Forecasting Macroeconomic Variables and Their Effect on Poverty

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A B S T R A C T

Forecasting macroeconomic variables is crucial to measure dynamic changes during uncertain economic conditions. This study examines and analyzes the appropriate and accurate forecasting model to predict macroeconomic variables in Maluku Province. The main variables used are economic growth, unemployment, inflation, and poverty. The modeling used in this study were Bayesian Vector Autoregressions Model and the Univariate Benchmark Model. The results of this study indicate that the two models have different specifications and forecasting directions. The value of the Univariate Benchmark model's forecast error size is relatively smaller than that of the Bayesian Vector Autoregressions Model. The results of forecasting macroeconomic variables in Maluku Province have a relatively good level of accuracy and are close to the actual value of the sample period. The Error Correction Model test results show that only the Error Correction Term variable significantly affects the poverty level in the short term. Meanwhile, in the long term, the unemployment rate has a significant effect, and the model used is proven valid. The forecasting results from the model show that the Maluku provincial government must maintain the stability of macroeconomic variables, especially the inflation rate and unemployment rate, because they tend to increase in the coming year. It can have an impact on reducing people's purchasing power.

A B S T R A K

Peramalan variabel ekonomi makro sangat penting sebagai ukuran perubahan dinamis di tengah ketidakpastian kondisi perekonomian. Penelitian ini bertujuan mengkaji dan menganalisis model peramalan yang tepat dan akurat untuk memprediksi variabel ekonomi makro di Provinsi Maluku. Variabel utama yang digunakan adalah pertumbuhan ekonomi, tingkat pengangguran, tingkat inflasi dan tingkat kemiskinan. Pemodelan yang digunakan dalam penelitian ini menggunakan Bayesian Vector Autoregressions Model dan Benchmark Univariate Model. Hasil penelitian ini menunjukkan bahwa kedua model memiliki spesifikasi dan arah peramalan yang cenderung berbeda. Nilai ukuran kesalahan peramalan Benchmark Univariate Model relatif lebih kecil dibandingkan dengan Bayesian Vector Autoregressions Model. Hasil peramalan variabel ekonomi makro di Provinsi Maluku memiliki tingkat akurasi yang cukup baik serta mendekati nilai aktual dari periode sampel. Berdasarkan hasil pengujian Error Correction Model menunjukkan dalam jangka pendek hanya variabel Error Correction Term yang berpengaruh signifikan terhadap tingkat kemiskinan, sedangkan, dalam jangka panjang tingkat pengangguran berpengaruh signifikan serta model yang digunakan terbukti valid. Hasil peramalan dari model yang digunakan menunjukkan bahwa Pemerintah Provinsi Maluku harus menjaga stabilitas variabel makroekonomi terutama tingkat inflasi dan tingkat pengangguran karena cenderung meningkat di tahun mendatang. Hal ini dapat berdampak pada penurunan daya beli masyarakat.

1. INTRODUCTION

The current state of the world economy is full of uncertainty. The Covid-19 pandemic, climate change, and war can trigger crises and extreme poverty (World Bank Group, 2020). Economic projections change in response to current

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developments. In the 2022 World Economic Outlook, the International Monetary Fund (IMF) predicts a global economic slowdown from 5.9 in 2021 to 4.4 in 2022, while the projection for 2023 is 3.8 percent. The emergence of a new variant of Omicron has resulted in several countries re-implementing restrictions on people's mobility. Rising prices and energy supply disruption have caused inflationary fluctuations, especially in the United States (International Monetary Fund, 2022). The war between Russia and Ukraine has made the situation even more difficult, indirectly impacting global commodity prices and directly impacting the goods and services market, capital market, and foreign exchange market, including the Indonesian economy.

Forecasting macroeconomic variables is essential for measuring dynamic changes in uncertainty. The main variables used are economic growth, unemployment, inflation, and poverty. These four variables are macroeconomic indicators often used to measure economic development's success at the national and regional levels, especially in Maluku Province. Precise and accurate economic projections are crucial for planning and making strategic decisions to improve people's welfare. Therefore, it is also necessary to study and analyze the effect of these three variables on poverty. This study seeks to develop an appropriate forecasting model for predicting economic growth, unemployment, inflation, and poverty.

Each quantitative model has two primary objectives: correctly representing the system's structure being studied, explaining the interrelationships and relationships between variables, and accurately forecasting new observations (Baluga & Nakane, 2020). Historically, the forecasting of econometric models has been a test full of uncertainty. The main challenge is designing the underlying framework accurately and using the right variables to provide the required information. Forecasting frameworks must be specific to the observed country because many complex models with macroeconomic linkages are not as expected. Another challenge in developing countries is that the available time series data is volatile, and sometimes certain variables are unavailable (Iyer & Gupta, 2019).

Understanding the future of macroeconomic forecasting requires an understanding between measurement and theory and the appropriate evolution of non-structural and structural approaches to forecasting. Non-structural macroeconomic forecasting methods seek to exploit the reduced form relationship in the observed macroeconomic time series by not relying solely on economic theory. On the other hand, structural models view and interpret economic data through the views of certain economic theories (Diebold, 1998). Accuracy and consistency of forecasting theory and models are important, but simple forecasting is also necessary (Carriero et al., 2009).

Research related to macroeconomic forecasting in Indonesia tends not to use macroeconomic variables simultaneously but only for macroeconomic variables partially, like the research conducted by Juhro & Iyke (2019). The study proposed a large-scale inflation forecast model with significant results regarding inflation forecasts in Indonesia. Likewise, research conducted by Teguh & Bashir (2019) investigated and predicted the level of economic growth in Indonesia and advised the government to carry out good economic planning and have a consistent strategy to maintain stability and high growth. On the other hand, the results of Nugroho et al. (2020) showed that the inflation and economic growth rates could be instruments for estimating the poverty rate.

This study differs from previous studies by simultaneously forecasting macroeconomic variables with four main indicators: economic growth, inflation, unemployment, and poverty. It also analyzes their effects on poverty by combining forecasting and other dynamic models. Another novelty of this study is using a new Bayesian Vector Autoregression Model in forecasting macroeconomic variables. So far, economic forecasting has only used the Univariate Benchmark Model, while this research combines the two models to compare the best and most accurate forecasting model. In addition, research on forecasting macroeconomic indicators in Indonesia during the Covid-19 pandemic is still minimal. Therefore, conducting this study to obtain an overview of economic conditions in the next few years is important.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

Research results related to developing appropriate forecasting models in dynamic systems vary widely. In their research, Bańbura et al. (2015) described the projection of a set of interesting variables in dynamic systems. The study developed large vector autoregressions (VARs) and large dynamic factor (DFM) models for the quarterly macroeconomic dataset and financial indicators from the 26-euro area. Both approaches show the same scenario of forecasting and assessment. In addition, the forecast results explain the stability of dynamic relations in the euro area during the recent financial turmoil.

Gurkaynak et al. (2014) examined the Dynamic Stochastic General Equilibrium (DSGE) and evaluated macroeconomic variables' efficiency and forecasting ability. The study found different results between the DSGE model and the autoregressive method and concluded that no single model is the most accurate every time. However, this study did not support using the Bayesian Vector Autoregressive forecasting model as a benchmark for assessing the accuracy of the DSGE forecasting model. Furthermore, Sugita (2022) examined the differences in the direct and iterative methods using the Bayesian Vector Autoregressions (BVAR) model with different priorities to see the performance of multi-period forecasting. It was found that the Stochastic Search Variable Selection (SSVS) model is superior in iterative forecasting. In addition, VAR models are often used for macroeconomic forecasting and serve as a benchmark model for comparing the performance of new models and methods. The VAR model has parameters, and the Bayesian method can incorporate previous information to improve forecasting accuracy (Chan et al., 2019)

Various studies on forecasting tend to compare VAR's forecasting accuracy with Univariate Benchmark Models' forecasting accuracy (Clark & Mccracken, 2014). Steiner et al. (2018) found that the factor model structure is better than benchmarks in most tests and, in many cases, also BVAR. The covariance analysis matrix of sectoral forecasting errors shows that the advantages of the factor model can be traced back to its ability to capture sectoral movements more accurately. In addition, BVAR is also a tool that can be used for real-time forecasting and nowcasting through mixed frequency data sets (Miranda et al., 2018).

This study also looks at the effect of macroeconomic variables, namely economic growth, unemployment, and inflation, on poverty. Pham & Riedel (2019) examined the effect of sectoral economic growth on poverty in Vietnam. The study results indicated that poverty reduction is influenced by growth in the agricultural and industrial sectors. However, an increase in the proportion of the service sector can lead to an increase in the poverty rate. Furthermore, it is also shown that the increase in the number of workers positively affects poverty alleviation, while economic growth has no significant effect. Harsmar (2022) showed that economic growth is significant for poverty alleviation, mainly driven by the growth of the agricultural sector. Increased productivity in this sector can be a prerequisite for broader economic growth and poverty reduction.

The correlation between economic growth and poverty is often debated. The relationship between growth and poverty is also shown. In research in India, Datt et al. (2020) indicated an acceleration of poverty reduction accompanied by post-reform economic growth, although the gap is still relatively large. Gao (2021) suggested that combining economic growth and implementing poverty alleviation policies can cause poverty alleviation. On the other hand, according to Zhu et al. (2022), economic growth must be driven by poverty alleviation policies. In addition, Sasmal & Sasmal (2016) showed that economic growth significantly impacts poverty reduction and can be a driving force for poverty alleviation. The results of this study also reinforced Vanegas (2014), who stated that economic growth and inequality strongly influence and significantly impact poverty.

Furthermore, Kusumaningsih et al. (2022) found a significant impact of economic growth on poverty, but on the contrary, unemployment did not have a significant effect. The link between increasing economic growth and increasing living standards or reducing poverty in Indonesia was also confirmed by Hill (2021). It was found that during 1966-1996, economic growth and expansion of formal sector employment in Indonesia tended to be faster. But on the other hand, poverty reduction tends to be slower; there is labor market segmentation, and inequality increases after 1999. Meanwhile, a study conducted by Soltero (2020) on the relationship between poverty and the employment economic sector for Mexican immigrants in Chicago revealed a difference in the probability of falling into poverty between economic sectors. In addition, Siyan et al. (2016) found a reciprocal relationship between inflation and poverty and unemployment and poverty in Nigeria from 1980 to 2014. A study conducted by Azam et al. (2016) proved that inflation causes poverty in high-income countries. Meanwhile, Faharuddin et al. (2021) indicated a negative impact of rising food prices on decreasing household welfare and increasing poverty in Indonesia. This impact is more felt by rural households than urban ones. Based on the above discussion, the hypotheses in this study are:

H_1: Macroeconomic variables in Maluku Province can be predicted accurately.

H2: Macroeconomic variables have a significant effect on poverty, both in the short and long term.

3. RESEARCH METHOD

Data Types and Sources

This study uses secondary time series data from 2005 to 2021, including variables of economic growth, unemployment, inflation, and poverty rates in Maluku Province. The data was sourced from the Central Bureau of Statistics (BPS) of Maluku Province and was supported by other relevant agencies/institutions in Maluku Province.

Model Specification

The preparation of this research model also considered the criteria of a good model based on the views of Insukindro (1999), consisting of (1) parsimony, (2) identifiability, (3) data coherency, (4) data admissibility, (5) theoretical consistency, (6) predictive power, and (7) encompassing. The modeling used in this study referred to the model developed by Baluga & Nakane (2020), who forecasted macroeconomic variables in the Maldives using the Bayesian Vector Autoregressions (BVAR) Model and Benchmark Model.

$$X_t = c + \sum_{i=1}^{p} \emptyset_i X_{t-i} + \sum_{k=1}^{1} \beta k \ \ as_k + \varepsilon_t \qquad (1)$$

where c,∅i,i=1,…p, and βk,k=1,…,q is the coefficient matrix of the lag of the vector set Xt. The dummy annual season ask and εt variables are innovation vectors. Furthermore, time series data usually shows a pattern over time, and the pattern can be used to forecast future values. The univariate approach uses the Box-Jenkins specification of economic growth, unemployment, and the consumer price index (inflation) where the series is the specification of the Autoregressive Integrated Moving Average (ARIMA) (p,d,q) process (ARIMA process d=i).

$$Y_t = \alpha_0 + \varepsilon_t + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{q} \beta_i \ \ \varepsilon_{t-i} + \sum_{k=1}^{1} \beta_k \, as_k \qquad (2)$$

Meanwhile, to measure the effect of macroeconomic variables on poverty, this study referred to the model developed by Hoover et al. (2008), which used SUR analysis to see the short-term effect of economic turmoil on poverty levels. This research used the Error Correction Model (ECM) to analyze the short-term and long-term effects between variables. The ECM model was also utilized to answer the need for dynamic specifications in economic analysis, especially if the observed economic conditions are imbalanced. In addition, ECM can check the consistency of empirical and theoretical models (Insukindro, 1999). It is also possible to test the causality of variables in the short and long term using an ECM-based model (Musakwa & Odhiambo, 2019). The basic model is presented below.

$$Pov *_t = a_0 + a_1 EG_t + a_2 Unemp_t + a_3 Inf_t + \varepsilon_t \quad (3)$$

where Pov*t is the poverty rate, EGt is economic growth, Unempt is the unemployment rate, and Inft is the inflation rate during the observation period. Furthermore, the formation of the ECM model and parameterization of the model was carried out so that it becomes:

$$\begin{aligned} \Delta Pov_t \ = \ & \delta_0 + \delta_1 \Delta EG_t + \delta_2 \Delta Unemp_t + \delta_3 \Delta Inf_t \\ & + \delta_4 EG_{t-1} + \delta_5 Unemp_{t-1} + \delta_6 Inf_{t-1} \\ & + \delta_7 (EG_{t-1} + Unemp_{t-1} + Inf_{t-1} \\ & - Pov_{t-1}) \qquad (4) \end{aligned}$$

Before the above equation is estimated, testing the degree of integration and cointegration is necessary. It is to ensure that all variables in the model are cointegrated at the same degree of integration (Nugraha et al., 2021)

4. DATA ANALYSIS AND DISCUSSION

Stationarity and cointegration test stationarity testing was carried out early before forecasting or projecting all research variables and testing the short-term and long-term effects between variables. This test was conducted to see the trend and behavior of the data during the research period through unit roots testing using the Elliott Rothenberg Stock Point Optimal (ERS) method. The results of the unit root test on the research variables used can be seen in Table 1. The test results with the ERS method show that all variables are stationary at a significance level of 5 percent, so the prerequisites for continuing forecasting using the BVAR and univariate benchmark models have been fulfilled.

Table 1. Results of level form stationarity test (ERS)

Variable	Statistical Value ERS	Critical Value ERS
	Intercept	Intercept
Economic Growth (EG)	3.411	2.970
Unemployment (UNEMP)	21.45	2.970
Inflation (INF)	12.99	2.970
Poverty (POV)	152.4	2.970

Notes: Critical Value on $\alpha = 5\%$

The integration test results show that all research variables are stationary at the same degree (first difference form), which can be seen as the absolute value of the ERS statistics is greater than the absolute critical value at the 5 percent significance level. Thus, the prerequisites to proceed to the cointegration test can be fulfilled. The results of the integration degree test are shown in Table 2.

Table 2. Results of the first difference stationarity test (ERS)

Variable	Statistical Value ERS	Critical Value ERS
	Intercept	Intercept
Economic Growth (EG)	5.105	2.970
Unemployment (UNEMP)	2.944	2.970
Inflation (INF)	372.0	2.970
Poverty (POV)	6.590	2.970

Notes: Critical Value on $\alpha = 5\%$

Meanwhile, the cointegration test results show that the initial equation model, as previously described, has a cointegration relationship between variables. It is shown from the results of the residual stationarity test in the form of levels and the first differences (Error Correction Term/ECT) obtained from the initial model estimation (Equation 3). It can be seen that the absolute value of the ERS statistic (4.138) is greater than the critical value (2.970) in the level form, and the absolute value of the ERS statistic (2.987) is greater than the critical value (2.970) at the first difference with a significance level of 5 percent. Thus, it can be said that the behavior of the data from the cointegration equation model has a long-term equilibrium relationship, as suggested by the theory.

Macroeconomic Variable Forecasting

After the stationarity and cointegration tests, the next step is projecting the macroeconomic variables of Maluku Province. The time series data for the 2005-2021 period were used for the projections for 2022-2024. The model developed here is not intended for structural analysis; rather, the VAR's shape specification decreases in the forecast's direction. Meanwhile, an in-sample and out-of-sample forecast evaluation exercise was conducted to see the model's accuracy in predicting macroeconomic variables such as economic growth, unemployment, inflation, and poverty. It is expected to show stable estimation results.

Modeling is intended to capture complex and dynamic relationships in macroeconomic variables. Forecasting is done in the short term for the next three years (2022-2024)—future period; then a cumulative amount commensurate with the year-on-year growth rate. Meanwhile, the measure used to compare the error between variables from the model is Root Mean Square Error (RMSE): a sample forecast that shows the actual and forecast values in the specified period. The forecast error of the RMSE statistic is determined by the scale of the dependent variable. It is used as a benchmark against the same forecast for different models. The ability of a good forecasting model can be seen from the smaller the error. The results of forecasting macroeconomic variables in Maluku Province using the BVAR and ARIMA methods are presented in detail as follows.

Forecasting Macroeconomic Variables with the Bayesian VAR Model

The size of the forecast error of the calculated projections for macroeconomic variables is presented in the table below. Using the BVAR model, on the RMSE criteria, the EG variable has the lowest RMSE value compared to UNEMP, INF, and POV. It shows that the economic recovery after the Covid-19 pandemic in Maluku Province is getting better with an upward trend. The increase in economic activity in all sectors has accelerated the rotation of the economy in the regions, especially the revival of the real sector, which had slumped during the Covid-19 pandemic and is getting better so that it has an impact on increasing people's income and reducing poverty. Therefore, according to estimates that forecasting macroeconomic variables with the BVAR method can produce a more precise and better fit

Table 3. Forecast error measures – EG, UNEMP, INF, and POV

	Root Mean Square Error	Mean Absolute Error	Mean Absolute Percentage Error	Theil Inequality Coefficient
Variable	RMSE	MAE	MAPE	Theil
EG	1.683	1.225	26.57	0.158
UNEMP	3.437	3.174	63.92	0.237
INF	15.58	15.25	73.87	0.570
POV	12.48	12.14	138.8	0.418

Figure 1 shows that the projected economic growth in Maluku Province will increase from 3.48 percent in 2022 to 3.66 percent and 4.00 percent in 2023 and 2024, respectively. On the other hand, the projected unemployment rate shows an increasing trend, so a more optimal workforce absorption is needed through increasing quality economic growth. Meanwhile, the inflation rate tends to fluctuate, whilst the poverty rate shows a downward trend during the forecasting period, recorded at 17.66 percent in 2022, 17.57 percent in 2023, and 17.48 percent in 2024.

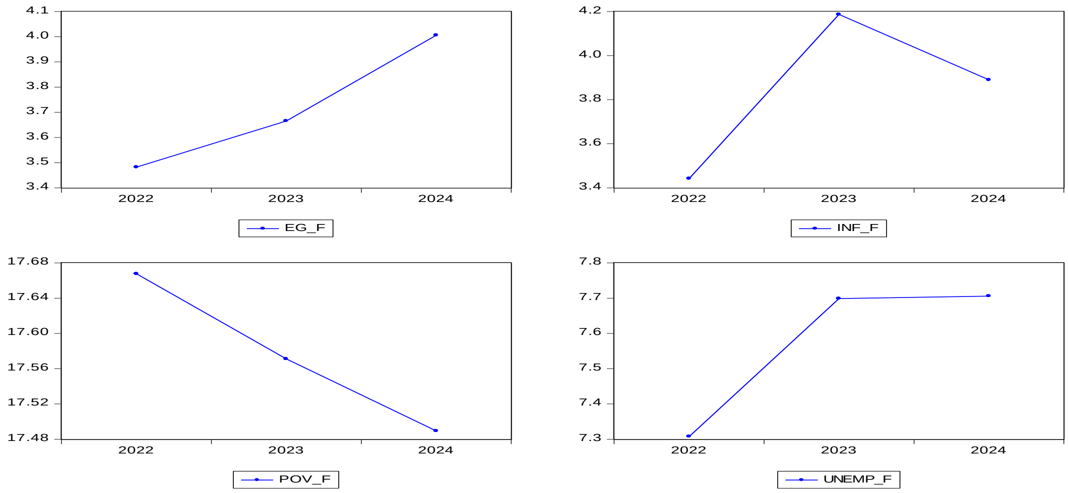

Figure 1. Forecasting of macroeconomic variables with the bayesian VAR model in 2022-2024

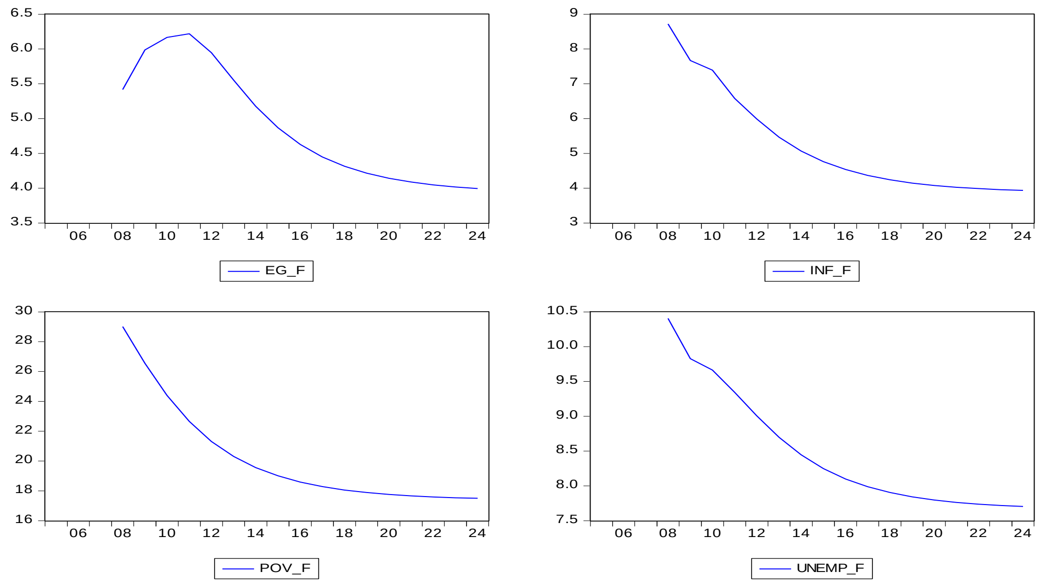

Figure 2. Forecasting of macroeconomic variables using the Bayesian VAR model

Table 4 presents actual data for the sample period (2005-2021) and forecasting results (2022-2024) on macroeconomic variables in Maluku Province. Furthermore, in the development of forecasting models, the use of the model is expected to have the ability to minimize forecasting errors and to show accurate direction estimates. From the results of forecasting using BVAR and ARIMA models on macroeconomic variables in Maluku Province, both models can minimize errors and predict accurately close to or equal to the actual value of each variable.

Table 4. Results of forecast EG, UNEMP, INF, and POV with BVAR (%)

Year	EG_ Actual	EG_ Forecast	UNEMP_ Actual	UNEMP_ Forecast	INF_ Actual	INF_ Forecast	POV_ Actual	POV_ Forecast
2005	5.07	-	15.01	-	16.67	-	32.28	-
2006	5.55	-	14.45	-	4.79	-	33.03	-
2007	5.62	-	12.20	-	5.85	-	31.14	-
2008	4.81	-	10.67	-	9.34	-	29.24	-
2009	4.86	-	10.57	-	6.48	-	27.29	-
2010	6.47	-	9.97	-	8.78	-	25.32	-
2011	6.34	-	7.38	-	2.85	-	22.45	-
2012	7.16	-	7.51	-	6.73	-	20.76	-
2013	5.24	-	9.75	-	8.81	-	19.27	-
2014	6.64	-	10.51	-	6.81	-	18.44	-
2015	5.48	-	9.93	-	5.92	-	19.51	-
2016	5.76	-	7.05	-	3.28	-	19.18	-
2017	5.82	-	9.29	-	9.41	-	18.45	-
2018	5.91	-	7.27	-	1.62	-	18.12	-
2019	5.41	-	7.08	-	3.24	-	17.69	-
2020	-0.92	-	7.57	-	0.09	-	17.44	-
2021	3.04	-	6.93	-	4.05	-	17.87	-
2022		3.48		7.30		3.44		17.66
2023		3.66		7.69		4.18		17.57
2024		4.00		7.70		3.89		17.48

The results of research and forecasting conducted by Hoover et al. (2008) in the Maldives showed that the Univariate and ARDL benchmark models have simpler specifications and produce smoother forecasting directions. On the other hand, BVAR was found with a more complex and flexible forecast direction. BVAR performs better than Univariate Benchmarks in certain respects and standard deviation (Carriero et al., 2009). Furthermore, Miranda et al. (2018) indicated that the BVAR model inference method could be used for economic and financial variables, structural analysis, and forecasting. The BVAR model is the most popular for macroeconomic modeling and time series data (Baurle et al., 2018).

Forecasting Macroeconomic Variables with the ARIMA Model

Table 5 presents the size of the forecasting error of the projection results for macroeconomic variables using the ARIMA model. The results of the measurement of forecasting errors show that the UNEMP variable has the lowest RMSE value compared to EG, INF, and POV.

Table 5. Forecast error measures – EG, UNEMP, INF, and POV

	Root Mean Square Error	Mean Absolute Error	Mean Absolute Percentage Error	Theil Inequality Coefficient
Variable	RMSE	MAE	MAPE	Theil
EG	2.436	2.176	55.619	0.269
UNEMP	2.156	1.603	18.876	0,104
INF	3.358	2.803	84.211	0.289
POV	8.069	7.697	38.673	0.157

The initial stage in forecasting macroeconomic variables using the ARIMA model is to select a model according to econometric criteria. Based on the results of the model selection for each variable, it shows that the best model is ARIMA (1,1,0) for the economic growth variable, ARIMA (0,0,2) for the unemployment rate variable, ARIMA (1,1,0) for the inflation rate variable, and ARIMA (1,1,0) for the poverty level variable. The ARIMA model has the best significance level with the largest coefficient of determination and the smallest AIC and SC values as required.

Economic Growth

From the results of selecting the best model for economic growth variables, ARIMA (1,1,0) was obtained as the best model. Table 6 presents the model results, while Figure 3 and Figure 4 show the forecasting results. This model has the best significance level with the largest coefficient of determination and the smallest AIC and SC values compared to other models. This model also has a relatively small size of forecasting error. The results of this model are not much different from the forecasting results of Iyer & Gupta (2019) using ARIMA, which can track the growth dynamics that occur.

Table 6. EG model estimation results – ARIMA

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.236	0.619	-0.381	0.709
AR(1)	-0.553	0.506	-1.091	0.294
R-squared = 0.261		AIC = 4.364		
F-statistic = 2.306		SC = 4.509		
DW = 4.371		Inverted AR Roots = -0.55		

Notes: Dependent variable is D(EG)

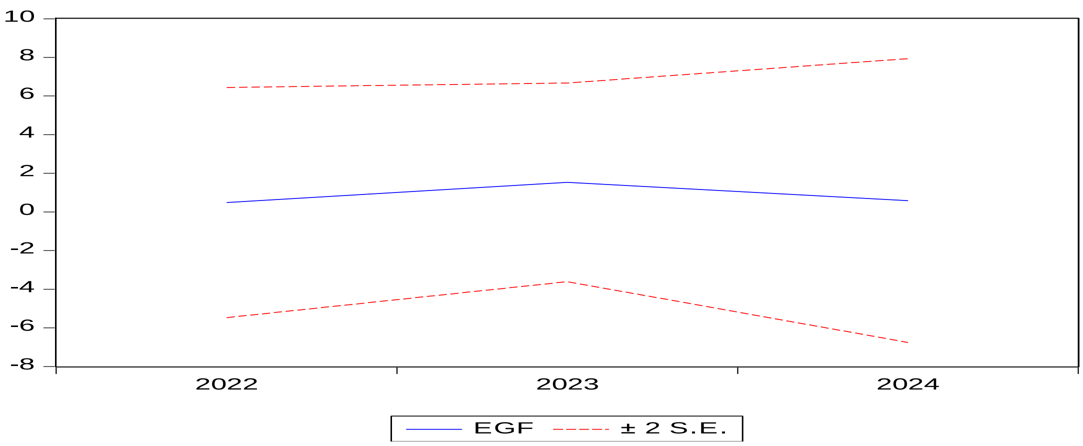

Figure 3. Forecasting economic growth and standard errors with the ARIMA model in 2022-2024

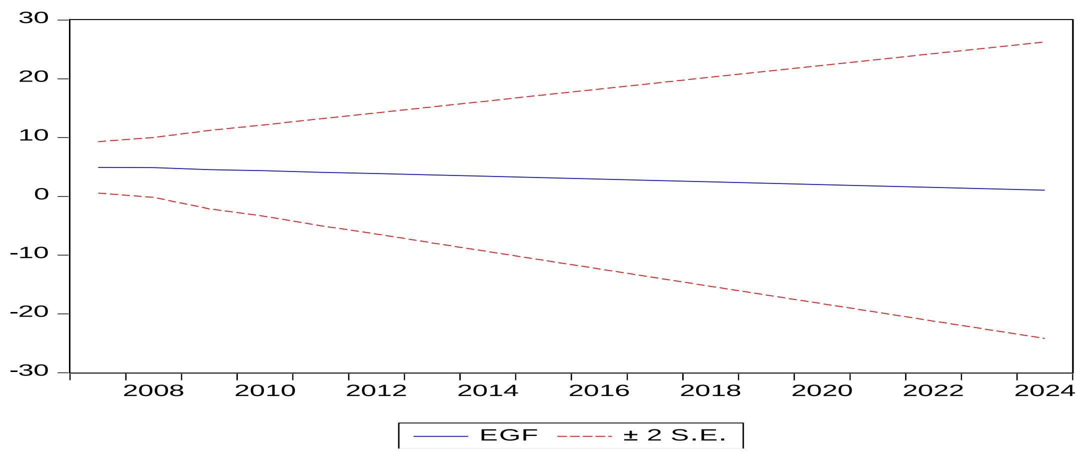

Figure 4. Forecasting economic growth and standard errors using the ARIMA model in 2005-2024

The size of the forecast error from the calculated projections for the EG variable is presented in Figure 5. The projection results using the ARIMA model, on the RMSE criteria, the EG variable has a relatively small RMSE value of 2.436. It shows the trend of improving economic recovery with a relatively small level of projection error.

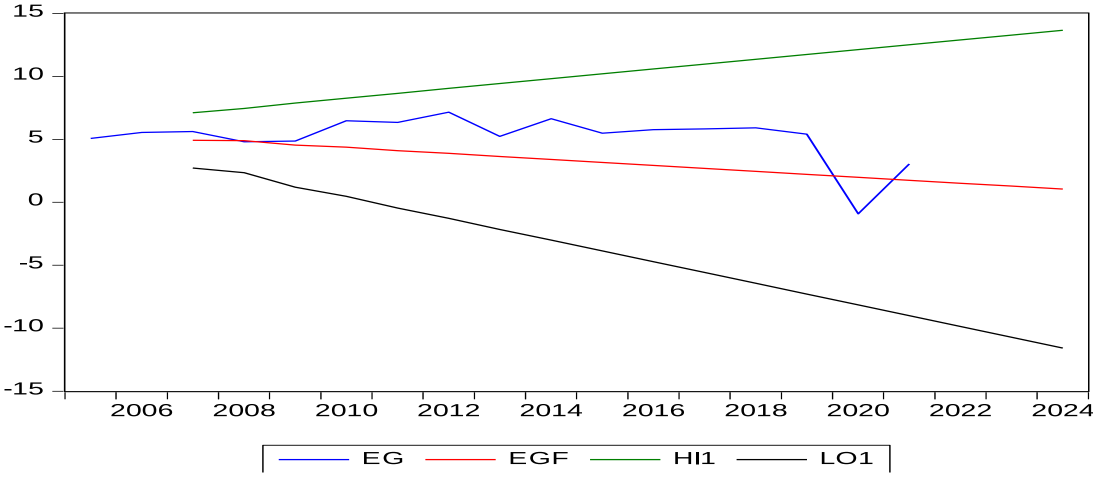

Figure 5. Actual economic growth, forecasting, and standard errors with the ARIMA model in 2005-2024

Unemployment Rate

From the results of determining the best model for the variable unemployment rate, ARIMA (0,1,2) was obtained as the best model. The model is presented in Table 7. The model also has the best significance level with the largest coefficient of determination and the smallest AIC and SC values compared to other models. This model also has a relatively small mean absolute error.

Table 7. UNEMP model estimation results - ARIMA

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.490	0.309	-1.584	0.137
MA(2)	-0.171	0.276	-0.621	0.544
R-squared = 0.036		AIC = 3.955		
F-statistic = 0.244		SC = 4.099		
DW = 2.403		Inverted AR Roots = 0.41		

Notes: Dependent variable is D(UNEMP)

Figure 6 below shows the trend of forecasting results for the unemployment rate variable, which tends to decrease toward its actual value. The projected unemployment rate in Maluku Province in 2022 is 6.67 percent, 6.18 percent in 2023, and 5.69 percent in 2024. This condition reflects the absorption of new workers as economic activity recovers after the Covid-19 pandemic.

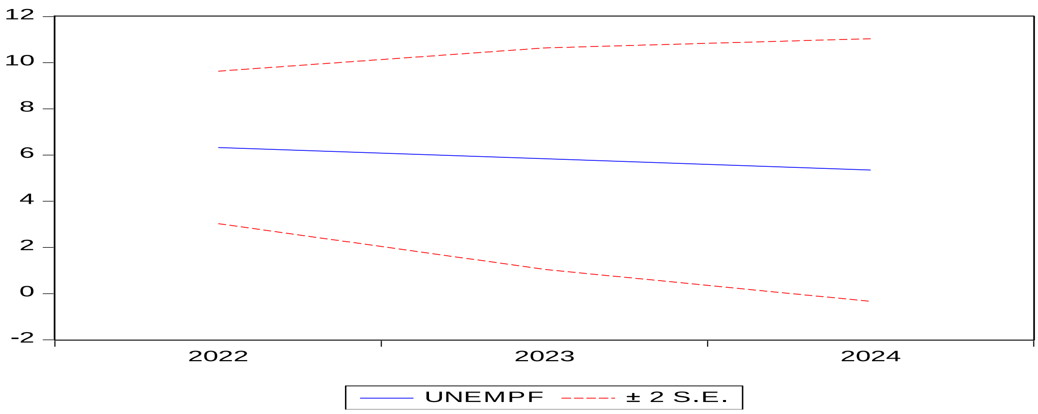

Figure 6. Forecasting unemployment rate and standard errors with the ARIMA model in 2022-2024

The size of the forecast error from the calculated projections for the UNEMP variable is presented in Figure 7 and Figure 8. The projection results using the ARIMA model, on the RMSE criteria, the UNEMP variable has a relatively small RMSE value of 2.156. It indicates a downward trend in the unemployment rate with a relatively small level of projection error.

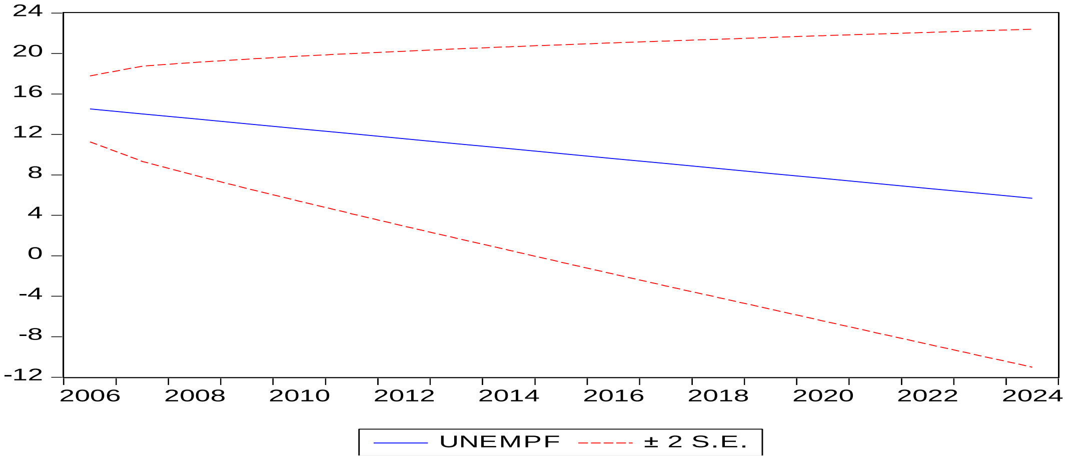

Figure 7. Forecasting unemployment rate and standard errors using the ARIMA model in 2005-2024

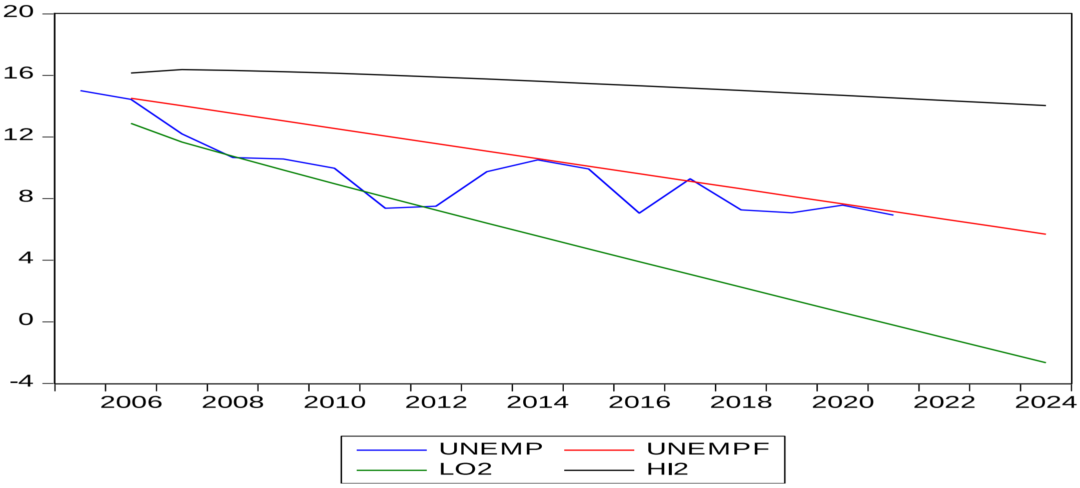

Figure 8. Actual unemployment rate, forecasting, and standard errors with the ARIMA model in 2005-2024

Inflation Rate

The best model for the inflation variable is ARIMA (1,1,0). The results of the model selection using auto ARIMA are presented in Table 8. This model also meets the criteria of the best model by having a probability of less than 0.05 and the largest coefficient of determination, and the smallest AIC and SC values compared to other models. The model also has a relatively small mean absolute error. In addition, forecasting inflation variables using this model also has an accuracy level that is close to or equal to its actual value throughout the sample period.

Table 8. INF model estimation results - ARIMA

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.622	0.662	-0.938	0.365
AR(1)	-0.665	0.150	-4.431	0.000
R-squared = 0.323		AIC = 5.946		
F-statistic = 3.101		SC = 6.091		
DW = 1.635		Inverted AR Roots = -0.67		

Notes: Dependent variable is D(INF)

Figure 9 shows the trend of forecasting results for the fluctuating inflation rate variable. The projected inflation rate in Maluku Province in 2022 is 0.37 percent in 2023, 1.78 percent, and -0.18 percent in 2024.

Thus, it is estimated that Maluku Province will experience deflation (price reduction) at the end of the year forecasting.

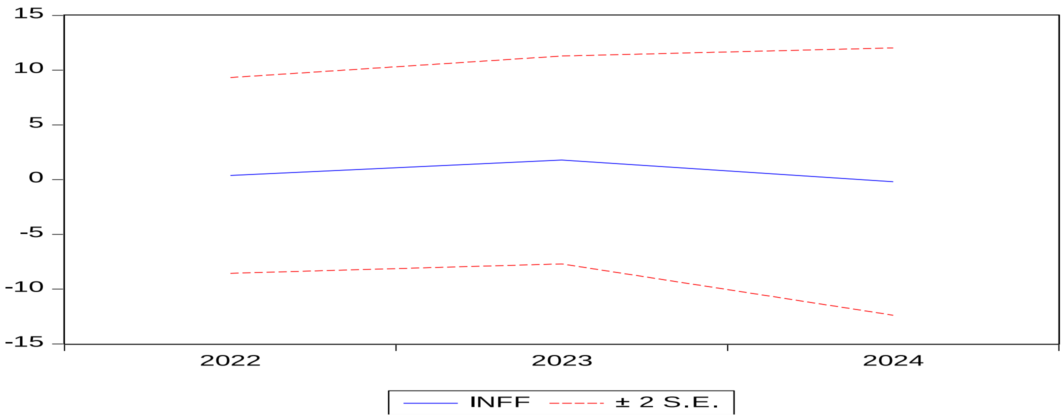

Figure 9. Forecasting inflation rate and standard errors with the ARIMA model in 2022-2024

The size of the forecast error from the calculated projections for the INF variable is presented in Figure 10 and Figure 11. The projection results using the ARIMA model, on the RMSE criteria, the INF variable has a relatively small RMSE value of 3.358. It indicates an upward trend in inflation with a relatively small level of projection error.

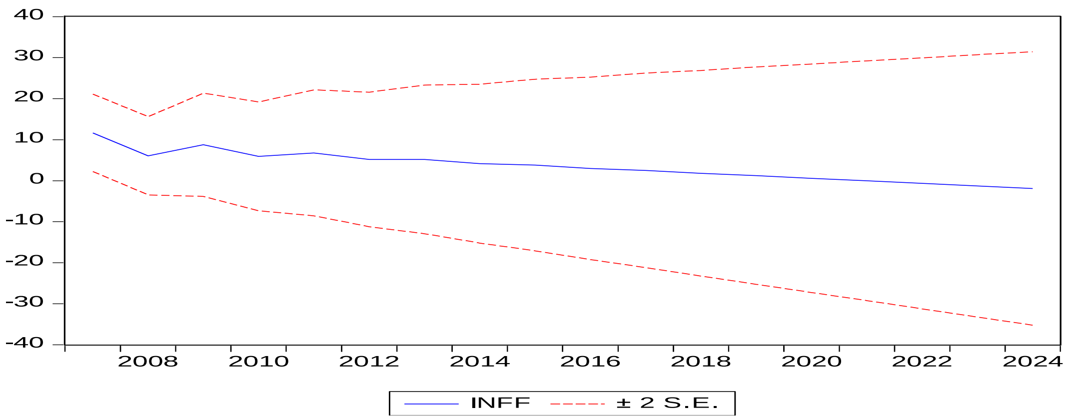

Figure 10. Forecasting inflation rate and standard errors using the ARIMA model in 2005-2024

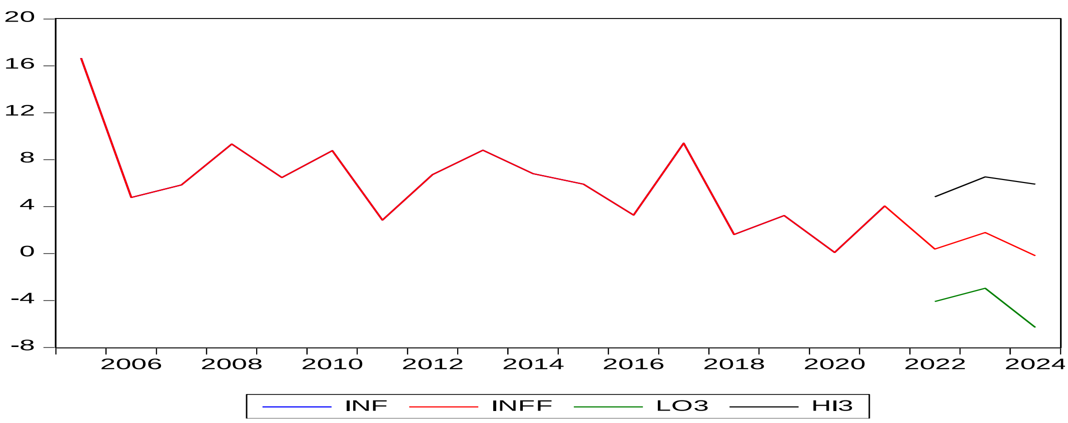

Figure 11. Actual inflation rate, forecasting, and standard errors with the ARIMA model in 2005-2024

Poverty Level

The best model for the poverty level variable is ARIMA (1,1,0). The results of the model selection using auto ARIMA are presented in Table 9. This model also meets the criteria of the best model by having a probability of less than 0.05 and the largest coefficient of determination, and the smallest AIC and SC values compared to other models.

Table 9. POV model estimation results - ARIMA

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.694	0.477	-1.452	0.170
AR(1)	0.562	0.239	2.346	0.035
R-squared = 0.277		AIC = 3.072		
F-statistic = 2.492		SC = 3.217		
DW = 1.919		Inverted AR Roots = 56		

Dependent Variable: D(POV)

As seen in Figure 12, the trend of forecasting results for the poverty rate variable continues to decline. The projected poverty rate in Maluku Province in 2022 is 17.80 percent, 17.47 percent in 2023, and 16.97 percent in 2024. Thus, the continuation of economic recovery, reduction of employment and unemployment, and stability of inflation will also impact reducing the poverty rate in Maluku Province in the future.

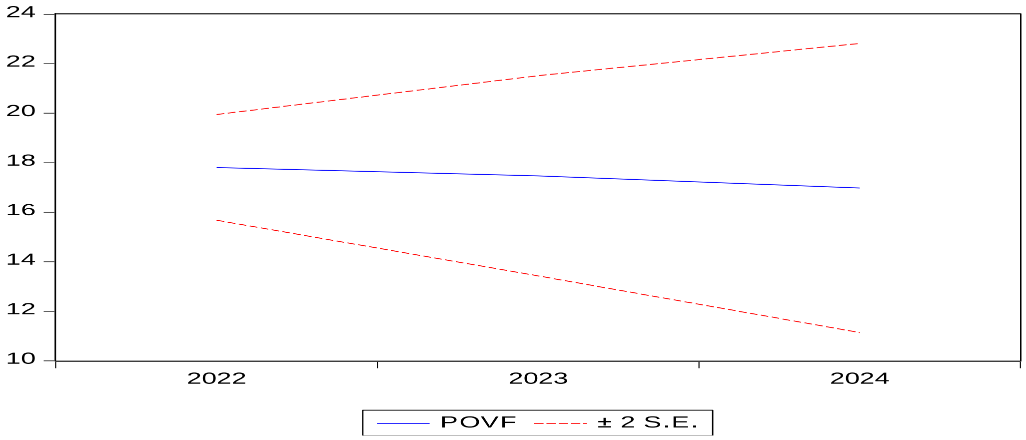

Figure 12. Forecasting poverty level and standard errors with the ARIMA model in 2022-2024

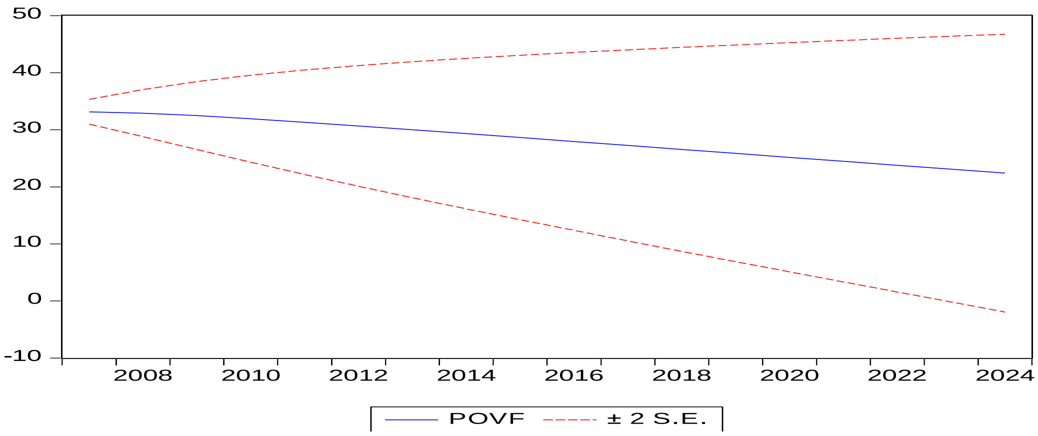

Figure 13. Forecasting poverty level and standard errors using the ARIMA model in 2005-2024

The size of the forecast error from the calculated projections for the POV variable is presented in Figure 14. The projection results using the ARIMA model, on the RMSE criteria, the POV variable has a relatively small RMSE value of 8.069, as Figure in 14 and Table 10. It shows a downward trend in the poverty rate with a relatively small level of projection error, although it is the highest among the RMSE values of the EG, UNEMP, and INF variables.

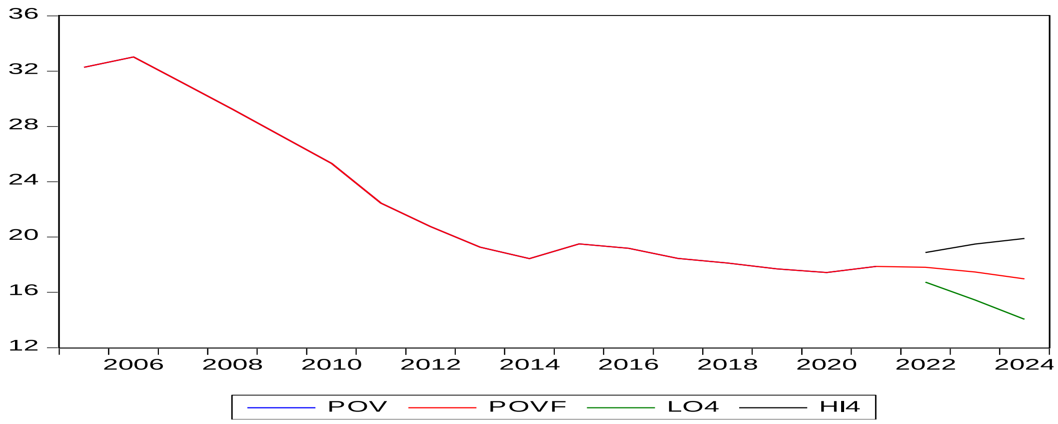

Figure 14. Actual poverty level, forecasting, and standard errors with the ARIMA model in 2005-2024

Table 10. Forecast EG, UNEMP, INF, and POV results with ARIMA (%)

Year	EG_ Actual	EG_ Forecast	UNEMP_ Actual	UNEMP_ Forecast	INF_ Actual	INF_ Forecast	POV_ Actual	POV_ Forecast
2005	5.07	-	15.01	-	16.67	-	32.28	-
2006	5.55	-	14.45	-	4.79	-	33.03	-
2007	5.62	-	12.20	-	5.85	-	31.14	-
2008	4.81	-	10.67	-	9.34	-	29.24	-
2009	4.86	-	10.57	-	6.48	-	27.29	-
2010	6.47	-	9.97	-	8.78	-	25.32	-
2011	6.34	-	7.38	-	2.85	-	22.45	-
2012	7.16	-	7.51	-	6.73	-	20.76	-
2013	5.24	-	9.75	-	8.81	-	19.27	-
2014	6.64	-	10.51	-	6.81	-	18.44	-
2015	5.48	-	9.93	-	5.92	-	19.51	-
2016	5.76	-	7.05	-	3.28	-	19.18	-
2017	5.82	-	9.29	-	9.41	-	18.45	-
2018	5.91	-	7.27	-	1.62	-	18.12	-
2019	5.41	-	7.08	-	3.24	-	17.69	-
2020	-0.92	-	7.57	-	0.09	-	17.44	-
2021	3.04	-	6.93	-	4.05	-	17.87	-
2022		1.51		6.67		0.37		17.80
2023		1.27		6.18		1.78		17.47
2024		1.04		5.69		-0.18		16.97

ECM Estimation Results

Furthermore, the error correction model (ECM) estimation used the Ordinary Least Square (OLS) method. This stage was carried out to determine the short-term effect of the research variables and the validity of the estimation model, which can be seen from the coefficient of the ECT variable. Meanwhile, the resulting error correction coefficient shows the phenomenon of correcting deviations toward balance (Nugraha et al., 2021). Thus, the estimation results can be said to be consistent with the theory. If the error regression coefficient (ECT) is significant, it also means that there is a long-term or equilibrium effect (Insukindro, 1999). The ECM estimation results are presented in Table 11.

Table 11. Short-term estimation results

Variable	Coefficient	t-Statistic	Prob	Description
C	-0.086	-0.069	0.946	
D(EG)	-0.042	-0.261	0.800	Not significant
D(UNEMP)	0.386	1.548	0.160	Not significant
D(INF)	-0.085	-0.612	0.557	Not significant
EG(-1)	-0.246	-1.396	0.200	Not significant
UNEMP(-1)	0.095	0.584	0.575	Not significant
INF(-1)	-0.051	-0.254	0.805	Not significant
ECT(-1)	-0.268	-3.836	0.005	Significant

Notes: Dependent variable is the POV
Description: α=5% $R^2 = 0.773$ F Stat = 3.893 DW = 2.501

As shown in the equation, the results show that in the short term, variable ECT_{t-1} is significant at 5 percent, with a short-term effect of -0.268. This finding is consistent with research expectations, while other variables are insignificant. In other words, the above results are appropriate to serve as a valid empirical model and prove the existence of a long-term relationship or balance. The results also show that the short-term macroeconomic variables do not significantly affect poverty in Maluku Province. It indicates that there was a shock in the economy during the study period, and it will be corrected by itself so that it can return to normal in the long term. The estimated results of the regression coefficient ECT_{t-1} in Table 11 are significant, which is in line with the opinion of Insukindro (1999) in his study, which stated that the significance of ECT_{t-1} shows that the estimation results are feasible to be selected as an empirical model. These results also show that the absolute value of the coefficient ECT_{t-1} is -0.268, meaning that about 26 percent of the discrepancy between the actual value of the poverty level in Maluku Province in the short term and the equilibrium value of the poverty level in the long term will be corrected annually.

In addition, the ECM estimation also passes various diagnostic tests or classical assumptions. Thus, from the short-term model (Equation 5), the long-term effect of the EG, UNEMP, and INF variables on POV can be estimated in Table 12.

Table 12. Long-term estimation results

Variable	Coefficient	t-Statistic	Prob	Description
C	2.945	0.714	0.487	
EG	0.229	0.475	0.642	Not significant
UNEMP	2.071	4.710	0.000	Significant
INF	-0.197	-0.657	0.522	Not significant

Dependent Variable: POV
Description: α=5% $R^2 = 0.724207$ F Stat = 11.37895 DW = 0.832902

The estimation results above show that in the long term, the UNEMP variable significantly affects POV at the level of = 5 percent, while EG and INF are not significant. The higher the unemployment rate in Maluku Province, the poverty rate will increase. The existence of restrictions on people's activities and mobility, especially during a pandemic, triggers layoffs and an increase in the number of workers sent home, thereby increasing poverty. The analysis results also illustrate that changes in the poverty level are quite responsive to macroeconomic variables, primarily the unemployment rate. Reducing the unemployment rate can encourage a decrease in the poverty rate. On the other hand, an increase in the unemployment rate can increase the poverty rate in Maluku Province. Meanwhile, the volatility of data on economic growth and inflation, which tends to be unstable during the observation period, causes the effect of these variables on the poverty level in Maluku Province to be insignificant.

These results differ from Hoover et al. (2008), which found the effect of economic growth on poverty. In addition, the estimation results of the inflation variable in this study also tend to be different from Cuong (2011), which investigated that high inflation can increase the poverty rate in Vietnam. These results are also inconsistent with the findings of Datt et al. (2020), which indicated a poverty response to growth in India. Thus, the stability of macroeconomic variables in Maluku Province, especially economic growth and inflation, must be maintained. In addition, the current economic growth does not reflect completeness, so economic disparities persist. Furthermore, the impact of government policies has not reached all levels of society, and Maluku Province still has low access to resources. On the other hand, the number of less affluent people in Maluku Province is dominated by people in rural than in urban areas. Thus, the government's attention to rural development needs to be raised through empowering rural communities and optimizing the allocation and utilization of village funds.

Meanwhile, the role and contribution of the agricultural sector (in rural areas) to the economic growth of Maluku Province, which so far has been quite extensive, has increasingly shifted to increasing the contribution of the processing, services, and government administration sectors (in urban areas). Thus, the productivity of the agricultural and processing sectors needs to be continuously encouraged to increase people's income, especially in rural areas. It is in line with a study conducted by Harsmar (2022), which showed that increased productivity in the agricultural sector could be a prerequisite for broader economic growth and poverty reduction. Furthermore, Pham & Riedel (2019) indicated that poverty reduction is affected by the increase in agricultural and industrial sectors, while poverty rate increase could be affected by an uptrend proportion of the service sector.

5. CONCLUSION, IMPLICATION, SUGGESTION, AND LIMITATIONS

Based on the forecasting and analysis results stated above, it can be concluded from this study that the Univariate Benchmark Model (ARIMA) and Bayesian VAR have different specifications and forecasting directions. The value of Forecast Error Measures with the ARIMA model is relatively lower than the Bayesian VAR model. The results of forecasting macroeconomic variables in Maluku Province have a relatively good level of accuracy and are close to the actual values of the sample period. Meanwhile, the cointegration test results show a long-term equilibrium relationship between research variables. Furthermore, the results of the ECM test show that in the short term, only the ECT variable significantly affects the poverty rate. In contrast, the other variables are not significant. However, the unemployment rate has a significant effect in the long run. In addition, significant ECT variables indicate a long-term relationship between research variables. Besides that, it also proves the validity of the research model.

The forecasting results from the model show that it is suggested that Maluku Provincial Government maintain the stability of macroeconomic variables, especially the inflation and unemployment rates because they tend to increase in the coming year. It can have an impact on reducing people's purchasing power. This research is only limited to forecasting macroeconomic variables in Maluku Province. Further research can be conducted by developing or adding forecasting models to find the best model accuracy. Forecasting macroeconomic variables can also be done nationally or internationally according to the phenomena occurring and research gaps.

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