Factors Influencing Indonesia's Food Inflation: An ARDL Approach, 2020–2024

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ABSTRACT

This study aims to analyze the impact of natural disasters, food production, and the exchange rate on food inflation in Indonesia. Employing a quantitative approach, the research utilizes the Autoregressive Distributed Lag (ARDL) model. The Bound Test results indicate a cointegrating relationship among the variables, suggesting the existence of a long-run relationship. Short-run estimations reveal that food inflation is significantly influenced by its values from the preceding three periods, as well as natural disasters at the first lag. Conversely, food production and the exchange rate do not have a significant short-term effect. In the long term, only natural disasters significantly affect food inflation.

INTRODUCTION

Inflation is one of the key macroeconomic indicators used to measure the economic stability of a country (Li, Zhang, & He, 2023). Samuelson (2001) defines inflation as a condition in which there is a general increase in price levels, including the prices of goods, services, and the costs of production factors. A controlled inflation rate reflects stable purchasing power and the effectiveness of fiscal and monetary policies.

In developing countries such as Indonesia, inflation is significantly influenced by food prices. A large portion of household expenditure is allocated to food, particularly among low-income groups, for whom food commodities constitute the largest share of their consumption (Pratikto & Ikhsan, 2016). Therefore, fluctuations in food prices have a direct impact on purchasing power and overall societal welfare.

Indonesia's Central Statistics Agency (Badan Pusat Statistik/BPS) classifies inflation based on expenditure groups, one of which is food inflation. Food inflation is measured based on the "food, beverages, and tobacco" category within the Consumer Price Index (CPI) published by BPS. Indonesia's inflation data for 2024 shows a downward trend in the annual inflation rate (year-on-year), from 2.57% in January to 1.57% in December. The "food, beverages, and tobacco" expenditure group has been the main contributor to overall inflation, with the highest recorded in March at 7.43%, surpassing the general inflation rate of 3.05% during the same period.

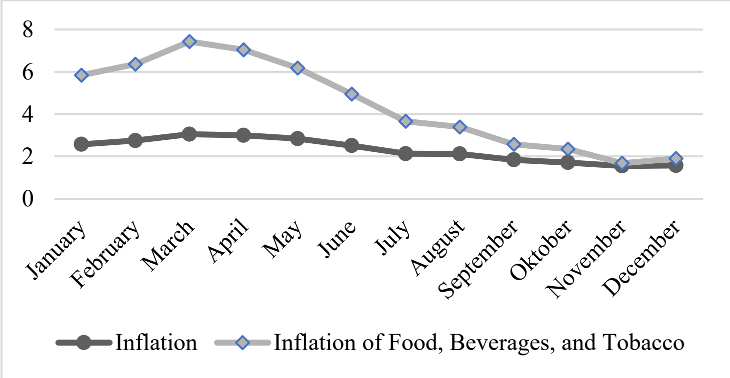

Figure 1. Indonesia's Inflation in 2024 (Y-on-Y) (2022=100) and Inflation by Group and Subgroup 01: Food, Beverages, and Tobacco (Percent)

Source: Badan Pusat Statistik (2024)

The food, beverages, and tobacco group recorded significantly higher inflation compared to general inflation in the first half of the year, reflecting strong price pressures, particularly from food commodities. After March, inflation in this group began to decline significantly, reaching 1.90% in December. This pattern indicates that inflation in food, beverages, and tobacco was the primary driver of national inflation early in the year. The substantial contribution of the food, beverages, and tobacco group to overall inflation underscores the vital role of food as a basic necessity for the public, making it highly susceptible to various factors. These factors include domestic influences like agricultural production and government policies, as well as external factors such as climate change and global price dynamics. One crucial aspect to observe is the impact of disasters.

Parker (2018) found that inflation increases after climate shocks; while earthquakes raised energy, clothing, and footwear prices, food prices appeared to decline in the first few quarters following the shock. Weather-related disasters cause a temporary yet statistically significant increase in key consumer prices, peaking at 0.5 percent two months after the event (Gautier et al., 2023). A study by Duprey & Fernandes (2025) indicated that the impact of disasters can affect the overall Canadian economy: during periods of strong GDP growth, natural disasters are almost always inflationary. However, when GDP growth is weak, natural disasters are more likely to be deflationary due to falling housing costs.

Hallegatte et al. (2022) developed an economic model simulation to understand the impact of very large-scale disasters on the economy. Their results showed that disasters cause supply shocks (scarcity of goods and services due to damage) and demand shocks (urgent needs for reconstruction), both of which drive prices up. This surge in inflation impacts household consumption through real income. The effect of disasters on inflation is highly heterogeneous across product categories. Essential categories like food, beverages, clothing, and housing tend to experience inflationary pressure due to supply shocks. Meanwhile, inflation in household equipment is more driven by increased demand for reconstruction (Beirne et al., 2024).

BPS data recorded a 3% decrease in national rice production in 2024 compared to the previous year. This was largely due to extreme weather conditions and environmental damage (Coordinating Ministry for Food, 2025). For instance, a major flood in South Kalimantan in early 2025 inundated approximately 1,200 hectares of rice fields. Conversely, droughts caused by watershed degradation and climate change have reduced irrigation water availability. A study by Rahmayanti et al. (2022) noted that in 2021, out of 209,884 hectares of recorded agricultural land in South Kalimantan, about 188,895 hectares of rice fields were damaged by floods.

According to the Ministry of Agriculture's Center for Data and Agricultural Information, Indonesia's rice commodity imports in 2024 reached approximately USD 2.44 billion. This high import figure makes Indonesia more vulnerable to external pressures, one of which is the fluctuation of the rupiah's exchange rate. Exchange rate depreciation has a positive and significant effect on inflation only when the depreciation exceeds a monthly threshold of 0.51% (Sumba, Nyabuto, & Mugambi, 2024). A study by Garzón and Hierro (2022) showed that a 1% appreciation of the euro against the US dollar can reduce the inflation rate by 0.0244 percentage points in the short term and 0.046 in the long term in the Eurozone. Conversely, in the cases of the UK and Japan, exchange rate variations did not significantly mitigate the impact of oil prices on inflation.

Based on this background, it's clear that inflation is inseparable from the complex interaction of domestic and global factors. Disruptions to food production due to climate disasters, declining land productivity, and exchange rate fluctuations create supply-side pressures. At the same time, increased post-disaster demand strengthens demand-side inflationary pressures. The reliance on rice imports amidst rupiah depreciation further intensifies domestic inflationary pressure. Therefore, this research aims to analyze the variables influencing inflation in Indonesia during the 2020-2024 period, with a specific focus on food inflation. Using ARDL analysis is expected to capture both short-term and long-term relationships and provide a clearer quantitative picture of food inflation's vulnerability to these dynamic variables.

RESEARCH METHOD

This study employs a quantitative approach using monthly time series data from January 2020 to December 2024 in Indonesia. The data used are secondary data sourced from the Central Statistics Agency (BPS), the National Disaster Management Agency (BNPB), the Ministry of Trade, Bank Indonesia (BI), and other relevant sources. Food inflation is measured using monthly percentage changes (month-to-month), food production data refers to the National Food Crop Production (tons) for rice, and disaster events are recorded by their frequency, along with the exchange rate of the rupiah against the US dollar.

The estimation model used is the Autoregressive Distributed Lag (ARDL) model implemented with EViews 13 software. The ARDL model is chosen because it can accommodate variables integrated at different levels, namely I(0) and I(1), and is suitable for short-term data and limited sample sizes. The initial step involves stationarity testing using the Augmented Dickey-Fuller (ADF) and/or Phillips-Perron (PP) tests. Next, the optimal lag length is determined based on information criteria such as the Akaike Information Criterion (AIC). Subsequently, the Bounds Testing approach is applied to test for the existence of a long-term relationship among the variables. If a long-term relationship is found, estimation proceeds with both long-term coefficients and short-term dynamics.

The ARDL model estimation is formulated as follows:

INF_PANGAN = C(1)*INF_PANGAN(-1) + C(2)*INF_PANGAN(-2) + C(3)*INF_PANGAN(-3) + C(4)*INF_PANGAN(-4) + C(5)*BENCANA + C(6)*BENCANA(-1) + C(7)*BENCANA(-2) + C(8)*PROD + C(9)*KURS + C(10)

RESULTS AND DISCUSSION

The analysis results were obtained using the Autoregressive Distributed Lag (ARDL) method to examine both short-term and long-term relationships between food inflation and supporting variables such as natural disasters, production, and exchange rates. First, stationarity tests were conducted to determine the integration order of each variable.

Table 1. Stationarity Test Using Augmented Dickey-Fuller (ADF)

Variabel	Prob (Level)	Prob (1st Diff)
INF_PANGAN	0.0001	0.0000
BENCANA	0.0106	0.0000
PROD	0.0000	0.0000
KURS	0.0879	0.0000

Source: Data processed by the author, 2025

The results of the panel stationarity test using the Augmented Dickey-Fuller (ADF) method indicate that, overall, the data are stationary, with very low p-values (below 0.05). Individually, the variables INF_PANGAN (food inflation), BENCANA (disaster), and PROD (production) are stationary at level, while the variable KURS (exchange rate) is not stationary as its p-value exceeds 0.05. After applying first differencing, all variables, including KURS, show significant p-values, indicating that KURS becomes stationary at order I(1).

Given the presence of variables integrated at different orders (I(0) and I(1)), the ARDL method is an appropriate choice because it can handle varying integration orders without requiring all variables to be integrated at the same level. Next, to determine the most suitable ARDL model, the optimal lag length was selected based on information criteria such as the Akaike Information Criterion (AIC). Selecting the optimal lag is important to accurately capture the dynamic relationships between variables in both the short and long term. The chosen optimal lag serves as the foundation for building the ARDL model and for conducting the cointegration test using the Bounds Test.

Table 2. Bound Test

Test Statistic	Value	k
F-statistic	11.92411	3
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	2.72	3.77
5%	3.23	4.35
2.5%	3.69	4.89
1%	4.29	5.61

Source: Data processed by the author, 2025

The optimal lag length based on the Akaike Information Criterion (AIC) was recorded as (4, 2, 0, 0), followed by the Bounds Test to identify the existence of a long-term relationship between food inflation and other independent variables, namely natural disasters, production, and exchange rates. The Bounds Test results show an F-statistic value of 11.92411, which is significantly higher than the upper bound (I1) critical value of 4.35 and the lower bound (I0) critical value of 3.23 at the 5% significance level. Since the F-statistic exceeds all critical values, including those at the 1% significance level, the null hypothesis stating that no long-term relationship exists can be rejected. Therefore, it can be concluded that there is a significant cointegration relationship among the variables in the model, indicating the presence of a long-term linkage between food inflation, natural disasters, production, and exchange rates.

The existence of long-term cointegration means that although the variables may fluctuate independently in the short term, they share an equilibrium relationship or move together in the long run. In other words, there is an economic force that will pull these variables back to their equilibrium path after shocks or deviations occur. With evidence of cointegration, the analysis can proceed to estimate the long-run coefficients within the ARDL framework to measure the magnitude of each variable's impact on food inflation in the long term.

Before interpreting the long-run coefficient estimates in the ARDL model, it is important to ensure that the model meets the classical regression assumptions. Overall, the diagnostic tests—Histogram for normality, Breusch-Godfrey (Serial Correlation LM Test) for autocorrelation, Breusch-Pagan-Godfrey for heteroscedasticity, and Variance Inflation Factor (VIF) for multicollinearity—indicate that the model adequately satisfies these assumptions. With the classical assumptions met, the model is considered to produce unbiased and efficient coefficient estimates, allowing for valid statistical interpretation of both short- and long-term relationships.

Table 3. ARDL Result

Cointegrating Form				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(INF_PANGAN(-1))	0.641894	0.189157	3.393445	0.0014
D(INF_PANGAN(-2))	0.414676	0.169248	2.450110	0.0181
D(INF_PANGAN(-3))	0.538784	0.137761	3.911009	0.0003
D(BENCANA)	-0.000959	0.002718	-0.352923	0.7258
D(BENCANA(-1))	-0.009946	0.002705	-3.676500	0.0006
D(PROD)	-0.000000	0.000000	-0.518244	0.6068
D(KURS)	0.000300	0.000199	1.505764	0.1390
CointEq(-1)	-1.340264	0.205782	-6.513037	0.0000
Cointeq = INF_PANGAN - (0.0071*BENCANA - 0.0000*PROD + 0.0002 *KURS -4.5450)				
Long Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
BENCANA	0.007118	0.001953	3.644464	0.0007
PROD	-0.000000	0.000000	-0.508067	0.6138
KURS	0.000224	0.000147	1.521552	0.1350
C	-4.544961	2.464085	-1.844482	0.0716

Source: Data processed by the author, 2025

The ARDL (4, 2, 0, 0) model includes 4 lags for INF_PANGAN, 2 lags for BENCANA, and no lags for PROD and KURS. The data consisted of monthly observations from January 2020 to December 2024, resulting in 56 usable observations for the estimation after adjusting for the specified lags.

The short-term estimation results (cointegrating form) indicate that changes in food inflation over the previous three periods (lags 1 to 3) significantly influence current food inflation, with coefficients of 0.64, 0.41, and 0.54 respectively, all with p-values below 0.05. This suggests a strong dynamic in the short-term movement of food inflation. Among the independent variables, only changes in NATURAL DISASTERS (BENCANA) at lag 1 have a significant negative effect on food inflation (coefficient = -

0.0099; p = 0.0006), while changes in PRODUCTION (PROD) and EXCHANGE RATE (KURS) do not show significant effects in the short term.

This phenomenon may indicate that after the initial shock, which might have raised prices, there are adjustment mechanisms or interventions (such as emergency aid or accelerated distribution) that suppress inflation in subsequent periods, or it may reflect a decline in demand following the initial disaster impact. These findings align with Beirne et al. (2024), who reported that core inflation rises after disasters but that this effect is short-lived. Gautier et al. (2023) add that weather-related disasters cause a temporary but statistically significant increase in core consumer prices, peaking at 0.5 percent two months after the event. Similar findings show that major disasters such as Hurricane Katrina caused extreme inflation fluctuations, with inflation initially rising sharply and then falling (Chavleishvili & Moench, 2024).

Changes in natural disasters during the current period (D(BENCANA)), food production (D(PROD)), and exchange rates (D(KURS)) do not have significant short-term effects on food inflation. This suggests that fluctuations in these three variables do not exert immediate pressure on changes in food inflation within the same period. This is consistent with findings by Duprey and Fernandes (2025), who showed that floods do not have a significant average impact on overall inflation. However, floods can drive increases in core inflation (excluding food and energy components) through rising housing sector prices. Conversely, food prices, especially in restaurants, tend to decline during winter storms due to reduced out-of-home consumption.

The Error Correction Term (ECM) coefficient in CointEq(-1) is -1.340264 and is statistically significant (Prob. = 0.0000). The negative and significant coefficient confirms the existence of cointegration and indicates the speed of adjustment of food inflation toward long-term equilibrium after a deviation occurs. The value of -1.340264 implies that approximately 134.02% of the previous period's disequilibrium in food inflation is corrected in the current period, indicating a very rapid adjustment or overshooting toward the equilibrium condition.

In the long run, the estimation results show that the occurrence of natural disasters (BENCANA) has a positive and significant effect on food inflation, with a coefficient of 0.007118 (Prob. = 0.0007). This finding is consistent with the argument that disasters can disrupt supply chains, damage agricultural land, and hinder distribution, thereby causing persistent price pressures on food commodities. Beirne et al. (2024) found that the impact of disasters on inflation is highly heterogeneous across product categories. Essential needs such as food, beverages, clothing, and housing tend to experience inflationary pressure due to supply shocks. Meanwhile, inflation in household equipment is more driven by increased demand for reconstruction. This result aligns with the study by Hallegatte et al. (2022), which states that disasters cause supply shocks (scarcity of goods and services due to damage) and demand shocks (urgent reconstruction needs) that push prices upward. This inflation surge impacts household consumption through real income.

On the other hand, food production (PROD), which in this study refers to rice production, and the exchange rate (KURS) do not show statistically significant effects on food inflation in the long run, with coefficients close to zero (Prob. PROD = 0.6138; Prob. KURS = 0.1350). Garzón and Hierro (2022) showed that a 1% appreciation of the euro against the US dollar could reduce inflation by 0.0244 percentage points in the short term and 0.046 in the long term in the Eurozone. Conversely, in the cases of the UK and Japan, exchange rate variations did not significantly mitigate the impact of oil prices on inflation.

The final stage of the ARDL model is the CUSUM (Cumulative Sum) test, which is conducted to examine the stability of the ARDL model parameters throughout the observation period. This test assesses whether there are significant structural changes in the model's coefficients. A CUSUM plot that remains within the critical bounds (confidence band) indicates that the model parameters are stable over the sample period. Conversely, if the plot crosses these bounds, it suggests parameter instability and the potential presence of structural breaks.

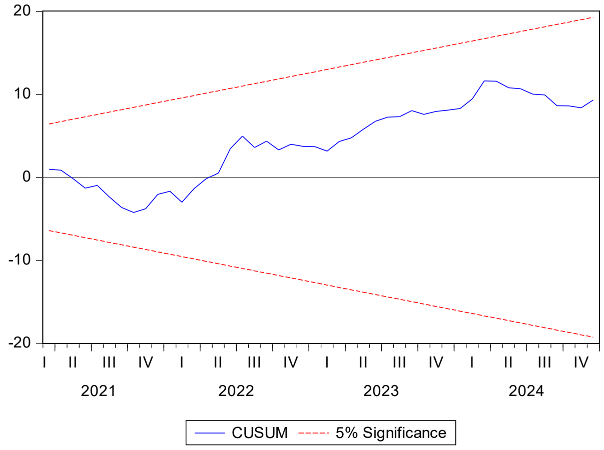

Figure 2. CUSUM Test

Source: Data processed by the author, 2025

In this study, the CUSUM test results indicate that the test graph remains entirely within the critical bounds at the 5% significance level, suggesting that the ARDL model employed exhibits good parameter stability throughout the 2020–2024 period. Therefore, the model can be considered reliable in representing both the short-term and long-term relationships between food inflation and the explanatory variables analyzed.

CONCLUSION

This study analyzes the relationship between food inflation, natural disasters, food production, and exchange rates in Indonesia using a quantitative approach with the Autoregressive Distributed Lag (ARDL) model on monthly data from 2020 to 2024. Stationarity tests indicate that the variables are integrated at orders I(0) and I(1), making the ARDL method appropriate.

The Bounds Test confirms the existence of a long-run cointegration relationship among the variables, implying that food inflation and the explanatory variables maintain a long-term equilibrium that adjusts after shocks. The Error Correction Term (ECM) coefficient is negative and highly significant (-1.340264), indicating a rapid speed of adjustment toward equilibrium. Furthermore, the estimated model meets classical diagnostic assumptions (no autocorrelation, homoscedasticity, and no multicollinearity) and demonstrates parameter stability based on the CUSUM test.

In the long run, a key finding is that natural disasters have a positive and significant impact on food inflation, consistent with literature stating that disasters disrupt supply chains and exert price pressures. Conversely, food production and exchange rates show no significant long-term effect on food inflation. In the short run, only changes in natural disasters at lag one have a significant negative effect on food inflation, possibly reflecting post-disaster adjustments or interventions such as aid distribution or reduced demand, which temporarily suppress food inflation. Meanwhile, contemporaneous changes in disasters, food production, and exchange rates do not significantly affect short-term food inflation.

Overall, the findings emphasize the vulnerability of food inflation to natural disaster shocks, particularly in the long term. The insignificant impact of production and exchange rates suggests these factors are less dominant in influencing long-term food inflation trends. These results underscore the importance of incorporating natural disaster risk mitigation in policies aimed at controlling food inflation and maintaining price stability.

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