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THE EFFECT OF RICE PRICE ON THE INDONESIAN INFLATION IN A NEW INSTITUTIONAL ECONOMIC PERSPECTIVE

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ABSTRACT

The aim of this research is to identify and verify whether rice prices do play a role in driving national inflation using time series data. The time series data for this study spans from 2017 to 2023 on a monthly basis. To facilitate our analysis, we subject the data to standardized stationary tests, serving two essential purposes. Firstly, these tests ascertain the constancy of mean, standard deviation, variance, and covariance for each observation. Secondly, they aid in determining the extent of integration among the variables under scrutiny. For this particular purpose, we employ the Augmented Dickey-Fuller Test for Unit Roots. The outcomes of these stationary tests provide crucial insights, directing policy decisions to effectively address the challenge of inflation. It is widely acknowledged that the factors driving inflation rates, not only in Indonesia but globally, can be classified into two primary categories, the first being associated with the money supply. The research findings distinctly demonstrate that while rice certainly plays a role, it is not the exclusive or singular underlying cause of fluctuations in the inflation rate.

Keywords: *augmented dickey-fuller test, inflation dynamics, rice price, stationary tests, time series*

BACKGROUND

Two crucial factors that shape the context of the Indonesian economy are inflation, considered a macro policy objective, and rice, regarded as a strategic commodity. Inflation, defined as the persistent and widespread rise in the prices of goods (Rahardja & Manurung, 2008), encompasses three core dimensions: the propensity for actual price growth, the ongoing nature of price increases, and the influence on the overall price level. Thus, inflation is distinguished by its steady escalation in prices, signifying a general inclination for goods and services to become pricier over time. This price surge consequently erodes the currency's purchasing power, as each unit of currency can procure a diminished quantity of goods and services compared to previous periods.

As stated by Bank Indonesia, the Central Bank of Indonesia, maintaining low and consistent inflation serves as a fundamental prerequisite for fostering sustainable economic growth, which subsequently contributes to the enhancement of people's well-being (Bank Indonesia, 2023). Therefore, inflation represents an inherent aspect of the economy when it remains within moderate bounds. However, should inflation fall within the realm of moderate to high levels, it can decidedly impose substantial repercussions on a nation's economic landscape. According to the perspective put forth by Rahardja and Manurung (Rahardja & Manurung, 2008), inflation's primary causative factors within Indonesia encompass a range of elements, notably including monetary influences (core

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inflation). This entails aspects such as the money supply, thereby placing the responsibility on Bank Indonesia (BI) to regulate the circulation of currency. Second. Changes in administered prices, namely the prices of certain goods and services whose price levels are determined unilaterally by the government, state owned companies (BUMN), and cartels such as the price of fuel oil (BBM), water and electricity, school fees, etc. The third influential factor is the occurrence of supply-shock phenomena, characterized by abrupt and substantial shifts in the availability of goods or production factors, exerting a notable influence on the economy. These supply shocks have the potential to manifest on both domestic and international fronts, with their repercussions extending across diverse sectors of the economy.

Consumer price index (CPI) is a commonly the used measure of inflation. It tracks changes in the average price level of a basket of goods and services purchased by households over time. It provides insight into how the cost of living is changing for consumers. As mentioned before the basket of goods is Indonesia encompass three groups: the core inflation component, the administered prices, and volatile foods. In general, the way the CPI composed and calculated is as follows:

1. Selection of Goods and Services: The first step in creating the CPI is selecting a representative "basket" of goods and services that are commonly purchased by households. This basket reflects the spending patterns of an average consumer. It includes items like food, housing, transportation, healthcare, education, entertainment, and more.
2. Data Collection: Prices for the items in the basket are collected on a regular basis. This is usually done by government agencies or statistical organizations, which send surveyors to various locations to record prices. Online prices are also increasingly being used for data collection.
3. Weighting: Not all items in the basket have the same importance in a consumer's budget. Some items, like housing and food, have a higher weight because they consume a larger portion of an average consumer's income. These weights reflect the relative importance of each item in the consumer's spending.
4. Price Collection and Index Calculation: The prices of the items in the basket are collected periodically (e.g., monthly) over time. The CPI is calculated by comparing the total cost of the basket of goods and services in the current period to the cost of the same basket in a base period (usually a previous year). The ratio of these costs is multiplied by 100 to create the index number.
5. CPI = (Cost of Basket in Current Period / Cost of Basket in Base Period) * 100.
6. Inflation Calculation: Changes in the CPI over time indicate inflation or deflation. If the CPI goes up, it suggests that, on average, the cost of living has increased, which is inflation. If the CPI goes down, it suggests deflation or a decrease in the cost of living.
7. Sub-Indices: Sometimes, CPI is calculated for different categories or sub-indices, such as food, housing, transportation, etc. This provides a more detailed picture of how different sectors contribute to overall inflation. In the case of Indonesian inflation, sub-indices of volatile foods covers the sub indices of rice, chicken meat, chicken eggs, beef, shallot, garlic, red chilli, cayenne pepper. cooking oil, and sugar.

The primary objective of this article is to establish a comprehensive understanding of the correlation between inflation, the Consumer Price Index (CPI), and its respective sub-indices, especially of volatile foods. By doing so, we aim to provide a robust foundation for determining whether the price of rice (as a sub-index) genuinely holds the position of being the primary contributor to national-level inflation, especially when compared to other relevant sub-indices.

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Hence, the aforementioned factors are interconnected and can collectively yield intricate consequences, contributing to the emergence of inflation. Apart from the monetary aspects involving currency circulation and interest rates, which play a role in influencing inflation (Prasasti et al., 2020; Mankiw, 2000), non-monetary elements like alterations in government regulations, disruptions in supply chains, and shifts in fiscal policies also hold the potential to impact inflation.

A notable contributor to national inflation within Indonesia is the commodity of rice. Over recent years, rice has emerged as a significant driver of inflation growth at the national level. The socio-cultural dynamics embedded in the Indonesian population's heavy reliance on rice as a primary food source result in supply oscillations for rice, consequently bearing implications for both political and economic domains (Kusumah, 2019). On a socio-cultural front, the general Indonesian populace shares a deeply rooted connection with rice as a foundational dietary staple that holds cultural and traditional significance.

Rice consumption data from the Central Statistics Agency (BPS) noted that in the last five years there has been an increase in rice consumption every year in Indonesia. In 2018 rice consumption of all types, including local, superior quality, and imported rice, averaged 1,404 kg per capita per week. This number then dropped to 1,374 kg per capita per week in 2019. However, when the pandemic hit, the average consumption rose to 1,379 kg per capita per week. Consumption also continues to increase in the second year of the pandemic, namely to 1,451 kg per capita per week in 2021. The Indonesian people's rice consumption rate is expected to increase to 31.7 million tons in 2045 in line with population growth (Octania, 2021).

The extensive consumption of rice in Indonesia finds its explanation in the fact that apart from directly catering to household needs, rice serves as a crucial raw material within various industrial sectors, including rice flour production and other segments of the food industry (Wibowo, 2000). Consequently, the demand for rice extends its influence to both political and economic spheres. From a political standpoint, rice consistently assumes the role of a strategic commodity in the agenda of every Indonesian president (Kusumah, 2019; McCulloch & Timmer, 2008). This political perspective becomes evident through governmental policies and measures aimed at regulating rice production, distribution, and pricing, all geared towards achieving specific political objectives. The paramount economic indicators that underscore the significance of rice encompass consumption patterns, production trends, and import/export activities (Riawanti, 2011, Dawe, 2008, McCulloch & Timmer, 2008).

This study endeavors to comprehensively assess the magnitude of rice's impact on the overall national inflation rate. In the context of policy discourse within Indonesia concerning food inflation, prevailing discussions underscore significant elements such as supply-demand disparities, inadequate infrastructure, climate change ramifications, financial investments, and the influence of seasonal occurrences as pivotal contributors to food inflation. Nonetheless, investigations pertaining to the specific influence of escalating rice prices on the broader national inflation within Indonesia remain notably scarce. Thus, this study aims to bridge this research gap by empirically examining the tangible effect of rice price fluctuations on the national inflation rate.

Because of this distinct feature Indonesian economic policy is continuously challenged to make a policy mix that copes this issue. At this setting Indonesian policy maker is in ever need to find new knowledge on both to cope with this challenge. Taking a macroeconomic perspective, we know that to explain the problem of inflation in Indonesia, we can take two approaches. The first is what so called a monetary approach. The second is the one that emphasizes the role of the supply of money as a cause of inflation and second, an approach that explains more about the price of rice as the main cause of price. Mentioning that rice price is a main influential factor to the inflation should be put in caution. In the context of Indonesia, highlighting rice prices as a primary influencing factor of inflation can indeed pose certain risks and challenges:

1. Cultural Sensitivity: Rice is not only a staple food in Indonesia but also deeply embedded in the cultural fabric of the nation. It carries social and symbolic significance that goes beyond its economic role. Associating rice directly with inflation could be seen as undermining its cultural importance and might elicit negative reactions.
2. Social Impact: Any indication that rice prices significantly contribute to inflation could lead to concerns about affordability and access to a basic necessity for many Indonesians. This could spark social unrest or public dissatisfaction, particularly among lower-income segments of the population.
3. Political Pressure: Acknowledging rice prices as a major driver of inflation might put added pressure on the government to manage and stabilize rice prices effectively. This could create challenges in balancing economic policies and political considerations.
4. Market Behaviour: Publicly identifying rice prices as a central cause of inflation might lead to market speculation and behaviour that exacerbate price fluctuations. This can complicate efforts to maintain stable prices.
5. Economic Complexity: While rice is undeniably important, inflation is influenced by a complex interplay of factors, including monetary policy, energy prices, supply chain disruptions, and external economic conditions. Simplifying it to just rice prices could lead to an incomplete understanding of the issue.

Given the potential risks involved, conducting research on the relationship between rice prices and inflation in Indonesia demands a meticulous and nuanced strategy that considers both economic and socio-cultural dimensions. The primary objective of this research is to comprehensively understand the influence of rice on the national inflation rate and provide empirical evidence concerning the nature and extent of fluctuations in rice prices and their impact on the overall inflation rate at a national level.

This study is centered around seeking tangible and measurable evidence regarding the repercussions of variations in rice prices on the broader national inflation landscape. To achieve this, the research methodology relies on utilizing secondary time series data. These data are sourced from reputable institutions vested with legal authority, such as the Information Center for Strategic Food Prices (PIHPS), ensuring the reliability and credibility of the information used in the study. By employing such data, the study aims to unveil insights into the intricate dynamics between rice price changes and their corresponding effects on the national inflation scenario.

RESEARCH METHODS

In time series econometric analysis, data that has high volatility will be very risky to be used as a basis for forecasting. This might happen to the data we employed, namely the time series data of volatile commodity prices in Indonesia. Under these conditions, the behavior of the time series data is very different from the assumptions that have been the study of mainstream econometrics, namely

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that time series data tends to have a constant error term variant from time to time. It means that the residual variance of this time series data is not constant and changes from one period to another or contains elements of heteroscedasticity. The variance of the residuals is no longer just a function of the independent variables but always changes, depending on how big the residuals are in the past. Therefore, before estimating the model, several tests such as stationary and cointegration tests are carried out as stages to meet the necessary and sufficient conditions for estimating the error correction mechanism (Suharno et al., 2017). All the data treatment, processing and calculation is conducted under E-View Program.

Data and Variables Definition

This study employed time series data. Aligned with the study's objectives and analytical requirements, we diligently gathered monthly inflation rates and consolidated prices of nine key food items. These data points were meticulously sourced from The Information Center for Strategic Food Prices (PIHPS) in Indonesia. The scope of our data collection spans from the year 2017 up to June 2023, comprising a total of 78 data series. To enhance clarity, the variables extracted from the available dataset have been comprehensively elucidated and outlined in Table 1 for easy reference.

Table 1. Variables Definition.

Variable Name	Name of the Items (unit)	E views Code
Inflation	Inflation rate (%)	Inf
Rice	Change in Rice Price (%)	Rice
Chicken	Change in Chicken Meat Price (%)	Ch
Beef	Change in Beef Price (%)	B
Chicken Egg	Change in Chicken Egg price (%)	Egg
Shallot	Change of Shallot price (%)	Slot
Garlic	Change in Garlic price (%)	G
Red Chili	Change in Red chili price (%)	Rc
Cayenne Pepper	Change in Cayenne pepper Price (%)	Cp
Cooking Oil	Change in cooking oil price (%)	Co
Sugar	Change in Sugar price (%)	Sg
Log natural	A natural logarithm; example lrc	L
Differencing	D Legitimized Difference; Example: dlrc	lrc

Augmented Dicky Fuller Test (ADF - Stationarity Test)

Because of the status as a series data we perform to the data the Augmented Dickey-Fuller test (ADF Test) to test. The purpose is to verify whether our 78 series data is stationary or not. In the first step we use Pearson Correlation coefficient to see the degree of correlation between observed variables. Positive coefficient means the presence of two events that have a positive connection. Pearson correlation coefficient is the most used statistic to measure linear relationships between variables. It is important to note though, that it has no causality meaning. As the definition indicates Pearson correlation coefficient only relates the mean and standard deviation of two variables. We can conclude anything about their dependency. The positive relationship is merely a mathematical result since we know the two series are related in only one direction. More precisely, past values of Y1 are linearly related to actual values of Y2 (vice-versa is not valid). Our scope is to make a practical demonstration of this statement.

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Special Edition: 621-636, June 2024

Granger Causality Performance

As stated the ultimate aim of this study is to provide an empirical evident regarding the direction and magnitude of rice price influence on the inflation rate in Indonesia. In this case we employed 78 time series data of monthly inflation variables. The measurement on which we reliant is Granger Causality statistic performance. Granger Causality Analysis is a statistical technique used to determine whether one time series can be used to predict another time series. Named after the Nobel Prize-winning economist Clive Granger, the operation of Granger Causality is directed to reveal the relationship between two time-dependent variables needs to be explored. Here's a step-by-step breakdown of how Granger Causality Analysis works: after data being collection:

1. Setting the Null Hypothesis: the past values of variable A do not significantly improve the prediction of variable B, beyond the information contained in the past values of variable B itself.
2. Lag Selection: Choosing an appropriate number of lagged time steps for both variables. Lag refers to how many past time points one wants to include in the analysis. This step is crucial because it determines the amount of historical data you consider for prediction.
3. Model Fitting: to build autoregressive models for both variables using the selected number of lagged time steps. An autoregressive model is a regression of a variable against its own past values. The idea is to predict the current value of the variable using its past values.
4. Hypothesis Testing: to compare the performance of two models:
   Model 1: to redict variable B's current value using its own past values;
   Model 2: to predict variable B's current value using its own past values and the past values of variable A.
5. Statistical Test: Apply a statistical test (usually based on the F-test) to determine whether the inclusion of lagged values from variable A significantly improves the prediction of variable B. If the test yields a statistically significant result, one can reject the null hypothesis and conclude that variable A Granger-causes variable B.

We understand the note that Granger causality doesn't establish a true cause-and-effect relationship in the traditional sense. It only indicates whether one variable helps predict another based on their historical behavior. It's also sensitive to the choice of lags and can be influenced by other variables that might be omitted from the analysis.

RESULT AND DISCUSSION

Inflation Rate and Prices of Food Group

In pursuit of addressing our study objective, we embarked on a comprehensive data collection endeavor focusing on both the inflation rate and the prices within various volatile food groups. This meticulous process involved not only the gathering of relevant data points but also meticulous treatment to ensure its accuracy and reliability. Upon successfully collecting and refining the raw data, we meticulously processed it, employing rigorous methodologies to enhance its quality. These refined datasets were subsequently harnessed to perform crucial calculations, particularly in determining correlations—an essential aspect of our analysis.

The culmination of these efforts finds its representation in the data presented in Table 2. This tabulated presentation provides a succinct overview, offering a glimpse into the rich tapestry of information that we've meticulously curated and prepared. Through the presentation of this data, we

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Special Edition: 621-636, June 2024

aim to shed light on the relationships and trends between inflation rates and the prices associated with various food groups. The significance of this table lies not only in its presentation of numbers but in the insights it harbors. Each entry is a testament to the meticulousness of our data collection and preparation processes. As we proceed with our analysis, this table serves as a foundational reference, enabling us to draw informed conclusions that contribute to our study's overarching objectives.

The process to address our study's objectives involved a series of conscientious steps: data collection, refinement, and presentation. Table 2 encapsulates the results of these endeavors, acting as a key artifact that underscores the depth of our analytical pursuits. Through the correlations drawn from this data, we anticipate unlocking valuable insights that will contribute to a better understanding of the complex interplay between inflation rates and the prices of diverse food groups.

Table 2. Data Sketch and Variables Definition.

2017				Inf	Inflation rate (%)
				Rice	Change in Rice Price (%)
2018				Ch	Change in Chicken Meat Price (%)
				B	Change in Beef Price (%)
				Egg	Change in Chicken Egg price (%)
2019				Slot	Change of Shallot price (%)
				G	Change in Garlic price (%)
2020				Rc	Change in Red chilli price (%)
	Cells of data	Cells of data	Cells of data		
2021				Co	Change in cooking oil price (%)
				Sg	Change in Sugar price (%)
				L	A natural logarithm; example lrc
2022				Lrc	D Logaritmized Difference; Example: dlrc
2023					

Augmented Dicky Fuller Test (ADF - Stationarity Test)

The Augmented Dickey-Fuller (ADF) test is a common test for assessing the stationarity of a time series. Stationarity is important in time series analysis because many statistical methods assume that the data exhibit constant statistical properties over time. Non-stationary data can lead to spurious correlations and unreliable results. The ADF test helps determine if a unit root is present in the data, which indicates non-stationarity.

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Table 3. ADF TEST (Stationarity Test).

Variables	Constant		Constant and Trend	
Inf	-1.425922	0.5653	-1.0301148	0.9332
D (inf)	-7.007755	0.0000	-7.030815	0.0000
Rice	-3.231385	0.0222	-6.770115	0.0000
D (rice)	-7.144904	0.0000	-7.093937	0.0000
Chicken	-5.672042	0.0000	-6.522893	0.0000
D (chicken)	-9.033771	0.0000	-8.961616	0.0000
Beef	0.089761	0.9629	-4.378250	0.0042
D(beef)	-10.16178	0.0001	-10.22230	0.0000
Egg	-4.054933	0.0020	-6.112032	0.0000
D (egg)	-9.599245	0.0000	-9.534087	0.0000
Shallot	-3.506431	0.0103	-4.318396	0.0050
D (shallot)	-9.738781	0.0000	-9.675450	0.0000
Garlic	-3.418880	0.0132	-3.324441	0.0700
D (garlic)	-9.731483	0.0000	-9.733468	0.0000
Red chili	-2.908905	0.0489	-3.426715	0.0553
D (red chili)	-8.334200	0.0000	-8.288711	0.0000
Cayenne pepper	-3.487391	0.0109	-3.935181	0.0151
D (CP)	-10.10815	0.0000	-10.05066	0.0000
Cooking oil	-0.938350	0.7709	-2.288442	0.4349
D (cooking oil)	-10.68534	0.0001	-10.70209	0.0000
Sugar price	-2.876836	0.0527	-3.043138	0.1276
D (sugar price)	-10.51705	0.0001	-10.46928	0.0000

We performed the test, the ADF test on multiple variables, and we have results for both constant and constant with trend models. The ADF test results are presented as follows:

1. Variables: These are the variables for which we’ve conducted the ADF test;
2. The column Constant: provides the ADF test statistic for the null hypothesis that a unit root is present (i.e., the data is non-stationary) against the alternative that the data is stationary with a constant;
3. Constant and Trend: This column provides the ADF test statistic for the null hypothesis that a unit root is present against the alternative that the data is stationary with both a constant and a trend;
4. Test Statistic, 0.05 Value, Prob.: These columns show the ADF test statistic, the critical value at the 5% significance level, and the associated p-value, respectively;
5. For the variable "Inf": In the "Constant" model, the ADF test statistic is -1.425922, and the p-value is 0.9332. In the "Constant and Trend" model, the ADF test statistic is -1.0301148, and the p-value is 0.9332. In both cases, the p-value is much larger than 0.05. This suggests that you do not have enough evidence to reject the null hypothesis of a unit root (non-stationarity) for the variable "Inf."

In both the "Constant" and "Constant and Trend" models, the ADF test statistic is significantly lower than their respective critical values (in this case, it's very close to 0). The p-value is reported as 0.0000, indicating strong evidence to reject the null hypothesis of a unit root. This suggests that the first difference of the variable "Inf" is stationary.

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Correlation

Upon completing the process of data collection and refinement, we come to a pivotal phase of our study—calculating correlations. Using E-Views program the results of correlation calculation is presented in Table 4. Each entry in this table is a numeric evident to the strength and direction of the connections we've unveiled between inflation rates and the prices encompassed within various food groups. Table 4 stands as a tangible result of our data analysis. As we navigate its contents, we discern patterns that speak to the complex dynamics at play. The positive, negative, or neutral correlations deliver a narrative that enriches our understanding of the economic relationship involved in Table 4.

1. Each row and column header corresponds to a time series variable;
2. The values in the cells represent the correlation coefficient between the variables at the intersection of the row and column;
3. The range of the correlation coefficient is from -1 to 1;.
4. A value of 1 indicates a perfect positive correlation, meaning when one variable goes up, the other variable also goes up by a proportional amount;
5. A value of -1 indicates a perfect negative correlation, meaning when one variable goes up, the other variable goes down by a proportional amount;
6. A value close to 0 indicates a weak or no linear correlation between the variables.

Table 4. Variable Correlations.

	LSLOT	LSG	LRICE	LRC	LINF	LG	LEGG	LCP	LCO	LCH	LB
LSLOT	1										
LSG	0.6139***	1									
LRICE	-0.0691	0.0467	1								
LRC	0.414***	0.088	-0.288*&	1							
LINF	0.108	0.143	0.124	0.065	1						
LG	0.294***	0.381***	0.150	-0.195***	0.279***	1					
LEGG	0.620***	0.369***	-0.180	0.562	0.038	-0.142	1				
LCP	0.321***	0.109	-0.118	0.769***	0.0106	0.005	0.363***	1			
LCO	0.501***	0.363***	-0.058	0.5304***	0.327***	-0.0502	0.5206***	0.472***	1		
LCH	0.303***	0.058	-0.14606	0.3417***	-0.148	-0.211	0.587***	0.331***	0.365***	1	
LB	0.4872***	0.307***	-0.092	0.549***	0.1909*	-0.077	0.598***	0.508***	0.8907***	0.402***	1

Notes:
*** : strong significant
** : weaker significant
* : the weakest significant

In accordance with the data presented earlier, Table 4 forms a comprehensive foundation for our study's conclusions. These correlations serve as a basis upon which we make our interpretations and insights. They underscore the significance of our research, shedding light on the ways in which inflation interacts not only with the prices of rice but also distinct food groups. From the correlation matrix of Table 3 we can draw three categories of variable relationship.

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1. Variables with strong positive correlations (values closer to 1):
    a. LSLOT and LSG (0.6139)
    b. LSLOT and LEGG (0.620)
    c. LSG and LEGG (0.369)
    d. LSG and LCO (0.363)
    e. LSG and LB (0.307)
    f. LRC and LSG (0.414)
    g. LG and LSG (0.381)
    h. LG and LEGG (0.279)
    i. LCO and LB (0.508)
    j. LB and LCH (0.402)
    k. LB and LCO (0.8907)
2. Variables with weaker correlations (values closer to 0):
    a. LRICE and LRC (-0.288)
    b. LINF and LCH (0.365)
    c. LINF and LG (0.279)
    d. LINF and LSG (0.143)
3. Variables with negative correlations (values closer to 0):
    a. LRICE and LINF (0.124)
    b. LRICE and LCH (-0.146)
    c. LRC and LG (-0.195)
    d. LRC and LCO (-0.058)

As mentioned previously, this study aims to examine the influence of rice prices on Indonesia's national inflation rate. At this stage the primary focus is on determining the correlation coefficient between monthly inflation and changes in the prices of food commodities categorized as volatile foods. This correlation coefficient serves as an early indicator of a close relationship between the two variables, without implying a causal connection. To enable a comparison and gain further insights, the analysis also encompasses price variables for other commodities beyond rice, in order to identify their correlation with the national inflation rate.

Upon analyzing Table4, which presents correlation data, empirical evidence emerges indicating that rice prices fall within the category of weak correlation food prices. Within this category, there exists a slight negative correlation of approximately 0.124 between rice prices (LRICE) and the national monthly inflation variable (LINF). This empirical evidence suggests that both inflation and rice prices share a weak or negligible linear correlation. Our investigation of the 2017 to 2023 time series data yields no substantial correlation between inflation and rice prices.

For drawing comparisons and fortifying the strategies to price stabilize policy combating unexpected inflation, the research could expand its scope by posing the question: Among the volatile foods group, which commodity exhibits a significant correlation with national inflation? Referring to Table 3, it becomes evident that there isn't a strong and noteworthy correlation between national inflation and food commodities within the volatile foods group. The inflation variable demonstrates only a weak negative correlation with chicken meat, shallots, and cooking oil among these commodities. Realizing this, we continue the investigation to the level, how much the rice price variable affects the inflation rate. Combined with the results of the casuistic analysis, policy proposals that are in accordance with empirical facts can be developed.

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Special Edition: 621-636, June 2024

Cointegration Test (Johansen)

The cointegration test is used as a basis for determining whether the equation used has a long-term balance or not, if the equation is proven to be cointegrated through this Johansen test, then the estimation equation has a long-term balance. Table 5 is the output from a Johansen cointegration test using the trace statistic. This test is used to determine the number of cointegrating relationships among a set of inflation rate (variables). Cointegration implies a long-term equilibrium relationship between these variables. Going through each part of the output we understand how to read and interpret it:

1. Trace Statistic: The trace statistic tests the null hypothesis that the number of cointegrating vectors is less than or equal to a specified rank. It is presented in the third column of Table 5.
2. Maximum Eigenvalue Statistic (the second column of Table 5): This tests the null hypothesis that the number of cointegrating vectors is equal to a specified rank.
3. Critical Values (in the fourth column of Table 5) is the ones for the trace and maximum eigenvalue statistics. These critical values are based on tabulated values from the Johansen test distribution.

The Table 5 shows that the trace statistic value is 336.9838. The 0.05 value is 285.1425. Since the trace statistic value is greater than the 0.05 value, we can reject the null hypothesis of at most 1 cointegrating equation and conclude that there are at least two cointegrating equations at the 0.05 level of significance. So, the trace test indicates that there are 2 cointegrating equations at the 0.05 level.

Table 5. Cointegration Test Johansen (Trace Statistic).

Unrestricted Cointegration Rank Test (trace)				
Hypothesized No. of CE (S)	**Eigenvalue**	**Trace Statistic**	**0.05 Value**	**Prob.****
None*	0.678619	336.9838	285.1425	0.0000
At Most 1*	0.501653	249.5791	239.2354	0.0157
At Most 2	0.427419	195.9518	197.3709	0.0587
At Most 3	0.403432	153.0165	159.5297	0.1069
At Most 4	0.340011	113.2412	125.6154	0.2210
At Most 5	0.290060	81.24523	95.75366	0.3243
At Most 6	0.225027	54.86692	69.81889	0.4246
At Most 7	0.202590	35.23756	47.85613	0.4355
At Most 8	0.155111	17.80582	29.79707	0.5805
At Most 9	0.052760	4.827491	15.49471	0.8269
At Most 10	0.008456	0.653893	3.841466	0.4187

[a] Trace test indicates 2 cointegrating eqn (s) at the 0.05 level
[b] * denotes rejection of the hypothesis at the 0.05 level
[c] ** MacKinnon-Haug-Michelis (1999) p-values

Table 5 shows the results of the Unrestricted Cointegration Rank Test (trace) for different hypothesized numbers of cointegrating equations. The table contains four columns: No. of CE (S), Eigenvalue, Trace Statistic, and two additional columns for critical values and probabilities 1. The number of cointegrating equations is indicated by S in column No. of CE (S). The Eigenvalue column shows the eigenvalues associated with each number of cointegrating equations. The Trace Statistic column shows the test statistic for each number of cointegrating equations. The last two columns provide critical values and probabilities for each test.

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According to the Johansen cointegration test results, there are two cointegrating equations based on the trace statistic. The trace statistic tests the null hypothesis that there is r or fewer cointegrating vectors against the alternative hypothesis that there is r+1 cointegrating vectors. In this case, the trace test indicates 2 cointegrating equations at the 0.05 level 1. Cointegration measures the long-term relationship between two variables. It is used to identify pairs of variables that are related in the long run and can be used to predict each other. Cointegration is a statistical property of time series variables that indicates that they share a common stochastic trend. If two variables are cointegrated, it means that they will converge to their long-run equilibrium relationship after being shocked by a temporary disturbance.

In our work, the long-term equation model obtained from running the data into program tool is as follows (Table 6). These two cointegration, they represent the number of linear combinations of the variables (inflations rate) that are stationary and in other words, these two equations show how the variables are related in the long run and how they have a long-run equilibrium relationship; they share common stochastic trends to deviations from this long-run equilibrium. The fact that we found that there are two of cointegrating vectors, we actually can use the estimated coefficients from the Johansen test to identify which pairs of variables are cointegrated.

Table 6.

Cointegrating Eq:	**CointEq1**	**CointEq2**									
DINE(-1)	1.000000	0.000000									
DLB(-1)	0.000000	1.000000									
DLCH(-1)	-1.071562	5.232746									
	(0.35573)	(0.98169)									
	[-3.01228]	[5.33036]									
DLCO(-1)	-3.384756	-3.874168									
	(0.43488)	(1.20011)									
	[-7.78318]	[-3.22817]									
DLCP(-1)	0.557878	0.334739									
	(0.17057)	(0.47070)									
	[3.27072]	[0.71115]									
DLEGG(-1)	2.713070	-5.767528									
	(0.31863)	(0.87930)									
	[8.51479]	[-6.55921]									
DLG(-1)	-1.089168	-2.450545									
	(0.15838)	(0.43707)									
	[-6.87701]	[-5.60681]									
DLRC(-1)	-1.051621	1.641201									
	(0.18585)	(0.51289)									
	[-5.65831]	[3.19991]									
DLRICE(-1)	0.037049	-0.501084									
	(0.05049)	(0.13933)									
	[0.73380]	[-3.59630]									
DLSG(-1)	0.012716	4.812453									
	(0.63386)	(1.74922)									
	[0.02006]	[2.75119]									
DSLOT(-1)	0.246637	2.361777									
	(0.18461)	(0.50945)									
	[1.33600]	[4.63592]									
C	0.022388	-0.020217									
Error Correction:	D(DINF)	D(DLB)	D(DLCH)	D(DLCO)	D(DLCP)	D(DLEGG)	D(DLG)	D(DLRC)	D(DLRICE)	D(DLSG)	D(DSLOT)
CointEq1	-0.171262	0.121824	-0.071456	0.129375	0.086701	-0.400853	0.071257	0.162026	-0.599648	-0.089720	-0.255022
	(0.08690)	(0.08938)	(0.09388)	(0.05341)	(0.18970)	(0.10293)	(0.16146)	(0.13723)	(0.57622)	(0.03638)	(0.15051)
	[-1.97082]	[1.36302]	[-0.76114]	[2.42228]	[0.45705]	[-3.89460]	[0.44133]	[1.18069]	[-1.04066]	[-2.46609]	[-1.69440]
CointEq2	-0.028695	-0.048342	-0.050620	0.040235	-0.051661	0.023123	0.074979	-0.226604	0.614269	-0.024400	-0.099045
	(0.02880)	(0.02962)	(0.03111)	(0.01770)	(0.06286)	(0.03411)	(0.05350)	(0.04547)	(0.19094)	(0.01206)	(0.04987)
	[-0.99648]	[-1.63220]	[-1.62718]	[2.27333]	[-0.82184]	[0.67796]	[1.40139]	[-4.98314]	[3.21701]	[-2.02390]	[-1.98588]
D(DINE(-1))	-0.411505	-0.367662	0.296301	0.106114	0.043120	0.456116	0.190794	0.014046	0.162739	0.170339	0.182171
	(0.12402)	(0.12756)	(0.13398)	(0.07623)	(0.27073)	(0.14689)	(0.23043)	(0.19585)	(0.82236)	(0.05192)	(0.21480)
	[-3.31808]	[-2.88231]	[2.21150]	[1.39210]	[0.15927]	[3.10512]	[0.82800]	[0.07172]	[0.19789]	[3.28067]	[0.84809]
D(DLB(-1))	0.193936	-0.414506	0.146958	-0.003687	-0.083685	0.001563	0.087895	-0.016597	-0.026117	-0.007240	0.090548
	(0.10675)	(0.10980)	(0.11533)	(0.06561)	(0.23304)	(0.12644)	(0.19835)	(0.16858)	(0.70787)	(0.04469)	(0.18490)
	[1.81668]	[-3.77512]	[1.27424]	[-0.05620]	[-0.35911]	[0.01236]	[0.44314]	[-0.09845]	[-0.03689]	[-0.16198]	[0.48972]
D(DLCH(-1))	-0.116623	-0.054571	-0.458862	-0.069922	0.067760	-0.289061	-0.333445	0.642184	-2.081839	0.022833	0.119936
	(0.15096)	(0.15527)	(0.16309)	(0.09278)	(0.32954)	(0.17880)	(0.28048)	(0.23839)	(1.00101)	(0.06320)	(0.26146)

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	[-0.77254]	[-0.35146]	[-2.81359]	[-0.75359]	[0.20562]	[-1.61666]	[-1.18882]	[2.69380]	[-2.07974]	[0.36128]	[0.45871]
D(DLCO(-1))	-0.160746	0.101800	-0.206838	-0.062235	-0.012256	-0.549801	0.475227	-0.282003	0.738405	-0.303337	-0.316189
	(0.23370)	(0.24037)	(0.25247)	(0.14364)	(0.51016)	(0.27680)	(0.43422)	(0.36906)	(1.54965)	(0.09784)	(0.40477)
	[-0.68783]	[0.42351]	[-0.81924]	[-0.43327]	[-0.02402]	[-1.98627]	[1.09445]	[-0.76412]	[0.47650]	[-3.10029]	[-0.78116]
D(DLCP(-1))	-0.015310	0.055444	-0.003192	-0.120265	-0.818675	0.034064	-0.088484	-0.244711	-0.291736	-0.028605	0.219091
	(0.08346)	(0.08584)	(0.09017)	(0.05130)	(0.18219)	(0.09885)	(0.15507)	(0.13180)	(0.55343)	(0.03494)	(0.14455)
	[-0.18344]	[0.64588]	[-0.03540]	[-2.34447]	[-4.49348]	[0.34459]	[-0.57061]	[-1.85668]	[-0.52715]	[-0.81864]	[1.51562]
D(DLEGG(-1))	0.005652	-0.301584	-0.035670	0.071144	-0.092354	0.126150	-0.104953	-0.924756	3.523138	0.097069	-0.085054
	(0.17829)	(0.18338)	(0.19261)	(0.10958)	(0.38920)	(0.21117)	(0.33126)	(0.28155)	(1.18223)	(0.07464)	(0.30880)
	[0.03170]	[-1.64461]	[-0.18519]	[0.64924]	[-0.23729]	[0.59739]	[-0.31683]	[-3.28450]	[2.98009]	[1.30044]	[-0.27543]
D(DLG(-1))	-0.067136	-0.020665	-0.053158	0.203643	-0.056395	-0.329898	-0.506744	-0.419169	0.954106	-0.142609	-0.703784
	(0.09988)	(0.10274)	(0.10791)	(0.06139)	(0.21804)	(0.11831)	(0.18559)	(0.15774)	(0.66233)	(0.04182)	(0.17300)
	[-0.67214]	[-0.20115]	[-0.49262]	[3.31710]	[-0.25864]	[-2.78851]	[-2.73050]	[-2.65741]	[1.44053]	[-3.41023]	[-4.06810]
D(DLRC(-1))	0.221306	0.108347	0.174883	0.142496	0.483048	-0.083188	0.231327	0.114995	-1.098165	0.008465	0.034080
	(0.11913)	(0.12252)	(0.12870)	(0.07322)	(0.26005)	(0.14110)	(0.22134)	(0.18812)	(0.78991)	(0.04987)	(0.20633)
	[1.85776]	[0.88428]	[1.35889]	[1.94619]	[1.85755]	[-0.58959]	[1.04514]	[0.61128]	[-1.39023]	[0.16972]	[0.16518]
D(DLRICE(-1))	0.004994	-0.034328	0.016523	0.009485	0.045468	0.029594	0.043870	-0.020065	-0.507516	-0.000799	0.000867
	(0.01776)	(0.01826)	(0.01918)	(0.01091)	(0.03876)	(0.02103)	(0.03299)	(0.02804)	(0.11773)	(0.00743)	(0.03075)
	[0.28125]	[-1.87979]	[0.86143]	[0.86915]	[1.17311]	[1.40727]	[1.32984]	[-0.71561]	[-4.31074]	[-0.10746]	[0.02818]
D(DLSG(-1))	0.166292	-0.471784	0.088232	0.351347	0.397093	-0.121090	0.086973	0.520056	-3.821598	-0.473850	0.446795
	(0.28138)	(0.28941)	(0.30398)	(0.17294)	(0.61424)	(0.33327)	(0.52280)	(0.44435)	(1.86581)	(0.11780)	(0.48735)
	[0.59099]	[-1.63017]	[0.29025]	[2.03157]	[0.64648]	[-0.36334]	[0.16636]	[1.17038]	[-2.04823]	[-4.02240]	[0.91679]
D(DSLOT(-1))	0.013990	0.229702	0.090602	-0.232013	-0.015867	0.072478	-0.039687	0.303301	-1.021706	0.004352	-0.141546
	(0.08966)	(0.09221)	(0.09686)	(0.05510)	(0.19571)	(0.10619)	(0.16658)	(0.14158)	(0.59450)	(0.03754)	(0.15528)
	[0.15604]	[2.49096]	[0.93540]	[-4.21038]	[-0.08107]	[0.68252]	[-0.23824]	[2.14221]	[-1.71859]	[0.11594]	[-0.91153]
C	0.002458	-0.002651	-0.001629	0.000687	0.004318	-0.001054	-0.001283	0.000836	0.010792	-0.001371	0.000327
	(0.01316)	(0.01354)	(0.01422)	(0.00809)	(0.02873)	(0.01559)	(0.02445)	(0.02078)	(0.08727)	(0.00551)	(0.02280)
	[0.18677]	[-0.19587]	[-0.11455]	[0.08488]	[0.15031]	[-0.06763]	[-0.05245]	[0.04024]	[0.12366]	[-0.24874]	[0.01434]
R-squared	0.483486	0.490096	0.483451	0.622351	0.453035	0.557866	0.415553	0.556979	0.606614	0.643621	0.535777
Adj. R-squared	0.349192	0.357521	0.349148	0.524162	0.310825	0.442911	0.263597	0.441794	0.504333	0.550963	0.415079
Sum sq. resids	0.552746	0.584744	0.645126	0.208809	2.634003	0.775430	1.908178	1.378451	24.30397	0.096885	1.658149
S.E. equation	0.105142	0.108143	0.113589	0.064623	0.229521	0.124534	0.195355	0.166039	0.697194	0.044019	0.182107
F-statistic	3.600211	3.696745	3.599712	6.338306	3.185662	4.852907	2.734694	4.835504	5.930885	6.946161	4.438994
Log likelihood	61.24358	59.44280	56.29812	92.39488	11.28004	50.41100	21.59543	32.00146	-59.82827	116.9677	26.08973
Akaike AIC	-1.476362	-1.420087	-1.321816	-2.449840	0.084999	-1.137844	-0.237357	-0.562546	2.307134	-3.217740	-0.377804
Schwarz SC	-1.004106	-0.947832	-0.849560	-1.977584	0.557254	-0.665588	0.234899	-0.090290	2.779389	-2.745484	0.094452
Mean dependent	0.002912	-0.001657	-4.23E-05	-0.000345	0.001223	0.000183	5.27E-05	0.001306	-8.84E-05	-0.000786	0.002794
S.D. dependent	0.130332	0.134918	0.140798	0.093683	0.276477	0.166849	0.227650	0.222235	0.990281	0.065690	0.238110
Determinant resid covariance (dof adj.)		2.61E-21									
Determinant resid covariance		1.73E-22									
Log likelihood		604.5991									
Akaike information criterion		-13.39372									
Schwarz criterion		-7.456794									
Number of coefficients		176									

Selection Criteria

As for how to make an introduction for this table, you can start by providing a brief background on what led to conducting this test and why it is important. You can then introduce the table by stating that it shows the selection criteria for each lag order in a Johansen cointegration test conducted on two time series. You can also mention what each column in the table represents and how to interpret them based on what we discussed earlier 1.

As explained previously the objective of finding the long-term relationship among the data we have has led us to the Table 7 which presents a selection criterion. As in the previous explanation The Table 7 shows the results of a Johansen cointegration test conducted on two time series. The table contains the selection criteria for each lag order, which are used to determine the optimal number of lags to include in the model. The selection criteria include the log-likelihood (LogL), the sequential modified LR test statistic (LR), the final prediction error (FPE), and three information criteria: Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ)

Table 7. Selection Criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	559.7864	NA	1.22e-20	-14.63430	-14.29441	-14.49859
1	976.8996	700.7502*	4.69e-24*	-22.53066*	-18.45188*	-20.90204*
2	1083.286	147.5218	8.40e-24	-22.14095	-14.32329	-19.01944
3	1189.200	115.8000	2.20e-23	-21.73867	-10.18213	-17.12427

[a] * indicates lag order selected by the criterion

[b] LR: Sequental modified LR test statistic (each test at 5% level)

[c] FPE: final prediction error

[d] AIC: Akaike information criterion

[d] SC: Schwarz information criterion

[d] HQ: Hannan-Quinn information criterion

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As an interpretation to this table, please look at the lag order selected by each criterion, indicated by an asterisk in column LR. For example, in this case, the lag order selected by LR is 1. Knowing that we then examine the values of each criterion for that lag order. For instance, for lag order 1, we have LogL = 976.8996, LR = 700.7502, FPE = 4.69e-24, AIC = -22.53066, SC = -18.45188, and HQ = -20.90204

Granger Causality Analysis

As stated the ultimate aim of this study is to provide an empirical evident regarding the direction and magnitude of rice price influence on the inflation rate in Indonesia. In this case we employed 78 time series data of monthly inflation variables. The measurement on which we reliant is Granger Causality statistic performance. The fundamental idea behind Granger causality is that if a time series A Granger-causes another time series B, then the past values of time series A should provide useful information in predicting the future values of time series B, beyond what can be predicted by looking at the past values of time series B alone. Table 8 summarized the pairwise causality relationship of and among the variables.

Table 8. Summary of Engel Granger Causality - Pairwise Granger.

Variables	F statistic	Probability
Beef > chicken	4.41396	0.0391
Cooking oil > beef	7.62150	0.0073
Beef > cooking oil	2.90030	0.0928
Beef > inflation	4.32303	0.0367
Beef > sugar	3.00531	0.0872
Beef > shallot	9.03462	0.0036
Cooking oil > chicken	4.24257	0.0429
Egg > chicken	3.08181	0.0833
Chicken > garlic	3.57413	0.0626
Chicken > inflation	4.328899	0.0338
Red chili > chicken	5.57008	0.0209
Chicken > red chili	2.80844	0.0980
Shallot > chicken	2.86567	0.0947
Cooking oil > chicken	2.86567	0.0947
Cooking oil > egg	8.11829	0.0057
Cooking oil > inflation	7.685818	0.0071
Cooking oil > red chili	3.36647	0.00706
Cooking oil > shallot	5.47347	0.0220
Cayenne pepper > red chili	3.08437	0.0832
Red chili > egg	9.57921	0.0028
Shallot > egg	3.81435	0.0546
Rice > garlic	2.88622	0.0935
Garlic > rice	2.93197	0.0910
Sugar > garlic	3.43450	0.0678
Garlic > garlic	4.84973	0.0308
Rice > inflation	2.45187	0.0920

The concept of pairwise causality becomes instrumental in assessing whether A Granger-causes B by transmitting informative insights. In the context of our investigation, our focus is directed towards the intricate relationship between inflation and other variables. By analyzing the outcomes showcased in Table 6, we can

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deduce various causal relationships. Notably, there are four variables that stand out as potential Granger causal factors for Indonesian inflation: beef, chicken meat, cooking oil, and rice.

Among these, rice exhibits the least significant influence on Indonesian inflation. This observation delivers a significant message, debunking the misconception that rice prices play a pivotal role in causing Indonesian inflation. The empirical data spanning from 2017 to 2023 refutes the notion that rice prices are a primary driver of Indonesian inflation. This discovery holds noteworthy implications for Indonesian authorities, as it provides a substantial basis for explaining the underlying causes of inflation. Given the potential repercussions of falsely attributing Indonesian inflation to rice prices, this empirical evidence stands to serve as a valuable tool for crafting effective economic communication strategies. By incorporating this finding into economic stabilization policies, it is anticipated that it will contribute to fostering a more stable economic environment.

CONCLUSION AND SUGGESTION

This study is based on an analysis of correlation and causality involving 78 series of monthly data on inflation and price changes of key food items, categorized as volatile foods in inflation calculations. The primary focus is on understanding the connection between changes in rice prices and the national inflation rate of Indonesia. The outcomes of the correlation analysis indicated a weak link between changes in rice prices and the inflation rate. The subsequent Engel–Granger causality analysis, conducted on a time series dataset spanning from 2017 to 2023, revealed empirical evidence that the inflation rate in Indonesia is significantly influenced by the inflation of four major food items: beef, chicken, cooking oil, and rice. Notably, the change in rice prices does not stand as the sole determinant of the Indonesian inflation rate.

Furthermore, based on the variance decomposition test, market shocks—particularly dramatic price changes—have a major impact on the national inflation rate, with four key food items—red chili, garlic, chicken eggs, and chicken meat—exerting a substantial influence. Surprisingly, fluctuations in rice prices do not trigger corresponding shocks in the inflation rate. Considering the results of the correlation test, the inflation rate demonstrates a significant positive correlation not only with rice but also with cooking oil. Cooking oil is also significantly correlated with other variables. As a result, it becomes evident that rice alone cannot be considered the primary catalyst for changes in the inflation rate. The implications derived from this research suggest several courses of action:

1. Stabilization Policy: Stabilization policies should encompass a broader range of volatile food items beyond just rice. The analysis underscores the importance of considering other influential factors in addition to rice prices.
2. Institutional Aspects: Stabilization efforts need to extend beyond market and technological considerations to encompass institutional factors. This includes addressing policy processes and agribusiness arrangements, recognizing the role they play in shaping inflation dynamics.

In summary, this study's findings shed light on the complex relationship between rice prices and the inflation rate in Indonesia. While rice remains a factor, it is not the sole driver of inflation. These insights suggest the need for comprehensive policies that account for a diverse array of factors, both in terms of food items and institutional considerations, to effectively manage and stabilize inflation in the country.

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