Dynamic impact of macroeconomic factors and government expenditure shocks to food inflation in Indonesia during and after COVID-19

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Abstract. This study analyzes the dynamic effects of macroeconomic factor and government expenditure on food inflation in Indonesia (2020–2024) using a Time-Varying Vector Autoregressive (TV-VAR) model. The results reveal that food inflation is dynamic and unstable during the pandemic transition period, forming a pronounced V-shape pattern. The Impulse Response Function (IRF) analysis shows that shocks to government expenditure significantly and permanently increase food inflation in both periods (during and after the pandemic). This indicates that expansionary fiscal policies, while effective in stimulating economic recovery, also create persistent inflationary pressures. GDP shocks have a positive but short-lived impact. Meanwhile, the exchange rate effect exhibits a structural shift: relatively small during the pandemic, but becoming stronger and faster in the post-pandemic period, where depreciation significantly drives up food inflation. These findings confirm that maintaining food price stability to safeguard food security in Indonesia requires adjusting fiscal and monetary policies to reduce the risk of macroeconomic shocks. It is essential to strengthen policy responses during and after periods of disaster, such as the ongoing pandemic, to stabilize food prices, protect household purchasing power, and ensure sustainable economic recovery.

1 Introduction

Food security refers to a state in which every individual, at any time, has reliable access to adequate, safe, and nutritious food that meets their dietary requirements and preferences, thereby maintaining an active and healthy life [1]. This concept encompasses six main pillars: Availability, Access, Utilization, Stability, Sustainability, and Agency [2]. Stable food prices are crucial for achieving food security, particularly for low-income communities that allocate a significant portion of their budget to food. Unstable food prices can trigger speculation and hoarding of food supplies, thereby worsening the balance of food supply, reducing people's economic access to nutritious food, causing a shift to cheaper but less nutritious food, making long-term food planning difficult, and potentially triggering prolonged food crises as well as dependence on cheaper imported food [3]. Therefore, maintaining the stability of food supply and prices has become a government policy priority to mitigate broader socio-economic impacts.

At the beginning of 2020, Indonesia faced significant challenges to food security in the wake of a series of shocks caused by the COVID-19 pandemic. Not only did this medical crisis impact the health sector, but it also triggered economic unrest worldwide, including in Indonesia. The unregulated deceleration, driven by currency devaluation, negatively impacts Gross Domestic Product (GDP) growth and puts pressure on various sectors of the economy. In response, the government increased government expenditure in early 2021. The policy stimulated job creation and promoted economic output growth [4]. However, amid efforts to restore the economy, food inflation has remained a critical challenge to this day. Several economic factors have been shown to influence food inflation: the exchange rate has a long-term relationship with and a positive impact on food inflation, as well as a bidirectional causal relationship [5], the relationship between GDP and food inflation is nonlinear [6]. and the relationship between government expenditure and food inflation is also nonlinear [6]. To conduct an in-depth analysis of how government spending shocks and other macroeconomic factors affect food inflation, the Vector Autoregressive (VAR) approach can be employed.

Vector Autoregressive (VAR) modelling is a statistical approach used to analyse the dynamic relationships among several time series variables. In a VAR framework, each variable is expressed as a function of its own past values as well as the past values of the other variables in the system. This method enables the capture of complex interactions and feedback effects across variables [7]. One of the most significant advantages of the VAR model is that it can track how the effect of a shock on a variable propagates throughout the system over time. This shock can be analysed using

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impulse response functions (IRF), which measure the impact of an instantaneous shock to one variable on the other variables in the system during the current and future periods [8].

However, the standard VAR model has a limitation in that it assumes the parameters or coefficients describing the relationships among variables remain constant over time. It is worth noting that this assumption may not hold, particularly during periods of high uncertainty, such as those caused by the COVID-19 pandemic. During such periods, drastic changes can be observed in economic structures and policy responses, and nonlinear relationships can be identified among variables [9]. To address this limitation, this study employs an extension of the VAR model, namely the Time-Varying Vector Autoregressive (TV-VAR) model. The TV-VAR model allows parameters to change flexibly at each point in time. This dynamic parameter adjustment enables TV-VAR to capture more complex relationship dynamics and provides greater flexibility and robustness compared to the standard VAR model [10].

The TV-VAR model has gained increasing popularity across various fields and in academic research. For example, it has been used to study the dynamic impact of weather changes on the fluctuating prices of vegetables in China's Shandong Province [11], examining the dynamic interactions among GDP growth, renewable and non-renewable energy consumption, and CO_2 emissions in India [12], analyzing the impact of various driving factors on the formation of European Union carbon futures prices across different periods [13]. , studying the relationships among depressive symptoms [14] and investigating the dynamic effects of renewable energy prices on agricultural prices in China [15].

Nevertheless, its application in the context of food security and food inflation in developing countries such as Indonesia—particularly in analyzing structural shifts resulting from the COVID-19 pandemic—remains relatively limited. Therefore, this study fills that gap by applying the TV-VAR methodology to explicitly model how the effectiveness of government spending and the influence of macroeconomic variables on food inflation fluctuate over time. This approach is expected to provide a richer and more accurate understanding of the underlying dynamics, which the standard VAR model or other time-invariant models cannot capture.

2 Methods

2.1 Data source

The variables used in this study are government expenditure, exchange rate, gross domestic product (GDP) growth rate, and food inflation rate, with data obtained from BPS (https://www.bps.go.id/id) and FRED (https://fred.stlouisfed.org/). Each variable consists of monthly data from January 2020 to December 2024, resulting in 60 observations for each variable.

2.2 Time-varying VAR

A Vector Autoregressive (VAR) model is essentially an Autoregressive (AR) model expanded to handle multiple variables simultaneously. Its core principle is that all variables are considered endogenous, meaning they are all treated as interconnected and mutually influence one another within the model. In a first-order VAR model, also known as VAR(1), each variable at time t is predicted by all variables (including itself) at time $t-1$, which can be written in the following mathematical equation.:

$$\boldsymbol{X_t} = \boldsymbol{A} + \boldsymbol{C}\boldsymbol{X_{t-1}} + \boldsymbol{\varepsilon_t} \tag{1}$$

where $\boldsymbol{X_t}$ is an $n \times 1$ vector of endogenous variables at time t, $\boldsymbol{A}$ is an $n \times 1$ vector of intercept coefficients, C is an $n \times n$ matrix of lag coefficients and $\boldsymbol{\varepsilon_t} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{H})$. Let $\boldsymbol{Z_t} = \boldsymbol{I} \otimes \boldsymbol{X_{t-1}}$ and $\boldsymbol{B} = Vec([\boldsymbol{A}, \boldsymbol{C}])$, where the $Vec()$ operator denotes stacking the columns of a matrix into a vector and $\otimes$ is the Kronecker product. Equation (1) can be rewritten as:

$$\boldsymbol{X_t} = \boldsymbol{Z_t}\boldsymbol{B} + \boldsymbol{\varepsilon_t} \tag{2}$$

Then, to transform the VAR(1) model in Equation (2) into a time-varying model, the coefficients are assumed to vary over time, and can be written as:

$$\boldsymbol{X_t} = \boldsymbol{Z_t}\boldsymbol{B_t} + \boldsymbol{\varepsilon_t} \tag{3}$$

so that the coefficient $\boldsymbol{B_t}$ can now take values that are not constant over time.

The TV-VAR model in Equation (3) appears to have no significant difference compared to the VAR model in Equation (2)—the main distinction between the two lies in the treatment of the coefficients. Nevertheless, estimating the coefficients in the TV-VAR model is not as straightforward as in the standard VAR model, because time-varying coefficients result in a considerable number of parameters as the number of time observations increases, making them difficult to estimate using classical methods. To address this issue, the estimation of coefficients or parameters in the TV-VAR model is carried out using a Bayesian approach by assuming that $\boldsymbol{B_t}$ follows a random walk, which can be written as follows:

$$\boldsymbol{B}_t = \boldsymbol{B}_{t-1} + \boldsymbol{\theta_t} \tag{4}$$

with $\boldsymbol{B}_1 \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{D})$ and $\boldsymbol{\theta_t} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{Q})$. Then, assume that $\boldsymbol{\varepsilon_t}$ and $\boldsymbol{\theta_t}$ do not vary over time, or $\boldsymbol{H}_{t+1} = \boldsymbol{H}_t = \boldsymbol{H}$ dan $\boldsymbol{Q}_{t+1} = \boldsymbol{Q_t} = \boldsymbol{Q} = diag(\{\sigma_i{}^2\})$ with $i = n(n+1)$. Equation (4) allows $\boldsymbol{B}_t$ o vary gradually over time by imposing a penalty on large changes between successive values, with the joint distribution of $\boldsymbol{B} = \boldsymbol{B}_1, \boldsymbol{B}_2, \cdots \boldsymbol{B}_T$ being a normal distribution, or $\boldsymbol{B} | \boldsymbol{Q} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{K^{-1}})$.

Then, the analysis in this study is conducted based on the following prior distributions: $\boldsymbol{H} \sim \boldsymbol{IW}(\boldsymbol{v_1}, \boldsymbol{S_1})$ and $\sigma_i \sim \boldsymbol{IG}\left(\frac{v_{i,2}}{2}, \frac{s_{i,2}}{2}\right)$ with $\boldsymbol{v_1} = n+3$, $\boldsymbol{S_1} = \boldsymbol{I}$, $\boldsymbol{v_{i,2}} = 0.01$, $\boldsymbol{D} = 5 \times I$, where $\boldsymbol{IW}$ denotes the inverse Wishart distribution and $\boldsymbol{IG}$ denotes the inverse gamma distribution. Posterior inference is carried out using Markov Chain Monte Carlo (MCMC) by sequentially sampling from the posterior distributions $\pi(\boldsymbol{B} \mid \boldsymbol{X}, \boldsymbol{H}, \boldsymbol{Q})$, $\pi(\boldsymbol{H} \mid \boldsymbol{X}, \boldsymbol{B}, \boldsymbol{Q})$ and $\pi(\boldsymbol{Q} \mid \boldsymbol{X}, \boldsymbol{B}, \boldsymbol{H})$. The MCMC algorithm proceeds as follows:

1. Sample $\pi(\boldsymbol{B} \mid \boldsymbol{X}, \boldsymbol{H}, \boldsymbol{Q}) \sim N(\widehat{\boldsymbol{B}}, \boldsymbol{P}^{-1})$ with $\boldsymbol{P} = \boldsymbol{K} + \boldsymbol{Z}'(\boldsymbol{H}^{-1})\boldsymbol{Z}$ and mean $\widehat{\boldsymbol{B}} = \boldsymbol{P}^{-1}\boldsymbol{Z}'(\boldsymbol{H}^{-1})\boldsymbol{X}$
2. Sample, $\pi(\boldsymbol{H} \mid \boldsymbol{X}, \boldsymbol{Q}) \sim IW\left(\boldsymbol{v_1} + \boldsymbol{T}, \boldsymbol{S_1} + \sum_{t=1}^{T}(\boldsymbol{X_t} - \boldsymbol{Z_t}\boldsymbol{B_t})(\boldsymbol{X_t} - \boldsymbol{Z_t}\boldsymbol{B_t})'\right)$
3. Sample $\pi(\boldsymbol{Q} \mid \boldsymbol{X}, \boldsymbol{H}) \sim IG\left(\frac{v_{i,2}+T-1}{2}, \frac{s_{i,2}+\sum_{t=2}^{T}(B_{t,i}-B_{t-1,i})^2}{2}\right)$

3 Results and discussion

3.1 Data preparation

This study uses four variables: food inflation, exchange rate, gross domestic product (GDP) growth rate, and government expenditure shocks. Each variable consists of 60 monthly observations, covering the period from January 2020 to December 2024. The dataset is then divided into two periods: the COVID-19 period (January 2020 – June 2023) and the post-COVID-19 period (July 2023 – December 2024). The datasets for food inflation, exchange rate, GDP growth rate, and government expenditure shocks are shown in Fig. 1.

Fig. 1. Trends in variables during and post COVID-19 period.

Figure 1 shows that the data is divided into two parts: the COVID-19 pandemic period (red area) and the post-COVID-19 period (blue area). In the food inflation plot, it is evident that there was an increase at the beginning of 2020. This condition occurred due to turbulence in Indonesia's economic conditions as well as panic buying by the public amid the uncertainty of the pandemic. After this initial spike, food inflation declined until around the end of 2021. This situation coincided with the government introducing a shock to government expenditure by massively increasing spending, as can be observed in the GDP growth rate plot—during this period, Indonesia's economic growth plummeted, even turning negative, indicating that the country had entered a recession.

Following the government's shock to expenditure, Indonesia's economic growth improved, continuing until the end of 2024. However, the situation was somewhat different for the exchange rate and food inflation. The exchange rate exhibited a similar pattern to food inflation in the early stages, with the rupiah–US dollar exchange rate increasing at the onset of the pandemic and then declining a few months later, until around 2021. This condition occurred not because Indonesia's economy had improved, but because the global economy was also in turmoil, causing currencies such as the US dollar to weaken. This is further evidenced by the fact that, although Indonesia's economic growth improved, the exchange rate rose.

A similar pattern occurred for food inflation, which declined initially but then increased afterward. However, food inflation differed slightly from the exchange rate in that, after reaching its highest level during the 2020–2024 period, it began to decline toward the end of the pandemic. This was due to Indonesia's economy gradually improving as a result of the government expenditure shock. Following the pandemic, food inflation rebounded, although it declined toward the end of 2024. This indicates that the relationship between food inflation and macroeconomic factors, as well as government expenditure, is not constant over time; under certain conditions and at specific times, the relationship between food inflation and other variables can change.

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3.2 Time-varying VAR model

After preparing the data, a TV-VAR model will be constructed using the four aforementioned datasets. The model to be constructed has the following equation:

$$\boldsymbol{X_t} = \boldsymbol{A_t} + \boldsymbol{C_t X_{t-1}} + \boldsymbol{\varepsilon_t} \quad (5)$$

where:

$$\boldsymbol{X_t} = \begin{bmatrix} Z_t \\ Y_{1,t} \\ log(Y_{2,t}) \\ log(Y_{3,t}) \end{bmatrix}$$

$$\boldsymbol{A_t} = \begin{bmatrix} A_{1,t} \\ A_{2,t} \\ A_{3,t} \\ A_{4,t} \end{bmatrix}$$

$$\boldsymbol{C_t} = \begin{bmatrix} C_{11,t} & C_{12,t} & C_{13,t} & C_{14,t} \\ C_{21,t} & C_{22,t} & C_{23,t} & C_{24,t} \\ C_{31,t} & C_{32,t} & C_{33,t} & C_{34,t} \\ C_{41,t} & C_{42,t} & C_{43,t} & C_{44,t} \end{bmatrix}$$

$$\boldsymbol{X_{t-1}} = \begin{bmatrix} Z_{t-1} \\ Y_{1,t-1} \\ log(Y_{2,t-1}) \\ log(Y_{3,t-1}) \end{bmatrix}$$

$$\boldsymbol{\varepsilon_t} = \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{bmatrix}$$

$\boldsymbol{Z_t}$, $\boldsymbol{Y_{1,t}}$, $\boldsymbol{Y_{2,t}}$, $\boldsymbol{Y_{3,t}}$ are, respectively, the variables food inflation, GDP growth rate, government expenditure shock, and exchange rate at time t. $\boldsymbol{A_t}$ is the intercept coefficient for each variable, $\boldsymbol{C_t}$ is the lag coefficient, and $\boldsymbol{\varepsilon_t}$ is the model residual assumed to follow $\boldsymbol{\varepsilon_t \sim N(0, H)}$. The changes in the coefficients of this TV-VAR model are shown in Fig. 2

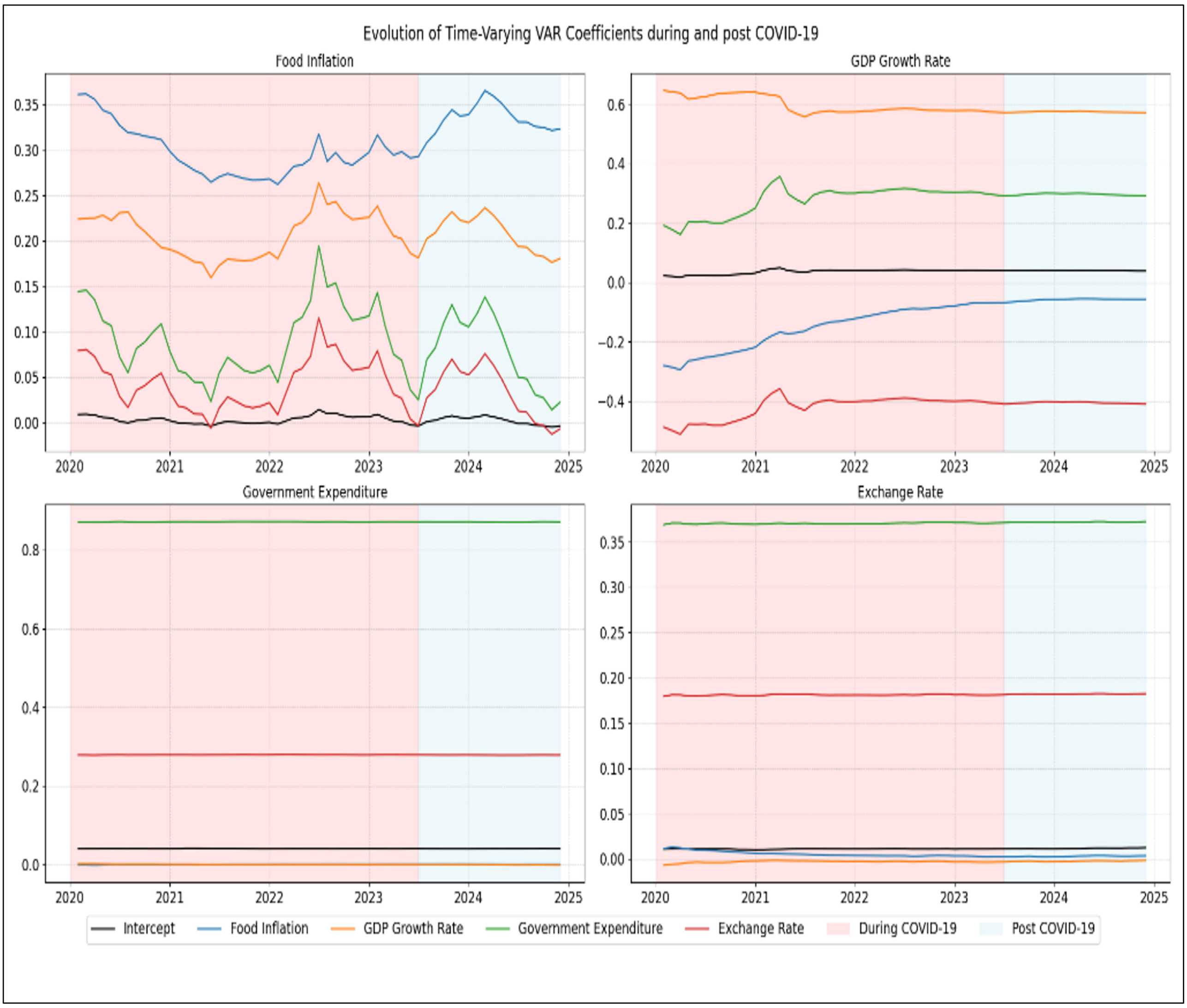

Fig. 2. Evolution of time-varying VAR coefficients during and post COVID-19 for each variable

Figure 2 illustrates how the coefficients of each variable in the previously constructed TV-VAR model changed during and after COVID-19. In the food inflation plot, the coefficients are seen to fluctuate considerably over time, indicating that the relationship between food inflation and the other variables was highly dynamic during this period. The GDP growth rate plot shows some fluctuations in the coefficients at the beginning, but they tend to stabilize thereafter. This suggests that in the early part of the period, each variable had a dynamic and shifting influence on GDP growth; however, over time, these relationships became more established andpredictable. The stability of these influences (reflected in the flatter coefficients) became one of the factors supporting the steady pace of economic growth after the pandemic subsided, reinforcing the observation in Fig. 1 GDP growth rate that GDP growth rate tended to stabilize after experiencing a significant decline.

In the government expenditure plot, the situation is markedly different. Almost all coefficients (the effects of other variables on government expenditure) tend to remain stable or flat throughout the period. The most significant coefficient influencing government expenditure during this period is from the variable itself (green line), with a high and stable value (around 0.8–0.9). This suggests that government expenditure is highly persistent and is driven more by its own policy decisions over time, exhibiting limited responsiveness to short-term shocks from food inflation, the GDP growth rate, or the exchange rate.

Meanwhile, the exchange rate plot also shows a stable level of coefficients throughout the observation period. Although the exchange rate itself (as shown in Fig. 1) was highly volatile, the model suggests that its structural relationship with food inflation, GDP growth rate, and government expenditure remained relatively unchanged. The most influential coefficient is from the variable itself (orange line).

Then, if we re-examine the food inflation plot, at the end of the pandemic period (at the end of the red area), the coefficients of each variable experienced a decline. This indicates that the influence of each variable was weakening. However, this weakening did not last long. Immediately afterward, in the post-pandemic period (start of the blue area), the coefficients of each variable rose again. This increase indicates that each variable once more contributed to strengthening the upward pressure on food inflation. The sharp "V-shape" pattern in the coefficients during this transition period reflects instability in the adaptation process. The easing of food inflation shocks at the end of the pandemic was temporary and was quickly replaced by new pressures in the post-pandemic era. Following the initial surge at the start of the post-pandemic period, the coefficients began to exhibit a more gradual downward trend. It is also worth noting that none of the coefficients were negative during this period, indicating that none of these variables contributed to reducing pressure on food inflation.

Then, Fig. 3 illustrates the performance of the constructed TV-VAR model by comparing the predicted values (orange line) with the actual data (blue line). Visually, the model demonstrates powerful performance (high goodness-of-fit) across all variables. The predicted lines closely track the movement patterns of the actual data with high accuracy. For government expenditure and GDP growth rate, the model's performance appears exceptional, as the predicted lines almost perfectly overlap with the actual lines. This indicates that the model successfully captures the underlying trends in government expenditure and GDP growth. For food inflation and exchange rate, the model also shows impressive capability. It effectively captures most of the trends in the data, confirming that the model can adapt to the dynamics and shocks that occurred during the observation period. This strong performance validates that the model is both accurate and reliable for further analysis.

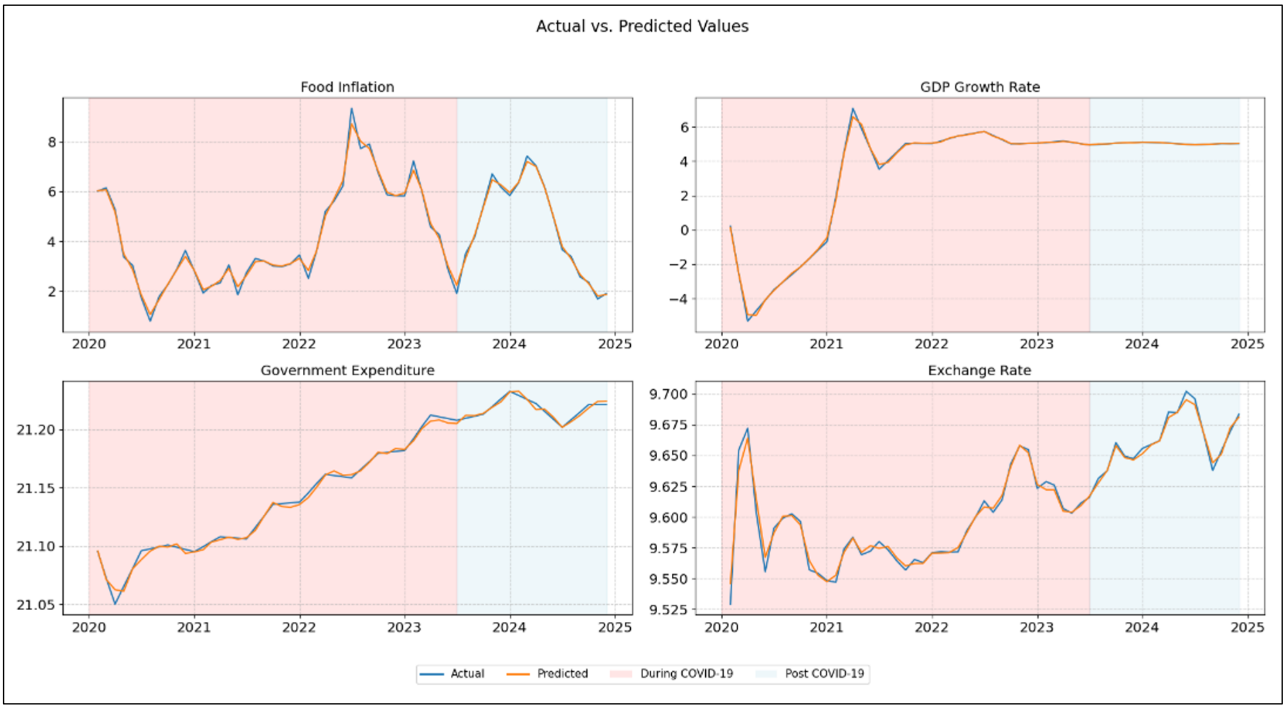

Fig. 3. Model performance evaluation: Actual vs. predicted values

3.3 Impulse response function

The Impulse Response Function (IRF) is used to understand the changing relationships within a TV-VAR model. It shows how a sudden, unexpected change (shock) in one variable impacts the other variables in the system over time. The IRF illustrates how each variable responds over time to shocks originating from itself and other variables. As a result, the IRF is employed to determine the current effect on a dependent variable when it experiences a shock or improvement from an independent variable equal to one standard deviation. It is important to note that in the TV-VAR model, the IRF is computed for each observation period because the coefficients vary over time. Subsequently, the average response across all observation periods is calculated to assess the overall impact of shocks. The impulse responses of food inflation ($\boldsymbol{Z_1}$) to shocks from GDP growth rate ($\boldsymbol{Y_1}$), government expenditure shock ($\boldsymbol{Y_2}$) and exchange rate ($\boldsymbol{Y_3}$) are shown in Fig. 4 dan Fig. 5

Figure 4 and Figure 5 illustrate the average response of food inflation to shocks from GDP growth, government expenditure, and exchange rate during and after the COVID-19 period. It is evident that in both periods, food inflation responds positively to shocks in the GDP growth rate. The peak response occurs within the 1–2 period horizon before declining rapidly toward zero. Although the overall shape of the response curve remains relatively consistent, the post-COVID-19 period tends to exhibit slightly wider confidence intervals. Nevertheless, the short duration of the response suggests that the shocks to food inflation are temporary.

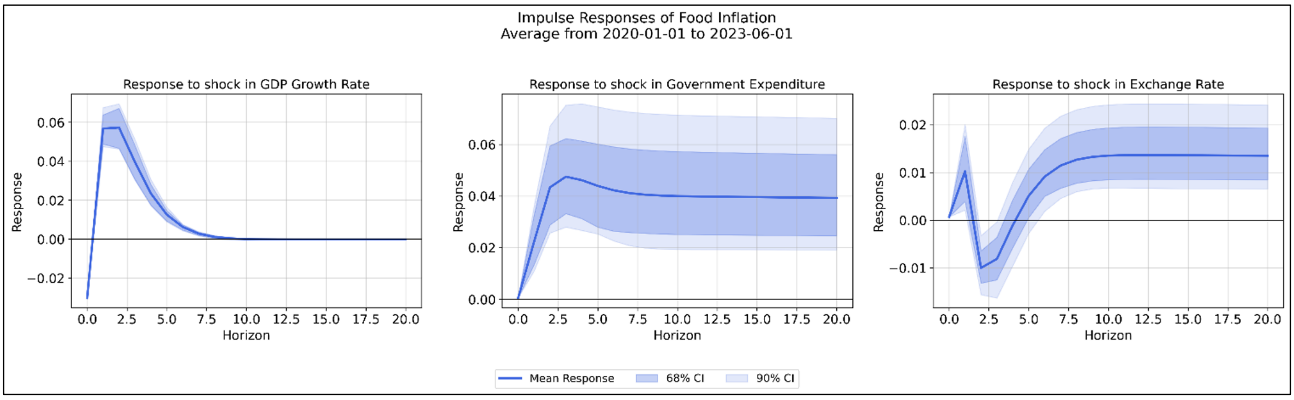

Fig. 4. Average impulse responses function during COVID-19

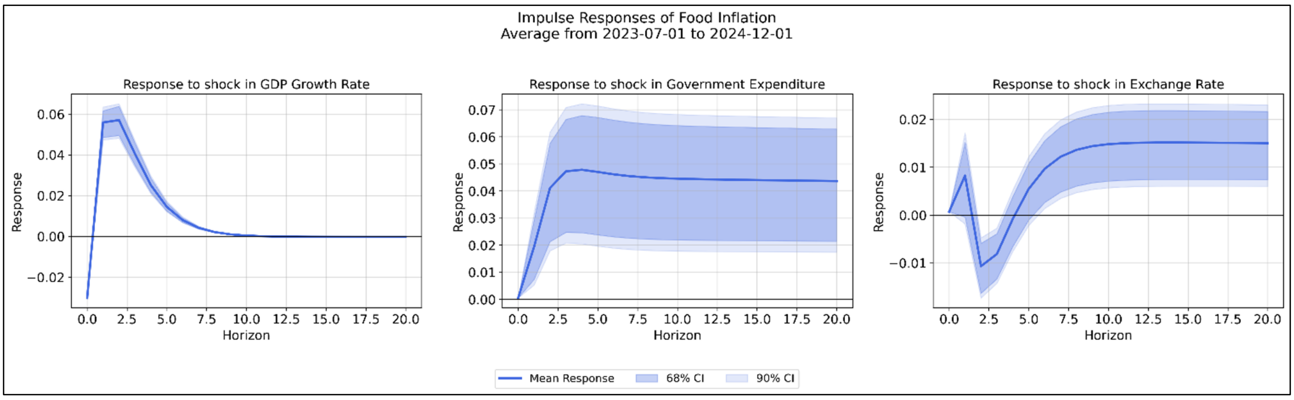

Fig. 5. Average impulse responses function post COVID-19

Shocks from government expenditure exhibit a positive impact on food inflation in both periods. During the COVID-19 period, a positive shock to government expenditure led to a sharp surge in food inflation. The average response line (blue) remains permanently at a high level without returning to zero. In contrast, the relatively narrow confidence interval (shaded area), entirely above the zero line, confirms that this inflationary effect is substantial and statistically significant. In the post-COVID-19 period, the response pattern remains similarly positive. However, the key difference lies in the significantly wider confidence interval, indicating increased uncertainty regarding the exact magnitude of the impact during this period. This suggests that expansionary fiscal policies aimed at stimulating the economy also carry the consequence of persistent pressure on food inflation.

Next is the response of food inflation to exchange rate shocks, which shows a distinct difference between the two periods. During the pandemic, the effect of the exchange rate on food inflation appeared slow and modest, indicating that exchange rate fluctuations had a limited influence on food prices during this period, compared to the post-COVID-19 period, where the IRF shows a stronger response. This suggests that the depreciation of the exchange rate (its value increasing) leads to higher food inflation.

These findings indicate that during crises such as COVID-19, fiscal and monetary policy responses must be more adaptive and timely to minimise the impact of food inflation. This is supported by the estimation results, which show that food inflation experienced a sharp V-shaped pattern during the transition from the pandemic to the post-pandemic period, reflecting high price instability. Moreover, the consistently positive coefficients for exchange rate, GDP growth, and government expenditure shocks suggest that fiscal expansion, economic growth, and currency depreciation tend to push food inflation upward, although with varying intensity over time. The IRF results further reveal that the impact of fiscal policy shocks is permanent, while the influence of exchange rate shocks strengthened significantly after the pandemic. These conditions emphasise the need for policy strategies that can contain food inflation pressures without hindering economic recovery, particularly through targeted mitigation measures to maintain price stability during and after crises.

4 Conclusion

This study examines the dynamic impact of macroeconomic shocks and government expenditure on food inflation in Indonesia, both during and after the COVID-19 pandemic, using the Time-Varying Vector Autoregression (TV-VAR) approach. The TV-VAR model reveals dynamic relationships between food inflation and other variables, as indicated by the time-varying coefficients of food inflation. The coefficients display a sharp "V-shaped" pattern, reflecting instability in food inflation during the transitional phase between the pandemic and post-pandemic periods. The results also show that exchange rate, GDP growth rate, and government expenditure shocks have a positive impact on food inflation, as evidenced by consistently positive coefficients throughout 2020–2024, despite fluctuations in their magnitude over time.

The plot comparing the model's predicted values with the actual observations demonstrates strong performance in capturing the dynamics of the real data, thereby validating the model's accuracy and reliability for further analysis. The average Impulse Response Function (IRF) of food inflation to shocks in the variables yields the following conclusions:

1. Government expenditure shocks: Shocks to government expenditure have a positive, significant, and permanent effect on food inflation in both the during- and post-pandemic periods. This suggests that expansionary fiscal policies aimed at stimulating the economy also lead to persistent inflationary pressures on food prices.
2. GDP growth shocks: Shocks to GDP growth also have a positive effect on food inflation; however, the response is short-lived and tends to dissipate rapidly.
3. Exchange rate shocks: The impact of exchange rate shocks on food inflation exhibits structural changes. During the pandemic, the effect was relatively small and slow to materialize; however, in the post-COVID-19 period, the response became stronger and faster, with currency depreciation significantly contributing to increased food inflation.

Overall, this study confirms that food inflation in Indonesia has a dynamic and positive relationship with macroeconomic factors and government expenditure. This finding highlights the existence of a complex policy trade-off for the government. On the one hand, increased public spending has proven effective in helping to restore economic growth following the pandemic-induced recession. On the other hand, such policies have also been a driver of rising food inflation. Moreover, the heightened uncertainty surrounding the impact of fiscal policy and the increased sensitivity of inflation to exchange rate fluctuations in the post-pandemic era present new challenges. These require more careful policy calibration to maintain food price stability, safeguard household purchasing power, and ensure Indonesia's food security.

From a theoretical contribution perspective, this study extends the TV-VAR literature, particularly in research related to economic dynamics and food security. Nevertheless, this study has several limitations, including the relatively short observation period (2020–2024) and the focus of analysis that is limited to domestic factors. Consequently, future research is expected to broaden the scope by applying a more extended period of data, incorporating more variables (such as global food prices, energy, or climate shocks), conducting cross-country comparisons, or applying alternative models to analyse the factors influencing food inflation.

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