



Dynamic Spatial Modeling of Fuel Price Hikes and Their Impact on Inflation and Basic Necessities in Indonesia

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ABSTRACT

In 2022, the Indonesian government implemented a fuel price increase policy to reduce the fiscal burden of energy subsidies, a measure that has important implications for regional inflation dynamics. Given the heterogeneity of economic structures and market integration across regions, the inflationary impact of fuel price hikes is unlikely to be spatially uniform. This study aims to examine the effect of fuel price increases on regional inflation in Indonesia while accounting for spatial interaction and temporal dynamics. To this end, a Dynamic Spatial Model is employed, incorporating spatial lag dependence, spatial error dependence, and temporal persistence, with rice and cooking oil prices included as control variables to capture essential commodity price effects. The estimation results provide strong evidence of significant spatial spillover effects and dynamic adjustment processes in regional inflation. The findings indicate that fuel price increases have a statistically significant impact on inflation, with the magnitude and direction of the effects varying across regional groups, reflecting differences in cost-push and demand-pull inflation mechanisms. These results highlight the importance of considering both spatial interdependence and dynamic effects when evaluating the inflationary consequences of fuel price policies, and they offer valuable insights for regionally differentiated policy design in Indonesia.

Keywords: *Dynamic Spatial Model, Fuel Oil, Inflation.*

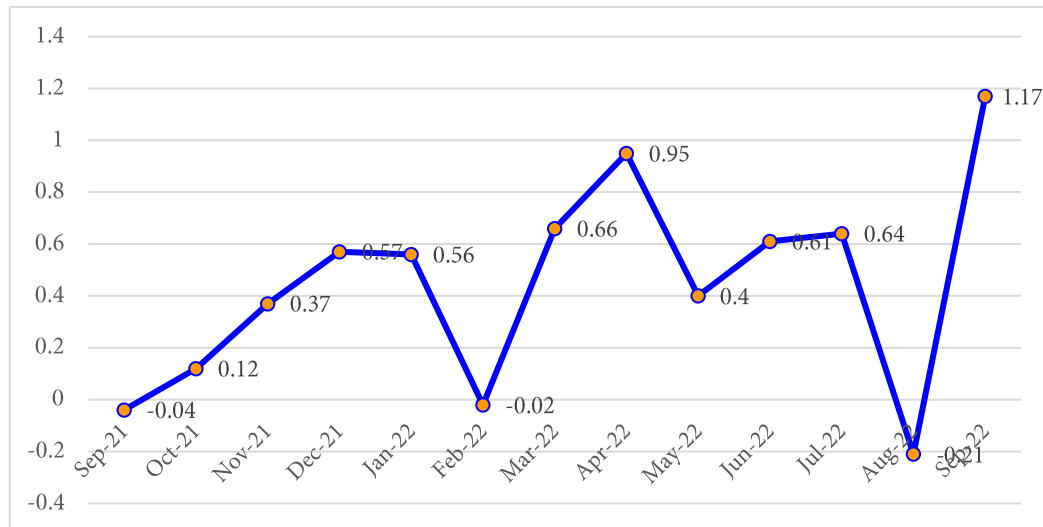
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1. Introduction

In the third quarter of 2022, the Indonesian government issued a policy to increase the prices of pertalite, pertamax and diesel fuel. The price of pertalite fuel increased by 31%, firstx by 16%, and diesel by 32%. This policy was taken because the amount of fuel subsidies in 2022 has reached 3x what was planned at the beginning of the year. This step was taken to avoid the state budget deficit. The policy of increasing fuel prices has become a pro and con for the community. People who support the policy consider that the subsidy costs are considered not well-targeted because those who enjoy subsidies come from the upper middle class. Meanwhile, people who oppose this policy consider that this step is considered inappropriate in the situation after the Covid-19 pandemic, where economic conditions have not fully recovered. Regardless of the pros and cons, the policy of increasing fuel prices is not the first time the Indonesian government has done so. Since the 1997 reform era, the Indonesian government has changed fuel prices 41 times, either increasing or decreasing fuel prices. The fuel price increase in September 2022 is the highest increase after 2013.

Rising fuel prices have an impact on the increase in transportation costs and the price of basic necessities, which is directly proportional to the high inflation rate. Inflation is the process of declining real value of money and rising

prices in general and continuously. According to Bank Indonesia projections, the increase in fuel prices will cause the potential increase in inflation in 2022 to exceed the government's threshold of 4%. According to data from the Central Statistics Agency (BPS), Indonesia's inflation in September 2022 amounted to 1.17 percent, a significant increase from the -0.21 percent deflation experienced in August. On a calendar year basis, Indonesia's inflation from January-September has reached 4.84 percent or exceeded the target set by the government. as in Figure 1. The development of Indonesia's inflation from September 2021 - September 2022 can be seen in Fig. 1.



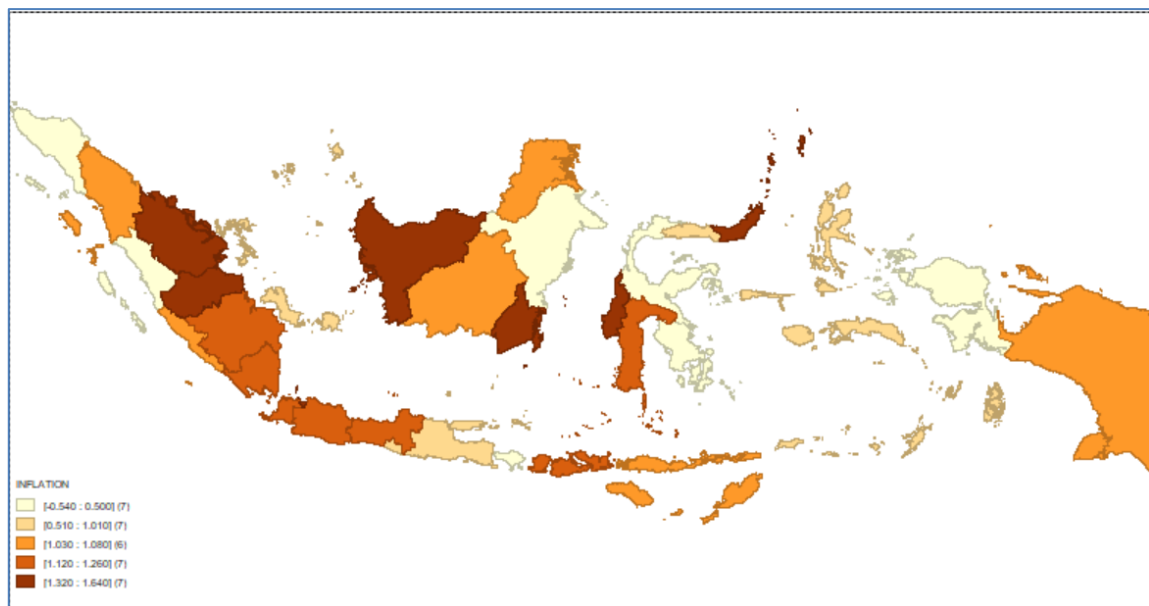
Source: BPS-Statistics Indonesia, 2022

Fig. 1. Indonesia Inflation September 2021-September 2022

The increase in inflation is a big focus of the government because it is feared that it will erode people's purchasing power. As is known, pertalite fuel consumption is the largest in total gasoline consumption in Indonesia. This will risk reducing household consumption growth, which is the main engine of Indonesia's economic growth. Inflation can be caused by cost-push inflation or demand-pull inflation [1]. Cost-push inflation is inflation caused by rising prices of goods. This condition will result in economic contraction. Meanwhile, demand-pull inflation is inflation caused by an excessively high demand for goods or services. This condition is caused by increased public demand for certain goods. Inflation due to fuel increases is a direct result of adjustments in transportation tariffs. According to [2], [3] changes in fuel prices have a positive effect on inflation. The pattern of changes in the value of inflation due to an increase in fuel prices is that the fuel price change policy is directly responded by an increase in inflation, this means that the value of inflation in the month of the fuel price increase will increase in the same month. Some research on changes in fuel prices to inflation and economic growth [4]–[6].

Changes in inflation lasted for 12 months from the intervention and afterwards the inflation rate returned to normal. The increase in fuel prices causes food prices that are transported between regions to increase in price. The farther the delivery of logistics, the more expensive the delivery cost will be. From the industrial sector, the cost of transporting raw materials and shipping costs will increase so that the industrial sector will increase production prices. According to [7] an increase in food prices can increase inflation and macroeconomic imbalances. Some countries, especially Indonesia, which still depend on the agricultural sector, changes in food prices can affect the inflation rate. Based on [8], [9], there are several things that affect inflation in Indonesia, some of them are Elnino event, government spending and infrastructure. This condition is exacerbated if a region has spatial dependency with other regions (spatial dependency). Price increases will have different impacts on Indonesia's regions. Thus, an increase in fuel prices has a different impact on each region. The spillover effect arises because of the formation of growth poles, in this case the center of the price increase. The spillover effect occurs when an increase in the price of goods will spread out, so that it will affect price increases in other regions. Moghadam defines the spillover effect because of the implementation of policies in one region that can affect other regions through trade or financial processes [10].

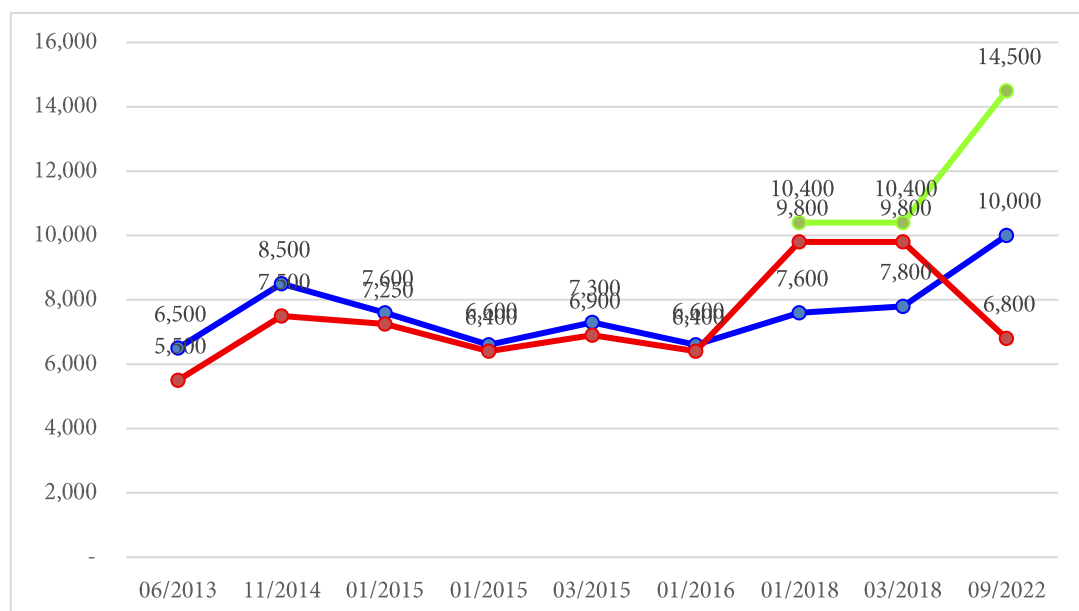
As a result of the time and distance of logistics delivery between regions, the balance of aggregate demand and supply is disrupted, resulting in regional inflation fluctuations as shown in Fig. 2.



Source: BPS-Statistics Indonesia, 2022

Fig. 2. Inflation Spread by City in Indonesia, September 2022

The impact of fuel price increases on inflation in a region varies depending on whether there are inter-regional linkages. In addition, the distance that makes logistics transportation bloated causes price increases. The impact of the fuel increase on each commodity group also varies. Setyawan found that the sector most affected by the fuel increase was the transportation sector [11]. Based on these conditions, the purpose of this study is to determine how much impact the fuel increase had on inflation by commodity group, with the control factors of rice price and cooking oil price. The price of rice is used as a control variable because rice is consumed by all Indonesians, so the price of rice is a control factor in calculating inflation. A few months ago, high oil prices were also one of the triggers of inflation. Therefore, the price of oil is also considered as an inflation controller.

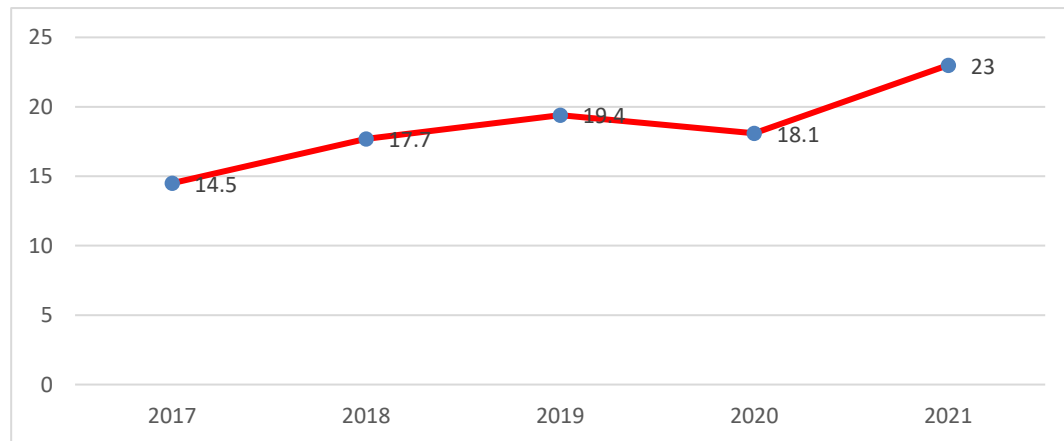


Source: Pertamina

Fig. 3. Price of Peralite (blue), Solar (red), and Pertamina (green) from June 2013 - September 2022

The Indonesian government raised fuel prices at the risk of increasing the burden on the state budget. Since becoming an oil and gas importer, the subsidy burden for fuel has increased from year to year. One way to reduce the state budget deficit is to increase fuel prices. There have been 8 fuel price changes in the last ten years as shown below.

The fuel price set by the government is the price that applies at Public Fuel Filling Stations (SPBU) owned by PT Pertamina. Many people buy at gas stations and then resell in retail form so that the selling price is higher than the price at the gas station. According to data from the Ministry of Energy and Mineral Resources in 2021, pertalite gasoline is the type of fuel most consumed by the public, around 79 percent compared to other types of fuel. The consumption of pertalite gasoline from year to year has increased.



Source: Ministry of Energy and Mineral Resources, 2021

Fig. 4. Pertalite Gasoline Consumption by the Public, 2017-2021

Due to the increase in fuel consumption from year to year and the burden of subsidies borne by the state budget, the government issued a policy to increase the price of pertalite, pertamax and diesel fuel. The fuel price increase policy in the third quarter of 2022, as explained earlier, shows differences in the impact of inflation between regions in Indonesia. This condition indicates spatial heterogeneity and spatial dependency between regions, where price changes in one region can affect prices in other regions through trade mechanisms, logistics distribution, and supply chain linkages. This phenomenon is in line with the spillover effect concept proposed by Myrdal [12], whereby economic shocks (such as fuel price increases) in central regions can spread to surrounding regions. In this context, the Dynamic Spatial Model (DSM) is relevant because it can capture the spatial lag effect and time lag effect in the process of interregional price adjustment. In other words, DSM allows for analysis that not only looks at the direct relationship between fuel price increases and local inflation, but also the transmission of its impact on inflation in other regions that are geographically and economically close.

The application of the Dynamic Spatial Model in the context of fuel price increases in Indonesia can explain how changes in energy prices drive inflation between regions dynamically over time. The proposed Dynamic Spatial Model is well suited to address the research problem because the impact of fuel price hikes on inflation and basic commodity prices in Indonesia is inherently spatial and evolves over time. Price adjustments in one region may generate spillover effects to neighboring regions through interregional trade linkages, distribution networks, and market integration, which cannot be adequately captured by conventional models. Moreover, the effects of fuel price increases are not instantaneous but occur gradually, requiring a dynamic framework to distinguish short-run and long-run responses. By jointly incorporating spatial dependence and temporal dynamics, the model provides more efficient and unbiased estimates, offering a comprehensive understanding of regional inflationary transmission and supporting evidence-based policy formulation. As explained by [13], [14], DSM allows for parameter estimation that takes into account the spatial autoregressive coefficient (ρ), which represents the influence of inflation in neighboring regions, as well as temporal dynamics (λ), which shows the influence of inflation in the previous period on the current period. In the case of Indonesia, regions with strong logistical connections, such as between Java and Kalimantan, will show significant spatial coefficients due to the transmission of commodity prices and transportation costs. Thus, spatial dynamic analysis provides a more comprehensive understanding of the phenomenon of inflation after fuel price increases, where the impact is not only local and temporary, but also spreads across regions and persists over several periods.

2. Method Details

2.1. Inflation

Inflation is the tendency of prices of goods and services to rise continuously. The increase in the price of goods and services causes a decrease in the value of money. Thus, inflation can also be interpreted as a decline in the value of money against the value of goods and services in general [15]. Inflation can be defined as any increase in output prices in an economy [12]. The short definition of inflation is the tendency of prices to rise generally and continuously. An increase in the price of just one or two goods is not called inflation, unless the increase extends to (or contributes to a rise in) most of the prices of other goods.

There are several alternatives in calculating inflation, BPS uses the consumer price index (CPI) as an indicator for calculating inflation. Inflation is the percentage change in the CPI at any one time and is formulated as follows [15]

$$\text{Inflation} = \frac{I_t - I_{t-1}}{I_{t-1}} \times 100 \quad (1)$$

where I_t the CPI of month t and I_{t-1} is the CPI of the previous month ($t-1$).

The CPI is calculated by BPS by covering 248-273 commodities consumed by people in 90 cities in Indonesia. The CPI is presented according to goods/services which are grouped into 11 groups, i.e.:

- a. Food, beverages and tobacco
- b. Clothing and footwear
- c. Housing, water, electricity and household fuel
- d. Health
- e. Supplies, equipment and routine maintenance of the household
- f. Information, communication, and other services
- g. Education
- h. Provision of food, drink/restaurants
- i. Personal care and other services
- j. Transportation

Inflation calculated based on presentation time can be divided into monthly inflation month to month (m to m), calendar year inflation which accumulates from January to a certain month, and year on year inflation which compares inflation in a certain month compared to the same month in the previous year.

There are many factors that can cause inflation, namely demand-pull inflation and cost-push inflation. Demand pull inflation is inflation caused by a shift in the aggregate demand curve. When the increase in aggregate demand is at the same level as the increase in aggregate supply, the products offered can meet the demand needs. However, if the increase in demand exceeds the increase in supply, then the goods and services offered are insufficient to meet the demand and prices will rise, causing inflation. Cost-push inflation occurs due to an increase in costs on the supply side, which is characterized by an increase in prices and a decrease in production. This situation arises due to a decline in aggregate supply because of an increase in production costs. If this situation lasts long enough, inflation will occur [16].

2.2. Previous Studies on Fuel Prices Impact to Inflation

Fuel price increases have different impacts on inflation in a region. Generally, an increase in fuel prices will increase costs from the supply or production side or cost-push inflation. According to Kilian dan Zhou, there is no evidence to suggest that rising oil prices can increase inflation in the long run in the United States [17]. In the short term, an increase in oil prices can affect inflation even though it is small. According to Kpodar dan Liu, using the dynamic least square method shows that the increase in crude oil prices affects the movement of inflation [5]. According to Mien, the increase in international oil prices affects the CPI in several African countries [19].

Related to the policy of increasing fuel prices in Indonesia, according to Harunurrasyid, using multiple linear regression, changes in fuel prices have a positive and significant effect on Indonesia's inflation rate[3]. Changes in fuel prices tend to have a greater impact on inflation in the foodstuff group, and the transportation and communication group than on other expenditure groups. According to Wasni dan Projo using the ARIMA time series method shows that the pattern of changes in the value of inflation due to the intervention of fuel price increases, namely the fuel price change policy is directly responded by an increase in inflation, this means that the value of inflation in the month of

the fuel price increase will increase in the same month[20]. Changes in inflation lasted for 12 months from the intervention and afterwards the inflation rate returned to normal.

2.3. Variabel and Data

The data used in this study are secondary data, namely the CPI published by the Central Statistics Agency of the Republic of Indonesia, BUMN, namely PT Pertamina, the Ministry of Agriculture from December-October 2022. The research variables used include:

Table 1. The Variables and Sources

No	Variables	Scale	Sources
1	CPI of food, beverages, and tobacco (y_1)	Ratio	BPS-Statistics Indonesia
2	CPI of transportation (y_2)	Ratio	BPS-Statistics Indonesia
3	CPI of provision of food & drink/restaurants (y_3)	Ratio	BPS-Statistics Indonesia
4	Pertalite's price (Z_1)	Ratio	Pertamina
5	Solar's price (Z_2)	Ratio	Pertamina
6	Pertamax's price (Z_3)	Ratio	Pertamina
7	Dexlite's price (Z_4)	Ratio	Pertamina
8	Rice commodity price (X_1)	Ratio	PIHPS
9	Cooking oil price (X_2)	Ratio	PIHPS

The form of data used is balanced panel data, with a time series (T) of 10 times starting from January-October 2022 and cross section data (N) of 34 provinces. The observation unit is all 34 provinces in Indonesia, so the total number of observations used in this study is 340 observations.

2.4. Empirical Model

The inflation model used is a dynamic spatial model with panel data. The use of dynamic model is to see the effect of previous period inflation on observed period inflation [21], [22]. The form of dynamic spatial model as follows:

$$\begin{aligned}
 y_{it} &= \tau y_{(it-1)} + \rho \mathbf{W}y_{it} + \eta \mathbf{W}y_{(it-1)} + \mathbf{F}_{it}\beta_1 + x_{it1}\beta_2 + x_{it2}\beta_3 + \mu_{it}, \\
 u_{it} &= \lambda \mathbf{W}u_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma^2)
 \end{aligned}
 \tag{2}$$

where i is cross section unit (spatial unit), $i = 1, \dots, N$, t is time period, $t = 1, \dots, T$, y_{it} is dependen variable cross section i at time t , x_{it1} is price commodity price at cross section i time t , x_{it2} is cooking oil price at cross section i time t , β_1 & β_2 parameter for predictor, τ is coefficient of the previous dependent variable (y_{it-1}), η is spatial autoregressive coefficient of the previous dependent variable ($\mathbf{W}y_{it-1}$), ρ is spatial autoregressive coefficient of dependent variable, λ is spatial autoregressive of error, $\mathbf{F}$ is common factor of fuel oil price, $\mathbf{W}$ is spatial weight matrix, and ε_{it} is error term.

The estimation method for both model 1 and model 2 uses maximum likelihood estimation (MLE) or quasi maximum likelihood estimation (QMLE) developed by [14], [25].

The model specification based on equation (1) uses 3 response variables, i.e.:

1. Inflation of food, beverages, and tobacco group (y_1),
2. Inflation of transportation group (y_2),
3. Inflation of provision food and drink/restaurants group (y_3)

The selection of inflation groups from 11 groups with the consideration that the 3 inflation groups have the biggest impact due to the fuel increase.

2.5. Construction of Common Factor (F)

Factor analysis is a statistical analysis that aims to reduce the dimensionality of data by expressing the original variable as a linear combination of several factors, such that the number of factors is able to explain as much as possible the diversity of data explained by the original variable.

The factor analysis model is:

$$\begin{aligned}
 \mathbf{Z}_1 &= c_{11}\mathbf{F}_1 + c_{12}\mathbf{F}_2 + c_{13}\mathbf{F}_3 + \dots + c_{1m}\mathbf{F}_m + \varepsilon_1 \\
 \mathbf{Z}_2 &= c_{21}\mathbf{F}_1 + c_{22}\mathbf{F}_2 + c_{23}\mathbf{F}_3 + \dots + c_{2m}\mathbf{F}_m + \varepsilon_2 \\
 \mathbf{Z}_3 &= c_{31}\mathbf{F}_1 + c_{32}\mathbf{F}_2 + c_{33}\mathbf{F}_3 + \dots + c_{3m}\mathbf{F}_m + \varepsilon_3 \\
 &\vdots \\
 \mathbf{Z}_p &= c_{p1}\mathbf{F}_1 + c_{p2}\mathbf{F}_2 + c_{p3}\mathbf{F}_3 + \dots + c_{pm}\mathbf{F}_m + \varepsilon_p
 \end{aligned} \tag{3}$$

In the form of a matrix, it can be written into equation 4

$$\begin{bmatrix} \mathbf{Z}_1 \\ \mathbf{Z}_2 \\ \mathbf{Z}_3 \\ \dots \\ \mathbf{Z}_p \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & \dots & c_{1m} \\ c_{21} & c_{22} & c_{23} & \dots & c_{2m} \\ c_{31} & c_{32} & c_{33} & \dots & c_{3m} \\ \dots & \dots & \dots & \dots & \dots \\ c_{p1} & c_{p2} & c_{p3} & \dots & c_{pm} \end{bmatrix} \begin{bmatrix} \mathbf{F}_1 \\ \mathbf{F}_2 \\ \mathbf{F}_3 \\ \dots \\ \mathbf{F}_m \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \dots \\ \varepsilon_p \end{bmatrix} \tag{4}$$

where:

$\mathbf{Z}_1, \mathbf{Z}_2, \mathbf{Z}_3, \dots, \mathbf{Z}_p$ is the origin variable,

$\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_m$ is the common factor,

c_{ij} is the weight (loading) of the i^{th} origin variable on the j^{th} factor,

$\varepsilon_1, \varepsilon_2, \varepsilon_3, \dots, \varepsilon_p$ is error term.

The relationship between the variance of the original variable, the variance of the factor and the error variance is as follows:

$$\begin{aligned}
 Var(\mathbf{Z}_i) &= \text{variance explained by the factor for the } i^{th} \text{ origin variable} + \text{var}(\text{error}) \\
 &= \text{communality} + \text{specific variance} \\
 &= h_i^2 + \psi_i \\
 &= (c_{i1}^2 + c_{i2}^2 + c_{i3}^2 + \dots + c_{im}^2) + \psi_i
 \end{aligned} \tag{5}$$

The amount of weight c_{ij} can be estimated using the principal component method or maximum likelihood. The principal component method is divided into two methods, namely non-iterative and iterative. The estimated value of c_{ij} obtained by the non-iterative method for the standardized origin variable is:

$$c_{ij} = \frac{a_{ji}\sqrt{\lambda_j}}{s_{x_i}} \text{ or } c_{ij} = a_{ji}\sqrt{\lambda_j} \tag{6}$$

Where:

c_{ij} is the weight (loading) of the i^{th} origin variable on the j^{th} factor,

a_{ji} is the coefficient of the i^{th} origin variable for the j^{th} principal component,

λ_j is the eigenvalue for the j^{th} principal component,

s_{x_i} is the standard deviation of the i^{th} origin variable.

The algorithm for the iterative principal component method is as follows:

1. Start
2. Determine the initial communality values for all origin variables ($h_i^2; i = 1, 2, \dots, p$), $0 \leq h_i^2 \leq 1$
3. Replace the diagonal value of the correlation matrix with the value of h_i^2 ($r_{ii} = h_i^2$)
4. Determine the eigenvalues and eigenvectors of the correlation matrix
5. Determine the weight value (loading) $c_{ij} = a_{ji}\sqrt{\lambda_j}$
6. Determine the communality value c $h_i^2 = (c_{i1}^2 + c_{i2}^2 + c_{i3}^2 + \dots + c_{im}^2)$

7. If the communality value in the last two iterations is considered the same, then proceed to 9
8. Go to step 3
9. End

For the sake of interpretation, it is often necessary to name each factor according to the absolute weight. It is expected that each origin variable is dominant in only one of the factors (The absolute value of the weight of the origin variable is close to 1 in one factor and close to 0 for the other factor). This expectation sometimes cannot be met; to overcome this, rotation of the weight matrix C is required. Some of the rotation techniques available in the statistical package program are: varimax, quartimax, equamax, parsimax. The formula for each of these rotations is:

$$\max \left[\frac{1}{p} \sum_{j=1}^m \left\{ \sum_{i=1}^p \left(\frac{c_{ij}}{h_i} \right)^2 - \frac{\gamma}{p} \left(\sum_{i=1}^p \frac{c_{ij}}{h_i} \right)^2 \right\} \right] \quad (7)$$

where: γ = Rotation, 0 = Quartimax, 1 = Varimax, $\frac{m}{2}$ = Equamax, and $\frac{p(m-1)}{p+m-2}$ = Parsimax

Rotation result weight matrix (C^*) can be expressed as $C^* = CT$, T is the transformation matrix. The magnitude of the factor score can be expressed as:

$$\mathbf{F} = \mathbf{C}^* \mathbf{S}^{-1} (\mathbf{Z}_j - \bar{\mathbf{Z}}), j = 1, \dots, n \quad (8)$$

Equation (8) describes the computation of factor scores based on the rotated weight matrix. The rotated matrix $C^* = CT$ is obtained by applying the transformation matrix T to the original weight matrix C , thereby aligning the factor structure for improved interpretability. The factor score vector F is then calculated as a linear combination of the standardized variables, expressed as the deviation of the j -th observation Z_j from its mean $\bar{Z}$, weighted by the inverse of the covariance (or correlation) matrix S^{-1} , for $j = 1, \dots, n$. This formulation ensures that the resulting factor scores consistently reflect the underlying latent factors while accounting for the intercorrelation structure among the observed variables.

2.6. Construction of The Spatial Weights Matrix (W)

The spatial weight matrix (W) can be obtained based on distance information from the neighborhood, or in other words from the distance between one region and another. Specifically, a distance-based weighting scheme is employed, such as inverse distance or inverse distance squared, so that geographically closer regions receive larger weights, while more distant regions receive smaller or zero weights. This structure is necessary to formally represent spatial interaction and potential spillover effects arising from market integration, transportation networks, and regional economic linkages, which are central to the transmission of inflation and price dynamics across regions. The spatial weight matrix is typically row-standardized to ensure comparability across regions and to facilitate interpretation of spatial parameters. Under this standardization, the elements of W are non-negative, with diagonal elements equal to zero, and each row summing to one, implying that the expected range of the weights lies between 0 and 1, where values closer to 1 indicate stronger spatial influence from neighboring regions and values closer to 0 indicate weak or negligible spatial interaction. There are several methods to define the contiguity relationship between these areas. According to Le Sage these methods include linear contiguity (edge contiguity), rook contiguity (side contiguity), bishop contiguity (corner contiguity), queen contiguity (side-angle contiguity)[13].

For example, rook contiguity defines = 1 for regions that share a common side with the region of interest, = 0 for other regions. As an illustration, consider the figure below which represents five regions shown on a map.

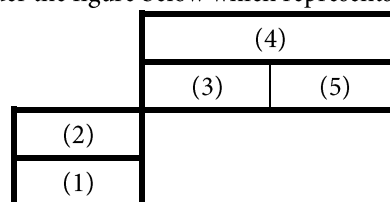


Fig. 5. Illustration of Regions on a Map

If the rook contiguity method is used, a 5×5 matrix arrangement is obtained, as follows:

$$\mathbf{W}_0 = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \end{pmatrix}$$

where rows and columns represent regions on the map and are unnormalized weights. Because the spatial weight matrix is a symmetric matrix, and with the rule that the main diagonal is always zero. Often normalization is done to get a unit number of rows, i.e. the number of rows equal to one. So the matrix becomes:

$$\mathbf{W} = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0,5 & 0,5 \\ 0 & 0 & 0,5 & 0 & 0,5 \\ 0 & 0 & 0,5 & 0,5 & 0 \end{pmatrix}$$

In this study using a map of Indonesia by province so that there are 34 spatial units, so the $\mathbf{W}$ matrix built is 34×34 .

2.7. Data Analysis Procedure

This study applies a dynamic spatial econometric framework to investigate the impact of fuel price increases on regional inflation in Indonesia, accounting for both temporal persistence and spatial interaction across regions.

1. The analysis is based on regional panel data covering inflation rates, fuel prices, rice prices, and cooking oil prices across Indonesian regions over the study period. All variables are harmonized to ensure consistency across regions and time. Descriptive statistics are first examined to capture regional variation and temporal patterns in inflation. When necessary, variables are transformed to stabilize variance and improve statistical properties.
2. Spatial interaction among regions is modeled using a spatial weight matrix $\mathbf{W} = [w_{ij}]$, constructed based on interregional geographic distance. Each element w_{ij} represents the inverse distance between region i and region j , with diagonal elements set to zero. The matrix is row-standardized so that the weights in each row sum to one. This normalization facilitates interpretation and ensures comparability of spatial effects across regions.
3. Spatial Dependence Diagnostics. Prior to model estimation, spatial dependence is formally tested. Global spatial autocorrelation in inflation is assessed using Moran's I statistic. Subsequently, Lagrange Multiplier (LM) and Robust LM tests for spatial lag and spatial error dependence are conducted. The rejection of the null hypothesis of no spatial dependence provides empirical justification for employing a dynamic spatial econometric specification.
4. Dynamic Spatial Model Specification based on the diagnostic results, the following Dynamic Spatial Model in equation 2.
5. Model parameters are estimated using the Maximum Likelihood Estimation (MLE) method, which allows for efficient and consistent estimation in the presence of spatial and temporal dependence. Statistical inference is conducted using Wald (z) tests based on asymptotic standard errors to assess the significance of individual coefficients, particularly the spatial autoregressive parameter (ρ) and the spatial error parameter (λ).
6. Model adequacy is evaluated using goodness-of-fit measures, including the log-likelihood, the coefficient of determination (R^2), and the estimated error variance (σ^2). Where appropriate, likelihood ratio tests are employed to compare the dynamic spatial model with more restrictive specifications. The estimated coefficients are then interpreted to assess the magnitude, direction, and heterogeneity of inflationary responses to fuel price increases across regional groups, highlighting the role of spatial spillovers and dynamic adjustment processes.

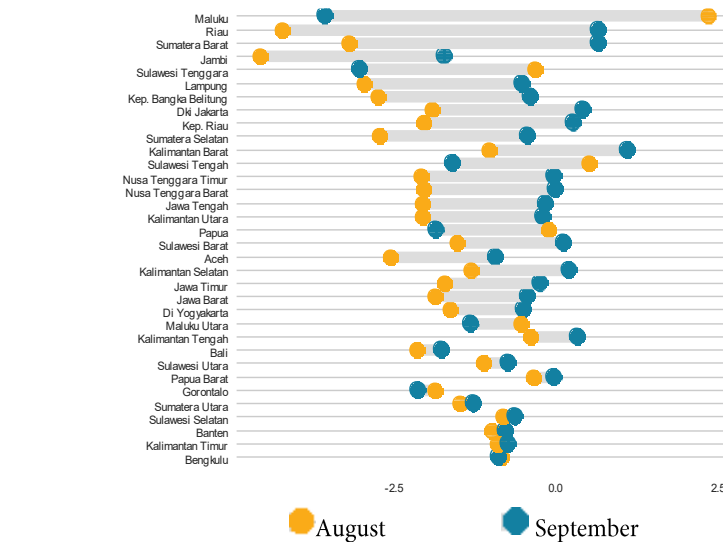
3. Results and Discussion

The results of this research are divided into several parts, namely: description of inflation, description of research data results, Dependent Lag and Error Dependent Testing, and The Effect of Fuel Price on Inflation Group

3.1. Inflation Description

3.1.1 Inflation of Food, Beverage and Tobacco Group

The progress of inflation in the food, beverage and tobacco group form Agustus- September 2022 can be seen in the Fig 6. Based on Fig 6, in September 2022, most of them suffered inflation in food, beverages, and tobacco, except in certain provinces that suffered deflation. Some provinces that suffered deflation were Maluku, Southeast Sulawesi, Central Sulawesi, Papua, and North Maluku.

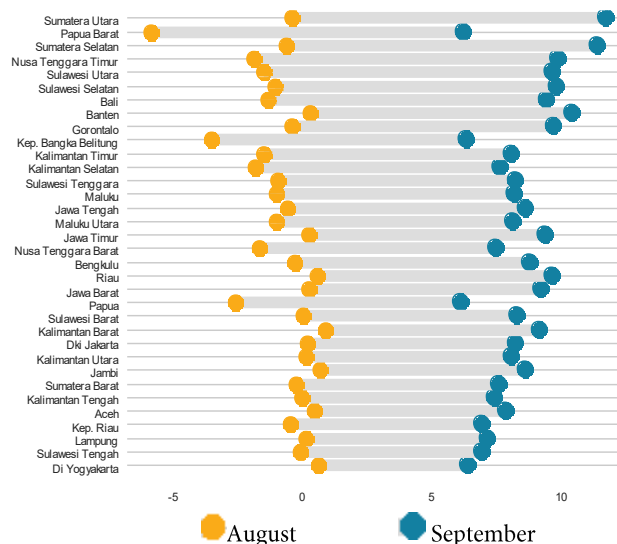


Source: BPS-Statistics Indonesia

Fig. 6. Inflation of Food, Beverages and Tobacco Group in August-September 2022 by Province in Indonesia

3.1.2. Inflation of Transportation Group

The progress of inflation in transportation group form Agustus- September 2022 can be seen in the Fig. 7.



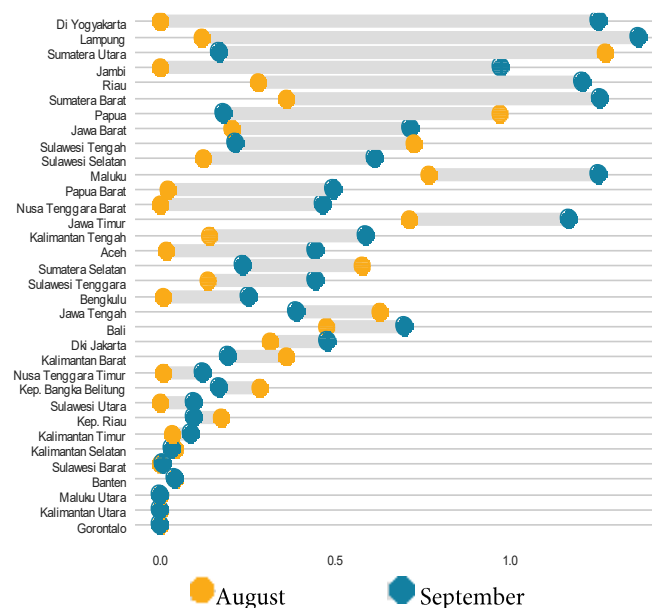
Source: BPS-Statistics Indonesia

Fig. 7. Inflation of Transportation Group in August-September 2022 by Province in Indonesia

According to Fig. 7, all provinces suffered inflation in the transportation group in September 2022, north Sumatra province had highest transportation group inflation in September 2022, while Papua province had the lowest

3.1.3. Inflation of Provision Food and Drink/ Restaurants Group

The progress of inflation in provision food and drink/restaurants group form Agustus- September 2022 can be seen in the Fig. 8.



Source: BPS-Statistics Indonesia

Fig. 8. Inflation of Provision Food and Drink/Restaurants Group in August-September 2022 by Province in Indonesia

Based on Fig. 8, almost every province had inflation in the food and drink/restaurant group, except Sumatera Utara, Papua, Sulawesi Tengah, Sumatera Selatan, Jawa Tengah, Kalimantan Barat, dan Kep. Bangka Belitung. Lampung had the highest inflation in the food and drink/restaurant group, while Gorontalo had the smallest.

3.2. Statistic Descriptive

The statistic descriptive of the research variables can be seen in the Table 2. The average monthly inflation in group 1 is 0.3987 percent, the average monthly inflation in group 2 is 1.594 percent, while the average monthly inflation in group 3 is 0.4257 percent. Group 2 had highly fluctuating inflation, from a minimum value of -5.826 percent to a maximum of 11.734 percent, with a standard deviation of 2.9 percent.

Table 2. Statistic Descriptive of Research Variable

Variable	Mean	St.Dev	Variance	Minimum	Maximum
Inflation of group 1*	0.3987	1.6644	2.7702	-4.7525	5.2755
Inflation of group 1*	1.594	2.900	8.410	-5.826	11.734
Inflation of group 3*	0.4257	0.6199	0.3842	-2.2569	3.9745
Factor of rising fuel oil price	0.1214	0.9682	0.9374	-1.2743	2.0648
Rice commodity price	13.792	2.421	5.863.285	10.200	25.000
Oil cooking price	22.554	4.191	17.568.447	13.100	32.450

*Note: Group 1: food, beverage, and tobacco

Group 2: transportation

Group 3: provision of food and drink/restaurants

The fuel increase factor score has an average of 0.1214, with a fairly small data variation of 0.9682. The data range for the fuel increase factor score is also quite small, between -1.2743 and 2.0648.

The average price of rice per kg is 13.792 rupiah, with a minimum range of 10.200 rupiah/kg and a maximum of 25.000 rupiah/kg. While the average price of cooking oil per liter is 22.554 rupiah, with a minimum range of 13.100 rupiah/liter and a maximum of 32.450 rupiah/liter.

3.3. Lag Dependence and Error Dependence Test

The results of lag dependence and error dependence test can be seen in the Table 3.

Table 3. Lag Dependence and Error Dependence

Test	Statistic	Probability
LM spatial lag	131.074	0.000
Robust LM spatial lag	33.005	0.000
LM spatial error	102.281	0.000
Robust LM spatial error	4.211	0.000

Based on LM test and Robust LM test on Table 3. indicates the presence of both spatial lag dependence and spatial error dependence in the model. This conclusion is supported by the significance of the LM and Robust LM test statistics for both the spatial lag and spatial error specifications, with all associated p-values equal to 0.000, well below the 5% significance level. The significant LM and Robust LM spatial lag tests suggest that the dependent variable in one region is influenced by the values observed in neighboring regions, indicating spatial spillover effects. At the same time, the significant LM and Robust LM spatial error tests imply spatial correlation in the disturbance terms, reflecting the influence of unobserved regional factors that are spatially correlated. The simultaneous significance of both robust tests suggests that neither a pure spatial lag model nor a pure spatial error model is sufficient, thereby justifying the use of a more general spatial model, such as the Spatial Durbin Model or a combined spatial autoregressive specification. Therefore, further modelling can be carried out.

3.4. The Effect of Fuel Price on Inflation Group

The effect of fuel price increase on inflation group with control variables of rice price and cooking oil price was modeled by Dynamic Spatial Model. The estimation results of the Dynamic Spatial Model can be seen in the following Table 4.

Table 4. Model Estimation Results

Variable	Group 1	Group 2	Group 3
Y_{t-1}	0.578275	0.723375	0.764399
WY_{t-1}	-0.439623	-0.663775	-0.123411
ρ	0.824268	0.863768	0.245500
λ	-0.538460	-0.586913	-0.139146
Factor of rising fuel oil price	-0.076195	0.578399	0.111407
Rice commodity price	-0.017984	0.029307	-0.023742
Oil cooking price	0.003794	0.003708	0.002093
R^2	0.9132	0.9674	0.9836
Sigma ²	0.8681	1.2673	0.3226
Log Likelihood	-539.59284	-618.49188	-295.04272

The results in table 4 show that the increase in fuel prices has a significant effect on inflation in the food and beverage group, transportation group and food and beverage group. Parameter inference in the Dynamic Spatial Model is conducted within a maximum likelihood estimation framework, which allows for the simultaneous estimation of dynamic effects, spatial dependence, and control variables. Statistical significance of individual parameters is assessed using Wald (z) tests based on the ratio of each estimated coefficient to its asymptotic standard error, with significance determined by conventional confidence levels. In particular, the spatial autoregressive parameter (ρ) and the spatial error parameter (λ) are tested to confirm the presence of spatial spillover effects and spatially correlated disturbances, respectively. Overall model adequacy is evaluated using goodness-of-fit measures such as the log-likelihood, R^2 , and the estimated error variance, and, where appropriate, likelihood ratio tests are employed to compare the dynamic spatial specification with more restricted alternative models. Similar to research (Harunurrahyid. and Rangasamy which show that the increase in fuel prices has an impact on rising inflation [2], [3]. The largest regression coefficient of the fuel price factor among the 3 inflation groups is the transportation group. This indicates that the commodity group most affected by the increase in inflation is the transportation group. In line with Setyawan research which also found that the sector most affected by the fuel increase was the transportation sector.

Wasni, D., & Projo found that the fuel price change policy is responded directly by an increase in inflation[20]. This means that the inflation value in the month of the fuel price increase will increase in the same month. Kilian and Zhou also stated that the effect of oil price increases is short term on inflation. with no visible impact on the long term [17]. Inflation in the previous period had a significant effect on the movement of current inflation. Lag dependency and Error dependency also have a significant impact. meaning that the increase in inflation is mutually affected by neighboring regions. The existence of interconnected economic relations between regions creates a spillover effect on neighboring regions. Oil price as a control variable only positively affects inflation in the food, beverage and tobacco group. while rice price has no effect on the three inflation groups.

4. Conclusion

The results of the study can be concluded that the increase in fuel prices has a significant effect on inflation in the food and beverage group. The transportation group and the food and beverage group. The group most affected by the fuel increase is the transportation group. The increase in inflation between neighboring regions is interrelated. The price of cooking oil as a control variable only positively affects inflation in the food, beverage and tobacco groups. while rice has no effect on the three inflation groups.

This study is subject to several limitations. The analysis is conducted at an aggregated regional level, which may obscure intraregional heterogeneity, and it assumes a stable spatial dependence structure over time, despite potential changes in interregional interactions due to policy shifts or economic shocks. In addition, the set of explanatory variables is limited, and the results depend on the availability and consistency of official data. Future research may address these limitations by employing more disaggregated data, adopting time-varying or adaptive spatial weight matrices, incorporating additional structural and policy-related variables, and exploring nonlinear or regime-switching dynamic spatial models to better capture heterogeneous inflation responses across regions and periods.

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