Exploring the food-energy inflation relationship through Fourier methods: Asymmetric and nonlinear causality

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Abstract

This study investigates the long-run relationship and Granger-type predictive causality between food and energy inflation in Türkiye, with a particular focus on asymmetric transmission, price stickiness, and structural changes. Monthly data covering the period from January 2003 to February 2025 are employed. The analysis begins with linearity testing, followed by the application of Fourier-based unit root and cointegration tests to account for structural shifts. Long-run coefficients are estimated using Dynamic OLS, Fully Modified OLS, and Canonical Cointegration methods. In addition, Hatemi-J asymmetric causality tests are conducted within a Granger framework to examine the direction and nature of shocks. The findings reveal that a 1% increase in energy inflation leads to a 1.13% increase in food inflation in the long run. Bidirectional Granger-type causality is detected for positive shocks, whereas negative shocks exhibit weaker and asymmetric linkages. These results support the presence of price stickiness and nonlinear transmission mechanisms. Overall, the study provides a comprehensive framework for understanding energy-food inflation dynamics and highlights the importance of accounting for asymmetries in policy design.

Keywords: food inflation, energy inflation, Fourier cointegration test, asymmetric causality, price stickiness.

JEL classification: E31, C32, C58, Q11, Q43

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1. Introduction

In recent years, volatility in global energy markets has coincided with rising food prices. This development has raised concerns about macroeconomic stability. Changes in energy prices directly affect agricultural production and transportation costs. As a result, they influence food inflation. Understanding how energy and food prices move together over time has therefore become important for both researchers and policymakers.

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This study examines the long-term relationship between food and energy inflation. Rising food prices and energy market volatility have increased cost pressures in agriculture and logistics. Traditional linear models may not fully capture these dynamics. There is a growing need for approaches that allow for nonlinear behavior and asymmetric shock effects. To address this issue, this study combines Fourier-based structural break analysis with asymmetric causality tests.

Much of the existing literature analyzes the energy-food relationship under linear and symmetric assumptions. However, some evidence suggests that increases in energy prices may have stronger and more persistent effects on food prices than decreases. This pattern points to possible asymmetric adjustment dynamics. Therefore, methods that account for structural breaks and nonlinear behavior are needed.

For Türkiye, empirical studies on asymmetric causality between energy and food inflation remain limited. Research that jointly considers structural breaks and nonlinear dynamics using Fourier methods is also scarce. This study focuses on the time-varying and asymmetric features of the relationship between energy and food inflation. The objectives are:

i. To investigate the nonlinearity of the series,
ii. To analyze stationarity properties using the Fourier unit root test,
iii. To examine the long-term relationship through the Fourier cointegration test,
iv. To estimate long-term coefficients using FMOLS, DOLS, and CCR methods,
v. To assess shock-direction-based Granger-type causality using the Hatemi-J Asymmetric Causality Test.

This paper is organized into five main sections. Following the Introduction, the second section reviews the relevant literature and highlights the study's contributions. The third section details the methodology and data. The fourth section presents the empirical findings, and the fifth section discusses the results and concludes with policy implications.

1.1. Theoretical background: Price stickiness

Price stickiness is a central concept in macroeconomics. It refers to the idea that prices do not adjust immediately to changes in supply or demand. In classical theory, prices are assumed to be flexible and markets clear automatically. However, Monetarist, Keynesian, and New Keynesian approaches recognize that prices may be slow to adjust, especially in the short run. When prices do not respond quickly, imbalances such as unemployment or idle capacity can persist (Keynes, 1936; Phillips, 1958; Friedman, 1968; Phelps, 1967; Lucas, 1972; Sheshinski & Weiss, 1977; Taylor, 1979; Mankiw, 1985; Mankiw & Reis, 2002).

Keynes (1936) argued that downward rigidity in wages and prices may prevent the economy from returning quickly to full employment. Later, New Keynesian models formalized this idea. Mankiw (1985) introduced the concept of "small menu costs," suggesting that even minor costs of changing prices can lead firms to delay adjustments. Empirical studies by Blinder (1991) and Ball and Mankiw (1994) show that firms tend to respond more quickly to positive shocks than to negative ones. Price increases are often implemented faster than price reductions.

This framework helps explain the interaction between energy and food prices. Increases in energy prices quickly raise production and transport costs in agriculture. In contrast, energy price declines may pass through more slowly. Such patterns are consistent with price stickiness. Therefore, analyzing the energy–food inflation relationship requires attention not only to how much prices change, but also to the direction and speed of those changes.

2. Literature

Fluctuations in energy prices can significantly affect food production and distribution costs, making the interaction between food inflation and energy inflation a critical area of study. Below is a summary of the relevant literature covering both developed and developing countries.

Table 1 – Literature Review[1]

Author(s)	**Country & Time**	**Data Set**	**Method**	**Findings**
Bello & Sanusi (2019)	Nigeria (1995:Q1-2018:Q2)	Food Inflation, Core Inflation, Marginal Cost, Imported Inflation, Exchange Rate	STR, NKPC	Inflation occurs under low and high regimes; exchange rate becomes main driver in high regime.
El-Karimi & El-Ghini (2020)	Morocco (1998:Q1-2018:Q1)	Global Oil, Global Food Prices, Domestic Inflation	BC Causality Test	Food prices have a stronger short-term impact on inflation; asymmetry observed in shocks.
Ganioglu (2020)	EU-27 (2003:01-2018:07)	Inflation Expectations, Food & Energy Prices, Interest Rate, Unemployment	SADF, GSADF, Panel Regression	Food and energy prices show extreme deviations influencing expectations and macro indicators.
Odondo (2021)	Kenya (2017:01-2020:02)	Manufacturing Growth, Core, Food, and Energy Inflation	Johansen, VECM, Wald Test	Long-term link between manufacturing growth and inflation types; short-term causal effects detected.

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[1] STR: Smooth Transition Regression. NKPC: Nonlinear New Keynesian Phillips Curve. BC: Breitung and Candelon Causality Test. SADF: Supremum Augmented Dickey-Fuller Test. GSADF: Generalized Supremum Augmented Dickey-Fuller Test. VECM: Vector Error Correction Model. LP: Local Projection Method. SVAR: Structural Vector Autoregression. Panel SVAR: Panel Structural Vector Autoregression FSHIN: Fourier Shin Cointegration Test. FMOLS: Fully Modified Ordinary Least Squares. TY: Toda-Yamamoto Causality Test FTY: Fourier Toda-Yamamoto Causality Test. WC: Wavelet Coherence. QGC: Quantile Granger Causality. QQR: Quantile-on-Quantile Regression. QR: Quantile Regression. TVP-VAR: Time-Varying Parameter Vector Autoregression. GCQ: Granger Causality in Quantiles. RALS: Residual Augmented Least Squares. EG Cointegration: Engle-Granger Cointegration Test. SPE: Static Panel Estimator. DPE: Dynamic Panel Estimator. WEM: Within Effects Model. MIA: Multiplicative Interaction Approach. NARDL: Nonlinear Autoregressive Distributed Lag Model.

Author(s)	Country & Time	Data Set	Method	Findings
Kohlscheen (2022)	OECD (1990-2020)	Food Price Inflation, Current & Expected Inflation, Output Gap	LP Method	Weak link between domestic and global food prices after exchange rate adjustment.
Kose & Unal (2022)	Latin America (2003:01-2020:12)	Temperature, Oil Price, Exchange Rate, Agricultural Wages, Food Prices	SVAR, Panel Granger	Oil prices and temperature are significant; exchange rate less so long-term.
Ali et al. (2022)	Pakistan (2005:09-2020:10)	Food Inflation, Monetary Policy, Transportation Prices	QR, VAR, ARDL	Monetary policy and transport costs significantly affect food inflation across quantiles.
Arintoko et al. (2023)	Indonesia (2001:01-2022:12)	World Oil Prices, CPI, Exchange Rate	QR, DOLS	Asymmetric long-term impacts of oil price changes on CPI.
Škare et al. (2023)	44 Countries (2005:Q1-2021:Q1)	HCPI, ECPI	Panel SVAR	Energy shocks have significant but temporary effects; high sensitivity in emerging economies.
Ozayturk (2023)	Turkey (2016:02-2023:04)	Energy and Agricultural Inflation	FSHIN, FMOLS, TY, FTY	Positive co-integration and bidirectional causality between energy and agricultural inflation.
Kartal & Depren (2023)	Turkey (2004:01-2021:06)	Domestic Food Prices, Global and National Factors	WC, QGC, QQR, TY, QR	Food prices show asymmetric relations across time, frequency, and distribution dimensions.
Tasdoken & Kahyaoglu (2023)	Global (2003:03-2022:09)	Commodity Prices, Food Commodities, Crude Oil, Baltic Dry Index	TVP-VAR	Food prices highly interact with global inflation and shipping costs.
Derindag et al. (2023)	India (1999:01-2022:08)	Local Food Prices, Oil Prices, Exchange Rate, EPU Index	WC, QQR, GCQ, QR	Strong multi-frequency relations between food prices and external factors.
Demirtas, (2023)	Türkiye (2003:01-2022:09)	Oil Prices, Food Prices	RALS, DOLS, FMOLS, CCR	Negative long-term impact of oil prices on food prices; inflation main driver.
Borisov (2024)	Euro Area (2019-2024)	Food Inflation (HICP), Energy Prices (HICP Subgroup)	Regression, Granger	Energy price increases significantly impact food prices with six-month lag.
Arintoko et al. (2024)	Indonesia (2001:01-2023:02)	CPI, Global Energy and Food Prices, Exchange Rate, Money Supply	NARDL, QR	Energy price drops reduce inflation; exchange rate is the dominant factor.
Khan et al. (2024)	Pakistan (2019:01-2023:05)	Energy Price Index, Food Price Index	EG Cointegration, Granger	Energy prices have significant and long-term effects on food prices.
Ikue et al. (2024)	Nigeria (2016:Q1-2024:Q2)	Oil Product Prices, Exchange Rate, Headline and Food Inflation	SPE, DPE, WEM, MIA	Oil prices and exchange rate fluctuations strongly affect inflation.

Author(s)	Country & Time	Data Set	Method	Findings
Ikue (2024)	Nigeria (2010:Q1-2024:Q2)	Oil Prices, Headline and Food Inflation, Exchange Rate	NARDL	Positive shocks in energy prices have stronger and lasting inflationary effects.
Dash & Padhan (2024)	South & Southeast Asia (2012:05-2022:04)	Global Crude Oil Prices, Food Inflation	NARDL	Strong and asymmetric effect of oil prices on food inflation.
Borrallo et al. (2024)	Euro Area (Recent decades)	Food and Energy Commodity Prices, Food Consumer Prices	Extended Food Value-Chain Model, Asymmetry Analysis	Persistent and asymmetric effects of commodity price shocks on food prices; positive shocks have stronger effects than negative ones.

* The literature table was meticulously compiled by the author during the period from March 10 to April 20, 2025.

Core inflation excludes volatile items such as energy and food and helps identify underlying inflation trends. SVAR-based studies show that energy price shocks play a significant role in European inflation dynamics (Gartner & Wehinger, 1998; Wehinger, 2000). By separating core components, researchers can distinguish between temporary and persistent inflationary pressures.

Relative price variability also shapes inflation dynamics. In Europe, changes in logistics and market structures have affected how energy shocks transmit into prices. However, the relationship between relative price variability and inflation is not always positive. Market integration and fiscal frameworks may reduce the inflationary impact of energy shocks (Fielding & Mizen, 2000).

Inflation persistence in the Euro Area has also been linked to policy frameworks. Tighter institutional settings tend to weaken the transmission of cyclical shocks and reduce inflation persistence (Cournède et al., 2005). Energy crises and environmental constraints further introduce uncertainty, influencing agricultural production and global trade (Irwin & Penn, 1975).

Most existing studies have primarily focused on examining the effects of food and energy inflation on overall inflation using linear models. However, the possibility that price movements may exhibit asymmetric characteristics – particularly that upward shocks in food prices are more rapid and persistent while downward shocks are more limited and delayed – has not been sufficiently explored.

For Türkiye, studies investigating asymmetric causality between energy and food inflation are particularly scarce. Furthermore, comprehensive analyses that simultaneously account for structural breaks and nonlinear dynamics using Fourier transformation are rarely encountered in the literature.

This study offers a novel contribution by examining the relationship between energy and food prices in Türkiye through:

- The dimension of asymmetric causality;
- The impact of price stickiness;
- A detailed methodological framework based on the Fourier approach that incorporates structural breaks.

In doing so, it aims to fill an important gap in the existing literature concerning asymmetric transmission effects and price stickiness.

3. Methodology and data

In the first stage of the Fourier KSS test, equation (1) is estimated, similar to the first stage of the FADF test. In the estimation of this equation using the ordinary least squares method, it is crucial to determine the frequency number k. The value of k corresponding to the model with the minimum sum of squared residuals is selected as the appropriate frequency number. The model with the selected k value is considered the model to be evaluated in the first stage. The selected model is then estimated as described, and the residuals are obtained (Hepsag, 2022):

$$y_t = a + \gamma_1 \sin(\frac{2\pi kt}{T}) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \varepsilon_t \tag{1}$$

In Equation (1), π represents pi (approximately 3.14), k is the frequency, t refers to the deterministic trend, and T is the number of observations. The sin and cos terms are trigonometric components included as deterministic elements. In the Fourier KSS test, the second stage differs from the FADF test: Christopoulos and Leon-Ledesma (2010) assume that the residuals follow an ESTAR process, allowing for a direct unit root test using a first-order Taylor expansion.

$$\Delta\hat{\varepsilon}_t = \delta\hat{\varepsilon}_{t-1}^3 + \sum_{i=1}^{m} \Delta\,\hat{\varepsilon}_{t-i} + v_t \tag{2}$$

After estimating the test regression in Equation (2) using the ordinary least squares (OLS) method, the null hypothesis indicating the presence of a unit root ($\delta = 0$) is tested against the alternative hypothesis indicating stationarity ($\delta < 0$). The test statistic, referred to as $F - t_{NL}$, is calculated as follows:

$$F - t_{NL} = \frac{\hat{\delta}}{SE(\hat{\delta})} \tag{3}$$

$\hat{\delta}$ is the estimated value of the δ parameter in Equation (3), and SE($\hat{\delta}$) is its standard error. If the absolute value of the $F - t_{NL}$ statistic is smaller than the critical values by Christopoulos & Leon-Ledesma (2010), the null hypothesis of a unit root cannot be rejected; otherwise, it is rejected, indicating stationarity. If the series is stationary, it is necessary to test the significance of the sine and cosine coefficients (γ_1 and γ_2) in Equation (1), following Becker, Enders & Lee (2006). As Christopoulos & Leon-Ledesma's (2010) test considers only constant models, the $F_\mu(\hat{k})$ statistic is used for this purpose.

$$F_{\mu}(\hat{k}), F_t(\hat{k}) = (\frac{ESS_R - ESS_{UR}(k)/2}{ESS_{UR}\, k/(T-q)}) \tag{4}$$

In Equation (4), ESS_R and ESS_{UR} represent the sum of squared residuals for the restricted and unrestricted models, respectively; T is the number of observations, and q is the number of parameters in the unrestricted model. If the calculated $F_{\mu}(\hat{k})$ or $F_t(\hat{k})$ statistic exceeds the critical values by Becker, Enders & Lee (2006), the null hypothesis is rejected, confirming at least one significant trigonometric coefficient and the stationarity of the series (Christopoulos & Leon-Ledesma, 2010). Otherwise, the standard KSS unit root test is recommended (Hepsag, 2022). Shin (1994) introduced a cointegration test based on the KPSS unit root framework, which was later extended by Tsong et al. (2016) with trigonometric terms to account for structural breaks, resulting in the Fourier-Shin (FShin) cointegration test.

$$y_t = a + \gamma_1 \sin(\frac{2\pi kt}{T}) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \theta x'_t + \sum_{i=-l}^{l} \psi_i \Delta x'_{t-i} + \varepsilon_t \tag{5}$$

$$y_t = a + \beta_t \gamma_1 \sin(\frac{2\pi kt}{T}) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \theta x'_t + \sum_{i=-l}^{l} \psi_i \Delta x'_{t-i} + \varepsilon_t \tag{6}$$

In Equations (5) and (6), k represents the frequency number, T denotes the number of observations, t refers to the deterministic trend, π is the mathematical constant approximately equal to 3.14, and *-l* and *l* indicate the lag lengths for past and future periods, respectively. The sin and cos functions represent the trigonometric terms, which are other deterministic components included in the regression.

The model with the appropriate frequency number k determined in the first stage is considered the baseline model for estimation. In the second stage of the test, the residuals obtained from the model where the appropriate k has been selected are subjected to the Shin (1994) cointegration test. The null hypothesis ($\sigma_u^2 = 0$) indicating the existence of cointegration is tested against the alternative hypothesis ($\sigma_u^2 > 0$), which suggests the absence of cointegration. The test statistic to be calculated for this purpose is as follows:

$$CI_f^0, CI_f^1 = \frac{1}{T^2} \frac{\sum_{t=1}^{T} S_t(k)^2}{\sigma^2} \tag{7}$$

In Equation (7), CI_f^0 and CI_f^1 represent the test statistics for models with only a constant term and with both a constant and a trend, respectively. $S_t(k)$ denotes the cumulative sum of residuals from the model estimated with the appropriate frequency k, T is the number of observations, and σ^2 is the long-run variance. If CI_f^0 or CI_f^1 is smaller than the critical values (Tsong et al., 2016), the null hypothesis of cointegration cannot be rejected; otherwise, it is rejected in favor of no cointegration.

After establishing cointegration, the significance of the sine and cosine coefficients (γ_1 and γ_2) in Equations (5) and (6) is tested using the restriction-based $F^m(k^*)$ statistic.

$$F^m(k^*) = (\frac{ESS_R - ESS_{UR}(k)/2}{ESS_{UR}\ k/(T-q)}) \tag{8}$$

In Equation (8), ESS_R denotes the sum of squared residuals from the restricted model, ESS_{UR} represents the sum from the unrestricted model, T is the number of observations, and q is the number of parameters in the unrestricted model. If the $F^m(k^*)$ statistic exceeds the critical values by Tsong et al. (2016), the null hypothesis ($\gamma_1 = \gamma_2 = 0$) is rejected, indicating that at least one trigonometric coefficient is significant ($\gamma_1 \neq \gamma_2 \neq 0$). If the $F^m(k^*)$ statistic falls below the critical values, the null hypothesis cannot be rejected, implying insignificance. In this case, the Shin (1994) cointegration test is recommended (Hepsag, 2022).

For the asymmetric causality analysis, the integrated series y_1t and y_2t are defined by random walk processes as shown in Equations (9) and (10) (Hatemi-J, 2012: 449).

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{t} \varepsilon_{1t} \tag{9}$$

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{20} + \sum_{i=1}^{t} \varepsilon_{2t} \tag{10}$$

In Equations (9) and (10), t=1,2,.,T. y_{10} and y_{20} represent the initial values. ε_{1t} and ε_{2t} are white noise error terms. The positive and negative shocks of the variables are defined as follows (Hatemi-J, 2012):

$$\varepsilon_{1t}^{+} = \max(\varepsilon_{1t}, 0), \quad \varepsilon_{2t}^{+} = \max(\varepsilon_{2t}, 0), \quad \varepsilon_{1t}^{-} = \min(\varepsilon_{1t}, 0), \quad \varepsilon_{2t}^{-} = \min(\varepsilon_{2t}, 0) \tag{11}$$

$$\varepsilon_{1t} = \varepsilon_{1t}^{+} + \varepsilon_{1t}^{-} \ and\ \varepsilon_{2t} = \varepsilon_{2t}^{+} + \varepsilon_{2t}^{-}$$

As shown in Equation (11), the variables can be expressed through positive and negative shocks as follows.

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{t} \varepsilon_{1t}^{+} + \sum_{i=1}^{t} \varepsilon_{1t}^{-} \tag{12}$$

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{20} + \sum_{i=1}^{t} \varepsilon_{2t}^{+} + \sum_{i=1}^{t} \varepsilon_{2t}^{-} \tag{13}$$

The cumulative positive and negative shocks of each series are expressed as shown in Equation (14).

$$y_{1t}^{+} = \sum_{i=1}^{t} \varepsilon_{1t}^{+}, y_{1t}^{-} = \sum_{i=1}^{t} \varepsilon_{1t}^{-}, and\ y_{2t}^{+} = \sum_{i=1}^{t} \varepsilon_{2t}^{+}, y_{2t}^{-} = \sum_{i=1}^{t} \varepsilon_{2t}^{-} \tag{14}$$

The causality relationship between the components of the variables in terms of cumulative positive shocks is represented as shown in Equation (15).

$$y_{t}^{+} = v + A_{1} y_{t-1}^{+} + \cdots + A_{p} y_{t-1}^{+} + u_{t}^{+} \tag{15}$$

Causality testing can be conducted using a VAR(p) model of order p. Here, y_t^+ represents a (2x1) vector of variables, v is a (2x1) vector of intercept terms, u_t^+ is a (2x1) vector of error terms, and A_r (for r=1,2,...,p) are (2x2) matrices representing the lag orders. In the Hatemi-J (2012) approach, the null hypothesis (H_0) states that the element at the k-th column and w-th row of the A_r matrix is zero. This hypothesis is tested for lag orders r=1,2,...,p. Hatemi-J emphasizes that traditional tests may be inadequate, especially when variables are not normally distributed and ARCH effects are present. Therefore, he suggests that it is more reliable to use critical values obtained through bootstrap simulations. Accordingly, in this study, the causality relationship between the variables was first investigated using the Hacker and Hatemi-J (2006) Bootstrap Causality Test. Subsequently, the Hatemi-J Asymmetric Causality Test was applied to reveal asymmetric relationships based on positive and negative shocks.

It should be noted that the causality results are conditional on the selected VAR specification, lag length, and the maximum integration degree (dmax). Although bootstrap critical values reduce size distortions under non-normal errors and potential ARCH effects, the findings remain sensitive to model specification and the chosen information criterion. Therefore, the results should be interpreted within the limits of the econometric framework.

3.1. Data set

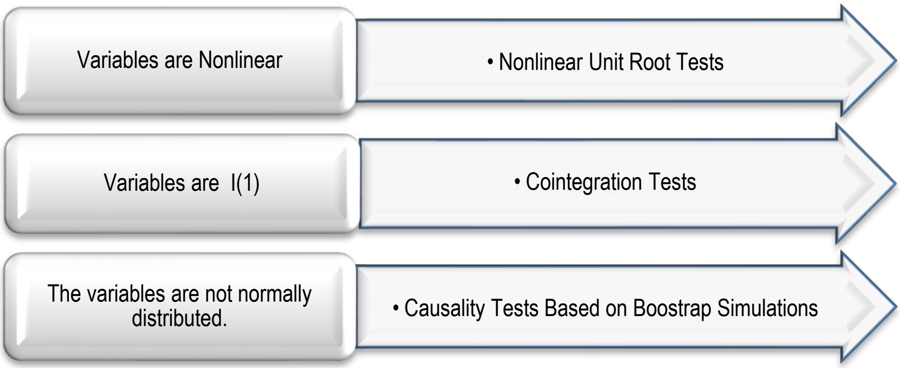
In this study, monthly data covering the period from January 2003 to February 2025 were used to examine the food and energy inflation indicators of the Turkish economy. The data (Food Price Index and Energy Price Index) were obtained from EVDS (Electronic Data Delivery System) in their level values. Natural logarithm transformation is frequently employed in statistical analyses for data transformation and modeling purposes. The natural logarithm of the series obtained in level form was taken using the formula $ln(x) = log_e(x)$. Logarithmic transformation reduces the impact of large values and softens the influence of outliers, resulting in a more balanced modeling process.

Table 2 – Variables and Their Descriptions

Variable	Description	Data Range
LNFPI	Logarithmic of Food Price Index	2003:01-2025:02
LNEPI	Logarithmic of Energy Price Index	2003:01-2025:02

Table 2 summarizes the names and data ranges of the variables used in the analysis. The selection scheme of the tests to be applied in the analysis is shown below in Figure 1.

Figure 1 – Decision Diagram



Nonlinear unit root tests were preferred for variables identified as nonlinear. Variables confirmed as I(1) were subjected to cointegration analysis. Additionally for variables not normally distributed, asymmetric causality tests developed by Hacker & Hatemi-J (2006) and Hatemi-J (2012), employing bootstrap simulations, were conducted.

4. Findings

Descriptive statistics, covariance and correlation coefficients for the variables LNFPI and LNEPI are presented in Table 3.

Table 3 – Descriptive Statistics, Covariance and Correlation Analyses

Descriptive Statistics	**LNFPI**	**LNEPI**
Mean	5.751598	5.681614
Median	5.539222	5.591248
Maximum	8.322623	7.865061
Minimum	4.539030	4.589244
Std. Dev.	0.960416	0.813334
Skewness	1.055694	0.941132
Kurtosis	3.374312	3.303932
Jarque-Bera	50.96196	40.29118
Probability	0.000000	0.000000
Sum	1529.925	1511.309
Sum Sq. Dev.	244.4355	175.3009
Observations	266	266
Covariance Analysis	LNFPI	LNEPI
LNFPI	0.918930	
LNEPI	0.773394	0.659026
Correlation Analysis	LNFPI	LNEPI
LNFPI	1.000000	
LNEPI	0.993821	1.000000

Table 3 presents descriptive statistics for LNFPI and LNEPI. Mean and median values are close, indicating a balanced distribution. LNFPI shows greater volatility (standard deviation: 0.96) than LNEPI (0.81). Skewness, kurtosis, and Jarque-Bera test results ($p < 0.01$) confirm that neither variable follows a normal distribution. Covariance and correlation analyses reveal a strong positive relationship, with a correlation coefficient of 0.9938, indicating that the two variables move closely together. However, since both variables are non-stationary at levels, this high correlation may reflect a common stochastic trend. Therefore, cointegration analysis is required to determine whether the relationship represents a stable long-run equilibrium rather than a spurious association.

Table 4 – Linearity Test Results

Variables	**Harvey et al. (2008)**
LNFPI	4.64*
LNEPI	12.88***

Note: Critical values for Harvey et al. (2008) test at 1%, 5%, and 10% are 9.21, 5.99, and 4.60 respectively. *, **, and *** denote rejection of the null hypothesis of linearity at the 10%, 5%, and 1% significance levels, respectively.

The linearity test results presented in Table 4 indicate that the LNFPI variable is nonlinear at the 10% significance level according to the Harvey et al. (2008) test. The LNEPI variable is nonlinear at the 1% significance level based on the same test.

The results of the FKSS unit root tests for the LNFPI and LNEPI series are presented in Tables 5 and 6. The test results have been evaluated separately for models with intercept and models with intercept and trend.

Table 5 – FKSS Unit Root Test for LNFPI

LNFPI	**k**	$\boldsymbol{F-t_{NL}}$	$\boldsymbol{F_\mu(\hat{k})}$	**optimallag**	**MinSSR**
Constant	1	1.92354	81.85614**	1	150.65545
	k	$F-t_{NL}$	$F_t(\hat{k})$	optimallag	MinSSR
C&T	1	-1.85523	400.39865**	1	7.53467
	k	$F-t_{NL}$	$F_\mu(\hat{k})$	optimallag	MinSSR
ΔConstant	1	-4.02993**	15.11483**	1	0.15168
	k	$F-t_{NL}$	$F_t(\hat{k})$	optimallag	MinSSR
Δ C&T	1	-4.07950**	10.45863**	1	0.13714

Note: * and ** denote significance at the 10% and 5% levels, respectively. Δ denotes the first difference of the series.

Table 5 presents the optimal frequency number k for both Constant and C&T models, the $F-t_{NL}$, $F_\mu(\hat{k})$, and $F_t(\hat{k})$ statistics, optimal lag lengths (AIC-based), and MinSSR values. For the constant model, the $F-t_{NL}$statistic for LNFPI is 1.92354, which is smaller than the 5% critical value in absolute terms (-3.67), indicating non-stationarity. However, the $F_\mu(\hat{k})$, statistic of 81.85614 exceeds the critical value of 4.651, confirming the significance of trigonometric terms. Similarly, in the trend model, the $F-t_{NL}$ statistic of -1.85523 indicates non-stationarity, but the $F_t(\hat{k})$ value of 400.39865 shows significance. After first differencing, stationarity is achieved in both models. The differenced $F-t_{NL}$ statistics are -4.02993 (constant) and -4.07950 (C&T), satisfying the stationarity conditions. $F_\mu(\hat{k})$, and $F_t(\hat{k})$ statistics also confirm this. These results validate the FKSS unit root test proposed by Christopoulos and Leon-Ledesma (2010), indicating that LNFPI follows an I(1) process.

MinSSR values significantly decrease after differencing (from 150.65545 to 0.15168 for the constant model, and from 7.53467 to 0.13714 for the C&T model), reflecting a better model fit.

Table 6 – FKSS Unit Root Test for LNEPI

LNEPI	**k**	$F - t_{NL}$	$F_\mu(\hat{k})$	**optimallag**	**MinSSR**
Constant	1	1.86934	65.18885**	1	117.20068
	k	$F - t_{NL}$	$F_t(\hat{k})$	optimallag	MinSSR
C&T	1	-1.80719	302.85973**	1	6.24205
	k	$F - t_{NL}$	$F_\mu(\hat{k})$	optimallag	MinSSR
ΔConstant	1	-12.12755**	6.14751**	0	0.26687
	k	$F - t_{NL}$	$F_t(\hat{k})$	optimallag	MinSSR
Δ C&T	1	-11.65276**	6.10070**	0	0.25394

Note: * and ** denote significance at the 10% and 5% levels, respectively. Δ denotes the first difference of the series.

In Table 6, for the constant model, the $F - t_{NL}$ statistic for the LNEPI series is 1.86934, smaller than the 5% critical value in absolute terms (-3.67), indicating non-stationarity. However, the $F_\mu(\hat{k})$ statistic is 65.18885, exceeding the 5% critical value of 4.651, confirming the significance of the trigonometric terms. In the trend-included model (C&T), the $F - t_{NL}$ statistic is -1.80719, also indicating non-stationarity, but the $F_t(\hat{k})$ statistic of 302.85973 confirms the significance of the trigonometric terms. After first differencing, stationarity is achieved in both models. The differenced $F - t_{NL}$ statistics are -12.12755 (constant model) and -11.65276 (C&T model), both satisfying stationarity conditions. Corresponding $F_\mu(\hat{k})$ and $F_t(\hat{k})$ statistics also support this conclusion. These results validate the FKSS unit root test by Christopoulos and Leon-Ledesma (2010), confirming that LNEPI follows an I(1) process.

The results of the Fourier cointegration test, which incorporates trigonometric terms to account for structural breaks, are presented in Table 7.

Table 7 – Fourier Cointegration Test

Dependent Variable: LNFPI					
With Constant			**Critical Values**		
Min SSR*	k	CI_f^0	%1	%5	%10
0.15470	1	0.04312	0.200	0.276	0.473
F-Statistics for Fourier Cointegration Analysis					
l_{opt}	k	$F^m(k^*)$	%1	%5	%10
6	1	16.92172	3.352	4.066	5.774
With Constant & Trend			**Critical Values**		
Min SSR*	k	CI_f^1	%1	%5	%10
0.15191	1	0.04325	0.078	0.099	0.163
F-Statistics for Fourier Cointegration Analysis					
l_{opt}	k	$F^m(k^*)$	%1	%5	%10
6	1	17.11439	3.306	4.019	5.860

Note: In the Fourier cointegration test, the critical values used to test the presence of a cointegration relationship and the critical values for the F-statistic used to test the significance of the trigonometric terms are obtained from Tsong et al. (2016: 1190). *SSR represents the sum of squared residuals.

Table 7 presents the frequency number k, the CI_f^0 test statistic for the constant model, the CI_f^1 test statistic for the constant and trend model (C&T), the $F^m(k^*)$ test statistic, the minimum sum of squared residuals (MinSSR), and the optimal lag length $l_{opt}\left(T^{\frac{1}{3}}\right)$. For the constant specification, the CI_f^0statistic (0.04312) is lower than the 5% critical value (0.276). Therefore, the null hypothesis of cointegration cannot be rejected, indicating the presence of a cointegration relationship between LNFPI and LNEPI. The $F^m(k^*)$statistic (16.92172) exceeds the corresponding 5% critical value (4.066), confirming the statistical significance of at least one trigonometric term.

Similarly, in the C&T model, the CI_f^1statistic (0.04325) is below the 5% critical value (0.099). Accordingly, the null hypothesis of cointegration cannot be rejected, indicating a long-run relationship between LNFPI and LNEPI. The $F^m(k^*)$statistic (17.11439) exceeds the corresponding 5% critical value (4.019), confirming the statistical significance of the trigonometric terms. These findings are consistent with the presence of a cointegration relationship as suggested by the Fourier cointegration framework of Tsong et al. (2016). Additionally, the low MinSSR values (0.15470 for the constant model and 0.15191 for the C&T model) further support the stability of the estimated long-run relationship.

Table 8 presents the long-term estimation results obtained using FMOLS, DOLS, and CCR methods, with LNFPI as the dependent variable and LNEPI as the independent variable.

Table 8 – Long-Term Estimation

Dependent Variable: LNFPI				
Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)				
		DOLS		
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LNEPI	1.133976	0.026362	49.71483	0.0000
SIN1	0.066522	0.007624	8.72490	0.0000
COS1	-0.049658	0.008095	-6.13416	0.0000
C	-0.573004	0.117116	-13.43114	0.0000
R-squared	0.9929931	Mean dependent var	5.7244206	
Adjusted R-squared	0.9924862	S.D. dependent var	0.8858281957	
S.E. of regression	0.0767856	Sum squared resid	1.3855695434	
Long-run variance	0.028569			

FMOLS

Variables	Coefficient	Std. Error	t-Statistic	Prob.
LNEPI	1.135595	0.014866	76.38875	0.0000
SIN1	-0.048303	0.016671	-2.897421	0.0041
COS1	0.095651	0.014433	6.627120	0.0000
C	-0.696335	0.084982	-8.193965	0.0000
R-squared	0.992938	Mean dependent var	5.756174	
Adjusted R-squared	0.992856	S.D. dependent var	0.959324	
S.E. of regression	0.081082	Sum squared resid	1.715884	
Long-run variance	0.025481			

CCR

Variables	Coefficient	Std. Error	t-Statistic	Prob.
LNEPI	1.136126	0.015065	75.41369	0.0000
SIN1	-0.047859	0.016832	-2.843336	0.0048
COS1	0.096103	0.014142	6.795633	0.0000
C	-0.699196	0.085848	-8.144563	0.0000
R-squared	0.992931	Mean dependent var	5.756174	
Adjusted R-squared	0.992849	S.D. dependent var	0.959324	
S.E. of regression	0.081122	Sum squared resid	1.717586	
Long-run variance	0.025481			

The results reported in Table 8 indicate that the long-run coefficient of LNEPI is statistically significant across all estimation methods, suggesting the presence of a stable long-run relationship between LNEPI and LNFPI. The DOLS, FMOLS, and CCR estimators produce highly consistent coefficients (1.133976, 1.135595, and 1.136126, respectively), indicating robustness across alternative long-run estimation techniques. The statistical significance of the sine and cosine terms confirms the relevance of the Fourier components in capturing structural shifts and periodic fluctuations.

In particular, the DOLS estimator yields a coefficient of 1.133976 with a standard error of 0.026362 and a t-statistic of 49.71483, indicating statistical significance at conventional levels. Similar results are obtained under FMOLS and CCR specifications. Overall, the consistency of the estimated coefficients across methods suggests a stable long-run association between LNEPI and LNFPI.

Following these estimations, an asymmetric causality test was performed, and the results are presented in Table 9. The Hacker and Hatemi-J (2006) causality test builds on the Toda–Yamamoto (1995) augmented VAR framework and evaluates Granger-type predictive causality using bootstrap critical values. Accordingly, the results indicate predictive directional dependence within the specified VAR system and should not be interpreted as evidence of structural economic causality.

Table 9 – Causality Test Results

Hacker-Hatemi-J (2006) Causality Test Results

Null Hypothesis	Test Statistic	Bootstrap Critical Values		
		%1	%5	%10
Y≠>X Rejection	21.259***	18.398	13.186	10.992
X≠>Y Rejection	17.226**	18.372	13.454	11.106

Hatemi-J (2012) Asymmetric Causality Test Results

Null Hypothesis	Test Statistic	Bootstrap Critical Values			Null Hypothesis	Test Statistic	Bootstrap Critical Values		
		%1	%5	%10			%1	%5	%10
Y(+)≠>X(+) Rejection	55.78***	22.177	16.188	13.872	X(+)≠>Y(+) Rejection	22.272**	23.696	16.665	14.107
Y(-)≠>X(-) Acceptance	0.010	19.631	7.338	4.615	X(-)≠>Y(-) Acceptance	0.248	18.331	6.658	4.405
Y(-)≠>X(+) Rejection	11.794*	29.018	14.592	11.073	X(+)≠>Y(-) Rejection	17.939**	29.790	14.219	11.076
Y(+)≠>X(-) Acceptance	5.949	27.699	19.154	15.730	X(-)≠>Y(+) Acceptance	6.558	27.519	18.883	15.594

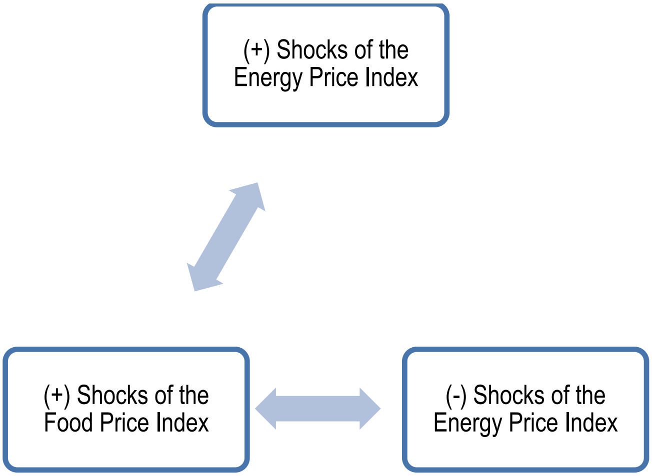
Note: In this table, Y represents LNEPI and X represents LNFPI. The expression X(+)⇏Y(+) corresponds to the null hypothesis stating that "positive shocks in LNFPI do not cause positive shocks in LNEPI". If the null hypothesis is rejected, it indicates the presence of directional causality. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

According to Table 9, the results suggest bidirectional Granger-type predictive causality between LNEPI (Y) and LNFPI (X) at conventional significance levels. The null hypothesis that positive shocks in LNFPI do not Granger-cause positive shocks in LNEPI (X(+) ⇏ Y(+)) is rejected (Wstat = 22.272 > 16.665). Similarly, the reverse null hypothesis (Y(+) ⇏ X(+)) is also rejected, indicating bidirectional predictive dependence within the Granger framework. No statistically significant predictive causality is detected for negative shocks (X(−) ⇏ Y(−), Y(−) ⇏ X(−)), suggesting that negative price movements are not systematically followed by corresponding negative movements in the other sector.

Regarding cross-shock dynamics, the null hypothesis X(+) ⇏ Y(−) is rejected (Wstat = 17.939 > 11.076), indicating that positive shocks in food prices are followed by negative movements in energy prices. Similarly, Y(−) ⇏ X(+) is rejected at the 10% level (Wstat = 11.794 > 11.073), pointing to asymmetric cross-shock interactions. These findings reflect asymmetric predictive dynamics between positive and negative shocks. However, it should be emphasized that the results indicate Granger-type predictive causality and do not imply structural economic causality. Although the bootstrap approach enhances robustness against non-normal error distributions and small-sample distortions, the causality results remain conditional on model specification, lag selection, and the information set included in the VAR framework. Therefore, the findings should be interpreted within the limits of the econometric model.

The causality relationships are illustrated in Figure 2.

Figure 2 – Asymmetric Causality Diagram



These findings suggest that asymmetric Granger-type predictive relationships between positive and negative shocks appear only under specific directions and statistical conditions.

5. Discussion

The findings show that the relationship between energy and food prices in Türkiye is nonlinear, cointegrated, and asymmetric. The FKSS unit root tests (Tables 5 and 6) indicate the integration properties of the series, while the Fourier Cointegration Test (Table 7) points to a persistent long-run relationship between the variables. Long-term coefficient estimates (Table 8) suggest that a 1% increase in energy prices is associated with approximately a 1.13% increase in food prices in the long run. This result is consistent with studies such as Borrallo et al. (2024), Wehinger (2000), and Gartner & Wehinger (1998), which emphasize the role of energy costs in food price dynamics and the relevance of core inflation analyses for policymakers.

The Asymmetric Causality Test (Table 9) provides evidence of bidirectional Granger-type predictive causality for positive shocks, whereas no statistically significant predictive relationship is found for negative shocks. This asymmetric pattern may be consistent with price adjustment frictions, including potential price stickiness, as discussed by Fielding & Mizen (2000) and Borrallo et al. (2024). In this setting, upward adjustments appear to be transmitted more systematically than downward adjustments.

This study contributes to the literature by combining asymmetric causality analysis with Fourier transformations to examine how energy price fluctuations are transmitted to food prices. The results indicate that the interaction between the two sectors involves nonlinear and asymmetric predictive dynamics rather than purely symmetric short-term movements.

From a policy perspective, the findings suggest the importance of considering sectoral interdependencies and technological factors such as energy-efficient agricultural practices (Armah et al., 2009). Moreover, global shocks, including the COVID-19 pandemic and geopolitical tensions, highlight the need for flexible policy responses (Borisov, 2024; Irwin & Penn, 1975). The empirical results remain conditional on model specification, lag selection, and the information set included in the VAR framework. Therefore, they should be interpreted as evidence of predictive relationships rather than structural economic causality.

6. Conclusion

This study identifies a long-term relationship between energy and food prices using Fourier-based cointegration tests. The results indicate persistent linkages between these markets over the sample period. The findings suggest that shocks in energy and food prices are associated with sustained movements in the respective price indices, shaping inflation dynamics over time. Increases in energy prices are linked to higher food production costs, particularly in developing economies where such pressures can significantly affect living costs.

The long-term coefficient estimates imply an elasticity of approximately 1.13 between energy and food prices. Accordingly, a 1% increase in energy prices is associated with about a 1.13% increase in food prices in the long run. These results underline the importance for central banks and policymakers – especially those operating under inflation-targeting regimes – to monitor developments in both energy and food markets. The Hatemi-J asymmetric causality analysis further provides evidence of bidirectional Granger-type predictive causality and asymmetric predictive dynamics. Positive shocks appear to be followed by more persistent adjustments than negative shocks, which may be consistent with price stickiness. Upward price movements are transmitted more systematically than downward movements within the limits of the econometric framework.

Although the study contributes to the literature by combining Fourier methods with asymmetric causality analysis, the results remain conditional on model specification and the data structure for Türkiye. Future research may extend the analysis to additional countries and incorporate exchange rate dynamics, agricultural input costs, and global supply shocks. Further work on the implications of the energy transition and renewable energy adoption for food production processes could provide additional insights for economic policy design.

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