



ΣΠΟΥΔΑΙ / SPOUDAI

Journal of Economics and Business
<http://spoudai.org>



Dominant Price Relationships, Wavelet Coherence and Wavelet Power Spectrum Between the Futures Markets of the Arabica and Robusta Coffee Varieties

Dimitrios Panagiotou* Sophia Siori† Panos Fousekis ‡

*Corresponding Author, Department of Economics, University of Ioannina, Greece.

Email: dpanag@uoi.gr

†Department of Economics, University of Ioannina, Greece.

Email: s.siori@uoi.gr

‡Department of Economics, Aristotle University of Thessaloniki, Greece.

Email: fousekis@econ.auth.gr

Abstract

The present work investigates the contemporaneous co-movement between the futures prices of Arabica and Robusta coffee varieties using the highly flexible Wavelet Local Multiple Correlation analysis. The data are daily observations between 2010 and 2025. The empirical findings indicate that the correlation of returns tends to increase as the timescale increases, except for the Covid-19 period. Dominant heatmaps show that Arabica acts as the dominant variable, suggesting that the futures prices of the Arabica variety incorporate the adjustment process in the Arabica-Robusta relationship. The moderate level of the realized volatility in high and medium frequencies suggests potential diversification benefits for short-term traders, while the dominant variable offers a useful reference for forecasting between the two varieties.

JEL classification: Q13, C10

Keywords: Coffee; Prices; Wavelet; Correlation; Dominance

1. Introduction

Coffee is one of the major traded commodities worldwide and is second only to oil (Pançsira, 2022). Globally, an estimated 2.25 billion cups of coffee are consumed every day (Roberts, 2021). Coffee is mainly produced by developing countries located in South America, Africa, and Southern Asia (Yang et al., 2022). The top producers and exporters of coffee are Brazil, Vietnam, Colombia, and Indonesia (Purwawangsa et al., 2024). Political aspects of the coffee commodity are not to be ignored either, as coffee is mainly produced in politically unstable countries that suffered dictatorships and political mismanagement for years (Stavrakoudis and Panagiotou, 2016). There are two distinct varieties of coffee, Arabica and Robusta. The Arabica variety is grown primarily at high altitude areas in Latin America and northeastern Africa. The Robusta variety is grown at low altitudes and in humid areas in Asia, in southern and western Africa, and in Brazil. The Arabica with the low level of caffeine (1.2%) and the strong aroma occupies the upper part of the spectrum. On the other hand, the Robusta, with the higher level of caffeine (2.2%) and the harsh taste, is at the lower part of the spectrum (Condelli et al., 2022). Coffee prices are strongly determined by the quality of coffee (Adugna, 2021; Li et al.,

2022) and have shown considerable volatility in the past (Zhang et al., 2022). Arabica and Robusta, although traded separately, are linked through substitution and shared fundamentals such as the weather, input costs, and the economic environment (Ngure and Watanabe, 2024). Symmetric responses between Arabica and Robusta coffee prices can be attributed to shared macroeconomic factors such as the strength of the USD (\$), global demand shocks, as well as disruptions in freight and logistics costs (Hernandez et al., 2020). More specifically, both coffee varieties - as dollar-denominated commodities - become more expensive for importers when the USD becomes stronger (Vijayakumar, 2022). The outcome was that both prices fell. Global demand shocks might affect these two coffee varieties in a similar way. Post-COVID rebounds (2021) increased Arabica and Robusta prices (Newman and Van Huellen, 2022). On the other hand, recent recessions depressed them both (Varangis et al., 2003). Disruptions in freight and logistics costs might also symmetrically affect Arabica and Robusta coffee prices: the Red Sea crisis in 2024 (shipping disruption) increased the prices of both varieties.¹ Unlike Arabica, which is more vulnerable to weather and diseases (like leaf rust), Robusta is more resistant to heat, rainfall variations and pests (Haile, 2018). Accordingly, asymmetries can arise from factors specific to Arabica or Robusta. These factors might be: i) supply shocks specific to one of the two coffee varieties: the Brazilian frost of 2021 drove Arabica prices up but had little or no effect on Robusta prices. Brazil produces 39% of the world's coffee, and it is all of the Arabica variety. ii) diverging demand trends: the growth of the specialty coffee sector disproportionately benefits Arabica, creating sustained demand pressure that may outpace Robusta. Conversely, the growth of instant coffee consumption in emerging markets (like Southeast Asia) disproportionately benefits Robusta. Lastly, during economic downturns, consumers might switch to the cheaper Robusta variety, and the premium shrinks. The strength and the pattern of price linkages between Arabica and Robusta have been studied in the relevant literature with the use of different econometric tools. Copulas were employed in the studies by Stavrakoudis and Panagiotou (2016), Fousekis and Grigoriadis (2017) and Fousekis (2017). Vector Error Correction models (VECM), Threshold VECM, and Momentum threshold autoregressive (M-TAR) models were utilized by Cariappa and Sinha (2021), by Jácome Gagnay (2017), and by Ghoshray and Mohan (2021), respectively. VAR and VEC-Granger causality were employed by Vijayakumar (2022). Deina et al. (2022) used Extreme Learning Machines (ELMs) neural networks. Lastly, Fousekis and Grigoriadis (2022) employed penalized quantile regressions to assess tail price risk spillovers. Literature findings are mixed. Empirical results indicated strong (Cariappa and Sinha, 2021) and weak (Fousekis and Grigoriadis, 2017) linkages as well as symmetric (Mai et al., 2018) and asymmetric (Stavrakoudis and Panagiotou, 2016) dependence between the prices of the Arabica and Robusta coffee varieties. However, despite the existing literature, it remains unclear whether the relationships between Arabica and Robusta are uniform or vary across time and investment horizons. Although they examined integration, asymmetries, causality, and price transmission, limited attention has been drawn to the (changing) sign and the size of their relationship from a multidimensional perspective. The same pattern holds for both returns and realized volatility. The investigation of both allows provides further information since returns can show whether price co-movement benefits traders, while realized volatility reveals information about the risk and uncertainty for each variety. Since coffee traders operate at different time horizons, the relationship between Arabica and Robusta may vary at different frequencies. Unlike wavelet coherence, which mainly provides a squared measure of association with significance contours, WLMC provides a localized multiple correlation coefficient with confidence intervals. This is useful because the upper and lower bounds provide additional information about the uncertainty and precision of the estimated dependence structure. In contrast, dynamic conditional correlation (DCC) and rolling window correlations are suitable for showing how correlation evolves. However, they fail to uncover whether the correlation originates from

short-, medium-, and long-horizon. On the other hand, frequency-domain spillover indices are flexible for quantifying connectedness and transmission at different frequencies. Nevertheless, the scope of our study focuses on local interactions between the two varieties WLMC addresses this by estimating the sign and the size of the multiscale dependence at each point in time. To address this gap, the present study applies the wavelet local multiple correlation (WLMC) methodology to the Arabica-Robusta futures pair. WLMC is suitable for this purpose since it addresses these limitations by estimating the localized multiscale correlations. The contribution of the study is threefold. First, to show that the Arabica- Robusta futures market should not be considered as uniform, especially during a crisis period. Economic cycles and crisis episodes may affect the two varieties differently at each horizon, so WLMC allows us to investigate whether the Arabica- Robusta relationship strengthens or weakens during crises and recovery periods, and whether these episodes are associated with higher volatility levels. Second, the study provides a more complete picture of the two markets with returns and volatility since a shock may synchronize prices without necessarily synchronizing risk levels or vice versa. This overview offers more precise guidance on hedging or diversification strategies. Third, the identification of the dominant variable, namely the series that maximizes the local multiple correlation at each scale, is unique to the WLMC framework and provides direct economic insight into which market is strongly associated with the multiscale dependence structure over time. To this end, the WLMC framework is the preferred method for analyzing multi-horizon traders operating in commodity futures markets. Our contribution is therefore not simply the application of a new technique, but the provision of scale-dependent, time-varying, and dominance-based characterization of the Arabica-Robusta futures price linkages. This framework enables us to show that Arabica and Robusta integration depends on the timescale and differs between returns and realized volatility. The WLMC framework has been introduced by Fernández-Macho (2018), who analyzed correlations of oil-related products. (Bouri et al., 2023; Shah et al., 2022) applied WLMC to analyze linkages between oil and carbon emissions, and agricultural and metal commodities, respectively, while Fousekis and Grigoriadis (2025) employed this approach to analyze multiscale correlations between soybean and its derivatives. In contrast to traditional methods, the WLMC approach captures both the timing and the scale of correlation during turbulence periods and not only. Wavelet power spectrum figures, wavelet coherence diagrams, and dominant heatmaps are also provided in order to identify lag-lead and dominance patterns between the coffee varieties of Arabica and Robusta. Compared to previous empirical research, the present work presents a more thorough presentation of the integration between the markets of Arabica and Robusta coffee varieties by assessing the intensity and the mode of price co-movement both at different market states as well as at different time frequencies. The study is structured as follows: Section 2 contains the Analytical framework. Section 3 presents the data, Section 4 the empirical results and Section 5 the discussion. Section 5 offers conclusions.

2. Analytical Framework

All time series are decomposed using the Maximal Overlap Discrete Wavelet Transform (MODWT), introduced by Percival and Walden (2000). A decomposition of $j = 1, 2, \dots, J$ refers to wavelet coefficients representing specific timescales

$$\tau_j = 2^{j-1}$$

The decomposition ensures that the analysis captures variability across different frequencies where each j corresponds to a specific period range of $[2^j, 2^{j+1})$ days.

The MODWT is implemented with the least asymmetric (LA) wavelet filter of length 8, LA(8), a member of the Daubechies family. The LA(8) filter is selected because it offers near-symmetry, reducing boundary coefficient artifacts and providing a more accurate alignment of wavelet coefficients with the original time series. The MODWT decomposition is performed up to $J = 7$ levels, yielding wavelet coefficients for scales $j = 1, 2, \dots, 7$. For daily data, scale j corresponds to a period range of $(2^j, 2^{j+1})$ days. The maximum scale of $2^8 = 256$ trading days is well within the sample length of approximately 4,132 daily observations, ensuring that boundary effects do not dominate the estimation.

The interpretation of the time scales is as follows: $j = 1$ (2–4 days: very short-term), $j = 2$ (4–8 days: one to two trading weeks), $j = 3$ (8–16 days: two to three trading weeks), $j = 4$ (16–32 days: one to two trading months), $j = 5$ (32–64 days: two to three trading months), $j = 6$ (64–128 days: three to six trading months), $j = 7$ (128–256 days: six to twelve trading months). These timescales allow for capturing correlations across short-, medium-, and long-horizons.

The biwavelet package in R is applied for the wavelet power spectrum and wavelet coherence analyses, presented in Figures 2 and 3. For both analyses, the Morlet mother wavelet was employed with a scale resolution $dj = 1/12$, the smallest scale $s_0 = 2$ and zero-padding enabled. The maximum scale of 256 trading days, and statistical significance was evaluated using 1,000 Monte Carlo randomizations. No additional smoothing parameters were imposed. Smoothing was handled internally according to the default implementation of the biwavelet package. The Cone of Influence (COI) is also computed internally by the biwavelet package shown in Figures 2–3 in order to identify regions where estimates can be affected by boundary effects. Accordingly, the interpretation mainly focuses on the regions outside of the COI.

The WLMC framework is used to examine dynamic dependencies in a multivariate stochastic process X_t . This method estimates a local linear regression function $m(x)$ by minimizing a weighted sum of squared residuals:

$$\hat{m}(x) = \arg \min_{a,b} \sum_{t=1}^T w_t(x) [y_t - a - b(x_t - x)]^2$$

where $w_t(x)$ represents the kernel weighting function. The weights assign greater importance to observations located closer to x , allowing the estimation to capture time-varying dependence patterns.

The local linear regression in Equation (2) employs a Gaussian weighting window, which corresponds to a Gaussian kernel of the form:

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-u^2/2}.$$

In the empirical implementation of the WLMC framework, the window length was set equal to $M = 260$ observations, which corresponds approximately to one trading year. All wavelet scales are handled with the same window specification to ensure comparability of the WLMC estimates in both dimensions. This parameter controls the degree of the time-local smoothing in the WLMC estimates. This means that larger values of M produce smoother estimates and smaller values allow stronger local variation.

The strength of the local linear relationship is quantified through the local coefficient of determination, R^2 , which measures the proportion of local variance explained by the model:

$$R_j^2(x) = 1 - \frac{RSS_j(x)}{TSS_j(x)}$$

where $RSS_j(x)$ denotes the residual sum of squares and $TSS_j(x)$ denotes the total sum of squares at scale j .

The Wavelet Local Multiple Correlation is defined as the square root of the localized coefficient of determination. For a given scale j and time t , it is expressed as:

$$LMC_j(t) = \sqrt{R_j^2(t)}$$

where the measure is between $[0,1]$.

For every specific time-scale j , the dominant variable is identified by Martínez et al. (2018) as the one that maximizes the WLMC at a specific scale and period (Fousekis and Grigoriadis (2025), Bouri et al. (2023)).

The statistical significance level is a construction of $(1 - \alpha)$ confidence intervals. Following the Fisher transformation, the confidence interval for the estimated local correlation is given by:

$$CI_{1-\alpha} = \tanh\left(\operatorname{arctanh}\left(\hat{R}_j(t)\right) \pm \frac{z_{1-\alpha/2}}{\sqrt{T_j-3}}\right)$$

where $z_{1-\alpha/2}$ represents the critical value of the standard distribution related to the significance level, and T_j denotes the effective number of wavelet coefficients available at scale j . The reported 95% confidence intervals are obtained by setting $\alpha = 0.05$.

For each time point and scale, the WLMC routine returns the estimated local multiple correlation coefficient together with its lower and upper confidence bounds.

In this approach, inference is based on the asymptotic approximation embedded in the WLMC estimation procedure rather than on a separate bootstrap, Monte Carlo, or model-based correction for serial correlation and heteroskedasticity. Accordingly, the confidence intervals are treated as approximate intervals for the local multiscale dependence, while the use of return and realized volatility transformations, together with the wavelet decomposition across scales, contributes to reducing the persistence in the analyzed components.

All computations were performed in R. Data handling and interpolation were carried out using the tidyverse and zoo packages. Wavelet power spectrum and wavelet coherence figures were produced using the biwavelet package. The WLMC analysis was performed using the implementation proposed by Fernández-Macho (2018), while dominant heatmaps were generated using the VisualDom package by Polanco-Martínez (2023).

3. Data

The data are daily closing futures prices of the Arabica and Robusta varieties obtained from Investing.com (2026). The sample period starts from January 1, 2010, and ends on December 31, 2025. For Arabica coffee, the present work uses the ICE Futures US Coffee C futures contract, which is the global benchmark for high-quality Arabica. The contract is quoted in U.S cents per pound, has a contract size of 37,500 pounds, and is physically settled. The listed delivery months are March, May, July, September, and December (Intercontinental Exchange, 2026). For Robusta coffee, the study employs the ICE Futures Europe Robusta futures contract, which appears as the global benchmark for Robusta. The contract unit is quoted in U.S dollars per metric tonne, has a contract size of 10 metric tonnes, and is physically settled. The delivery months are in January, March, May, July, September, and November. The analysis uses the

futures prices as reported by the data source and does not manually reconstruct individual delivery-month contract series or apply a separate rollover/ back adjustment procedure. However, to address potential concerns related to the construction of continuous futures series, we additionally provide robustness figures in the Appendix section (Figure 8).

We construct alternative continuous futures series using an explicit contract-month rollover rule combined with a backward ratio adjustment, and then compare the results of the adjusted series against the raw series. Figure 8 presents the backward-ratio adjusted log returns and the raw log returns. Visual inspection reveals that both series exhibit similar patterns. Because the dataset includes non-trading days and missing observations, the two price series are first fully joined and ordered chronologically. The missing values from the merged frame are handled with the linear interpolation process. Log-prices were then computed for both contracts, and daily log-returns were defined as

$$rt = \ln(P_t) - \ln(P_{t-1}).$$

In addition, the logarithmic price spread was calculated as

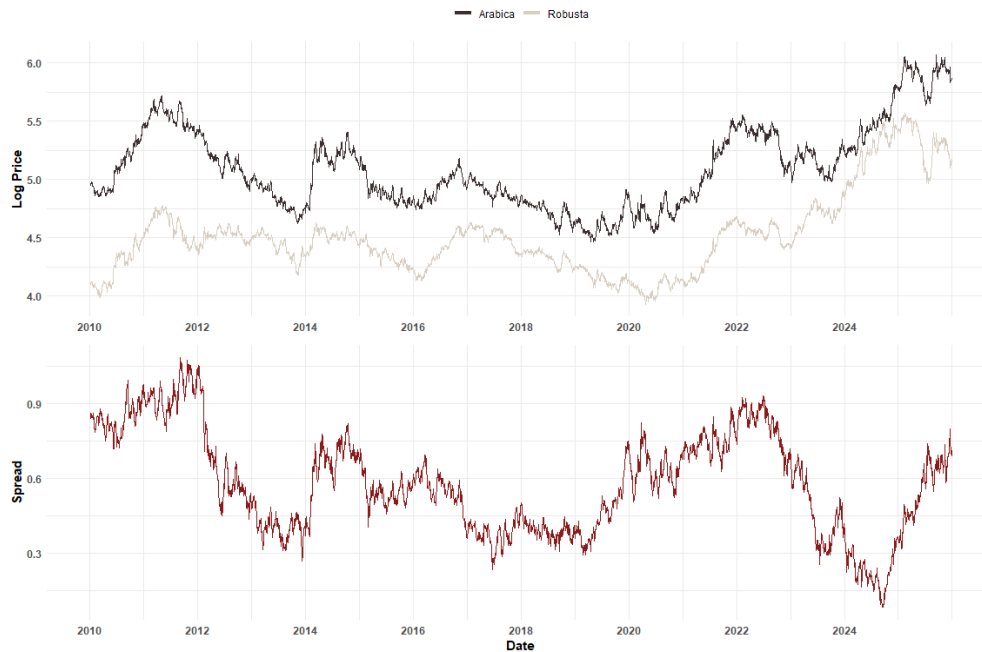
$$\ln(P_{tArabica}) - \ln(P_{tRobusta}),$$

while squared logarithmic returns approximated the realized volatility. After the removal of the initial missing observations, the final aligned dataset covers the period from 01-01-2010 to 31-12-2025 and consists of 4132 observations. The application of ADF and PP tests (Appendix: Table 1 and Table 2) suggested that price levels contained a unit root, whereas the price returns were stationary. Figure 1 shows the logarithmic prices and the spread between Arabica and Robusta for the time period 2010-2025. A critical point for cross-commodity futures analysis is that the two contracts are denominated in different units: Arabica is quoted in US cents per pound, while Robusta is quoted in US dollars per metric ton (1 metric ton = 2,204.62 pounds). Direct comparison of price levels or price spreads in absolute terms is therefore not meaningful without unit conversion. However, all empirical analysis in this paper is conducted using log-returns, ($rt = \ln(P_t) - \ln(P_{t-1})$), and log-price differences, $\ln(P_{tArabica}) - \ln(P_{tRobusta})$, both of which are dimensionless. Log-returns are standard in financial econometrics for comparing assets with different units, as they represent continuously compounded percentage changes. The spread in log-prices is equivalent to the log of the price ratio. This approach avoids any unit-conversion issues and ensures that correlation, coherence, and wavelet analyses are based on comparable, dimensionless quantities.

The upper panel presents the price evolution of the coffee varieties. Both prices move together. Their highest peak is observed in recent years (2025), while the lowest trough for both commodities was during the pandemic period. Between 2019- 2020, excess supply conditions in the global coffee market resulted in lower prices, while the Covid-19 pandemic initially disrupted demand and supply chains (FAO, 2020; ICO, 2020). The upward trend in the post-pandemic period is associated with continuous supply disruptions in the coffee market. Arabica recorded a stronger rise than Robusta due to the recovery of the pandemic, tighter conditions related to production shortfalls in Brazil, and poor weather conditions in Colombia. From 2023 onward, a surge in coffee prices began, caused by constrained supply in Vietnam and Indonesia as well as deteriorating weather conditions, affecting production in Brazil, with prices continuing to rise FAO (2025).

Figure 1:

Evolution of the log-Prices and of the spread for the Arabica and Robusta coffee varieties



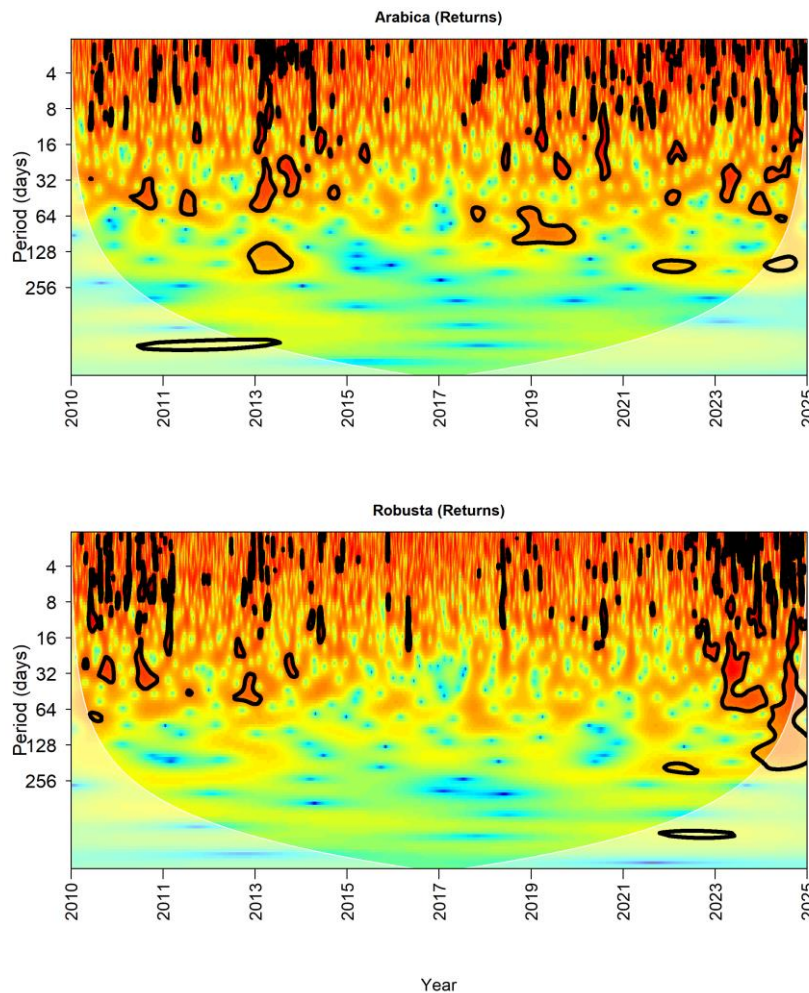
Arabica trades at a significant premium due to its superior flavor profile, lower caffeine content, and more challenging cultivation requirements (Poltronieri and Rossi, 2016). It is smoother, and it has more complex acidity and aroma. Robusta is the hardy bean and it is higher in caffeine compared to Arabica. It is more bitter, it has a stronger taste and it is primarily used in instant coffee and as a filler in lower-grade espresso blends. The lower panel in Figure 1 presents the spread between the log prices of the Arabica and Robusta varieties. The strength, the

mode and the pattern of the contemporaneous linkage between the two prices are contributing factors behind the spread. The spread is watched closely by traders in order to exploit profit opportunities. Positive values of the spread over the period indicate that Arabica trades consistently at higher prices than Robusta. Fluctuations through the years reflect higher (in increases) or lower (in decreases) trading opportunities. During 2012-2014, the decreasing spread indicates a gradual compression of the price divergence between the two varieties, resulting in a lower Arabica premium relative to Robusta. During the pandemic period, the spread increased significantly; however, it remains lower than its 2010 level. Arabica became relatively more expensive than Robusta, increasing the price premium. For market participants, in order to reduce their costs, substitution toward Robusta may have become more attractive. Traders can exploit movements in the spread by taking positions in the two markets. When the spread becomes excessively wider, traders may anticipate that it will narrow over time, taking short positions in Arabica and long positions in Robusta, in order to benefit from the expected correction in the price differential. However, the spread reached its lowest level in 2025, suggesting a significant decline in the Arabica premium relative to Robusta (related to tighter supply conditions). The narrowing of the spread indicates that market participants had less incentive to substitute Arabica with Robusta, while trading opportunities related to the spread became more limited. Supply and demand shocks create trading opportunities in the Arabica-Robusta price spread. If traders expect the premium to shrink, they will short Arabica and/or long Robusta. The rationale is that high Arabica prices provide incentives to farmers to plant more, while roasters substitute with Robusta. Hedging with Robusta is common in this occasion: coffee roasters may blend more Robusta when Arabica gets pricier (Nhung et al., 2020). On the other hand, if traders expect the premium to grow, they will long Arabica and short Robusta.

4. Empirical Results

Figure 2 presents the wavelet power spectrum for Arabica and Robusta coffee returns during 2010-2025 for each timescale. Warmer colors represent regions where episodes of variance are more intense, while milder colors indicate less volatile patterns.

Figure 2: Arabica exhibits greater and sporadic episodes of variance during 2010- 2025



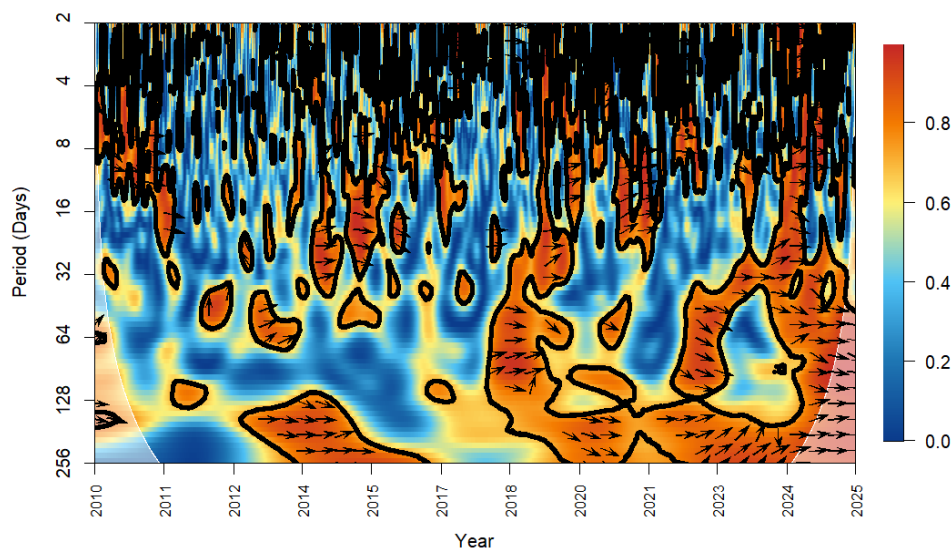
Arabica coffee exhibits sporadic episodes of variance mainly at short and medium timescales. During 2013 and late 2019, returns appear to have a noncontinuous but more long-lasting variance. Robusta coffee exhibits a less volatile behavior in returns. Partial episodes of variance are observed at short scales and mainly during 2010-2011, and again in 2024. Between the two markets, Arabica returns present a more volatile pattern at high frequencies, with no major changes exhibited during crisis periods. The higher vulnerability of the Arabica market is associated with the sensitivity of production to weather conditions and diseases Dias et al. (2024).

4.1 Wavelet Spectrum and Wavelet Coherence for returns

Figure 3 presents the wavelet coherence between the two varieties. Warmer colors imply stronger coherence and milder colors suggest lower coherence. Arrows represent the phase difference between commodities, indicating local lead-lag relationships. Gouhier et al. (2013) describes the direction of the arrows as follows: arrows pointing to the right indicate the same

direction, while arrows pointing to the left indicate the opposite direction. Therefore, left-downward and right-upward arrows indicate that the first variable of the pair leads and the second lags. However, left-upward and right-downward arrows indicate that the second variable leads and the first lags. Phase Arrows at all timescales are pointing right, implying positive relationships between Arabica and Robusta. At short horizons (2-8 days), there are no major episodes of statistically significant weak or strong coherence. At medium horizons (8-64 days), partial and short-lived episodes of coherence are observed, particularly during the pandemic period and during 2023-2025. The relationship between them became stronger compared to high frequencies. Therefore, in 2020, most arrows point right-upward, suggesting that Arabica leads and Robusta lags during the COVID-19 pandemic. Although between 2023 and 2025, arrows are mixed with areas where Robusta leads and Arabica lags (right-downwards). This shift may be associated with the narrowing spread between the two varieties in recent years, as the lower Arabica premium suggests a relatively stronger role of Robusta in their price dynamics. At long horizons (128-256 days), the coherence remains strong with more long-lasting episodes, especially during 2020-2025. Consistently, at lower frequencies, the lead-lag relationship indicates that Arabica leads after the pandemic.

Figure 3: Wavelet Coherence: Arabica and Robusta coffee returns



4.2 The WLMC results for returns

Figure 4 shows the scale-dependent and time-varying correlation coefficients for Arabica and Robusta returns. The green line represents the estimated correlation relationship, and the red dashed lines represent the 95% confidence interval. The shaded regions correspond to the three sub-periods (Pre-Covid, Covid-19 and the Russia-Ukraine war). For the small timescales (namely 2-8 days), the correlation is positive, statistically significant, and increases between 2012 and 2022 (increased demand during the Covid-19 crisis). During 2022-2025, the green area captures a small downward trend in correlation, with values not falling below 0.50. In 2024, major supply disruptions related to adverse weather conditions affected both markets, although the short-term effect on their correlation remains weak (e.g., dry and hot weather in Brazil and Vietnam) FAO (2025). At medium horizons (between 16 and 64 trading days), the correlation remains positive and statistically significant, reaching the lowest values in 2012, close to 0.25; however, it appears to be volatile during the pandemic and the war period.

Interestingly, while at smaller timescales correlation reached 0.76, during the COVID-19 period, medium horizons exhibited lower values close to 0.30. The reverse pattern is observed during the War period, where correlations at high frequencies reached 0.50, whereas at medium frequencies increased to 0.75. However, this sub-period coincides with supply and weather issues in major producing countries. Hence, the stronger correlation at medium horizons may capture broader common market conditions rather than the effects of war alone. The influence of the pandemic on the Arabica-Robusta relationship is scale-dependent rather than uniform, as COVID-19 affected multiple stages of the coffee value chain and its effects are emerging over time Hernandez et al. (2020). By contrast, the correlation pattern observed during the war period suggests that short horizons capture the influence of market-specific factors (weather shocks or different supply disruptions in producing countries), while longer horizons show common demand and macroeconomic shocks Gilbert (2010).

Figure 4: WLM correlations of returns between Arabica and Robusta Coffee



At longer horizons (128-256 days), the volatile pattern has disappeared, and correlation retains a strong and stable level for most timescales. Importantly, a sharp decline appears towards the end of the sample, in the war sub-period. In line with the long-term pattern, shared fundamentals and common macroeconomic factors such as global demand shocks and changes in the USD can contribute to the strengthening of their relationship Hernandez et al. (2020). On the other hand, at short horizons (especially during crisis periods), extreme movements may appeal to temporary speculators, whose trading activity has exhibited causal effects on prices for both varieties Ngure and Watanabe (2024). In general, the multiscale pattern of correlation between the coffee varieties is consistent with (Fousekis and Grigoriadis, 2017, 2022; Stavrakoudis and Panagiotou, 2016). Compared to Arabica varieties, Arabica and Robusta tend to co-move more weakly. The former study highlights asymmetric dependence between Arabica and Robusta, reinforcing the instability in correlation observed in our results, especially at medium horizons.

Figure 5: The Dominant Heatmap of returns

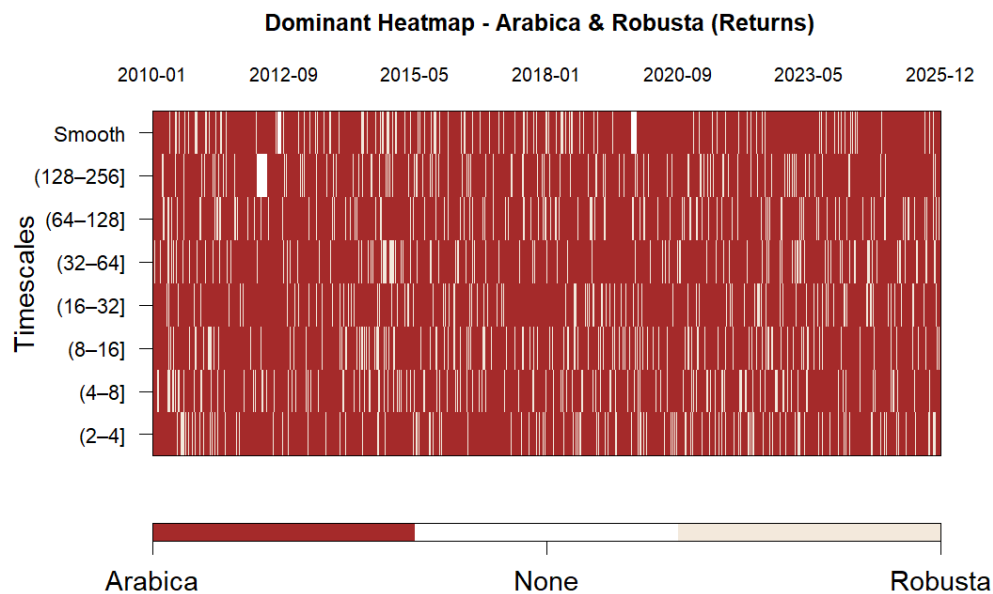


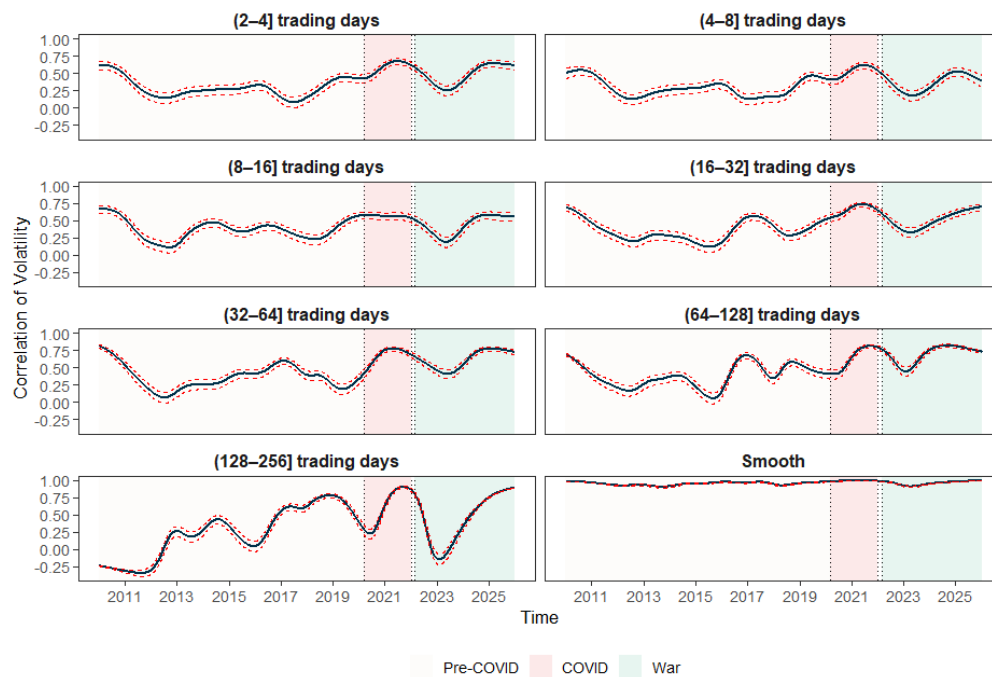
Figure 5 shows the dominant heatmap of returns for the Arabica-Robusta pair. In the WLMC framework, the dominant variable is defined as the most dependent, indicating which coffee variety maximizes the local correlation on each timescale (Martínez et al., 2018). Dominance is also associated with phase differences, indicating whether the dominant variable tends to follow (locally) the changes of others (Martínez et al., 2018; Polanco-Martínez, 2023). White areas represent statistical insignificance. The larger part of the heatmap is covered by Arabica coffee. Before 2018, at short and medium horizons, Arabica held almost absolute dominance (e.g., (2-4) timescale in 2015). Robusta appears to have more frequent dominance patches in the post-pandemic period and mostly at high frequencies. The less frequent dominance of Robusta is consistent with evidence that shows spillovers between Arabica and Robusta are generally weaker than those observed in Arabica Fousekis and Grigoriadis (2022). The dominance of Arabica suggests that the adjustment in the Arabica-Robusta linkages is more strongly reflected in Arabica returns. Therefore, given the phase difference implied by the WLMC framework, Arabica returns tend to follow or adjust sequentially to the common dynamics of the two varieties. A plausible explanation for the dependent role of Arabica is associated with the substitutability between the two coffee varieties. Since Arabica and Robusta are commonly used in coffee blends, market participants closely monitor their relative prices. When shocks in Arabica occur, its prices become relatively more expensive than Robusta, leading roasters to substitute a part of their blends (or whole) with Robusta. This, in turn, triggers changes in demand across the two markets and puts pressure on prices to re-adjust. This mechanism tends to push the relative price relationship back toward a more sustainable level. The local maximization of correlation in Arabica means that Arabica more strongly incorporates changing demand conditions between the two markets and adjusts in order to restore the long-run equilibrium. Fousekis and Grigoriadis (2022) provide evidence that shocks generated from higher quality varieties tend to be transmitted to lower quality, contributing to the stability of their relative price relationship.

4.3 The WLMC results for volatility

Figure 6 presents the realized volatility (squared returns) (Andersen and Bollerslev (1998)) for the Arabica-Robust pair across timescales and horizons. At high frequencies, the correlation of

volatility remains positive and statistically significant. Synchronized volatility dynamics in multiple investment horizons provide useful information to investors and traders, suggesting more informed hedging, diversification, and risk forecasting decisions. The positive correlation indicates that the two markets present synchronized movements in their volatility levels (periods of high or low fluctuations tend to occur together). For timescales up to two weeks, correlations present a similar moderate and positive pattern with no clear upward or downward trend. However, timescales up to one month present a highly volatile pattern (especially during 64-128 days) with repeated upward and downward movements per year. Interestingly, in 2013, at most timescales, correlations are statistically insignificant. For the timescale (128-256], before 2013, correlations are negative and statistically significant and shift to positive, with strong fluctuations over the years.

Figure 6: WLM correlations of volatility between Arabica and Robusta Coffee



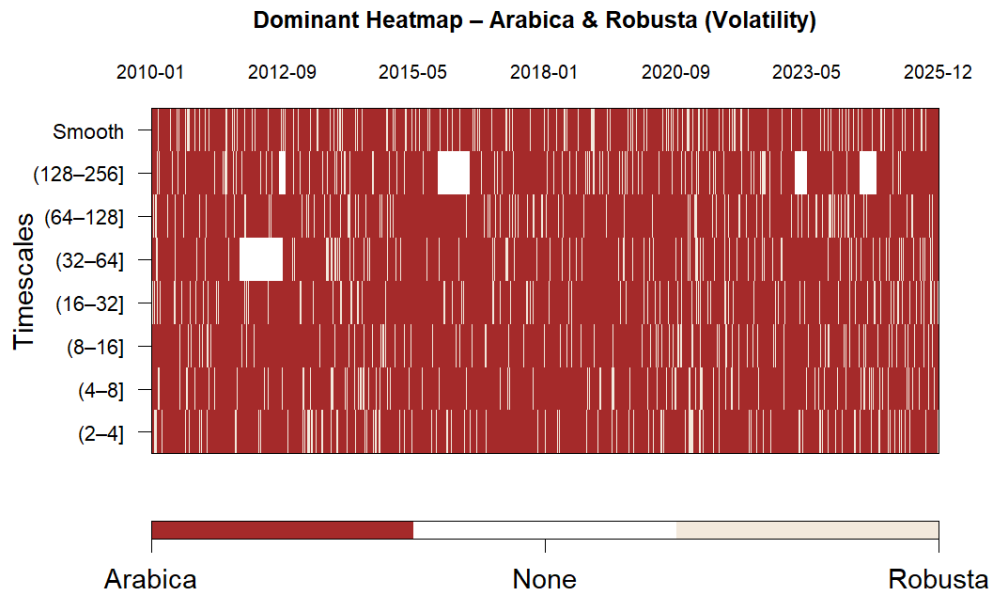
Negative correlations may be associated with different responses in Arabica compared with returns. ICO (2012) reported that increased prices are observed in Arabica during 2012, while Robusta noted a modest rise. At all timescales, correlations during the pandemic strengthen as the timescale increases. On the other hand, during the war period, the correlation of volatility remains moderate as the timescale increases. The Russia-Ukraine war caused increased production costs due to higher energy and fertilizer prices, which in turn increased the cost of agricultural inputs, affecting global food markets (including coffee) Food and Agriculture Organization of the United Nations (FAO) (2023). Lower production and disruptions related to weather in Brazil were behind volatility in Arabica prices, while Robusta was partially stabilized owing to increasing exports from Vietnam and Indonesia World Bank (2022). In recent years, at all timescales, the correlation has increased significantly, reversing from a downward trend to an upward trend.

Figure 7 presents the dominant heatmap for realized volatility. Similar to the heatmap of returns, Arabica coffee dominates in the majority of the timescales and years. More frequent episodes of Arabica's dominance appeared at short and medium horizons, suggesting that, due to the phase-difference, Arabica volatility tends to follow the volatility of the Robusta market. In this framework, Arabica appears to be a recipient of instability from the Robusta market.

Volatility shocks are more often reflected in Arabica as the market adjusts more strongly in order to maintain the dynamic linkages between the two markets. When the price of Arabica becomes too high relative to Robusta, roasters, especially for mass-market

blends, have an incentive to blend in more of the cheaper Robusta to cut costs. This increased demand for Robusta pushes its price up, while the reduced demand for the overpriced Arabica pulls its price down.

Figure 7: WLM correlations of realized volatility between Arabica and Robusta Coffee



5. Conclusions

The present study examines price linkages in the futures markets of Arabica and Robusta coffee varieties with the utilization of wavelet frameworks. Wavelet coherency, wavelet spectrum, and Wavelet Local Multiple Correlation approaches are applied to capture scale-dependent and time-varying relationships of returns and realized volatility for the Arabica-Robusta pair. Dominant heatmaps are used to identify the most dependent variable between the varieties. Data are daily closing futures prices (front-month) of Arabica and Robusta coffee from 01/01/2010 to 31/10/2025. The empirical results reveal evidence of a positive and increasing correlation as the timescale increases. More specifically:

- Wavelet Power Spectrum exhibits more frequent and long-lasting variance episodes (during 2010-2025) at medium scales for Arabica than for Robusta. Both varieties exhibit increased volatility at all timescales during 2024-2025 due to severe supply disruptions related to adverse weather conditions, such as dry and hot weather in Brazil and Vietnam.
- Wavelet Coherency reveals a positive relationship between Arabica and Robusta, especially at medium and low frequencies. The lead-lag relationship shows no clear leader over the sample period, as local phase arrows change. In the long run, Arabica tends to hold the leading role during 2023-2024, while Robusta tends to lead mostly at medium scales.

- Results of the WLMC method reveal that correlation of returns tends to increase from shorter to larger scales, with highly volatile patterns during medium horizons. During the Covid-19 pandemic, the correlation was lower at short scales and higher at large scales, while the reverse pattern was shown in the early years of the Russo- Ukrainian war.
- Correlation of realized volatility is moderate for most timescales, with statistically insignificant or negative correlation values near 2012. The realized volatility strengthened during the pandemic, while decreasing at the beginning of the War period. Weather conditions in major producing countries and increased production costs due to higher energy prices (due to the War) may have contributed to a partial weakening of the volatility relationship between Arabica and Robusta, as the two markets responded differently to supply conditions.
- Dominant heatmaps show that Arabica is the most dependent variable, maximizing the local multiscale coefficients in their relationship. The dominance of Arabica at most timescales indicates that adjustments in the Arabica-Robusta linkages are more strongly reflected in Arabica returns. This may be attributed to the substitution between the two varieties, as Arabica tends to follow their common dynamics to re-adjust to the long-run equilibrium. In summary, symmetrical linkages are driven by macro-factors affecting the entire coffee complex (USD strength, global demand, logistics costs). On the other hand, asymmetrical exceptions can be driven by micro-factors specific to one bean, such as weather in a key growing region, as well as diverging demand patterns. The substitution effect acts as the primary economic force that re-correlates them after a divergence. Therefore, while Arabica and Robusta prices trend together on a macroeconomic tide, they are frequently jolted apart by specific supply and demand shocks, only to be pulled back into a relative balance by the mechanics of the market. Future work may explicitly examine the effects of the COVID-19 and/or the Russo-Ukrainian conflict on the Arabica - Robusta price linkages.

Appendix

Figure 8: Raw and backward-ratio-adjusted log-returns of Arabica and Robusta varieties

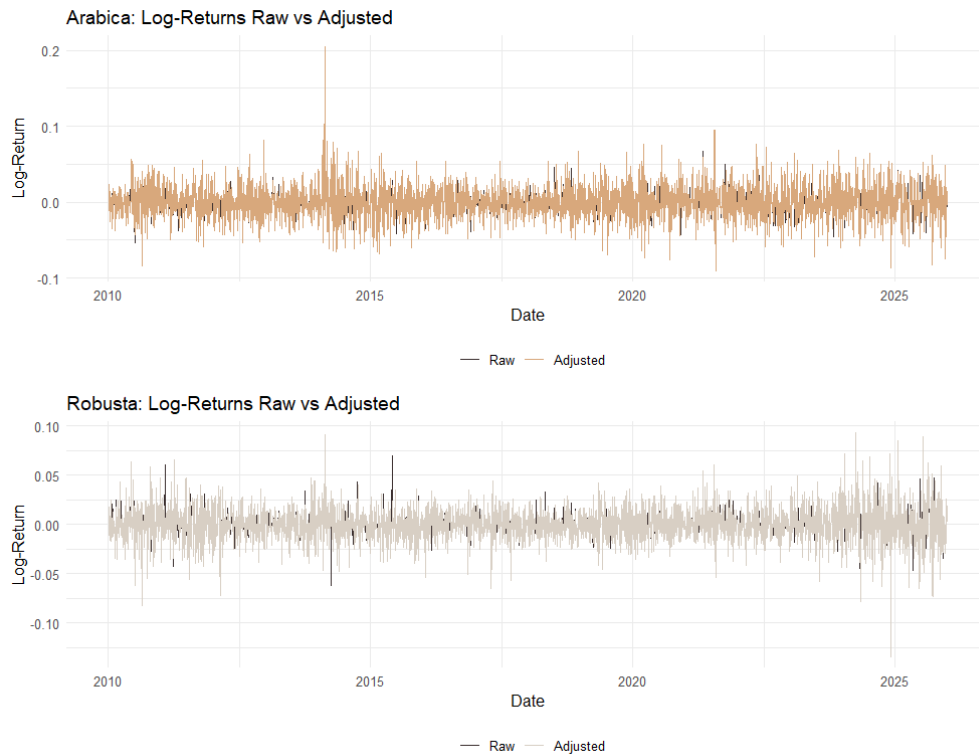


Table 1: Augmented Dickey-Fuller (ADF) Test

	Constant	Constant & Trend
Levels		
Arabica	-1.2328	-1.4887
Robusta	-1.2011	-1.5635
First Differences		
Δ Arabica	-44.880***	-44.885***
Δ Robusta	-43.622***	-43.619***

Notes: Δ denotes first differences. *, **, *** indicate rejection of the null hypothesis of a unit root at the 1% (-3.43), 5% (-2.86), and 10% (-2.56) significance levels, respectively.

Table 2: Phillips–Perron (PP) Test

	Constant	Constant & Trend
Levels		
Arabica	-1.2883	-1.5428
Robusta	-1.2110	-1.5788
First Differences		
Δ Arabica	-65.851***	-65.854***
Δ Robusta	-62.488***	-62.483***

Notes: Δ denotes first differences. *, **, *** indicate rejection of the null hypothesis of a unit root at the 1% (-3.43), 5% (-2.86), and 10% (-2.56) significance levels, respectively.

References

- Abugna, B. G. (2021). Factors affecting coffee (*coffea arabica* l.) quality in ethiopia: A review. *American Journal of Agriculture and Forestry*, 9(5):288–296.
- Andersen, T. G. and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International economic review*, pages 885–905.
- Bouri, E., Nekhili, R., and Todorova, N. (2023). Dynamic co-movement in major commodity markets during crisis periods: A wavelet local multiple correlation analysis. *Finance Research Letters*, 55:103996.
- Cariappa, A. and Sinha, M. (2021). Are the indian arabica and robusta coffee prices cointegrated? a vector error correction approach. *Indian Journal of Agricultural Marketing*, 35:44–59.
- Condelli, N., Cela, N., Di Cairano, M., Scarpa, T., Milella, L., Ascrizzi, R., Flamini, G., and Galgano, F. (2022). Drivers of coffee liking: Effect of physicochemical characteristics and aromatic profile on consumers' acceptability of mono-origin and mono-variety coffees. *Journal of Food Science*, 87(10):4688–4702.
- Deina, C., do Amaral Prates, M. H., Alves, C. H. R., Martins, M. S. R., Trojan, F., Stevan Jr, S. L., and Siqueira, H. V. (2022). A methodology for coffee price forecasting based on extreme learning machines. *Information Processing in Agriculture*, 9(4):556–565.
- Dias, C. G., Martins, F. B., and Martins, M. A. (2024). Climate risks and vulnerabilities of the arabica coffee in brazil under current and future climates considering new cmip6 models. *Science of The Total Environment*, 907:167753.
- FAO (2020). The global coffee market and the covid-19 pandemic. FAO Report.
- FAO (2025). Fao knowledge repository publication. Accessed: 6 March 2026.
- Fernández-Macho, J. (2018). Time-localized wavelet multiple regression and correlation. *Physica A: Statistical Mechanics and its Applications*, 492:1226–1238.
- Food and Agriculture Organization of the United Nations (FAO) (2023). Food outlook: Biannual report on global food markets. FAO report.
- Fousekis, P. (2017). Price co-movement and the hedger's value-at-risk in the futures markets for coffee. *Agricultural Economics Review*, 18(1):35–47.
- Fousekis, P. and Grigoriadis, V. (2017). Joint price dynamics of quality differentiated commodities: copula evidence from coffee varieties. *European Review of Agricultural Economics*, 44(2):337–358.
- Fousekis, P. and Grigoriadis, V. (2022). Conditional tail price risk spillovers in coffee markets across quality, physical space, and time: Empirical analysis with penalized quantile regressions. *Economic Modelling*, 106:105691.
- Fousekis, P. and Grigoriadis, V. (2025). Returns and volatility linkages in the us soybean industry: An empirical analysis across time and frequencies. *Modern Finance*, 3(3):133–149.
- Ghoshray, A. and Mohan, S. (2021). Coffee price dynamics: an analysis of the retail-international price margin. *European Review of Agricultural Economics*, 48(4):983–1006.
- Gilbert, C. L. (2010). How to understand high food prices. *Journal of agricultural economics*, 61(2):398–425.
- Gouhier, T. C., Grinsted, A., Simko, V., Gouhier, M. T. C., and Rcpp, L. (2013). Package 'biwavelet'. *Spectrum*, 24:2093–2102.
- Haile, M. Y. (2018). A review on impacts of climatic variability on arabica coffee improvement in ethiopia. *International Journal of Forestry and Horticulture*, 4(1):9–18.
- Hernandez, M. A., Pandolph, R., Sängner, C., and Vos, R. (2020). Volatile coffee prices: Covid-19 and market fundamentals, volume 2. *Intl Food Policy Res Inst*.
- ICO (2012). Coffee market report: July 2012. <https://www.ico.org/documents/cmr-0712-e.pdf>. Monthly Coffee Market Report.
- ICO (2020). Impact of covid-19 on the global coffee sector: Survey of ico exporting members.
- Intercontinental Exchange (2026). Coffee c futures: Contract specifications. <https://www.ice.com/products/15/Coffee-C-Futures>.

- Investing.com (2026). Historical prices for energy commodities: Crude oil, heating oil, natural gas and gasoline. <https://www.investing.com/commodities/>.
- Jácome Gagnay, A. R. (2017). Coffee prices volatility and transmission: Developing risk management instruments for coffee growers in Ecuador. PhD thesis, Agronomica.
- Li, R., Laroche, M., Richard, M.-O., and Cui, X. (2022). More than a mere cup of coffee: When perceived luxuriousness triggers chinese customers' perceptions of quality and self-congruity. *Journal of Retailing and Consumer Services*, 64:102759.
- Mai, T. C., Shakur, S., and Cassells, S. (2018). Testing vertical price transmission for vietnam's robusta coffee. *Australian Journal of Agricultural and Resource Economics*, 62(4):563–575.
- Martínez, J. M. P., Abadie, L. M., and Fernández-Macho, J. (2018). A multi-resolution and multivariate analysis of the dynamic relationships between crude oil and petroleum-product prices. *Applied energy*, 228:1550–1560.
- Newman, S. and Van Huellen, S. (2022). Understanding commodity markets to effectively address price increases and volatility in a post-covid-19 world. Technical report, ÖFSE Working Paper.
- Ngure, G. M. and Watanabe, K. N. (2024). Coffee sustainability: leveraging collaborative breeding for variety improvement. *Frontiers in Sustainable Food Systems*, 8:1431849.
- Nhung, N. T., Ngan, N. N., Hong, T. T., and Nguyen, D. C. (2020). Hedging with commodity futures: evidence from the coffee market in vietnam. *Investment Management & Financial Innovations*, 17(4):61.
- Pancsira, J. (2022). International coffee trade: a literature review. *Journal of Agricultural informatics*, 13(1).
- Percival, D. B. and Walden, A. T. (2000). Wavelet methods for time series analysis, volume 4. Cambridge university press.
- Polanco-Martínez, J. M. (2023). Visualdom: An r package for estimating dominant variables in dynamical systems. *Software Impacts*, 16:100514.
- Poltronieri, P. and Rossi, F. (2016). Challenges in specialty coffee processing and quality assurance. *Challenges*, 7(2):19.
- Purwawangsa, H., iqbal Irfany, M., and Haq, D. A. (2024). Indonesian coffee exports' competitiveness and determinants. *Jurnal Manajemen & Agribisnis*, 21(1):59–59.
- Roberts, A. (2021). Caffeine: an evaluation of the safety database. In *Nutraceuticals*, pages 501–518. Elsevier.
- Shah, M. I., Foglia, M., Shahzad, U., and Fareed, Z. (2022). Green innovation, resource price and carbon emissions during the covid-19 times: New findings from wavelet local multiple correlation analysis. *Technological Forecasting and Social Change*, 184:121957.
- Stavrakoudis, A. and Panagiotou, D. (2016). Price dependence and asymmetric responses between coffee varieties. *Agricultural Economics Review*, 17(2):5–22.
- Varangis, P. N. et al. (2003). Dealing with the coffee crisis in Central America: Impacts and strategies, volume 2993. World Bank Publications.
- Vijayakumar, A. (2022). Impact of the us dollar index and crude oil on prices of arabica and robusta varieties of indian coffee. *Business Perspectives and Research*, page 22785337221077399.
- World Bank (2022). Commodity markets outlook: The impact of the war in ukraine on commodity markets. <https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099606104272239809>.
- World Bank report.
- Yang, C.-Y., Lu, C.-C., Chiu, Y.-H., and Lin, T.-Y. (2022). Analysis of coffee production efficiency and productivity strategy in african and non-african countries. *Agribusiness*, 38(4):946–969.
- Zhang, W., Saghalian, S., and Reed, M. (2022). Influences of power structure evolution on coffee commodity markets: Insights from price discovery and volatility spillovers. *Sustainability*, 14(22):15268.