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An Application of The Panel Vector Autoregressive Model To Analyze Inflation and GRDP Growth Rates

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Abstract
The Panel Vector Autoregressive (PVAR) model is an extension of the traditional Vector Autoregressive (VAR) framework that is specifically designed for panel data, allowing the integration of time-series and cross-sectional information across multiple regions. One of the main advantages of the PVAR approach is its ability to treat all variables as endogenous and to capture dynamic interdependencies simultaneously. This study aims to examine the dynamic relationship between inflation and regional economic growth, as measured by Gross Regional Domestic Product (GRDP) growth, across provinces in Indonesia using a PVAR model. The empirical analysis begins with panel unit root testing employing the Im–Pesaran–Shin (IPS) test to ensure stationarity of the variables, followed by optimal lag length determination based on the Moment and Model Selection Criteria (MMSC). Model estimation is conducted using the Generalized Method of Moments (GMM) to address endogeneity and unobserved heterogeneity. The validity of the instruments is evaluated through the Sargan–Hansen test, while causal linkages between variables are investigated using the Granger causality test. The results reveal evidence of a bidirectional relationship between inflation and economic growth in several provinces, indicating dynamic feedback effects. Stability tests confirm that the estimated PVAR model is stable. Furthermore, Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) analyses illustrate how shocks to inflation and economic growth propagate over time. These findings provide valuable insights for designing more effective and regionally targeted economic policies in Indonesia.

Keywords: *Gross regional domestic product, inflation, panel data, economic growth*

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1. INTRODUCTION

In the complexity of today's global economic system, two primary concepts that remain the focus of discussion and analysis are inflation and economic growth [1]. Developing countries generally face economic challenges such as high inflation and slow growth. Economic growth is defined as a country's long-term ability to produce an expanding range of goods for its growing population [2]. When a government fails to boost its economic growth, new economic and social issues may arise. Growth is typically measured by Gross Domestic Regional Product (GDRP) [3]. Inflation is a critical economic indicator, with efforts made to keep its rate low and stable to prevent macroeconomic problems. High and unstable inflation reflects economic instability, leading to a continuous rise in the prices of goods and services and, ultimately, an increase in poverty levels within the country.

A time series is a collection of observational values recorded over some time, usually with equally long intervals [4]. Time series data can be recorded in various periods such as daily, weekly, monthly, annually, or other consistent periods. This data analysis can be categorized based on the number of variables observed. If the data includes only one variable, it is called a univariate time series. Analysis with two variables is known as a bivariate time series, which provides better results when additional variables are involved. Furthermore, multivariate time series are used to analyze several interrelated variables in a system. Thus, observations of one variable are not only influenced by previous observations of that variable, but also by observations of other variables. One model that can be used for quantitative analysis of multivariate time series is the Vector Autoregressive (VAR). In general, time series data related to the economy tend to be non-stationary. Therefore, it is necessary to perform differentiation two to three times, and so on, until stationary data is obtained. The method used in this stationarity test is the unit root test developed by Dickey-Fuller. Unit root testing aims to determine whether there is a unit root in the data. If the data contains unit roots, then the data is considered non-stationary [5].

The VAR model is a development of the Autoregressive (AR) model [6]. In the AR model, there is only one variable being analyzed, while in the VAR model, there are many variables that are all considered endogenous variables [7]. Endogenous variables are variables whose values are affected by other variables in the model, also known as dependent variables or dependent variables. Modeling using VAR only focuses on time series data from a single individual. However, in economic research, there are often data limitations that cannot represent the variables used in the analysis. These limitations can be an insufficient number of time units in time series data or a limited number of individuals in cross-section data. These data limitations can affect the accuracy of the two-way relationship analysis results in economic research. Therefore, combining both types of data, namely time series, and cross-section, into panel data can be done to analyze the relationship. The use of panel data has the advantage of explicitly accommodating heterogeneity among individuals [8].

Panel data analysis using the VAR method is called Panel Vector Autoregressive (PVAR). The PVAR model outperforms the traditional VAR technique by eliminating serious biases in the estimation. The PVAR model has clear advantages over covariance, which makes it possible to treat all variables considered in the regression as endogenous with panel data procedures, allowing for unobserved individual heterogeneity [9]. PVAR imposes all variables as endogenous and checks for unobserved heterogeneity [10] in both a dynamic and static sense, although in some relevant cases, exogenous variables can be included. Many methods are unable to address endogeneity, which results in biased estimates and inconsistent estimators. To overcome these issues, the Generalized Method of Moments (GMM) is employed [11]. The PVAR model itself uses GMM estimation to determine its parameters [12]. Unlike average-based estimators, PVAR employs variance decomposition and impulse response functions to observe variable behavior over time. Consequently, detailed trends are revealed, proving useful for policy decision-making.

Many authors have been studying the causal relationship between inflation, GRDP, interest rate, the rupiah exchange rate against the US dollar using VAR or PVAR. Study by [13] demonstrated a long-term causal relationship among the examined variables, while in the short term, inflation affected Bank Indonesia's interest rate and GRDP was linked to other macroeconomic variables. [14] examined the implementation of the Panel Vector Auto Regression Model to study the relationship between inflation and the growth of the money supply in six ASEAN countries from 1994 to 2020. Their findings revealed a bidirectional causal relationship: an increase in inflation would decrease the growth of the money supply, whereas an increase in the money supply would, in turn, elevate inflation. Furthermore, [11] and [15] conducted research using the PVAR-GMM model on energy data, investigating renewable energy, financial development, and greenhouse gas emissions. Their results indicated a significant relationship between renewable energy and greenhouse gas emissions.

2. LITERATURE REVIEW

2.1. Panel Data and Stationarity

Panel data consists of observations from multiple individuals over time, combining both cross-section (i) and time-series (t) dimensions. It can be balanced or unbalanced, and classified as short ($N > T$) or long ($T > N$). The advantage of panel data lies in its ability to improve estimation efficiency through a larger number of observations. Stationarity implies constant mean and variance over time, and is crucial in panel data analysis to avoid biased inference due to heterogeneity. One commonly used method to test for stationarity in panel data is the Im, Pesaran, and Shin (IPS) test, which examines unit roots in each cross-section.

The IPS test starts by estimating the ADF regression for each cross-section unit:

$$\boldsymbol{Y_t} = \boldsymbol{\phi Y_{t-1}} + \boldsymbol{e_t}\,, t = 1, 2, \cdots, T \tag{1}$$

The OLS estimator for ϕ_i is:

$$\widehat{\phi}_i = \frac{\sum_{t=1}^{n} Y_{i,t-1} Y_{i,t}}{\sum_{t=1}^{n} Y_{i,t-1}^2} \tag{2}$$

The ADF test statistic for each unit is computed as:

$$t_i = \frac{\widehat{\phi}_i - 1}{s_{\widehat{\phi}_i}} = \frac{\widehat{\phi}_i - 1}{\left[\sigma_{e_i}^2 \left(\sum_{t=1}^{n} Y_{i,t-1}^2\right)^{-1}\right]^{\frac{1}{2}}} \tag{3}$$

The IPS statistic is the average of individual ADF statistics:

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_{pi} \tag{4}$$

The null hypothesis $H_o\colon \phi_i = 1$ (non-stationary) is rejected if $\underline{t}$ is less than the critical value, indicating that the panel data is stationary [16].

2.2. Differencing

Differencing occurs when the panel data is non-stationary, meaning the original time series is replaced with its differenced series. For each cross-section unit, the initial form of differencing is as follows.

$$\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1} \tag{5}$$

where

$\Delta Y_{i,t}$: first difference variable for the i-th individual at time t.

$Y_{i,t}$: variable for the i-th individual at time t.

$Y_{i,t-1}$: variable for the i-th individual at time $(t - 1$

2.3. Vector Autoregressive (AR) Model

The Vector Autoregressive (VAR) model is a multivariate extension of the Autoregressive (AR) model, widely used in economic forecasting and policy analysis. It captures the dynamic interrelationships among endogenous variables over time, with all variables explained by their own past values and the past values of other variables in the system [17].

The general form of a VAR(p) model is:

$$\boldsymbol{Y_t} = c + \sum_{i=1}^{p} \boldsymbol{A_i y_{t-i}} + \boldsymbol{\varepsilon_t} \quad ; p > 0 \tag{6}$$

where Y_t is an $n \times 1$ vector of endogenous variables, c is a constant vector, A_i are coefficient matrices, and ε_t is a vector of white noise errors.

2.4. Panel Vector Autoregressive (PVAR) Model

The Panel Vector Autoregressive (PVAR) model extends the standard VAR model to panel data, which combines cross-section and time series dimensions. All variables in the PVAR framework are treated as endogenous and dynamically interrelated across individuals and over time. The general form of the PVAR model with lag order p and fixed effects is given by:

$$\boldsymbol{y_{it}} = \boldsymbol{A_1 y_{it-1}} + \cdots + \boldsymbol{A_P y_{it-p}} + \boldsymbol{\eta_i} + \boldsymbol{e_{it}} \tag{7}$$

where y_{it} is an $m \times 1$ vector of endogenous variables for unit i at time t, A_1 are $m \times m$ coefficient matrices, η_i captures unit-specific fixed effects, and e_{it} is the error term.

2.5. Parameter Estimation Generalized Method of Moment (GMM)

The Generalized Method of Moments (GMM), introduced by [18], is used for consistent parameter estimation when classical assumptions are violated (e.g., heteroskedasticity, autocorrelation). In PVAR estimation, the presence of lagged dependent variables and individual effects leads to endogeneity, requiring transformation typically via Forward Orthogonal Deviation (FOD) to eliminate fixed effects.

The transformed model is:

$$\boldsymbol{y_{it}^*} = \boldsymbol{A_1 y_{i,t-1}^*} + \cdots + \boldsymbol{A_P y_{i,t-p}^*} + \boldsymbol{e_{it}^*} \tag{8}$$

GMM uses instrument variables Q_i, defined as:

$$Q_i = diag(q_{i1}', \cdots, q_{iT_1}') \tag{9}$$

where $r \geq 1$. Instrument validity is tested before parameter estimation.

2.6. Identification of the PVAR Model Order

Determining the lag order p in a PVAR model is crucial to ensure model adequacy. An inappropriate lag length may lead to underfitting or overfitting. Andrews and Lu developed the Model and Moment Selection Criteria (MMSC) for GMM estimation, extending traditional criteria like AIC, BIC, and HQIC using Hansen's J-statistic.

The MMSC formulas are as follows:

$$MMSC_{BIC,n}(k,p,q) = J_n(k^2p, k^2q) - (|q| - |p|)k^2 \ ln \ ln \ n \tag{10}$$

$$MMSC_{AIC,n}(k,p,q) = J_n(k^2p, k^2q) - 2k^2(|q| - |p|) \tag{11}$$

$$MMSC_{HQIC,n}(k,p,q) = J_n(k^2p, k^2q) - Rk^2(|q| - |p|) \ ln \ ln \ \ ln \ ln \ n \tag{12}$$

where J_n is Hansen's J-statisti, k is the number of variables, p is lag order, q is the number of moment conditions, and n is the number of observations. The optimal lag is selected based on the minimum MMSC value, with BIC and HQIC preferred due to their consistency properties [14].

2.7. Parameter Significance Test

The parameter significance test is conducted to assess how significant the effect of the explanatory variables is on the response variable. This effect is measured using a partial test. The t-value formula is as follows [19]:

$$t_{value} = \frac{vec\ (\hat{\Phi})}{Se(vec\ (\hat{\Phi}))} \tag{13}$$

where $vec\ (\widehat{\Phi})$ is the result of the parameter estimation and $Se\left(vec\ (\widehat{\Phi})\right)$ is the standard error of the estimated parameter value [12].

The hypotheses are as follows:

H_0 : $vec\left(\widehat{\Phi}\right) = 0$

H_1 : $vec\left(\widehat{\Phi}\right) \neq 0$

The decision rule is to reject H_0 if the calculated t-value is greater than the critical t-value at significance level α, or if the p-value is ≤ α, indicating that the explanatory variables have a significant effect on the response variable.

2.8. Instrument Variable (Q_i) Validity Test

The validity of the instrument variables (Q_i) in the GMM estimation of the PVAR model is tested using the Sargan-Hansen statistic J_n:

$$J_n = nm_n'\hat{\Omega}^{-1}m_n \tag{14}$$

where

$$m_n = \frac{1}{n}\sum_{i=1}^{n}(I_k \otimes Q_i)'vec\ (\Delta^* \tilde{E}_{i,t}) \tag{15}$$

The hypotheses used are as follows.

H_0 : $E\left((I_k \otimes Q_i)'vec(\Delta^* \tilde{E}_{i,t})\right) = 0$ (the instrument is valid)

H_1 : $E\left((I_k \otimes Q_i)'vec(\Delta^* \tilde{E}_{i,t})\right) \neq 0$ (the instrument is not valid)

Reject H_0 if J_n exceeds the critical value χ_r^2 or if the p-value is less than the significance level α. Otherwise, H_0 is not rejected, indicating valid instruments.

2.9. Causality Test of Variables

The Granger Causality Test determines if a causal relationship exists between two variables, which can be unidirectional or bidirectional. The test is conducted after ensuring data stationarity. The Wald test statistic for each unit is:

$$W_{i,T} = \hat{\theta}_i'R'(\hat{\sigma}_i^2 R(Z_i'Z_i)^{-1}R')^{-1}R\hat{\theta}_i \tag{16}$$

For panel data, the test statistic is:

$$W_{N,T}^{Hnc} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T} \tag{17}$$

H_0 is rejected if $W_{N,T}^{Hnc}$ exceeds the critical value of χ_p^2 or if the p-value is less than the significance level ($\alpha = 0.05$).

2.10. Stability Test of the PVAR Model

The stability test determines if the PVAR model is stable, as instability may invalidate the Impulse Response Function (IRF) and Variance Decomposition estimations. Stability is assessed by examining the eigenvalues of the coefficient matrix. A model is stable if all eigenvalues lie within the unit circle (modulus < 1). If any eigenvalue has a modulus ≥ 1, the model is unstable, necessitating adjustments such as altering lag length or estimation method. For a real eigenvalue, the modulus is its absolute value, and for a complex eigenvalue $\lambda = a + bi$ the modulus is:

$$|\lambda| = \sqrt{a^2 + b^2} \tag{18}$$

2.11. Impulse Response Function (IRF)

The Impulse Response Function (IRF) evaluates the response of endogenous variables over time to shocks in a specific variable and the duration of these shocks. It measures both positive and negative reactions of a variable to changes in another and indicates the time required for a variable to return to its equilibrium after a shock. The IRF's accuracy relies on the underlying estimator, making it essential to use the GMM estimator for reliable results with good finite sample properties [20].

2.12. Forecast Error Variance Decomposition (FEVD)

Forecast Error Variance Decomposition (FEVD) is used to assess the extent to which shocks in one variable affect others in a PVAR model. It decomposes the forecast error variance of a variable by analyzing the contributions from each variable over several periods. This reveals the relative importance of each variable in explaining the movements of others. The FEVD for variable y_i at horizon h is calculated as:

$$\omega_{i,j}(h) = \frac{\sum_{k=0}^{h-1}(\Psi_k)_{i,j}^2}{\sum_{k=0}^{h-1}\sum_{j=1}^{N}(\Psi_k)_{i,j}^2} \tag{19}$$

where $\omega_{i,j}(h)$ is the contribution of variable j to variable i, Ψ_k is the impulse response matrix for lag k, and N is the number of variables in the model.

2.13. Autocorrelation Test

Autocorrelation is an important consideration in time series and cross-section data analysis, as it indicates when residuals from one period are correlated with those from previous periods, which can lead to biased and inefficient estimates. The Durbin-Watson test is commonly used to detect autocorrelation. The test statistic is calculated as:

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{20}$$

where e_t is the residual at time t, and n is the number of observations. The results are interpreted by comparing the DW statistic with the critical values from the Durbin-Watson table (dU and dL). The decision rule is as follows:

3. METHOD

This study uses individual units consisting of 34 provinces in Indonesia, while the time units analyzed cover the period from 2015 to 2024. Then the causal relationship between time series variables will be seen using Granger causality. To see the effect of a variable shock on other variables (see the impact of exogenous changes in each endogenous variable with other variables) in the PVAR system is done by estimating the Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD). FEVD is used to see how changes in a variable, as indicated by changes in error variance, are affected by other variables.

3.1. Data and Variables

The data used in this study consists of secondary data obtained from the official websites of the Central Bureau of Statistics (BPS) for each province in Indonesia. The dataset includes information on the inflation rate and the growth rate of Gross Regional Domestic Product (GRDP) for Indonesian provinces from 2015 to 2024. The data is panel data, which combines both time series and cross-sectional units. The time series unit in this study consists of annual observations spanning from 2015 to 2024, while the cross-sectional unit comprises data from 34 provinces across Indonesia. These provinces are: Aceh, North Sumatra, West Sumatra, Riau, Jambi, South Sumatra, Bengkulu, Lampung, Bangka Belitung Islands, Riau Islands, DKI Jakarta, West Java, Central Java, DI Yogyakarta, East Java, Banten, Bali, West Nusa Tenggara, East Nusa Tenggara, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Kalimantan, North

Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Maluku, North Maluku, Papua, and West Papua. The following are the variables used in the study:

$Y_{1,i,t}$: GRDP of province i in year t (in percentage)
$Y_{2,i,t}$: Inflation of province i in year t (in percentage)

3.2. Research Metodology

The empirical analysis was conducted using Stata software, which was employed to perform descriptive statistical analysis, data visualization, panel data stationarity tests, lag order identification, parameter estimation, parameter significance testing, instrumental variable validity tests, Granger causality tests, model stability tests, Impulse Response Function (IRF) analysis, and Forecast Error Variance Decomposition (FEVD).

The stages carried out in this research are as follows.

1. Conduct descriptive statistical analysis for each observed dataset and visualize GRDP growth rate and inflation rate through plotting.
2. Perform panel data stationarity testing using the Im, Pesaran-Shin (IPS) test (using Equation 1, 2 and 3). If the data is not stationary, apply differencing.
3. Identify the order (p) for the PVAR model using the MMSC method. The corresponds to the lowest values of $MMSC_{BIC}$, $MMSC_{AIC}$ and $MMSC_{HQIC}$ (see Equation 10, 11 and 12). The PVAR structure is as follows:
$$\boldsymbol{y_{it}} = \boldsymbol{A_1 y_{it-1}} + \cdots + \boldsymbol{A_P y_{it-p}} + \boldsymbol{\eta_i} + \boldsymbol{e_{it}}$$
with $\boldsymbol{y_{it}} = \begin{bmatrix} GRDP_{i,t} \\ Inflation_{i,t} \end{bmatrix}$, $\boldsymbol{A_k} = \begin{bmatrix} \phi_{11,t-k} & \phi_{12,t-k} \\ \phi_{21,t-k} & \phi_{22,t-k} \end{bmatrix}$, $\boldsymbol{\eta_i} = \begin{bmatrix} \eta_1 \\ \eta_2 \end{bmatrix}$, $\boldsymbol{e_{it}} = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$
4. Construct the instrument variable (Q_i) using Equation 9.
5. Estimate the parameters of the Panel VAR model using the Generalized Method of Moments (GMM).
6. Conduct significance testing for the parameters in the PVAR model.
7. Validate the instrument variables (Q_i) using the Sargan-Hansen test using Equation 13.
8. Perform the Granger causality test on panel data to determine the direction of the relationship between the two variables using Equation 17.
9. Test the stability of the PVAR model using the modulus in Equation 18.
10. Analyze the Impulse Response Function (IRF).
11. Conduct Forecast Error Variance Decomposition (FEVD) analysis.
12. Interpret the PVAR model results.

4. RESULT AND DISCUSSION

4.1. Descriptive Statistics

Before further discussing the relationships between variables, a descriptive analysis of the research variables is presented in Table 1.

Table 1. Descriptive Statistic Analysis

Variable	N	Mean	Std. Dev.	Minimum	Maximum
GRDP	340	4.60	3.61	-15.74	22.94
Inflation	340	2.92	1.43	-0.79	7.43

Based on Table 1 the average GRDP growth rate was 4.60%, with Papua experiencing the lowest growth of -15.74% in 2019 and North Maluku the highest at 22.94% in 2022. The average inflation rate was 2.92%, with the lowest of -0.79% in Gorontalo (2024) and the highest of 7.43% in West Sumatra (2022). The standard deviation indicates that GRDP growth varied more across provinces compared to inflation, which tended to be relatively stable.

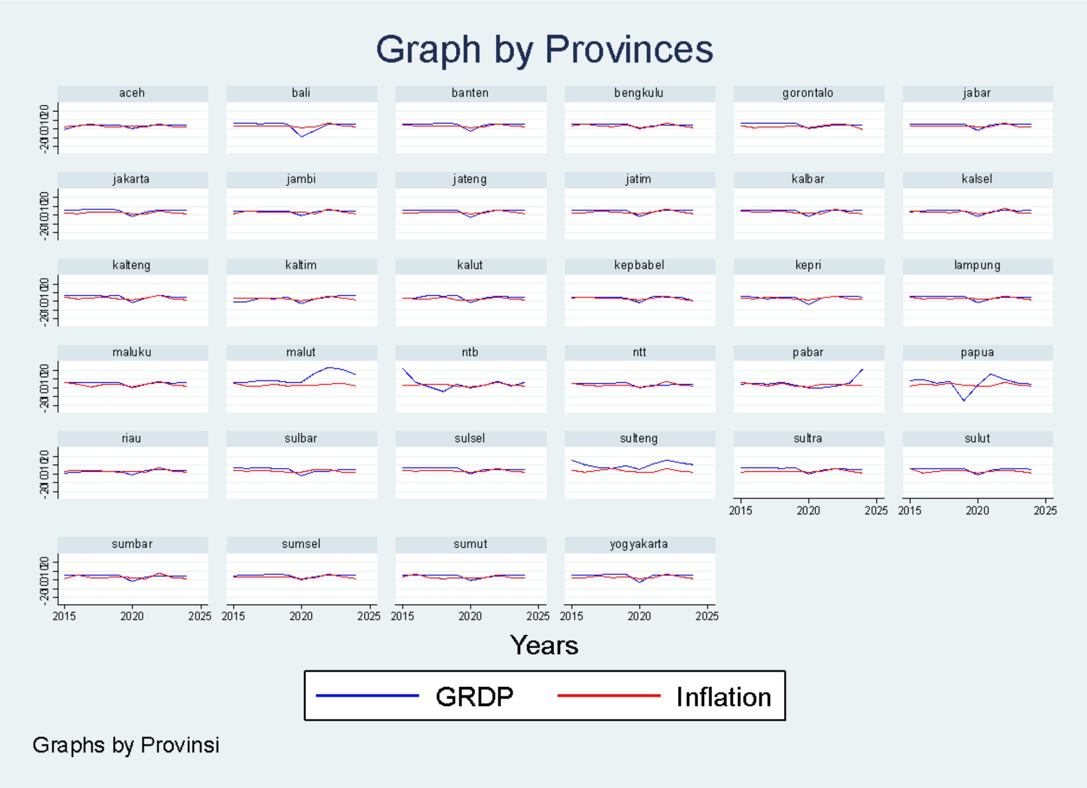

Figure 1. Plot of GRDP Rate and Inflation Rate.

The plot of the GRDP rate and inflation rate is shown in Figure 1. The plots illustrate the relationship between inflation and GRDP across 34 Indonesian provinces over time. GRDP shows larger fluctuations than inflation, reflecting differences in regional economic growth, shocks, and recovery patterns. Inflation is relatively more stable and follows similar trends across provinces, indicating the influence of national price controls and monetary policy. In several provinces, changes in GRDP are not immediately followed by changes in inflation, suggesting weak short-term transmission between economic output and prices. Overall, the graphs highlight regional heterogeneity in economic dynamics while showing that inflation tends to be less volatile and more synchronized than provincial GRDP

4.2. Panel Data Stationarity Test

In the analysis of data containing time series components, a stationarity test is typically conducted; a similar approach is also applied to panel data. For panel data, stationarity is tested using the Im, Pesaran, and Shin (IPS) test.

Table 2. Stationarity Assessment Using IPS Test

Variable	$\underline{t}$ Statistic	p-value	conclusion
GRDP	-2.4433	0.0102	Stationary
Inflation	-6.2785	0.0000	Stationary

Based on the results in Table 2. the GRDP variable has a p-value of 0.0102 while the inflation variable has a p-value of 0.0000. Since both variables have p-values less than α (α = 0.05) we reject H_0 and conclude that both variables are stationary, eliminating the need for differencing.

4.3. Identification of the Order (p) of the PVAR Model

Before constructing the Panel Vector Autoregressive (PVAR) model, it is essential to determine the optimal lag length (p).

Table 3. Descriptive Statistic Analysis

Lag	$MMSC_{AIC}$	$MMSC_{BIC}$	$MMSC_{HQIC}$
1	28.8248	-8.8047	13.5551
2	-4.7988	-29.8852	-14.9785
3	-1.2391	-13.7823	-6.3290

Based on Table 3, it can be observed that the values of $MMSC_{AIC}$, $MMSC_{BIC}$, $MMSC_{HQIC}$ indicate that lag 2 has the lowest values among the tested lags. This suggests that a PVAR model with lag 2 provides the best balance between model fit and complexity. Considering the results from these three information criteria, lag 2 is selected as the optimal lag for estimating the PVAR model. This implies that the appropriate order for the PVAR(p) model in this study is $p = 2$.

4.4. Identification of Parameter Significance Test

The parameters were estimated using the GMM method, with lag 1 - 4 of GRDP and inflation as instruments. After eliminating individual effects using the forward orthogonal deviation (FOD) method, a two-step estimation was performed.

Table 4. Estimated Values and Parameter Significance Test

Dependent	Parameter	Coefficient	p-value	Significance
GRDP	$a_{11}^{(1)}$	0.1097	0.489	Not Significant
	$a_{11}^{(2)}$	-0.3435	0.003	Significant
	$a_{12}^{(1)}$	0.3987	0.109	Not Significant
	$a_{12}^{(2)}$	0.6487	0.012	Significant
Inflation	$a_{21}^{(1)}$	0.0118	0.735	Not Significant
	$a_{21}^{(2)}$	-0.2522	0.000	Significant
	$a_{22}^{(1)}$	-0.0474	0.503	Not Significant
	$a_{22}^{(2)}$	-0.3233	0.000	Significant

Based on the parameter estimation of the PVAR (2) model in Table 4, the matrix equation can be written as follows:

$$\begin{bmatrix} y_{1,i,t} \\ y_{2,i,t} \end{bmatrix} = \begin{bmatrix} 0.1097 & 0.3987 \\ 0.0118 & -0.0474 \end{bmatrix} \begin{bmatrix} y_{1,i,t-1} \\ y_{2,i,t-1} \end{bmatrix} + \begin{bmatrix} -0.3435 & 0.6487 \\ -0.2522 & -0.3233 \end{bmatrix} \begin{bmatrix} y_{1,i,t-2} \\ y_{2,i,t-2} \end{bmatrix} + \begin{bmatrix} e_{it}^{(1)} \\ e_{it}^{(2)} \end{bmatrix}$$

The equation above can be rewritten in a linear form as follows:

$$y_{1,i,t} = 0.1097\, y_{1,i,t-1} + 0.3987\, y_{2,i,t-1} - 0.3435\, y_{1,i,t-2} + 0.6487\, y_{2,i,t-2} + e_{it}^{(1)}$$
$$y_{2,i,t} = 0.0118\, y_{1,i,t-1} - 0.0474\, y_{2,i,t-1} - 0.2522\, y_{1,i,t-2} - 0.3233\, y_{2,i,t-2} + e_{it}^{(2)}$$

Based on Table 4, only second lags are significant. GRDP is negatively affected by its own second lag and positively by past inflation. Inflation is negatively influenced by both GRDP and inflation from two periods ago. This confirms the presence of lagged effects in the dynamic relationship between GRDP and inflation across provinces.

4.5. Instrument Variable (Q_i) Validity Test

Table 5. Instrument Variable Validity Test

J_n **Test Statistic**	**p-value**
11.20118	0,1906

Based on Table 5, the results of the J-statistic test show a p-value greater than the significance level of 0.05, Therefore, the decision is to accept H_0, leading to the conclusion that the instrumental variable (Q_i) used is valid.

4.6. Identification of Bidirectional Relationship

Table 6. Granger Causality Test

Variable	**Test Statistics**	**p-value**	**Conclusion**
GRDP concern Inflation	6.448	0.040	Variable GRDP influence Inflation
Inflation concern GRDP	46.756	0.000	Variable Inflation influence GRDP

Based on the results of the Granger causality test in Table 6, the decision is to reject H_0, it can be concluded that the GRDP growth rate and inflation rate variables influence each other. This is evident from the p-value, where all p-values are less than α, with α equal to 0.05.

4.7. PVAR Model Stability Test

Table 7. PVAR Model Stability Test

Eigen Value		**Modulus**
Real	Imaginary	
0.3340	0.7093	0.7840
0.3340	-0.7093	0.7840
-0.3028	-0.5960	0.6685
-0.3028	-0.5960	0.6685

Based on Table 7. it can be seen that the modulus which is obtained using formula = $\sqrt{[\boldsymbol{eigen}(\boldsymbol{real})]^2 + [\boldsymbol{eigen}(\boldsymbol{imaginary})]^2}$ less than 1, indicating that the model is stable. Stability can also be confirmed by examining the roots of the comparison matrix, where the model is considered stable if the values remain within the circle with a diameter of

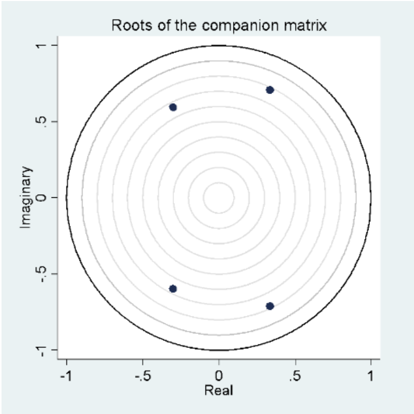

Figure 2. The Stability of the PVAR Model.

As shown in Figure 2, all the eigenvalues are still within the unit circle, indicating that the model is stable. Therefore, it can be concluded that the estimated PVAR model is suitable for use in this case.

4.8. Impulse Response Function (IRF)

The Impulse Response Function (IRF) is conducted to evaluate the dynamic effects and statistical significance of a one-unit shock in one endogenous variable on the current and future values of other variables. IRF illustrates how each endogenous variable responds over time to a one-unit shock in another variable. The vertical axis shows the response magnitude, while the horizontal axis represents future periods after the shock. The solid blue line indicates the estimated response, and the shaded area represents the 95% confidence interval.

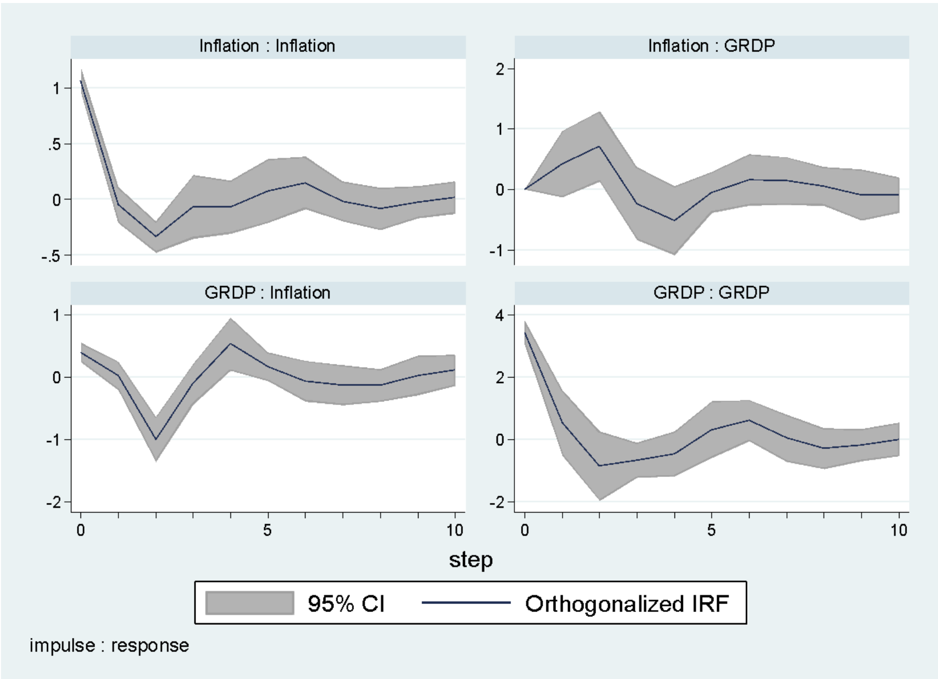

Figure 3. Impulse Response Function.

From Figure 3, it is evident that both inflation and GRDP respond significantly to their own shocks, particularly in the first period. The response of inflation to an inflation shock and GRDP to a GRDP shock is significant in early periods, as indicated by the blue line lying outside the confidence band. However, the effect fades and becomes insignificant in later periods. In contrast, cross-variable shocks (inflation to GRDP and vice versa) generally yield responses within the confidence interval, indicating statistically insignificant effects. This suggests that the immediate impact of own-variable shocks is stronger and more consistent than the cross-variable effects.

4.9. Forecast Error Variance Decomposition (FEVD)

Forecast Error Variance Decomposition (FEVD) shows how much of each variable's forecast error variance is explained by shocks to itself and to other variables in the PVAR model.

Table 8. Forecast Error Variance Decomposition (FEVD)

Periode	GRDP		Inflation	
Respons	GRDP	Inflation	Inflation	GRDP
1	1	0	0.1244	0.8756
2	0.9855	0.0145	0.1245	0.8755
3	0.9494	0.0506	0.4809	0.5191
4	0.9473	0.0527	0.4825	0..5175
5	0.9309	0.0691	0.5365	0.4635
6	0.9312	0.0688	0.5402	0.4598
7	0.9314	0.0686	0.5365	0.4635
8	0.9301	0.0698	0.5391	0.4609
9	0.9304	0.0696	0.5404	0.4596
10	0.9300	0.0699	0.5404	0.4596

Based on Table 8. GRDP is mainly explained by its own shocks (93% at period 10), indicating strong internal stability. Inflation, initially driven by itself (87.5%), becomes increasingly influenced by GRDP, reaching 54% by the 10th period. This suggests GRDP is self-sustaining, while inflation is more sensitive to economic growth fluctuations.

4.10. Autocorrelation Test

Table 9. Autocorrelation Test Results

Sum Squared Resid	Durbin-Watson	Cutoff Criterion	Result
643.533	2.222	dU < DW < 4 - dU	No Autocorrelation

Based on Table 9, the Durbin-Watson statistic is 2.222. Using a 5% significance level, with a sample size (n) of 340 and one independent variable ($k = 1$), the Durbin-Watson table provides a lower bound (dL) of 1.735 and an upper bound (dU) of 1.750. Since the DW value of 2.222 is greater than dU and less than 4−dU, it can be concluded that there is no autocorrelation.

4.11. Interpretation of the PVAR Model

Based on the parameter estimation results of the PVAR model, it is found that the previous year's GRDP growth (t−1) positively affects the current year's GRDP growth (t) by 0.11%, while the effect from two years prior (t−2) is smaller at 0.01%, indicating a diminishing but persistent influence. GRDP growth from the previous year also increases the current inflation rate by 0.40%, whereas the effect from two years prior slightly reduces inflation by 0.05%. Inflation itself exhibits strong persistence, where a 1% increase in the previous year's inflation raises current inflation by 0.65%, although inflation from two years ago has a corrective effect, reducing it by 0.32%. Furthermore, inflation negatively impacts economic growth, as a 1% increase in the previous year's inflation decreases GRDP growth by 0.34%, and inflation from two years prior reduces it by 0.25%. These findings highlight the importance of maintaining price stability, as high inflation can hinder sustainable economic growth.

5. CONCLUSION

This study aims to construct a Panel Vector Autoregressive (PVAR) model and to identify the direction of relationships among variables in panel data on GRDP growth rates and inflation rates in Indonesia over the period 2015–2024. Based on the panel data analysis of GRDP growth and inflation rates across 34 provinces in Indonesia from 2015 to 2024, the results indicate a bidirectional relationship between the two variables GRDP growth influences inflation, and inflation also affects GRDP growth. The estimated PVAR model is as follows:

$$\begin{aligned} GRDP_{i,t} = {} & 0.1097\, GRDP_{i,t-1} - 0.3435\, Inflation_{i,t-1} + 0.0118\, GRDP_{i,t-2} \\ & - 0.2522\, Inflation_{i,t-2} + e_{i,t} \end{aligned}$$

$$\begin{aligned} Inflation_{i,t} = {} & 0.3987\, GRDP_{i,t-1} + 0.6487\, Inflation_{i,t-1} - 0.0474\, GRDP_{i,t-2} \\ & - 0.3233\, Inflation_{i,t-2} + e_{i,t} \end{aligned}$$

Based on the estimated PVAR model, there is a dynamic relationship between GRDP growth and inflation, with both variables influencing each other in both the short run and the long run. The model shows that a 1% increase in GRDP growth from the previous year raises the current GRDP growth by 0.1097% and inflation by 0.3987%, while the effect from two years prior is minimal and slightly deflationary. Conversely, a 1% increase in inflation from the previous year reduces current GRDP growth by 0.3435% and increases inflation by 0.6487%, indicating persistent inflation that negatively affects growth. Inflation from two years ago also reduces current GRDP growth (by 0.2522%) and inflation (by 0.3233%), reflecting long-term adjustment mechanisms. These findings confirm a dynamic two-way interaction, where economic growth tends to fuel inflation in the short run, but sustained inflation can hinder growth, emphasizing the need for balanced macroeconomic policy coordination.

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