-Leverage Profile
C4	97	8.23%	0.32%	3.53×	Moderate-Profitability, Lower-Leverage Profile

Cluster 1 represents a **Severe-Loss Profile** and contains only four bank-year observations. Its mean NPM of -412.04% and ROA of -6.49% are substantially below those of the other clusters. Importantly, its average DER of 5.47 times is not the highest among the four groups. The defining feature of this cluster is therefore the magnitude of its losses rather than leverage alone. Although C1 contains only four observations, these observations share markedly extreme profitability characteristics and therefore represent a distinct financial profile within the sample.

Cluster 2 represents the **High-Profitability, Low-Leverage Profile**. It records the highest average NPM (35.00%) and ROA (3.32%) while simultaneously exhibiting the lowest average DER (2.66 times). Cluster 3 presents a different configuration. Its NPM and ROA remain positive at 21.31% and 1.01%, respectively, but its average DER reaches 8.24 times, substantially exceeding all other clusters. It is therefore characterized primarily as a **High-Leverage Profile** rather than simply as a lower-performing version of Cluster 2. Cluster 4, which contains more than half of all bank-year observations, combines an average NPM of 8.23%, ROA of 0.32%, and DER of 3.53 times. Relative to the other groups, it is appropriately characterized as a **Moderate-Profitability, Lower-Leverage Profile**.

The cluster structure therefore reveals that differences among Indonesian listed banks cannot be reduced to a single continuum from weak to strong performance. Instead, the banks exhibit different combinations of profitability and leverage. This is consistent with the broader clustering literature in banking. Farnè and Vouldis (2021), for instance, identify distinct groups of euro-area banks and show that the resulting groups differ in performance and risk indicators. Cyree et al. (2020) likewise demonstrate that financial-statement-based clusters capture meaningful structural heterogeneity among banks. These studies differ from the present analysis in their variables and interpretation of clusters, but they reinforce the broader proposition that clustering can uncover economically distinct bank profiles rather than merely partitioning observations statistically.

The present findings also add an Indonesian perspective to Aditiya et al. (2026), who classified 25 Indonesian banking issuers during 2022–2024 using ROA, ROE, and LDR. While their findings demonstrate the feasibility of financial-ratio-based clustering among Indonesian banks, the present study uses profitability and leverage dimensions to reveal four distinct profiles across 47 banks. More importantly, the pooled specification makes it possible to examine whether individual banks remain within these profiles or move between them over time.

c. Persistence and Migration of Financial-Performance Clusters

The next analysis tracked each bank's membership across three consecutive annual transitions: 2022–2023, 2023–2024, and 2024–2025. The transition matrices are presented in Table 4.

Table 5. Cluster Transition Matrices, 2022–2025

Panel A. 2022–2023

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Origin	C1	C2	C3	C4	Total
C1	**1 (50.0%)**	0	0	1 (50.0%)	2
C2	0	**7 (100.0%)**	0	0	7
C3	0	0	**12 (100.0%)**	0	12
C4	0	1 (3.8%)	2 (7.7%)	**23 (88.5%)**	26
Panel B. 2023–2024					
Origin	**C1**	**C2**	**C3**	**C4**	**Total**
C1	**1 (100.0%)**	0	0	0	1
C2	0	**7 (87.5%)**	1 (12.5%)	0	8
C3	0	0	**13 (92.9%)**	1 (7.1%)	14
C4	0	1 (4.2%)	0	**23 (95.8%)**	24
Panel C. 2024–2025					
Origin	**C1**	**C2**	**C3**	**C4**	**Total**
C1	0	0	1 (100.0%)	0	1
C2	0	**7 (87.5%)**	0	1 (12.5%)	8
C3	0	1 (7.1%)	**13 (92.9%)**	0	14
C4	0	1 (4.2%)	1 (4.2%)	**22 (91.7%)**	24

Note: Cells report the number of banks, with row percentages in parentheses. Percentages are conditional on the originating cluster. Bold diagonal cells indicate persistence

The transition matrices reveal substantial persistence in financial-performance profiles. Between 2022 and 2023, 43 of 47 banks (91.5%) remained in their existing cluster. Persistence increased to 44 banks (93.6%) between 2023 and 2024 before declining slightly to 42 banks (89.4%) between 2024 and 2025. Across all three periods, 129 of the 141 possible bank-transitions represented persistence, corresponding to an overall persistence rate of **91.5%**. Only 12 transitions, or **8.5%**, involved movement between clusters.

This finding is particularly notable when compared with previous evidence on bank-group stability. Marques and Alves (2020) explicitly distinguish between persistent and non-persistent banks in their clustering of European banking business models, demonstrating that temporal stability itself represents a meaningful characteristic of bank classification. Custodio João et al. (2023), using a substantially more sophisticated dynamic clustering framework for 299 European banks, similarly find that only around 3% of banks transition between clusters per quarter on average. Their quarterly frequency and dynamic model make the magnitude not directly comparable with the annual transitions reported here; nevertheless, both results point toward substantial persistence in bank-level group membership.

The closest comparison is provided by Ayadi et al. (2021), who identify bank business models for more than 3,000 European banks and subsequently track their evolution. They report that business models are generally stable and identify 2,058 migrations among 23,883 bank-year observations, equivalent to approximately 8.6%. This proportion is numerically close to the 8.5% migration rate observed in the present study. The similarity should not be interpreted as statistical equivalence, since Ayadi et al. (2021) employ different variables, a different institutional setting, and a stricter definition designed to identify stable business-model migrations. Nevertheless, the comparison provides useful evidence that a relatively small proportion of annual migrations can coexist with meaningful cross-sectional heterogeneity in banking.

The temporal distribution of the clusters also reveals that no bank remained in the Severe-Loss Profile (C1) in 2025. This should not be interpreted as the disappearance of financial distress from the Indonesian banking sector. Rather, it means specifically that none of the 47 banks met the multivariate financial characteristics associated with C1 in that year. The result illustrates why longitudinal tracking provides information beyond a static clustering exercise: it reveals not only which profiles exist, but also whether banks remain within or move away from them.

d. Bank-Level Migration Patterns

The high transition-level persistence is also

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evident when the analysis is conducted at the individual-bank level. Table 6 summarizes the number of banks according to their persistence across the three annual transitions.

Table 6. Bank-Level Cluster Persistence

Persistence Rate	Interpretation	Number of Banks	Percentage
100.0%	No cluster changes	38	80.9%
66.7%	One migration	7	14.9%
33.3%	Two migrations	1	2.1%
0.0%	Migration in all three transitions	1	2.1%
Total		47	100.0%

Thirty-eight of the 47 banks (80.9%) remained in the same cluster throughout all three transitions. Only nine banks changed cluster at least once. Seven migrated once, one migrated twice, and one changed cluster in each consecutive period. These nine banks generated the 12 migration events identified in the transition matrices.

Table 7. Banks Experiencing Cluster Migration

Bank	2022	2023	2024	2025	Migration Events
AMAR	C4	C2	C2	C2	1
BANK	C1	C4	C4	C4	1
BBKP	C1	C1	C1	C3	1
BBSI	C2	C2	C2	C4	1
BBYB	C4	C4	C4	C2	1
BGTG	C4	C4	C2	C2	1
MASB	C4	C3	C3	C3	1
MEGA	C2	C2	C3	C2	2
BINA	C4	C3	C4	C3	3

The migration paths indicate that changes in cluster membership were concentrated among a relatively small subset of banks and, in several cases, coincided with substantial changes in their underlying financial conditions. AMAR, for example, moved from C4 to the high-profitability C2 profile in 2023 and remained there through 2025. This transition coincided with a substantial improvement in its financial performance. In 2023, Amar Bank reported net profit of IDR 177.9 billion, representing year-on-year growth of 214.5%, while operating income increased by 42.8%. The improvement was supported by growth of 40.5% in net interest income and 48.7% in non-interest income (PT Bank Amar Indonesia Tbk., 2024). The subsequent persistence of AMAR in C2 suggests that its initial migration was not merely a one-year change in relative position.

BANK presents a different trajectory. Its membership in the Severe-Loss Profile (C1) in 2022 coincided with a particularly weak profitability position. Bank Aladin Syariah reported a net loss of IDR 264.9 billion in 2022, compared with a net loss of IDR 121.3 billion in the previous year. The bank attributed the deterioration partly to higher operating expenses associated with its ongoing transformation into a digital bank (SustainabilityReports.com, 2026). Bank Aladin subsequently moved to C4 in 2023 and remained there through 2025. Thus, its migration is more appropriately interpreted as movement away from the extreme profitability characteristics defining C1 rather than as evidence that the bank had immediately achieved a high-profitability position.

Not all migrations represented a sustained movement toward a new profile. MEGA temporarily moved from C2 to C3 in 2024 before returning to C2 in 2025, whereas BINA changed cluster in every annual transition, following a C4–C3–C4–C3 sequence. BINA's movement is particularly illustrative of a less stable financial profile, as the bank alternated between C4 and C3 in each consecutive transition. Rather than indicating a sustained shift toward a new profile, this sequence

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suggests repeated changes in BINA's relative combination of profitability and leverage within the common clustering structure.

These contrasting trajectories indicate that migration can represent either a relatively persistent shift in financial characteristics or a temporary change followed by reversion. This distinction is consistent with previous evidence that bank cluster membership can exhibit both persistence and movement over time. Marques and Alves (2020) distinguish persistent from non-persistent banks in their analysis of European banking business models, while Ayadi et al. (2021) document different migration trajectories among European banks. The clusters examined in the present study represent financial-performance profiles rather than business models, and the underlying mechanisms are therefore not directly comparable. Nevertheless, these studies reinforce the value of tracking cluster membership longitudinally rather than treating clustering as a purely cross-sectional classification.

Overall, the findings reveal two simultaneous characteristics of Indonesian listed banks. First, substantial cross-sectional heterogeneity exists, as reflected in four distinct combinations of profitability and leverage. Second, this heterogeneity is predominantly persistent at the individual-bank level: 38 of 47 banks never changed cluster, while only nine banks accounted for all 12 migration events. The selected cases further indicate that changes in cluster membership correspond to observable changes in the financial characteristics underlying the clustering solution. These case-level observations should not be interpreted as establishing the causes of migration; rather, they provide contextual evidence that the identified migrations reflect economically observable changes in banks' relative financial positions.

4.1.4. Key Findings

The empirical findings address the three research questions as follows. First, four financial-performance clusters were identified among Indonesian listed banks during 2022–2025: the Severe-Loss Profile, High-Profitability and Low-Leverage Profile, High-Leverage Profile, and Moderate-Profitability and Lower-Leverage Profile. Second, the clusters differed in their combinations of profitability and leverage. C1 was characterized by extreme losses; C2 combined the highest mean NPM and ROA with the lowest mean DER; C3 exhibited the highest mean DER; and C4 represented moderate profitability with lower leverage relative to C3. Third, cluster membership was predominantly persistent over time. Of the 141 possible annual bank transitions, 129 (91.5%) remained in the same cluster and 12 (8.5%) involved migration. At the individual-bank level, 38 of 47 banks (80.9%) maintained their original cluster membership across all three transitions, while nine banks migrated at least once.

These findings address the research questions through cluster identification, comparison of financial characteristics, and longitudinal tracking. The study did not conduct causal hypothesis testing; therefore, the results are interpreted descriptively.

4.1.5. Visual Presentation of Results

Tables 1–6 provide the principal visual presentation of the empirical findings. Table 1 summarizes the distributions of the financial indicators, Table 2 compares the candidate cluster solutions, and Table 3 presents the characteristics of the four retained clusters. Table 4 documents transitions between clusters, while Tables 5 and 6 summarize persistence and identify banks that migrated.

Together, these tables provide a consistent basis for comparing financial profiles and examining their evolution during 2022–2025. No additional numerical values or figures are introduced beyond those reported in the original analysis.

4.2. Research Discussion

4.2.1. Interpretation of Key Findings

The findings demonstrate that Indonesian listed banks exhibit substantial financial heterogeneity that cannot be adequately represented by a single performance continuum. The four clusters reflect different combinations of profitability and leverage rather than a simple ranking from weak to strong performance.

The Severe-Loss Profile (C1) was characterized by extremely low profitability, with mean NPM of -412.04% and mean ROA of -6.49%. Its mean DER of 5.47× was not the highest among the clusters, indicating that the defining characteristic was the magnitude of its losses rather than leverage alone. C2 represented a contrasting profile, combining the highest mean NPM (35.00%) and ROA (3.32%) with the lowest mean DER (2.66×).

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C3 exhibited positive profitability but the highest mean DER (8.24×), distinguishing it from C2. C4 combined moderate profitability with a lower mean DER of 3.53×.

These differences show why profitability and leverage should be considered jointly when identifying financial profiles. Banks with relatively high profitability may have different financial structures, while institutions with moderate profitability may operate with comparatively lower leverage.

The second key finding concerns temporal persistence. The overall persistence rate was 91.5%, and 80.9% of sampled banks maintained the same cluster membership across all three annual transitions. These results indicate that the identified financial profiles were generally stable during the observation period, although migration occurred among a small subset of institutions.

The migration cases further illustrate that changes in cluster membership can represent different trajectories. AMAR moved from C4 to C2 and remained there, whereas MEGA returned to its original cluster after a temporary change. BINA alternated between C4 and C3 throughout the observation period. These cases illustrate differences in the observed persistence of financial profiles but do not establish the causes of those changes.

4.2.2. Comparison with Previous Studies

The identification of four financial-performance clusters is consistent with previous research demonstrating that financial statement information can reveal meaningful heterogeneity among banking institutions. Cyree et al. (2020) showed that financial-statement-based peer groups could capture differences in bank structures and provide explanatory value beyond size-based classifications. Similarly, Farnè and Vouldis (2021) identified distinct groups of euro-area banks with different performance and risk characteristics.

The present study extends this evidence by identifying four profiles based on NPM, ROA, and DER across 47 Indonesian listed banks and by applying a common clustering structure throughout 2022–2025. Unlike a purely cross-sectional classification, this approach allows individual banks' financial profiles to be followed across consecutive years.

The findings also complement Aditiya et al. (2026), who applied financial-ratio clustering to 25 Indonesian banking issuers during 2022–2024 using ROA, ROE, and LDR. Whereas their analysis identified three groups, the present study identified four clusters using a different combination of profitability and leverage indicators and a broader sample. The difference in the number of clusters should be understood in relation to the indicators, sample coverage, observation period, and clustering specification rather than interpreted as evidence that one classification is inherently superior.

Regarding temporal stability, the observed annual migration rate of 8.5% is numerically close to the approximately 8.6% reported by Ayadi et al. (2021), who identified 2,058 migrations among 23,883 bank-year observations. However, the two studies differ in their institutional settings, variables, and definitions of migration. Their rates should therefore not be interpreted as statistically equivalent.

Marques and Alves (2020) distinguished between persistent and non-persistent banks in their analysis of European banking business models. Custodio João et al. (2023) likewise reported that approximately 3% of banks transitioned between clusters per quarter on average using a dynamic clustering framework. Although their quarterly estimates are not directly comparable with the annual transitions in this study, both studies reinforce the importance of examining temporal stability in banking classifications.

The findings concerning AMAR and BANK also provide contextual evidence of different migration trajectories. AMAR's movement to C2 coincided with reported improvements in profitability, whereas BANK's movement from C1 to C4 represented movement away from the extreme-loss profile without necessarily indicating immediate achievement of a high-profitability position. These observations are consistent with the broader argument that cluster migration can involve different changes in relative financial characteristics. However, the case evidence does not establish that the observed financial changes caused the migrations.

4.2.3. Theoretical Contributions

This study contributes to the literature on bank financial performance by extending the application of financial-ratio clustering from static classification to longitudinal tracking. The findings

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demonstrate that cross-sectional heterogeneity and temporal persistence can coexist: banks exhibit distinct combinations of profitability and leverage, yet most retain their cluster membership over consecutive annual periods.

The study also reinforces a multidimensional perspective on financial performance. The four clusters cannot be arranged adequately along a single continuum because profitability and leverage vary in different combinations. The High-Leverage Profile, for example, exhibits positive profitability but a substantially higher mean DER than the High-Profitability and Low-Leverage Profile. This distinction supports the use of multiple complementary indicators when classifying banks according to financial characteristics.

Furthermore, the study contributes a descriptive approach to evaluating cluster persistence and migration using a common set of cluster centers. By pooling observations across the four-year period, the analysis makes annual membership assignments comparable within the same classification structure. This provides an accessible framework for investigating whether financial profiles remain stable or change over time without requiring a more complex dynamic clustering model.

4.2.4. Practical and Policy Implications

The findings have implications for financial benchmarking and monitoring. Investors, financial analysts, and other users of bank financial information may use the identified profiles as a complementary means of comparing institutions with similar combinations of profitability and leverage. This approach can provide additional context beyond examining individual ratios or comparing banks solely with industry averages.

The findings also suggest that financial monitoring should distinguish between persistent profiles and changes in relative financial positions. Banks that remain in a particular cluster over several years exhibit a different observed trajectory from banks that migrate repeatedly. Tracking these movements can help analysts identify changes warranting further examination, although cluster membership alone does not establish financial distress, improved resilience, or future performance.

For bank managers and other stakeholders, the four-cluster structure provides a descriptive reference for assessing the interaction between profitability and leverage. In particular, a high-profitability profile should not automatically be equated with every dimension of financial strength, nor should moderate profitability alone be interpreted as evidence of financial weakness. The interpretation should consider the combination of indicators represented by each cluster.

These implications should remain within the scope of the evidence. The study identifies financial profiles and their observed transitions; it does not establish causal effects, predict future bank failures, or evaluate the effectiveness of particular regulatory interventions.

4.2.5. Integration with the Research Gap

The study addresses the identified research gap concerning the limited evidence on the temporal persistence of financial-performance clusters among Indonesian listed banks. Previous Indonesian research established the usefulness of clustering for identifying bank profiles, but less attention was given to tracking individual institutions across a common classification structure over consecutive years.

By analyzing 47 banks from 2022 to 2025, the present study identifies four financial-performance profiles and documents their persistence and migration across three annual transitions. The finding that 129 of 141 possible transitions (91.5%) remained within the same cluster, while 12 (8.5%) involved migration, provides direct descriptive evidence of temporal stability within the observed sample.

The bank-level results further clarify this pattern: 38 of 47 banks (80.9%) maintained the same profile throughout all three transitions, while nine banks accounted for all migration events. The study therefore extends the analysis beyond identifying heterogeneous financial groups to examining whether individual banks retain or change their relative financial positions over time.

The contribution lies in the combination of a common financial-performance classification and longitudinal tracking in the Indonesian listed banking context. This approach provides a basis for further research into the determinants and consequences of migration without presuming that these mechanisms have been established by the present analysis.

4.2.6. Acknowledgement of Study Limitations

The findings should be interpreted in light of

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the specific financial dimensions and observation period covered by the analysis. The four clusters reflect NPM, ROA, and DER and may not capture other aspects of bank condition, including liquidity, asset quality, capital adequacy, and operational efficiency. The four-year observation period also limits the assessment of longer-term financial trajectories. In addition, the descriptive analysis identifies changes in cluster membership but does not establish why these changes occur or whether they lead to subsequent improvements or deteriorations in bank performance. Finally, the migration cases provide contextual evidence rather than causal explanations. Although certain transitions coincided with observable financial changes, the analysis does not isolate the effects of those changes on cluster membership. Accordingly, the findings are most appropriately interpreted as evidence of financial heterogeneity, persistence, and migration within the sampled banks during 2022–2025.

5. Conclusion

5.1 Summary of Key Findings

This study examined financial-performance profiles among Indonesian listed banks and tracked their evolution during 2022–2025. Using 188 bank-year observations from 47 banks, the analysis combined Ward's hierarchical clustering and K-Means clustering to identify four profiles based on NPM, ROA, and DER: the Severe-Loss Profile, High-Profitability and Low-Leverage Profile, High-Leverage Profile, and Moderate-Profitability and Lower-Leverage Profile. The findings demonstrate substantial financial heterogeneity among the sampled banks. The four clusters exhibited different combinations of profitability and leverage, indicating that their financial characteristics could not be adequately represented by a single performance dimension. The longitudinal analysis revealed considerable temporal persistence. Of the 141 possible annual bank transitions, 129 (91.5%) remained within the same cluster, while 12 (8.5%) involved migration. At the individual-bank level, 38 of 47 banks (80.9%) maintained the same cluster membership across all three annual transitions. Only nine banks migrated at least once, and their trajectories included both persistent changes and temporary movements followed by a return to an earlier cluster.

5.2 Theoretical Contributions

The study extends financial-ratio clustering by combining the identification of heterogeneous bank profiles with longitudinal tracking of individual cluster membership. Rather than treating clustering exclusively as a static classification exercise, the analysis demonstrates how a common cluster structure can be used to examine the persistence and movement of financial profiles over time. The findings also reinforce the multidimensional nature of bank financial performance. Different combinations of profitability and leverage produce distinct profiles that cannot be interpreted adequately through a single ranking of financial strength. The study therefore provides a descriptive framework for examining both cross-sectional heterogeneity and temporal stability among Indonesian listed banks.

5.3 Practical and Policy Implications

The identified clusters may provide investors, analysts, bank managers, and other users of financial information with a complementary framework for financial benchmarking. Comparing banks with similar financial profiles can provide context beyond individual financial ratios or broad industry averages. The longitudinal results also highlight the value of monitoring changes in cluster membership. Persistent profiles and repeated migrations represent different observed patterns that may warrant further financial examination. However, cluster membership should be used as a descriptive analytical aid rather than as a standalone measure of financial distress, future performance, or regulatory risk.

5.4 Limitations of the Study

The findings are limited to three financial ratios and a four-year observation period. Consequently, the identified profiles do not encompass every dimension of bank performance, and the observed transitions may not reflect longer-term changes in financial conditions. The descriptive clustering approach also does not identify the determinants or consequences of migration. These limitations restrict the interpretation of the findings to the observed financial profiles and their movements within the sampled banks during 2022–2025.

5.5 Directions for Future Research

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Future research could extend the observation period to determine whether the identified financial profiles remain persistent over longer horizons or change as banking conditions evolve. Additional indicators, including liquidity, asset quality, capital adequacy, and operational efficiency, could also be incorporated to provide a more comprehensive representation of bank financial performance. Further studies could investigate the factors associated with cluster migration and examine whether persistent or changing profiles are related to subsequent financial outcomes. Alternative longitudinal or dynamic clustering methods could also be applied to compare the stability of classifications across different analytical approaches. These extensions would help clarify whether observed migrations represent temporary fluctuations in relative financial positions or more persistent changes in banks' financial characteristics.

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