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FORECASTING MODEL FOR THE DYNAMICS OF THE CONSUMER PRICE INDEX IN THE HEALTH SECTOR IN EAST JAVA USING THE ARIMA-GARCH MODEL

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ABSTRACT

The Consumer Price Index (CPI) is a measure of development success and inflation rates in a country. The CPI is often used to assess the general rate of increase in the prices of goods and services and as a consideration in adjusting salaries, wages, pensions, and other contracts. Therefore, forecasting the CPI is very useful for formulating future policies, including in the health sector. This study aims to create a CPI forecasting model for the health sector in East Java using the ARIMA-GARCH model, namely the integration of the ARIMA model with the GARCH model. The data used were monthly CPI data from January 2020 to December 2023 obtained from the Central Statistics Agency (BPS). The ARIMA model is used to capture long-term trends, while the GARCH model is applied to handle residual heteroscedasticity. The identification results showed that the best ARIMA model is ARIMA(2, 2, 2) with all coefficients statistically significant but heteroscedasticity occurs in the therefore, GARCH modeling is applied to the residuals. Based on the lowest Akaike Information Criterion (AIC) value of 8.342491, the GARCH(1,0) model was selected as the best model. The combined ARIMA(2,2,2)–GARCH(1,0) model produced an AIC value of 18.583 and an RMSE of 0.251383. Residual diagnostic tests indicated that the resulting model meets the assumptions of normal distribution and homogeneity, and there is no significant autocorrelation. The results of this study are expected to contribute to providing predictive information that can be used by the government as a reference in formulating health sector policies, particularly regarding managing the prices of goods and services to maintain economic stability in East Java.

Keywords: *ARIMA-GARCH Model, Consumer Price Index, Forecasting, Residual Heteroscedasticity*

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INTRODUCTION

The Consumer Price Index (CPI) is a key economic indicator that provides information on the price movements of goods and services paid by consumers and is often used to measure a country's inflation rate. The success of a region's development can be assessed using appropriate measuring tools, such as the price index, which serves as a barometer of the overall economic condition. The quantity, type, and quality of goods and services, as well as their weighting within the CPI, are determined based on the Cost of Living Survey conducted by the Central Statistics Agency (BPS). The CPI is often used to measure a country's inflation rate and is used as a consideration in adjusting salaries, wages, pensions, and other contracts. Through the price index, leaders or managers can manage existing data to understand the development of their businesses or activities, such as identifying factors that influence economic progress, measuring the level of economic progress, or as a tool for the government in determining pricing policy (increasing or decreasing prices) (Dimashanti & Sugiman, 2021).

CPI is an index that reflects the average price of goods and services consumed by households. This index compares prices in a given month with the previous month, with the previous month's prices used as a reference for the base year in calculating the CPI. The CPI is often used to assess the general level of price increases for goods and services that constitute basic necessities for a country's population, as well as to consider adjustments to salaries, wages, pensions, and other contracts (Djami & Nanlohy, 2022). The CPI consists of several groups/sectors, namely (1) foodstuffs (2) processed foods, beverages, cigarettes and tobacco (3) housing, water, electricity, gas and fuel (4) clothing (5) health (6) education, recreation and sports (7) transport, communication and financial services. The consumer price index according to the health group needs to be discussed because health is a very important aspect for humanity in the continuation of daily routines (Wanto & Windarto, 2017).

Based on this, CPI forecasting is very useful for formulating future policies, including in the health sector. Forecasting is an analytical process that uses historical data objectively to predict future conditions. Forecasting aims to describe events or circumstances that may occur in the future. This process is carried out by utilizing past data and mathematical calculations to generate projections of future events (Islamy, Anas, & Muhammad, 2024). CPI forecasting plays a crucial role, providing benefits such as understanding the rate of income growth and the prices of goods and services in a region. Furthermore, CPI forecasting can also support the government in formulating economic policies to address future inflation (Ristyasari & Ahdika, 2024).

CPI data is a time series that can be analyzed using time series models such as the Autoregressive Integrated Moving Average (ARIMA), which assumes constant variance. However, this assumption is not always met in CPI data because its variance can change due to economic fluctuations, giving rise to heteroscedasticity effects that can be addressed with the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The GARCH model is a development of the ARCH model. The basic concept of GARCH is that the variance is not only affected by the residuals that have occurred, but also by the lag of the conditional variance itself. Although the ARIMA model excels at analyzing long-term trends, and the GARCH model is effective in handling short-term volatility fluctuations, applying either model alone is often insufficient to fully capture the characteristics of the data. Therefore, a combination of ARIMA and GARCH models is used to integrate the advantages of both, resulting in more accurate CPI predictions. ARIMA is used to model data, while GARCH is used to model residuals from ARIMA. The integrated form of the two is ARIMA-GARCH, which is by adding the two models. (Fadhilah, Parmikanti, & Ruchjana, 2024).

Previous research in 2023 used the ARIMA-GARCH model to forecast the stock price of PT Adhi Karya (Persero) Tbk (ADHI.JK). The results showed that the ARIMA residuals contained heteroscedasticity, so GARCH modeling was continued. The best hybrid model was ARIMA (1,1,1)-GARCH(1,1) (Talumewo, Nainggolan, & Langi, 2023). In the following year, the ARIMA-GARCH model was used to forecast stock returns in the banking subsector. The best model from the study was ARIMA(2,0,2)-GARCH(1,1) with an RMSE value of 0.01628 (Fadhilah, Parmikanti, & Ruchjana, 2024). In 2024, a study on forecasting inflation rates in Indonesia used the ARIMA-GARCH model based on Kalman filter optimization. The results showed that the best model obtained was the ARIMA (0,1,1) – GARCH (1,1) model (Intan, Haris, & Arum, 2024). In the same year, another study on the application of the ARIMA model to forecast global gold prices showed that the data used contained elements of heteroscedasticity, so a hybrid ARIMA-GARCH model was used. Of several tentative models, ARIMA(6,1,6)-GARCH(6,0) had the smallest AIC value and was therefore selected as the best model. This model produced a MAPE value of 0.647981% (Beeg, Paendong, & Manahonas, 2024).

Based on the description above, the purpose of this study is to forecast the CPI in the health sector in East Java using the ARIMA-GARCH model. The results of this study are expected to assist the government and related parties in determining policies related to the CPI in the health sector in East Java province.

MATERIALS AND METHODS

Research Data

The data in this study are secondary data, namely CPI data according to health groups in East Java from January 2020 to December 2023. The data were obtained from the Central Statistics Agency (BPS) of East Java Province.

Data Analysis

Data Stationarity Test

Data stationarity test was performed using Augmented Dicky Fuller (ADF) (Mutiara, Fitriyati and Mahmudi 2023). The ADF test hypothesis is as follows (Yusrini, et al. 2024):

H_0 : $\hat{\beta} = 0$ (a unit root is detected in the data or the data is not stationary)

H_1 : $\hat{\beta} < 0$ (there is no unit root in the data or the data is stationary)

Test statistics:

$$ADF = \left|\frac{\hat{\beta}}{se(\hat{\beta})}\right| \quad (1)$$

with ADF is ADF test value, $\hat{\beta}$ ia a sstimated value of parameter β, and $se(\hat{\beta})$ is standard error of the estimated value of the parameter β. the decision making criteria are H_0 is rejected if the statistic from the ADF test has a smaller value than the critical region.

ARIMA Modeling

ARIMA is one of the time series-based forecasting methods that utilizes the correlation relationship between data in the time series. This method was first intensively developed by George Box and Gwilym Jenkins in 1970. The ARIMA model is based on the principle that the value of the current observation (Z_t) depends on one or more previous observations (Z_{t-k}). ARIMA model are represented by the notation ARIMA(p,d,q).

The parameter p indicates the number of lags in the autoregressive process, d indicates the level of differencing required to make the data stationary, and q indicates the number of lags in the moving average process. If d = 0 and q = 0, then the model includes only the autoregressive process and is referred to as AR(p). Conversely, if d = 0 and p = 0, then the model involves only the moving average process and is referred to as MA(q). However, if all three components are used, the model is called autoregressive integrated moving average (ARIMA(p,d,q))(Djami dan Nanlohy 2022).

The general form of the ARIMA model can be expressed in the following equation (Landa, Hatidja and Langi 2024):

$$Z_t = (1-\phi_1)Z_{t-1} + (\phi_1 - \phi_2)Z_{t-2} + \cdots + (\phi_p - \phi_{p-1})Z_{t-p} + \theta_0 - \theta_1\gamma_{t-1} - \theta_2\gamma_{t-2} - \cdots - \theta_q\gamma_{t-q} \quad (2)$$

where Z_t is data in period t, γ_{t-1} is error in period t, $\phi_1, \phi_2, \cdots, \phi_{p-1}$ are AR model parameters, and $\theta_0, \theta_1, \cdots, \theta_q$ are MA model parameters

Parameter Estimation and Significance Testing

Parameter estimation is used to obtain the coefficient values of the ARIMA (p,d,q) model ('Aina, Hendikawati and Walid 2019). Parameter estimation is performed using the Ordinary Least Squares (OLS) method. The OLS method aims to minimize the sum of the squares of the differences between the actual values and the values predicted by the model, thus obtaining parameters that produce the smallest error. Formula of OLS method presented by

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

The significance test has the aim of seeing the significance of the model parameters with the hypothesis (Yusrini, et al. 2024):

H_0 : $\beta = 0$ insignificant parameter

H_1 : $\beta \neq 0$ significant parameters

Test statistics:

$$t_{count} = \left|\frac{\hat{\phi}}{SE(\hat{\phi})}\right| \quad (3)$$

If $|t_{count}| > t_{table}$ then reject H_0, where t_{table} is found using the t distribution table with $n-k$ degrees of freedom and $a/2$ significance level

Diagnostic Check (White noise test)

In this test, it is carried out using the Ljung-Box test. The Ljung-Box formula is expressed as follows:

$$Q = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}\hat{\rho}_k^2$$

Where n is the number of observations in the time series, K is the number of lags tested, k is the lag difference and $\hat{\rho}_k$is the value of the autocorrelation coefficient at lag$-k$.

The hypothesis formulation used is:
H_0:residuals are not autocorrelated
H_1:residuals are autocorrelated

The decision criteria used are reject H_0 if $H_0 > x^2_{\alpha,db}$. Do not reject H_0if $H_0 > x^2_{\alpha,db}$with degree of freedom table $(db) = K - p$ or $p - value < 5\%$ (Anisa, Yudistira, & Yulianto, 2015).

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Autoregressive Conditional Heteroscedastic (ARCH) Model The ARCH model is an autoregressive model used to overcome non-constant errors in time series data (Kustiara, Nur and Utami 2020). The ARCH model was first introduced by Engle in 1982. The error variance (σ_t^2) in the ARCH model is strongly influenced by the error in the previous period (ε_{t-1}^2). The general form of the ARCH(p) model is (Beeg, Paendong and Manahonas 2024):

$$\sigma_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + \cdots + a_p\varepsilon_{t-1}^2 \quad (4)$$

A model designed to overcome the problem of heteroscedasticity was first introduced by Engle in 1982 with the ARCH model. In 1986, Bollorsev developed the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model as an extension of the ARCH model. The basic concept of GARCH is that the variance is not only affected by the residuals that have occurred, but also by the lag of the conditional variance itself. Bollerslev (1986) recommends the GARCH (p,q) model as a better model with the following formulation (Beeg, Paendong and Manahonas 2024):

$$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + \cdots + a_p\sigma_{t-p}^2 + a_1\varepsilon_{t-1}^2 + \cdots + a_q\varepsilon_{t-q}^2 \quad (5)$$

The ARCH (p) model is a GARCH (p,q) model with order $q = 0$.

Forecasting Accuracy

The accuracy of a forecasting method can be seen from the RMSE or Root Mean Square Error (RMSE) value. The size of the forecasting error can be calculated using the RMSE value. The RMSE value can be calculated using the following formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_t - \hat{r}_t)^2} \quad (6)$$

with:
$N =$ Observation value in period t
$\hat{r}_t =$ Forecasting value in period t
$r_t =$ Number of data

RESULTS AND DISCUSSION

Data Stationarity Test

The data in this study are CPI data according to health groups in East Java from January 2020 to December 2023. The data is divided into two parts: training data and testing data. The training data, which is CPI data from January 2020 to December 2022, is used to build the model. The testing data, which is CPI data for 2023, is used to evaluate the model. CPI data in the health sector in East Java from 2020 to 2023 can be seen in Figure 1.

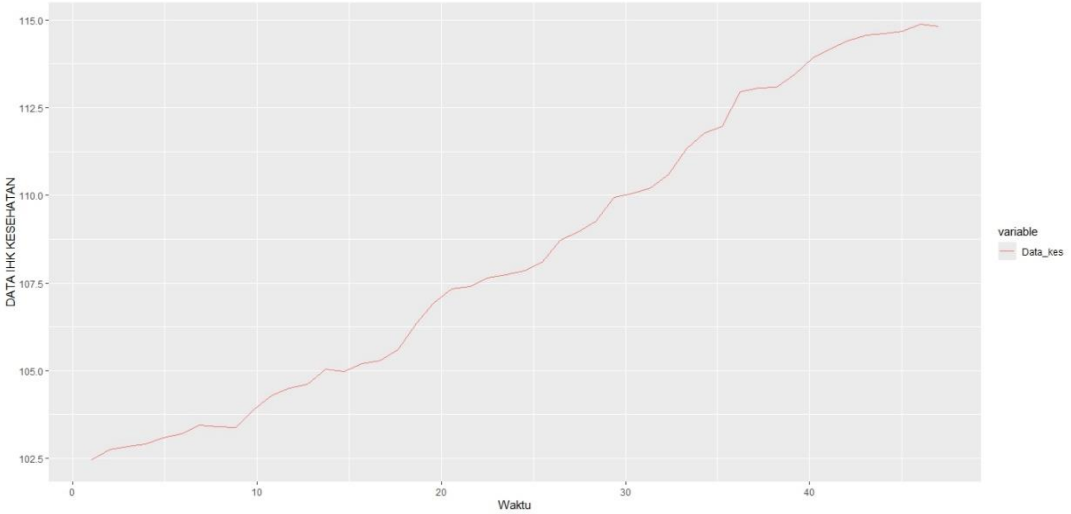

Figure 1. CPI Data Plot

Figure 1 shows that the CPI data plot for the health sector in East Java province continued to increase from 2020 to 2023. Therefore, this data pattern is considered an upward trend. The graph in Figure 1 shows a consistent upward trend from the beginning to the end of the observation period. The health sector CPI rose from around 102 at the beginning of the period to nearly 115 at the end. This indicates a sustained increase in prices for goods and services in the health sector.

The first step in modeling time series data is to test the stationarity of the data. In this study, the Augmented Dickey-Fuller test is used, with data said to be stationary if the $p-value < (0.05)$, then reject H_0 or stationary data. However, if the ADF test results show that the data is not stationary then a differencing process is required. The ADF test results are presented in the following table:

Table 1. ADF Test Results

Data	$p-value$	Description
Before differencing	0.4289	Non-stationary
Differencing 1	0.3863	Non-stationary
Differencing 2	0.01	Stationary

Table 1 shows that before differencing, the p-value obtained is $0.4289 > 0.05$, indicating that the data is not stationary so that a differencing process is needed. At first differencing, the p-value obtained is $0.3863 > 0.05$ which indicates that the data is not stationary so second differencing is needed. In differencing 2, the p-value is $0.01 < (0.05)$, which indicates that the data has been stationary.

ARIMA Model Identification

After detecting the problem of data stationarity and differencing, the next step is to identify the ARIMA model for the health sector CPI data in East Java. Determining the order of the ARIMA model is done by comparing several models based on the Akaike Information Criterion (AIC) value. The AIC value reflects the balance between the complexity of the model and the model's ability to explain the data; the model with the lowest AIC value is considered the most optimal. The following models and the resulting AIC values can be observed in Table 2:

Table 2. Model and resulting AIC values

Model	AIC
ARIMA(1,2,1)	61.45186
ARIMA(1,2,2)	35.4253
ARIMA(2,2,2)	28.82365
ARIMA(2,2,1)	46.72481

From the AIC results of each model, it is found that the best model with the smallest AIC value is the ARIMA (2,2,2) models.

Parameter Estimation and Significance Test of Model Parameters

After obtaining the best model, the next step is to estimate the parameters and test the significance of the model parameters. The purpose of this step is to observe whether the data is significantly influenced or not. The parameter estimation results can be observed in Table 3 below:

Table 3. Parameter estimation results of ARIMA (2,2,2) model

Model	Estimate	Coefisient	$p-value$	Description
ARIMA (2,2,2)	$\emptyset_1$	-0.5146	0.0001626	Significant
	$\emptyset_2$	-0.4233	0.0015052	Significant
	θ_1	-1.9842	< 2.2e-16	Significant
	θ_2	1.0000	< 2.2e-16	Significant

Based on Table 3, it can be seen that all parameters have a significant effect because the p-value is less than 0.05. The ARIMA (2,2,2) model can be written as the equation (7)

$$Z_t = -0.5146Z_{t-1} - 0.4233Z_{t-2} - 1.9842a_{t-1} + 1a_{t-2} \tag{7}$$

Based on equation (7), it can be seen that the CPI in periods $t-1$ and $t-2$ has a negative influence on the CPI value in period t. Besides that, the residual in period $t-1$ also has a negative influence on the CPI value for period t, while the residual for period $t-2$ has a positive influence. If the CPI for period $t-1$ increases by one unit and the variables in the other parameters are constant, the CPI for period t will decrease by 0.5146 times. If the CPI for period $t-2$ increases by one unit and the variables in the other parameters are constant, the CPI for period t will decrease by 0.4233 times. If the residual of period $t-1$ increases by one unit and the variables in the other parameters are constant, the CPI of period t will decrease by 1.9842 times. If the residual of period $t-2$ increases by one unit and the variables in the other parameters are constant, then the CPI of period t will increase by 1 time.

White Noise Test

The next stage in ARIMA modeling is the white noise test. This stage is carried out to observe that the model has residuals that are random (white noise) so that the model is able to explain the data well. The white noise test results using the Ljung-Box test are as follows:

Table 4. White noise test results

Lags	Statistics	df	p-value
5	5.172824	1	0.02294289
10	14.701035	6	0.02271389
15	21.381126	11	0.02963076
20	27.917981	16	0.03234024
25	33.187158	21	0.04418257
30	37.850712	26	0.06252057

Tabel 4 show that p-value smaller than 0.05 indicates that there are some patterns in the residuals that are not completely white noise. However, at higher lags (lag 30), $p > 0.05$, which indicates the residual pattern is getting closer to white noise. However, the white noise test results show that the residuals are not completely random at some low lags. This could be an indication that the model can still be improved further, so it is continued with the GARCH modelling.

GARCH Modeling

The ARCH (p) model is a GARCH (p,q) model with order $q = 0$. The GARCH modeling process begins by testing several model configurations to determine which one is the best based on the AIC value. The tested models include GARCH(1,0), GARCH(2,0), GARCH(3,0), GARCH(1,1), GARCH(1,2), and GARCH(1,3). The AIC value of the GARCH model can be seen in Table 5

Table 5. AIC Value of GARCH Model

Model	AIC
GARCH (1,0)	8.342491
GARCH (2,0)	11.27679
GARCH (3,0)	13.11141
GARCH (1,1)	10.34267
GARCH (1,2)	13.29782
GARCH (1,3)	15.06944

From the calculation results, the GARCH (1,0) model has the smallest AIC value, which is 8.342491. Therefore, this model is chosen as the most suitable for further analysis. The parameter estimation results and significance test of the GARCH (1,0) model can be observed in Table 6 below:

Table 1. Estimation of ARCH (1) Model

Model	Parameter	Estimation	*P-value*	Description
GARCH (1,0)	a_0	0.06183	0.000822	Significant
	a_1	0.04286	0.779255	Insignificant

Based on the estimation results, the intercept (a_0) has a value of 0.06183 and is statistically significant with a p value of 0.000822 ($p < 0.001$). Meanwhile, the ARCH coefficient of 0.04286 is not significant with a p value of 0.779255 ($p > 0.05$). These results indicate that although the intercept has a significant influence, the contribution of previous volatility to current changes is relatively small, so the GARCH model obtained is $\sigma_t^2 = 0.06183 + 0.04286\sigma_{t-1}^2$.

Residual diagnostic tests were conducted to ensure the suitability of the GARCH(1,0) model. The Jarque-Bera test gives a p value of 0.8268, indicating that the residuals are normally distributed. In addition, the Box-Ljung test on the squared residuals yielded a p value of 0.945, confirming the absence of significant autocorrelation. Thus, the GARCH(1,0) model is considered capable of adequately describing the volatility pattern in the data.

The final model value obtained is ARIMA(2,2,2)-GARCH (1,0).

$$Z_t = -0.5146Z_{t-1} - 0{,}4233Z_{t-2} - 1{,}9842a_{t-1} + 1a_{t-2} - 0.06183\sigma_{t-1}^2 - 0.04286\sigma_{t-2}^2$$

From this model, the RMSE value is 0.251383. Based on the RMSE value, it can be said that this model is included in the category of good enough to forecast the CPI by health group in East Java.

CONCLUSION

This study uses the ARIMA-GARCH method to forecast the Consumer Price Index (CPI) for the health sector in East Java. The best model identified is ARIMA(2,2,2)-GARCH(1,0) presented by

$$Z_t = -0.5146Z_{t-1} - 0{,}4233Z_{t-2} - 1{,}9842a_{t-1} + 1a_{t-2} - 0.06183\sigma_{t-1}^2 - 0.04286\sigma_{t-2}^2$$

This model has an AIC value of 18,583 and RMSE of 0.251383. Based on the RMSE value obtained, it can be concluded that this model is quite good in predicting the CPI in the health group in East Java.

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