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GARCH As An Inflation Prediction Tool: An Empirical Study Of Indonesian Economic Data

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Abstract: This study is important because inflation volatility has a significant impact on macroeconomic stability and monetary policy decisions in Indonesia. Therefore, the objective of this research is to evaluate the performance of the GARCH (1,1) model in forecasting inflation volatility and analyzing its dynamic behavior. This study is an experiment aimed at forecasting inflation data for the next five years based on actual data from the 2015–2024 period. The data were obtained from Statistics Indonesia (BPS) and Bank Indonesia (BI). The results show that the GARCH (1,1) model can adequately capture the trend of volatility, as indicated by a Mean Squared Error (MSE) of 0.566398. However, the model's accuracy in predicting monthly fluctuations remains low, with a Mean Absolute Percentage Error (MAPE) of 99.19%. The implications of these findings suggest that while the GARCH (1,1) model is useful for identifying long-term volatility trends, further improvements—such as exploring advanced GARCH variants and incorporating additional macroeconomic variables—are necessary to support the formulation of more effective inflation control policies.

Keywords: Inflation, Volatility, GARCH (1,1), Forecasting, Indonesia, Time Series.

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A. INTRODUCTION

Inflation is one of the most important macroeconomic indicators as it reflects the level of price stability and purchasing power in a country. Fluctuations in inflation not only affect domestic economic activity, but also impact the expectations of market participants, investment, and monetary policy as a whole. Therefore, the ability to accurately predict the inflation rate is crucial for the government and financial authorities in developing strategies to control inflation and maintain macroeconomic stability. However, inflation prediction is not an easy task as inflation data often shows non-linear, heteroscedastic patterns, and is influenced by various external and internal factors, such as global commodity prices, exchange rates, fiscal policy, and domestic demand dynamics. The high volatility in inflation data complicates the use of conventional forecasting methods, requiring an approach that can more accurately capture the complex dynamics and volatility of the data variance.

Various methods have been developed to forecast inflation, ranging from classical statistical approaches to machine learning-based approaches. Methods such as linear regression, ARIMA (Autoregressive Integrated Moving Average), and VAR (Vector Autoregression) are often used due to their ability to capture historical patterns of time series data (Fejriani et al., 2020). However, these methods have limitations in handling conditions of non-constant or heteroscedastic variance, which is a common characteristic of inflation data (Panggabean et al., 2021). To overcome this problem, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was introduced as an effective approach in capturing the fluctuation and volatility of economic data. The GARCH model allows the variance of prediction errors to change over time, making it more suitable for modeling inflation data that is dynamic and vulnerable to economic shocks (Razi et al., 2024). Therefore, this model is a promising alternative in inflation forecasting studies, especially in the context of economies with high price volatility such as Indonesia (Inflasi et al., 2025).

Various empirical studies show that the use of GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model as an inflation prediction tool in Indonesia produces mixed findings. Although the GARCH model is designed to capture volatility in time series data, its effectiveness in predicting inflation specifically is still questionable, especially when compared to other methods that focus more on underlying economic relationships. For example, Alfan's study (2023) shows that although GARCH is able to model stock price volatility on the Indonesia Stock Exchange (JCI), the ARIMA model provides a better level of prediction accuracy. Similar findings were presented by Yanti and Soebagyo (2020), which states that although GARCH can capture variance volatility, the model is not necessarily effective in predicting inflation, especially if it does not consider the influence of other economic variables. Their research also shows that exchange rate has a significant effect on inflation, while money supply does not (Asiva, 2015). Furthermore, Lubis (2020) found a long-term relationship between inflation and economic growth, confirming that inflation dynamics are influenced by various complex factors beyond just volatility. Therefore, a number of researchers consider that GARCH is inappropriate if used alone to predict inflation, so a more comprehensive approach is needed by considering other macroeconomic variables to improve forecasting accuracy (Sartika, 2017).

Exploration of the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model as an inflation prediction tool in Indonesia reveals a number of research gaps that still need to be bridged. These gaps mainly stem from the methodological limitations used in previous studies as well as the need for a more comprehensive data analysis approach. Most of the previous studies, such as the one conducted by (Arum et al., 2023), The GSTAR-SUR model still relies on traditional econometric models such as Granger-Causality and path analysis which are less able to capture the nature of volatility in inflation data. On the other hand, while the GSTAR-SUR model offers an innovative approach, it still faces problems in detecting correlated residuals, suggesting the need for further refinements in modeling techniques (Asiva, 2015). In addition, the limited data coverage in terms of both time period and geographical area, as seen in the study (Trisdian et al., 2015). which only covers regional inflation volatility from 1999-2009, limits the generalizability of the results. The restriction of the variables studied, such as focusing only on money supply and exchange rate without considering the effect of fiscal policy or other macroeconomic indicators, also reduces the comprehensiveness of inflation prediction. Although the GARCH model offers great potential in capturing volatility dynamics, the reliance on historical data and specific variables may overlook new economic trends or ongoing structural changes (Astuti et al., 2020). Therefore, future research is recommended to integrate machine learning-based approaches to improve prediction accuracy and adaptability to changing economic dynamics (Anggraeni et al., 2022).

Based on this background, this study aims to analyze the effectiveness of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in predicting inflation in Indonesia by utilizing monthly data for the period 2015 to 2024 obtained from official sources such as the Central Statistics Agency (BPS) and Bank Indonesia (BI). The main focus of this research is to evaluate the extent to which the GARCH model is able to capture the volatility characteristics inherent in inflation data, which is characterized by dynamic fluctuations over time. In addition, this study also aims to assess the model's prediction performance in the medium term, particularly for the next five years, through the analysis of statistical indicators such as Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). Thus, this study not only contributes methodologically in the context of economic time series modeling, but also practically provides implications for policy makers in formulating a more data-based and predictive inflation control strategy.

B. METHOD

This research uses an explanatory quantitative method with a quantitative approach based on time series analysis. This method aims to explain and analyze the dynamic behavior of inflation data and test the ability of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in predicting inflation rates in Indonesia. The data used in this study is secondary data in the form of monthly inflation rates obtained from official sources such as the Central Bureau of Statistics (BPS) and Bank Indonesia (BI), with a certain period coverage that is long enough to capture inflation volatility patterns. The data collection technique is done through documentation method, with the data arranged in time series format for further analysis.

The data analysis process is carried out through several systematic stages. First, stationarity test is conducted using Augmented Dickey-Fuller (ADF) Test to ensure the stability of inflation variable in the analyzed period. After the data is declared stationary, ARIMA model identification is performed to overcome autocorrelation in the average data. Furthermore, ARCH effect test using Lagrange Multiplier (LM) Test is conducted to detect heteroscedasticity. If ARCH effect is found, then proceed to build and estimate the most suitable GARCH(p,q) model, with model selection based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. Model validation is performed with diagnostic tests such as the Ljung-Box Test for residual autocorrelation and the residual normality test.

The best GARCH model obtained is then used to predict the inflation rate in a certain period. The accuracy of the prediction results is measured using indicators such as Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). MSE calculates the average square of the difference between the actual value and the predicted value, so the smaller the MSE value, the more accurate the model in representing the data pattern. MAPE measures the absolute error as a percentage, making it easier for policy makers and non-technical parties to understand. All data processing and analysis is done using statistical software such as EViews, R, or Python. The results of this modeling are interpreted to draw conclusions about the effectiveness of the GARCH model in predicting inflation in Indonesia, as well as to provide recommendations for the development of future inflation prediction models.

The GARCH (p, q) model can be written as follows:

$$\sigma^2\_t = \omega + \Sigma(\alpha\_i * \varepsilon^2\_(t-i)) + \Sigma(\beta\_j * \sigma^2\_(t-j))$$

σ^2_t = Conditional variance at time t
ω = Constant
α_i = ARCH (Autoregressive Conditional Heteroskedasticity) coefficient
$\varepsilon^2\_(t-i)$ = Square of residuals at time t-i
β_j = GARCH coefficient
$\sigma^2\_(t-j)$ = Conditional variance at time t-j
p = GARCH order
q = ARCH order

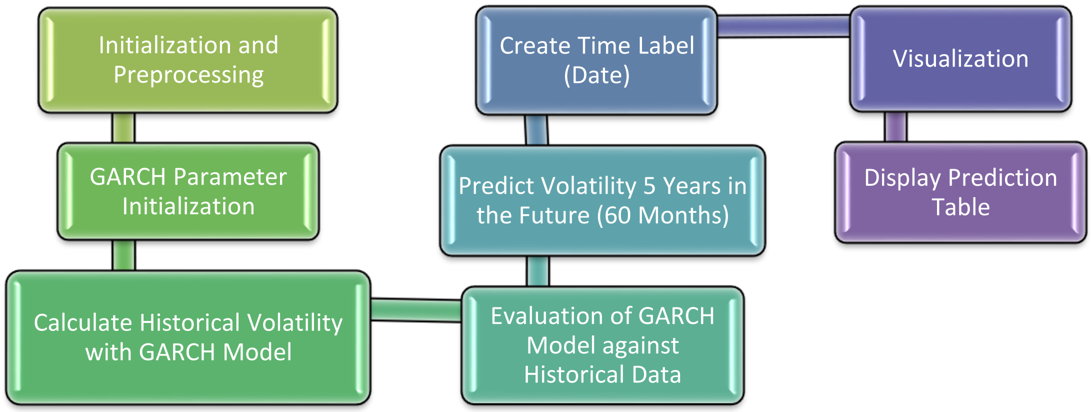

Figure 1. Algorithm for Predicting the poor with GARCH

The figure illustrates the flow of the inflation volatility modeling and prediction process using the GARCH approach. The process starts with the initialization and preprocessing stage, which is processing monthly inflation data to obtain returns that will be analyzed further. Next, we initialize the GARCH model parameters consisting of intercept parameters, ARCH components, and GARCH components. The next step is to calculate historical volatility using the GARCH model, where the conditional variance is calculated iteratively based on previous parameters and residuals. After the historical volatility value is obtained, the performance of the GARCH model is evaluated against historical data through two main metrics, namely Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). The evaluated model is then used to predict volatility for the next five years (60 months) with a forward forecasting approach based on the last volatility value. To present the results in an informative manner, time (date) labels are created that correspond to the prediction period. Finally, the prediction results are visualized in graphical form, and also displayed in the form of a prediction table to facilitate interpretation of the results.

C. RESULTS AND DISCUSSION

1. Data Description

Table 1. Data To Be Predicted

Month	Inflasi(%)
Januari	2,87
Februari	3,00
Maret	3,63
April	3,31
Mei	2,77
Juni	2,12
Juli	1,91
Agustus	2,01
September	1,77
Oktober	1,44
November	1,46
Desember	1,28

Based on Table 1, Indonesia's monthly inflation data is relatively high with 2.87% in January and 3.00% in February, before peaking in March. After that, there was a gradual decline, where in May inflation was recorded at 2.77%, and in June it fell again to 2.12%. This downward trend continued in the second half of the year, with July inflation at 1.91%, August at 2.01%, and September at 1.77%. The data shows that despite a slight uptick in August, the overall trend remained downward. Inflation in October reached 1.44%, rose slightly to 1.46% in November, before falling back to its lowest rate in December. Statistically, the highest average inflation data was recorded in March at 3.63%, indicating strong inflationary pressures in the first quarter of the year. After March, the inflation rate started to show a continuous downward trend. In April, inflation declined slightly to 3.31%, and then continued to slope until it reached 1.28% in December. This pattern indicates a trend of easing price pressures over time.

2. Forecasting Results and Decision Making

Table 1. Examples of Images with Good Resolution

Month	Years				
	2025	2026	2027	2028	2029
Januari	0.6502	0.5660	0.5148	0.4849	0.4680
Februari	0.6416	0.5607	0.5117	0.4831	0.4669
Maret	0.6333	0.5555	0.5086	0.4814	0.4660
April	0.6253	0.5506	0.5057	0.4797	0.4651
Mei	0.6176	0.5459	0.5030	0.4781	0.4642
Juni	0.6102	0.5414	0.5003	0.4766	0.4634
Juli	0.6031	0.5371	0.4978	0.4752	0.4626
Agustus	0.5963	0.5330	0.4954	0.4739	0.4618
September	0.5897	0.5290	0.4931	0.4726	0.4611
Oktober	0.5834	0.5252	0.4909	0.4713	0.4604
November	0.5774	0.5216	0.4888	0.4702	0.4598
Desember	0.5716	0.5181	0.4868	0.4690	0.4591

Based on the prediction results of the GARCH (1,1) model, the monthly volatility value is estimated for the next five years, from 2025 to 2029. In general, the volatility pattern shows a consistent downward trend over time. In January 2025, the volatility is estimated at 0.6502 and gradually decreases to 0.4680 in January 2029. This trend also occurs in other months, such as February which decreases from 0.6416 in 2025 to 0.4669 in 2029, and December which decreases from 0.5716 to 0.4591 in the same period.

This decrease indicates that the level of instability or fluctuation in the modeled inflation data tends to be more stable in the next five years. This can be interpreted as a positive signal in the context of more effective inflation control or macroeconomic policy. Nonetheless, small fluctuations still remain on a monthly basis, but with increasingly lower magnitudes over time. Overall, these projections show that the GARCH model successfully captures the exponentially decreasing volatility characteristics, in line with the nature of the model that tends to dampen shocks over time.

3. Description of Data on the Poor

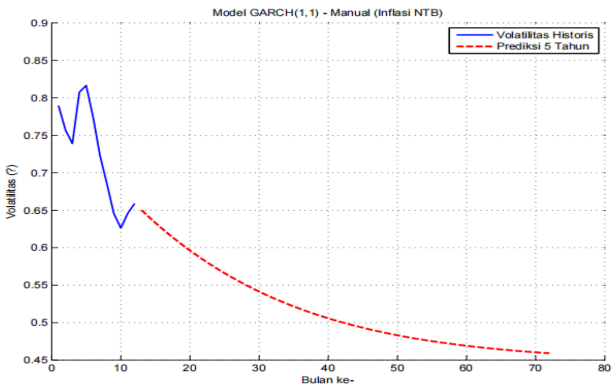

Figure 2. Graphics

Figure 2 presents the results of modeling and predicting inflation volatility in West Nusa Tenggara (NTB) Province using the GARCH (1,1) model. The horizontal axis shows the time sequence in months, while the vertical axis represents the magnitude of the conditional volatility (σ_t). The solid blue curve represents the historical volatility, which is calculated based on monthly inflation data over the period 2016 to 2024. There are significant fluctuations at the beginning of the period, reflecting the dynamics of price volatility in that period. Meanwhile, the dashed red curve shows the predicted volatility for the next five years (2025-2029), based on the modeling results.

From the prediction results, it appears that the volatility value tends to decrease gradually, indicating a tendency to stabilize inflation in the medium term if economic conditions do not experience significant shocks. This pattern is consistent with the characteristics of the GARCH model, which predicts that volatility will subside over time if there is no new shock in the system.

Table 3. MSE and MAPE Values

MSE	**MAPE**
0.566398	99.19%

Table 3 presents two evaluation measures of the GARCH (1,1) model, namely Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). The MSE value of 0.566398 indicates the average squared difference between the actual variance value (calculated from the residuals) and the variance value estimated by the model. The smaller the MSE value, the better the model represents the historical data. Meanwhile, the MAPE value of 99.19% indicates that the average absolute error in the estimated variance is relatively very high when compared to the actual value. This sizable MAPE value indicates that although the GARCH (1,1) model is able to capture the general trend of volatility, the accuracy of the model's predictions of daily or monthly fluctuations still requires improvement. Therefore, this result suggests the need for further testing or refinement of the model to improve the estimation accuracy.

D. CONCLUSIONS AND SUGGESTIONS

This study aims to analyze the dynamic behavior of inflation in Indonesia and evaluate the effectiveness of GARCH (1,1) model in predicting inflation volatility based on monthly data from BPS and BI. The analysis shows that the GARCH (1,1) model is generally able to represent inflation volatility well, indicated by the low MSE value (0.566398), although the monthly prediction accuracy is still low due to the high MAPE value (99.19%). To improve the prediction accuracy in the future, it is recommended to explore advanced GARCH models (such as EGARCH, TGARCH, or GARCH-M), as well as the integration of macroeconomic exogenous variables and alternative approaches such as VAR-GARCH, ARIMA-GARCH, or machine learning methods such as LSTM. The use of longer-term or higher-frequency data is also recommended to improve the precision of the estimates. The results of this modeling are expected to serve as a foundation for the government and monetary authorities in formulating more effective and sustainable inflation control policies.

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