**Financing MSMEs in Indonesia: Credit and Financial Inclusion**

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## Abstract

MSMEs, also known as micro, small, and medium-sized enterprises, are the backbone of the economy in developing countries. Empirical studies indicate that SMEs generally face obstacles, particularly in financing. This study focuses on two main aspects: indexing financial inclusion using principal component analysis (PCA), and analyzing credit and financial inclusion using vector autoregression (VAR) for forecasting. Through a two-stage indexing methodology, the study emphasizes the importance of geographical reach in financial inclusion availability compared to demographic reach, with availability being the most crucial dimension compared to accessibility and usage. VAR models and forecasting were developed for the period from March 2012 to July 2022 in Indonesia, incorporating other variables, such as access to credit, credit risk, and real GDP. The use of VAR demonstrates consistency, accuracy, and reliability in producing predictions that closely approximate reality, providing a critical basis for policymakers.

**Keywords**: Micro, small, and medium enterprises (MSMEs) financing, principal component analysis (PCA), financial inclusion index, credit, vector autoregression (VAR), forecasting, Indonesia

**JEL Classification**: C32, E44, G21, O16

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# Financing MSMEs in Indonesia: Credit and Financial Inclusion

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## I. Introduction

### 1.1 Background

The majority of economic activities in developing countries are dominated by small producers and businesses. Most of them are non-corporate, unlicensed, and unregistered entities, including small-scale farmers, producers, craftsmen, traders, and independent merchants operating in the informal sector, both in urban and rural areas. However, there is still a need to allocate more financial resources for small entrepreneurs, especially in the agricultural sector and the informal sector in urban and rural areas, which often struggle to access credit at reasonable interest rates. To address this need, various microfinance services have emerged in developing countries. Economic studies consistently emphasize that one of the main obstacles to the development of micro, small, and medium enterprises (MSMEs) is the availability of financing access (Todaro and Smith, 2015).

Guo et al. (2023) also stated that the Chinese government has long been aware of the challenges faced by MSMEs in obtaining loans or funding, thus implementing various credit policies to help them gain access to bank credit. MSMEs in China have experienced significant difficulties in obtaining credit from financial institutions, with inadequate financing institutions being a major factor influencing the difficulty of accessing credit (Ma et al., 2019). Aysan and Disli (2019) revealed that banks play a crucial role for MSMEs in Turkey, leaving them with few other options to finance their investments externally. However, because MSMEs rely on bank funding, they are vulnerable to changes in the dynamics of the banking system. Therefore, interest in understanding the credit relationship between banks and MSMEs is increasing.

Indonesia experienced a decrease in Gross Domestic Product (GDP) growth by -2.07%, indicating a year-on-year economic downturn in 2020 compared to 2019 (The World Bank, 2021). This was due to the impact of the COVID-19 pandemic, which affected the global economy and reshaped social order. One of the sectors significantly affected by this pandemic is the micro, small, and medium enterprises (MSMEs) sector (Central Statistics Agency, 2021). According to Law Number 20 of 2008, micro, small, and medium enterprises (MSMEs) are defined based on net worth and annual sales revenue.

| Size | Net Worth (Rupiah) | Annual Revenue (Rupiah) |
|---|---|---|
| Micro enterprise | Maximum 50 million | Maximum 300 million |
| Small enterprise | Between 50 million and 500 million | Between 300 million and 2.5 billion |
| Medium enterprise | Between 500 million and 10 billion | Between 2.5 billion and 500 billion |

**Table 1.** The Definition of Micro, Small, and Medium Enterprises (MSMEs) in Indonesia

Source: Law No. 20 of 2008

Based on data from the Coordinating Ministry for Economic Affairs in 2021, MSMEs contributed approximately 61.07% to Indonesia's Gross Domestic Product (GDP), successfully absorbing around 97% of the total workforce and collecting 60.4% of total investment. This data indicates that the MSME sector in Indonesia plays a significant and strategic role in economic development.

According to the Otoritas Jasa Keuangan (OJK) in 2020, MSMEs face various problems, one of which is financing. Banks are the largest creditors or providers of funding for MSMEs, but MSMEs have limited access to bank credit and face financing constraints from the banking sector. According to the Indonesian Financial System Statistics (SSKI) by Bank Indonesia in February 2021, MSME credit only accounts for 19.72% of total bank credit. Therefore, this research focuses on the problem of financing constraints for MSMEs, particularly in the area of credit.

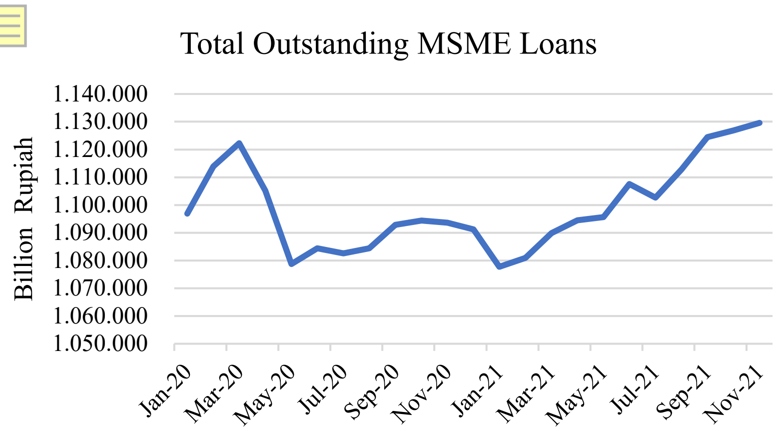



**Figure 1.** The Development of MSME Credit

Source: Bank Indonesia

Since the beginning of the COVID-19 pandemic, MSME credit performance has declined, as has overall credit performance in 2020. This decline in credit performance is evidenced by the decrease in outstanding credit. The development of outstanding MSME credit has decreased since March 2020 by 3.57% from Rp1.12 trillion to Rp1.08 trillion as of March 2021, and began to show an increase indicating recovery after April 2021. Todaro and Smith (2015) also explained that economic research consistently finds that the availability of access to credit is a major constraint for the development of micro, small, and medium enterprises (MSMEs).

According to Ahamed and Mallick (2019), engagement in financial services, such as savings, payments, risk management, and credit, has positive social and economic impacts. Research by Bruhn and Love (2014) also indicated that access to financial services has a positive impact on economic growth and facilitates the formation of new businesses. The government has prioritized expanding banking access to the entire population in order to achieve financial inclusion, as advocated by Demirguc-Kunt et al. (2015).

Financial inclusion in MSME financing demonstrates broader and fairer access to financial services, such as credit, savings, and other products, enabling MSMEs to develop their businesses and improve economic welfare. Credit spreads, which represent the difference between commercial loan interest rates and bank deposit interest rates, indicate MSMEs' lending policies as well as their access to various types of funding. Real GDP is also important in MSME financing as it influences lending policies, loan feasibility evaluations, and provides guidance on economic conditions that can affect MSME growth and sustainability.

Research on credit and financial inclusion in MSME financing in Indonesia will provide vital analysis for policymakers to support MSMEs in strengthening their business capital. The objective of this research is to analyze the dynamic relationship between access to credit, credit risk, financial inclusion index, credit spreads, and economic growth in Indonesian MSME financing. Additionally, this research aims to analyze the reliability of the Vector Autoregression (VAR) model in predicting future data related to access to credit, credit risk, financial inclusion index, credit spreads, and economic growth for policymakers involved in financing micro, small, and medium enterprises (MSMEs) in Indonesia.

Access to credit is the main engine of economic growth. Credit constraints prevent companies from accessing attractive investment opportunities (Campello et al., 2010) and hinder company productivity (Butler and Cornaggia, 2011), ultimately reducing company growth, especially for small and medium-sized enterprises (Nkurunziza, 2010). Osei-Tutu and Weill (2022) found that bank efficiency can improve access to credit for companies. Their findings support policies that encourage increased access to credit.

Buyukbasaran et al. (2022) explained that an expansive credit supply shock, which simultaneously reduces credit spreads and increases credit growth, is accompanied by currency depreciation and higher inflation. Guo et al. (2023) also found that pro-MSME credit policies in China resulted in a decrease in loan interest rates. The Chinese government has implemented various pro-MSME credit policies aimed at facilitating access to banking credit. MSMEs in China face serious difficulties in obtaining credit from financial institutions, with the most determining factor being the lack of financing institutions in China (Ma et al., 2019). Aysan and Disli (2019) also revealed that MSMEs in Turkey are highly dependent on bank loans. However, MSMEs' dependence on bank financing makes them highly vulnerable to dynamics within the banking system.

Credit risk in the form of non-performing loans (NPLs) has become a serious burden on bank credit growth. In a sample of Caribbean countries, Tracey and Leon (2011) found that an increase in NPLs reduces bank lending. Furthermore, Aysan and Disli (2019) explained that the MSME credit market is more vulnerable to market failures. High NPLs will reduce bank profitability and lead to higher funding costs, thereby reducing credit supply, which will impact MSMEs that are more reliant on bank financing. During the COVID-19 pandemic, credit risk increased due to economic downturns, causing banks to become more cautious about risk, and credit costs to increase (Naiborhu and Ulfa, 2023). Dang and Nguyen (2022) also revealed that higher banking uncertainty can increase credit risk.

Financial inclusion has become a top priority in public policy, especially after the COVID-19 pandemic and the implementation of social mobility restrictions. Ahamed and Mallick (2019) stated that financial inclusion enables access to financial services, such as savings, payments, risk management, and credit, for households and companies with different needs. Research by Bruhn and Love (2014) also found that access to financial services has a positive impact on economic development and facilitates the establishment of new businesses. Allen et al. (2016) demonstrated that financial inclusion is positively associated with stronger legal systems and stable political environments. Di Patti and Dell'Ariccia (2004) showed that in an inclusive financial sector, banks with lower marginal costs can reduce credit risk-taking and increase access to credit.

Financial inclusion is crucial to ensure that poor households and MSMEs with limited collateral or no credit history can still access financial services (Gopalan and Rajan, 2018). An inclusive financial system has the potential to reduce social and economic inequalities while also fostering a more dynamic economy and higher economic growth (Swamy, 2014). If a financial system is not inclusive, poor households and MSMEs will be excluded from financial services due to market failures arising from imperfections in financial markets, such as asymmetric information, high transaction costs, or weak contract enforcement (Gopalan and Rajan, 2018). It is generally agreed that financial inclusion has many dimensions, but there is still debate about which dimensions should be included and how each dimension contributes to defining financial inclusion. Therefore, developing a financial inclusion index and capturing multiple dimensions following Kabede et al. (2021) becomes crucial to obtain a comprehensive understanding of financial inclusion in Indonesia and its relationship with other economic variables.

### 1.2 Research Purpose

This research provides new insights into the literature on the Indonesian financial inclusion index, which has been compiled monthly over the past ten years (2012–2022), overcoming limitations of available data. Additionally, this research identifies which dimensions of financial inclusion need improvement in Indonesia and analyzes lending from various perspectives, including MSMEs, bank funding providers, and policy authorities. Predictions for related variables are also made using the VAR method as the main analytical framework, while considering findings from other analytical methods. This study is expected to provide a more comprehensive understanding and more accurate predictions regarding lending and financial inclusion for MSMEs, with the potential for broad contributions to MSME studies beyond Indonesia, as well as the global understanding of the importance of financial inclusion in supporting MSME growth worldwide.

## II. Data and Methodology

### 2.1 Data

Before processing time series data, a stationarity test must be conducted first. The unit root test is used to determine whether the time series data is stationary or not. Stationarity is a property in which time series statistics (such as mean and variance) remain constant over time. If the data is stationary at the level, the ordinary least square (OLS) method or vector autoregression (VAR) method is selected. If it is not stationary at the level, the next step is to conduct cointegration and optimum lag tests. Cointegration testing is conducted to help understand the long-term relationship between variables and to perform accurate prediction analysis. The optimum lag test is used to find the optimal number of lags in the model. Lags refer to previous observations of variables that can affect their current or future value. If the data is cointegrated, the error correction model (ECM) is selected. If the data is not cointegrated, the VAR model at the first-difference level is selected.

In this study, access to credit is measured using the ratio of total MSME credit to total banking credit, using data from the Indonesian Financial System Statistics of Bank Indonesia (SSKI BI). The SSKI BI data includes various components of MSME indicators, one of which is the ratio of MSME credit to GDP. The ratio of MSME credit to GDP is expressed as a percentage and calculated using the following formula:

$$\boldsymbol{The\ Ratio\ of\ MSMEs\ Credit\ to\ GDP = \frac{Total\ MSMEs\ credit\ (month\ t)}{Total\ current{-}price\ GDP\ (year\ t)}\ x\ 100} \qquad (1)$$

Meanwhile, credit risk in this study is measured through the percentage of non-performing loans (NPL) in the banking sector. NPL in this study is used as an indicator of credit risk that affects the provision of financing to MSMEs. NPL data is sourced from SSKI BI within the Indonesian MSME indicators. NPL for MSME credit is expressed as a percentage and calculated using the following formula:

$$\boldsymbol{NPL = \frac{Total\ MSMEs\ credit\ classified\ as\ \text{"}Kurang\ Lancar, Diragukan, Macet\text{"}\ (month\ t)}{Total\ MSMEs\ credit\ (month\ t)}\ x\ 100} \qquad (2)$$

Financial inclusion is measured using time series data from March 2012 to July 2022. To index financial inclusion, a two-stage approach is used: first with dimensions, and second with the overall financial inclusion index. Following the literature by Kebede et al. (2021), this study uses three main dimensions to evaluate financial inclusion:

availability, accessibility, and usage. The availability dimension includes demographic and geographic reach. Demographic reach encompasses the number of ATMs and bank branches per 100,000 adult population, while geographic reach is the number of ATMs and bank branches per 1,000 square km. Accessibility is measured by the proportion of adults with bank accounts per 1,000 adult population. Lastly, the usage dimension is represented by the percentage of private sector credit to GDP. All data on these indicators are obtained from the Indonesian Financial System Statistics (SSKI) of Bank Indonesia.

| Indicator | Definition |
|---|---|
| ATMperpop | Number of Automated Teller Machines (ATMs) per 100,000 adult population |
| ATMperkm$^2$ | Number of Automated Teller Machines (ATMs) per 1,000 km$^2$ |
| Bankperpop | Number of bank branches per 100,000 adult population |
| Bankperkm$^2$ | Number of bank branches per 1,000 km$^2$ |
| Accessibility | Number of bank accounts per 1,000 adult population |
| Usage | Total bank credit to the private sector (% of GDP) |

**Table 2.** Financial Inclusion Indicators

### 2.2 Methodology

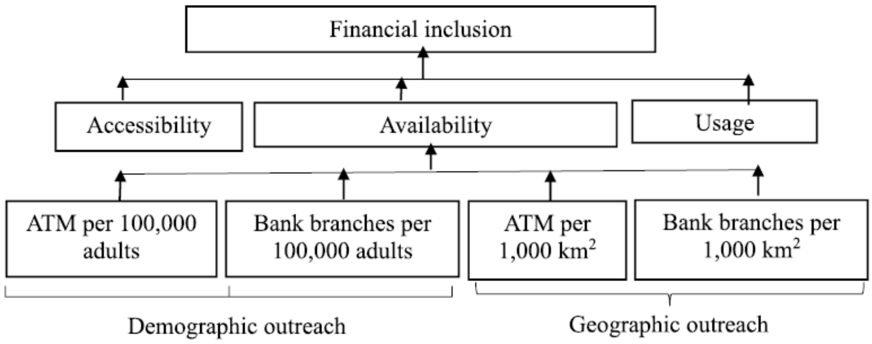



**Figure 2.** Financial Inclusion Dimension Based on Kabede et al. (2021)

Financial inclusion is multidimensional. Before indexing, each indicator is normalized so that the measurement scale becomes irrelevant. From the results of normalization, it is known that the closer the value is to one, the more inclusive the financial system is in terms of indicator X, while the closer the value is to zero, the more exclusive the financial system is in terms of that indicator. Thus, the financial inclusion indicators are normalized using the following formula:

$$X_{it,n} = \frac{X_{it} - X_{min}}{X_{max} - X_{min}} \quad (3)$$

in which $X_{it,n}$ represents the normalized value of indicator X for Indonesia at time t. $X_{it}$ represents the actual value of indicator X for Indonesia at time t. $X_{min}$ and $X_{max}$ represent the minimum and maximum values of indicator X, respectively. $X_{it,n}$ ranges from 0 to 1, indicating a country's performance in terms of financial inclusion from the perspective of indicator X. The closer it is to one, the more inclusive the financial system is in terms of indicator X, while the closer it is to zero, the more exclusive the financial system becomes.

After normalizing each indicator, a composite index of financial inclusion is developed from its dimensions. Indexing is carried out using a two-stage principal component analysis (PCA) approach.

1. First-stage Indexing

The first stage of PCA aims to develop the availability aspect in financial inclusion by utilizing four indicators. These indicators are further grouped into demographic reach (number of ATMs per 100,000 adult population and number of bank branches per 100,000 adult population) and geographic reach (number of ATMs per 1,000 km² and number of bank branches per 1,000 km²).

$$\boldsymbol{Availability_t = \gamma_1 ATMperpop_t + \gamma_2 Bankperpop_t + \gamma_3 ATMperkm^2{}_t + \gamma_4 Bankperkm^2{}_t + v_t} \quad (4)$$

If the eigenvectors of the correlation matrix are denoted by τ, the principal components are:

$$\boldsymbol{PC_{1,t} = \tau_{11} ATMperpop_t + \tau_{12} Bankperpop_t + \tau_{13} ATMperkm^2{}_t + \tau_{14} Bankperkm^2{}_t} \quad (5)$$

2. Second-stage Indexing

After indexing the availability dimension, this study further creates a comprehensive measure of financial inclusion by considering the dimensions of availability, accessibility, and usage. This study uses the same method that is used when indexing availability. Therefore, the overall financial inclusion is determined as follows:

$$\boldsymbol{Financial\ Inclusion_t = \widetilde{\delta}_1 Availability_t + \widetilde{\delta}_2 Accessibility_t + \widetilde{\delta}_3 Usage_t + \varepsilon_t} \quad (6)$$

Credit spread is the difference between commercial loan interest rates and bank deposit interest rates. Data is obtained from the Indonesian Economic and Financial Statistics (SEKI) of Bank Indonesia for the period 2012–2022. The last variable is the constant-price GDP (base year 2010). The data used comes from the Statistics Indonesia (Badan Pusat Statistik/BPS) and covers the period 2012–2022. Natural logarithm (ln) is applied to the real GDP variable. The credit spreads indicator is formulated as follows:

$$\boldsymbol{Credit\ Spreads_t = Commercial\ loan\ interest\ rates_t - Bank\ deposit\ interest\ rates_t} \quad (7)$$

Stationarity is a key characteristic in time series analysis, as many time series analysis methods are only applicable to stationary data. In time series analysis, it is critical to ensure stationarity before moving on to more advanced analysis, such as forecasting and model estimation. The unit root test is an essential tool in time series analysis for determining whether time series data is stationary or not. There are various types of unit root tests, including the Augmented Dickey-Fuller (ADF) test and the widely used Phillips-Perron (PP) test. The null hypothesis (H0) of the ADF test is $\delta = 0$ and the alternative hypothesis is $\delta < 0$. If H0 is rejected, then the time series data is stationary. The null hypothesis of the Phillips-Perron test is $\pi = 0$.

Augmented Dickey-Fuller (ADF) Test

$$\boldsymbol{\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t} \quad (8)$$

Phillip-Perron (PP) Test

$$\boldsymbol{\Delta y_t = \pi y_{t-1} + \beta_i D_{t-i} + \varepsilon_t} \quad (9)$$

The next step is to conduct a cointegration tests. This test aims to assess whether two or more variables move together in the long run. This study used the Engle-Granger test to assess cointegration. In the research data, no long-term cointegration was found, so the most appropriate method is to use the VAR method.

In time series analysis, determining the number of lags or time periods needed to explain changes in the data is often a crucial factor, as it can impact the analysis results. Choosing the appropriate lag can improve the accuracy of analysis and forecasting. The Akaike Information Criterion (AIC) is used as a consideration. In this study, the results of the stationarity test (unit root) indicate stationarity at the first-difference level, and the results of the Engle-Granger cointegration test indicate no cointegration. The result of the optimal lag test is 6, thus it is concluded that the suitable model for this research is vector autoregression (VAR).

The standard form of the VAR model with n variables and order p, VAR(p), which is expressed for each endogenous variable as a linear combination of its own lags and the lags of other variables in reduced form (Enders, 2015) can be written with the following formula:

$$\boldsymbol{x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + \cdots + A_p x_{t-p} + e_t} \tag{10}$$

in which $x_t$ is a *n* x 1 vector containing each of the *n* variables included in *VAR*. $A_0$ is a *n* x 1 vector representing intercept. $A_1, A_2, \ldots, A_p$ are coefficient matrices from the lagged endogenous variables. $e_t$ is a *n* x 1 vector representing the error term at time *t.*

In this study, the multivariate model uses **VAR (6)** with the following formula:

$$\boldsymbol{x_t = A_0 + A_1 x_{t-1} + A_2 x_{t-2} + A_3 x_{t-3} + A_4 x_{t-4} + A_5 x_{t-5} + A_6 x_{t-6} + e_t} \tag{11}$$

in which $x_t$ is a 5 x 1 vector containing each of the five variables included in VAR. $A_0$ is a 5 x 1 vector representing intercept. $A_1, A_2, \ldots, A_6$ are 5 x 5 coefficient matrices. $e_t$ is a 5 x 1 vector representing the error term.

## III. Results and Discussion

This study observes the data behavior between March 2012 to July 2022 (125 observations). Each variable were described statistically and represented graphically. The variables include access to credit, credit risk, financial inclusion index, credit spreads, and real Gross Domestic Product (GDP). All tables in this chapter are the results of Stata 17 processing.

### 3.1 Results

1. Results of Financial Inclusion Index Processing
   a. First Stage

PCA reports two components, namely principal correlations and eigenvectors. A total variance of four was generated, which is equal to the total processed variables ($x_1$ is the number of ATMs per 100,000 adult population, $x_2$ is the number of bank branches per 100,000 adult population, $x_3$ is the number of ATMs per 1,000 km$^2$, and $x_4$ is the number of bank branches per 1,000 km$^2$). This results in an increase in the eigenvalue to four (3.297 + 0.689 + 0.012 + 0.000105 = 4). Consequently, the first component accounts for 82.44% of the total variation in the data, which is calculated as 3,297/4*100. The second, third, and fourth components account for 17.23%, 0.32%, and 0.01% of the variation in the data, respectively. The last column indicates the cumulative proportions that add up to one. Rho (ρ) = 1.00 in the first panel implies that all variations in the data have been explained. According to the literature, the PC with an eigenvalue greater than 1 (PC1) is used to calculate the availability dimension. Therefore, the availability dimension is calculated using the following formula:

$$\boldsymbol{Availability_t = 0.4921\ ATMperpop_t + 0.4906\ Bankperpop_t + 0.5080\ ATMperkm^2{}_t + 0.5090\ Bankperkm^2{}_t} \quad (12)$$

| | | | | | |
|---|---|---|---|---|---|
| Number of Observations | 125 | | | | |
| Number of Components | 4 | | | | |
| *Rho (ρ)* | 1.00 | | | | |
| Components | Eigenvalue | Difference | Proportion | Cumulative | |
| Comp1 | 3.29789 | 2.60875 | 0.8245 | 0.8245 | |
| Comp2 | 0.689134 | 0.67626 | 0.1723 | 0.9968 | |
| Comp3 | 0.012874 | 0.0127684 | 0.0032 | 1.0000 | |
| Comp4 | 0.00010555 | . | 0.0000 | 1.0000 | |
| Principal Components | | | | | |
| Variables | Comp1 | Comp2 | Comp3 | Comp4 | Unexplained |
| ATMperpop | 0.4921 | -0.5360 | 0.5047 | -0.4645 | 0 |
| Bankperpop | 0.4906 | 0.5425 | 0.5122 | 0.4502 | 0 |
| ATMperk2 | 0.5080 | -0.4601 | -0.4803 | 0.5473 | 0 |
| Bankperk2 | 0.5090 | 0.4546 | -0.5023 | -0.5311 | 0 |

**Table 3.** First Stage PCA Result

b. Second Stage

| | | | | |
|---|---|---|---|---|
| Number of Observations | 125 | | | |
| Number of Components | 3 | | | |
| *Rho (ρ)* | 1.00 | | | |
| Components | Eigenvalue | Difference | Proportion | Cumulative |
| Comp1 | 2.27855 | 1.64751 | 0.7595 | 0.7595 |
| Comp2 | 0.631933 | 0.540612 | 0.2103 | 0.9699 |
| Comp3 | 0.0904214 | . | 0.0301 | 1.0000 |
| Principal Components | | | | |
| Variables | Comp1 | Comp2 | Comp3 | Unexplained |
| Availability | 0.6344 | -0.2313 | -0.7376 | 0 |
| Accessibility | 0.6058 | -0.4439 | 0.6603 | 0 |
| Usage | 0.4801 | 0.8657 | 0.1414 | 0 |

**Table 4.** Second Stage PCA Result

In the second stage, this study indexed the dimensions of financial inclusion with the variables, namely availability, accessibility, and usage. Eigenvalues greater than 1 were found only in the first principal component (PC1), which accounted 75.95% of the variation in the data. The other two main components, PC2 and PC3, had eigenvalues less than 1 each, accounting for the remaining 21.03% and 3.01% of the total variation in the data. Following the literature, only PCs with eigenvalues greater than 1 were used, with the same argument as in the first stage's results. The results indicate that availability explains most of the variation in the data, followed by accessibility. Therefore, the authors calculated the overall financial inclusion index with the following equation:

$$\boldsymbol{Financial\ Inclusion_t = 0.6344\ Availability_t + 0.6058\ Accessibility_t + 0.4801\ Usage_t} \quad (13)$$

c. Validation of Indexing Results using Kaiser-Meyer-Olkin (KMO) Test

| Variable | KMO |
|---|---|
| Availability | 0.5381 |
| Accessibility | 0.5504 |
| Usage | 0.6860 |
| Overall | **0.5662** |

**Table 5.** Kaiser-Meyer-Olkin Test Result

The use of KMO in this analysis aims to evaluate the quality of the data used in forming the financial inclusion index. The results of the KMO test show a value of 0.5662, which indicates that the generated financial inclusion index has reached an acceptable level of acceptance in empirical studies. Therefore, it can be concluded that the data used in this analysis overall has met the requirements to produce a reliable financial inclusion index. This financial inclusion result will be a variable in the vector autoregression (VAR) model analysis, along with the other four variables.

2. Stationarity Test with Unit Root Test

Unit root tests for each time series variable were conducted using the Augmented Dickey Fuller (ADF) and Phillips-Perron methods. The testing was performed both at the data level and after taking the first difference. The results of these tests are presented in the tables below.

| Variable | Level | | *First Difference* | |
|---|---|---|---|---|
| | *t-stat* | *p-value* | *t-stat* | *p-value* |
| Access to credit | -2.090 | 0.248 | -5.177 | 0.000 |
| Credit risk | -2.088 | 0.249 | -5.274 | 0.000 |
| Financial inclusion index | -2.259 | 0.185 | -4.924 | 0.000 |
| Credit spreads | -2.664 | 0.080 | -2.645 | 0.084 |
| Real GDP (ln) | -1.695 | 0.433 | -4.77 | 0.000 |

**Table 6.** Augmented Dickey Fuller (ADF) Test Result

| Variable | Level | | *First Difference* | |
|---|---|---|---|---|
| | *t-stat* | *p-value* | *t-stat* | *p-value* |
| Access to credit | -3.596 | 0.005 | -10.677 | 0.000 |
| Credit risk | -2.394 | 0.143 | -14.624 | 0.000 |
| Financial inclusion index | -3.600 | 0.005 | -9.042 | 0.000 |
| Credit spreads | -1.787 | 0.387 | -8.883 | 0.000 |
| Real GDP (ln) | -1.602 | 0.482 | -4.742 | 0.000 |

**Table 7.** Phillip-Perron (PP) Test Result

Stationarity tests using the ADF method indicate that all variables are stationary at the first difference level. Testing at the first difference level shows that all variables are stationary at the 1% significance level. Stationarity tests using the PP method also indicate that all variables are stationary at the first difference level. The results of the unit root tests using both methods suggest that all variables are stationary at the first difference level, meeting the assumption of permanent effects without long-term trends or patterns. The developed model can provide consistent and relevant estimates for the long-term relationships among the economic variables.

3. Cointegration Test

| | *Test statistics* | 1% *critical value* | 5% *critical value* | 10% *critical value* |
|---|---|---|---|---|
| Z(t) | -3.567 | -5.137 | -4.529 | -4.218 |

**Table 8.** Engle-Granger Test

After conducting the unit root tests, the next step is to perform cointegration tests to determine the best method to use. The Engle-Granger test is used to examine the cointegration relationship between two or more variables. Cointegration happens when two or more variables exhibit similar time trends despite lacking a direct causal relationship with one another. The null hypothesis in the Engle-Granger cointegration test states that there is no cointegration relationship, while the alternative hypothesis suggests that there is cointegration. The results of the statistical test indicate values below the three critical values, implying that there is no cointegration among the variables. This is the suitable method to be used when there is no cointegration at the first difference level of the vector autoregressive model (VAR).

4. VAR Model Estimation

a. Optimal Lag Length

| Lag | LL | LR | df | p | FPE | AIC | HQIC |
|---|---|---|---|---|---|---|---|
| 0 | 245.975 | | | | 1.2e-08 | -4.084 | -4.036 |
| 1 | 303.446 | 114.94 | 25 | 0.000 | 6.7e-09 | -4.634 | -4.348 |
| 2 | 340.729 | 74.565 | 25 | 0.000 | 5.4e-09 | -4.842 | -4.318 |
| 3 | 393.855 | 106.25 | 25 | 0.000 | 3.4e-09* | -5.319 | -4.556* |
| 4 | 408.507 | 29.304 | 25 | 0.251 | 4.1e-09 | -5.144 | -4.143 |
| 5 | 434.891 | 52.767 | 25 | 0.001 | 4.1e-09 | -5.167 | -3.928 |
| **6** | 469.56 | **69.338*** | 25 | 0.000 | 3.5e-09 | **-5.331*** | -3.853 |

**Table 9.** Criteria for Lag Selection

*optimal lag

- LR: Sequential modified Likelihood Ratio test (5% level)
- FPE: Final Prediction Error
- AIC: Akaike Information Criterion
- HQ: Hannan-Quinn Information Criterion

In the autoregressive model, the criteria for determining the optimal lag length is used to determine the number of lag variables to be included in the regression model. Lag 6 was selected based on criteria from AIC and LR. The choice of lag 6 was made because the AIC and LR methods are more proportionally used in time series as AIC provides a balance between model fit and complexity, allowing the selection of the most suitable model while taking complexity into account. This approach is supported by theoretical considerations underlying the classic maximum likelihood principle (Akaike, 1998).

b. Short-run in First-difference

In the short term, using the standard VAR in first difference form shows how variables respond to a one-unit shock at a particular time, and the results are then represented through these equation models:

$$\begin{aligned}\boldsymbol{dAccesstoCredit_t} &= \boldsymbol{\alpha_1} \\ &+ \left[\sum_{i=1}^{6} \boldsymbol{\beta_1 dAccesstoCredit_{t-i}} + \boldsymbol{\beta_2 dCreditRisk_{t-i}} + \boldsymbol{\beta_3 dFinInclusionIndex_{t-i}} \right. \\ &\left. + \boldsymbol{\beta_4\, dCreditSpreads_{t-i}} + \boldsymbol{\beta_5 dlnGDPreal_{t-i}}\right] + \boldsymbol{\varepsilon_t}\end{aligned} \tag{14}$$

$$\begin{aligned}\boldsymbol{dCreditRisk_t} = \boldsymbol{\alpha_1} &+ \left[\sum_{i=1}^{6} \boldsymbol{\beta_1 dAccesstoCredit_{t-i}} + \boldsymbol{\beta_2 dCreditRisk_{t-i}} + \boldsymbol{\beta_3 dFinInclusionIndex_{t-i}} \right. \\ &\left. + \boldsymbol{\beta_4\, dCreditSpreads_{t-i}} + \boldsymbol{\beta_5 dlnGDPreal_{t-i}}\right] + \boldsymbol{\varepsilon_t}\end{aligned} \tag{15}$$

$$\begin{aligned}\boldsymbol{dFinInclusionIndex_t} &= \boldsymbol{\alpha_1} \\ &+ \left[\sum_{i=1}^{6} \boldsymbol{\beta_1 dAccesstoCredit_{t-i}} + \boldsymbol{\beta_2 dCreditRisk_{t-i}} + \boldsymbol{\beta_3 dFinInclusionIndex_{t-i}} \right. \\ &\left. + \boldsymbol{\beta_4\, dCreditSpreads_{t-i}} + \boldsymbol{\beta_5 dlnGDPreal_{t-i}}\right] + \boldsymbol{\varepsilon_t}\end{aligned} \tag{16}$$

$$\begin{aligned}\boldsymbol{dCreditSpreads_t} &= \boldsymbol{\alpha_1} \\ &+ \left[\sum_{i=1}^{6} \boldsymbol{\beta_1 dAccesstoCredit_{t-i}} + \boldsymbol{\beta_2 dCreditRisk_{t-i}} + \boldsymbol{\beta_3 dFinInclusionIndex_{t-i}} \right. \\ &\left. + \boldsymbol{\beta_4\, dCreditSpreads_{t-i}} + \boldsymbol{\beta_5 dlnGDPreal_{t-i}}\right] + \boldsymbol{\varepsilon_t}\end{aligned} \tag{17}$$

$$\begin{aligned}\boldsymbol{dlnGDPreal_t} = \boldsymbol{\alpha_1} &+ \left[\sum_{i=1}^{6} \boldsymbol{\beta_1 dAccesstoCredit_{t-i}} + \boldsymbol{\beta_2 dCreditRisk_{t-i}} + \boldsymbol{\beta_3 dFinInclusionIndex_{t-i}} \right. \\ &\left. + \boldsymbol{\beta_4\, dCreditSpreads_{t-i}} + \boldsymbol{\beta_5 dlnGDPreal_{t-i}}\right] + \boldsymbol{\varepsilon_t}\end{aligned} \tag{18}$$

$R^2$: 0.2704(*AccesstoCredit*) 0.5724(*CreditRisk*) 0.3325(*FinInclusionIndex*)

0.5726(*CreditSpreads*) 0.7467(*lnGDPreal*).

The VAR estimation from the data is quite effective in capturing the underlying relationships or dynamics, as evidenced by the significant R-squared values and F-statistics.

c. VAR Stability and Autocorrelation

| Lag | Chi2 | df | Prob>chi2 |
|---|---|---|---|
| 1 | 38.92 | 25 | 0.0375 |
| 2 | 27.88 | 25 | 0.3132 |
| 3 | 46.70 | 25 | 0.0053 |
| 4 | 44.02 | 25 | 0.0107 |
| 5 | 42.95 | 25 | 0.0141 |
| **6** | 16.45 | 25 | **0.9006** |

**Table 10.** Autocorrelation

The null hypothesis states that there is no autocorrelation at the lag order, so at lag 6, the null hypothesis is not rejected. Therefore, it can be concluded that there is no autocorrelation at lag 6. The VAR model with lag 6 has met the assumption of no autocorrelation. In the VAR stability test, all eigenvalues fall within one-unit circle, indicating that the model meets the stability condition. As a result, it is concluded that there is no autocorrelation in the VAR and that it meets the stability assumption.

d. Granger Causality Test

| Equation | Excluded | chi2 | df | Prob>chi2 |
|---|---|---|---|---|
| Access to credit | All | 40.75 | 24 | 0.018 |
| Credit risk | All | 70.619 | 24 | 0.000 |
| Financial inclusion index | All | 42.569 | 24 | 0.011 |
| Credit spreads | All | 102.84 | 24 | 0.000 |
| Real GDP (ln) | All | 40.779 | 24 | 0.018 |

**Table 11.** Granger Causality Test Result

Granger causality tests were also conducted to examine whether there is a long-term relationship between variables. If the p-value associated with the Granger causality test is below the selected significance level, for example 0.05, this indicates evidence of Granger causality between those variables. In conclusion, overall, there is a long-term relationship between the variables.

5. Forecasting VAR (in-out of sample)

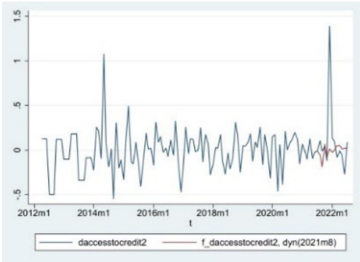
In conducting forecasting in this study, both in-sample and out-of-sample analyses were performed. The in-sample analysis was carried out from March to July 2021, while the out-of-sample analysis used the most recent one-year period in the observations, from August 2021 to July 2022.

| **Variable** (first-difference) | **RMSE** | **MAE** | **MAPE** |
|---|---|---|---|
| Access to credit | 0.80867883 | 1.6013969 | 1.9297684 % |
| Credit risk | 0.04823066 | 0.12532384 | 1.0534684 % |
| Financial inclusion index | 0.0157902 | 0.02870528 | 1.316432 % |
| Credit spreads | 0.01849659 | 0.04802294 | 1.1779347 % |
| Real GDP (ln) | 0.00151736 | 0.00428512 | 0.78887607 % |

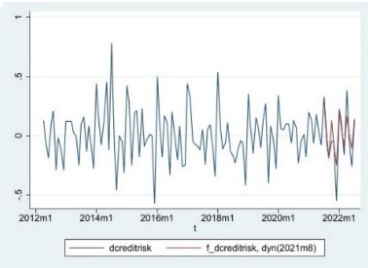
**Table 12.** Out-of-Sample Forecasting Performance of VAR Model

*RMSE: Rooted Mean Squared Error
*MAE: Mean Absolute Error
*MAPE: Mean Absolute Percentage Error

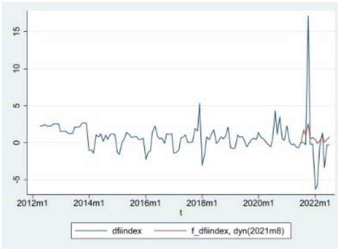
Below are the forecasting results, with the blue line representing the actual data and the red line representing the out-of-sample forecasted data.



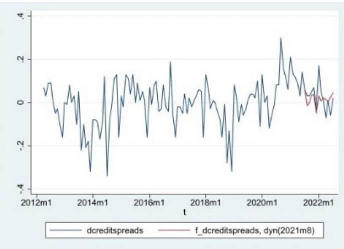

Access to Credit



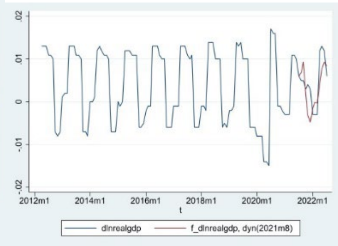

Credit Risk




Financial Inclusion Index




Credit Spreads




Real GDP (ln)

**Figure 3.** Forecasting Graph of All Variables with VAR Method

a. Changes in Access to Credit

Rooted Mean Squared Error (RMSE) calculates the average of the squared differences between actual and predicted values, and then takes the square root of that result. The lower the RMSE value, the smaller the prediction error of the model. In this context, an RMSE of 0.80867883 indicates that the average prediction error of the model is approximately 0.80867883. Mean Absolute Error (MAE) calculates the average of the absolute differences between actual and predicted values. The lower the MAE value, the smaller the prediction error of the model. In this context, an MAE of 1.6013969 indicates that the average prediction error of the model is approximately 1.6013969.

Mean Absolute Percentage Error (MAPE) calculates the average of the absolute percentage errors between actual and predicted values. The lower the MAPE value, the smaller the relative prediction error of the model compared to the actual value. In this context, a MAPE of 1.9297684% indicates that the average relative prediction error of the model compared to the actual value of access to credit is approximately 1.9297684%. Based on these test results, it can be concluded that the VAR forecasting model successfully provides accurate predictions with low prediction error rates for changes in access to credit.

b. Changes in Credit Risk

With an RMSE value of 0.04823066, the model in this study exhibits a very small level of prediction error. The MAE value of 0.12532384 indicates that the prediction error of the model is also low. The MAPE value of 1.0534684% suggests that the relative error of the model in this study compared to the actual value of credit risk (first-difference) is relatively low. Based on these test results, it can be concluded that the VAR forecasting model in this study provides excellent estimates of changes in credit risk.

c. Changes in Financial Inclusion Index

The RMSE value of approximately 0.0157902 indicates that the VAR model in this study is capable of providing estimates of changes in the financial inclusion index with a high level of accuracy. The low MAE value of around 0.02870528 suggests that the prediction error of the model is also very low in absolute terms. With an MAPE value of 1.316432%, the relative error of the VAR model in this study is also low. The high accuracy and proven consistency of this research model can serve as a tool for making decisions related to financial inclusion.

d. Changes in Credit Spreads

With an RMSE value of 0.01849659, this model exhibits a relatively low level of prediction error. This means that the average prediction error of the model is around 0.01849659. Additionally, the low MAE value of approximately 0.04802294 indicates that the prediction error of the model is also generally low. The MAPE value of 1.1779347% suggests that the relative error of the model in this study is also low. With an average absolute error percentage of around 1.1779347%, this research model provides consistent and accurate estimates of the actual credit spreads (first-difference).

e. Changes in Real GDP

With a very low RMSE value of 0.00151736, the model in this study exhibits a very small level of prediction error. The low MAE value of around 0.00428512 indicates that the prediction error of the model is also minimal. Additionally, the low MAPE value of 0.78887607% suggests that the relative error of the model in this study is also low. The VAR model in this research can be used as an effective tool due to its high level of accuracy and consistency in understanding and predicting future changes in real GDP.

6. Forecasting VAR vs ARIMA (1,1,1)

| Variable | RMSE | | MAE | | MAPE | |
|---|---|---|---|---|---|---|
| *(first-difference)* | VAR | ARIMA | VAR | ARIMA | VAR | ARIMA |
| Access to Credit | 0.808679 | 1.207972 | 1.6013969 | 0.785704 | 1.93% | 9.57% |
| Credit Risk | 0.048231 | 0.075575 | 0.12532384 | 0.066538 | 1.05% | 4.19% |
| Financial Inclusion Index | 0.01579 | 0.064054 | 0.02870528 | 0.034872 | 1.32% | 5.08% |
| Credit Spreads | 0.018497 | 0.014334 | 0.04802294 | 0.011492 | 1.18% | 1.93% |
| Real GDP (ln) | 0.001517 | 0.000566 | 0.00428512 | 0.000495 | 0.79% | 1.26% |

**Table 13.** VAR vs ARIMA (1,1,1) Forecasting Result

*RMSE: Rooted Mean Squared Error
*MAE: Mean Absolute Error
*MAPE: Mean Absolute Percentage Error

ARIMA (Autoregressive Integrated Moving Average) is another method in data analysis and forecasting used to model and predict time series data. By comparing the results of VAR testing with ARIMA, we can determine which method is more accurate for this research.

a. Changes in Access to Credit

Comparison of the interpretation of forecasting results for the access to credit variable (first-difference) using the ARIMA and VAR methods provides an understanding of the capabilities of both methods in predicting changes in access to credit. Specifically, the higher RMSE and MAE values and the relatively higher MAPE (9.57%) indicate that the ARIMA model may have a higher error rate in predicting the relationship between access and credit variables. However, in the VAR method, there are lower RMSE and MAE values, as well as a lower MAPE (1.93%), indicating that the VAR model is better at predicting changes in access to credit.

b. Changes in Credit Risk

The low RMSE, low MAE, and relatively low MAPE (4.19%) indicate that the ARIMA model can predict changes in credit risk with a low error rate. The forecasting results from the VAR model provide estimates of how the credit risk variable is influenced by and influences other variables in the system. In this case, the low RMSE, higher MAE, and very low MAPE (1.05%) suggest that the VAR model provides more accurate predictions for changes in credit risk compared to the ARIMA model.

c. Changes in Financial Inclusion Index

In this case, the relatively low RMSE, low MAE, and fairly low MAPE (5.08%) indicate that the ARIMA model can predict changes in the financial inclusion index with a fairly low error rate. The VAR model provides estimates of how the financial inclusion index is influenced by and influences other variables in the system. In this case, the very low RMSE, low MAE, and lower MAPE (1.32%) suggest that the VAR model provides highly accurate predictions for the financial inclusion index (first-difference) compared to the ARIMA model.

d. Changes in Credit Spreads

In this case, the low RMSE, low MAE, and relatively low MAPE (1.93%) indicate that the ARIMA model can predict changes in credit spreads with a low error rate. However, with the VAR method, although the RMSE is higher than ARIMA, the lower MAE and MAPE (1.18%) suggest that the VAR model successfully provides fairly accurate predictions for changes in credit spreads.

e. Changes in Real GDP

The ARIMA model with low RMSE, low MAE, and relatively low MAPE (1.26%) indicates that it can predict changes in real GDP effectively. On the other hand, the VAR model, despite having a higher RMSE than ARIMA, but with lower MAE and MAPE (0.79%), suggests that it can also provide fairly accurate predictions for changes in real GDP.

## IV. Conclusion

In this study, the author aimed to achieve two main objectives: indexing financial inclusion using principal component analysis (PCA) and further analyzing lending and financial inclusion using vector autoregression (VAR) up to forecasting. The indexing of financial inclusion was conducted in two stages. The results of the first-stage indexing showed that indicators of geographic coverage were more significant than demographic coverage in explaining the availability dimension. The results of the second stage showed that the availability dimension was the most important in explaining overall financial inclusion.

The author then used the VAR model to analyze the relationships among variables, such as access to credit, credit risk, and others, which proved to be more effective in predicting variables compared to other autoregressive models. The VAR method provided reliable projections of future interactions and developments of variables, supporting decision-making in various contexts.

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