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BANK BEHAVIOR IN DETERMINING SUPPLY OF CREDIT IN INDONESIA

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Abstract

With the constant diruptions in the economy stemmed from global market turbulence, technological changes, and shift toward a more sustainable way of life, understanding banking behavior become a priority to maintain financial stability. This study examines the credit allocation behavior of banks in Indonesia, influenced by economic conditions, regulatory frameworks, technological advancements, and sector-specific challenges. Bank credit plays a vital role in macroeconomic stability, and economic fluctuations impact banks procyclical credit behavior. The Indonesian banking sector faces complex pressures and sectoral risks, emphasizing the need for solid policies from Bank Indonesia to maintain financial system stability. This research addresses two main questions: how client relationships affect credit supply decisions and how structural changes such as interest rates, climate change, and cybersecurity influence bank behavior. Utilizing primary and secondary data as well as machine learning (ML) methods, the study reveals insights into credit supply practices in Indonesian banks and the potential of big data and ML for a detailed assessment of credit distribution patterns. The findings highlight the importance of stricter oversight, technological integration, and sector-specific strategies, especially for SMEs and high-risk sectors such as tourism and mining. The study emphasizes integrating green finance, RegTech, and SupTech to enhance banking sector resilience and align credit activities with sustainability goals. By applying these insights, Indonesia can create a stable credit environment, support economic growth, and ensure banks are prepared to manage evolving risks in the financial landscape.

Keywords: bank behavior, credit growth, credit supply, machine learning

JEL Classifications: E51, G21, G28

1. Introduction

1.1 Background

Bank credit plays a crucial role in the macroeconomic dynamics, enhancing financial mobility, economic growth, and the development of a country's economy (Mian et al., 2020; Wu et al., 2022). However, the behavior of bank credit tends to fluctuate due to economic pressures, impacting the waves of less stable financial cycles (Tobal & Menna, 2020). Indeed, highly procyclical bank credit behavior can sometimes trigger economic growth slowdowns and financial crises (Belkhir et al., 2022). For instance, the Subprime Mortgage Crisis in the United States highlights how weak oversight by the Federal Reserve contributed to this crisis through bank credit behavior (Yun, 2020). The impact of this crisis extended to global markets, including developing countries like Indonesia, which experienced pressure on macroeconomic variables and a decline in economic growth (Hofmann et al., 2019).

In Indonesia, the complexity of pressures on the monetary and fiscal sectors urges all institutions, especially Bank Indonesia, to effectively establish appropriate policies for financial stability and economic growth (Satria & Juhro, 2011). Economic growth slowdowns and pressures from all sectors pose several challenges, including the need to revitalize the economic structure within a short timeframe at significant costs (Karakosta et al., 2021). On the other hand, financial intermediation in Indonesia is suboptimal due to the slow economic recovery post-pandemic (scarring effect) resulting from weakened financial interconnections with other countries, as well as the impacts of high US interest rates and sectoral risks (Prabheesh et al., 2021). Meanwhile, in these complexities, the challenges presented by elections, climate change, trade wars, geopolitical tensions, supply disruptions, import/export restrictions, economic sanctions, cybersecurity risks, challenges in Micro Small Medium-sized Enterprises (MSMEs) lending, tourism sector lending, and mining sectors lending are significant.

In facing these changes, demands for stricter supervision and adaptation to structural changes become increasingly urgent to maintain financial stability. However, some banking sectors exhibit vulnerability, with banks inadequately applying precautionary principles in their activities, leading to increased non-performing loans across the industry (Sobarsyah et al., 2020). Therefore, enhancements in supervision and stricter implementation of precautionary principles are required to mitigate their negative impacts on overall financial stability.

In 2023, the credit sector in Indonesia showed a growth rate of 10.3% year-over-year (YoY). Banking still dominates Indonesia's financial system, signifying the crucial role of bank credit in supporting the economy. However, this growth also highlights risks associated with economic conditions. Stringent regulations and government policies play a crucial role in controlling banking behavior. Thus, banks must adapt and implement careful risk management (Yun, 2020). Prudent risk management strategies and awareness of pro-cyclical behavior are key to maintaining financial sector stability amid changing economic conditions and regulations. Banks should consider the economic cycle's impact on credit portfolios, reduce excessive credit risks when economic risks increase, and adapt to regulatory changes to minimize risks and comply with regulations (Berger et al., 2020).

Previous studies have provided relevant analyses regarding bank credit allocation behavior. Research by Hirtle (2009) highlights the impact of credit derivatives on bank credit supply, indicating the complexity of financial market dynamics. Becker & Ivashina (2014) also found a relationship between bank credit supply and business cycle evolution at the firm level. Meanwhile, Mian et al. (2020) examined the impact of credit supply shocks on the real economy, particularly in the United States, in the 1980s, revealing the transmission mechanisms involved in the process. Based on these studies, it is important to predict bank credit performance granularly to provide information on optimal lending achievements measured by Bank Indonesia and insights into policies that Bank Indonesia can implement in a targeted manner.

Utilizing Machine Learning (ML) is also highly relevant in this context. A study by Sargeant (2023) reveals the potential use of ML models to predict behaviors that can be extrapolated to the banking sector, helping understand and forecast bankers' behavior in decision-making processes. Similar findings are also noted by Araujo et al. (2023), who highlight the potential application of ML in detecting and analyzing abnormal behaviors by bankers related to credit activities. Meanwhile, Agriyanto et al. (2022) explore psychological factors influencing banker behavior, especially in profit-sharing contract implementation, suggesting ML adoption as a tool better for understanding bankers' decision-making processes in financial contracts. Therefore, ML can be used to conduct granular assessments of individual bank credit distribution tendencies. Using big data to observe historical and sectoral credit distribution and payment system transactions can provide new information to enhance banking credit outlook performance.

1.2 Problem Statement and Research Question

Based on the background, this research will address the following questions:

1. Does its relationship with existing clients influence the behavior of bank credit allocation, and how does this affect banking decisions in determining the credit supply? Additionally, how can using big data in analyzing historical credit allocation and sectors provide new insights that could enhance the performance outlook of bank credit?
2. How do structural changes such as interest rates, societal preferences, climate change, and cyber security influence bank credit allocation?

1.3 Research Objective

In this research, we observe the bank behavior with the intentions as follows:

1. To analyze historical and sectoral banking behavior in determining the supply of credit can provide new information and enhance the performance outlook of bank credit by utilizing big data.
2. To analyze the influence of structural changes such as interest rates, societal preferences, climate change, and cyber security on bank credit allocation.

This research is done by gathering primary data via a survey of the Indonesian banking industry in combination with secondary data from banking reports to the banking authorities of Indonesia. The analysis is done using various machine learning methods.

2. Literature Review

2.1 Bank Lending Behavior

According to the Banking Law No. 10 of 1998, banks function as intermediaries that gather funds from the public through deposits and redistribute them, primarily as credit, aiming to enhance societal welfare. This underscores the significant influence of bank behavior on economic development. Notably, policies governing lending practices and risk management exemplify such behavior, shaping factors like credit availability, interest rates, and economic growth (Botos, 2016).

In line with this, Bank Indonesia Regulation No. 11/25/PBI/2009, amending the earlier Regulation No. 5/8/PBI/2003 on risk management for commercial banks, highlights the crucial role of risk management in banking operations. Risk management for banks is crucial to understand, especially credit risk management (Ariefianto et al., 2024). Risks arising from the provision of credit by bankers to borrowers significantly impact economic growth. OJK Regulation No. 18/POJK.03/2016, dated 22 March 2016, states that credit risk arises from the failure of debtors and other parties to fulfill obligations to the bank.

One of banks' primary activities is channeling funds to borrowers through credit. The funds disbursed by banks to borrowers are in the form of third-party funds obtained from creditors. A bank's profitability is determined by the amount of credit disbursed (Sofyan, 2019). When disbursing bank credit to borrowers, bankers require information about the characteristics of the borrowers. However, in reality, the information about borrowers possessed by bankers is limited (asymmetric information), which can create opportunities for the emergence of banking credit risks (Bernanke, 2018). Financial institutions or banks failing to provide banking credit will adversely affect the economy (Acharya et al., 2014).

Besides factors related to credit risk, several other elements impact risk aversion behavior within the banking industry, including liquidity and capital sufficiency. Risk aversion is the behavior of banks that tends to avoid risks to minimize the possibility of significant losses. When risk aversion increases, banks shift their preferences from risky to less risky assets. According to Bonner et al. (2013), the inclination of financial institutions to bolster liquidity reserves (buffer) and their hesitancy to extend loans during economic downturns may be viewed as a strategy for self-protection against potential rises in liquidity risk and credit risk, which cannot be offset solely by raising loan interest rates.

During the lending process, bankers may face various constraints. These constraints include credit demand, banking regulations, and the bank's desire to profit (Botos, 2016). As the key decision-makers in credit disbursement, bankers' behavior in deciding the credit supply must always be appropriate. This is to minimize the risks arising from the disbursement of bank credit to borrowers. Therefore, bankers must be selective when providing borrowers with bank credit loans to avoid the adverse effects of the risks (Bernanke, 2018). According to (Hamdaoui, 2020), appropriate banking capital regulations and optimal supervision can help prevent risks and adverse impacts such as banking crises.

2.2 Machine Learning in Credit Risk Assessment

The primary activity of the banking industry is lending money to deficit units. Assessing datasets could inform decisions to issue loans or reject customer applications (Pandey et al., 2017). Pławiak et al. (2019) observed that four primary factors merit consideration when assessing the creditworthiness of borrowers, which are feature extraction and selection mechanisms, the selection process for classification algorithms, model parameter optimization, and outcome evaluation.

Furthermore, Pandey et al. describe various techniques for evaluating credit datasets to enhance and ensure reliable credit risk analysis. These techniques include the Bayesian Classifier, Naive-Bayes Classifier, Decision Tree, K-nearest neighbor (KNN), K-means, Multilayer Perceptron (MLP), Extreme Learning Machine (ELM), Support Vector Machine, Artificial Neural Network, etc.

1. The Bayesian Classifier is a statistical model represented by a directed acyclic graph illustrating a joint probability distribution over a set of random variables.
2. The Naive-Bayes classifier, based on Bayes' rule, is a simple probabilistic classifier.
3. The Decision Tree is a predictive model that maps observations about an item represented in branches to conclusions about a target value represented in leaves.
4. K-Nearest Neighbors (KNN) is a non-parametric method used for classification and regression, employing a training set of positive and negative cases, often referred to as a lazy algorithm.
5. K-Means is utilized in unsupervised learning when dealing with unlabeled data. It aims to identify groups in the data, with the number of groups determined by the variable k.
6. Multilayers Perceptons (MLP) has been extensively used in the financial sector for credit risk assessment, employing the backpropagation algorithm for supervised learning. It comprises an input layer, an output layer, and one or more hidden layers, with processing elements in each layer (except the input layer) referred to as nodes, behaving akin to neurons.
7. Extreme Learning Machine (ELM) is developed for generalized single hidden layer feedforward networks. It randomly selects hidden node parameters to represent the network as a linear system, enabling the computation of output weights analytically.
8. Support Vector Machine (SVM) is a supervised learning algorithm that examines data for classification and regression tasks, constructing hyperplanes or sets of hyperplanes in high—or infinite-dimensional space.
9. Artificial Neural Networks comprise interconnected neural networks with weighted nodes, mimicking neurons, with synaptic connections among neurons analogous to connections among nodes.

In 2019, Shuomo et al. stated that identifying patterns in loan defaults has become easier, more precise, and more efficient with machine learning algorithms. Machine Learning enables computers to behave and learn like humans, improving their learning capability through real-world interactions and observations. Shuomo et al. conducted a comparative analysis using tuned supervised learning algorithms such as Support Vector Machine, Random Forest, Extreme Gradient Boosting, and Logistic Regression to identify defaulters. Combining a tuned Support Vector Machine and Recursive Feature Elimination with Cross-Validation has shown great promise in identifying loan defaulters. Therefore, the proposed model can assist financial institutions in accurately identifying defaulters and preventing further losses. They conclude that support vector machines can outperform other tree-based models or regression models under similar experimental setups.

Lappas & Yannacopoulos (2021) advocate for a combination strategy integrating soft computing methods with expert knowledge. Engaging experts in the credit scoring process enhances the interpretability of each feature's predictive power in the credit dataset. Expert insights are integrated to address credit scoring formulated as an optimization problem, subject to constraints, employing soft computing techniques rooted in supervised machine learning and evolutionary optimization algorithms. Various machine-learning algorithms and decision-making tools can be employed within the framework in hybrid synthesis. This includes unsupervised machine learning algorithms and decision-making tools like the Analytic Hierarchy Process for modeling and controlling subjective judgments.

2.3 Credit Market in Indonesia

The Indonesian credit market is undergoing significant digital transformation, particularly driven by technological advancements and the emergence of fintech companies. Despite a slight slowdown in credit growth, Bank Indonesia's data indicates that the banking sector's role in credit intermediation remains intact. In March 2024, banking credit growth reached 12.24% (yoy), signifying continued positive credit extension activities, with working capital loan (KMK) being the primary contributor at 56.70% of total credit growth. Credit expansion is primarily fueled by loans from state-owned enterprise (SOE) and private banks.

Banks significantly increase their Loan Loss Provision (LLP) during the pandemic, however manage to maintain a safe Non-Performing Loans (NPL). This confirms the condition that in general the banking system did not contribute any vulnerabilities to the economy during the overall downturn. The LLP gradually declined post pandemic as banks increase confidence in the return of normalcy. Nevertheless, this does not mean banks immediately go back to the normal lending behavior. 2023 was the first year the credit growth reached double digit growth. This research is interested in what the banks will do next with the recovery of the economy.

Post-pandemic banking liquidity also appears to be adequate in supporting intermediation, as reflected in the high Liquid Assets/Third-Party Deposits (AL/DPK) ratio in January 2024. AL/DPK ratio reached 27.41% during that period, significantly surpassing the safe threshold of 10% and exceeding the 2012-2019 period mean of 20.66%. Despite a slight decrease in liquidity compared to the previous year, it remains above the safe threshold. This indicates stable banking liquidity conditions, providing ability to support the lending to the economy.

3. Methodology

3.1 Survey Design

The survey instrument was designed to collect comprehensive data on the lending practices of banks operating within the Indonesian financial landscape. This instrument targeted loan officers and bank management using online survey methodologies and Focus Group Discussions (FGD). The survey's main objective is to understand how financial institutions navigate the complexities of the modern economic environment. Specifically, the survey aims to uncover how these entities adjust their credit provision strategies in response to dynamic market trends, evolving consumer behavior, digital transformations, and the increasing influence of climate-related risks.

To ensure the accuracy and consistency of the research instrument, validity and reliability tests were conducted. The findings of these tests are detailed in Appendix (A1). The results indicate that the questionnaire items meet the necessary standards for both validity and reliability, demonstrating that the instrument is robust and suitable for supporting the research analysis and findings.

Table 1. Description of Survey Instrument

This table describes the survey instrument used in the study.

No	Part	Description
1	General Information	a. Bank Name: (Optional) b. Area of Operation: Headquarters/branch c. Bank Size (core capital in Rupiah): • KBMI 1 (≤6 trillion) • KBMI 2 (6-14 trillion) • KBMI 3 (14-70 trillion) • KBMI 4 (>70 trillion)
2	Loan Focus Shift and Consumer Behavior	a. Observation of recent trends in loan focus shift from corporate loans to mortgage loans b. Factors driving the potential shift in loan focus c. Envisioned shifts in addition to mortgages d. Factors driving the envisioned shifts e. Adaptation of credit products and services to evolving consumer behavior changes f. Determinants of interest rate pricing and promotional activities if maintaining loan focus g. Identification of alternative sources of financing for the corporate sector
3	Digitalization and Cybersecurity	a. Impact of digitalization on the bank's credit approval process b. Implementation of new online platforms or tools for loan application and approval c. Utilization of AI for credit application and approval processes d. Balancing robust cybersecurity needs with providing a secure digital credit experience e. Observation of the impact of price competition or assertive pricing approaches in digitalization and cybersecurity on investment strategies
4	Climate Transitions and Risk Management	a. Offering credit products incentivizing climate-friendly practices b. Integration of climate risk assessments into credit approval processes c. Perception of climate transitions impacting credit supply strategy and risk management practices d. Perception of price competition impacting the ability to offer competitive rates for climate-friendly credit products
5	Practices and Challenges in MSMEs Lending	a. The significance of MSME financing in the bank's credit portfolio b. Key criteria used by the bank to evaluate MSME loan applications c. The main challenges faced by the bank in providing MSME financing d. Key growth areas or sectors for MSME lending that the bank is focusing on
6	Tourism Sectors Lending	a. The significance of the challenges faced by the bank in tourism sector financing b. Key criteria used by the bank to evaluate tourism sector loan applications c. The significance of tourism sector financing in the bank's credit portfolio
7	Mining	a. The significance of the challenges faced by the bank in

No	Part	Description
	Sectors Lending	mining sector financing b. How the bank assesses and mitigates risks associated with the mining sector c. Key criteria used by the bank to evaluate mining sector loan applications d. The significance of mining sector financing in the bank's credit portfolio
8	Additional Comments	Participants are encouraged to share any additional insights or comments regarding their bank's approach to credit supply in the current environment.

3.2 Data Analysis

This study employs both supervised and unsupervised learning methods. Data were gathered through online surveys targeting specific loan officers and bank management personnel cohorts, as well as from the Bank Indonesia General Banking Report. The supervised learning method is utilized to estimate the model and determine the supply of credit. Meanwhile, an unsupervised learning method is employed for bank clustering using clustering algorithms, as performed by Moldovan & Mutu (2015) and Mercadier et al. (2021).

This research aims to explore the behavior of banks in determining the supply of credit in Indonesia, utilizing statistical techniques to analyze data collected from various sources. The initial phase involves data collection through surveys and financial reports, as well as macroeconomic and household indicators. Following this, data preparation techniques such as data cleaning, handling missing values, and aggregating different data sources are essential to ensure consistency and readiness for analysis. Exploratory data analysis (EDA) is then conducted to understand data distribution and relationships between variables, along with feature selection and Principal Component Analysis (PCA) for dimensionality reduction, enhancing the relevance of the features used in subsequent modeling. This research framework is presented in Figure 1.

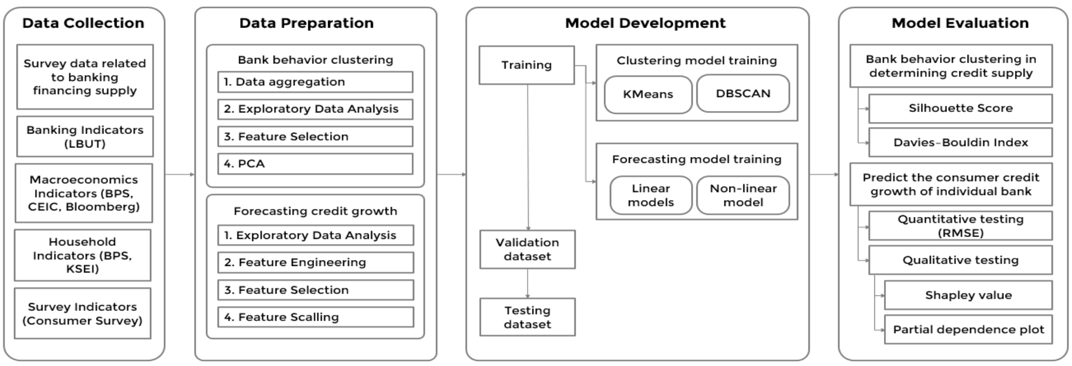

Figure 1. The Research Framework

3.2.1 Clustering of Banking Behavior

This study analyzes banking behavior in determining credit supply using unsupervised machine learning, specifically clustering, inspired by Ozgur et al. (2021). Data were sourced from two primary datasets: a survey on bank credit supply with 78 respondents and the Integrated General Bank Reports, including data such as consumer credit. The aim is to identify patterns in bank credit distribution, focusing on shifts from corporate loans to mortgages and other types of loans, as well as the factors driving these changes. The variables and their definitions are presented in Appendix (A2).

The data preparation involved several steps. First, survey data were aggregated by bank, followed by an exploratory data analysis (EDA) to understand key patterns. Feature selection was then performed to choose variables for the clustering model. Principal Component Analysis (PCA) was applied to reduce dimensionality, producing two main components: PCA1 representing factors behind the shift to mortgage credit and PCA2 representing other credit purposes (Abedin et al., 2023).

Two clustering techniques were applied to categorize the banks: k-Means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN). First, the k-Means algorithm, which clusters banks based on numerical attributes, was employed to identify hidden patterns in banking behavior (Abdulnassar & Nair, 2023). One challenge with k-Means is determining the optimal number of clusters (k) and the placement of initial centroids, which can affect clustering results. The elbow method was used to select the optimal number of clusters, and the algorithm iteratively assigned each point to its nearest centroid until stabilization was reached (Mercadier et al., 2021). The resulting clusters were visualized on scatter plots, with points labeled according to consumer credit growth and bank asset classification (KBMI). The Silhouette Score was used to evaluate the clustering performance, with the k-Means model yielding a score of 0.532, indicating reasonably good separation between the clusters (Caruso et al., 2020).

In addition to k-Means, the DBSCAN algorithm was employed to capture the underlying density distribution of the data. DBSCAN is effective at identifying clusters of varying shapes and sizes, especially in datasets with noise (Qian et al., 2024). The algorithm relies on two key parameters: Eps, which represents the maximum distance between two points to be considered part of the same neighborhood, and MinPts, which determines the minimum number of points required to form a dense region. Starting with a randomly chosen center point, DBSCAN searches for all points within the Eps radius. If the number of points within this distance meets or exceeds MinPts, the center point is designated as a core point. Any point within the Eps radius of a core point is also included in the cluster. This process iterates, expanding clusters by incorporating density-reachable points, until all points are categorized (Wei et al., 2024). Points that do not belong to any cluster due to low density are labeled as noise or outliers.

DBSCAN offers an advantage over k-Means in that it does not require specifying the number of clusters beforehand and is better suited for datasets with noise or irregular cluster shapes. By using DBSCAN, additional clusters were identified that reflected variations in credit supply behaviors that were not captured by k-Means. The combination of these two clustering techniques provided a more comprehensive view of the patterns within the data.

This study applies k-Means and DBSCAN to explore bank behavior concerning credit supply in Indonesia. The preprocessing steps involved data cleaning, handling missing values, and standardizing variable formats for consistency. Exploratory data analysis identified relationships between variables, and feature engineering improved the clustering features' relevance. The best clustering method will be selected and serve as a basis for forecasting credit growth within each bank cluster.

3.2.2 Forecasting Bank Credit Growth

This section explores the use of machine learning (ML) methodologies, specifically supervised machine learning through regression, to project consumer credit growth for each bank cluster. The forecasting approach is conducted for each cluster, where clusters were identified from prior analysis using k-Means and DBSCAN. Each cluster groups banks with similar behaviors related to credit supply, enabling forecasts that reflect these shared characteristics. This cluster-specific forecasting method aims to enhance accuracy in predicting consumer credit growth for each group of banks. The data includes banking indicators, macroeconomic indicators, household metrics, and survey data, sourced from Integrated Commercial Bank Reports (LBUT), the Central Bureau of Statistics (BPS), CEIC, Bloomberg, the Central Securities Depository (KSEI), and consumer surveys. The objective is to forecast consumer credit growth over a six-month horizon per cluster, using data from January 2017 to May 2024. Variables and their definitions are outlined in Appendix (A3).

Data preparation included several steps to optimize the regression model, with forecasting tailored to each bank cluster. The modeling process applied supervised regression techniques for each bank cluster, using both linear models—such as Linear Regression, Ridge Regression, Lasso Regression, and Elastic Net—and non-linear models like Support Vector Regression (SVR), k-Nearest Neighbors (kNN), Decision Tree, Random Forest, Gradient Boosting, Extreme Gradient Boosting (XGBoost), and Gaussian Process Regression (GPR). The model evaluation considered quantitative and qualitative assessments within each bank cluster to ensure robust and accurate forecasts. Quantitative evaluation used Root Mean Square Error (RMSE) to measure performance for each cluster model, while qualitative assessment included interpretability analysis through Shapley values and Partial Dependence Plots (PDP) to understand the impact of features In developing the forecasting model for each bank cluster, various macroeconomic indicators were used, including real GDP, household consumption, BI rate, consumer price index (CPI), exchange rates, 10-year government bond yields, export commodity price indices, and oil prices. Banking indicators like consumer credit, household metrics such as motor vehicle sales, wages, financial assets, and liabilities, and survey indicators, including the Consumer Confidence Index (CCI), were also incorporated. These diverse variables provided a comprehensive approach for forecasting future consumer credit growth tailored to each cluster's characteristics on predictions within each cluster.

4.Results and Analysis

4.1 Brief Summary of General Findings

This research surveyed to evaluate how banks adapt their credit supply practices in response to a multifaceted financial landscape. According to Figure 6, the distribution of bank participation in the survey, including 78 respondents, reveals that most respondents belong to the KBMI 1 category, providing banks with a core capital of less than 6 trillion Rupiah, representing 56.4% of the total participants. Banks classified under KBMI 2 (core capital between 6 and 14 trillion Rupiah) account for 26.9%, while those in KBMI 3 (core capital between 14 and 70 trillion Rupiah) contribute 10.3%. Banks with a core capital exceeding 70 trillion Rupiah (KBMI 4) represent only 6.4% of the respondents. These findings indicate a predominance of small to medium-sized banks in the survey, providing crucial insights into their adjustments to potential shifts from corporate loans to mortgage or other types of loans, evolving consumer behaviors, challenges related to digitalization and cybersecurity, climate transition risks, as well as practices and challenges in lending to Micro, Small, and Medium-sized Enterprises (MSMEs), the tourism sector, and the mining sector.

4.1.1 Loan Focus Shift and Consumer Behavior

As some banks shift their focus from corporate loans to mortgage loans, most banks (71.79%) maintain their loan portfolios with no significant changes (see Figure 2). Only a small number of banks have shown substantial increases or active diversification into mortgage lending, and these banks typically have higher mean asset levels. Conversely, approximately 12.82% of banks do not engage in mortgage lending, possibly due to strategic considerations or specific market segmentation. Overall, the trend toward focusing on mortgage loans has not yet become mainstream, and most banks continue to adhere to their existing loan strategies.

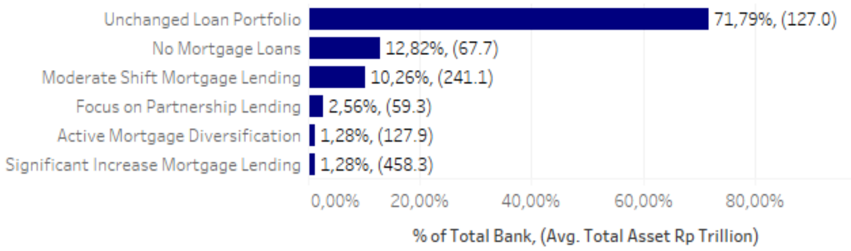

Figure 2. Distribution of Banks Based on the Shift in Loan Focus from Corporate Loans to Mortgage Loans

Most banks are shifting their loan focus primarily based on a "wait-and-see" approach, indicating a cautious stance amid uncertain market conditions, as illustrated in Figure 3. This approach is followed by other reasons, such as a focus on SMEs, strategic alignment, and loan expansion, although these factors have a smaller impact than the "wait-and-see" strategy. Banks opting for a "wait-and-see" approach generally have larger assets, suggesting that institutions with greater financial capacity delay decisions until market conditions become clearer.

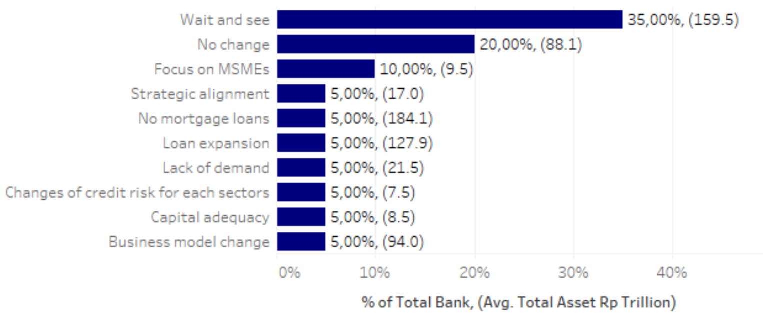

Figure 3. Distribution of Reasons for Shifting Loan Focus Among Banks

4.1.2 Digitalization and Cybersecurity

Digitalization and artificial intelligence (AI) have significantly transformed credit approval processes across various banking groups, with mid-sized banks (KBMI 3) experiencing the most considerable impact from these technologies (see Figure 4). This trend indicates that mid-sized and larger banks are leading in leveraging digitalization and AI to enhance their credit decision-making, reflecting a growing reliance on advanced technologies among banks with more significant resources and capabilities.

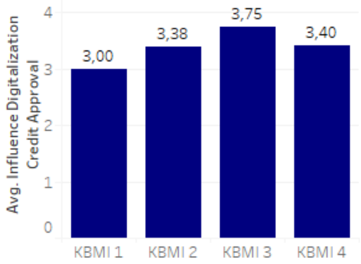

Figure 4. Mean Influence of Digitalization on AI Credit Approval by KBMI

However, as reliance on these technologies grows, so does the cybersecurity challenge. Figure 5 indicates that while most banks have not experienced a cyber attack, those that have faced such incidents report a higher level of impact, particularly among more prominent institutions. This pattern suggests a correlation between a bank's asset size and the severity of cyber attack impacts, highlighting the critical need for robust cybersecurity measures, especially for larger financial institutions.

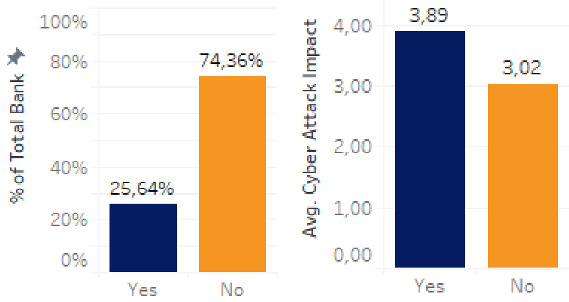

Figure 5. Mean Cyber Attack Impact and Proportion of Banks Experiencing Cyber Attacks

In response to these challenges, banks are balancing the need for robust cybersecurity with providing a smooth digital credit experience (see Figure 6).

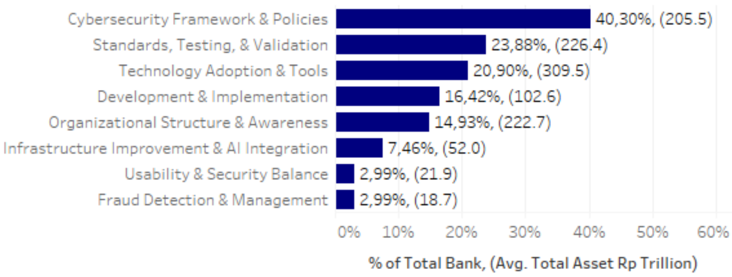

Figure 6. Prioritization of Cybersecurity Aspects Among Banks

As digitalization and AI continue to reshape the landscape of credit approval and cybersecurity, banks are encountering opportunities and challenges. While mid-sized and larger banks are leveraging these technologies to enhance their credit decision-making processes, they also face distinct challenges related to cybersecurity. Balancing advanced technological adoption with robust security measures is becoming increasingly critical.

4.1.3 Climate Transitions and Risk Management: Green Strategies for Sustainable Bank Lending

Climate change and the transition to a green economy increasingly impact the banking sector. While 50% of banks report changes in their business processes and portfolios due to these factors (see Figure 7), those implementing changes perceive the impacts as more significant. This finding suggests that although the prevalence of climate change and green economy influences is evenly distributed among the banks studied, these changes' perceived significance and impact vary.

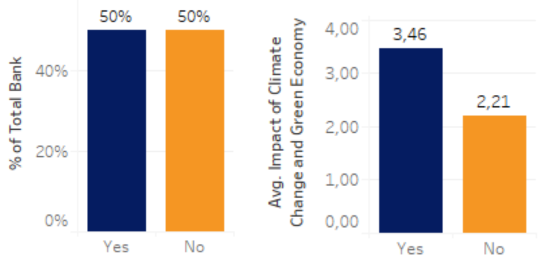

Figure 7. Comparing Climate Change Impact on Affected vs. Non-Affected

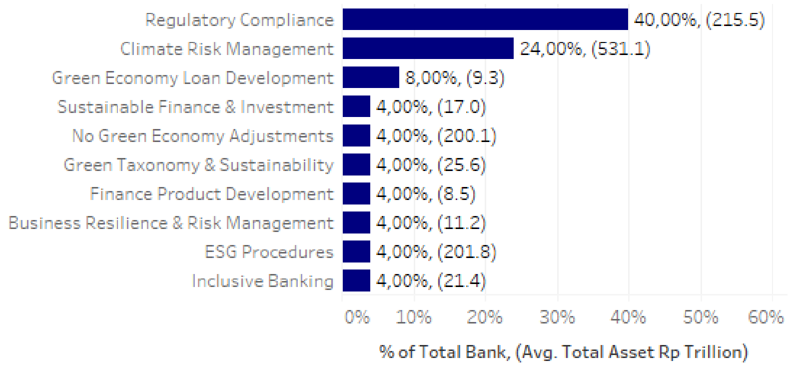

Figure 8. Distribution of Banks by Green Economy Risk Assessment Categories and Mean Assets

The varied responses among banks reflect differing strategic priorities and capacities. Banks have distinct focuses when assessing green economy risks, influenced by their asset size and strategic objectives. Most banks (40%) prioritize regulatory compliance, underscoring the growing regulatory demands in the financial sector concerning environmental standards and sustainability (see Figure 8). Additionally, 24% of banks emphasize climate risk management, highlighting the increasing importance of mitigating risks related to climate change.

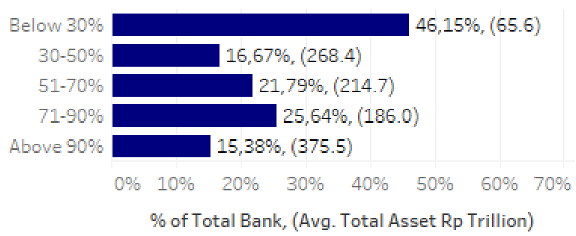

Figure 9. Analysis of Green Economy Loan Approval Rates and Bank Asset Size Correlation

Despite these efforts, green economy financing within banks' credit portfolios remains varied and is not yet a top priority for many institutions. Although some banks show high approval rates for green economy projects, most (46.15%) have approval rates below 30%, suggesting that many banks are still cautious or less focused on financing the green sector (see Figure 9).

4.1.4 Practices and Challenges in MSMEs Lending

The distribution of MSME financing within the credit portfolios of surveyed banks reveals significant variation. Approximately 31.1% of banks allocate MSME financing in 10-20% or 20-30% of their total credit portfolio, while another 31.1% have MSME financing of less than 10% (based on Figure 10). This indicates that most banks maintain MSME financing in the mid to low range. This pattern becomes more evident when comparing banks with MSME financing exceeding 40%, which tend to have smaller mean assets than those with MSME financing in the 10-30% range. Conversely, banks with less than 10% MSME financing generally have larger mean assets. This highlights the diversity in MSME financing strategies among banks and suggests a potential relationship between the proportion of MSME financing and bank asset sizes.

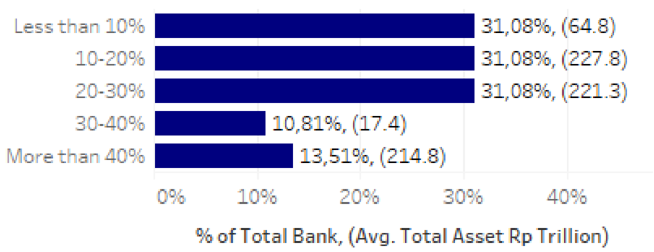

Figure 10. Distribution of MSME Loan Products by Bank Type and Mean Assets

Regarding loan products, "Buy Now, Pay Later" (BNPL) loans for MSMEs are the most offered, with 21.43% of banks providing this product (as shown in Figure 11). In contrast, products such as Warehouse Receipt Financing and Ultra Micro Financing are relatively rare, each offered by approximately 7.14% of banks. Regional government-supported MSME credit programs also show some level of participation, though not as prominently as BNPL. Other products like supply chain financing and bank guarantees are available but in smaller proportions. Banks not offering specific MSME loan products tend to have substantial assets, indicating they may focus on other loans or corporate sectors.

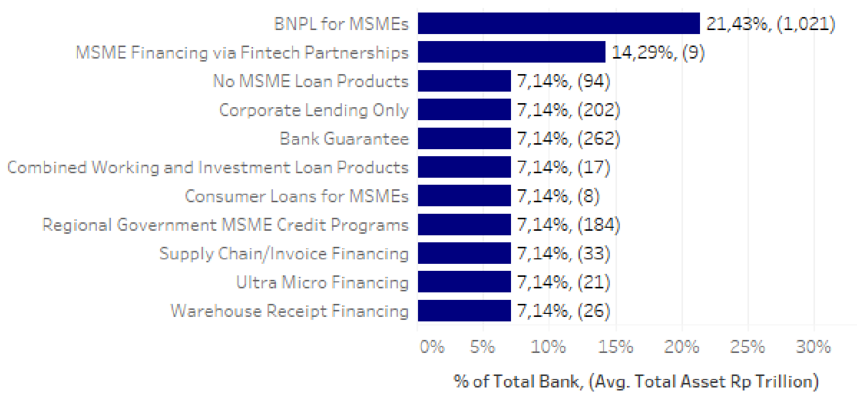

Figure 11. Distribution of MSME Loan Products by Bank Type and Mean Assets

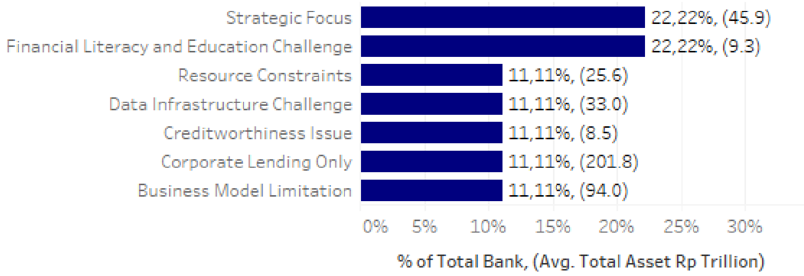

Figure 12. Key Challenges in MSME Financing Faced by Banks

Banks face significant challenges in financing Micro, Small, and Medium Enterprises (MSMEs). Key challenges include limitations in business models and strategic focus, affecting 11.11% of banks (according to Figure 12). This makes it difficult for these banks to shift attention from large corporate clients and tailor their services to MSMEs. Additionally, 11.11% of banks struggle with resource constraints and data infrastructure issues, which hinder their ability to process and manage MSME credit information effectively. Financial literacy and education challenges are the most significant hurdle, impacting 22.22% of banks. This highlights the need for programs to improve financial understanding among MSMEs. Banks must develop more inclusive strategies focused on MSMEs to address these challenges and enhance the infrastructure and resources supporting financing processes.

4.1.5 Practices and Challenges in Tourism Sectors Lending

Many banks often view the tourism sector as too risky and unpredictable, leading them to adopt more cautious approaches in managing loans for this industry. To mitigate risks, banks generally implement more selective strategies, such as comprehensive credit analysis, regular credit reviews, credit history checks, and the application of financial and operational covenants. When evaluating loan applications in the tourism sector, banks primarily prioritize industry experience and the economic strength of applicants. They also consider cost-benefit analysis, potential negative issues, the background of management and shareholders, business trends, regulations, and management experience. The main priorities for banks when assessing loan applications for the tourism sector are experience, capital, and comprehensive risk evaluation.

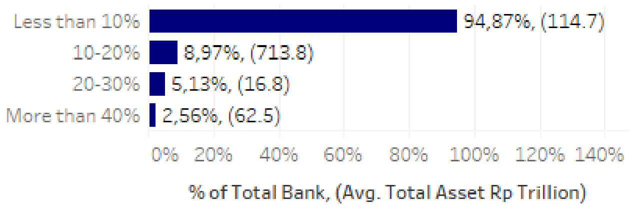

Figure 13. Distribution of Banks' Exposure to Tourism Sector Financing

Despite these careful considerations, data reveals that the tourism sector is relatively minor in most banks' credit portfolios. Nearly 95% of banks have shallow exposure to tourism financing, with less than 10% of their credit portfolio allocated to this sector (see Figure 13). Only a few banks have moderate to high exposure to tourism financing, and these banks have varying asset sizes. Overall, the data suggests that most banks take a cautious approach to financing the tourism sector, likely because this sector tends to be vulnerable to external shocks such as economic downturns or global events.

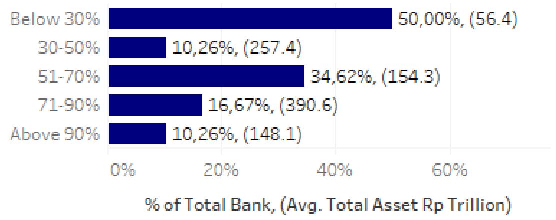

Figure 14. Distribution of Loan Approval Rates for the Tourism Sector by Banks

In line with this cautious stance, the approval rates for loans to the tourism sector also reflect a similar trend. Figure 14 shows that most banks have a low loan approval rate for the tourism sector, with 50% approving less than 30% of loan applications. This suggests that banks are cautious or have strict criteria when granting loans to businesses in this sector. Meanwhile, only a small percentage of banks (10.26%) have a loan approval rate above 90%, indicating that very few banks highly support the tourism sector in lending. Additionally, banks with higher mean assets tend to have higher loan approval rates for this sector, possibly because they have a greater capacity to take on risk.

4.1.6 Practices and Challenges in the Mining Sectors Lending

In the mining sector, banks face unique challenges and risks when considering lending opportunities. One of the primary concerns for banks is commodity price risk, given the inherent volatility of commodity prices. This fluctuation necessitates careful risk assessment and mitigation strategies. Environmental impact is another significant factor, as mining operations must comply with stringent environmental regulations. Therefore, banks pay close attention to a company's industry experience and regulatory adherence, underscoring the importance of a solid track record and an in-depth understanding of applicable rules. Furthermore, the strength and stability of sponsors and supporting groups are vital considerations, reflecting the need for robust structural support from related parties. While financial covenants and credit history are also evaluated, they tend to have a less substantial impact than the primary concerns.

When evaluating loan applications from mining companies, banks strongly emphasize a comprehensive analysis of the client's profile. This aspect is deemed the most critical factor in the lending decision. Experience and regulatory compliance are also highly prioritized, reflecting the bank's focus on an applicant's track record and adherence to regulations. Additionally, banks carefully assess commodity market risks due to the high volatility of commodity prices. Although factors such as project feasibility, future industry trends, and credit analysis are also considered, they carry relatively less weight than the bank's primary focus on the client's overall evaluation, industry experience, and regulatory compliance.

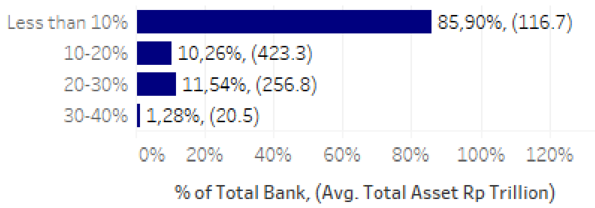

Figure 15. Distribution of Mining Sector Financing in Bank Credit Portfolios

The significance of mining sector financing within bank credit portfolios is generally limited. As depicted in Figure 15, most banks allocate a relatively small portion of their credit portfolios to the mining sector. Specifically, about 85.9% of banks allocate less than 10% of their total credit portfolio to mining, indicating a limited focus on this sector. Conversely, only a small fraction of banks have a mining sector financing share between 30-40%, and those with higher allocations typically have smaller asset sizes. This pattern suggests that mining sector financing holds limited importance for most banks, which prefer to maintain relatively low exposure to this sector.

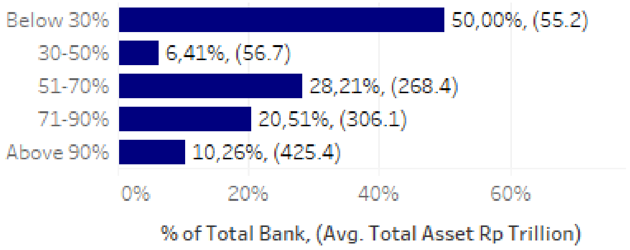

Figure 16. Distribution of Loan Approval Rates for the Mining Sector by Banks

Further reinforcing this conservative approach, Figure 16 highlights the distribution of loan approval rates for the mining sector across banks. It reveals that many banks are cautious about lending in the mining sector, with half of the banks (50%) having a loan approval rate below 30%. Only a small percentage (10.26%) of banks are willing to approve more than 90% of loan applications in this sector. Moreover, a noticeable correlation exists between a bank's asset size and loan approval rate: banks with larger mean assets tend to have higher loan approval rates. This trend indicates that larger banks may exhibit more flexibility or a less conservative approach in granting loans to the mining sector compared to smaller banks with more limited assets.

4.2 Credit Supply Challenges and Shifts in Banks

Based on Table 2, the analysis of credit supply challenges across banks of varying sizes (KBMI) reveals several notable patterns and differences that reflect differing bank behaviors. Larger banks (KBMI 3 and KBMI 4) face more pronounced shifts in mortgage demand compared to smaller banks (KBMI 1). Specifically, the mean scores for mortgage demand shifts are 3.25 and 3.60 for KBMI 3 and KBMI 4, respectively, in contrast to a lower mean score of 2.89 for KBMI 1. This indicates that larger banks are significantly more impacted by changes in mortgage demand, which could be attributed to their larger operational scales and greater capacity to manage higher transaction volumes and complex mortgage portfolios.

Table 2. Indicators of Credit Supply Challenges and Shifts in Banks Based on KBMI

Indicators	KBMI 1	KBMI 2	KBMI 3	KBMI 4	Mean
Demand shift to mortgage	2.89	3.57	3.25	3.60	3.33
Risk-driven shift to mortgage	2.82	3.57	2.88	3.00	3.07
Regulatory impact on mortgage shift	2.75	3.48	2.88	3.20	3.08
Mortgage shift for MSMEs	3.61	3.43	2.75	3.60	3.35
Mortgage shift for small projects-base financing	2.91	3.00	2.50	3.00	2.85
Mortgage Shift for Syndicated with other banks for large project	3.05	3.14	3.25	3.20	3.16

Indicators	KBMI 1	KBMI 2	KBMI 3	KBMI 4	Mean
Digitalization's impact in credit supply	3.00	3.38	3.75	3.40	3.38
Cybersecurity in credit supply	3.14	3.67	2.75	3.00	3.14
Climate change challenges in credit supply	2.57	3.00	3.13	4.00	3.17
Working capital lending challenges in credit supply	4.18	4.19	3.88	4.20	4.11
Investment loans challenges in credit supply	3.84	3.71	3.25	4.00	3.70
Micro loan challenges in credit supply	3.05	3.24	3.13	3.00	3.10
KUR in credit supply	2.45	3.33	3.00	3.20	3.00
Tourism lending challenges to in credit supply	3.30	3.14	3.38	3.40	3.30
Mining lending challenges to in credit supply	3.23	3.24	2.13	4.00	3.15

In terms of risk-driven shifts toward mortgages, medium-sized banks (KBMI 2) report a higher mean score of 3.57, suggesting they experience more substantial impacts from risk-related factors compared to smaller banks, which have an mean score of 2.82. Medium-sized banks might be more vulnerable to fluctuations in credit risk and the associated impacts on mortgage lending.

Similarly, regulatory impacts on mortgage shifts are also notably significant for medium-sized and larger banks, with mean scores of 3.48 for KBMI 2 and 3.20 for KBMI 4, compared to a lower mean score of 2.75 for KBMI 1. This suggests that larger and medium-sized banks face greater regulatory pressures due to their broader scope of operations and the complexity of their regulatory compliance requirements.

Regarding mortgage credit for Micro, Small, and Medium Enterprises (MSMEs), smaller banks demonstrate a higher level of engagement, with an mean score of 3.61. This contrasts with larger banks, which show greater variability in their support for MSMEs. This trend indicates that smaller banks focus more on supporting smaller enterprises and may have specialized programs tailored for MSMEs. In financing challenges, smaller banks encounter fewer difficulties with small project financing, reflected in an mean score of 2.91, but face moderate challenges with large project financing, scoring 3.05. This suggests that while smaller banks may handle smaller projects relatively easily, they experience increased complexity and difficulty when dealing with larger projects.

The effects of digitalization and cybersecurity present more significant challenges for larger banks. Large banks have higher mean scores for digitalization (3.75) and cybersecurity (3.00), indicating that they face more intense issues related to technology adoption and securing digital transactions. This increased challenge may be due to their operations' larger scale and complexity, necessitating greater investments in technological infrastructure and security measures.

Larger banks also report greater challenges related to climate change and working capital loans. The mean score for climate change challenges is 3.17 for larger banks, highlighting the significant impact of environmental risks on their operations. Similarly, the mean score for working capital lending challenges is 4.11, indicating substantial difficulties in managing and providing working capital. This is likely due to their financial activities' larger scale and complexity and the need to balance extensive portfolios.

Investment and microloan challenges are also more pronounced for larger banks, with mean scores of 3.70 for investment loans and 3.10 for microloans. This suggests that larger banks face higher obstacles in managing investment and micro-lending portfolios, which may be influenced by their larger and more diverse credit portfolios and the associated risks.

4.3 Clustering Bank Behavior in Determining Supply of Credit

4.3.1 Choosing the Best Clustering Model for Bank Grouping

The clustering results from the k-Means algorithm indicate that bank behavior is generally divided into two clusters, represented by red areas (cluster labeled ●) and blue areas (cluster labeled x). As illustrated in Figure 16, each data point is labeled according to the bank's code. The k-Means clustering results yield a Silhouette Score of 0.532, which suggests that the two identified clusters are reasonably well-separated in classifying banks. This finding aligns with the research by Caruso et al. (2020) and Ozgur et al. (2021), which states that effective clustering can enhance the understanding of bank behaviors. Each bank is represented with a marker color reflecting the direction of year-on-year consumer credit growth in July 2024. Banks showing positive growth are marked in blue, while those experiencing negative growth or contraction are marked in red. The analysis reveals that 77% of banks facing a contraction in consumer credit exhibit similar characteristics, particularly in shifting their focus on credit distribution.

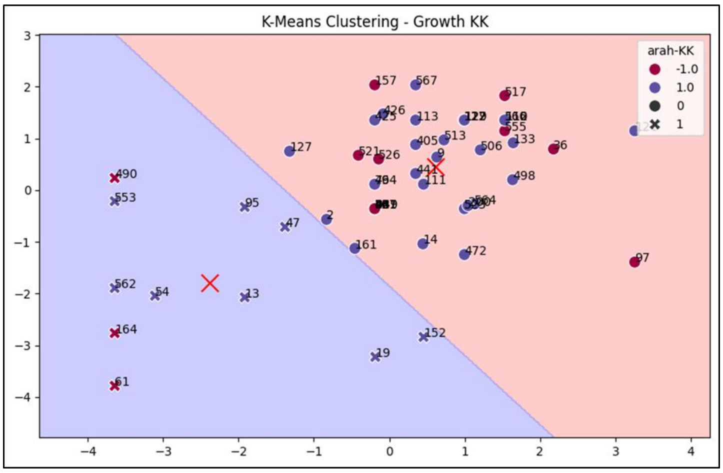

Figure 17. K-Means Clustering by Consumption Credit Growth

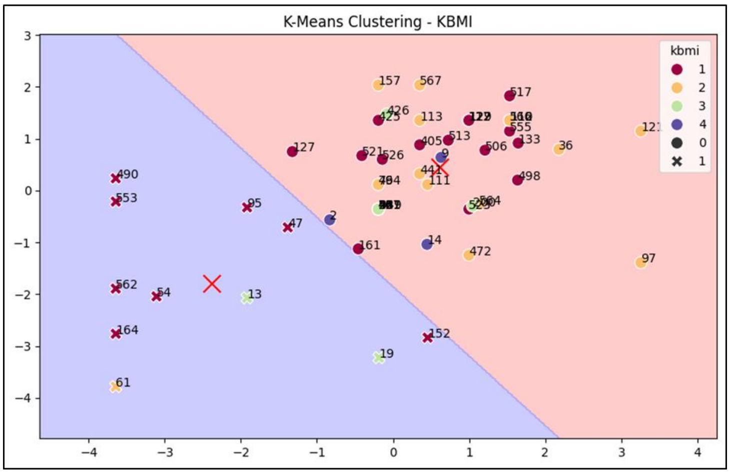

Figure18. K-Means Clustering by KBMI (Bank Size)

Furthermore, distinct patterns among different bank sizes are revealed by the clustering results using the k-Means algorithm, as shown in Figure 18. Each bank is marked with a color corresponding to its size based on the Bank Group by Core Capital (KBMI): red for KBMI 1 banks, yellow for KBMI 2, green for KBMI 3, and blue for KBMI 4. According to the results, all KBMI 4 banks and nearly all KBMI 2 banks share similar characteristics in their shift of focus on credit distribution. This is consistent with findings by Yuan et al. (2022), which highlight that larger banks often have more stable growth patterns. In contrast, banks in the KBMI 3 and KBMI 1 categories exhibit more mixed characteristics.

Additionally, the DBSCAN algorithm yields a Silhouette Score of 0.487, revealing that data points are grouped into several clusters based on the arah-KK parameter, which reflects the direction of growth for a certain metric, likely credit growth. These findings support the research conducted by Pranata et al. (2023), highlighting the effectiveness of clustering techniques in analyzing financial data. The markers in the visualization represent three distinct growth categories: positive (blue), negative (red), and neutral (black). Specifically, red markers (labeled -1.0) indicate data points associated with negative growth, while blue markers (labeled 1.0) signify positive growth. Black markers (labeled 0) denote neutral or unchanged growth. This classification enables a clear understanding of how banks are performing in terms of credit growth, facilitating better decision-making for stakeholders.

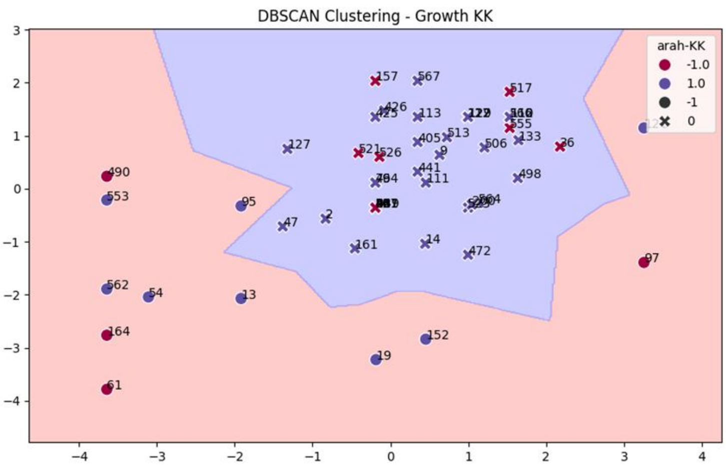

Figure 19. DBSCAN Clustering by Consumption Credit Growth

The background colors in Figure 19 correspond to the regions formed by the clustering algorithm. The red background indicates areas dominated by entities with negative growth, while the blue background highlights regions where positive or neutral growth is more prevalent. A significant concentration of entities with negative growth is observed in the left, red-shaded area, suggesting that these banks may face challenges or adverse market conditions. On the other hand, those with positive growth are spread across a broader range of areas, with a higher concentration in the center and right, blue-shaded areas, indicating healthier growth patterns. Neutral points are found across various regions but tend to overlap more with areas of positive growth, suggesting potential opportunities for improvement. These insights underscore the importance of clustering analysis in understanding banking behaviors and growth trends.

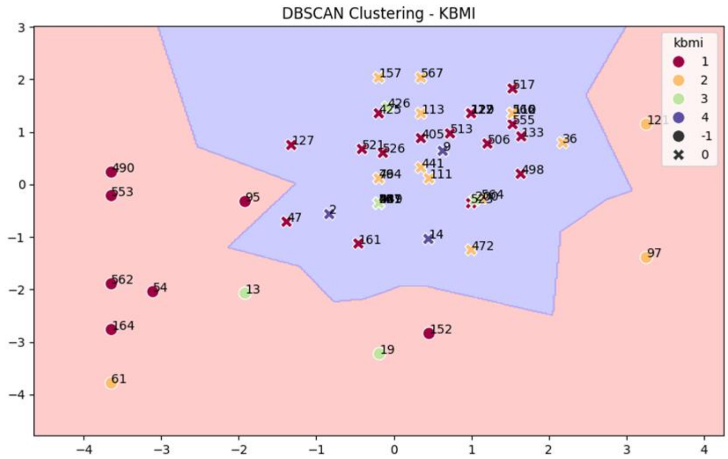

Figure 20. DBSCAN Clustering by KBMI (Bank Size)

Further insights from the DBSCAN clustering results reveal distinct patterns among different bank groups categorized by their KBMI classification. In Figure 20, each bank is marked with a color corresponding to its KBMI classification: red for KBMI 1, yellow for KBMI 2, green for KBMI 3, blue for KBMI 4, and black for neutral or undefined categories (-1 and 0). The results suggest that KBMI 1 banks (in red) are primarily concentrated in the red-shaded region on the left side of Figure 20, indicating a clustering of smaller banks facing similar challenges or trends. This observation aligns with previous research by Bello et al. (2023), which found that smaller banks often experience more volatility. Meanwhile, KBMI 2 banks (in yellow) and KBMI 3 banks (in green) are spread across both the red and blue-shaded regions, suggesting varied characteristics among these mid-sized banks. Lastly, KBMI 4 banks (in blue) are clustered more tightly in the central blue-shaded region, representing larger banks with more consistent trends or behaviors.

The analysis reveals that KBMI 4 banks and some KBMI 3 banks share more similarities in terms of their positioning in the cluster, while KBMI 1 banks show a higher degree of separation from the others, indicating distinct behaviors or strategic focuses. KBMI 2 banks display more diverse characteristics as they are distributed across different clusters and regions. Overall, the clustering shows clear distinctions between smaller and larger banks, with some overlap and diversity within the mid-sized bank categories.

The clustering results using k-Means and DBSCAN show that both methods successfully group bank behaviors based on consumer credit growth and bank size. k-Means creates two distinct clusters with a Silhouette score of 0.532, indicating a clear separation between the clusters, which makes it effective in identifying credit growth patterns and differences in bank characteristics, particularly based on bank size (KBMI). Additionally, the k-Means visualization is easier to interpret because it produces clearly defined clusters, facilitating further analysis. On the other hand, DBSCAN, with a Silhouette score of 0.487, results in a more diverse cluster distribution and is more sensitive to noise, making the separation less clear than k-Means. Therefore, k-Means is chosen as the best clustering model due to its ability to produce stable, well-defined clusters that are easier to understand in the context of analyzing credit growth and bank size.

4.3.2 Characteristics of Banks in Each Cluster

The k-Means clustering results based on the survey, using data from July 2024 (YoY), indicate that bank behavior can be grouped into two clusters, reflecting differences in characteristics across various aspects of credit and external challenges. Cluster 1 consists of banks with relatively smaller total assets, totaling Rp 47,636 trillion, and demonstrates high growth in consumer credit, with a mean of 634.21%. In contrast, Cluster 2, with significantly larger total assets of Rp 163,786 trillion, shows a much lower consumer credit growth at 46.56% (see Table 3). This suggests that banks in Cluster 1 prioritize consumer credit in their strategies despite having fewer assets. However, an interesting shift is observed in the aspect of investment credit: Cluster 1 experiences a decline, with a mean growth of -0.56%, while Cluster 2 shows a significant positive increase of 76.86%. These findings suggest that while Cluster 1 focuses more on consumer credit, Cluster 2 demonstrates a more aggressive approach to investments.

Table 3. Comparison of Banking Performance Indicators Across Clusters

This table presents the mean values of each indicator, categorized by Cluster 1 and Cluster 2, highlighting the differences in banking performance across these two clusters, July 2024.

No.	Indicators	Cluster 1	Cluster 2
1	Total Assets (Rp trillion)	47,636	163,786
2	Consumer Credit Growth (%)	634.21	46.56
3	Investment Credit Growth (%)	-0.56	76.86
4	Working Capital Credit Growth (%)	30.09	18.91
5	Credit Growth (%)	31.09	15.75
6	Demand Shift to Mortgage	1.89	3.65
7	Risk-driven Shift to Mortgage	2.11	3.51
8	Regulatory Impact Shift to Mortgage	2	3.34
9	Loan Shift to MSMEs	3.21	3.65
10	Loan Shift to Small Project Financing	2.25	3.27
11	Loan Shift to Syndicated Large Projects	2.68	3.36
12	Digitalization Impact	2.96	3.44
13	Cybersecurity Impact	2.39	3.73
14	Climate Change Challenge	2.21	3.02
15	Tourism Sector Challenge	2.68	3.61
16	Mining Sector Challenge	2.5	3.5
17	MSME Working Capital	3.85	4.42
18	MSME Investment Loan	3.8	3.86
19	MSME Micro Loan	2.4	3.45
20	MSME KUR	1.55	3.4

Furthermore, in terms of demand shifts, there are striking differences between the two clusters. Cluster 2 has higher values in the shift toward housing credit, which may be influenced by various factors such as risk, regulatory impact, and public demand. The scores achieved by Cluster 2 are 3.51 for risk, 3.34 for regulatory impact, and 3.65 for public demand. These figures indicate that banks in Cluster 2 are more responsive to various external factors affecting the housing sector, in contrast to banks in Cluster 1, which show lower scores on these indicators. The more limited response from banks in Cluster 1 reflects a lack of adaptation to changing needs in the housing sector, which could pose challenges in maintaining their competitiveness.

In facing external challenges, banks in Cluster 2 also show higher scores in the aspects of digitalization and cybersecurity, with scores of 3.44 and 3.73, respectively. This suggests that banks in Cluster 2 may have a better understanding of the importance of technology and data protection in their operations. Additionally, this cluster also records higher scores in challenges related to climate change, as well as the tourism and mining sectors, compared to Cluster 1. These findings indicate that banks in Cluster 2 may be more exposed to external risks and, therefore, require stronger and more comprehensive adaptation strategies to address various emerging challenges.

Moreover, Cluster 2 demonstrates a greater commitment to financing Micro, Small, and Medium Enterprises (MSMEs). This is evident from the higher scores on indicators such as working capital for MSMEs, MSME investment loans, as well as micro-financing and People's Business Credit (KUR). The higher values in Cluster 2 reflect the focus of banks in this group on supporting MSME financing, which can encourage local economic growth and contribute to the development of the small business sector. With this support, banks in Cluster 2 help promote job creation and enhance the overall welfare of the community. Based on this bank performance, the characteristics of the bank groups in Cluster 1 and Cluster 2 are summarized in Table 4.

Table 4. Characteristics of Bank Groups in Cluster 1 and Cluster 2

No.	Aspect	Cluster 1	Cluster 2
1	Total Assets	Has relatively smaller total assets	Has significantly larger total assets
2	Credit Focus	More focused on consumer credit	More aggressive investments
3	Adaptation to Housing Demand	Limited response to housing demand	Stronger response to housing demand
4	Technology Implementation	Lower levels of digitalization and cybersecurity	More advanced in digitalization and cybersecurity
5	Response to External Challenges	Less responsive to external challenges such as climate change	More responsive to external challenges like climate change
6	Support for MSMEs	Lower support for MSME financing	Greater focus on financing and developing MSMEs
7	Sustainability	Lacks a specific focus on sustainability	Begins to consider sustainability in financing
8	Geographic Focus	More oriented toward local markets	Tends to focus on syndicated and large projects
9	Regulatory Impact	Less affected by regulatory policies	More adaptive and responsive to policy changes
10	Involvement in Tourism Sector	Lower involvement in the tourism sector	More engaged in the tourism sector

No.	Aspect	Cluster 1	Cluster 2
11	Approach to Working Capital Credit	More conservative approach to working capital credit	More open to increasing working capital credit
12	Credit Accessibility for Small Projects	Greater focus on small-scale projects	More involved in large syndicated projects

4.4 Forecasting Banking Credit Growth

The table below presents a list of variables used in the forecasting model. Each variable includes the number of observations (Obs), the mean, and the standard deviation (Std. Dev), providing descriptive statistics of the data utilized. The variables cover a range of macroeconomic indicators, financial metrics, and consumer survey data, offering key insights into economic trends and market behaviors.

Table 5. Summary Statistics

No	Variable	Obs	Mean	Std. Dev
1	Credit Growth (KK)	91	218.283	17.586
2	Real GDP (GDPRL)	96	2814631.000	243909.100
3	Real Household Consumption (CSPRL)	96	1538084.000	115874.100
4	Consumer Price Index (IHK)	96	143.247	9.457
5	USD/IDR Exchange Rate (EXRATE)	96	14581.340	800.714
6	Indonesia's Export Commodity Price Index (IHKEI)	96	105.998	13.938
7	BI Rate (BI_RATE)	96	4.883	0.987
8	Purchasing Managers' Index (PMI)	89	50.267	4.282
9	World Oil Price (P_OIL)	89	68.566	19.236
10	10-Year Covernment Bond Yield (YIELDSBN_10Y)	96	6.957	0.549
11	Credit Default Swap (CDS)	89	101.611	29.184
12	Volatility Index (VIX)	89	19.175	7.766
13	Car Sales (CAR_SALES)	89	79402.420	21415.640
14	Motorcycle Sales (MOTOR_SALES)	89	467365.900	119474.000
15	Consumer Survey - Consumer Confidence Index (SK_IKK)	89	115.772	14.619
16	Consumer Survey - Current Economic Condition Index (SK_IKE)	89	101.075	20.077
17	Consumer Survey - Consumer Expectation Index (SK_IEK)	89	130.470	10.312
18	Consumer Survey - Current Income Index (SK_IPS)	89	108.895	22.044
19	Consumer Survey - Job Availability Index (SK_IKLK)	89	91.034	24.774
20	Consumer Survey - Durable Goods Purchase Index (SK_IPBTL)	89	103.295	15.301
21	Consumer Survey - Expected Income Index (SK_IEP)	89	138.354	11.030
22	Consumer Survey - Expected Job Availability Index (SK_IEKLK)	89	123.385	10.370
23	Retail Sales Survey - Real Sales Index (SPE_IPR)	89	210.725	15.402
24	Residential Property Price Index (IHPR)	96	212.618	7.962

No	Variable	Obs	Mean	Std. Dev
25	Wages (WAGE)	90	2866096.000	144535.000
26	Household Net Financial Worth (HH_Net_Fin_Worth)	89	1906531.000	332917.300
27	Household Financial Assets (HH_Fin_Asset)	89	4560595.000	830129.900
28	Household Liabilities (HH_Liabilities)	89	2654064.000	515077.500
29	Household Consumption (HH_Consumption)	89	8975898.000	1048012.000
30	Household Net Financial Worth ti Household Consumption Ratio (Net_Fin_Worth_Cons)	89	21.132	1.876
31	Household Investment (HH_Investment)	89	701359.800	365367.800
32	Individual Savings Deposit (DPK Perseorangan)	86	3328396300.000	436239908.000
33	Household Securities Ownership (Efek_RT_Nominal Total)	89	698.173	361.961
34	Household Outstanding Shares of Securities (Efek_RT_Outstanding_Shares)	87	995.097	373.595
35	Household Securities Market Capitalization (Efek_RT_Market_Capitalization)	87	576.763	289.028

4.4.1 Forecasting Credit Growth for Cluster 1

In conducting the forecasting of credit growth for banks in Cluster 1, we chose the Support Vector Regression (SVR) model due to its effectiveness in handling non-linear relationships and its robustness against overfitting. The SVR model demonstrates balanced Root Mean Squared Error (RMSE) values between the training and testing data, with a RMSE Train of 0.395 and a RMSE Test of 0.782 (see in Appendix (A4)). The low RMSE Train indicates the model's capability to learn data patterns, while the higher RMSE Test suggests challenges in generalization to new data. In contrast, XGBoost exhibits the lowest RMSE Test, indicating excellent generalization ability.

We also observed overfitting in models like Decision Tree, which showed a low RMSE Train but a high RMSE Test, indicating that the model is too complex and memorizes the noise in the training data. Conversely, the Linear Regression model displayed relatively high RMSE Train and RMSE Test values, suggesting potential underfitting due to its simplicity in capturing data patterns. By selecting the SVR model, we achieve stable and consistent predictions, while also considering other factors such as model interpretability and computational speed in determining the best model for use.

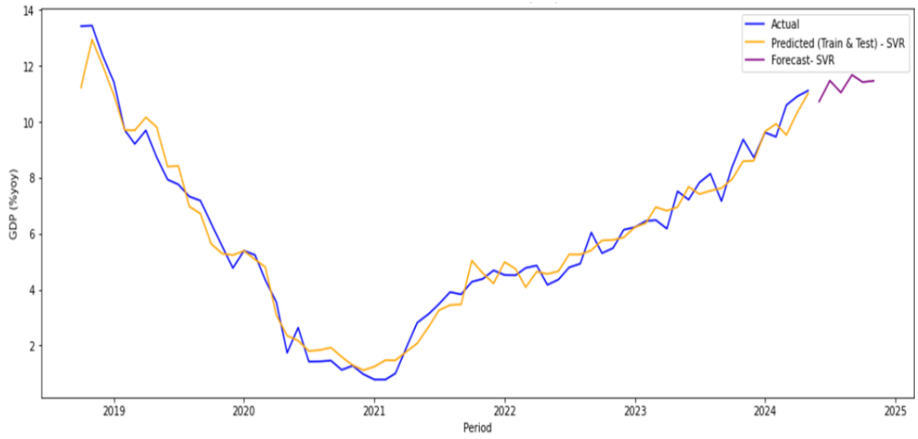

Figure 21. In-sample & Out-of-sample Prediction with SVR for Cluster 1

The model predictions for the training and testing data are visualized for the group of banks within cluster 1, as shown in Figure 21. This graph displays the blue line as the actual credit growth data, the orange line as the predictions from the SVR model, and the purple line as the forecast for future periods. The analysis indicates that the orange line closely follows the blue line, suggesting that the model effectively captures the credit growth patterns within this cluster with adequate accuracy. However, for the future periods represented by the purple line, there is greater uncertainty. Therefore, it is essential to utilize evaluation metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) to assess the model's prediction accuracy and to consider external factors that may influence credit growth fluctuations in the future.

To enhance the model's interpretability, an analysis of the variables with the greatest impact on credit growth forecasts was conducted using feature importance techniques, as shown in Figure 21. This analysis specifically focuses on the banking group in cluster 1, identified based on similar behaviors in credit supply. The results show that Consumer Credit Growth (g_kk) and Real GDP Growth (g_gdprl) have the highest impact, indicating that consumer credit growth and real GDP are the primary drivers of credit growth forecasts for this group. Other influential factors, such as the Consumer Survey - Current Income Index (sk_ips) and Household Liabilities (hh_liabilities), suggest that household income and liabilities also play a significant role in the forecasts. By identifying these variables, the model offers a clearer understanding of the factors that drive predictions for the banking group in cluster 1, improving transparency and helping prioritize areas for further analysis.

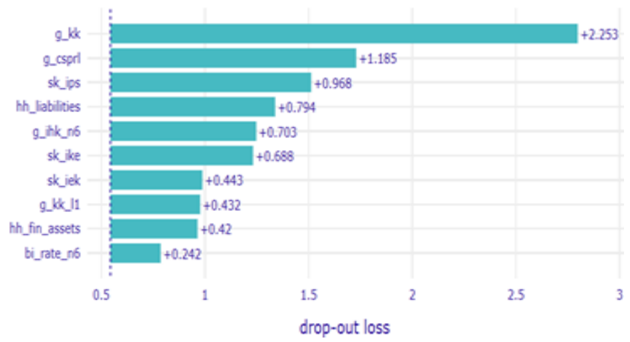

Figure 22. Feature Importance for Cluster 1

4.4.2 Forecasting Credit Growth for Cluster 2

In this analysis of cluster 2, we forecasted credit growth using twelve different algorithms and found that the SVR model yielded the best results. The SVR model demonstrates a balanced RMSE between the training (1.449) and testing (3.040) datasets, as presented in Appendix (A5). Selecting a model with balanced RMSE is crucial for minimizing the risk of overfitting and ensuring that the model performs reliably when applied to new data. Although other models had lower RMSE values for the training set, such as Gaussian Process Regression, their performance on the testing set was significantly poorer, indicating potential overfitting. This SVR model allows for more accurate predictions of credit growth, enabling banks within cluster 2 to make more precise and strategic decisions in planning their credit supply.

The visualization of the prediction results for both the training and testing data, shown in Figure 23, provides valuable insights into the model's performance. This graph illustrates how the SVR model forecasts credit growth for the banks in cluster 2, with the blue line representing actual credit growth, the orange line showing the SVR predictions on the training and testing data (in-sample), and the purple line indicating the forecast results using the same SVR model. The SVR model effectively captures the underlying patterns in the data, as evidenced by its ability to closely follow fluctuations in credit growth in both in-sample data and forecasted results, although some deviations occur, particularly towards the end of the forecast period. These findings highlight the model's good generalization capabilities, providing a strong basis for improved decision-making moving forward.

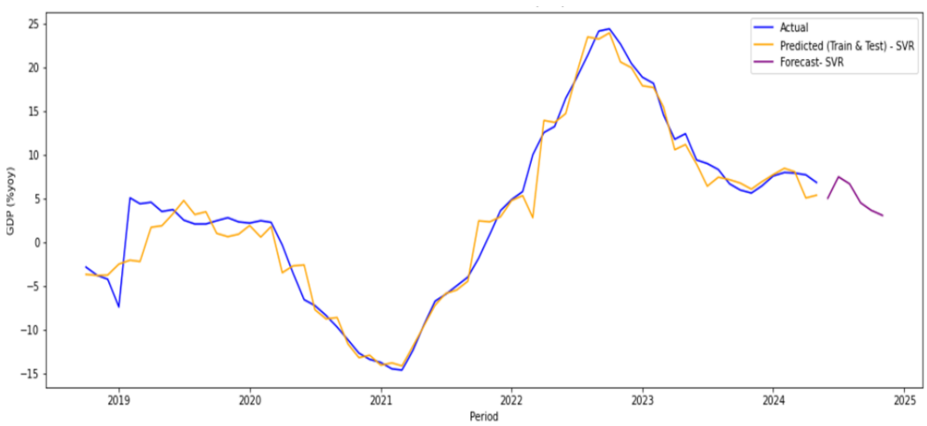

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Figure 23. In-sample & Out-of-sample Prediction with SVR for Cluster 2

The interpretability analysis of the model, which includes feature importance (Figure 23), enhances our understanding of the variables influencing credit growth forecasts in cluster 2, which consists of various banks. The feature importance indicates that the growth of the consumer price index (g_ihk) is the most significant variable, with a positive impact of +4.465. This suggests that an increase in the consumer price index is associated with higher credit growth, reflecting increased consumer spending and economic activity that benefit the banks within this cluster. Additionally, the growth of real GDP (g_gdprl), which has a positive impact of +4.104, shows that overall economic growth plays an important role in driving credit demand, as a strong economy can lead to increased bank lending.

In addition to these two main factors, other important variables influencing credit growth forecasts in cluster 2 include the Indonesia export commodity price index (ihkei), growth of household liabilities (g_hh_liabilities), and the consumer survey - consumer confidence index (sk_ikk). The positive contributions from these variables indicate that factors such as export commodity prices and consumer confidence also affect credit demand from bank customers. For example, higher export prices can improve economic conditions within cluster 2, subsequently boosting credit demand, while higher consumer confidence can encourage customers to take out loans for consumption and investment. Understanding these relationships helps bank management in cluster 2 identify key areas to focus on to enhance their credit growth strategies.

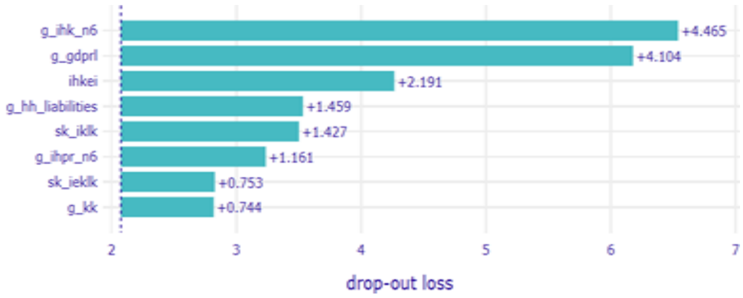

Figure 24. Feature Importance for Cluster 2

5. Implication / Policy Recommendation

To enhance the stability and effectiveness of bank intermediation in Indonesia, a series of policy recommendations is presented. First and foremost, it is important to strengthen regulatory frameworks. This entails the enhancement of oversight mechanisms to ensure that banks comply with prudent risk management practices, facilitated through regular stress testing and vigilant monitoring of credit portfolios.

Furthermore, the promotion of technological integration within the banking sector is of significant importance. Encouraging banks to adopt digital technologies and artificial intelligence can lead to streamlined credit approval processes while also providing incentives for investment in cybersecurity to protect against emerging digital threats.

Additionally, it is necessary to develop sector-specific strategies, particularly those focused on micro, small, and medium enterprises (MSMEs). Initiatives aimed at enhancing financial literacy among MSMEs can improve their access to credit, while targeted support for resource-constrained banks can facilitate the creation of loan products tailored to the needs of MSMEs. For high-risk industries, including tourism and mining, the development of tailored risk assessment frameworks is warranted. Such frameworks would encourage collaboration between banks and industry experts to better manage sector-specific risks and promote sustainable practices. Additionally, fostering green financing emerges as a vital component of this policy framework. Incentives for banks to offer green finance products, coupled with the mandatory incorporation of climate risk assessments into credit approval processes, will ensure that environmental considerations are integrated into lending decisions.

Lastly, the integration of Regulatory Technology (RegTech) and Supervisory Technology (SupTech) is poised to transform compliance and oversight within the banking sector. RegTech has the potential to improve compliance and risk management through automated reporting, advanced analytics for risk assessment, and enhanced Know Your Customer (KYC) and Anti-Money Laundering (AML) processes. Concurrently, SupTech can strengthen supervisory processes via real-time data analysis and monitoring, enabling regulators to proactively address emerging risks.

By implementing these comprehensive policy recommendations, Indonesia can enhance the resilience of its banking sector, promote sustainable economic growth, and ensure a stable credit supply across various sectors. This multifaceted approach will enable banks to effectively navigate the complexities of the modern financial landscape, manage risks, and capitalize on growth opportunities, thereby contributing to the overall stability and prosperity of the Indonesian economy.

To understand banking behavior, authorities can design SupTech by combining primary data collected from surveys and applying machine learning on the combined primary and secondary data to generate new information that can shed lights on the many questions that authorities have on bank behavior. This research has proven that it can be done and that different behavior of the groups of banks was capture. By being more sensitive about the bank behavior, authorities can be implement more targeted and effective policy to provide incentives and disincentives toward the most balanced outcome that can support sustainable economic growth. New bank behavior/performance indicators can also be produced to support the implementation of macro- and micro-prudential instruments.

6. Conclusion and Further Research

The behavior of banks in determining the supply of credit in Indonesia is a multifaceted issue influenced by economic conditions, regulatory frameworks, technological advancements, and sector-specific challenges. This analysis aims to provide a comprehensive understanding of these factors, utilizing both traditional statistical methods and advanced machine learning techniques such as k-means clustering and credit forecasting.

One significant finding of this study is the substantial impact of economic cycles and regulatory changes on bank credit supply. Banks tend to exhibit procyclical behavior, expanding credit during economic booms and contracting it during downturns, which can exacerbate economic volatility. Three main variables affecting bank performance are the risk-free interest rate as a reference, economic growth or business cycles, and credit risk, including non-performing loans and credit default swaps.

As these dynamics unfold, the adoption of digitalization and artificial intelligence (AI) has transformed credit approval processes, particularly among mid-sized and larger banks. However, this technological shift also brings heightened cybersecurity risks, necessitating robust security measures. In some cases, cybersecurity stress tests are performed on internal employees, focusing on threats like ransomware and phishing in KBMI4 banks.

Moreover, different sectors, such as micro, small, and medium enterprises (MSMEs), tourism, and mining, present unique challenges for banks under the KLM incentive policy. MSMEs still face hurdles related to financial literacy and resource constraints, while the tourism and mining sectors are perceived as high-risk due to their susceptibility to external shocks, such as travel bans and trade tariffs, as well as regulatory complexities.

Furthermore, the transition to a green economy increasingly influences bank behavior. Larger banks are more likely to integrate climate risk assessments and offer green finance products, although the overall emphasis on green financing remains varied. Particularly for KBMI4, there is a need for clear guidance on green projects, including hydropower, geothermal, and large-scale floating photovoltaic solar panels. However, greenwashing practices hinder banks' engagement in green projects, especially among smaller institutions.

Effective risk management practices are essential for maintaining financial stability, requiring banks to balance the demands of regulatory compliance, technological adoption, and sector-specific risks to ensure a sustainable credit supply. By understanding the interplay among these factors, banks can better respond to challenges and seize opportunities in a continuously evolving environment.

Having a set of dynamic tools to assess the bank behavior toward different economic and financial conditions is important for bank authorities. This is to ensure that authorities can really understand the tendency and most likely responses of banks toward policy deliberation. Authorities are usually one step behind from the innovation of the banks. This does not mean that authorities are not capable of projecting the bank responses toward policy implementation. In addition to recognizing the innovation strategies of banks, authorities need to also learn the strength and weaknesses of banks all the way to individual behavior. This will help authorities to gain wisdom to deliberate the best policy given the situation.

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Appendix

A1. Validity and Reliability Testing

No	Variable	Pearson Correlation
1	Demand shift to mortgage	0.6818
2	Risk-driven shift to mortgage	0.6104
3	Regulatory impact on mortgage shift	0.6289
4	Mortgage shift for MSMEs	0.4899
5	Mortgage shift for small projects-base financing	0.6589
6	Mortgage Shift for Syndicated with other banks for large project	0.5627
7	Digitalization’s impact in credit supply	0.4390
8	Cybersecurity in credit supply	0.5690
9	Climate change challenges in credit supply	0.3862
10	Working capital lending challenges in credit supply	0.3817
11	Investment loans challenges in credit supply	0.2559
12	Micro loan challenges in credit supply	0.5046
13	KUR in credit supply	0.6660
14	Tourism lending challenges to in credit supply	0.4809
15	Mining lending challenges to in credit supply	0.3932
Cronbach's Alpha		0.8027

Source: Author Calculation

A2. Variable Definitions for Clustering Banking Behavior

No.	Variable	Definition	Data Source
1	Total Asset	The total assets held by the bank, measured in Rp trillion.	LBUT
2	KBMI	Classification of the bank based on its asset size and risk profile. Bank size measured by KBMI a. KBMI 1 (≤ 6 trillion) b. KBMI 2 (6-14 trillion) c. KBMI 3 (14-70 trillion) d. KBMI 4 (>70 trillion)	LBUT
3	Demand shift to mortgage	The influence of consumer demand shifting from other loan types to mortgages, rated on a scale of 1 to 5.	Survey Respondents
4	Risk-driven shift to mortgage	Factors related to credit risk driving banks to prefer issuing mortgages, rated on a scale of 1 to 5.	Survey Respondents
5	Regulatory impact on mortgage shift	The effect of regulations on the shift towards mortgage lending, rated on a scale of 1 to 5.	Survey Respondents
6	Mortgage shift for MSMEs	The movement of mortgage lending towards Micro, Small, and Medium Enterprises (MSMEs), rated on a scale of 1 to 5.	Survey Respondents

No.	Variable	Definition	Data Source
7	Mortgage shift for small projects	Preference for mortgages as financing for small-scale projects, rated on a scale of 1 to 5.	Survey Respondents
8	Mortgage shift for syndicated loans	Use of syndicated loans for large-scale mortgage projects, rated on a scale of 1 to 5.	Survey Respondents
9	Digitalization's impact in credit supply	Effect of digital transformation on bank credit supply, rated on a scale of 1 to 5.	Survey Respondents
10	Cybersecurity in credit supply	Concerns about cybersecurity in credit provision, rated on a scale of 1 to 5.	Survey Respondents
11	Climate change challenges in credit supply	Issues related to climate change affecting credit supply, rated on a scale of 1 to 5.	Survey Respondents
12	Working capital lending challenges	Difficulties faced by banks in providing working capital loans, rated on a scale of 1 to 5.	Survey Respondents
13	Investment loans challenges	Challenges in issuing investment loans, rated on a scale of 1 to 5.	Survey Respondents
14	Micro loan challenges	Obstacles in providing microloans to borrowers, rated on a scale of 1 to 5.	Survey Respondents
15	KUR in credit supply	Challenges in distributing KUR (People's Business Credit) loans, rated on a scale of 1 to 5.	Survey Respondents
16	Tourism lending challenges	Issues related to providing credit to the tourism sector, rated on a scale of 1 to 5.	Survey Respondents
17	Mining lending challenges	Obstacles in offering loans to the mining industry, rated on a scale of 1 to 5.	Survey Respondents

Source: Integrated Commercial Bank Reports (LBUT) and Consumer Surveys

A3. Variable Definitions for Forecasting Bank Credit Growth

No	Variable	Definition	Source
1	Consumer Credit (KK)	Total credit extended to consumers	Bank Indonesia
2	Real GDP (GDPRL)	Gross Domestic Product adjusted for inflation	BPS
3	Real Household Consumption (CSPRL)	Consumer spending adjusted for inflation	BPS
4	Consumer Price Index (IHK)	Measure of the average change in prices paid by consumers	BPS
5	USD/IDR Exchange Rate	Exchange rate between	Bank

No	Variable	Definition	Source
	(EXRATE)	USD and Indonesian Rupiah	Indonesia
6	Indonesia's Export Commodity Price Index (IHKEI)	Index of prices for Indonesia's export commodities	BPS
7	BI Rate (BI_RATE)	Bank Indonesia's policy interest rate	Bank Indonesia
8	Purchasing Managers' Index (PMI)	Indicator of economic health in the manufacturing sector	CEIC
9	World Oil Price (P_OIL)	Global price of crude oil	Bloomberg
10	10-Year Government Bond Yield (YIELDSBN_10Y)	Yield on a 10-year government bond	Bloomberg
11	Credit Default Swap (CDS)	Financial derivative that insures against credit default	Bloomberg
12	Volatility Index (VIX)	Index measuring market volatility	Bloomberg
13	Car Sales (CAR_SALES)	Number of cars sold within a specific period	Bank Indonesia
14	Motorcycle Sales (MOTOR_SALES)	Number of motorcycles sold within a specific period	Bank Indonesia
15	Consumer Survey - Consumer Confidence Index (SK_IKK)	Index measuring consumer optimism about the economy	Bank Indonesia
16	Consumer Survey - Current Economic Conditions Index (SK_IKE)	Index measuring current economic conditions perceived by consumers	Bank Indonesia
17	Consumer Survey - Consumer Expectations Index (SK_IEK)	Index measuring consumer expectations of future economic conditions	Bank Indonesia
18	Consumer Survey - Current Income Index (SK_IPS)	Index of consumer perceptions on current income levels	Bank Indonesia
19	Consumer Survey - Job Availability Index (SK_IKLK)	Index measuring consumer perceptions of job availability	Bank Indonesia
20	Consumer Survey - Durable Goods Purchase Index (SK_IPBTL)	Index measuring consumer intent to purchase durable goods	Bank Indonesia
21	Consumer Survey - Expected Income Index (SK_IEP)	Index measuring consumer expectations of future income	Bank Indonesia
22	Consumer Survey - Expected Job Availability	Index measuring consumer expectations of future job	Bank Indonesia

No	Variable	Definition	Source
	Index (SK_IEKLK)	availability	
23	Retail Sales Survey - Real Sales Index (SPE_IPR)	Index measuring actual retail sales, adjusted for inflation	Bank Indonesia
24	Residential Property Price Index (IHPR)	Index tracking changes in residential property prices	Bank Indonesia
25	Wages (WAGE)	Total income earned by workers in the economy	BPS
26	Household Net Financial Worth (HH_Net_Fin_Worth)	The total value of household assets minus liabilities	Bank Indonesia
27	Household Financial Assets (HH_Fin_Assets)	Total value of financial assets held by households	Bank Indonesia
28	Household Liabilities (HH_Liabilities)	Total financial obligations of households	Bank Indonesia
29	Household Consumption (HH_Consumption)	Total household spending on goods and services	Bank Indonesia
30	Household Net Financial Worth to Household Consumption Ratio (Net_Fin_Worth_Cons)	Ratio of household wealth to consumption	Bank Indonesia
31	Household Investment (HH_Investment)	Total investment made by households in assets	Bank Indonesia
32	Individual Savings Deposit (DPK Perseorangan)	Total deposits in individual savings accounts	Bank Indonesia
33	Household Securities Ownership (Efek_RT_Nominal_Total)	Total value of securities owned by households	Bank Indonesia
34	Household Outstanding Shares of Securities (Efek_RT_Outstanding_Shares)	Total shares of securities held by households	Bank Indonesia
35	Household Securities Market Capitalization (Efek_RT_Market_Capitalization)	Total market value of household-owned securities	Bank Indonesia

Source: Integrated Commercial Bank Reports (LBUT), the Central Bureau of Statistics (BPS), CEIC, Bloomberg, the Central Securities Depository (KSEI), and Consumer Surveys

A4. RMSE Metrics for Cluster 1

Model Name	RMSE Train	RMSE Test
Linear Regression	1.017	1.252
Lasso Regression	1.189	1.105
Ridge Regression	1.055	1.139
Elastic Net	1.204	1.122

Model Name	RMSE Train	RMSE Test
Support Vector Regression (SVR)	0.395	0.782
k-Nearest Neighbour (kNN)	0.709	0.972
Decision Tree	0.687	1.602
Random Forest	0.418	1.177
Gradient Boosting	0.348	1.397
XGBoost	0.144	1.357
Light Gradient Boosting Machine (GBM)	0.430	1.244
Gaussian Process Regression (GPR)	0.419	0.940

Source: Author Calculation

A5. RMSE Metrics for Cluster 2

Nama Model	RMSE Train	RMSE Test
Linear Regression	3.715	4.225
Lasso Regression	2.566	2.737
Ridge Regression	2.560	2.723
Elastic Net	2.589	2.734
Support Vector Regression (SVR)	1.449	3.040
k-Nearest Neighbour (kNN)	3.300	3.494
Decision Tree	2.452	5.116
Random Forest	2.766	4.213
Gradient Boosting	0.801	3.708
XGBoost	1.003	3.596
Light Gradient Boosting Machine (GBM)	1.076	4.491
Gaussian Process Regression (GPR)	0.551	4.394

Source: Author Calculation