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Research Article

The Dynamics of Producer Food Prices: a Fourier–Wavelet Analysis of Exchange Rates and Agricultural Inputs*

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Abstract: This study is motivated by the persistent nature of food inflation in Türkiye, driven by exchange rate volatility and dependence on imported inputs, as well as the tendency of the existing literature to address these dynamics mostly within a linear framework. The analysis explores the long-term relationships, nonlinear structures, and time–frequency co-movements between the Food Producer Price Index (Food PPI), Agricultural Input Price Index (GFE), and exchange rates (USD/TRY, EUR/TRY). Monthly data covering the 2015:01–2025:05 period are used; the relevant series are seasonally adjusted and logarithmically transformed. Methodologically, the study applies the LR and Hansen (1999) tests to detect nonlinearity, while the Harvey–Mills (2002) and Kapetanios–Shin–Snell (2003) tests are employed to determine integration orders. The Fourier cointegration test examines long-term relationships; DOLS estimates capture the degree of exchange rate pass-through; and Wavelet Coherence (WTC) analysis reveals time–frequency interactions. The findings indicate that the Food PPI and exchange rates are I(1), while the GFE is I(2). Hence, cointegration analysis includes only exchange rates as explanatory variables. DOLS estimates the pass-through coefficients as 1.13 (USD) and 1.14 (EUR). WTC results highlight strong synchronization (→) and occasional exchange rate and GFE leadership (↗/↘), particularly after 2018. Structural breaks identified by the HM test align with exchange rate shocks (2016–2019), the 2020 pandemic, and post-2022 energy price surges. The study provides an original contribution by combining nonlinear tests, Fourier, and WTC analyses to examine the food PPI–exchange rate nexus in Türkiye.

Keywords: Food Inflation, Agricultural Input Price Index, Exchange Rate Pass-Through, Fourier Cointegration, Wavelet Coherence.
Jel Codes: E31, F31, Q18

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Üretici Gıda Fiyatlarının Dinamikleri: Döviz Kurları ve Tarımsal Girdilerle Fourier–Wavelet Analizi

Öz: Bu çalışma, gıda enflasyonunun kur oynaklığı ve ithal girdi bağımlılığı nedeniyle Türkiye'de kalıcılaşan bir sorun haline gelmesinden ve mevcut literatürün bu dinamikleri çoğunlukla doğrusal çerçevede ele almasından hareketle tasarlanmıştır. Analiz, Türkiye'de Gıda ÜFE ile tarımsal girdi fiyat endeksi (GFE) ve döviz kurları (Dolar/TL, Euro/TL) arasındaki uzun dönemli ilişkileri, doğrusal olmayan yapıları ve zaman-frekans boyutundaki eşgüdümü incelemektedir. 2015:01–2025:05 dönemine ait aylık veriler kullanılmış; gerekli seriler mevsimsellikten arındırılmış, tüm serilere logaritmik dönüşüm uygulanmıştır. Metodolojik olarak, LR ve Hansen (1999) testleriyle serilerin doğrusal dışı yapıları, Harvey–Mills (2002) ve Kapetanios–Shin–Snell (2003) testleriyle de bütünleşme dereceleri belirlenmiştir. Fourier koentegrasyon testi uzun dönemli ilişkileri sınamakta, DOLS tahminleri kur geçişkenliğini ölçmekte, Wavelet koherens (WTC) analizi ise zaman-frekans boyutundaki eşgüdümü ortaya koymaktadır. Bulgular, gıda ÜFE ve döviz kurlarının I(1), GFE'nin ise I(2) özellik taşıdığını göstermiştir. Bu nedenle koentegrasyon analizinde bağımlı değişken olarak gıda ÜFE, açıklayıcı değişkenler olarak yalnızca döviz kurları kullanılmıştır. Analiz, uzun dönemli ilişkiyi doğrularken; DOLS tahminleri kur geçişkenliği katsayılarını 1.13 (Dolar) ve 1.14 (Euro) düzeyinde hesaplamıştır. WTC analizleri, özellikle 2018 sonrası 2–4 yıllık periyotlarda güçlü senkronizasyon (→) ve zaman zaman döviz kurunun ve

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GFE'nin öncü rolünü (↗/↘) ortaya koymuştur. HM testiyle belirlenen kırılmalar, 2016–2019 kur şokları, 2020 pandemisi ve 2022 sonrası enerji fiyat artışlarıyla örtüşmektedir. Çalışma, doğrusal olmayan testler, Fourier ve WTC analizini birleştirerek Türkiye'de gıda ÜFE ile döviz kurları arasındaki uzun dönemli ilişkiyi inceleyen özgün katkılar sunmaktadır.

Anahtar Kelimeler: Gıda Enflasyonu, Tarımsal Girdi Fiyat Endeksi, Döviz Kuru Geçişkenliği, Fourier Koentegrasyon, Wavelet Koherens.
Jel Kodları: E31, F31, Q18.

1. Introduction

Inflation remains one of the most persistent and challenging issues of the Turkish economy. In particular, food prices, as a key component of consumer inflation, exert strong effects on both short-term fluctuations and long-term trends. The volatility of food inflation is driven by factors such as exchange rates, agricultural input costs, and global price shocks, creating a critical source of risk for macroeconomic stability.

Food inflation is not only an economic concern but also a social one, directly affecting all segments of society. In the case of Türkiye, sharp exchange rate increases since 2018 have rapidly raised the cost of import-dependent agricultural inputs (fertilizer, feed, energy). The surge in global energy prices and logistics costs in 2021–2022 further intensified this pressure. In addition, droughts and floods in 2023–2024, followed by a severe frost in the spring of 2025, triggered supply-side shocks. Combined with exchange rate volatility, these developments placed strong upward pressure on both consumer food prices and the agricultural producer price index.

These problems also highlight the structural vulnerabilities of food prices. Unplanned production, bargaining power imbalances within the supply chain, import dependency, and rising land rents contribute to the persistence of food inflation. The cost-underpricing strategies of large retailers suppress producer and farmer incomes, while import dependence weakens domestic production incentives. At the same time, external fragilities linked to exchange rate shocks generate significant risks for price stability.

Although there is extensive literature on the determinants of food prices, most existing studies are limited to linear models and fall short in addressing price dynamics in an integrated short- and long-run perspective. In reality, the effects of exchange rates and agricultural input prices may vary in intensity across different periods, making it necessary to analyze these dynamics within nonlinear frameworks. Moreover, despite the increasing use of time–frequency methods, studies that examine the relationship between food prices, exchange rates, and input costs from a spectral perspective in the Turkish context remain scarce.

This study aims to address these gaps by answering the following research questions:

- How do exchange rates (USD and EUR) affect producer food prices?
- What is the role of agricultural input prices (GFE) in shaping producer food prices?
- How do short- and long-term dynamics diverge in the time–frequency domain?

The main contribution of this paper lies in analyzing the effects of exchange rates on food inflation using Fourier and wavelet-based methods, thereby simultaneously capturing nonlinearities and time–frequency differentiations. In addition, the examination of the time series properties of agricultural input prices sheds light on the persistence of shocks, an issue that has not been sufficiently addressed in the literature, while offering a new framework for methodological debates in this field. In doing so, the study overcomes existing methodological limitations and opens the door to more flexible and realistic implications for policymakers.

The remainder of the paper is organized as follows: Section 2 reviews the related literature; Section 3 presents the dataset and methodology; Section 4 reports the empirical findings; and Section 5 concludes with a discussion of the results and policy recommendations.

2. Literature

This section reviews the literature under three main categories: international studies, studies focusing on Türkiye, and methodological contributions.

- **International Literature**

The significant impact of food prices on the overall economy has been widely documented in both developed and developing countries. The global financial crisis of 2009 triggered a severe economic downturn, leading to a marked decline in the world food price index. However, from the second half of 2010 onwards, the index resumed an upward trend, reaching one of its historical peaks in 2011. Adverse supply-side weather conditions were the main driver of this surge. Droughts in the United States, Argentina, Russia, Ukraine, and Kazakhstan; excessive rainfall in Canada and Australia; and wildfires affecting agricultural production areas in China and Russia all curtailed output, fueling an increase in food prices (Shama, 2011).

In addition to global supply shocks, the interaction between financial and agricultural markets has received increasing attention. Nazlioglu et al. (2013) investigated volatility transmission between oil and major agricultural commodities such as wheat, corn, and soybeans using daily data. They found that while no significant volatility spillover existed prior to the crisis, in the post-crisis period oil price volatility spilled over into agricultural markets (except sugar). These findings indicate that the relationship between energy and agricultural markets deepened not only at the price level but also at the risk level following the food crisis. Similarly, Nazlioglu and Soytas (2012) highlight the long-run interlinkages between oil prices, agricultural commodity prices, and exchange rates, emphasizing that agricultural prices tend to rise during periods of dollar depreciation. Earlier studies such as Trostle (2008), Harri et al. (2009), and Hatzenbuehler et al. (2016) also identify exchange rates, global demand, and energy prices as key determinants of food price dynamics.

From a macroeconomic perspective, the role of exchange rates differs across countries and economic structures. Chen et al. (2020) find that exchange rate sensitivity is particularly high in low-income oil-exporting economies. Similarly, Baek and Koo (2009) show that exchange rates and agricultural commodity prices significantly affect food prices in both the short and long run. Studies focusing on developing countries, such as Hasan and Masih (2018), Norazman et al. (2018), Iddrisu and Alagidede (2020) and Ferrucci et al. (2010) indicate that exchange rate pass-through to food prices varies across time horizons and may exhibit asymmetric patterns.

Recent contributions further emphasize the role of global food price dynamics and uncertainty. Anderl and Caporale (2025) demonstrate that both the level and volatility of global food prices have persistent effects on domestic food inflation. In addition, Doroshenko et al. (2025) show that commodity prices are shaped by time-varying and nonlinear relationships, particularly under economic and financial uncertainty. These findings highlight that food price dynamics are inherently complex and evolve across both time and frequency domains.

- **Literature on Türkiye**

Food inflation has become a major macroeconomic concern in Türkiye, driven by both domestic and external factors. Studies identify key determinants such as climate conditions, input costs, transportation expenses, labor costs, and taxation (Selvi and Cavlak, 2021). Eren et al. (2014) emphasize the role of supply-side factors, particularly producer prices and domestic production. Similarly, Özçelik and Uslu (2024) and Demir et al. (2023) show that energy costs and exchange rates significantly influence producer price dynamics, highlighting the importance of cost-based transmission mechanisms.

A growing body of literature focuses on the role of exchange rates in shaping food price dynamics. İçen et al. (2022) find a long-run cointegration relationship between oil prices, exchange rates, and food prices, with asymmetric effects across shocks. Kutlu, (2021), Demirağ and Sağır (2023) and Kolcu (2023) provide further evidence that exchange rates are among the most influential determinants of food prices in Türkiye. Earlier studies such as Tay-Bayramoğlu and Yurtkur (2015), Kılcı (2019) and Bayramoğlu et al. (2025) also highlight the dominant role of exchange rates, particularly in the short run. However, some studies report mixed findings, with Kofoğlu et al. (2018) and Eştürk and Albayrak (2018) identifying weaker or insignificant relationships.

More recent studies provide stronger and more nuanced evidence. Bilgili et al. (2024), using a wavelet approach, show that exchange rate pass-through varies across time and frequency, becoming stronger during periods of macroeconomic instability. Similarly, Daşdemir (2023) finds that exchange rate increases have a stronger impact on food prices compared to other price groups, suggesting that exchange rate movements operate as a key transmission channel shaping food price dynamics in Türkiye and amplifying inflationary pressures through cost and import dependency.

In addition to exchange rate effects, recent studies emphasize the importance of cost-side dynamics. Bor and Dağıstan (2024) and Bor and Sakarya (2026) demonstrate that agricultural input and fertilizer prices are significantly influenced by exchange rates and energy prices, with nonlinear and asymmetric effects. Bozkurt and Çamoğlu (2025) further show that food inflation is strongly linked to exchange rates and producer prices in the long run. Kaya and Ertuğrul (2024) also reveal that the relationship between global and domestic food prices varies across periods, indicating a dynamic and time-varying structure.

- **Methodological Literature**

Traditional time-series approaches often assume constant relationships over time, which may fail to capture the complex dynamics of food prices. In this context, several studies have documented that the relationship between exchange rates, agricultural inputs, and food prices is nonlinear, asymmetric, and time-dependent. For instance, Hasan and Masih (2018) show that the exchange rate–food price relationship differs between the short and long run, while Bor and Dağıstan (2024) provide evidence of asymmetric effects in fertilizer and exchange rate interactions. Similarly, Bor and Sakarya (2026) demonstrate that agricultural price dynamics exhibit nonlinear trends, highlighting the limitations of linear modeling frameworks.

Recent studies have therefore increasingly adopted advanced econometric techniques to address these limitations. Regime-switching and dynamic models, such as those used by Kaya and Ertuğrul (2024), reveal that the relationship between global and domestic food prices varies across different periods. Likewise, Anderl and Caporale (2025) show that both the level and volatility of food prices have persistent and time-varying effects on inflation. These findings indicate that the underlying relationships are not stable over time and require more flexible modeling approaches.

In this context, wavelet-based methods have gained prominence as they allow the analysis of relationships across both time and frequency domains. Bilgili et al. (2024) demonstrate that exchange rate pass-through differs across frequencies, while Doroshenko et al. (2025) highlight the ability of wavelet approaches to capture time-varying dependencies under economic uncertainty. These methods provide a more comprehensive framework compared to conventional techniques by simultaneously accounting for both temporal and frequency variations.

Despite these advances, studies jointly examining exchange rates, agricultural input costs, and food prices within a unified time–frequency framework remain limited. This study contributes to the literature by employing a Fourier–wavelet approach to capture nonlinear, asymmetric, and time-varying interactions among these variables.

2.1 Research Gap

Despite a substantial body of research, the determinants of food prices in Türkiye are generally examined within linear and time-domain frameworks, which may not fully capture the complexity of the underlying relationships. In particular, the roles of structural breaks, nonlinear adjustments, and time-varying interactions remain insufficiently addressed. Moreover, the joint dynamics between exchange rates, agricultural input costs, and food prices have not been adequately analyzed within a unified framework that accounts for both long-run structural changes and short-run frequency-based interactions.

This study addresses this gap by examining the relationship between exchange rates (USD, EUR) and food prices over the period 2015–2025 using both Fourier cointegration and wavelet coherence methods. While Fourier cointegration allows for the modeling of long-run relationships with structural breaks, wavelet coherence captures time-varying co-movements and lead–lag dynamics across different time horizons. In this way, the study provides a more comprehensive framework for understanding the transmission of exchange rate shocks to food prices.

3. Methodology and Data

This section presents the nonlinear time series tests employed in the study. First, to examine whether the data contain structural breaks and nonlinear transition dynamics, the LR test and Hansen's (1999) test are applied. Second, to evaluate the stationarity properties of the series within a nonlinear framework, the KSS (2003) and HM (2002) tests are conducted.

3.1 LR Test

The LR test, originally developed by Chan and Tong (1990) and Chan (1990, 1991), examines the structure of the SETAR model. The specification of the SETAR model is presented in Equation (1).

$$x_t = \phi_0 + \sum_{i=1}^{p} \phi_i x_{t-i} + I(x_{t-d} > r)\left(\beta_0 + \sum_{i=1}^{p} \beta_i x_{t-i}\right) + a_t \tag{1}$$

Here, r denotes the threshold value. I is the indicator function, where $I(x_{t-d} > r) = 1$ if $x_{t-d} > r$, and $I(x_{t-d} > r) = 0$ otherwise. The null hypothesis is defined as $H_0: \beta_i = 0$. The LR test statistic is given by (2):

$$\lambda = \frac{n(\hat{\sigma}_0^2 - \hat{\sigma}^2}{\hat{\sigma}^2} \tag{2}$$

where $n = T - p + 1$, with T denoting the number of observations. $\hat{\sigma}^2$ and $\hat{\sigma}_0^2$ are defined as in equations (3) and (4).

$$\hat{\sigma}^2 = \min_{r\epsilon\widehat{R},\theta,\phi} \left[\sum_{t=p+1}^{T} \{x_t - \phi_0 - \sum_{i=1}^{p} \phi_i x_{t-i} - I(x_{t-d} > r)\,(\beta_0 + \sum_{i=1}^{p} \beta_i x_{t-i})\}^2 \right] \tag{3}$$

$$\hat{\sigma}_0^2 = \min_{\phi} \left\{ \sum_{t=p+1}^{T} (x_t - \phi_i x_{t-i})^2 \right\} \tag{4}$$

The test statistics follows a standard distribution.

3.2 Hansen (1999) Test

The Hansen (1999) test provides an approach to analyzing nonlinearity of the SETAR type. It is used both to test for nonlinearity and to determine the number of regimes in the model.

The linear autoregressive model is expressed as in equation (5).

$$Y_t = a'_1 X_{t-1} + e_t \tag{5}$$

Where $X_{t-1} = (1Y_{t-1}Y_{t-2} \dots Y_{t-p})'$. A SETAR model with M regimes, denoted as SETAR (m), is expressed as (6):

$$Y_t = a'_1 X_{t-1} I_{1t}(\gamma, d) + \cdots + a'_m X_{t-1} I_{mt}(\gamma, d) + e_t \tag{6}$$

The parameters can be estimated using the least squares principle, as follows:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \sum_{t=1}^{n} (Y_t - a'_1 X_{t-1} I_{1t}(\gamma, d) - \cdots - a'_m X_{t-1} I_{mt}(\gamma, d))^2 \tag{7}$$

To compare a SETAR(j) model with a SETAR(k) alternative, the following test statistic is used:

$$F_{jk} = n(\frac{S_j - S_k}{S_k}) \tag{8}$$

where S_j, and S_k denote the sum of squared residuals for the models with j and k regimes, respectively, and n is the number of observations. The distribution of the test statistic is obtained through bootstrap methods (Güriş, 2020).

3.3 HM (2002) Test

Harvey and Mills (2002) proposed a new unit root test that employs a logistic transition function. Unlike the LNV (1998) test, their approach incorporates two transition functions. The test relies on three alternative specifications. Model A allows for smooth transition in the mean. Model B extends this by including a deterministic trend. Model C accounts for smooth transition in both the mean and the trend (Güriş, 2020).

The model specifications are presented in (9), (10), and (11) below:

$$\text{Model A: } y_t = \alpha_1 + \alpha_2 S_{1t}(\gamma_1, \tau_1) + \alpha_3 S_{2t}(\gamma_2, \tau_2) + v_t \tag{9}$$

$$\text{Model B: } y_t = \alpha_1 + \beta_1 t + \alpha_2 S_{1t}(\gamma_1, \tau_1) + \alpha_3 S_{2t}(\gamma_2, \tau_2) + v_t \tag{10}$$

$$\text{Model C: } y_t = \alpha_1 + \beta_1 t + \alpha_2 S_{1t}(\gamma_1, \tau_1) + \beta_2 t + S_{1t}(\gamma_1, \tau_1) + \alpha_3 S_{2t}(\gamma_2, \tau_2) + \beta_3 t S_{2t}(\gamma_2, \tau_2) + v_t \tag{11}$$

Here, $S_{it}(\gamma_i, \tau_i)$ denotes the logistic transition function, defined in (12).

$$S_{it}(\gamma_i, \tau_i) = [1 + \exp\{-\gamma_i(t - \tau_i T\}]^{-1} \quad i = 1,2 \tag{12}$$

In the testing procedure, the residuals obtained from the appropriate model specification are used in the generalized Dickey–Fuller regression, expressed in (13):

$$\Delta\hat{v}_t = p\hat{v}_{t-1} + \sum_{i=1}^{k} \delta_i \Delta\hat{v}_{t-i} + \eta_t \tag{13}$$

The unit root test statistic is computed as the t-statistic of the parameter p. For Model A, the statistic is denoted as S_{2a}; for Model B, as $S_{2a(\beta)}$; and for Model C, as $S_{2a\beta}$.

3.4 KSS (2003) Test

Kapetanios et al. (2003) extended the standard ADF-type unit root tests by developing a procedure that allows testing the unit root null against a nonlinear stationary STAR process, as specified in (14):

$$y_t = \beta y_{t-1} + \phi y_{t-1} F(\theta; y_{t-1}) + \varepsilon_t \tag{14}$$

where ε_t $iid(0, \sigma^2$and the exponential transition function is defined as $F(\theta; y_{t-1}) = 1 - \exp\{-\theta(y_{t-1} - c)^2\}$. In their study, Kapetanios et al. (2003) assume c = 0. Under this assumption, equation (15) is given as follows:

$$\Delta y_t = \alpha y_{t-1} + \phi y_{t-1}(1 - \exp\{-\theta(y_{t-1})^2\}) + \varepsilon_t \quad (15)$$

Here, y_t may represent the raw series, the demeaned series, or the series detrended by both mean and trend. The test procedure is based on the null hypothesis $\alpha = 0$, with the hypotheses defined as:

$H_0: \theta = 0$ (unit root)

$H_1: \theta > 0$ (nonlinear ESTAR stationarity).

If θ is positive, it determines the speed of mean reversion.

Since ϕ cannot be identified under the null hypothesis, the hypotheses cannot be directly tested. By applying a first-order Taylor expansion to equation (15), it can be rewritten as $\Delta y_t = \delta y_{t-1}^3 + \varepsilon_t$ (Güriş, 2020). Considering that the error terms may exhibit autocorrelation, it can be extended into a more general form as in equation (16).

$$\Delta y_t = \delta y_{t-1}^3 + \sum p_j \Delta y_{t-j} + \varepsilon_t \quad (16)$$

Instead of adding deterministic components, the test regression in (16) can be applied to the raw series, the demeaned series, or the detrended series (Hepsag, 2022). Based on this equation, the test statistic for the null hypothesis is computed as in (17):

$$t_{NL} = \frac{\hat{\delta}}{SE(\hat{\delta})} \quad (17)$$

Here, $\hat{\delta}$ denotes the OLS estimate of the parameter, and $SE(\hat{\delta})$ its standard error. If the absolute value of the t_{NL} statistic is smaller than the critical value of KSS (2003), the null of a unit root cannot be rejected. If it is larger, the null is rejected in favor of nonlinear ESTAR stationarity. Under this alternative, the series responds symmetrically to shocks, meaning that positive and negative shocks have the same effect on the mean-reverting process (Hepsag, 2022).

3.5 Cointegration Analysis

Shin (1994) introduced a cointegration test based on the KPSS unit root framework. Tsong et al. (2016) extended this by incorporating trigonometric terms to account for structural breaks, known as the Fourier–Shin (FShin) test. The cointegration equation is specified as follows (18, 19):

$$y_t = a + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \theta x'_t + \sum_{i=-l}^{l} \psi_i \Delta x'_{t-i} + \varepsilon_t \quad (18)$$

$$y_t = a + \beta_t \gamma_1 \sin(\frac{2\pi kt}{T}) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \theta x'_t + \sum_{i=-l}^{l} \psi_i \Delta x'_{t-i} + \varepsilon_t \quad (19)$$

In (18) and (19), k denotes the frequency, T the number of observations, t the deterministic trend, π the mathematical constant, and $-l$, l the lag lengths. The sine and cosine terms represent additional deterministic components (Hepsag, 2022). In the first stage, the model is estimated with the selected optimal frequency k. In the second stage, residuals from this model are subjected to the Shin (1994) cointegration test. The null hypothesis of cointegration ($\sigma_u^2 = 0$) is tested against the alternative of no cointegration ($\sigma_u^2 > 0$) using the statistic defined in (20).

$$CI_f^0, CI_f^1 = \frac{1}{T^2} \frac{\sum_{t=1}^{T} S_t(k)^2}{\sigma^2} \quad (20)$$

In equation (20), CI_f^0 refers to the model with a constant and CI_f^1 to the model with a constant and trend. $S_t(k)$ is the residual sum of squares, T the sample size, and σ^2 the long-run variance (Hepsag, 2022). If the statistics are below the critical values of Tsong et al. (2016) for k=1,2,3, cointegration cannot be rejected; otherwise, the null is rejected. After establishing cointegration, the restricted $F^m(k^*)$ test examines whether γ_1 and γ_2 are jointly insignificant ($\gamma_1 = \gamma_2 = 0$) or at least one is significant.

$$F^m(k^*) = (\frac{ESS_R - ESS_{UR}(k)/2}{ESS_{UR}\,k/(T-q)}) \tag{21}$$

In (21), ESS_R and ESS_{UR} are the residual sums of squares, T the sample size, and qqq the number of parameters. If $F^m(k^*)$ exceeds the critical values of Tsong et al. (2016), at least one trigonometric term is significant; otherwise, the Shin (1994) test is applied (Hepsag, 2022).

3.6 WTC Analysis

Wavelet coherence (WTC) is a powerful method for examining relationships between two time series in both time and frequency domains. Compared with traditional time-domain approaches, it provides richer insights for non-stationary data and allows co-movements between variables to be assessed simultaneously across different horizons (Crowley, 2007; Aguiar-Conraria & Soares, 2011; Liu et al., 2023).

WTC decomposes a series into the time–frequency space through the continuous wavelet transform (CWT). For a signal $x(t)$, the CWT is defined as follows (Yilanci & Pata, 2023):

$$W_x(\mathrm{m},\mathrm{n}) = \int_{-\infty}^{\infty} x(t)\,\frac{1}{\sqrt{n}}\psi(\frac{t-m}{n})dt \tag{22}$$

According to Aguiar-Conraria and Soares (2011), the wavelet coherence coefficient is defined as in equation (23):

$$R^2(\mathrm{m},\mathrm{n}) = \frac{|\delta(\mathrm{W}_{xy}(m,n))|^2}{\delta(|W_x(m,n)|^2).\,\delta(|W_y(m,n)|^2)} \tag{23}$$

In equation (23), $W_{xy}(m,n)$ denotes the cross-wavelet transform, $W_x(m,n)$ and $W_y(m,n)$ denote the individual wavelet transforms, and δ represents the smoothing operator in the time–frequency domain. The Morlet wavelet is usually represented as in equation (24) (Torrence & Compo, 1998):

$$\psi(t) = \pi^{-1/4}.\,e^{iw0t}.\,e^{-t^{2/2}} \tag{24}$$

Torrence and Compo (1998) suggested 0.6 as the dimensionless frequency parameter for the Morlet wavelet, while the statistical significance of WTC estimates is evaluated through Monte Carlo simulations.

In wavelet analysis, the Cone of Influence (COI) represents a methodological boundary that identifies the regions where edge effects arising from the finite sample size make the results less reliable. Therefore, the COI plays a critical role in assessing the statistical reliability of the estimated coefficients. Accordingly, findings within the COI are considered more reliable, while results outside the COI should be interpreted with caution.

3.7. Data

The analysis covers the period 2015:01–2025:05. This choice is mainly due to the availability of the Agricultural Input Price Index, which has been published only since January 2015. Hence, all series are evaluated over a common sample period. Moreover, the post-2015 era in Türkiye is marked by stronger exchange rate pass-through, heightened volatility in global commodity prices, and structural shifts in inflation dynamics. Therefore, this period ensures both consistency in data coverage and greater relevance in capturing the interaction between food inflation, input costs, and exchange rate movements.

Table 1. Data Sets

Variable	Period	Description
lnufegidasa	2015:01 – 2025:05	PPI – Food Products (seasonally adjusted) – TP.UFE1YI.T16
lngfesa	2015:01 – 2025:05	Agricultural Input Price Index (seasonally adjusted) – TP.TARIMGFE.GK378650484
lndk	2015:01 – 2025:05	(USD) U.S. Dollar – TP DK USD S TL
lneur	2015:01 – 2025:05	(EUR) Euro (Exchange Sale) – TP DK EUR S TL

Source: TURKSTAT (https://data.tuik.gov.tr).

Note: All variables are obtained in levels. Series with the suffix "-sa" are seasonally adjusted using the TRAMO/SEATS method. All series are log-transformed using the LN function in Excel to ensure suitability for econometric analysis. The analysis is conducted using WinRATS and R.

In this study, series exhibiting seasonality are adjusted using the TRAMO/SEATS method in EViews 12. The TRAMO and SEATS procedures developed by Gómez and Maravall (1996) are applied jointly. In the TRAMO stage, the appropriate ARIMA model is automatically selected using the "search all" option, based on the Akaike Information Criterion (AIC). In addition, outliers—including additive outliers (AO), level shifts (LS), and temporary changes (TC)—are automatically detected using the "auto detect all types" option. In the SEATS stage, the series are decomposed into trend, cyclical, seasonal, and irregular components, and seasonally adjusted series are obtained. The SEATS procedure is automatically executed after TRAMO, and a forecast horizon of 8 periods is used.

In this study, the food PPI (lnufegidasa) is taken as the dependent variable, while the agricultural input price index (lngfesa) and exchange rates (lndk, lneur) serve as explanatory variables. The input index, capturing fertilizer, seed, energy, and labor costs, is crucial since rising input costs directly elevate food prices and sustain inflationary pressures.

Exchange rates are equally important in an import-dependent economy like Türkiye, as currency fluctuations increase input costs and generate pass-through effects on producer prices. The dollar and euro are thus chosen as key indicators, enabling a joint assessment of domestic cost factors (lngfesa) and external dynamics (exchange rates) on food PPI.

4. Findings

This section presents the results of the analysis. The main features of the series and preliminary diagnostics are summarized in Table 2. Descriptive statistics show positive skewness and platykurtic distributions (kurtosis < 3) for all variables, while the Jarque–Bera test rejects normality at the 1% level.

Table 2. Descriptive Statistics

Stats	lnufegidasa	lngfesa	lndk	lneur
Mean	6.213078	4.942293	2.088263	2.198361
Median	5.887704	4.560641	1.852908	2.005544
Maximum	8.011421	6.603663	3.657261	3.778152
Minimum	5.102192	4.030766	0.846957	1.001040
Std. Dev.	0.958675	0.857671	0.875019	0.856762
Skewness	0.560228	0.660989	0.425401	0.386628
Kurtosis	1.841511	1.877104	1.812521	1.831165
Jarque-Bera	13.52875	15.66937	11.11443	10.22969
Probability	0.001154	0.000396	0.003860	0.006007
Sum	776.6348	617.7866	261.0329	274.7951
Sum Sq. Dev.	113.9631	91.21426	94.94161	91.02104
Observations	125	125	125	125

Table 2 summarizes monthly observations for 2015:01–2025:05 (N=125). Mean and median values are close for all variables, though the mean is slightly higher, consistent with positive skewness. Standard deviation is largest for lnufegidasa (0.959), followed by lndk (0.875), lngfesa (0.858), and lneur (0.857), indicating relatively higher volatility in food PPI. Skewness values (≈0.39–0.66) confirm right-tailed distributions, while kurtosis values below 3 (≈1.81–1.88) suggest platykurtic shapes. Jarque–Bera tests reject normality at the 1% level. These results imply that robust standard errors, median-based measures, or sensitivity checks for outliers may be appropriate in the modeling stage.

Table 3. LR Test

Series	Percentiles	Test Statistic	p-value
lnufegidasa	25, 75	25.52485*	0.0001
lngfesa	25, 75	114.1964*	0.0001
lndk	25, 75	16.28294*	0.0062
lneur	25, 75	10.05***	0.0760

*Critical values for the LR test are obtained by simulation. Symbols *,*,*** denote significance at the 1%, 5%, and 10% levels, respectively.

According to Table 3, the LR test statistics for all series are highly significant, with p-values close to zero at the 1%, 5%, and 10% levels. Thus, the null hypothesis of linearity is rejected, indicating strong evidence of nonlinearity. For *lneur*, the result is not significant at 1% or 5% but becomes significant at the 10% level, suggesting weaker but present nonlinear behavior. These findings justify the use of nonlinear unit root tests in the subsequent analysis.

Table 4. Hansen (1999) Test

Series	Test 1vs2	Test 1vs3	Test 2vs3
lnufegidasa	25.52485**	52.67607**	22.51633**
lngfesa	114.1964*	248.1244*	69.72006*
lndk	16.28294	44.92062**	25.31365*
lneur	10.05000	33.31029***	21.51642**

*, **,*** denote significance at the 1%, 5% and 10% levels, respectively.

The Hansen (1999) test provides evidence consistent with the LR test, supporting nonlinearity in all series. Notably, while *lneur* showed nonlinearity only at the 10% level in the LR test, Hansen's test indicates significance at the 5% and 10% levels, suggesting greater sensitivity in detecting nonlinear behavior. Overall, both tests confirm the presence of nonlinearity, justifying the application of nonlinear unit root tests in the following analysis.

Table 5 reports the results of nonlinear unit root tests, where the null hypothesis is H_0: unit root (I(1)) against the alternative H_1: nonlinear stationarity (I(0)). Test statistics and p-values are calculated according to the selected deterministic components and lag structures.

Table 5. HM (2002) Test

Series	Model	τ-statistic	Lag	Break τ_1	Break τ_2	Result
lngfesa	A	-2.29595	1	2024:01	2024:03	I(1)
	B	-2.51733	1	2016:05	2019:08	I(1)
	C	-2.88424	1	2019:12	2020:01	I(1)
lnufegidasa	A	-2.48327	0	2022:06	2019:07	I(1)
	B	-2.06441	0	2016:03	2019:08	I(1)
	C	-3.86438	0	2018:05	2021:11	I(1)
lndk	A	-5.61113	1	2017:10	2022:06	I(0)
	B	-2.50806	0	2016:06	2019:07	I(1)
	C	-3.80893	0	2018:05	2021:11	I(1)
lneur	A	-6.08487	1	2017:08	2022:07	I(0)
	B	-3.37166	0	2016:03	2019:05	I(1)
	C	-3.35328	0	2018:11	2019:05	I(1)

*Critical values are taken from Harvey and Mills (2002). The 5% critical values are: Model A = -5.27, Model B = -5.80, and Model C = -6.32.

The results in Table 5 are obtained from the Harvey and Mills (2002) nonlinear unit root test. While lndk and lneur are stationary (I(0)) under Model A, all other series remain nonstationary at the I(1) level. Test statistics generally exceed the 5% critical values, confirming nonstationarity.

Break dates reported in Table 5 are concentrated in two periods: 2016–2019 and post-2020. The former coincides with exchange rate shocks, credit expansion, and rising inflationary pressures in Türkiye, with late 2018 and early 2019 standing out as frequent break points. The latter reflects the impact of the COVID-19 pandemic and subsequent global inflationary shocks, as well as energy price volatility and the Russia–Ukraine war after 2022. Breaks observed in food and fertilizer price indices during 2021–2022 are also consistent with these developments. Overall, the timing of breaks aligns closely with global and domestic macroeconomic shocks.

Table 6. HM (2002) Test – First Differences

Series	Model	τ-statistic	Lag	Break τ_1	Break τ_2	Result
dlngfesa	A	-5.11332	0	2017:09	2021:03	I(2)
	B	-5.80340	0	2017:05	2021:05	I(1)
	C	-5.94077	0	2017:09	2021:09	I(2)
dlnufegidasa	A	-7.96168	0	2017:09	2020:03	I(1)
	B	-8.23035	0	2017:09	2021:06	I(1)
	C	-8.34421	0	2018:09	2018:12	I(1)
dlndk	A	-7.52772	0	2017:07	2020:10	I(0)
	B	-7.59653	0	2018:02	2020:02	I(1)
	C	-8.10100	0	2018:07	2018:08	I(1)
dlneur	A	-8.34920	0	2020:11	2020:02	I(0)
	B	-8.37946	0	2017:07	2020:02	I(1)
	C	-8.57829	0	2016:12	2019:09	I(1)

* Critical values are taken from Harvey and Mills (2002). The 5% critical values are: Model A = -5.27, Model B = -5.80, and Model C = -6.32.

The agricultural input price index (lngfesa) is nonstationary in levels, indicating the presence of a unit root. This implies that cost shocks are not temporary but exert persistent effects on price levels. The result is confirmed by the series being integrated of order I(1) and I(2), suggesting that increases in input costs do not fade in the short run but maintain lasting pressure on prices.

Similarly, the food price index and exchange rates display comparable dynamics. The food price index is I(1), reflecting permanent shocks at the level that disappear after differencing. Both the dollar and euro exchange rates are also nonstationary in levels but become stationary after first differencing. This indicates that exchange rate fluctuations generate persistent impacts, exerting long-term pressure on price dynamics. Overall, both the stickiness of agricultural input costs and the persistence of exchange rate shocks emerge as key structural drivers of food inflation in Türkiye.

Table 7. KSS (2003) Test

Series	Test Type	τ-statistic	Lag	5 % Critical	Result
lngfesa	Raw	2.67318	1	–2.22	I(1)
	Demeaned	0.65257	1	–2.93	I(1)
	Detrended	-1.67791	1	–-3.40	I(1)
lnufegidasa	Raw	6.44044	0	–2.22	I(1)
	Demeaned	1.01243	1	–2.93	I(1)
	Detrended	-1.70858	0	–-3.40	I(1)
lndk	Raw	3.89508	0	–2.22	I(1)
	Demeaned	0.45575	1	–2.93	I(1)
	Detrended	-1.61913	0	–-3.40	I(1)
lneur	Raw	4.17633	0	–2.22	I(1)
	Demeaned	0.54373	1	–2.93	I(1)
	Detrended	-2.08385	0	–-3.40	I(1)

* Critical values are from Kapetanios et al., (2003).

Table 7 presents the nonlinear unit root test results of Kapetanios et al. (2003) for Türkiye. In all cases, the test statistics are lower in absolute value than the 5% critical thresholds. Therefore, the null hypothesis of a unit root cannot be rejected, indicating that the series are nonstationary in levels. In other words, none of the variables are I(0); all contain unit roots and are integrated of order I(1).

Table 8. KSS (2003) Test – First Differences

Series	Test Type	τ-statistic	Lag	5 % Critical	Result
lngfesa	Raw	-2.91128	0	–2.22	I(2)
	Demeaned	-2.83274	0	–2.93	I(2)
	Detrended	-2.73489	0	–3.40	I(2)
lnufegidasa	Raw	-4.97609	0	–2.22	I(1)
	Demeaned	-5.35746	0	–2.93	I(1)
	Detrended	-5.40652	0	–3.40	I(1)
lndk	Raw	-5.33542	0	–2.22	I(1)
	Demeaned	-5.21144	0	–2.93	I(1)
	Detrended	-5.23877	0	–3.40	I(1)
lneur	Raw	-5.80939	0	–2.22	I(1)
	Demeaned	-6.00930	0	–2.93	I(1)
	Detrended	-6.04067	0	–3.40	I(1)

* Critical values are from Kapetanios et al., (2003).

The KSS test results reveal that the series become stationary after differencing. As shown in Table 7, lnufegidasa, lndk, and lneur exceed the 5% critical values across all specifications (Raw, Demeaned, Detrended), indicating I(1) behavior. In contrast, lngfesa remains nonstationary even after differencing, with τ-statistics falling below the critical thresholds.

These findings suggest that most variables share the same order of integration, while lngfesa is integrated of order two, I(2). Although the HM (2002) test indicated some evidence of stationarity for exchange rates, this disappeared once trends and structural breaks were considered. Similarly, the KSS (2003) test confirmed that all series, except lngfesa, are I(1).

Table 9. Zivot–Andrews Unit Root Test Results with Structural Break

Variable	Model	Break Date	t-Statistic	5% Critical Value	Decision
lnufegidasa	Intercept	2021M11	-4.9197	-4.93	Reject
	Intercept + Trend	2021M11	-4.7025	-5.08	Do not reject
lngfesa	Intercept	2021M10	-6.5283	-4.93	Reject
	Intercept + Trend	2021M10	-4.5223	-5.08	Do not reject
lndk	Intercept	2021M11	-4.8361	-4.93	Do not reject
	Intercept + Trend	2021M11	-4.5742	-5.08	Do not reject
lneur	Intercept	2021M11	-4.1760	-4.93	Do not reject
	Intercept + Trend	2021M11	-4.1382	-5.08	Do not reject

Note: The Zivot–Andrews test allows for a single endogenous structural break. The null hypothesis is the presence of a unit root with a structural break. Critical values are taken from Zivot and Andrews (1992).

Table 9 The Zivot–Andrews (1992) test reported in this table is employed as an additional check to assess the robustness of the findings obtained from the nonlinear unit root tests. The results indicate that structural breaks are largely concentrated around 2021 across all variables. This period corresponds to a phase in Türkiye characterized by policy rate cuts, sharp increases in exchange rates, and intensified inflationary pressures. Overall, the findings confirm that the series remain non-stationary and retain their I(1) properties, thereby supporting the subsequent cointegration analysis.

The identified break dates are broadly consistent with those obtained from the Harvey–Mills nonlinear unit root test, suggesting that the evidence of structural change is robust across different methodological approaches.

Since the agricultural input price index (lngfesa) attains stationarity only at I(2), it was excluded from further analysis. Accordingly, lnufegidasa was retained as the dependent variable, with lndk and lneur serving as explanatory variables. Based on this specification, the study proceeds to cointegration analysis to examine their long-run relationships.

Table 10. Cointegration Test

Dependent Variable: lnufegidasa			**Independent Variable: lndk**		
With Constant				Critical Values	
Min SSR*	k	CI_f^0	%10	%5	%1
0.02782	1	0.06595	0.095	0.124	0.198
		Fourier Cointegration F-Statistics			
l_{opt}	k	$F^m(k^*)$	%10	%5	%1
5	1	10.96948	3.352	4.066	5.774
With Constant & Trend					
Min SSR*	k	CI_f^1	%10	%5	%1
0.15191	1	0.05229	0.042	0.048	0.063
		Fourier Cointegration F-Statistics			
l_{opt}	k	$F^m(k^*)$	%10	%5	%1
5	1	11.16017	3.306	4.019	5.860
Dependent Variable: lnufegidasa			**Independent Variable: lneur**		
With Constant				Kritik Değerler	
Min SSR*	k	CI_f^0	%10	%5	%1
0.04510	1	0.03677	0.095	0.124	0.198
		Fourier Cointegration F-Statistics			
l_{opt}	k	$F^m(k^*)$	%10	%5	%1
5	1	3.82940	3.352	4.066	5.774
With Constant & Trend					
Min SSR*	k	CI_f^1	%10	%5	%1
0.15191	1	0.04220	0.042	0.048	0.063
		Fourier Cointegration F-Statistics			
l_{opt}	k	$F^m(k^*)$	%10	%5	%1
5	1	3.84632	3.306	4.019	5.860

Note: Critical values for the Fourier cointegration test and the F-statistics of trigonometric terms are taken from Tsong et al. (2016). SSR denotes the sum of squared residuals.

Table 10 reports the Fourier cointegration test results, where k denotes the frequency, CI_f^0 and CI_f^1 represent the test statistics for the constant and constant–trend cases, and $F^m(k^*)$ is the test for the significance of trigonometric terms. The optimal lag length (l_{opt}) is determined as $\left(T^{\frac{1}{3}}\right)$. The Fourier frequency (k) is determined by estimating alternative models and selecting the value that minimizes the sum of squared residuals (SSR). Accordingly, the frequency that yields the lowest SSR is chosen as optimal, and $k = 1$is obtained for both models.

For the model with *lndk* as the independent variable, CI_f^0=0.06595 (with k=1) is below the 5% critical value (0.124), indicating cointegration between *lnufegidasa* and *lndk*. The Fourier term is also significant since $F^m(k^*)$=10.96948>4.066 (5%). Similarly, in the constant–trend case, CI_f^1=0.05229 is below the 1% critical value (0.063), confirming cointegration, while $F^m(k^*)$=11.16017>4.019 shows at least one Fourier term is significant.

For the model with *lneur* as the independent variable, CI_f^0=0.03677 is below all 1%, 5%, and 10% thresholds, supporting cointegration between *lnufegidasa* and *lneur*. The Fourier term is significant at 10% since $F^m(k^*)$=3.82940>3.352. In the constant–trend case, CI_f^1=0.04220 is below the 1% and 5% critical values, again confirming cointegration, while $F^m(k^*)$=3.84632>3.306 indicates significance of at least one Fourier term.

Overall, these findings confirm that the Fourier cointegration test of Tsong et al. (2016) provides a robust framework for identifying long-run relationships between the series.

Table 11. Long-Run Coefficient

Method: DOLS				
	Dependent Variable: lnufegidasa			
Variable	Coefficient	Std. Error	t-Statistic	Prob.
lndk	1.128778885	0.008380500	134.69112	0.0000
SIN1	0.035142782	0.008491310	4.13868	0.0000
COS1	-0.027895261	0.008873980	-3.14349	0.0022
C	3.877029907	0.016452957	235.64336	0.0000
Adj. R-squared	0.9958391	Regression F(14,99)	1932.7754	0.0000
S.E. of regression	0.0581856192	S.D. dependent var	0.9020366445	
Variable	Coefficient	Std. Error	t-Statistic	Prob.
lneur	1.141040743	0.011146818	102.36470	0.0000
SIN1	0.044234302	0.011225295	3.94059	0.0001
COS1	-0.040452048	0.012017109	-3.36620	0.0010
C	3.710707981	0.024502906	151.43951	0.0000
Adj. R-squared	0.9910902	Regression F(14,99)	898.8363	0.0000
S.E. of regression	0.0851446569	S.D. dependent var	0.9020366445	

The DOLS estimation results in Table 11 reveal a strong and statistically significant long-run impact of exchange rates on food PPI. For the dollar, the coefficient of lndk is 1.13, indicating that a 1% increase in the exchange rate raises food PPI by approximately 1.13%. The significance of the Fourier terms (SIN1 and COS1) confirms the presence of nonlinear dynamics, suggesting that structural fluctuations enhance the explanatory power of the model.

Similarly, the euro coefficient is estimated at 1.14, implying that a 1% rise in EUR/TL leads to an almost proportional increase in food PPI. Again, the Fourier terms are significant, supporting the role of cyclical and structural components in shaping the relationship. The high adjusted R^2 values show that both models explain most of the variation in the dependent variable.

The WTC map further illustrates the time–frequency dependence between food PPI and exchange rates. Warm colors (red, yellow) indicate periods of strong and significant correlation, while cool colors (blue, purple) reflect weaker or insignificant linkages. Thus, red clusters represent phases of intensified co-movement, whereas blue areas mark periods of decoupling or limited interaction. Prior to the analysis, the series were transformed to achieve stationarity. This transformation was applied to remove trend components and to prevent non-stationary behavior from generating artificially high co-movement (spurious coherence) in the wavelet coherence analysis.

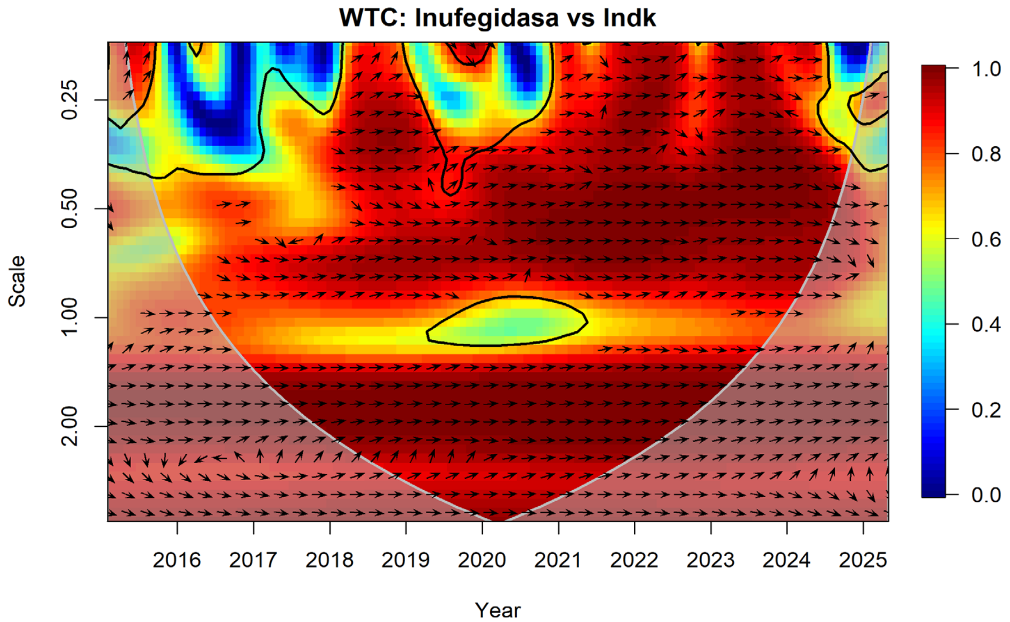

Figure 1. Wavelet Coherence Map of Food PPI and USD

In Figure 1, the long-term red regions observed after 2018 indicate that the Dollar/TL and food prices have moved together in a simultaneous and persistent manner. During this period, the arrows predominantly pointing to the right (→) show that the series are synchronized, revealing that currency crises directly translated into food prices. In some episodes, the arrows pointing to the upper-right (↗) indicate that the Dollar leads, while food prices follow exchange rate shocks with a certain lag. At the medium-term horizon (2016–2020), the yellow–orange regions display a similar dynamic, though the changing direction of the arrows suggests that sometimes the exchange rate, and at other times food prices, take the leading role. By contrast, in the short-term horizon (3–6 months), the blue regions with arrows pointing upward (↑) or downward (↓) imply that one variable lags the other by about a quarter period, indicating that short-term relationships are temporary and unstable in nature.

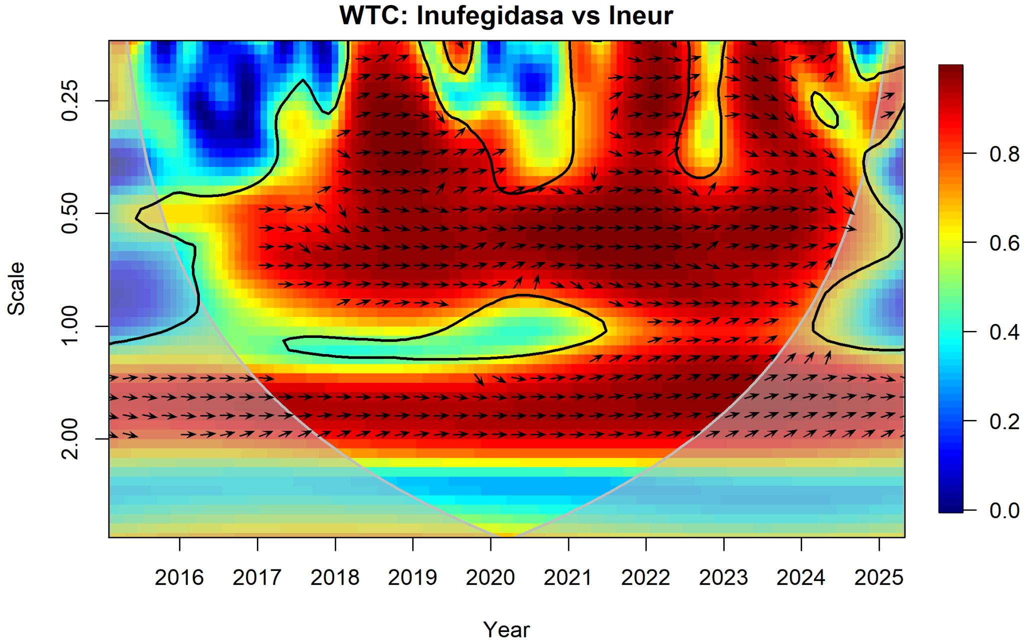

Figure 2. Wavelet Coherence Map of Food PPI and EURO

In Figure 2, the concentration of red regions in the long run—especially after 2018—indicates a strong synchronization between the Euro/TL and food prices. In these areas, the arrows predominantly pointing to the right (→) show that the variables move simultaneously, with structural exchange rate volatility directly reflected in food prices. In the medium-term bands, the yellow–orange regions with arrows pointing to the upper-right (↗) suggest that the Euro is the leading variable, while food prices follow exchange rate movements with a lag. However, in some episodes, arrows pointing downward (↓) imply that food prices may briefly anticipate movements in the Euro. In the short-term horizon (3–6 months), the blue regions show a weakening relationship, with arrows diverging in different directions, indicating frequent shifts in leading–lagging roles.

Overall, the graphs reveal that the relationship between food PPI and the exchange rate varies across scales: while long-term dynamics exhibit strong synchronization, medium-term effects are temporary but pronounced, and short-term interactions are more volatile and reciprocal in nature.

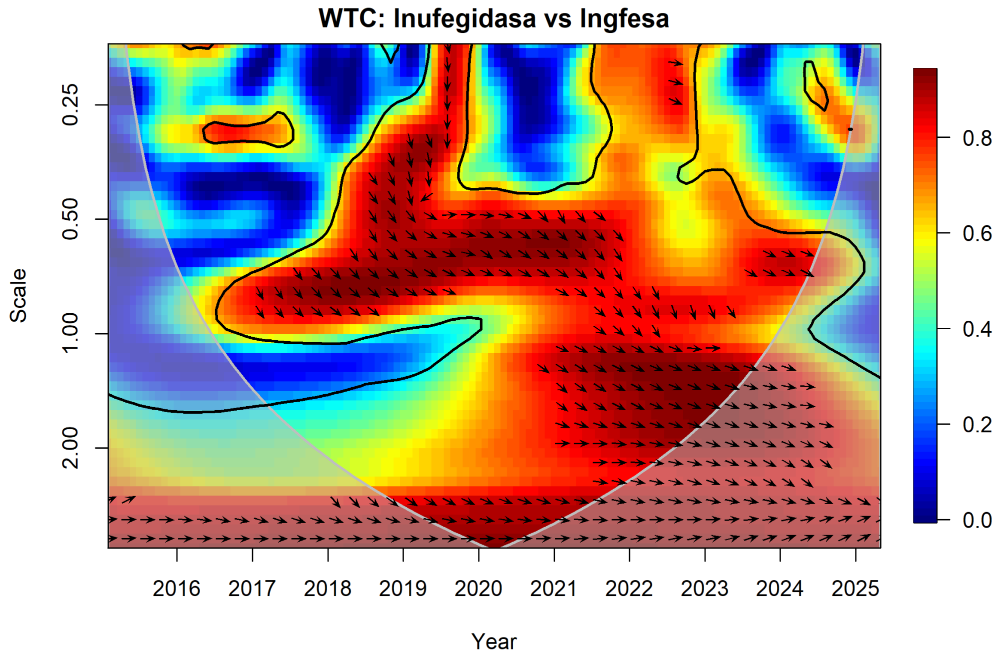

Figure 3. Wavelet Coherence Map of Food PPI and GFE

Figure 3 shows intense red regions between the agricultural input price index and the food producer price index (Food PPI), particularly during the 2017–2023 period. These areas indicate a strong medium- and long-term coherence between the two variables. The phase arrows pointing mostly to the right and downward (↘) suggest that agricultural input prices act as a leading variable, affecting food producer prices with a lag. This finding supports the existence of a cost-push transmission mechanism and highlights that agricultural input costs are a structural determinant of food inflation.

Table 12. Average Phase Differences (2018–2022)

Pair	Period	Scale (years)	Mean Phase (rad)	Mean Phase (deg)	Mean Coherence	Interpretation
lnufegidasa – lndk	2018–2022	0.5–2	0.0887	5.08	0.8951	Synchronous movement
lnufegidasa – lneur	2018–2022	0.5–2	0.0470	2.69	0.8776	Synchronous movement
lnufegidasa – lngfesa	2018–2022	0.5–2	-0.5368	-30.76	0.7787	lngfesa leads lnufegidasa

Note: Average phase differences are computed over the 2018–2022 period using significant regions outside the cone of influence (COI) within the 0.5–2 year frequency band.

To complement the visual interpretation of phase arrows, Table 12 reports the average phase differences for the 2018–2022 period. The results indicate that the phase differences between food PPI and exchange rates are very close to zero, confirming a strong synchronous co-movement. In contrast, the negative phase difference between food PPI and agricultural input prices reveals a clear lead–lag structure, where input costs lead food prices.

5. Discussion

This section interprets the findings in line with the study's three research questions, considering both the contributions of the applied methods (Fourier cointegration, DOLS, WTC) and data-related methodological limitations. The aim is to uncover the dynamics between exchange rates and producer food prices in both the short and long run, while also noting the effect of the integration issue in the agricultural input price series (GFE).

The results indicate a strong link between producer food prices and exchange rates in Türkiye. Fourier- and wavelet-based analyses reveal that this relationship is evident not only in the long run but also in short-term fluctuations. Since 2018, rising exchange rate volatility and global food price shocks have increased the sensitivity of producer food prices through cost and expectation channels. These findings are consistent with Demirağ and Sağır (2023) and Kolcu (2023), while this study's contribution lies in detailing the relationship within a time–frequency framework.

1. What is the impact of exchange rates (USD and EUR) on producer food prices?

The results show that both USD/TL and EUR/TL exert strong and persistent effects on food PPI. Exchange rate shocks are directly transmitted to food prices through imported inputs and production costs. While the USD plays a more prominent role in short-term interactions, the EUR demonstrates stronger long-term synchronization. These findings are consistent with Nazlıoğlu and Soytaş (2012) and İçen et al. (2022), who document long-run exchange rate–price linkages. Moreover, the wavelet results align with Hasan and Masih (2018), indicating that pass-through intensifies during crisis periods in Türkiye.

2. What is the role of agricultural input prices (GFE) in producer food prices?

The results for GFE are mixed: the HM test on differenced data (Model B) suggests I(1), whereas the KSS test indicates I(2). This ambiguity complicates the assessment of GFE's long-run impact on food PPI. Economically, this is expected, as GFE is largely driven by exchange rates, energy costs, and global commodity prices. Similar to Baskaya et al. (2008) and Demir et al. (2023), the findings underline the key role of currency and energy shocks in shaping cost pressures and price persistence.

The I(2) pattern of GFE implies that cost shocks are long-lasting and permanently incorporated into prices. Wavelet coherence analysis supports this view: Figure 3 reveals strong medium- and long-term coherence during 2017–2023, with phase arrows mostly pointing right and downward (↘), indicating that agricultural input prices lead and exert a sustained influence on food producer prices. Addressing food inflation in Türkiye therefore requires not only monetary policy but also exchange rate stability, reduced import dependence, and greater domestic input production within a coordinated framework.

3. How do the short- and long-run dynamics diverge in the time–frequency domain?

WTC results show that the relationship between GFE, exchange rates, and food PPI strengthens in the short run—especially during crisis periods—while maintaining strong and persistent synchronization in the long run. These findings align with Chen et al. (2020) and Reboredo & Ugando (2014), who emphasize that exchange rate shocks influence prices through both cost and financial channels. In the Turkish context, the results confirm Tay-Bayramoğlu and Yurtkur (2015) on the dominant role of exchange rates in agricultural producer prices, while also revealing consistent medium- and long-term coherence between GFE and food PPI. This coherence supports the cost-push channel driven by agricultural input prices and highlights the structural persistence of food inflation beyond temporary exchange rate shocks. Overall, food prices in Türkiye are mainly shaped by cost-push dynamics, implying that monetary policy alone is insufficient without exchange rate stability, energy cost control, and greater domestic input production.

6. Conclusion and Policy Implications

This study examined the interaction between producer food prices, exchange rates, and agricultural input costs in Türkiye by applying Fourier cointegration and wavelet coherence analysis. The findings show that food prices are sensitive to exchange rate shocks in both the short and long run, with synchronization between exchange rates and food prices strengthening especially after 2018. These results highlight that relying solely on monetary policy is insufficient and that structural measures are essential.

On the policy side, addressing structural issues such as unplanned production, bargaining asymmetries in supply chains, import dependence, and rising land rents must go hand in hand with exchange rate stability. Promoting contract farming supported by commodity exchange infrastructure could reduce waste and limit the immediate transmission of exchange rate shocks to prices. In retail markets, banning below-cost sales, imposing caps on brand concentration, and requiring hedging mechanisms for import-intensive products could slow the pass-through of exchange rate volatility. Establishing sustainable price anchors in dairy and red meat markets would protect producers from rising feed and energy costs while supporting supply security. Likewise, aligning import policies with domestic production through tariff quotas and forward contracts could buffer exchange rate fluctuations. Regulating land rents, by limiting foreign-currency contracts and linking rents to agricultural income and soil quality, would reduce cost surges driven by currency shocks. Strengthening inter-ministerial data sharing, developing region- and product-based planting plans, and creating early-warning systems for currency-sensitive products are also crucial.

The I(2) nature of agricultural input prices (GFE) further indicates that cost shocks are highly persistent and continuously elevate the price level. This reinforces the need for exchange rate stabilization, input localization programs, and contract farming policies that emphasize risk-sharing.

In sum, reducing food inflation on a lasting basis requires predictability, risk sharing, and fair market regulation. Key measures include expanding contract farming, ensuring fair competition in retail, establishing sustainable pricing in livestock markets, making import policies more transparent and complementary, and reforming land rent practices. If designed to reduce sensitivity to exchange rate shocks, such measures can help contain price pressures in the short term while ensuring supply security and production continuity in the medium and long term.

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