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The Persistence of the Food Price Change in Response to Fiscal, Monetary, and Natural Factors' Shocks in Indonesia

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ABSTRACT

The **subject** of the study is the dynamics of food prices and their variations influenced by internal and external factors. This study assesses the impact of rainfall, fuel prices, and interest rates on food price fluctuations and analyzes the relative contributions of these variables. This study **aims** to determine the extent to which internal (intrinsic) factors and external (exogenous) factors contribute to variations of food prices, determine the relative dominance of each factor, and provide policy recommendations to stabilize food prices. This study uses a **method** of the Vector Error Correction Model with exogenous variables (VECMX) to analyze the dynamic relationship between endogenous variables (food inflation) and exogenous variables, such as interest rates, rainfall, and fuel prices. The **relevance** of this study is to provide insight into the factors that influence the dynamics of food prices, which can be used as a basis for formulating a policy of food price stabilization. The **results** showed that the persistence of changes in food prices is relatively high if it is affected by shocks from fiscal policy factors, monetary policy, and natural factors. The average food price change takes about 20–30 months to return to its natural value (new equilibrium) after receiving a shock. Most variations in food prices (more than 70%) are influenced by internal factors. After a certain period, the impact of fuel prices becomes more dominant than rainfall and the benchmark interest rate has the least effect.

Keywords: food price; rainfall; fuel price; interest rate; vector error correction; exogenous variables; internal factors; persistence

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Устойчивость цен на продовольствие в ответ на шоки фискальных, монетарных и природных факторов в Индонезии

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АННОТАЦИЯ

Предметом исследования является динамика цен на продовольствие и их колебание под влиянием внутренних и внешних факторов. Оценивается влияние количества осадков, цен на топливо и процентных ставок на колебания цен на продовольствие, а также анализируется относительный вклад этих переменных. **Цель** исследования — оценить степень влияния внутренних (эндогенных) и внешних (экзогенных) факторов на колебания цен на продовольствие, определить относительную значимость каждого фактора и дать рекомендации по стабилизации цен на продовольствие. Используется **метод** векторной модели коррекции ошибок с экзогенными переменными (VECMX) для анализа динамической взаимосвязи между эндогенными переменными (продовольственной инфляцией) и экзогенными переменными (процентными ставками, количеством осадков и ценами на топливо). **Актуальность** исследования заключается в том, что оно позволяет понять, какие факторы влияют на динамику цен на продукты питания, что может послужить основой для разработки политики стабилизации цен на продовольствие. **Результаты**

показали, что изменения цен на продовольствие сохраняются в течение длительного времени, если на них влияют факторы налогово-бюджетной политики, денежно-кредитной политики и природные факторы. В среднем для того, чтобы цены на продовольствие вернулись к естественному уровню (новому равновесию) после потрясения, требуется около 20–30 месяцев. На большинство колебаний цен на продовольствие (более 70%) влияют внутренние факторы. Через некоторое время влияние цен на топливо становится более значимым, чем влияние количества осадков, а влияние базовой процентной ставки — наименьшим.

Ключевые слова: цены на продукты питания; количество осадков; цены на топливо; процентная ставка; векторная поправка на ошибку; экзогенные переменные; внутренние факторы; инерционность

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INTRODUCTION

The world is being overshadowed by the economic slowdown and global uncertainty. The movement of world food commodity prices has become increasingly volatile over the past two decades. This situation can, of course, lead to inflation on the global scale, including in Indonesia. Factors such as natural disasters, uncertain weather and climate conditions, exchange rate volatility, shifts in supply and global demand (for example as a result of policy changes), can affect food price fluctuations [1, 2]. *Figure 1* shows the increase in the world food price index from 2002 to 2008, with a very intense market instability beginning in 2006. Significant increase in food prices occurred in 2007–2008, due to very high oil prices in this period. The surge in global food prices then occurred again in 2010–2011, one year after the global surge in 2007–2008 due to the La Nina phenomenon, which disrupted food production in many countries. The price of food commodities rose again in 2016–2017 and even a surge in global food prices returned in 2020–2022 when COVID-19 pandemic occurred.

One of the main reasons for the increase in food prices is cost push inflation. Cost-push inflation occurs when production the costs increase so as to encourage producers to increase the price of food products. One of the main factors that can cause an increase in food production costs is the availability of limited food agriculture supply [3]. Limited food supply can be caused by various factors including natural disasters, disruption of distribution, and rising agricultural input costs. Natural disasters such as drought, floods, storms or bad weather can damage crops and disrupt agricultural production, reduce the availability of food supply and encourage price increases. Disruptions in supply chains, such as transportation or distribution issues due to limited infrastructure, can hamper food movements from producers to consumers, causing scarcity and price increases. Increased energy costs can raise the cost of agricultural production, including transportation and operational costs, which can then encourage an increase in food prices. The increase in labor costs, whether due to a rise in wages or changes in labor regulations, can also lead to an increase in the cost of agricultural production and eventually an increase in food prices. The increase in fertilizer prices, pesticides, and seeds can also increase production costs, which can then be reflected in the increase in the selling price of food products [4].

Figure 2 shows that the consumer price index curve (CPI) for food is more volatile than the general CPI curve and the average of non-food CPI in the last three years. This can indicate that demand for food has been higher than demand for non-food items. If food demand increases faster than product and service demand in general, the price of food may experience more pressure to rise, which can cause food inflation that is higher than general inflation. In addition, this indicates that food price fluctuations have a greater impact on general inflation, because the food sector has a greater weight in the calculation of general inflation than the non-food sector. Food inflation can be an important factor in determining changes in general inflation, because high food prices or significant price volatility can put a large pressure at the inflation rate in Indonesia. Based on *Fig. 2*, the consumer price index curve (CPI) for food is more fluctuating than the general CPI curve in the last three years. This can indicate that demand for food is higher than non-food. If food demand increases faster than product and service demand in general, the price of food may experience more pressure to rise, which could cause food inflation that is higher than general inflation. In addition, this indicates that food price fluctuations have a greater impact on general inflation, because the food sector has a greater weight in the calculation of general inflation than the non-food sector does.

Based on data from the Central Statistics Agency (BPS), the food, beverages and tobacco sectors, it have contributed the most to national inflation over the last four months of 2023 in a row. Specifically, in September, October, November, and December 2023, each amounting to 1.08 percent, 1.39 percent, 1.72 percent, and 1.60 percent. This significant contribution

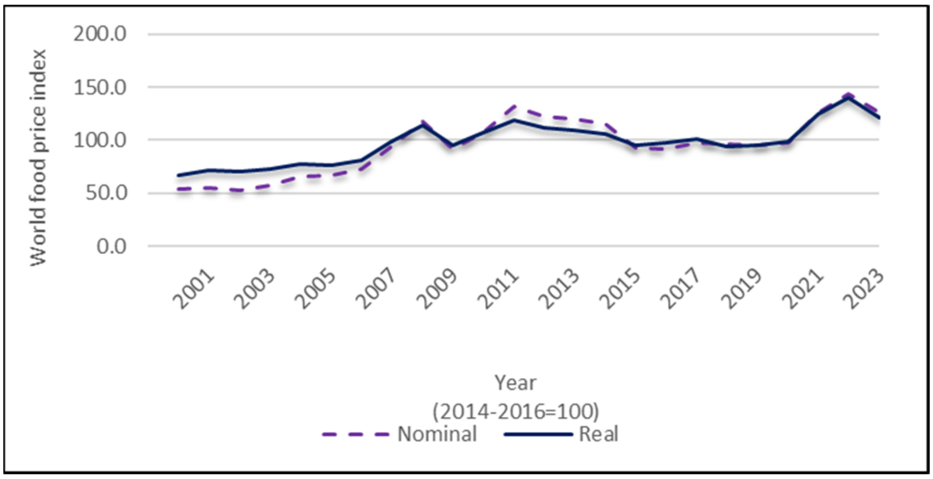

Fig. 1. **World's Food Price Index 2000–2023**
Source: FAO (2023), processed.

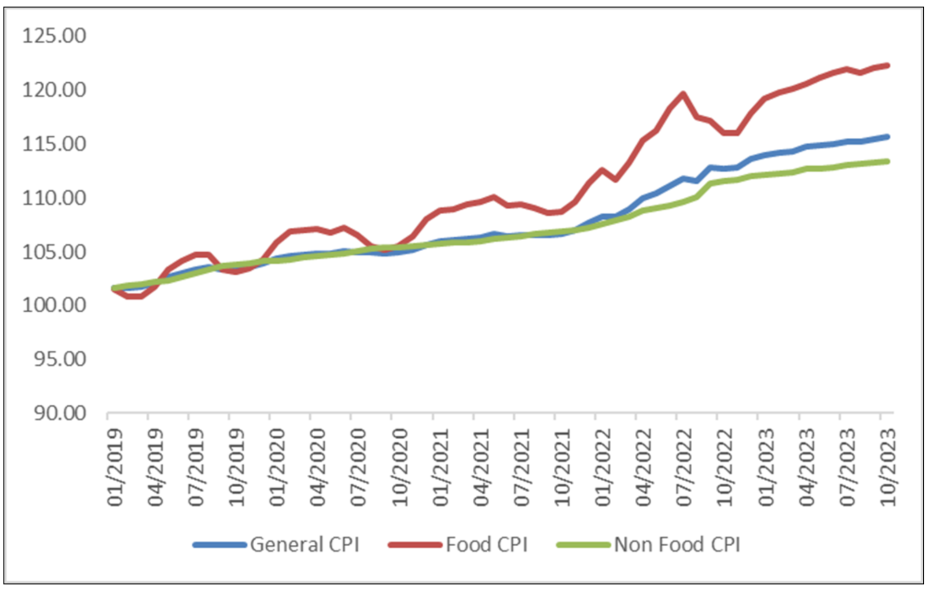

Fig. 2. **Indonesia's General CPI, Non-Food CPI, and Food CPI**
Source: BPS (2023), processed.

from the food sector shows that food commodities play a very important role in the dynamics of inflation in Indonesia. Among various food products, rice is the main commodity that has a big influence on national food prices. The price of rice, which is a product of rice, is one of the most sensitive factors in influencing inflation because rice is the staple food for most indonesians. The price increase in food commodities will immediately have an impact on increasing the cost of living of the community and encouraging overall inflation. Therefore, the stability in food prices is the key to controlling inflation in Indonesia.

Food prices change is influenced by various factors, including climate shocks, fuel prices, and interest rates [5, 6]. These three factors interact with each other in influencing food supply and demand. Climate, especially rainfall, plays an important role in food production, particularly in agrarian countries like Indonesia. The agricultural sector is very dependent on weather patterns, and significant changes in rainfall both in the form of drought and flooding can interfere with the process of production and distribution of food. For example, a long drought can cause crop failure, while excessive rainfall can damage plants or inhibit harvest activity. This condition increases production costs and lowering food supply, which ultimately encourages an increase in food prices. In addition, rainfall shock can also worsen the vulnerability of food supply chains, especially in areas that are already geographically vulnerable. Global climate change further aggravates the volatility of rainfall, making the prediction of weather patterns more difficult. This adds to the challenges in maintaining food price stability and strengthening the urgency to understand the relationship between rainfall shock and food prices. The second factor is the price of fuel, which is one of the main factors that affect food prices, both directly and indirectly. In the agricultural sector, fuel is used to run agricultural machines, harvest transportation, and other logistics operations. When the price of fuel increases, the cost of food production and distribution also rises, this then translates into higher prices for consumers. In addition, the increase in fuel prices often triggers the domino effect on other commodity prices, including fertilizers and pesticides which also use fuel as production inputs. This condition creates additional pressure on farmers, which in turn has an impact on the selling price of food products. Therefore, fluctuations in fuel prices become important variables that need to be considered in food price change analysis. The third factor is the interest rate which is a monetary policy tool used by the central bank to control inflation, including food inflation. When interest rates are raised, loan costs increase, which can reduce consumption and investment. However, in the context of food inflation, the influence of interest rates is not always direct. For example, high interest rates can hamper farmers' access to financing, thereby limiting their ability to increase production. As a result, the food supply can decrease, which has the potential to increase food prices. On the other hand, low interest rates can encourage food consumption and demand, which if not balanced by an increase in supply, can cause price surges. Thus, the relationship between interest rates and food prices is complex that requires in-depth analysis to understand its dynamics.

Referring to the phenomenon of increasing the fluctuations of food, beverages, and tobacco prices in several provinces in Indonesia, this study begins with the question of how long the level of food price to return to the balance position after fluctuations due to shocks from fiscal policy, monetary policy, and natural factors. The persistent food price indicates that the food price symptoms are not only temporary but can persist for a longer period of time. The persistence of food price that measures the speed of price to return to the balance position after experiencing shocks into an indicator of prolonged fluctuations or not. The results of previous studies showed differences in the level of food inflation persistence. Several studies in Indonesia show that the level of food inflation persistence is still high compared to other types of inflation, such as persistence of non-food inflation, general inflation persistence, administered inflation persistence, and the persistence of core inflation [7, 8]. Several studies abroad also show that food inflation persistence always ranks the highest compared to the persistence of other group inflation, such as the research conducted by [9] which shows that the persistence of food inflation is higher than the persistence of headline inflation and the persistence of core inflation in Pakistan. The research conducted by [10] shows the result that food inflation persistence is always higher than the persistence of non-food inflation, general inflation and core inflation in India. This shows that food price fluctuations tend to have a longer or more sustainable impact in the economy compared to general price fluctuations or core price fluctuations. Unlike some of the studies above, research conducted by [11, 12] showed that the level of persistence of food inflation and volatile food in Indonesia was lower than the persistence of other group inflation. In other words, price changes in food groups tend to have more impacts while compared to other inflation groups such as core inflation or headline inflation.

LITERATURE REVIEW

Inflation persistence is the speed convergence of inflation to balance aftershocks, so it can be said that inflation persistence is a measure of the inflation rate to return to the balance position after shocking. Inflation persistence is a phenomenon when inflation does not directly return to its natural value in the event of a shock [13, 14]. The faster the inflation rate to return to the balance point, the lower the level of persistence of the inflation. Conversely, the longer the level of inflation to return to the balance point, the higher the level of persistence of the inflation. If inflation persistence is high, the response to inflation shocks is long-term and difficult for the central bank to control. On the contrary, if the persistence of inflation in the country is low, the central bank can maintain the inflation rate in accordance with the target of inflation [15]. Inflation persistence is said to be high if the coefficient is close to 1. Previous research states that there are three types of inflation persistence, namely the positive serial correlation of inflation, the slow systematic monetary policy actions and the impact (its peak) to inflation, and the slow response of inflation to non-systematic policy actions [16]. Understanding of inflation persistence is very important to improve inflation forecasting capabilities, providing clarity on the dynamic effects of exogenous variable prices, providing information to improve monetary policy, and evaluate whether different monetary policy regimes will produce different levels of persistence [17].

A previous study by the univariate autoregressive approach states that the persistence of inflation in the food ingredients and the food group, beverages, cigarettes & tobacco in West Papua in the period from

January 2013 to June 2017 was very persistent [18]. The time needed by inflation in the group of foodstuffs and food groups, drinks, cigarettes and tobacco to return to their natural values is about 16 months and 33 months respectively. Research by [19] using the univariate autoregressive approach concluded that Kediri had the lowest degree of persistence and average food inflation compared to the cities of Surabaya, Malang, and Jember during the 2013–2017 period. Surabaya and Jember are the cities that need the most attention to the food sector because of the degree of persistence and the average inflation rate was higher than the two other cities in East Java. The results of this study are supported by research [11] which states that commodities with high persistence values in Surabaya are dominated by volatile food and controlled-price commodities. While the cause of the high persistence of inflation in Surabaya is caused by a combination of backward-booking inflation expectations and is dominated by forward-looking inflation expectations. Research conducted by [7] found a high degree of persistence in behavior, especially in core inflation, administered inflation, and volatile food inflation, following the application of flexible Inflation Targeting Framework (ITF) policies in Indonesia. The time needed for inflation to return to balance is between 1 to 8 months for each group. These results indicate that it is important for authority in improving their policies. Structural improvements are needed through monetary policy based on inflation expectations, increased transparency of food prices, and synergies.

Some previous research results recommend the development of national food security policies that consider environmental, agriculture, monetary, and administered prices factors to stabilize food prices. The results of research conducted by [20] and [21] concluded that there is a significant relationship between food prices and climate change. Other results of previous studies have shown that a decrease in crop production due to climate change has a greater impact on the increase in food prices compared to increasing plant production. Climate change tends to put negative pressure on the food system, especially when crop production is reduced. Studies that report a decrease in crop production due to climate change so that food prices increase, were stated by [22–30]. Conversely, studies that reported increases in crop production due to climate change so that food prices fall, concluded by [31, 32].

The increase in fuel prices can lead to an increase in the cost of the company's production in various economic sectors, especially those sectors that are very dependent on fuel such as the transportation, manufacturing and agriculture industries. Companies will reduce their production due to higher production costs. This leads to a shift in the aggregate supply curve to the left and causes a decrease in economic output. The impact of lower aggregate supply in facing the same level of demand is an increase in aggregate prices in the market. The results of the research conducted by [6] show a causal relationship with a long-term direction between oil prices (energy) and food prices. According to the supply-side theory, higher crude oil prices increase production costs and cause the supply curve to shift to the left, resulting in higher food prices. In line with the theory of the demand side, higher energy prices increase the demand for energy plants, which causes an increase in the area of land planted. Thus, the price of grain increases due to reduced production. However, [33] argues that oil prices have no significant influence on food prices in the European Union. This is evidenced by the high level of significance of the constant which shows that the model does not capture several variables or information. Previous research has also found no significant effect between the price of crude oil on the price of local rice in Indonesia [34]. This shows that Indonesian local food commodities are strongly influenced by domestic demand and supply factors. The price of rice in Indonesia is closely monitored by the government because the fluctuations in commodity prices can affect the welfare of the community.

The increase in agricultural credit interest rates will have an impact on increasing the cost of agricultural production and increasing food inflation. On the other hand, if there is a pressure, then interest rate increases are carried out to reduce consumption and reduce prices so that inflation can be controlled. Research by [35–37] shows a substantial correlation between interest rates and food prices. According to [35], interest rates and the price of agricultural commodities have a substantial correlation each other and a U-shaped relationship between them. The researchers concluded that if the interest rates rise, then the price of food is likely to also rise. Research conducted by [38] has also found a positive relationship between inflation and interest rates. Unlike the results of this research, other research conducted by [39] found that interest rates had a negative and significant effect on inflation in Indonesia from January 2013 to November 2017. When interest rates rise by 1%, inflation drops by 0.21% in the short term. In the long run, when interest rates have risen by 1%, inflation dropped by 6.95%. A previous study also stated that an increase in 1% at the previous year's inflation rate caused this year's interest rate to fall by 0.07188% [40].

DATA AND METHODOLOGY

This section explains the data and methodologies used in this study for identification and quantification.

Data and Source

The data used are monthly time series data for the period from January 2018 to December 2023. Data of food inflation, fuel prices, interest rates, and rainfall variables were obtained from the Central Statistics Agency of Indonesia (BPS), the Bank of Indonesia (BI), and the Meteorology, Climatology, and Geophysics Agency (BMKG). All the variables were transformed into the form of natural logarithms to ensure the stability of variance and facilitate the interpretation of elasticity.

Data Analysis: The VARX/ VECMX Model

This study uses the Vector Autoregressive with Exogenous Variables (VARX) model or the Vector Error Correction Model with Exogenous Variable (VECMX) to analyze the dynamic relationship between endogenous variables (food inflation) and exogenous variables (interest rates, rainfall, and fuel prices). Vector Autoregressive (VARs) are models by inserting exogenous variable vectors are called Vector Autoregressive with Exogenous variables (VARXs) [41]. The VARX model modeling short-term relationships through variable differentiated and long-term relationships through ECT. All variables remain included as endogenous variables to ensure that the two-way relationship between these variables is handled correctly. Variables such as *IR*, *FP*, and *CR* are included as endogenous variables in the VARX//VECMX model to prevent endogeneity. This is done because these variables have the possibility of a two-way relationship with the *CPI*. The VARX/ VECMX model requires that all variables that influence each other to be included as endogenous variables. Prevent bias from omitted variable bias and reversal causality. Ensure the validity of the parameter estimation in the model. Thus, the model used will be more accurate and can provide a more precise interpretation of the relationship between the *CPI*, *IR*, *FP*, and *CR*. The general form of VARX (*p, q*) by inserting exogenous variables as follows.

$$CPI_t = \mu + \sum_{i=1}^{p} \alpha_i \cdot CPI_{t-i} + \sum_{j=1}^{q} \beta_j \cdot IR_{t-j} + \sum_{j=1}^{q} \gamma_j \cdot CR_{t-j} + \sum_{j=1}^{q} \delta_j \cdot FP_{t-j} + \epsilon_t,$$

$$IR_t = \mu + \sum_{i=1}^{p} \alpha_i \cdot IR_{t-i} + \sum_{j=1}^{q} \beta_j \cdot CPI_{t-j} + \sum_{j=1}^{q} \gamma_j \cdot CR_{t-j} + \sum_{j=1}^{q} \delta_j \cdot FP_{t-j} + \epsilon_t,$$

$$CR_t = \mu + \sum_{i=1}^{p} \alpha_i \cdot CR_{t-i} + \sum_{j=1}^{q} \beta_j \cdot CPI_{t-j} + \sum_{j=1}^{q} \gamma_j \cdot IR_{t-j} + \sum_{j=1}^{q} \delta_j \cdot FP_{t-j} + \epsilon_t,$$

$$FP_t = \mu + \sum_{i=1}^{p} \alpha_i \cdot FP_{t-i} + \sum_{j=1}^{q} \beta_j \cdot CPI_{t-j} + \sum_{j=1}^{q} \gamma_j \cdot IR_{t-j} + \sum_{j=1}^{q} \delta_j \cdot CR_{t-j} + \epsilon_t.$$

If the cointegration exists, then a Vector Error Correction Model with Exogenous Variables (VECMX), can be estimated, which combines levels and differences, This can be done instead of using a VARX model in levels. The VECMX (*p, q*) regression equation is given by:

$$\Delta CPI_t = \nu + \rho \cdot ECT_{t-1} + \sum_{i=1}^{p} \theta_i \cdot \Delta CPI_{t-i} + \sum_{j=1}^{q} \phi_j \cdot \Delta IR_{t-j} + \sum_{j=1}^{q} \varphi_j \cdot \Delta CR_{t-j} + \sum_{j=1}^{q} \Psi_j \cdot \Delta FP_{t-j} + \varepsilon_t,$$

$$\Delta IR_t = \nu + \rho \cdot ECT_{t-1} + \sum_{i=1}^{p} \theta_i \cdot \Delta IR_{t-i} + \sum_{j=1}^{q} \phi_j \cdot \Delta CPI_{t-j} + \sum_{j=1}^{q} \varphi_j \cdot \Delta CR_{t-j} + \sum_{j=1}^{q} \Psi_j \cdot \Delta FP_{t-j} + \varepsilon_t,$$

$$\Delta CR_t = \nu + \rho \cdot ECT_{t-1} + \sum_{i=1}^{p} \theta_i \cdot \Delta CR_{t-i} + \sum_{j=1}^{q} \phi_j \cdot \Delta CPI_{t-j} + \sum_{j=1}^{q} \varphi_j \cdot \Delta IR_{t-j} + \sum_{j=1}^{q} \Psi_j \cdot \Delta FP_{t-j} + \varepsilon_t,$$

$$\Delta FP_t = \nu + \rho \cdot ECT_{t-1} + \sum_{i=1}^{p} \theta_i \cdot \Delta FP_{t-i} + \sum_{j=1}^{q} \phi_j \cdot \Delta CPI_{t-j} + \sum_{j=1}^{q} \varphi_j \cdot \Delta IR_{t-j} + \sum_{j=1}^{q} \Psi_j \cdot \Delta CR_{t-j} + \varepsilon_t.$$

Table 1

Descriptive Statistics

Measure	IR	FP	CR	CPI
Mean	4.727431	124.9926	7.995919	109.3491
Median	4.75	103.665	8.123431	108.27
Maximum	6	211.92	13.8172	125.1
Minimum	3.5	62.76	1.327283	97.85416
Std. Dev.	0.9766928	46.37254	2.860279	7.674339
Skewness	–0.0229727	0.7256736	–0 .252708	0.3962325
Kurtosis	1.400127	1.963012	2.491046	1.972901
Shapiro–Wilk	2.515	5.020	0.078	3.006
Shapiro–Francia	2.152	4.547	–0.269	2.585
Observations	72	72	72	72

Source: Authors' estimation derived from research data.

Note: IR – Interest Rate, *FP* – Fuel Price Index, *CR* – Climate-Rainfall, *CPI* – Food Consumer Price Index.

where CPI_t is food inflation vector; IR_t is interest rate vector; CR_t is climate-rainfall vector; FP_t is fuel price vector; α_i is parameter matrix sized p x p for each i = 1, 2, ..., p; ν and μ are vectors of constants; β_j, γ_j, δ_j, ϕ_j, φ_j, and Ψ_j are parameter matrix sized q x q for each j = 1, 2, ..., q; ρ is speed of adjustment; ECT_{t-1} (Error Correction Term) is the lagged value of the residuals obtained from cointegrating regression of the endogenous variable on the regressors. It contains long-run information derived from the long-run cointegrating relationships; ε_t and ϵ_t are residual vectors.

The persistence of food inflation illustrates how long the influence of shocks or changes on certain factors on food inflation lasted over time. These models make it possible to include exogenous variables, namely fiscal policy (fuel price), monetary policy (interest rates), and natural factors (climate-rainfall) that can affect inflation directly or indirectly. VARX/VECMX can help identify how the response of inflation to shocks or changes in these exogenous variables develops within a certain period of time, which can be interpreted as a form of persistence. The stages carried out when estimating data with VARX/ VECMX including stationary data test (unit root test), determination of the optimum lag (lag length criterion), VAR stability test, causality test, cointegration test, VARX/VECMX estimation, analysis of Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD).

In the range of data (72 months) in Indonesia experienced a large crisis during the pandemic in the first months of 2020. The crisis is estimated to have had a significant impact, causing break points on the data chart. Structural break testing in this study uses the Chow Test. If the results are significant, then a dummy variable is added to express the event of the crisis due to the pandemic.

EMPIRICAL RESULTS

Descriptive Statistics

Descriptive analysis in this study aims to provide a general picture of the characteristics of the main variable data used. These variables include benchmark interest rate (*IR*), fuel price index (*FP*), rain climate indicator (*CR*), and consumer price index for food (*CPI*). *Table 1* presents basic descriptive statistics for each variable, including average, median, maximum and minimum values, standard deviations, and distribution sizes such as skewness, kurtosis, and normality tests using the Shapiro-Wilk and Shapiro-Francia tests. In addition, the number of observations for each variable is also included to ensure adequate data representation. The results of this analysis will be the basis for understanding the patterns and nature of the data before conducting further analysis.

The average benchmark interest rate is 4.73%, indicating that interest rates in the entire observation period were relatively stable around this value. The median which is almost the same as the mean (4.75%) shows that the distribution of interest rate

Table 2

Unit Root Test

Variable	Ln IR	Ln FP	Ln CR	Ln CPI
Level				
ADF	–0.309	–0.868	–3.263**	0.400
PP	–0.896	–0.912	–3.571 ***	0.174
First Difference				
ADF	–4.557***	–6.668***	–8.648***	–5.566***
PP	–4.615***	–6.692***	–8.643***	–5.543***

Source: Authors' estimation derived from research data.

Note: $p < 0.01$***; $p < 0.05$**; $p < 0.1$*. *IR* – Interest Rate, *FP* – Fuel Price Index, *CR* – Climate-Rainfall, *CPI* – Food Consumer Price Index.

data tended to be symmetrical without a significant outlier. Relatively low standard deviation (around 0.98%) shows that interest rate data is not very volatile and tends to gather around the average. Interest rate data is not normally distributed, but the skewness and curtosis are low, so it can be assumed that the data is quite close to the normal distribution for most analysis. Meanwhile, the median of the fuel price index, which is lower than the mean shows that the distribution of data has a positive slope (positive skewness). A high standard deviation (around 46.37) shows that the fuel price index data varies greatly. This distribution tends to be leptocurtive and has a positive slope. In descriptive statistics of *CR*, the average rainfall climate indicator is 7.996, which may represent the average amount of rainfall in certain units (mm per month). Relatively low standard deviation (around 2.86) shows that rainfall data tends to be not too fluctuating. This distribution tends to be leptokurtic and has a negative slope. Finally, in the descriptive of *CPI* statistics, the median of the consumer price index for food is lower than its mean. The maximum value is 125.1, while the minimum value is 97.85416. This range shows variations that are in the consumer price index for food. The Shapiro-Wilk and Shapiro-Francia tests show that the data in general are not normally distributed. Therefore, the data should be transformed into the natural logarithm form.

Unit Root Test

Stationary data test (unit root test) is needed to determine the form of the VARX/VECMX model that will be used in the study. The existence of non-stationary variables in the VARX/VECMX system is important to observe because it can increase the possibility of cointegration relationship. This study uses an Augmented Dickey-Fuller (ADF) test because the ADF test is a popular method for testing stationary but it has weaknesses such as excessive sensitivity. The advantage of the ADF test is that it can overcome the problem of autocorrelation and correlation serials, provide critical values for significant testing, and is

Table 3

Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	HQ	SC
0	137.8963	NA	1.78e-07	–4.190202	–3.915733	–4.082438
1	440.6375	546.8873	1.72e-11	–13.43992	–12.61651*	–13.11663
2	465.0777	40.99658*	1.32e-11*	–13.71218	–12.33984	–13.17337*
3	476.6765	17.95943	1.55e-11	–13.57021	–11.64893	–12.81587
4	490.7748	20.01042	1.71e-11	–13.50886	–11.03864	–12.53899
5	507.0190	20.96031	1.80e-11	–13.51674	–10.49758	–12.33134
6	521.0649	16.31138	2.10e-11	–13.45371	–9.885611	–12.05278
7	545.8632	25.59819	1.81e-11	–13.73752	–9.620487	–12.12107
8	567.3910	19.44447	1.83e-11	–13.91584	–9.249866	–12.08386
9	586.2184	14.57609	2.17e-11	–14.00705	–8.792135	–11.95954

Source: Authors' estimation derived from research data.

Note: Sign * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: the Akaike information criterion; SC: the Schwarz information criterion; HQ: the Hannan-Quinn information criterion.

Table 4

VAR Stability Test

Root	Modulus
0.975790	0.975790
0.838806	0.838806
0.780557–0.152432i	0.795302
0.780557 + 0.152432i	0.795302

Source: Authors' estimation derived from research data.

flexible because it can handle trends, intercepts, or a combination of both [42, 43].

The ADF value presented in *Table 2* is significant at the difference level, indicating that the variables become stationary after the first difference. The PP value is also significant at the first difference level, the results that are consistent with the ADF test. This confirms that the variables are stationary after the first differencing.

Determination of Optimal Lag

Another important thing in the estimation of the VARX/VECMX model is the determination of the optimal lag in the model system. An optimal lag is needed in order to capture the effect of each variable on other variables in the model system. The optimal lag is determined by observing the smallest Final Prediction Error Criterion (FPE), the Akaike Information Criteria (AIC), the Schwarz Criterion (SC), and the Hannan-Quinn Information Criterion (HQ).

Based on the results of the lag length analysis criteria as shown in *Table 3*, lag order 2 is optimal for the model. The model will include two lags for each variable in the system. Using the optimal lag order, the model will be more stable, efficient, and easily interpreted for further analysis, such as IRF and Variance Decomposition.

VAR Stability Test

In this section, the VAR model stability testing steps will be discussed, the interpretation of the stability test results, and the implication of the reliability of the model in explaining the dynamics of the interaction between food prices, rainfall, fuel prices, and benchmark interest rates. This test is also the basis to ensure that the conclusions drawn from the FEVD and IRF analysis have strong statistical validity.

Table 4 above lists the modulus values of the roots of these characteristics. The polynomial in the food price model ranges from 0.795302 to 0.975790. These results show that all the modulus values of the root of the characteristic polynomial are less than one, therefore, the model can be said to be stable.

The Granger Casuality Test

The next stage is the Granger causality test. The Granger causality test is a statistical method used to determine if an exogenous variable can predict changes in the endogenous variable better than only using the lag values from the endogenous variable only. If the exogenous variable has additional information that is useful in predicting endogenous, it is said that exogenous "Granger causes" endogenous, so do the opposite.

Table 5 shows that all pairs of variables (*CPI–IR, CPI-FP* and *CPI–CR*) show bilateral causality (bidirectional), meaning that each variable affects each other in the VAR model. The benchmark interest rate can be used by the central bank to control inflation, while food inflation can be an important factor in monetary policy. The price of fuel is also very influential on food inflation, and vice versa. This is relevant because logistics costs and food production

Table 5

Granger Casuality Test

Granger Casuality	Chi2	Prob>Chi2	Direction of Causality
CPI does not Granger cause IR	7.166	0.0074	Unidirectional
IR does not Granger cause CPI	0.97	0.325	
CPI does not Granger cause FP	2.164	0.1413	Unidirectional (sig. level 10%)
FP does not Granger cause CPI	3.37	0.067	
CPI does not Granger cause CR	8.44	0.0037	Bidirectional
CR does not Granger cause CPI	4.02	0.045	

Source: Authors' estimation derived from research data.

Note: IR-Interest Rate, *FP*-Fuel Price Index, *CR*-Climate-Rainfall, the *CPI*-Food Consumer Price Index.

Table 6

Johansen Tests for Cointegration

Hypothesized No. of CE(s)	Eigen value	Trace		Maximum Eigenvalue	
		Statistics	0.05 CV	Statistics	0.05 CV
None*	0.293031	53.02828	40.17493	23.92698	24.15921
At most 1*	0.198809	29.10130	24.27596	15.29425	17.79730
At most 2*	0.158315	13.80704	12.32090	11.89214	11.22480
At most 3	0.027371	1.914900	4.129906	1.914900	4.129906

Source: Authors' estimation derived from research data.

are influenced by fuel prices. Likewise, rainfall can affect agricultural production and food inflation. Food inflation can also affect consumption patterns which then affects other economic activity.

Structural Break Test

Data series used in the 72-month span of time may be possible for the influence of the extreme macroeconomic policy or conditions in that time span. As explained in the previous section, the cyclical influence of extreme macroeconomic policies or conditions during that time is a crisis due to the Covid-19 pandemic which began in the first month of 2020.

Structural break testing using the Chow test showed a shock period that significantly affected the first month of 2020 (2020M01) with a significance level of 1% indicated by the probability value of 0.0000 and a F statistical value of 63.47. This means that the zero hypothesis decreases and there is a structural break in that period. Thus, the dummy variable is used in this study as a representation of the influence of the COVID-19 pandemic (*D_CVD*) crisis. Value 0 is given in the 2018M01–2019M12 period, and the value 1 is assigned for the period from 2020M01 to 2023M12.

Cointegration Test

This study uses Johansen's cointegration test to check whether the variables have a long-term relationship [44]. The Johansen test has two types of testing namely trace test and the maximum eigenvalue test. The Trace test is a test to measure the total number of cointegration relationships. Maximum eigenvalue test is a test used to measure the relationship of the cointegration individually. Both of these tests are almost equally strong, but in some situations, the trace test is stronger (more accurate). Therefore, it is recommended to use both of these two tests together to get more reliable results. However, if the condition is possible, the trace test can be used [45]. The final decision regarding the number of cointegration relationships is usually based on trace statistics, because this test is stronger in detecting overall cointegration relationships.

Based on the trace and maximum test of the *Table 6*, the "None" hypothesis is not rejected, meaning that there is at least one cointegration relationship. The null hypothesis (at most 1) is also rejected, meaning that there are more than one cointegration. The null hypothesis (at most 2) is rejected, meaning that there are more than two cointegration relationships. The null hypothesis (at most 3) is accepted, meaning that there are 3 cointegration relationships. Johansen's cointegration test results show cointegration relationship between variables in the model, so the VECMX model is more appropriate because it can capture long-term relationships through the mechanism of error correction.

VECMX Estimation

This section discusses VECMX estimates to analyze long-term and short-term relationships between variables, as well as error correction mechanisms that return the system to balance. This approach is relevant to understand the dynamic interactions between food prices, rainfall, fuel prices, and benchmark interest rates.

Table 7 shows the estimated results of the VECMX of D(*LN_CPI*) which divides the effect into two main parts namely short-run and long-run. In the short term, an increase in food prices in the previous one month (CPI_{t-1}) significantly affects food price this month (CPI_t). While interest rates (*IR*), fuel prices (*FP*), and rainfall (*CR*) do not have a significant impact in the short term. In the long run, statistically significant increase in interest rate is related to a decrease in food prices. This finding is in line with [46], who found that Bank Indonesia's interest rate has a significant negative effect on inflation in the long run, suggesting that monetary policy instruments remain effective

Table 7

VECMX Estimation

Variables	Short-Term		
	Coefficient	Std. Err	t-Statistics
CointEq1	−0.004217	0.00462	−0.91212
CointEq2	0.002813	0.00280	1.00447
CointEq3	0.000679	0.00469	0.14490
D(LN_CPI(−1))	0.335103**	−0.13231	2.53267
D(LN_CPI(−2))	−0.104254	−0.13907	−0.74963
D(LN_IR(−1))	−0.002301	−0.02965	−0.07761
D(LN_IR(−2))	0.006724	−0.02897	0.23210
D(LN_FP(−1))	0.010189	−0.01155	0.88194
D(LN_FP(−2))	0.013748	−0.01122	1.22481
D(LN_CR(−1))	0.002805	−0.00293	0.95717
D(LN_CR(−2))	0.002889	−0.00307	0.94164
Variables	**Long-Term**		
	Coefficient	**Std. Err**	**t-Statistics**
LN_IR(−1)	−2.782677***	0.13622	−20.4274

Source: Authors' estimation derived from research data.

Note: $p < 0.01$***; $p < 0.05$**; $p < 0.1$*. *IR* — Interest Rate, *FP* — Fuel Price Index, *CR* — Climate-Rainfall, *CPI* — Food Consumer Price Index.

in curbing price pressures in Indonesia even though their transmission may not be immediate. This result is also consistent with the work of [47], who applied a Vector Error Correction Model to inflation, the BI rate, and deposit interest rates in Indonesia and found that changes in the BI rate significantly influence inflation fluctuations, confirming the long-term linkage between monetary policy instruments and price dynamics as observed in this study.

Impulse Response Function (IRF)

Impulse Response Function (IRF) analysis is used to see the response of food inflation to a standard deviation of interest rates, rainfall, and fuel prices, as well as to measure the persistence of these impacts. By using IRF, we can find out the amount of food price index response to a standard deviation, the duration and persistence of the impact of the shock, and the policy implications that can be designed for mitigation of negative impacts [48].

Figure 3 shows a dynamic response from the price of food (*LN_CPI*) to the food price shock (*LN_CPI*) itself. In period 1, when there was a standard shock 1 deviation with food prices, the direct food prices increased by 0.00689 units. In the third period, the response decreased and then returned to rise in the 10th period. In the 10th period and so on, the response slowly increased until it reached a new equilibrium at 0.0088. This shows that changes in food prices have a direct and persistent effect on themselves. Food prices tend to increase stable stable and reach a new balance after around 20–30 months after-shock from themselves.

The upper right graph shows the dynamic response of the price of food (*LN_CPI*) to a 1 standard deviation shock in rainfall (*LN_CR*). The initial response to rainfall was 0. After several periods, the response increases gradually until the fourth period. The response reached its peak around the fourth period of 0.003651, then it slowly decreased. This shows that rainfall has a positive but indirect impact on food prices. The effect is visible after several periods. A shock in rainfall can lead to temporary imbalances (for example, floods that damage agricultural land), so that food prices to rise. Food prices tend to be stable and reach new equilibrium after around 25–30 months after rainfall.

The lower left graph shows the dynamic response of food prices (*LN_CPI*) to shocks of 1 standard deviation at BBM Prices (*LN_FP*), the initial response

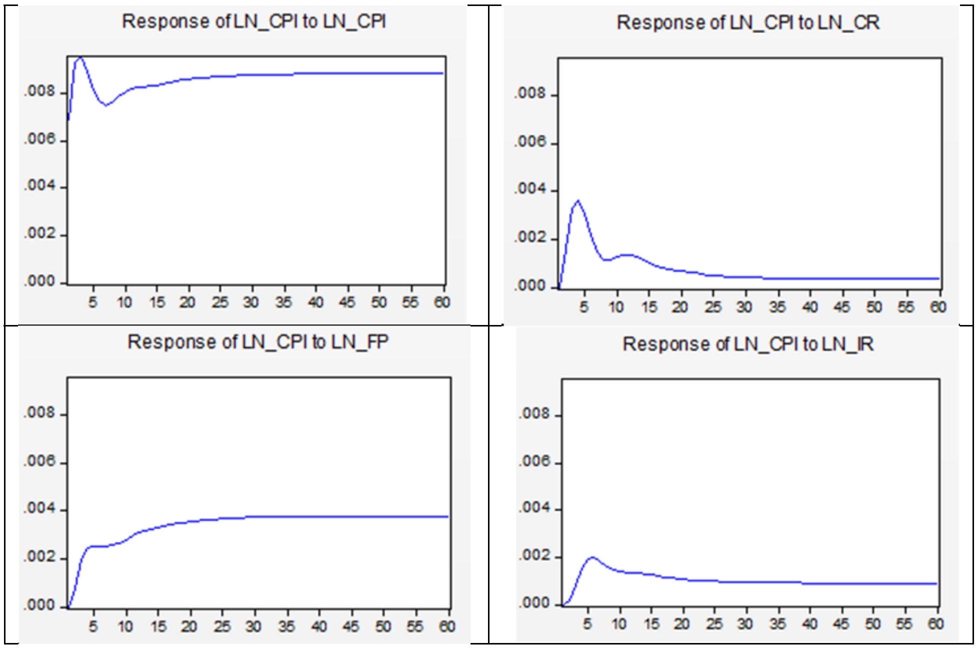

Fig. 3. **Response of Food CPI to Rainfall, Fuel Prices, and Interest Rates**

Source: Compiled by the authors.

to the price of food to the price of fuel prices is 0.000000. This can be caused by lag (delay) in the transmission mechanism from fuel prices to food prices. In the second period and so on, the response increased slowly until it reached a new equilibrium of 0.0038. Food Prices (*LN_CPI*) go to new equilibrium after around 20–30 periods after the shock to fuel prices (*LN_FP*).

The lower right graph shows the dynamic response of the price of food (*LN_CPI*) to a shock of 1 standard deviation in the BI benchmark interest rate (*LN_IR*). In the initial period, the response of food prices to the benchmark interest rate shock was 0.000000. Then increased until the sixth period. The peak response occurs in the sixth period, where the response increased to 0.00197. After that, the response decreased slowly until it reached the new equilibrium at 0.0009. Food Prices (*LN_CPI*) lead to a new equilibrium after around 20–30 post-shock period interest rates (*LN_IR*). This is consistent with the view of [49], who noted that aggressive interest rate hikes by central banks can take a considerable time before their full effect on inflation materializes, and in some cases may even generate unintended pressures on prices through their impact on the broader financial system.

The average food price change takes about 20–30 months to return to its natural value (new equilibrium) after receiving a shock from rainfall variable fuel oil prices, and the benchmark interest rate. This shows high persistence, which is in line with several studies of food inflation in developing countries [7, 11, 19].

The study period (2018–2023) includes the COVID-19 pandemic, which can cause data to be distorted due to non-standard shock such as lockdown and other changes. Therefore, this research also examines the strength of the results (robustness) by dividing the period into two sub-periods: "Before COVID-19" and "After COVID-19".

In both periods as shown in *Fig. 4*, it appears that the effect of the rainfall shock reaches a relative peak around the period 5–6, then fades slowly but remains persistent until the end of the period. Food prices tend to be stable and reach a new balance after about 10–30 months post-shock. The pattern of interest in shock interest rates is relatively consistent in both periods. However, the magnitude of the response is higher after COVID-19, which may be caused by extensive monetary policy during the pandemic.

Forecast Error Variance Decomposition (FEVD)

Forecast Error Variance Decomposition is used to understand how much each exogenous variable contributes to variations (fluctuations) in endogenous variables (*LN_CPI*) over time. Variance Decomposition of the *LN_CPI* variable (food prices) uses the Cholesky factor in this study.

Figure 5 shows that, at the beginning of the period, all variations in food prices (100%) were caused only by themselves (*LN_CPI*). No influence from rainfall, fuel prices, or interest rates was observed, because shocks from other variables had not had time to affect food prices. After running for several periods, the contribution of food prices began to decline slowly.

Response of Food CPI to Rainfall, Fuel Price, and Interet Rate Before COVID-19	**Response of Food CPI to Rainfall, Fuel Price, and Interet Rate After COVID-19**

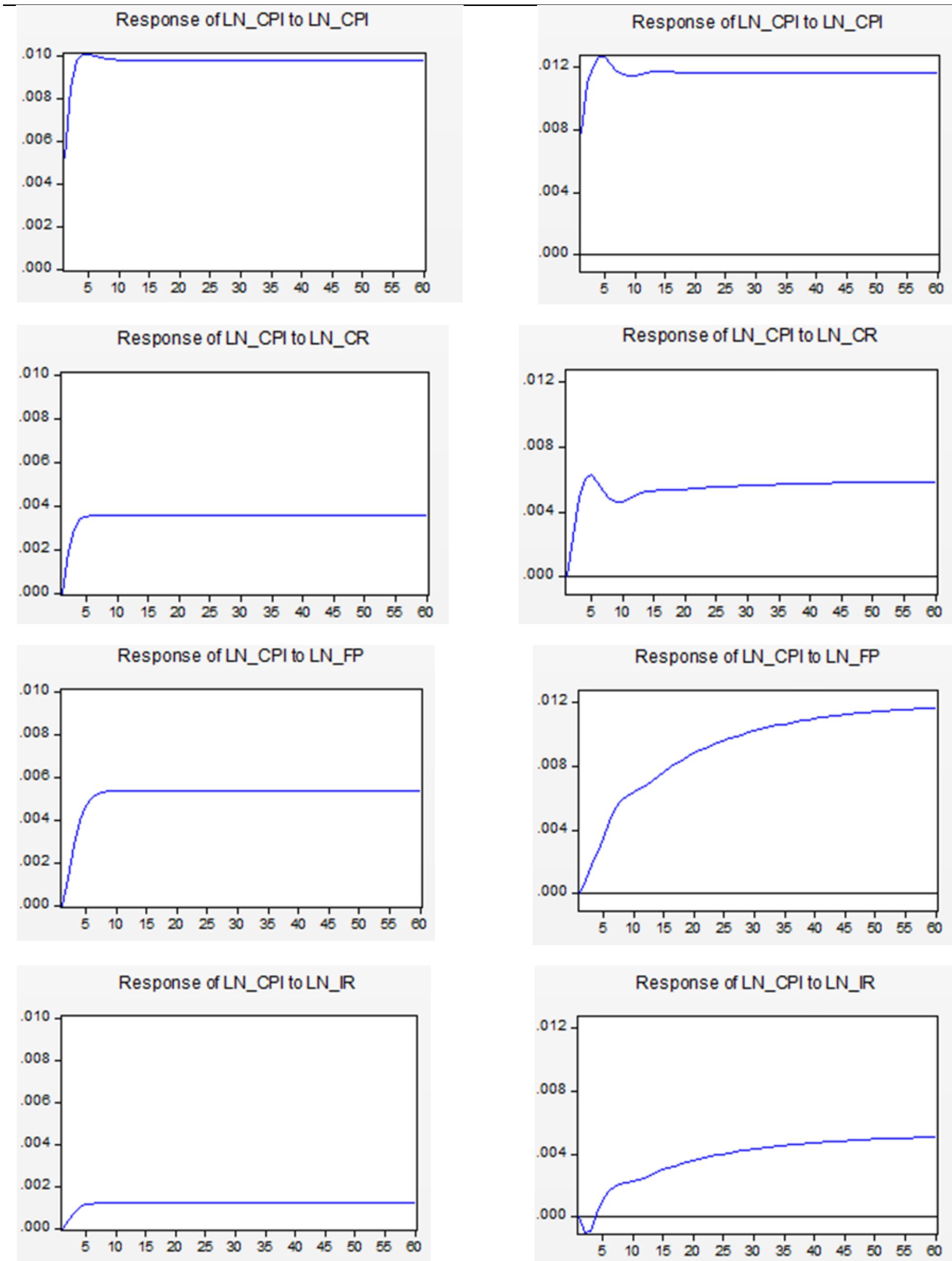

Fig. 4. **Robustness Test of the Response of Food CPI to Rainfall, Fuel Price, and Interest Rate**
Source: Compiled by the authors.

This shows the more variation in food prices caused by external factors. Over time, the contribution from fuel prices increased, although the price of food still dominated variations in food prices. In the 60th period, the price of food still dominated the variation in the prices of the food itself, with a contribution of around 83.91%. Fuel price is the most important external factor, with a contribution of around 13.58% of the total. Whereas rainfall and benchmark interest rates contribute contributions of around 1.19% and 1.31% respectively. This means that internal factors such as fluctuations in demand, production, and other market factors, play a dominant role in determining variations in food prices.

Variance decomposition graphics also show that food price variance is gradually influenced by exogenous variables (*LN_CR*, *LN_FP*, and *LN_IR*) over time. Initially, the impact of rainfall was higher than the fuel prices. However, after a few periods, the impact of the fuel price is higher than the rainfall, until the period so on. This is reinforced by the results of the robustness test by dividing the period into before COVID-19 period and after COVID-19 period.

As reported in *Fig. 6,* changes in the dominance of rainfall (*LN_CR*) over BBM Prices (*LN_FP*) reflect the dynamics of the influence of exogenous variables on food prices. Initially, rainfall had a greater impact as it has a direct relationship with food production, and agriculture is highly dependent on weather conditions. Rainfall shocks, such as floods or droughts, can cause direct disruptions to food supply, which then have an impact on prices. However, over time, the impact of fuel prices becomes more dominant because they have a cumulative impact that gets stronger over time. The increase in fuel prices leads to increased production costs, such as the use of fuel for agricultural equipment, distribution costs (transportation of goods), and other operational costs. While the benchmark interest rate has an impact on lower food prices than rainfall and fuel price, because of its relationship with the price of food (*LN_CPI*) is not directly. The benchmark interest rate is more often used to control inflation as a whole and maintain macroeconomic stability. The impact on food prices is only a small part of the broader impact on the entire economy. This supports [50]ʻ argument, who emphasized that the effectiveness of macroeconomic policy tools such as the key interest rate in influencing price dynamics is distributed unevenly across economic sectors. Structural and sectoral factors often play a more dominant role in influencing prices than monetary instruments alone. This uneven distribution of policy effectiveness is particularly evident in the food sector, where structural dynamics heavily outweigh monetary influences.

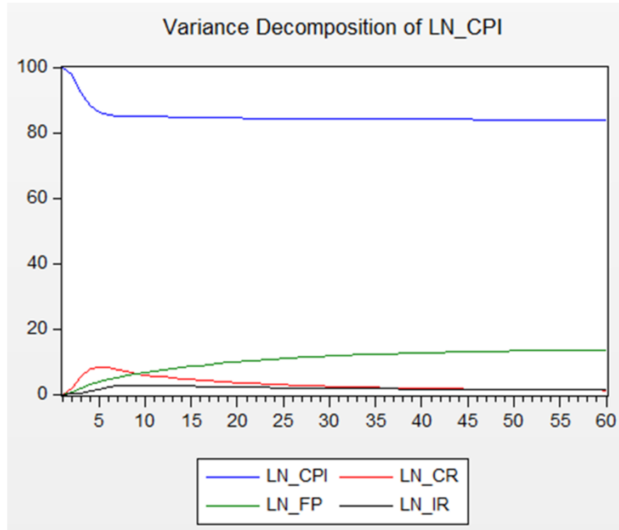

Fig. 5. **Variance Decomposition of Food CPI**
Source: Compiled by the authors.

Most of the variations in food prices (*LN_CPI*) are intrinsic or internal because they are influenced by factors such as food production, consumer demand, distribution and logistics, government policy, food reserves, and agricultural technology. These intrinsic variables have a direct relationship with the food supply chain and play a dominant role in determining food prices compared to exogenous factors such as rainfall, fuel prices, or interest rates. Agricultural technology used, seed quality, fertilizer use, and land management can all affect the supply of food. The level of efficiency in the production processes, such as irrigation, mechanization, and pest control, also affects production costs and food prices. Transportation infrastructure, such as roads, ports and terminals, affects the distribution

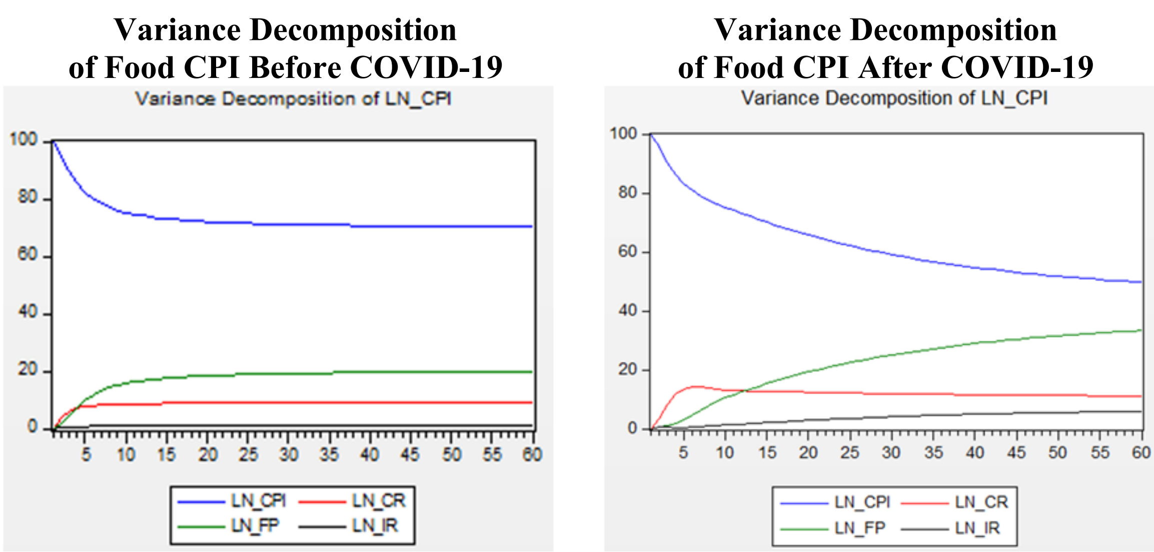

Fig. 6. **Robustness Test of Variance Decomposition of Food CPI**
Source: Compiled by the authors.

of food products on the market. If the distribution is disrupted, the price of food in certain areas may surge. The cost of storing and managing food stocks (for example, refrigerated warehouses for perishable products) also affects prices. If this cost is high, food prices tend to rise. Increased population and income of the community often increase demand for high quality food (for example, meat, fish, or processed products), which can affect the price of these commodities. Subsidies for farmers, such as fertilizer or seed subsidies, can reduce production costs and, in turn, stabilize food prices. This highlights the critical role of government intervention. Previous studies have demonstrated that food price inflation in Indonesia exhibits significant persistence in response to fiscal, monetary, and natural shocks, and that policy interventions such as the National Food Inflation Control Movement (GNPIP) play an important role [51]. Technological development, such as good agricultural process, modern irrigation, and other technologies can increase productivity and reduce production costs. The incentive for importing or exporting food can also affect domestic prices.

CONCLUSION

This study discusses an in-depth insight into the dynamics of food inflation and the factors that influence it. All variables dynamically influence each other. Based on the results of the IRF analysis, some important conclusions can be drawn about the relationship between the exogenous variables and food prices. The average food price change takes about 20–30 months to return to its natural value (new equilibrium) after receiving shocks from the rainfall variable, the price of fuel oil, and the benchmark interest rate. This shows that the persistence of changes in food prices is relatively high when it is affected by shocks from fiscal policy factors, monetary policy, and natural factors.

Food prices are very responsive to their own internal shocks, both in the short and long term. This can be caused by factors such as inflation expectations, vulnerable supply chains, or market uncertainty. An increase in food prices during the initial period (period 1–2) can strengthen inflation expectations among consumers and producers. These expectations can cause a higher price spiral if not controlled. Because food prices have the characteristics of persistence, price stabilization policies, such as subsidies or price control, need to be applied quickly to prevent prolonged shock impacts. The policy should also consider the long-term effects of price shocks, because the impact is not entirely lost.

Fuel price shocks have a significant but gradual impact on food prices. The response of food prices to fuel price shocks is marked by initial delays, gradual surges, and stabilization in the long run. An increase in fuel prices can affect food prices through supply chains, such as increased transportation and production costs. Therefore, mitigation policies, such as fuel subsidies or alternative energy development, can help reduce the negative impact of shocks on food prices. In the early days after shocks, interventions such as food assistance or price stabilization can help maintain market stability and protect consumers from significant price surges. A long-term focus should be given to improving the efficiency of the food supply chains, diversification of energy sources, and the development of logistics infrastructure.

Rainfall shocks have a significant impact on food prices, but temporarily. The response of food prices to rainfall shocks is characterized by initial delays, gradual surges, and long-term stabilization. Therefore, it is necessary to develop the right mitigation and adaptation strategies to reduce the vulnerability of the food sector to extreme weather fluctuations. Mitigation policies, such as the development of strong irrigation infrastructure to protect against floods or the diversification of food sources, can help reduce the negative impact of rainfall shocks. In the early days after shocks, interventions such as distribution of food aid or providing subsidies can help maintain price stability and protect consumers from significant price increases. Long-term planning: Because the impact of shocks is temporary, long-term focus should be given to increasing food security and adapting to climate change.

The IRF results also show that interest rate policies take time before they have an impact on food prices. Therefore, policy makers need to take this adjustment into account when designing monetary policy. Although the increase in interest rates initially decreases food prices (short-term effects), the long-term impact actually increases them. This needs to be taken into consideration to maintain price stability.

Based on Variance Decomposition graph analysis, although there are influences from exogenous variables such as rainfall, fuel prices, and benchmark interest rates, most of the variations in food prices (*LN_CPI*) are determined by internal factors such as food production, consumer demand, distribution, government policy, and agricultural technology. Exogenous variables have a gradual and limited impact, with fuel prices being more dominant than rainfall after a certain period. Therefore, the policy strategies must focus on strengthening internal factors to stabilize food prices and reduce vulnerability to external fluctuations. Policies ought to prioritize increased agricultural productivity, distribution efficiency, and management of food reserves in order to reduce the volatility of food prices. Interventions such as fuel subsidies for the agricultural sector, the development of irrigation technology, improving good agricultural processes and diversification of energy sources can help reduce the negative impacts from exogenous variables. In addition, strict regulations on price speculation and market monopoly can help maintain food price stability. Based on variance decomposition graph analysis, although there are influences from exogenous variables such as rainfall, fuel prices, and benchmark interest rates, most of the variations in food prices (*LN_CPI*) are determined by internal factors such as food production, consumer demand, distribution, government policy, and agricultural technology. Exogenous variables have a gradual and limited impact. Fuel prices are more dominant than rainfall after a certain period, so the policy strategy should focus on strengthening internal factors to stabilize food prices and reduce vulnerability to external fluctuations. Policies must prioritize increasing agricultural productivity, distribution efficiency, and management of food reserves to reduce the volatility of food prices. Interventions such as fuel subsidies for the agricultural sector, the development of irrigation technology, increasing good agricultural process and diversification of energy sources can help reduce the negative impacts of exogenous variables. Additionally, strict regulations against price speculation and market monopoly can help maintain stable food prices.

This study has several limitations, one of which is the use of precipitation as the only climate factor analyzed, without considering other climate variables such as temperature, drought, or other extreme events. This restriction is made taking into consideration the main focus of research, which is on the pattern of rainfall and its impact on prices. Therefore, it is recommended that further research can take additional climatic factors into account, such as daily average temperature, drought index, or the frequency of extreme events (for example, floods or a prolonged drought).

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