Original Research Article

 Macroeconomic Uncertainty Analysis to Credit Allocation of Indonesian Banking

ABSTRACT

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| The Loan to Asset (LTA) ratio indicates the ability of bank funds to meet credit demand. LTA decisions change over time to adjust to economic conditions, but the most dangerous influence is macroeconomic uncertainty. Therefore, the purpose of this study is to analyze macroeconomic uncertainty on credit allocation decisions of banks in Indonesia. Four indicators of macroeconomic uncertainty are used in this study. The method of uncertainty data analysis is Generalized Autoregressive Conditional Heteroscedasticity (GARCH), while the regression analysis uses Autoregressive Distributed Lag (ARDL). The results of the study confirm that macroeconomic uncertainty has a negative impact on credit allocation in Indonesian banks. The results of the study prove that banks in Indonesia act homogeneously in the face of macroeconomic uncertainty, namely tending to act more carefully in allocating credit. The implications of this study emphasize that monetary authorities must be careful in designing interest rate policies to support the development of the banking sector. Further research could examine policy interest rate uncertainty as a key to understanding macroeconomic uncertainty. |

*Keywords: Uncertainty Macroeconomics, Bank Credit Allocation, GARCH, Risk Decision.*

1. INTRODUCTION

Banks play a crucial role in a country's economy. As an intermediary institution, the main focus of banking lies in optimizing credit distribution to support economic activities. As is known, credit is one of bank fund allocation in the earning assets group (Sinungan, 2000). A higher LTA ratio indicates that most of the bank's resources are used for lending activities compared to storing securities or other assets (Baum et al., 2004). The LTA of Indonesian Banking recorded by the Financial Services Authority for the past seven years has tended to decline, but in the past three years it has started to increase. Various situations and conditions envelop Indonesia every year which have an impact on banks' decisions in allocating bank assets. It is true that Indonesia's conditions over the past seven years have not been free from uncertainty, most of which are triggered by global uncertainty. The research findings of Saputra & Hendri (2024) confirm that global events cause spillovers in other countries which can affect economic activity in a country as a result of the increasingly connected economy, finance, and politics. The impact of this uncertainty can affect the bank's risk perception towards credit returns. As explained in Investment Theory that an investment decision is a trade-off between risk and return, where uncertainty will worsen the risk and reduce real returns. Mouillon (2006) identified sources of uncertainty that by definition come from rapid shifts in events from a number of volatile variables, such as regulation, technology, competition, macroeconomics, and consumer preferences. In other words, rapid changes in various aspects of the economic and social environment can increase the risk of making decisions under uncertainty.

Uncertainty indicates that banks are faced with a risk. In asset management, risk will be considered to what extent banks are willing to bear it or referred to as risk tolerance. Markowitz in Modern Portfolio Theory explains that risk tolerance is a primary consideration in asset allocation decisions, both risks originating from internal and external sources. The Non-Performing Loan (NPL) ratio is the most important characteristic in explaining bank credit-granting behavior (Whyte, 2010). The NPL ratio of Indonesian Conventional Commercial Banks for the past seven years has indeed been in the healthy category, this makes banks feel confident to continue to channel credit amidst uncertainty. On the other hand, the Loan at Risk (LaR) ratio which tends to be in the high category (between 10 percent and 20 percent) indicates the potential for large credit risk. If LaR remains in the high category, the bank is at risk of experiencing large losses from non-performing loans. Unstable macroeconomic conditions can directly affect the bank's ability to manage credit risk, which ultimately determines the portion of credit allocation.

This external risk is referred to as market risk, which refers to volatile macroeconomic variables, such as economic growth, inflation, interest rates, and exchange rate movements (Bodie et al., 2013). Mankiw et al., (2013) explained that GDP is a measure of the income of each person in the economy and total expenditure on the output of economic goods. This means that the GDP rate reflects the economic conditions of a country that can determine the smoothness of loan repayments. When economic conditions are stable, banks expect that borrowers can repay the total loan according to the agreed agreement. Meanwhile, an inflation rate that is far from expected will harm lenders (Case & Fair, 2006). In other words, inflation reduces the allocation of bank credit. This condition is caused by the value of money being eroded over the term of the credit contract (Colin & Kacaribu, 2021). Then, the policy interest rate as a reference interest rate for banks in determining the cost of funds for loans and deposits. The higher the interest rate, the greater the cost of funds that must be borne by the bank, which can increase interest rate risk. The increase in credit interest rates due to the increase in the cost of funds can cause a decrease in credit demand and encourage banks to be more selective in credit distribution in order to avoid adverse selection. Finally, the depreciating exchange rate causes banks to reduce credit allocation because banks must meet the company's obligations in foreign denominations, this condition is related to changes in policy interest rates. Unstable macroeconomic conditions are a challenge for banking.

As explained above, the LTA ratio of Indonesian banking will change at any time based on the bank's risk tolerance, both considering internal and external risks. Market risk is the main factor for banks to make credit allocation decisions because this risk cannot be avoided and plays an important role in determining asset prices. The problem of this research begins with the inconsistency between the behaviour of Indonesian banking in determining the LTA ratio with macroeconomic conditions or what is often referred to as the first moment. Therefore, the main focus of this research is on economic conditions that result in risk or referred as second moment, which is very likely to influence bank decisions in credit allocation. According to Baum et al. (2009) and Whyte (2010), the second moment (measure of uncertainty) also has an important role for banks to be willing to allocate funds to credit.

Several previous studies have explained that macroeconomic uncertainty has a negative effect on bank credit allocation (Baum et al., 2004, 2009; Caglayan & Xu, 2016a; Colin & Kacaribu, 2021; Ndwiga, 2023; Talavera et al., 2012; Yang & Zhou, 2019). Meanwhile, Whyte (2010) found that uncertainty actually triggered banks in Jamaica to increase credit distribution. Uncertainty is created by high variability (Blanchard & Johnson, 2014). High variability of macroeconomic variables can complicate financial planning and trigger major risks for decision makers (Ghozali & Ratmono, 2017). According to research by Colin & Kacaribu (2021), macroeconomic uncertainty will disrupt the predictability of credit repayment by banks which ultimately reduces the bank's real return.

Previous studies have focused more on macroeconomic conditions, namely inflation, empirical research conducted in different countries does not avoid differences in results. The lack of studies discussing the effect of macroeconomic uncertainty on bank credit allocation in Indonesia is the main foundation and provides a new perspective. In addition, this study measures market risk variables using the GARCH model of each market risk variable, namely inflation, interest rates, exchange rates and business cycles. These things highlight the gaps in the fields of empirical review, methodology, and variable identification. Therefore, the analysis of the impact of macroeconomic uncertainty becomes a new perspective for banks in making decisions under uncertainty.

2. material and methods

2.1. Theoretical Review

The funds successfully collected by the bank are then placed in assets with a strategy that takes into account applicable policies. According to Sinungan (2000), the objectives of bank fund allocation are (i) Achieving a sufficient level of probability, and (ii) Maintaining public trust by maintaining a safe liquidity position. This is done by the bank to avoid idle funds and to ensure that funds are used for activities that can be reached by the bank's performance and the fairness of the bank's line of business. The asset allocation approach places bank funds into assets and is closely related to bank asset management (Sinungan, 2000). Bank asset management refers to the bank's strategy in managing assets based on three main objectives, namely maximum profit, low risk, and sufficient liquidity that must be met simultaneously (Mishkin, 2017).

**2.1.1 Modern Portfolio Theory (MPT)**

Basically, this theory understands the relationship between returns and risk. Over time, this theory has been widely adopted in the financial community. In other words, MPT has been applied and accepted by many individuals, institutions, and organizations involved in the financial sector. This theory has strong implications for portfolio management because it develops the concept of diversification into a more quantitative one, namely asset allocation (Jones, 2014). Asset allocation is a selection technique by thinking in asset classes. Different asset classes offer different potential returns and different levels of risk.

Asset diversification involves allocating funds to different types of assets that have low or negative correlation. The negative impact of changes in the value of an asset can be reduced by the good performance of other assets or called the diversification effect. In addition, diversification has the potential to produce a portfolio with a lower level of risk without sacrificing potential returns. Classification of asset diversification, namely allocation between asset classes and allocation within asset classes. The diversification effect on allocation between asset classes helps reduce risk concentration, while allocation within asset classes emphasizes further diversification in an effort to obtain higher potential returns.

Asset allocation refers to how much funds are allocated to an asset class. The weight of each asset class can range from 0 to 100 percent. Asset allocation is considered to be an important decision in optimizing profits and preserving wealth. Asset allocation decisions in Modern Portfolio Theory are determined by two things (Jones, 2014), namely time horizon and risk tolerance. Time horizon emphasizes the length of time funds are invested in assets to achieve investment goals. While risk tolerance refers to the availability to bear a number of risks. Risk tolerance in every asset allocation decision focuses on optimal risk management to achieve expected returns. Risk itself is grouped into two, namely specific risk and market risk. Optimal asset allocation aims to obtain expected returns with a level of risk that is willing to be borne. In the context of risk, asset allocation that refers to the principle of diversification can effectively reduce or even eliminate specific risks. However, there is a market risk that cannot be completely eliminated, namely when the market situation is very volatile. Volatile market conditions are an important concern in risk management which ultimately affects bank asset allocation decisions.

Bank credit allocation decisions by considering risk can reduce the possibility of bad debts. Credit risk will decrease along with the accuracy of credit allocation. This is because the right asset allocation shows good diversification so that asset-specific risks can be reduced or even eliminated. However, diversification cannot completely eliminate market risk (Jones, 2014). Market risk is a major concern for bank portfolio managers in allocating credit, because market risk plays an important role in determining credit prices and uncertainty about credit returns. That is what causes banks to change the proportion of credit allocation. By managing market risk properly, banks can maintain credit quality, increase profits, and maintain financial stability in the long term.

**2.1.2 Risk, Uncertainty and Volatility**

Risk is often referred to as something bad could happen. By definition, risk arises as a result of the uncertainty of an event that can cause losses to the business world (Djojosoedarso, 2003). Risk is uncertainty that can be predicted. Risk groups are divided into two (Bodie et al., 2013; Jones, 2014; Mankiw et al., 2013), namely specific risk and market risk. The Indonesian Financial Services Authority Regulation stipulates eight types of risks in banking, one of which is credit risk. As discussed earlier, this risk can be reduced by diversification. Therefore, market risk is a pillar that is the focus of this research analysis. Market risk has other names in financial analysis, such as systematic risk, external risk, non-diversifiable risk, and aggregate risk. The definition of market risk is the risk of a bank that originates from broad economic uncertainty such as the business cycle, interest rates, inflation rates, movements in domestic exchange rates against other countries' currencies (exchange rates), and others (Bodie et al., 2013).

Statistically, risk is measured by variance ($σ^{2}$) or standard deviation (𝜎). In general, standard deviation is more often used than variance because it has the same units as the original data (not squared). Standard deviation shows how far the data deviates from its mean value. Standard deviation is an absolute measure of variability (Van Horne & Wachowicz, 2009). High variability can increase uncertainty (Blanchard & Johnson, 2014). The higher the standard deviation value, the greater the uncertainty created. According to Ghozali & Ratmono (2017), high variability of macroeconomic variables can complicate financial planning and trigger major risks for decision makers. In addition, standard deviation can measure the volatility of a variable, namely how fluctuating the variable is (Mankiw, 2018).

Volatility reflects unstable conditions (fluctuating), where conditions of decline or increase occur extremely. The higher the volatility value, the greater the associated risk. High fluctuations make things uncertain. In addition to standard deviation, volatility can be measured using various methods such as Exponentially Weighted Moving Average (EWMA) dan GARCH. Many studies use GARCH to measure volatility that proxied uncertainty as this study does.

**2.1.3 Risk Decision**

Decision making becomes more difficult in uncertain situations. Each individual or company has a different level of willingness to bear risk. This is related to risk preferences, some are risk averse, some like risk, and some are neutral to risk (Pindyck & Rubinfeld, 2014). Preferences reflect certain choices of risk and expected returns based on how much risk aversion (Mankiw et al., 2013). Risk preferences can also be explained by the principle of marginal satisfaction in Satisfaction Theory (Salvatore, 2003), where marginal satisfaction can decrease, remain constant, or increase from increasing income or wealth. This is related to the type of decision under uncertainty, namely risk averse, risk neutral, and risk seeker.

Most individuals prefer to avoid risk (risk averse) which indicates a dislike of uncertainty (Mankiw et al., 2013). Risk averse behavior is intended for banks that do not want to bear risk at a certain level, unless there is adequate compensation for the action. Individuals or institutions that are very willing to avoid risk must be willing to pay a risk premium, which is the amount of money they are willing to spend to avoid uncertainty of return (Pindyck & Rubinfeld, 2014). The amount of the premium depends on the choice of risk faced. The level of risk aversion depends on the nature of the risk itself and the individual's income (Pindyck & Rubinfeld, 2014).

2.2. Previous Research

Baum et al. (2009) as pioneers in this topic, investigated how variations in macroeconomic uncertainty distorted the allocation of commercial bank loan funds over a quarter of a century. Macroeconomic uncertainty significantly distorted the allocation process and the magnitude of the effect found was a 6% to 10% change in the spread of bank loan-to-asset ratios in response to a doubling of macroeconomic uncertainty. This is a large enough magnitude in economic terms to suggest that the second moment is important and should not be ignored by economic policymakers.

Furthermore, Quagliariello (2009) explains the empirical results of his research in Italy. As the period of turbulence increases, banks receive noisy signals about expected loan returns, so they behave homogeneously. When the return on a particular investment is less predictable, better-informed banks can exploit their competitive advantage and behave differently than less-informed banks. This is also supported by Caglayan & Xu (2016b) that changes and sentiment of volatility have a significant negative impact on bank credit growth. Banks further reduce their loan growth when volatility sentiment reaches excessive levels. More specifically, inflation volatility exhibits a strong negative relationship with LTA ratio dispersion, across a sample of EU and non-EU countries (Caglayan & Xu, 2016a). Bank managers (i) have the discretion to lend more preferentially when inflation volatility is low, since they can predict the returns from each project more successfully; (ii) behave similarly during periods of high inflation volatility.

In contrast, Whyte (2010) found that exchange rate uncertainty and inflation rates had a positive effect on bank lending in the short term. However, uncertainty related to interest rates had a negative effect. Whyte believes that this result occurred because Jamaica coincided with a period of recession. The results also prove that macroeconomic uncertainty has no long-term impact on bank lending behavior in Jamaica.

Lodenius (2017) identified more diverse macroeconomic uncertainty variables. The results show that indices that are more based on human and societal expectations have a greater impact than the GARCH model based on the model. In addition, CPI is a better proxy than GDP, which may be due to the fact that many central banks have inflation targets. While Yang & Zhou (2019) identified a greater impact of uncertainty on unlisted Chinese commercial banks than on listed banks. In addition, his research proves that the level of trust is very important to reduce the negative impact of macroeconomic uncertainty.

As far as the ability to search for previous research, Colin & Kacaribu (2021) was the first to examine Indonesia's macroeconomic volatility in relation to credit distribution, like other previous studies. The results of his research prove that inflation volatility and GDP growth volatility have a negative relationship with credit distribution, while exchange rate depreciation volatility does not affect credit distribution. Juelsrud & Larsen (2022) produced a forward-looking study, that the impact of macroeconomic uncertainty is largely driven by monetary policy uncertainty, which suggests that uncertainty about the stance of monetary policy is key to understanding why macro uncertainty affects bank lending.

***Ha***: *Macroeconomic uncertainty is thought to have a significant negative impact on the bank credit allocation.*

2.3. Methodology

**2.3.1 Data Identification**

This study will adopt a quantitative approach with secondary data and then primary data. The secondary data of this study analyzes all Conventional Commercial Banks summarized in the Indonesian Banking Statistics. The data analysis method used in this research is GARCH and Autoregressive Distributed Lag (ARDL). The source of research data from the Indonesian Economic and Financial Statistics and The Indonesian Financial System Statistics from Bank Indonesia, SPI from OJK, The Central Statistics Agency of Indonesia, and The Global Economy. The observation period of the study covers 153 months or observations, namely from January 2012 to September 2024.

The credit allocation variable is the loan to asset ratio or a variable that shows the portion of bank assets in the form of credit. While the macroeconomic uncertainty variable is taken from each calculation and then modeled with GARCH for the volatility measure. As is known, the inflation variable is the calculation of the difference between the Consumer Price Index of the previous and current periods against the previous period. The exchange rate variable used is the exchange rate depreciation, while the business cycle variable uses the Industrial Production Index growth measure. And finally, the interest rate variable used is the bank spread interest rate.

**2.3.2 Measuring Macroeconomic Volatility**

In this study, macroeconomic volatility variables are created from the results of the GARCH model. However, before referring to the GARCH model, the Autoregressive Integrated Moving Average (ARMA) model is created first to obtain an average equation that has an Autoregressive Conditional Heteroscedasticity (ARCH) effect. The ARMA model is an approach to time series forecasting that utilizes the correlation between data values. The ARMA model consists of three processes, namely autoregressive (p) and moving average (q), or often denoted as ARMA (p, q). The ARMA model is a combination of the AR(p) and MA(q) models which are written as follows:

$$z\_{t}=δ\_{1}z\_{t-1}+…+δ\_{p}z\_{t-p}+ε\_{t}-θ\_{1}ε\_{t-1}-…-θ\_{p}ε\_{t-p}$$

Where, zt is the stationary time series data at a certain level, 𝜀t is a random shock, while 𝛿 and 𝜃 are the autoregressive and moving average coefficients, respectively. The ARMA model that found heteroscedasticity problems during the diagnostic test showed that the time series data contained volatile elements, where a period showed high volatility and residuals, then a period with low volatility and residuals (Ghozali & Ratmono, 2017). Therefore, the model must be continued with the GARCH model.

The GARCH model further handles time series data whose residual variance depends not only on the residuals of the previous period but also the residual variance of the previous period. According to Bollerslev, determining the existence of a GARCH model is important because models with high orders often make model specifications complex and difficult to implement (Box et al., 2016). The GARCH (1,1) model is the simplest low-order GARCH model compared to the GARCH (1,1), GARCH (2,1), and GARCH (1,2) models. The GARCH model can be written as follows:

$$Variance Equation: σ\_{t}^{2}= β\_{0}+β\_{1}ε\_{t-1}^{2}+ β\_{2}σ\_{t-1}^{2}$$

Where $σ\_{t}^{2}$ is the residual variance influenced by the previous period residual and the previous period residual variance $(σ\_{t-1}^{2})$. The process of building the model generally follows the Box-Jenkins approach (Box et al., 2016), which involves initial identification of the ARCH effect, followed by model parameter estimation, and ending with model evaluation to ensure its accuracy. In this model, the diagnostic test of the ARCH effect must be ensured to have disappeared.

**2.3.3 Autoregressive Distributed Lag (ARDL) Regression**

This study will use the ARDL approach. ARDL allows to analyze the influence of past values ​​(lag) of both dependent and independent variables on the current value of the dependent variable. The lag element in this method shows the effect of the lag of the independent variable affecting the dependent variable. The optimal lag for the research model is determined by the Akaike Info Criteria (AIC). The selected lag is the lag that provides the smallest AIC value. ARDL is able to estimate research variables with different levels of stationarity, namely stationary at the level (I(0)) and stationary at the first difference (I(1)). In addition, ARDL is suitable for use in small sample sizes. The ARDL model of this study is estimated based on the following equation:

$$AK\_{t} = α+ γAK\_{t-1}+β\_{1}VOL\_{INF}\_{t}+β\_{2}VOL\_{INF}\_{t-x}+β\_{3}VOL\_{IR}\_{t}+β\_{4}VOL\_{IR}\_{t-x}+β\_{5}VOL\_{ER}\_{t}+β\_{6}VOL\_{ER}\_{t-x}$$

$$+β\_{7}VOL\_{BC}\_{t}+β\_{8}VOL\_{BC}\_{t-x}+u\_{t}$$

Where α is the intercept, γ is the coefficient of the dependent lag, $β\_{1}…… β\_{8} $is the coefficient of the independent variables, AK is the credit allocation, VOL\_INF is the inflation volatility, VOL\_IR is the interest rate volatility, VOL\_ER is the exchange rate volatility, VOL\_BC is the business cycle volatility, *t* denotes the time period, *t-x* denotes the previous *x* time periods, and $u\_{t}$ is the error term.

The determination of the appropriate optimum lag in this study is determined based on the model information criteria, namely the AIC. The smaller the AIC value, the model is considered to be able to explain the data well. Finally, the regression results need to be tested for classical assumptions to prove that the model has met the Best Linear Unbiased Estimator (BLUE) criteria.

3. results and discussion

**3.1 Model Estimation Results**

**Table 1**. Unit Root Test

|  |  |  |
| --- | --- | --- |
| **Variable** | **Level** | ***First Difference*** |
| Inflation (INF) | -2.070627 | -9.717951\*\*\* |
| Interest Rate (IR) | -2.254841 | -5.505880\*\*\* |
| Exchange Rate (ER) | -3.691849\*\*\* | -13.90147\*\*\* |
| Business Cycle (BC) | -6.018193\*\*\* | -12.31202\*\*\* |

Note: P < 0.05, \*\* P < 0.01, dan \*\*\* P < 0.001

**Source:** Authors computation using E-views 10.0 (2025)

The unit root test or known as the stationarity test is shown in Table 4.1. It can be explained that the variables NT, and SB have been stationary at the level, while the variables INF and TB are stationary at the first difference level. After the stationarity of the variables is known, the next step is the formation of the ARMA model.

Identification of the ARMA model is known through the correlogram, namely analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) graphs to determine the order of p and q. Table 2 summarizes the results of the ARMA model estimation. Inflation (INF) variable has an ARIMA (1,1,0) model, the Interest Rate (IR) variable has an ARIMA (2,1,0) model, while the Exchange Rate (ER) variable has an ARMA (1,0) model, and the Business Cycle (BC) variable has an ARMA (1,1) model. In addition, the ARMA model of each variable has an ARCH effect as indicated by probability Chi2 value of less than five percent.

**Table 2.** ARMA Model Results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable** | **INF** | **IR** | **ER** | **BC** |
| Constant | -0.013 | -0.015 | 6.019\*\*\* | 3.389\*\* |
| AR(1) | 0.222\*\*\* | 0.15\*\*\* | 0.835\*\*\* | 0.765\*\*\* |
| AR(2) |  | 0.325\*\*\* |  |  |
| MA(1) |  |  |  | -0.259\*\*\* |
| Observation | 152 | 152 | 153 | 153 |
| AIC *rank* | 4 | 10 | 1 | 3 |
| *Prob.Chi2*(1) | 0.015 | 0.000 | 0.021 | 0.000 |

Note: P < 0.05, \*\* P < 0.01, dan \*\*\* P < 0.001

**Source:** Authors computation using E-views 10.0 (2025)

Table 3 shows the results of the GARCH model parameter estimation, where the ARMA model is the mean equation and the ARCH/GARCH model is in the variance equation. The estimation results of the INF variable with the ARIMA(1,1,0)-GARCH(1,1) model, the IR variable with the ARIMA(2,1,0)-GARCH(1,1) model, the ER variable with the ARMA(1,0)-GARCH(0,1) model and the BC variable with the ARMA(1,1)-GARCH(1,1) model. In addition, Table 2 shows the LM test of the INF, IR, ER, and BC variables which are more than 0.05 indicate that the GARCH model is free from the ARCH effect.

**Table 3**. GARCH Model Results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Variable** | **INF** | **IR** | **ER** | **BC** |
| **Mean Equation** |
| Constant | -0.070\*\* | -0.003 | 5.817\*\*\* | 4.315\*\*\* |
| AR(1) | 0.368\*\*\* | 0.425\*\*\* | 0.805\*\*\* | -0.045 |
| AR(2) |  | 0.127\* |  |  |
| MA(1) |  |  |  | 0.440\* |
| **Varians Equation** |
| Constant | 0.027\*\* | 0.002\*\*\* | 2.117 | 5.331\*\*\* |
| ARCH (1) | 1.252\*\*\* | 0.894\*\*\* | 0.167 | 0.654\*\*\* |
| GARCH (1) | 0.192\*\*\* | 0.250\*\*\* | 0.636\*\*\* | 0.255\*\* |
| Observation | 151 | 150 | 152 | 152 |
| *LM-Test* | 0.788 | 0.838 | 0.788 | 0.426 |

Note: P < 0.05, \*\* P < 0.01, dan \*\*\* P < 0.001

**Source:** Authors computation using E-views 10.0 (2025)

Table 3 shows the results of the GARCH model parameter estimation, where the ARMA model is the mean equation and the ARCH/GARCH model is in the variance equation. The estimation results of the INF variable with the ARIMA(1,1,0)-GARCH(1,1) model, the IR variable with the ARIMA(2,1,0)-GARCH(1,1) model, the ER variable with the ARMA(1,0)-GARCH(0,1) model and the BC variable with the ARMA(1,1)-GARCH(1,1) model. In addition, Table 3 shows the chi square probability on the INF, IR, ER, and BC variables which are more than 0.05 that indicate the GARCH model is free from the ARCH effect.

The volatility series obtained from the GARCH model will be continued to be estimated using the ARDL model. The ARDL model can handle data with mixed stationarity levels without transforming to full stationary form as in other methods. ARDL also allows the selection of optimal lags to analyze the delayed effects of independent variables. In addition, the ARDL model can show the response of the dependent variable from the influence of the dependent lag. Table 4 shows the results of the ARDL model estimation with the selected optimum lag being ARDL (1,1,0,3,1).

**Table 4.** ARDL Estimation Results

|  |  |  |  |
| --- | --- | --- | --- |
| **Variabel** | **Koefisien** | ***t-statistic*** | ***Prob.*** |
| AK(-1) | 0.979178 | 68.22226 | 0.0000 |
| VOL\_INF | -0.073486 | -1.806623\*) | 0.0730 |
| VOL\_INF(-1) | -0.075687 | -1.835744\*) | 0.0685 |
| VOL\_ER | -0.002002 | -0.236422 | 0.8135 |
| VOL\_BC | -0.000872 | -1.217046 | 0.2257 |
| VOL\_BC(-1) | -0.000121 | -0.154859 | 0.8772 |
| VOL\_BC(-2) | -0.001052 | -1.345869 | 0.1806 |
| VOL\_BC(-3) | -0.001611 | -2.351654\*) | 0.0201 |
| VOL\_IR | 0.444224 | 0.854419 | 0.3944 |
| VOL\_IR(-1) | -0.986885 | -1.901125\*) | 0.0594 |
| C | 1.564277 | 1.749320\*) | 0.0825 |
| *R2**Adjusted R2**F-statistic**Prob.(F-statistic)* | 0.977883 |  |
| 0.976280 |  |
| 610.1453 |  |
| 0.000000 |  |

Note: \*) t-statistic ≥ t-table, one tail, α=0.05.

**Source:** Authors computation using E-views 10.0 (2025)

Based on Table 4, the ARDL model proves that the adverse impact of macroeconomic uncertainty affects bank credit allocation in Indonesia. Interest rate volatility has the greatest influence, which is 98.7 percent, followed by inflation volatility with an influence of around 7%. Exchange rate volatility and business cycles have small influences of 0.2% and 0.16%, respectively. The determination of previous credit allocation plays an important role in determining the current allocation with an influence of 97.92%. All required classical assumption tests were met and it was concluded that there were no deviations from the homoscedasticity assumption, normality assumption, no relationship between residuals, and no multicollinearity problems were detected.

**3.2 Discussion**

**3.2.1 Inflation Uncertainty**

Inflation uncertainty refers to distortions in the price system. The price system in a market-oriented economy is the main mechanism by which resources are distributed to all potential alternatives (Caglayan & Xu, 2016a). In this study, inflation uncertainty is represented by inflation volatility. High inflation volatility does not reflect the actual price conditions, making it difficult for decision makers to act appropriately. This condition also results in the allocation of limited resources not being used optimally. In other words, resource allocation is directed to less productive sectors, which can disrupt economic efficiency.

In this study, the results of parameter estimation show that inflation volatility has been proven to reduce the allocation of Indonesian banking credit. Current inflation volatility and volatility in the previous month make banks reduce credit allocations at this time. This proves that the behaviour of Indonesian banks when inflation fluctuates highly tends to be more careful in distributing credit. The influence of the inflation volatility lag also proves that the inflation volatility of the previous period affects the perception of risk and bank management strategies in current credit allocation. This is because inflation volatility will make financial assets that promise fixed nominal payments in the future riskier (Blanchard & Johnson, 2014). Furthermore, Colin & Kacaribu (2021) in their research explain that inflation volatility creates uncertainty about the real return level of credit so that banks choose to be conservative in issuing or approving new loans. Banks in this condition will divert their fund allocation to other safer assets because banks do not want to take too high a risk on credit.

**3.2.2. Interest Rate Uncertainty**

The results of the study related to interest rate volatility show a negative effect on the allocation of Indonesian banking credit. This means that interest rate volatility has been proven to reduce bank credit allocation. In this study, interest rate volatility refers to the volatility of bank interest spreads. High fluctuations in interest spreads reflect instability in bank profit margins. In general, high bank interest spreads provide benefits to banks, but changes in the benchmark interest rate can cause bank deposit interest rates to increase faster than bank lending interest rates. This can narrow the spread and suppress bank profit margins. This situation requires banks to face interest rate risk. As stated by Mishkin (2017), increasing interest rate volatility will drive greater interest rate risk.

This interest rate risk causes banks to have greater liabilities than profits because banks must pay higher deposit interest as known as cost of funds raised, while credit interest income does not immediately increase. Banks hold back on increasing credit interest rates to avoid a decrease in credit demand that can trigger liquidity risk. If credit demand decreases drastically, banks will face difficulties in distributing funds that have been collected, and undisbursed funds have the potential to cause liquidity risk. This is what causes the influence of interest rate volatility in this study to have a lag.

In the next period, when the credit interest rate is raised, increasing interest rate volatility can increase the uncertainty of credit returns. Therefore, banks tend to be careful in allocating credit to avoid the risk of default. This is in accordance with what Mishkin & Eakins (2016) said, that large interest rate fluctuations cause large capital gains or losses and greater uncertainty about investment returns. According to Lugo (2008) lenders will adjust the amount of credit given when interest rates fluctuate to accommodate changes in the cost of capital and are more willing to provide credit if these conditions create opportunities for higher returns.

Mankiw also explained that increasing interest rate volatility will reduce credit demand from high-quality borrowers and increase demand from low-quality borrowers. This situation hinders potential borrowers with safe projects and banks also find it difficult to obtain accurate information regarding the profile of potential borrowers. Therefore, banks tend to be careful in providing new credit to avoid adverse selection. This is in line with the findings of Bohachova (2008), that higher interest rates tend to exacerbate adverse selection problems and ultimately increase credit risk on the bank's balance sheet.

According to Juelsrud & Larsen (2022) research findings, monetary policy uncertainty is key to understanding how macro uncertainty can affect bank lending. Monetary policy authorities must carefully design policy interest rates to support the development of the banking sector. This is important because the financial system of developing countries is a bank-based system, where the banking sector is the main facilitator of funds in the economy and plays an important role in increasing economic growth Tuna & Almahadin (2021).

**3.2.3. Exchange Rate Uncertainty**

The results of the exchange rate volatility estimation in this study confirm a negative but insignificant effect on the allocation of Indonesian banking credit. The absence of a lag effect indicates that the impact of exchange rate volatility does not necessarily occur in the same period significantly on credit distribution, but can have an effect in the future depending on economic conditions and monetary policies implemented by the central bank (Colin & Kacaribu, 2021; Suselo et al., 2008). When exchange rate volatility is high, the central bank tends to raise interest rates to stabilize the domestic currency. In this condition, borrowing costs become higher so that banks will tighten credit granting requirements to avoid future defaults, especially in sectors that are sensitive to exchange rate fluctuations, such as manufacturing, tourism, and agriculture.

The results of this study's estimation are in line with the research of Colin & Kacaribu (2021), which proves that the insignificant effect of exchange rate volatility on bank credit allocation in Indonesia is due to the credibility of Bank 98 Indonesia as a monetary authority capable of reducing public perception of exchange rate uncertainty. This allows banks to enjoy protection from the impact of unexpected shocks on real returns. In addition, the majority of credit in Indonesia is provided in Rupiah, not foreign currency, so that direct banking exposure to volatility tends to be limited. However, banks still need to be aware of the impact of exchange rate volatility in the future, especially those triggered by rising interest rates and sectors that are dependent on imports which will ultimately trigger an increase in credit risk.

**3.2.4. Business cycle Uncertainty**

This variable was proxied by the volatility of the Industrial Production Index has an effect on the decline in bank credit allocation. The results of the parameter estimation of this study indicate that business cycle volatility has a significant negative effect on Indonesian bank credit allocation at lag 3. This means that the impact of business cycle volatility cannot be felt in the current period, but it takes up to three months. The influence of business cycle volatility on bank credit allocation supports research (Baum et al., 2009; Colin & Kacaribu, 2021).

The lack of influence of business cycle volatility in the current period up to two months later can be caused by good cooperation between the government, financial authorities, and monetary authorities of Indonesia in controlling business cycle volatility. Policies issued during the volatility period, such as the national credit restructuring implemented during the Covid-19 pandemic, were able to keep credit distribution running to stimulate the economy. The significant influence that occurred in the third lag indicates the existence of a lag effect of business cycle volatility on credit allocation. This lag effect was triggered by the delay in bank awareness of potential credit risks so that banks began to be conservative in credit distribution. Bank managers' strategic decisions can be made in stages, usually after evaluating the performance of policies implemented by the government or financial authorities and/or monetary authorities. In addition, this lag effect is also related to other bank asset management objectives, namely the adequacy of Indonesian Banking liquidity as reflected in the increasing minimum Capital Adequacy Ratio (CAR) and Loan to Deposit Ratio (LDR) which tends to be within reasonable limits between 78 percent and 92 percent. These favourable conditions can limit banks' flexibility in quickly adjusting credit allocations when business cycle volatility increases. In addition, the indirect decrease in credit allocations during volatile periods is also influenced by Indonesian Financial Services Authority Policy regarding the strengthening of Credit Impairment Loss Reserves.

**3.2.5. Previous Period Credit Allocation**

Finally, the allocation of bank credit in the previous period has a significant and strong influence on the current credit allocation. Each increase in the allocation of credit in the previous period will increase the decision on the allocation of credit in the current period. The results of this study are in line with the research of Colin & Kacaribu (2021) which shows that the positive influence of the allocation of credit in the previous period on the allocation of credit in the current period is due to the role of credit accumulation. Credit disbursed in the previous period tends to have a follow-up effect in the following period. This happens because most credit has a certain tenor or term, so that the installment or management of the credit are still ongoing and influence the decision on the allocation of credit in the following period. In addition, this condition reflects the bank's strategy in maintaining a credit portfolio, including risk preferences, sector focus, or related to certain policies in order to maintain the continuity and stability of interest income.

4. Conclusion

The results of the research estimation prove that the four indicators of macroeconomic uncertainty, namely inflation volatility, interest rate volatility, and business cycle volatility have a significant negative impact on the credit allocation of Indonesian Banking, while exchange rate volatility has a negative but not significant effect. Banks in Indonesia tend to behave homogeneously, namely risk averse when in a period of turbulence or high macroeconomic volatility. This means that banks pay close attention to macroeconomic risk when making credit allocation decisions to avoid the risk of default. In addition, this study proves that good banking performance in managing risk also helps banks to be confident in distributing credit which can be seen from the increase in credit growth each year. By using the ARDL method, this analysis describes the reasons for the delay in the influence of volatility on bank credit allocation, which is an added value of this study.

In relation to the research results that have been presented, this study provides several implications for banks in Indonesia that are expected to always maintain risk averse behaviour in responding to all forms of macroeconomic uncertainty. Optimism about high credit distribution for high returns must always be evaluated continuously in order to maintain bank health, not only focusing on profit but also focusing on adequate liquidity and asset risk. In addition, monetary authorities must be careful in designing interest rate policies to support the development of the banking sector. Finally, the effect of sluggishness on business cycle volatility is a challenge for banks in adjusting credit allocation policies optimally.

**DISCLAIMER (ARTIFICIAL INTELLIGENCE)**

Author(s) hereby declared that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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