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Long-term casual analysis of the energy-food price relationship

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ABSTRACT

The energy price index is a key economic measure that tracks changes in the prices of energy commodities, such as petroleum, electricity, and gas. This study aims to explore how the energy price index influences the food price index, as both have significant impacts on the economy. The relationship between energy and food prices is complex and affected by various factors. The novelty of this research lies in identifying the time period during which increases in energy prices impact food prices due to inflation. A statistical approach is applied to investigate this effect, using data from Pakistan's energy and food price indices for the period between January 2019 and May 2023. The Augmented Dickey-Fuller (ADF) test is employed to assess whether the time series is stationary, followed by the Granger causality test to determine if the energy price index can be used to predict changes in the food price index. The Engle-Granger cointegration test is used to identify long-term relationships between non-stationary time series. Additionally, various lag tests are conducted to determine the minimum time period within which changes in energy prices influence food prices. This research has practical implications for policymakers. Government agencies can use the findings to predict potential changes in food prices, and the study may also be relevant to the United Nations' Sustainable Development Goals (SDGs), as shifts in food prices could directly or indirectly affect several SDGs.

1. Introduction

Based on research by the Borgen Project (Risse, 2005) on poverty in Pakistan, 31.3% of Pakistan's population lived below the poverty line in 2018, with projections that this rate would increase to 40% within two years, highlighting a concerning trend. According to the World Bank, Pakistan is a developing country with a population of approximately 220.9 million people. Despite having abundant natural resources, Pakistan's per capita income—a measure of a nation's standard of living and quality of life—does not support improvements in the population's living conditions. As a result, even slight increases in the prices of essential goods strain the budgets of ordinary citizens.

Food inflation is a challenge for many countries. Policymakers should not assume that excluding food price rises from core inflation data will reflect better inflation trends (Walsh, 2011). Pakistan has experienced steadily rising food prices for years, which affect the costs of cereals, vegetables, fruits, meat, and other food items. From 2020 to 2023, food prices in Pakistan increased significantly (see Fig. 1, economic trading report, tradingeconomics.com).

Beyond food prices, energy costs also have a significant impact on a nation's economy. The energy price index is an important economic measure that tracks changes in energy commodity prices, such as gasoline, natural gas, and electricity (Moshiri, 2015). This index is often used as an indicator of overall economic inflation and can greatly affect the economy (van de Ven and Fouquet, 2017). The energy price index provides insights into economic development, inflation, and international trade, which is why it is closely monitored by politicians, policymakers, economists, and investors (Chang et al., 2009). The economy can be changed a lot by both the food price index and the energy price index. A lot of people are looking into whether energy costs affect food prices and whether the different food groups in the food price index are linked in the same way (Kirikkaleli and Darbaz, 2021). The intricate relationship between energy costs and food prices depends on the food supply chain, the kind of food produced and eaten, and the degree of energy dependency in food production. Three key energy

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components are used in the Energy index. The energy index is comprised of the fuel, electricity, and gas indexes (Gooding, 2017; Liu et al., 2010). In this study, it is crucial to determine the correlation between energy prices and food prices. Moreover, it is important to consider the impact of this phenomenon on the various sub-groups within the food price index. Previous research has shown that during periods of economic crises, there was a significant increase in food costs, resulting in a doubling of their original values (Kirikkaleli and Darbaz, 2021). It is essential to determine how energy prices impact food prices and to identify the time period over which fluctuations in energy prices lead to changes in food prices. To analyze the impact of food and energy indexes on one another, it was required to make the two series stable. The Augmented Dickey-Fuller (ADF) test is used to ascertain the stationarity of a time series (Ahmad et al., 2012). It is converted from a non-stationary state to a stationary one. Non-stationary time series are susceptible to invalidating results due to the presence of autocorrelation functions (ACFs) and time-dependent means and variances (Muhammad et al., 2015). Correlation and causation are often misinterpreted. A change in one variable affects the other, which is correlation. Causation may not follow correlation. Cause and effect are two variables that are linked by a change in one. Causality involves more than a statistical relationship between two variables (Ahmad et al., 2012). The Granger casualty test needs a stationary series. The ADF test is often conducted before doing the Granger causality test. (Rodríguez-Caballero and Ventosa-Santaulària, 2014). If X is the Granger cause of Y, this test will reveal how the previous values of X may be used to predict Y (Seth, 2007). The lag time required to conduct a Granger causality test is determined by analyzing a variety of lag criteria tests (Lopez and Weber, 2017).

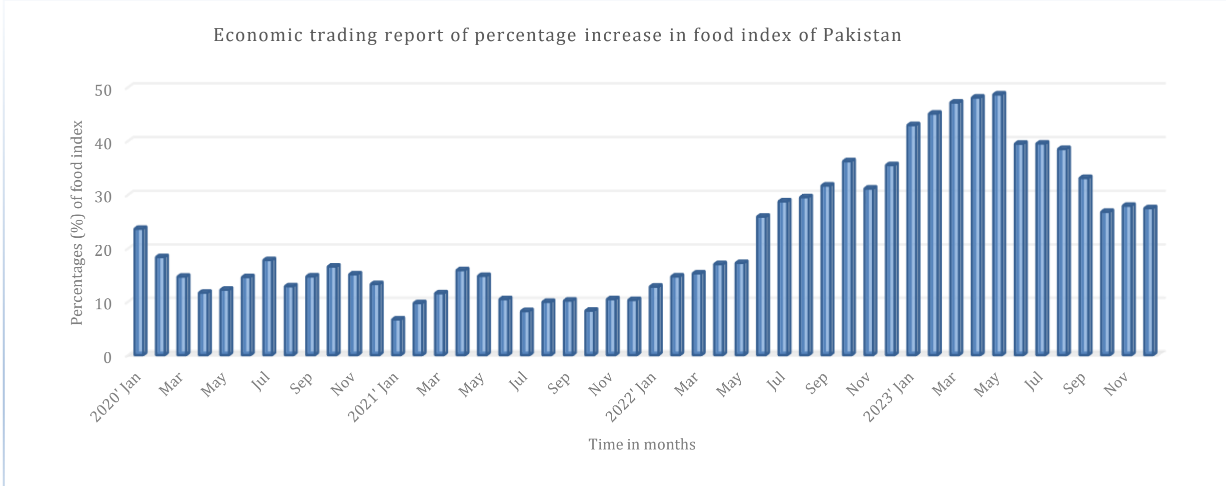

Fig. 1: Economic trading report of percentage increase in food index

Statisticians use cointegration tests to find long-term relationships between non-stationary time series (Muhammad et al., 2015). Engle-Grange cointegration test examines the long-term link between energy and food indexes (Chee-Yin and Hock-Eam, 2014). All these tests are used in this research to determine the number of lags (months) after which changes in energy prices begin to affect food prices.

2. Literature review

Gokal and Hanif (2004) examined several economic theories to understand the relationship between inflation and economic growth. When inflation is high, price fluctuations can reduce the profitability of investment projects, potentially slowing down economic growth and investment. Shrestha and Chaudhary (2012) explored the impact of rising food prices on poverty levels in Nepal, finding that a 10% increase in food prices could raise poverty rates by four percentage points across the country. The study suggests that a 1% rise in food prices could push an additional 100,000 people into poverty, with 180,000 more falling into poverty specifically due to food costs. This highlights the significant influence of inflation on food prices.

In Pakistan, the poverty rate was 31.3%, according to the 2018 report, and it was projected by the Business Recorder that this rate could reach 40%, with 87 million people in poverty by 2020. The 2017 Pakistan Census, conducted by the Pakistan Bureau of Statistics, shows that 36.44% of the population lives in urban areas, while 63.56% resides in rural regions. This high rural population percentage is concerning for the planning department, as food is an essential need and rising food prices could severely impact living standards.

Walsh (2011) found that lawmakers often exclude food prices from inflation measures due to their frequent and rapid fluctuations, which can lead to misinterpretations of inflation trends. However, given that food prices are influenced by multiple factors, including their own price index is essential for accurately understanding economic inflation. Köse and Ünal (2024) used statistical models to analyze the impacts of temperature, oil prices, exchange rates, and agricultural wages on food prices in Latin America. Their findings indicate that both monetary and fiscal policies, as well as energy prices, are crucial in managing food inflation in the region. Another study explored the possible connection between energy and food prices, examining the various subgroups within the food price index. The causality test used in this research showed a clear two-way causal relationship between energy and food prices (Kirikkaleli and Darbaz, 2021). These studies underscore the importance of the relationship between food and energy prices, although they do not specify the lag period (in months) after which food prices begin to respond to fluctuations in energy costs. Moshiri (2015) also found that changes in energy prices and wages affect individuals differently across income levels. Borrallo et al. (2024) examined the impact of energy prices on consumer food prices, finding that increases in food and energy commodity prices had a significant positive effect on consumer food inflation, while decreases had a smaller and asymmetrical effect on reducing consumer food prices. The literature shows that various researchers have examined the effects of energy variables alongside other significant economic variables. Ahmad et al. (2012) investigated the relationship between energy usage and economic growth in Pakistan, using GDP as the dependent variable and energy usage as the independent variable. The ADF test revealed that both variables were stable at the level. In contrast, Acibuca's (2024) study found that the ADF test indicated non-stationarity in the variables, necessitating the use of cointegration analysis or vector autoregression to account for non-stationarity and explore the variables' long-term relationships. Ahmad et al. (2012) further applied the Granger causality test, identifying a one-way relationship from GDP to energy usage. Correlation, a statistical method for assessing the linear relationship between two continuous variables, is frequently misused by specialists, leading some mathematicians to question its utility (Mukaka, 2012). Rohrer (2018) emphasized that correlation does not imply causation and introduced graphical causal models as tools for understanding complex variable interactions. Granger causality, a statistical approach to determine causality, suggests that if variable X "Granger-causes" variable Y, then historical values of X should provide more predictive information about Y than Y's own historical values (Seth, 2007). The Engle-Granger cointegration and Granger causality tests assess both short-term and long-term equilibrium relationships between variable groups (Chee-Yin and Hock-Eam, 2014; Makina, 2024).

In time series analysis, a lag represents the time difference between a data point and a previous similar point, often used to show autocorrelation. Statisticians utilize information criteria, such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), or Hannan-Quinn Information Criterion (HQIC), to determine the optimal lag count. The aim is to identify the lag count that produces the most accurate and practical model for the data by minimizing the chosen information criterion (Lopez and Weber, 2017).

3. Methodology

In this study, the energy index is calculated by taking the weighted average of fuel, electricity, and gas indices. Monthly data from January 2019 to May 2023 were obtained from the official website of the Pakistan Bureau of Statistics (PBS, 2019), providing a total of 53 monthly indices for both food and energy, as shown in Table 1.

3.1. Scatter diagram of food and energy index

For each group, distinct correlations between the two variables can be established. Scatter diagrams allow for predicting one variable's value based on another, especially when the variables have a high correlation. Visualizing data in this way makes it easier to identify patterns, correlations, outliers, and to project future values (Moran and Wuhrer, 2006).

Table 1: Energy and food index for the period of 2019 to 2023

	2019		2020		2021		2022		2023	
Years/months	Food index	Energy index	Food index	Energy index	Food index	Energy index	Food index	Energy index	Food index	Energy index
Jan	108.92	119.91	132.91	149.05	141.87	142.49	161.12	196.88	224.73	229.76
Feb	111.94	121.25	130.25	140.17	143.95	162.07	165.76	192.13	234.18	262.29
Mar	115.15	129.10	130.93	136.77	146.51	155.45	168.17	178.42	244.66	272.09
Apr	116.77	125.88	129.25	132.19	151.24	153.22	175.41	172.26	254.53	266.10
May	118.58	125.24	131.55	125.86	152.94	148.81	177.05	163.23	258.05	268.81
Jun	117.97	130.01	134.23	122.88	149.13	148.99	185.86	222.73		
Jul	118.77	138.43	138.89	133.10	151.66	153.46	193.81	267.15		
Aug	123.19	140.49	137.90	141.39	152.49	155.14	196.59	290.16		
Sep	123.11	138.14	142.73	141.08	158.53	164.10	207.23	191.14		
Oct	128.09	148.73	147.23	139.64	161.09	173.45	217.09	235.21		
Nov	131.67	148.55	149.77	136.76	167.96	185.64	216.54	234.85		
Dec	128.95	149.48	145.86	140.69	162.85	198.24	213.11	229.52		

Fig. 2 shows a strong positive linear correlation between the food and energy indices. The scatter diagram includes a best-fit regression line, with a coefficient of determination (R-squared) of 0.8478, suggesting a robust regression model. A higher R-squared value indicates a stronger association between the independent variable (energy prices) and the dependent variable (food prices), meaning that a substantial portion of the variability in food prices can be explained by changes in energy prices.

It is commonly believed that rising energy prices lead to higher food prices; however, correlation alone does not imply causation. Additional evidence is required to establish causal relationships. Thus, section 3.4 examines the causality between the two variables.

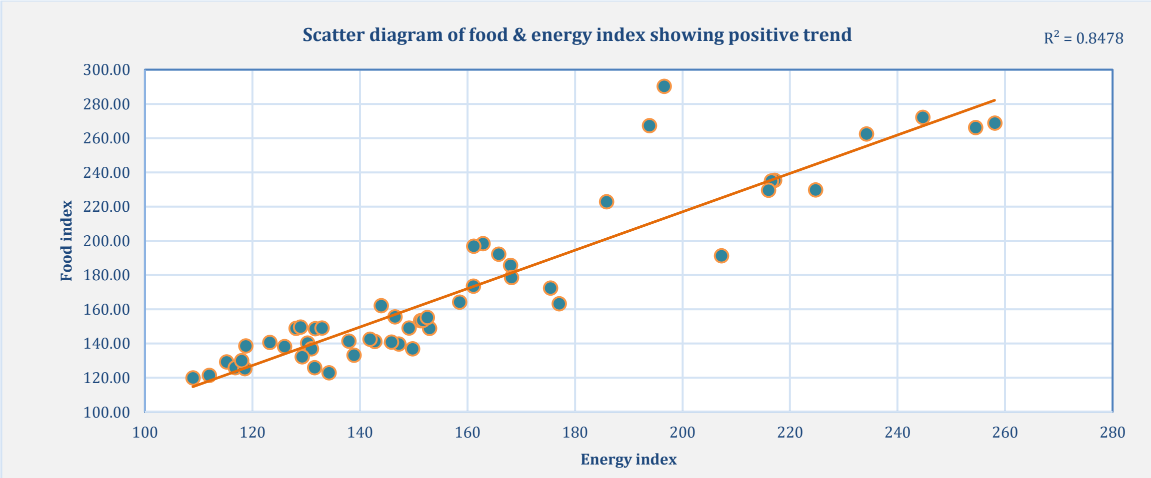

Fig. 2: Scatter diagram between energy and food indices along with the trend line

Among the various components of energy, fuel is considered the most influential factor driving changes in the overall energy index. Fig. 3 displays a strong positive linear relationship between the fuel index and food index, as shown in the scatter diagram. The coefficient of determination (R-squared) is notably high at 0.9003, indicating that 90% of the variation in food prices can be explained by changes in fuel prices.

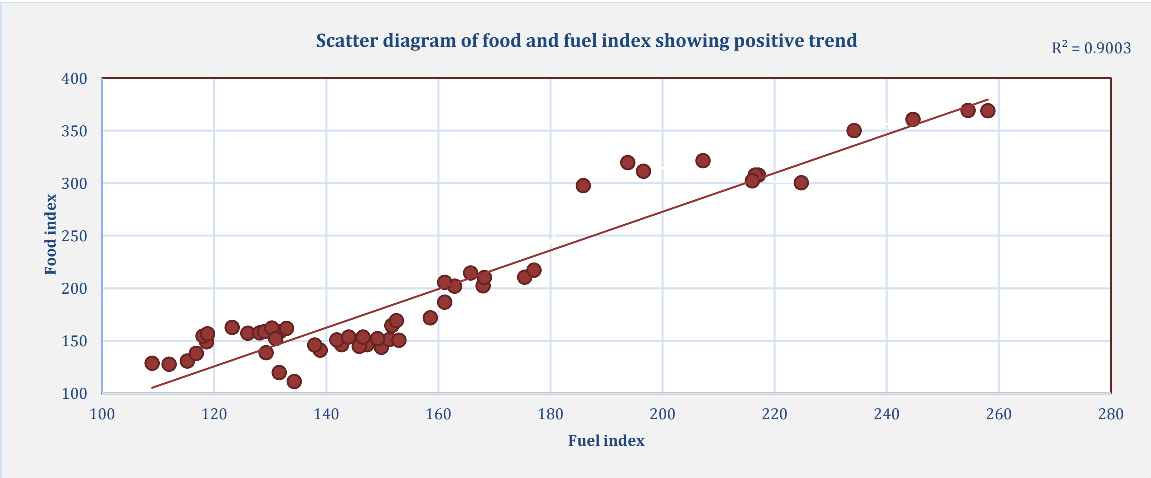

Fig. 3: Scatter diagram between fuel and food indices along with the trend line

3.2. Pearson's correlation and partial correlation

Correlation analysis can provide insights into the strength and direction of the association between two variables, guiding further research. When two variables show a significant positive correlation, an increase in one variable may suggest a similar rise in the other.

The correlation coefficient, a value between -1 and +1, quantifies how closely two variables move together. A +1 value indicates a perfect positive relationship, -1 represents a perfect inverse relationship, and 0 means there is no direct association between the two variables.

Table 2 presents the Pearson correlation between the food index and the energy index, as well as the individual components of the energy index (fuel, gas, and electricity charges). The correlations are significant at the 0.01 level. The correlation between food and energy is strong at 0.921, indicating a robust positive relationship. Among the energy components, all show positive correlations with food, but fuel exhibits the highest impact on food prices compared to gas and electricity.

Table 2: Correlation between food and energy (including energy components)

		Energy	Motor fuel	Gas charges	Electricity charges
Food	Pearson correlation	0.921	0.949	0.744	0.707
	Sig. (2-tailed)	0.000	0.000	0.000	0.000
	N	53	53	53	53

Partial correlation is a powerful statistical method that enables researchers to separate the direct association between two variables from the impact of additional confounding factors. When investigating the relationship between two essential items, it is important to take into account additional aspects that may complicate or confuse the link. This allows us to make better predictions or conclusions regarding the connection between these two items (Wang et al., 2016). Among all components of energy items, fuel shows a comparatively strong correlation with food (Table 2). Therefore, it can be concluded that fuel is the most important energy component that could potentially influence food prices. Therefore, a partial correlation is utilized to examine the impact of fuel on food while maintaining control over the other two energy components, namely electricity and gas. Table 3 shows a significant partial correlation of 0.839 between food and fuel, even after controlling the impact of electricity and gas on food.

Table 3: Partial correlation between food and fuel indices

Control variables		Motor fuel	
Electricity charges and gas charges	Food	Correlation	0.839
		Significance (2-tailed)	0.000
		Degree of freedom	49

3.3. ADF test

To conduct an accurate analysis, it was crucial to identify the causal relationship between the food and energy indices. For this purpose, the Granger causality test was applied using the EViews software. A time series with a unit root is non-stationary, meaning its statistical characteristics change over time, which can limit the predictive power of past values for future outcomes. This instability may reduce the accuracy of the Granger causality test results. Therefore, unit root tests are often used as a preliminary step before conducting Granger causality testing. To check for unit roots in a time series, the ADF test is conducted, which identifies non-stationary variables with unit roots. If the ADF test indicates non-stationarity, then cointegration analysis or vector autoregression may be needed to address non-stationarity and examine the variables' long-term relationships. Before applying a cointegration test, the time series must be made stationary by taking the first difference of the series. However, if the ADF test confirms that the variables are stable or stationary, then regression-based analysis can proceed (Acibuca, 2024).

A unit root implies that a series trends over time without reverting to a mean, indicating instability. By incorporating additional latent components in the regression equation, the ADF test allows for the detection of more complex self-correlation patterns in the data. Estimating the regression model required for the ADF test is outlined by Jalil and Rao (2019).

$$y_t = a + bt + uy_{t-1} + e_t \tag{1}$$
$$\Delta y_t = (u-1)y_{t-1} + a + bt + e_t \tag{2}$$

where, t is a time trend, y_{t-1} is the lagged value of the time series, Δy_t is the first difference of the lagged value, and e_t is the error term.

The ADF test is applied to the food and energy series to test the hypothesis of whether these two series are stationary, as causality testing is only valid for stationary series. Table 4 presents the results of the ADF test on the energy series to evaluate the following hypothesis.

H_{null}: Energy has a unit root and is not stationary
$H_{alternate}$: Energy has no unit root and is stationary

Table 4: Unit root test result (ADF test) for energy (n=52 observation)

		T-statistics	Probability
ADF test		0.370	0.9796
Test critical values	Level 1 %	-3.571	
	Level 5 %	-2.922	
	Level 10 %	-2.599	

The test probability is 0.9796, which is greater than the p-value of 0.05 (Table 4). The ADF test indicates that the dependent and independent variables in the equation are not stable, providing insufficient evidence to reject the null hypothesis. Consequently, the energy series is non-stationary, as stationarity requires statistical properties such as mean, variance, and autocorrelation to remain constant over time. Fig. 4 shows a trend in the index, further confirming that it is a non-stationary series. Stationarity is a fundamental assumption in many time series analysis methods. The series is made stationary by applying the first difference method. The ADF test is then re-applied to the transformed series, resulting in a probability close to zero, which is less than 0.05, as shown in Table 5. Fig. 5 also displays a horizontal trend around the mean zero. Based on this, the causality test can now be applied to the energy series, which has been adjusted by taking the first difference of the original energy index. A similar procedure is applied to the food series. Table 6 shows the result of the ADF test on the food series, with a test probability of 1.0. Therefore, there is insufficient evidence to reject the null hypothesis stated below.

H_{null}: Food has a unit root and is not stationary
$H_{alternative}$: Food has no unit root and is stationary

Similar results are shown graphically in Fig. 6, where the food series appears non-stationary. To address this, the first difference is taken to make the series stationary. The ADF test is then applied to the first-differenced food series, with Table 7 showing a probability of 0.0001, which is significantly less than 0.05. This allows for the rejection of the null hypothesis, confirming that the food series is now stationary. Fig. 7, based on the first-differenced series, demonstrates a trend around a mean of zero with consistent variation.

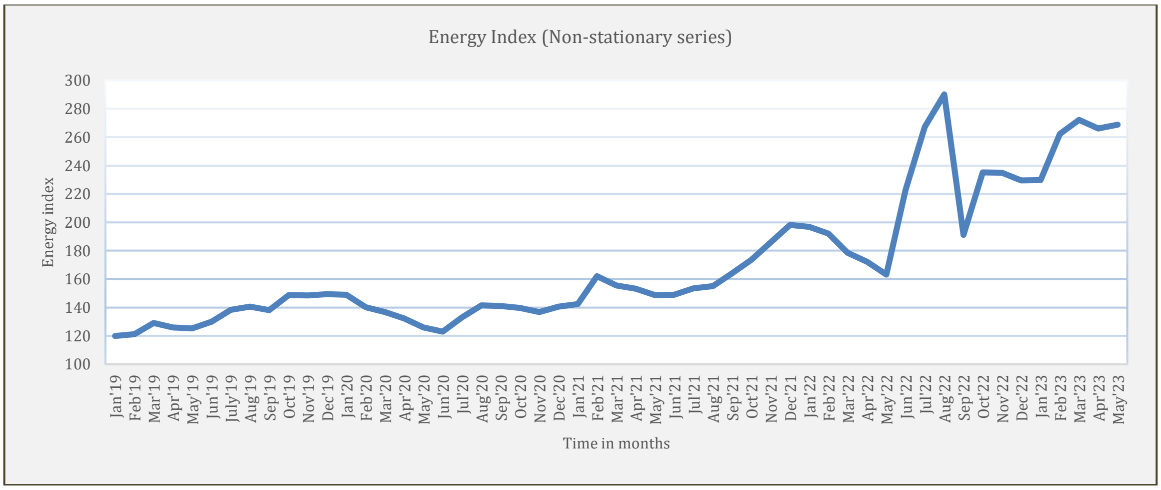

Fig. 4: Line graph of energy series

Table 5: Unit root test result (ADF test) for first difference energy1 (n=51 observation)

		T-statistics	Probability
ADF test		-8.128	0.0000
Test critical values	Level 1 %	-3.565	
	Level 5 %	-2.910	
	Level 10 %	-2.598	

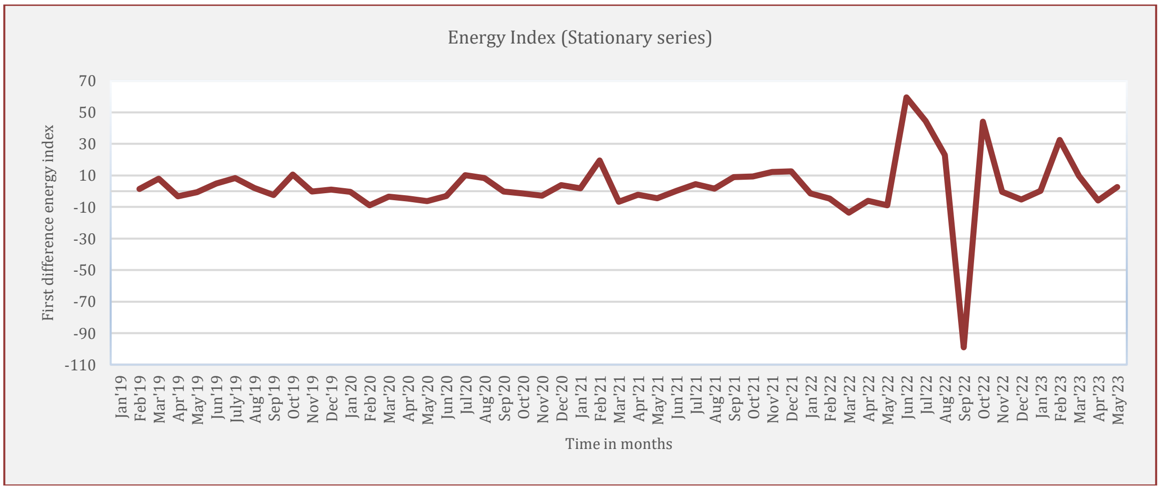

Fig. 5: Line graph of first difference energy series

Table 6: Unit root test result (ADF test) for food (n=52 observation)

		T-statistics	Probability
ADF test		3.543	1.0000
Test critical values	Level 1 %	-3.563	
	Level 5 %	-2.919	
	Level 10 %	-2.597	

3.4. Granger causality test

The Granger causality test is a statistical method used to assess predictive relationships between two data sets. After transforming the food and energy series to make them stationary, the test is applied. Assuming that variable Y (energy index) is the Granger cause of variable X (food index), the test is based on the premise that past values of Y should contain information that significantly enhances the prediction of X, beyond what is possible using only X's past values (Seth, 2007).

Table 8 presents the results of the pairwise Granger causality test, conducted on the stationary, transformed food and energy series using EViews. The test is applied at lags of 1, 2, and 3. In time series analysis, "lagging" refers to shifting the values backward by a set number of time steps, such as including values from one or more prior periods in the model to assess causal relationships. For instance, a lag of 1 includes values from the previous period as predictors, while a lag of 3 uses values from the three prior periods. The optimal lag order is the number of lags that best captures the dynamic relationship between the variables. Commonly, information criteria such as the AIC or the BIC are used to determine this lag length, balancing the model's complexity with its fit.

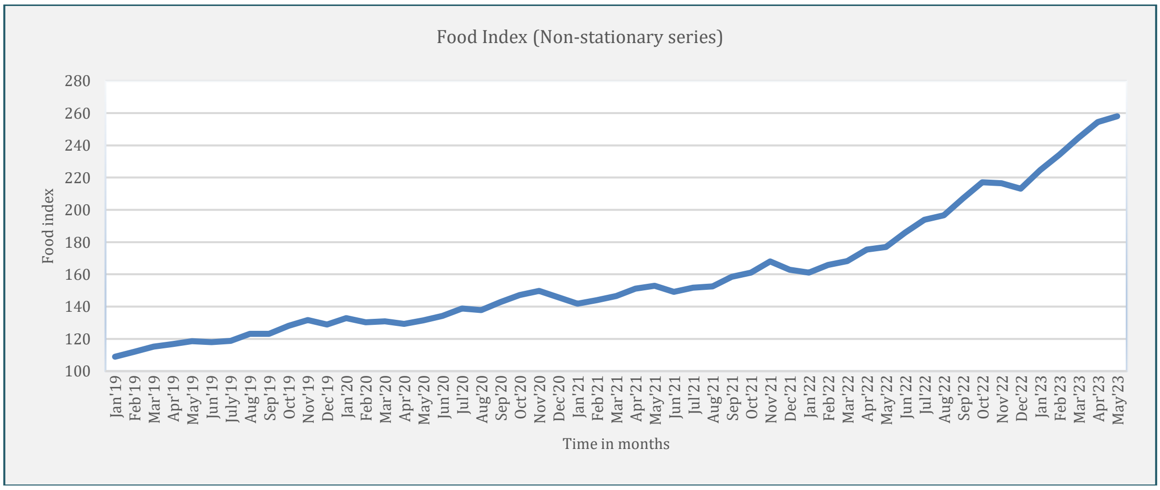

Fig. 6: Line graph of food series which is not stationary

Table 7: Unit root test result (ADF test) for first difference food1 (n=51 observation)

		T-statistics	Probability
ADF test		-5.150	0.0001
Test critical values	Level 1 %	-3.565	
	Level 5 %	-2.910	
	Level 10 %	-2.598	

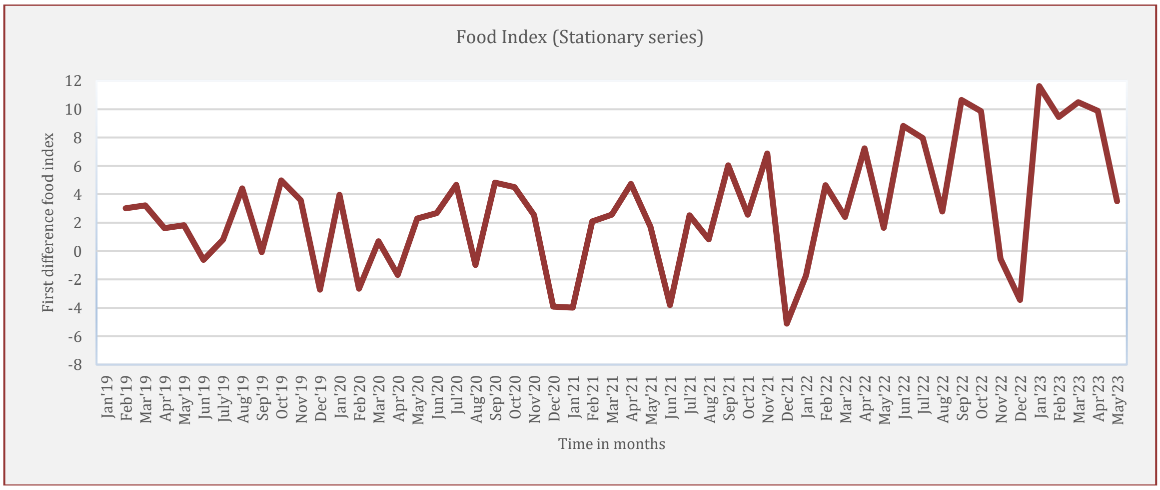

Fig. 7: Line graph of first difference food series

Table 8: Pairwise Granger causality test (first difference series)

	Lags 1 (51 observations)		Lag 2 (50 observations)		Lag 3 (49 observations)	
Null hypothesis	F-statistics	Probability	F-statistics	Probability	F-statistics	Probability
H_0: Food does not Granger cause energy	2.1117	0.1527	0.9780	0.3839	1.5110	0.2256
H_0: Energy does not Granger cause food	0.4697	0.4964	1.4739	0.2399	2.4011	0.0812

Table 9 demonstrates vector autoregression (VAR) lag order selection criterion using Likelihood ratio (LR) test statistic, Final Prediction Error (FPE), Akaike information criteria (AIC), Schwarz information criteria (SC), and Hannan-Quinn information criteria. Multiple time series variables may be effectively forecasted for future values using VAR models. VAR models capture the temporal relationships and historical trends in the data by adding lagged values to the variables. Because of this, they are effective at predicting future values from historical data on the variables. To determine the appropriate lag length, researchers typically estimate the model with different lag lengths and compare the corresponding information criteria, such as the AIC or the BIC. The lag length that minimizes the information criterion is often considered the optimal choice, as it represents the best balance between model fit and complexity. Table 9 shows the ideal lag order based on the given criteria.

As indicated in Table 9, a lag of 3 is recommended for conducting the Granger causality test. Table 8 shows that the likelihood of food Granger-causing energy is 0.2256, while the likelihood of energy Granger-causing food is 0.0812. Both values exceed the 0.05 threshold, indicating a lack of statistical significance. However, the probability of energy Granger-causing food is below 0.1, suggesting a potential relationship. Typically, a 95% confidence level requires a p-value below 0.05 to reject the null hypothesis, but if the p-value is under 0.1, the null hypothesis may be rejected at a 90% confidence level. This suggests that over a longer period, approximately three months, inflation in the energy index may influence the food index. Fig. 8 illustrates this trend; a three-lag shift of the food index reveals that it follows a similar trend to the energy index, with a delay of around three months. In other words, changes in the energy index occur first, and the food index subsequently follows with a time lag of about three months, indicating that the energy index drives changes in the food index despite the delay.

Fig. 8 presents a stacked line graph, which clearly shows the distribution and time-based changes in both indices. This visualization effectively illustrates how different factors influence the overall trend and highlights their impact at each time point.

Table 9: VAR lag order selection criteria (food and energy indices)

Lag	LR	FPE	AIC	SC	HQ
0	NA	7316.939	14.573	14.650*	14.602*
1	7.431	7331.629	14.575	14.807	14.663
2	4.263	7843.564	14.641	15.027	14.788
3	12.934*	6803.899*	14.497*	15.037	14.702

*: indicates lag order selected by the criterion

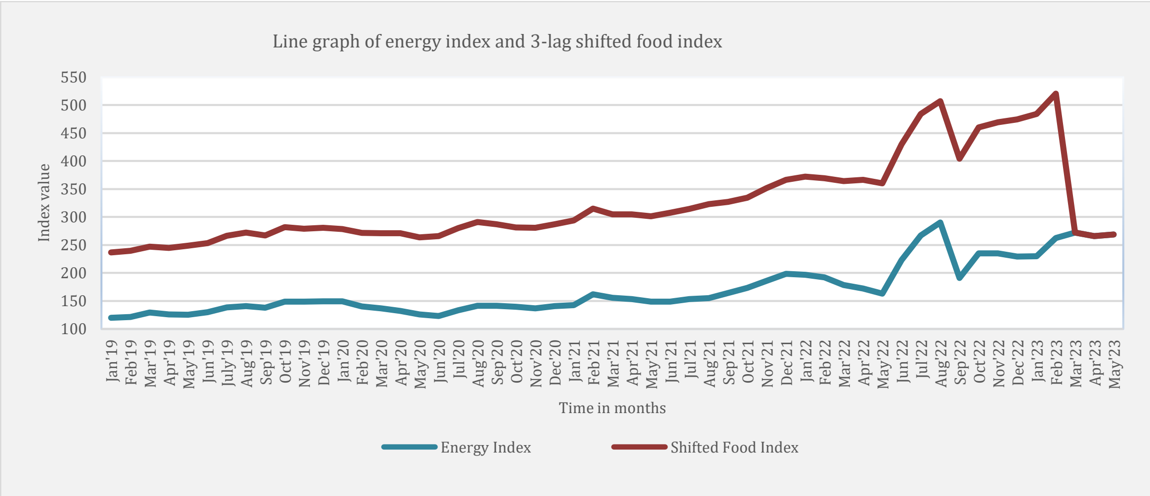

Fig. 8: Stacked line graph of energy index and three lag food index

3.5. Engle-Granger cointegration test

Correlation measures the strength of how two factors are linked in a straight line. On the other hand, cointegration is the relationship between two time series over the long term that have the same random trend. Cointegration represents a far more meaningful and insightful relationship, where two-time series exhibit a shared random trend over the long run, even if they display short-term deviations from this common path. It is a useful idea in finance and economics because it can be used to find pairs of assets that are likely to move together in the long run, even if they don't move together in the short run.

H_{null}: Series are not cointegrated
$H_{alternative}$: Series are cointegrated

Table 10 shows the result of the Engle-Granger cointegration test applied to food and energy indices. T-statistics and z-statistics of both the indices are less than 0.05, which indicates that the null hypothesis is rejected and it is accepted that the two series are cointegrated.

Table 10: Engle-granger cointegration test (food and energy indices)

Variables	T-statistics	Probability	Z-statistic	Probability
Energy	-4.606	0.003	-30.776	0.001
Food	-4.084	0.011	-26.729	0.005

Therefore, as a result of both the Granger causality test and the Engle-Granger cointegration analysis, it can be inferred that energy costs have the potential to have an influence on food prices. Both series reveal cointegration, indicating a long-term relationship between them. The impact of energy on food is seen to occur with a lag of three or more months, where each lag represents a monthly value.

4. Conclusion and recommendation

This research employs distinct statistical and econometric techniques to examine the impact of energy (fuel) costs on food prices. Both Granger causality and Engle-Granger cointegration tests indicate that energy costs can influence food prices over time, establishing a long-run relationship between the two variables. The cointegration between food and energy implies that energy affects food prices with a lag of approximately three months.

Each lag represents one month, reflecting how these two time series variables are linked over the long term. Although they may initially move in different directions, over time, they tend to align. The concept of "lag" is essential, as it dictates how much historical information is incorporated into the forecasting model. A lag of 1 month uses the previous month's price to help predict the current price, while this study demonstrates that a 3-month lag provides a more accurate prediction of current food prices.

The findings confirm that energy price increases have a substantial impact on food prices, observable within a three-month period. This allows policymakers sufficient time to adjust and regulate food prices accordingly. By analyzing energy and food pricing trends, policymakers and governments can improve decision-making, implement effective policies, and enhance economic and social welfare.

An increase in energy costs can significantly influence both essential and non-essential food prices. The extent of this impact varies depending on factors such as the type of food product, its production and consumption location, and the degree to which higher energy costs are passed on to consumers. Understanding the relationship between energy and food costs is critical for interpreting overall inflation and shifts in the cost of living.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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