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Returns and volatility linkages in the US soybean industry: An empirical analysis across time and frequencies

Panos Fousekis [1,*] and Vasilis Grigoriadis [2]

1 Department of Economics, Aristotle University, Greece, fousekis@econ.auth.gr
2 Department of Economics, University of Ioannina, Greece, v.grigoriadis@uoi.gr
* Corresponding author.

Abstract: The objective of this work is to investigate the links among price returns and among (realized) price volatilities in the US soybean industry. To this end, it employs daily futures prices from 2010 to 2025 and the flexible Wavelet Local Multiple Correlation (WLMC) approach. The joint returns link among soybeans, soybean meal, and soybean oil is positive, time-varying, and frequency-dependent (i.e., asymmetric). The vertical links (those between the input and each of the two co-products of the soybean crush) tend to be stronger than the horizontal link (between soybean meal and soybean oil). The joint link for realized volatility is also positive and asymmetric. For both returns and realized volatility, the input market appears to be a recipient of shocks from the co-products markets.

Keywords: soybean sector, returns, volatility, correlation, asymmetry

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1. Introduction

The soybean complex, which includes the production of soybeans, soybean meal, and soybean oil, is an important component of the US livestock feed, food, and renewable energy supply chains. According to a recent study by the National Oilseed Processors Association (NOPA, 2023), the soybean sector accounts for approximately 0.6 per cent of the US Gross Domestic Product.

The US is the second (after Brazil) soybean producer and exporter. Soybeans are processed ("crushed") into two co-products, namely, the soybean meal and the soybean oil. From the US-produced soybean meal, about 30 per cent is exported; the rest is used domestically as the primary protein source for livestock and aquaculture. From US-produced soybean oil, about 50 per cent is used as edible and restaurant frying oil as well as an input in the production of processed foods (e.g., margarines, dressings) and non-food products (e.g., lubricants, cosmetics), about 45 per cent is used in biodiesel production, and the rest is exported.[1] Historically, soybeans in the US had been mainly "crushed for meal"; in the last 15 years, however, the initiation of federal (RFS - Renewable Fuel Standard) and state-level (e.g., California's LCFS – Low Carbon Fuel Standard) policies alongside with the biodiesel tax credit have incentivised processors to switch to "crushing for oil" (e.g., Gerds, 2022).

The economic viability of soybean processing firms hinges upon the crush spread (margin) (i.e., the difference between the value of the two co-products and the cost of soybeans). The dynamics of the crush spread are difficult to predict. Soybeans, soybean meal, and soybean oil are traded internationally (and, thus, their prices are affected by exchange rates, global supply and demand, and geopolitical risks). More importantly, while the two co-products are subject to parallel supply shifts (soybean crushing typically

1. Information on the utilization of soybeans, soybean meal and soybean oil in the US is available at https://www.ers.usda.gov/data-products/oil-crops-yearbook.

results in 80 per cent meal and 20 per cent oil, a proportion that processors can hardly alter), they are consumed for widely different purposes (and, thus, are subject to largely independent demand shocks). To hedge the crush spread, processors may take opposite positions in the spot and the futures markets so that a loss (gain) in one market is offset by a gain (loss) in the other. Speculators long the crush spread (i.e., they buy meal and oil futures and sell soybean futures) when betting on a higher margin and sell it (i.e., they sell soybean futures and buy meal and oil futures) when betting on a lower margin. Alternatively, futures market participants may execute the soybean crush in a single trade. Relative to legging into the spread (that is, trading the individual components separately), the latter approach costs less and reduces the so-called "leg-risk". Nevertheless, legging may turn out to be more profitable, provided that a trader enters each leg of the spread at an advantageous moment (that means, in legging, timing matters).

Due to the unique characteristics of the soybean complex, information about the nature of price links is potentially useful for processors, speculators, investors, policymakers, and research economists. However, despite the practical and theoretical importance of the topic, the number of relevant empirical works is quite small.

Beutler and Brorsen (1985) employed a 3-variate Vector Autoregressive (VAR) model to assess the temporal (lead-lag) relationships among the spot prices of soybeans, soybean meal, and soybean oil. According to their results, the price of soybeans led the co-products' prices, while past oil prices had a negative impact on meal prices. Simon (1999), using the Engle-Granger approach, found that the three futures prices in the complex were cointegrated. Babula et al. (2004), relying on structural VAR models and Forecast Error Variance Decompositions, reported unidirectional causality from soybeans spot prices to oil spot prices and bidirectional causality between soybeans spot prices and meal spot prices. Adrangi et al. (2006), employing two bivariate Johansen cointegration models (one for the pair soybeans and meal and the other for the pair soybeans and oil), found that the futures prices in each pair were cointegrated and that the prices of the co-products led the price of soybeans. Fousekis (2023) relied on the Conditional Value-at-Risk (CoVaR) model to investigate the links among the US futures prices of soybeans, meal, and oil at different parts of their joint distribution (i.e., upper extremes, lower extremes, and median). He found strong positive links in the vertical direction and a negative link in the horizontal direction (especially under large positive price shocks).

A common implicit assumption of the earlier empirical works is that price linkages in the US soybean complex are stationary in two dimensions, namely, the time dimension and the frequency (timescale) dimension. Stationarity in the time dimension precludes the possibility that the intensity and the sign of price relationships may evolve in line with the supply and demand dynamics. Stationarity in the frequency dimension ignores the fact that traders in commodity futures markets are heterogeneous in terms of their investment horizons; therefore, different price co-movement structures may be relevant at different timescales (such as the short-, the medium, and the long-run). Non-stationary linkages in the time and/or the frequency dimension are evidence of asymmetric price connectedness (e.g., Chatziantoniou et al., 2023; Bouri et al., 2023, and Bouri et al., 2024).

To offer novel and richer insights into price links in the US soybean industry, the present work relies on the Wavelet Local Multiple Multicorrelation (WLMC) approach (Fernandez-Macho, 2018). The WLMC is a flexible tool that allows the association between stochastic processes to be both time-varying and frequency(timescale)-dependent. The WLMC has been employed by Fernandez-Macho (2018) to investigate co-movement dynamics among Eurozone stock markets, by Polanco-Martinez et al. (2018) to assess the links among crude oil and petroleum-product markets, by Shah et al. (2022) to analyze the effect of global energy innovation and resource prices on carbon emissions, by Bouri et al. (2023) to assess price and volatility connectedness among major commodity (crude oil, copper, gold, and wheat) futures markets, and by Bouri et al. (2024) to quantify the relationship between fear indices and S&P500 returns. All these recent empirical works have offered plenty of evidence in favor of dynamic and frequency-dependent links.

2. Analytical Framework

Let Y be an m-variate stochastic process at time t = 1, 2, …, T. Let also $y_i \in Y$ (i = 1, 2, …, m) and a fixed s in [1, 2, …, T]. Then, there is a local linear regression function $f_s(Y_{-i})$ minimizing the weighted sum of squared errors.

$$S_s = \sum_{t=1}^{T} \theta(t-s)(f_s(Y_{-i,t}) - y_{it})^2 \quad (1)$$

where $\theta(t - s)$ stands for a moving average weight function of the time lag between observations Y_t and Y_s. The local coefficients of determination over the different values of s are

$$R_s^2 = 1 - \frac{RSSWs}{TSSWs} \quad (2)$$

where RSS and TSS stand for the residual and the total sum of squares, respectively.

The application of the maximal overlap discrete wavelet transform (MODWT) (Percival & Walden, 2000) of order/decomposition level j = 1, 2, …, J to every $y_i \in Y$ obtains collections $W_{j,t} = (w_{1j,t}, w_{2j,t}, \ldots, w_{mj,t})$ that are the wavelet coefficients for timescale $\lambda_{j,t}$. Then, at each wavelet scale λ_j one can calculate a series of localized multiple correlation coefficients WLMC ($\Phi_{x,s}(\lambda_j)$) as the square roots of the coefficients of determination in (2) for the linear combination of variables $w_{mj,t}$ (i = 1, 2, …, m) where such coefficients of determination are maxima; that is,

$$\Phi_{x,s}(\lambda_j) = \sqrt{R_{j,s}^2} \quad (3)$$

for s=1, 2, …, T and j=1, 2, …, J (Fernandez-Macho, 2018). The variable maximizing the WLMC at a given period and timescale (i.e., the most dependent one) is termed as dominant (Shah et al., 2022; Bouri et al., 2023). As noted by Polanco Martinez et al. (2018) and Polanco-Martinez (2023), dominance in the context of the WLMC analysis indicates the presence of a phase difference between the dominant variable and the remaining variables in the dynamic system (i.e., the dominant process generally follows the others)[2].

Given that the coefficient of determination is equal to the squared correlation between the observed and the fitted values of a linear regression, one may express the consistent sample estimator of WLMC as

$$\phi_{x,s}(\lambda_j) = cor(\theta(t-s)^{0.5} w_{ijt}, \theta(t-s)^{0.5} \hat{w}_{ijt}). \quad (4)$$

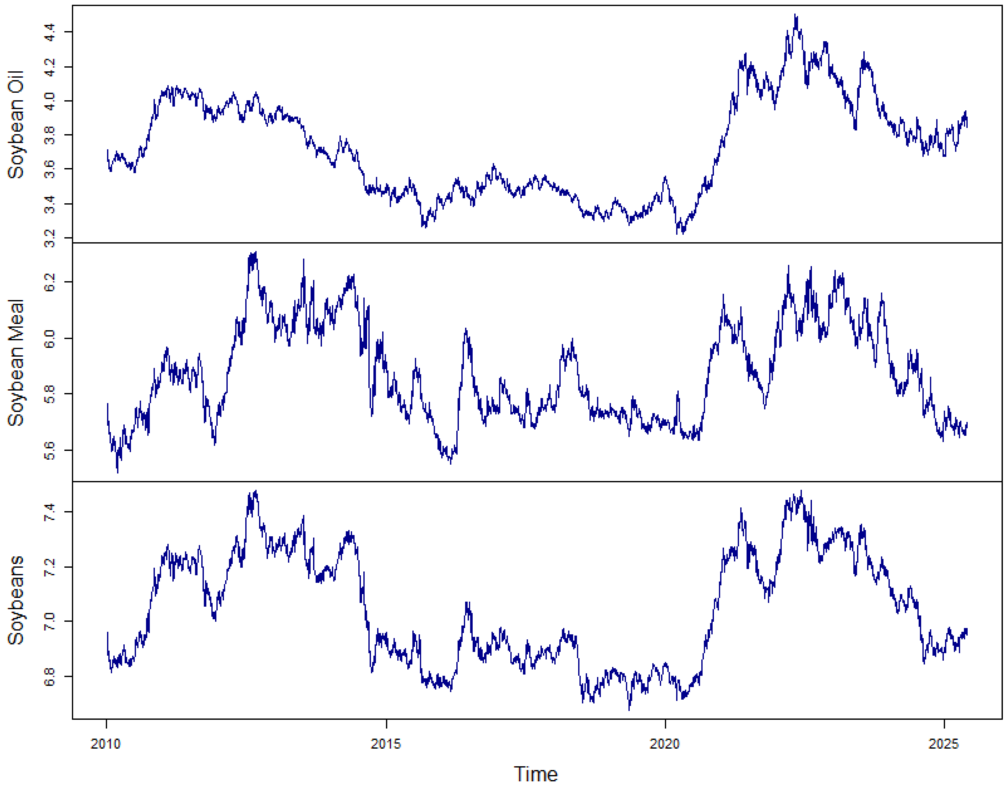
where W_{ij} is the dominant variable and $\hat{w}_{ij,t}$ is the vector of fitted values from the linear regression of the dominant on the set of the remaining regressors $\{w_{lj} : l \neq i\}$. The $(1 - \alpha)100\%$ confidence interval for the wavelet local correlations is

$$CI_{1-\alpha} = tanh\left[\text{arctanh}\ (\Phi_{x,s}\left((\lambda_j)\right) \pm \phi_{1-\alpha/2}^{-1}\sqrt{T/2^j - 3}\right] \quad (5)$$

where $\varphi^{-1}{}_{(1-\alpha/2)}$ is the $(1 - \alpha)100\%$ quantile of the standard normal distribution (Fernandez-Macho, 2018).

2. The interpretation relies on the notion of instantaneous/contemporaneous causality (Granger, 1969; Vinod, 2017). The empirical investigation of instantaneous causality can be conducted for three or more variables as the coefficient of determination from (for example) the linear model of Y on X and Z variables is not necessarily the same as that from the linear model of X on Y and Z variables.

Figure 1. The logarithmic price series



3. The data

The data for the empirical analysis are daily front-month futures prices of soybeans (in cents per bushel), meal (in $ per short ton), and oil (in cents per pound). They have been obtained from Yahoo Finance and refer to the period 1/1/2010 to 5/30/2025.[3] Figure 1 shows the evolution of their respective natural logarithms.

Comparing the prices of the two co-products is somewhat difficult as one price is denominated in short tons and the other in pounds. To overcome this problem, the industry evaluates the relative price of oil as the oil's share in the soybean crush (i.e., the revenue received from selling both meal and oil). The so-called oilshare is calculated as[4]

$$oilshare = \frac{(\text{oilshare})(0.11)}{(\text{oilshare})(0.11)+(\text{meal price})(0.022)} \tag{6}$$

3. Available at https://finance.yahoo.com/quote/ZS%3DF/history/, https://finance.yahoo.com/quote/ZM%3DF/history/, and https://finance.yahoo.com/quote/ZL%3DF/history/, for soybeans, soybean meal, and soybean oil, respectively. Accessed on 6/5/2025.

4. One bushel of soybeans crushed results in 44 pounds of meal and 11 pounds of oil. The multiplication by 0.022 converts meal price to the price of 44 pounds and the multiplication by 0.11 converts oil price to the price of 11 pounds. For details see https://www.cmegroup.com/articles/whitepapers/what-is-oil-share.html.

Figure 2. The evolution of the oilshare

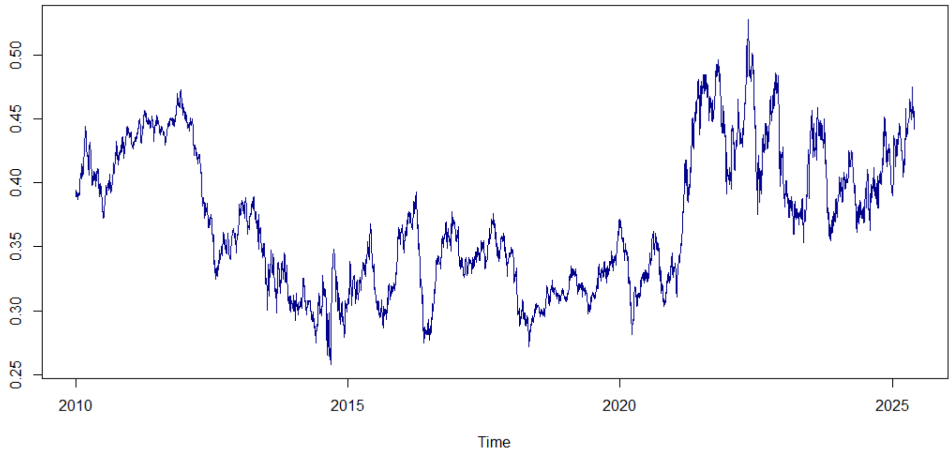


Figure 3. The evolution of the crush spread

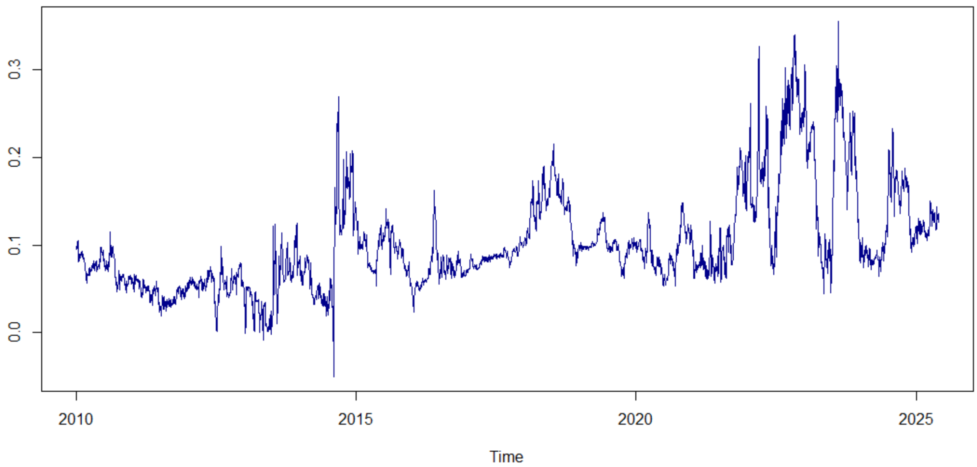


Figure 2 shows the evolution of the relative price of oil. The oilshare ranged between 40 and 45 per cent at the beginning of the sample; it dropped dramatically in 2012 and fluctuated between 25 and 35 per cent until 2020; it rose precipitously in 2021 and 2022; since then, it has been fluctuating at about 40 per cent. Although the oil share has exhibited very strong volatility, its trend during the last 10 years has been generally positive. This has been the result of an increasing demand for soybean oil by the biodiesel industry, combined with a relatively stable demand for soybean meal by the animal feeding industry (Gerdts, 2022).

Figure 3 shows the evolution of the spread (margin) per bushel of soybeans crushed, calculated as[5]

$$crush\ speed = (meal\ price)(0.022) + (oil\ price)(0.11) - (soybeans\ price)/100 \qquad (7)$$

The margin has shown considerable volatility and a generally upward trend. The drops in 2015-16 and 2023 were probably the result of global soybean oversupply, while those in 2018-20 were due to the US-China trade war, the African Swine Fever in China, and the demand uncertainties associated with the initial phase of the COVID-19 pandemic.

Table A.1.1 in the Appendix presents the results of the KPSS (Kwiatkowski et al., 1992) test on weak stationarity for the logarithmic price levels and the price returns. The

5. https://www.cmegroup.com/trading/agricultural/grain-and-oilseed/soybean-crush-spreads.html.

logarithmic price series is non-stationary. The returns series, however, are. Table A.1(b) shows, for comparison, the results from Hardi's (2000) panel unit root test. The null hypothesis (all series are stationary) is rejected for the logarithmic levels but not for the returns. Therefore, the empirical analysis subsequently relies on returns. Table A.2 provides descriptive statistics for the price returns. All series exhibit negative skewness and excess kurtosis; the null of normality is rejected everywhere.

Figure 4. WLM Correlations for soybean meal and soybean oil returns

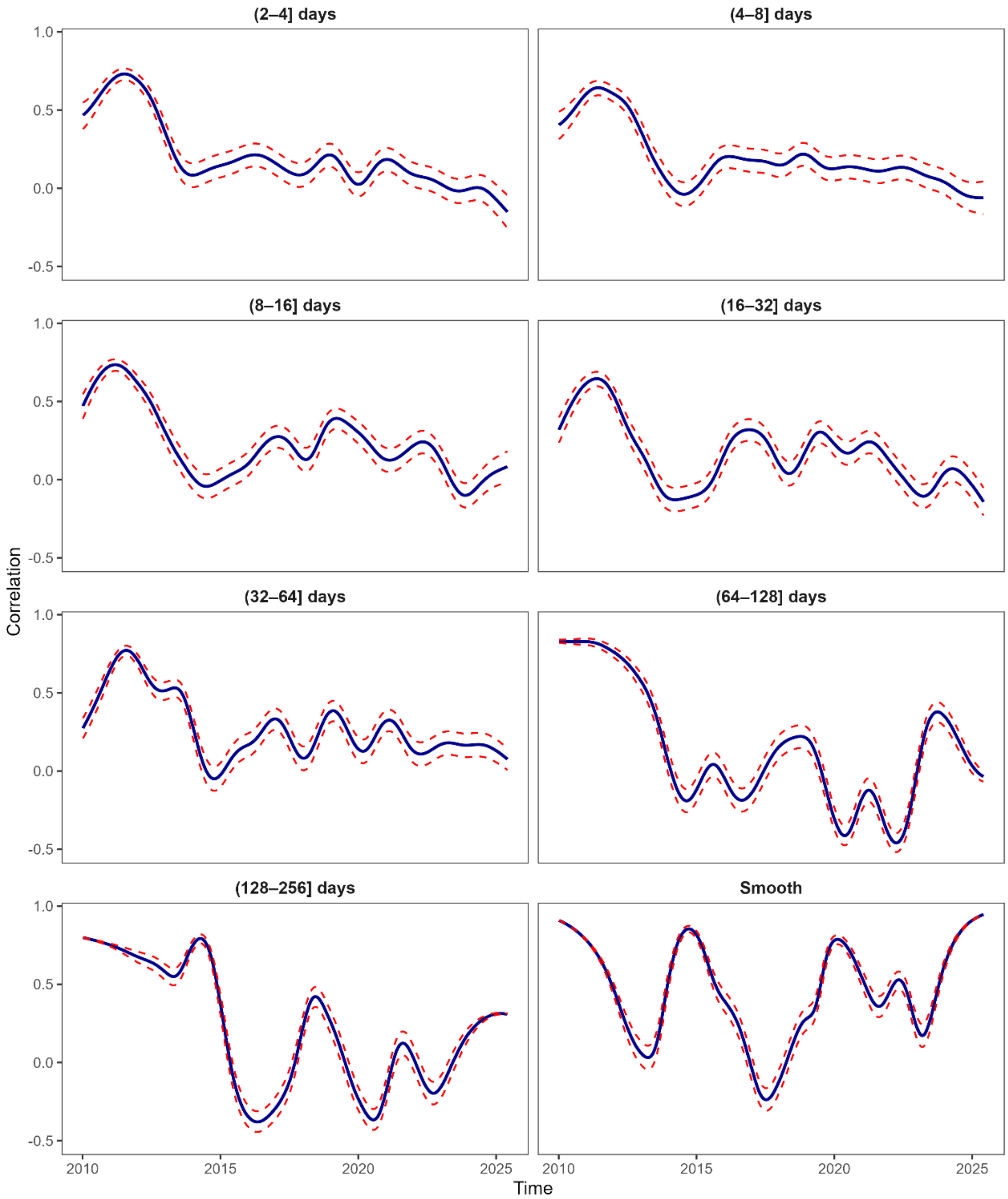
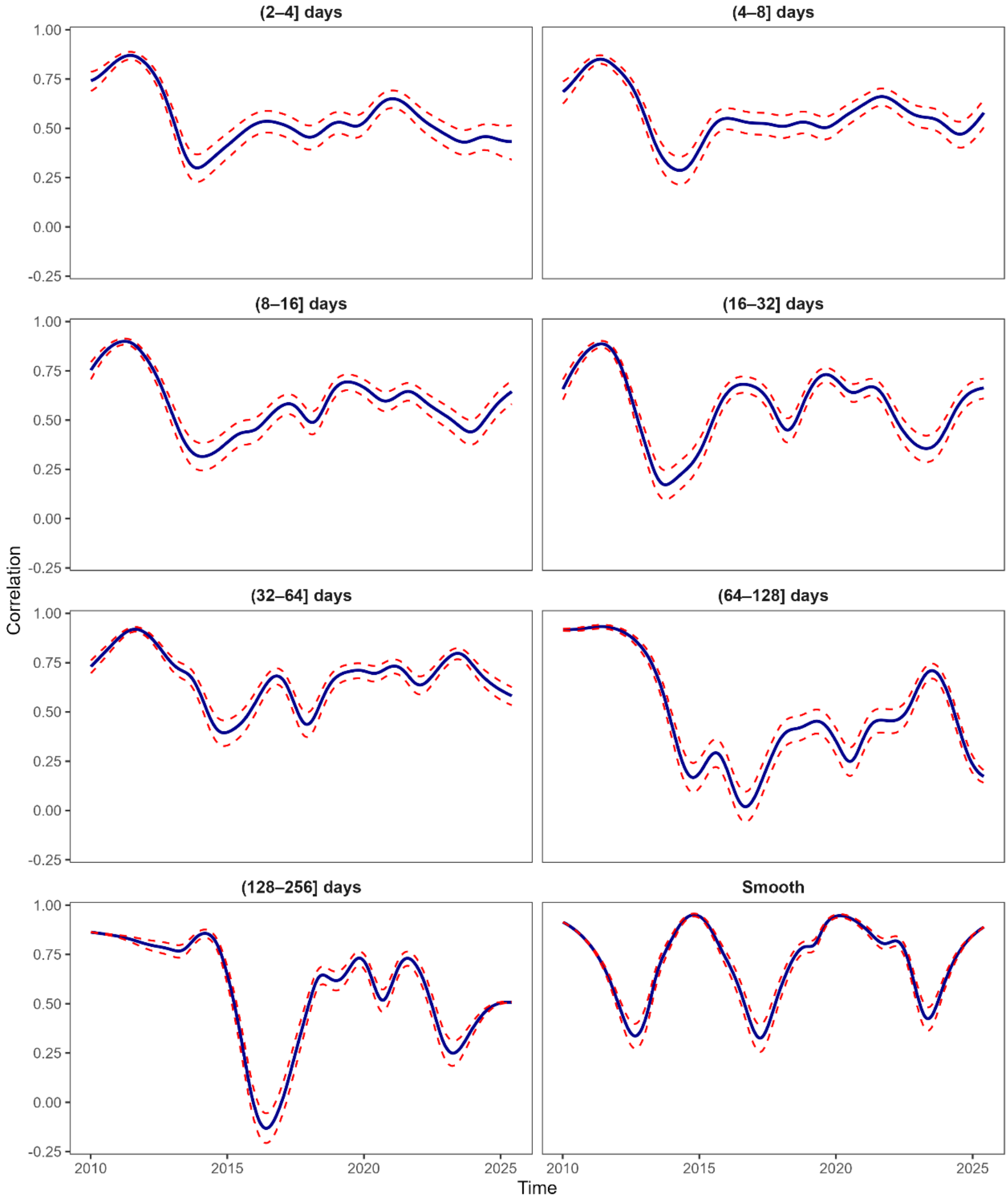


Figure 5. WLM Correlations for soybean oil and soybean returns



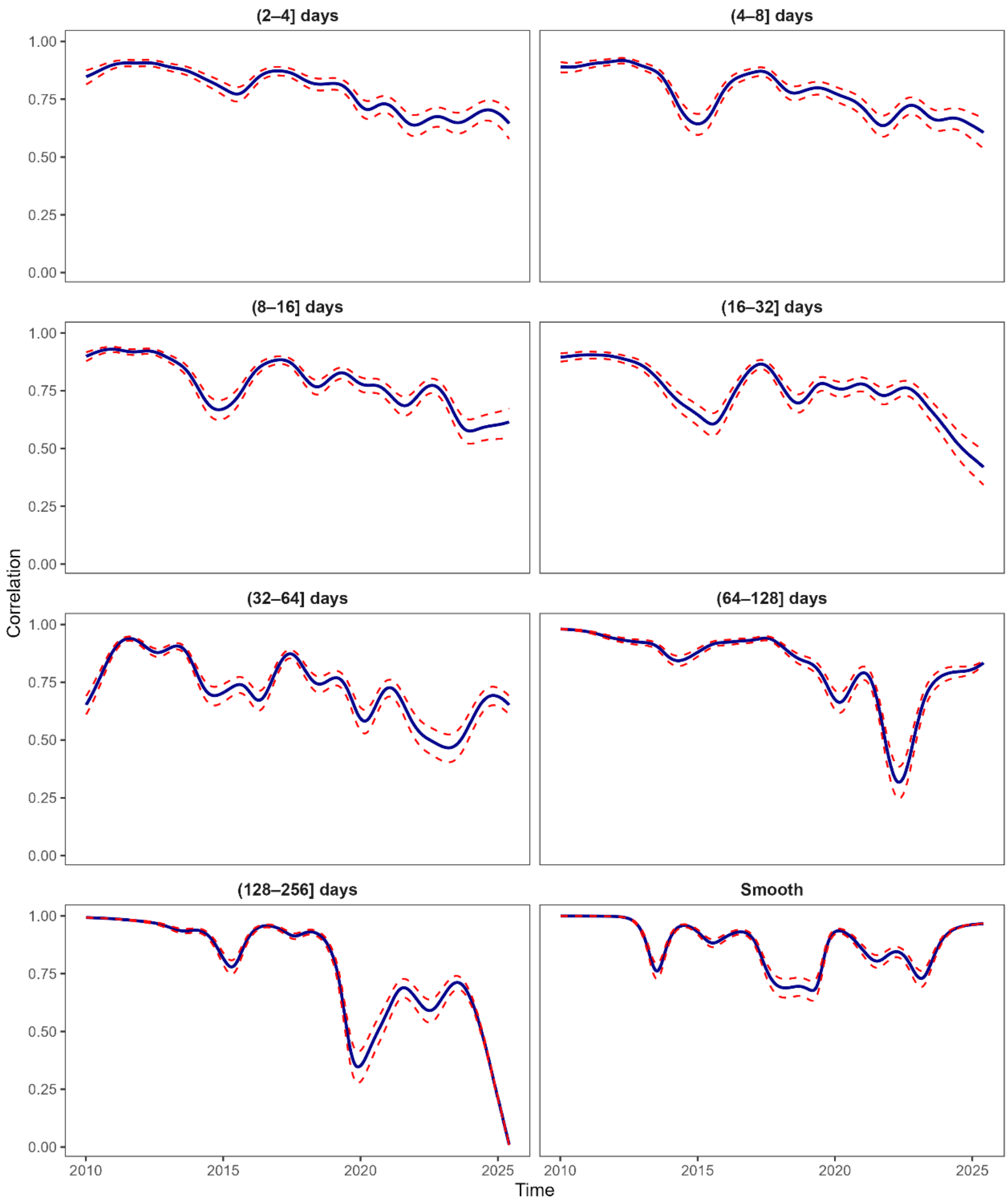
4. The empirical models and the results

4.1. The empirical models

The theoretical maximum decomposition level for the MODWT is the integer part of log2 (T) (Percival & Walden, 2000). In practice, however, J is usually set below the theoretical maximum to avoid boundary effects (as the number of feasible wavelet coefficients becomes critically small at high levels of J). Following Fernandez-Macho (2018) and Bouri et al. (2023) (who worked with sample sizes very similar to ours), J has been set equal to 7. With five daily observations per week, this produces wavelet coefficients at timescales 2-4 (very short-run), 4-8, 8-16, 16-32, 32-64, 64-128, 128-256 trading days. The timescale above 256 is the smooth (long-run).

As shown by Gencay et al. (2001), relatively long wavelet filters are necessary to analyze non-stationary correlation structures. Here, following Bouri et al. (2023) and Bouri et al. (2024), we employ the Daubechies least asymmetric filter of length 8 ("la8"). Finally, in line with most of the earlier applications of the WLMC, we use a Gaussian weight (rolling window) function (e.g., Polanco-Martinez et al., 2020; Shah et al., 2022; Bouri et al., 2023). The length of the rolling window has been set equal to 260 trading days (approximately one calendar year) as in Bouri et al. (2023) and Bouri et al. (2024). The choice avoids the introduction of excessive variability and, at the same time, ensures that associations at very small timescales can be isolated and studied. The empirical analysis has been conducted using the R package VisualDom (Polanco-Martinez, 2023).

Figure 6. WLM Correlations for soybeans and soybean meal returns



4.2. The WLMC coefficients for the price returns

Figures 4, 5, and 6 show (as a preliminary step) the time-varying and multiscale correlation coefficients for the bivariate cases (pairs (oil returns, meal returns), (oil returns, soybeans returns), and (meal returns, soybeans returns)) along with their respective 95 per cent confidence bands.

In Figure 4, for the small and medium timescales (that is, from 2 to 64 trading days) and in 2010-2012, the correlation is positive and increasing. It shows a strong downward trend from 2013 to 2014 and fluctuates around 0.1 until 2020. Negative and statistically significant coefficients (especially at the small timescales) appear towards the end of the sample. In the most recent periods and at larger timescales, the correlations are highly volatile; they assume positive and statistically significant values as high as 0.8 and negative and statistically significant values as low as -0.5. The presence of weak and/or negative correlations between oil and meal returns is entirely possible given that the co-products are subject to the same supply but independent demand shocks. The finding agrees with earlier evidence by Beutler and Brorsen (1985) and Fousekis (2023). Interestingly, for all timescales but the long run, the decreasing, weak, and/or negative connectedness coincide with the emergence and expansion of the biodiesel industry in the US (and the processors' switch to "crushing for oil").

The evolution of multiscale correlations for the pair (oil returns, soybeans returns) (Figure 5) is, in many respects, similar to that in Figure 4. Nevertheless, there is an important difference; there are hardly any negative and statistically significant associations, while the levels of positive ones are much higher for the same time-frequency combinations. This, to a larger degree, applies to the local wavelet correlations for the pair (meal returns, soybeans returns), where the vast majority of values well exceed 0.7 (Figure 6). Therefore, the pair (meal returns, soybeans returns) exhibits by far the highest degree of connectivity. From the visual comparison of Figures 4 to 6, it follows that the vertical price links in the US soybean complex are positive and stronger (in absolute value terms) than the horizontal price link. The result is consistent with what was reported by Fousekis (2023).

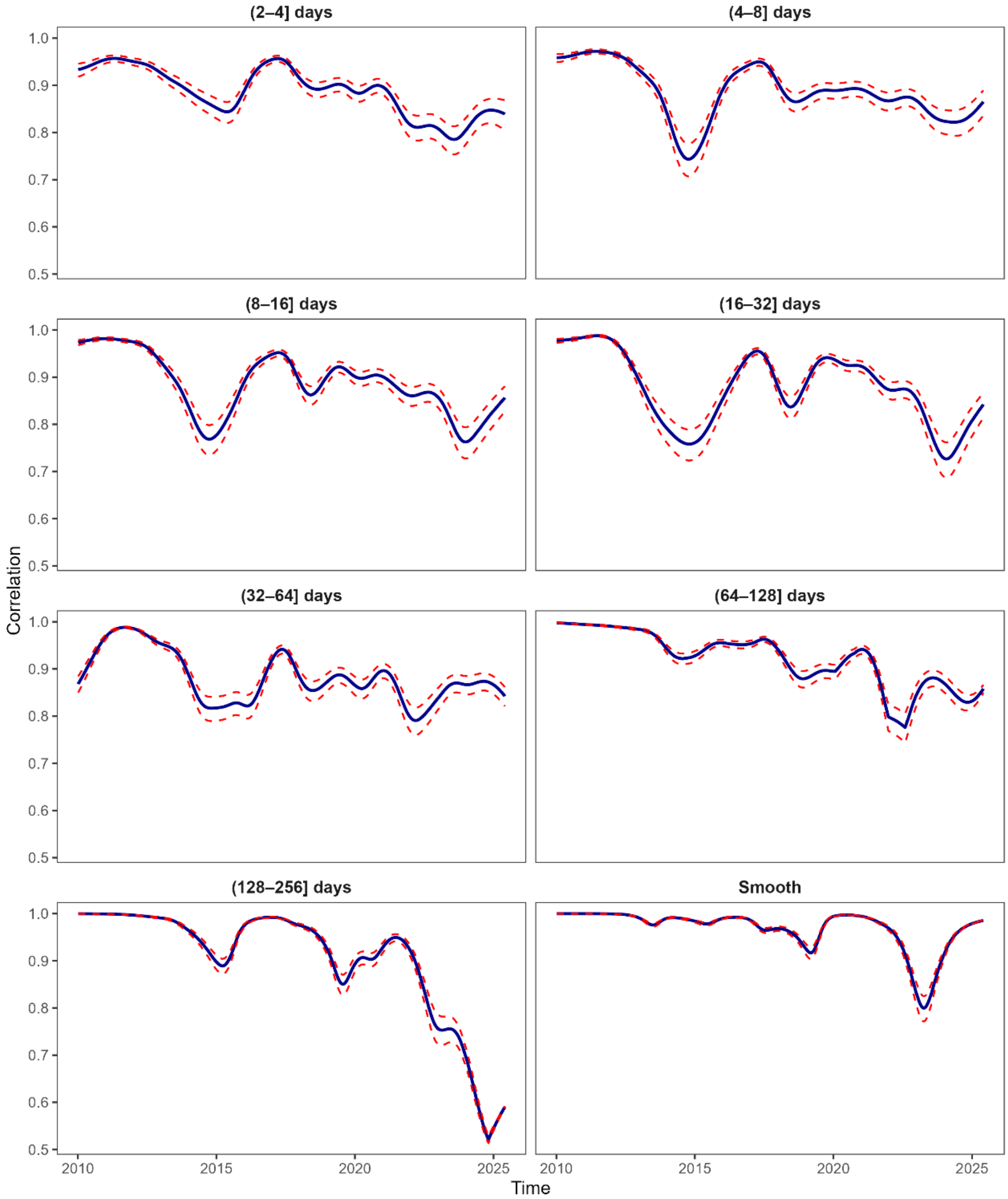
Figure 7 plots the dynamic multiscale structure of connectedness from the trivariate (joint) analysis. The correlation coefficients are positive and statistically significant across all periods and timescales. The average frequency-specific values range from about 0.8 on the small timescales to above 0.9 on the large timescales. The rise of correlations with the time horizon is natural, as the process of information diffusion is a gradual one. At larger timescales, there is little room for noise traders to influence the market outcomes. In any case, the strong connectedness indicates that the three markets in the complex are well integrated. The evidence is consistent with the well-established fact that commodity prices exhibit common cyclical behavior (e.g., Bouri et al., 2023) and the findings by Simon (1999).

The high correlation values at both the small and the large timescales point to the presence of pure (short-run) and fundamental-based (long-run) contagion, respectively (e.g., Gallegati, 2012; Bouri et al., 2023). The short- and the long-run contagion, in turn, suggest: First, the margin of soybean processing firms in the US is, to a certain extent, self-hedged[6]. Nevertheless, the need for commercial traders to hedge the crush spread by taking opposite positions on the spot and the futures markets is likely to be stronger in the short- than in the long-run. Second, the crush spread displays anti-persistence; that is, it tends to revert to its long-run equilibrium level (normal/fair value). The speed of mean-reversion is higher at larger timescales. Speculators may exploit anti-persistence by buying (selling) the crush spread when it is currently below (above) its fair value.

The timescale-specific correlations show considerable variability and exhibit troughs and peaks that are common in many of the frequencies considered. There is a trough centred in 2015 (global oversupply of soybeans); in 2019 (Asian Swine Fever in China); and another in 2022 (outbreak of the war in Ukraine and the associated with it sunflower oil shortage). There is a peak centred in 2017 (strong Chinese soybean meal demand) and another in 2020 (the initial phase of the COVID-19 pandemic).

6. A spread is self-hedged when the prices of inputs and outputs rise and fall in unison (Collins, 2000). Self-hedging is a direct outcome of the profit maximization postulate. A profit function is homogeneous of degree zero in output and input prices (that means, the profit level remains the same when the prices of all outputs and inputs change by the same percentage).

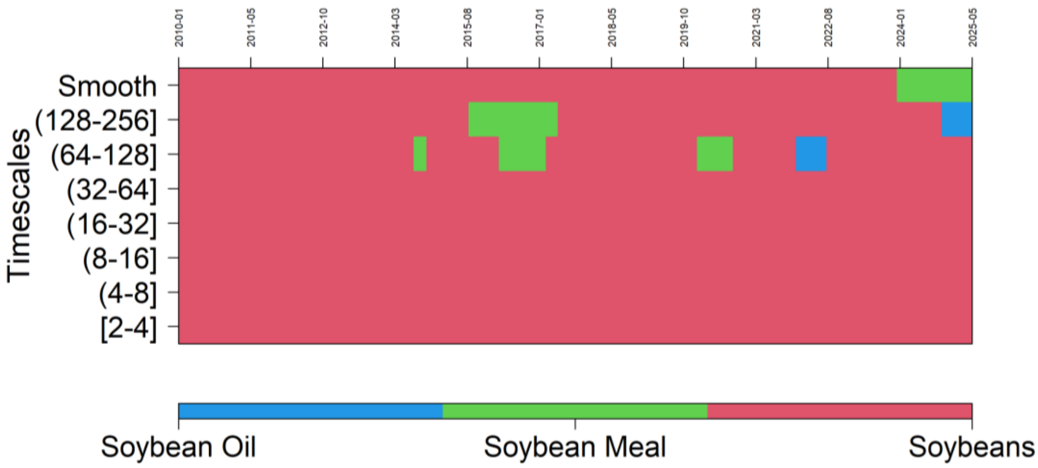
Figure 7. WLM Correlations for soybeans, soybean oil, and soybean meal returns



Almost all frequency-specific correlations show downward trends. One possible explanation for this development is the switch from "crushing for meal" to "crushing for oil". Another is that, while large parts of the US-produced soybeans and meal are exported, the US-produced oil is still predominantly directed to the domestic market. Moreover, the biodiesel tax credit favors domestic producers, making imports of other oils (e.g., palm) less competitive on the US market.

Figure 8 shows the heatmap of the dominant variable(s) in the trivariate system across time and frequencies. The soybean returns series maximizes the correlation coefficients in the vast majority of time-frequency combinations. Given that dominance in the context of the WLMC implies a phase difference, the prices of meal and oil are weakly exogenous processes, and convergence to the long-run equilibrium occurs through adjustments in the price of soybeans. The information in the US soybean complex flows from the downstream markets to the upstream (raw input) market; in other words, market integration in the US soybean complex is demand-driven.

Figure 8. The heatmap of dominant variable(s): Soybeans, soybean oil, and soybean meal returns



In the context of petroleum refining, demand-driven vertical market integration is taken as evidence in support of Verleger (1982) hypothesis, an implication of which is that the crack spread (difference between the value of the refined products and the cost of crude oil used to produce them) has a predictive power for the crude oil prices (e.g., Asche et al., 2003; Vides et al., 2023). The heatmap in Figure 8 suggests that the Verleger hypothesis is probably valid for the soybean complex as well.

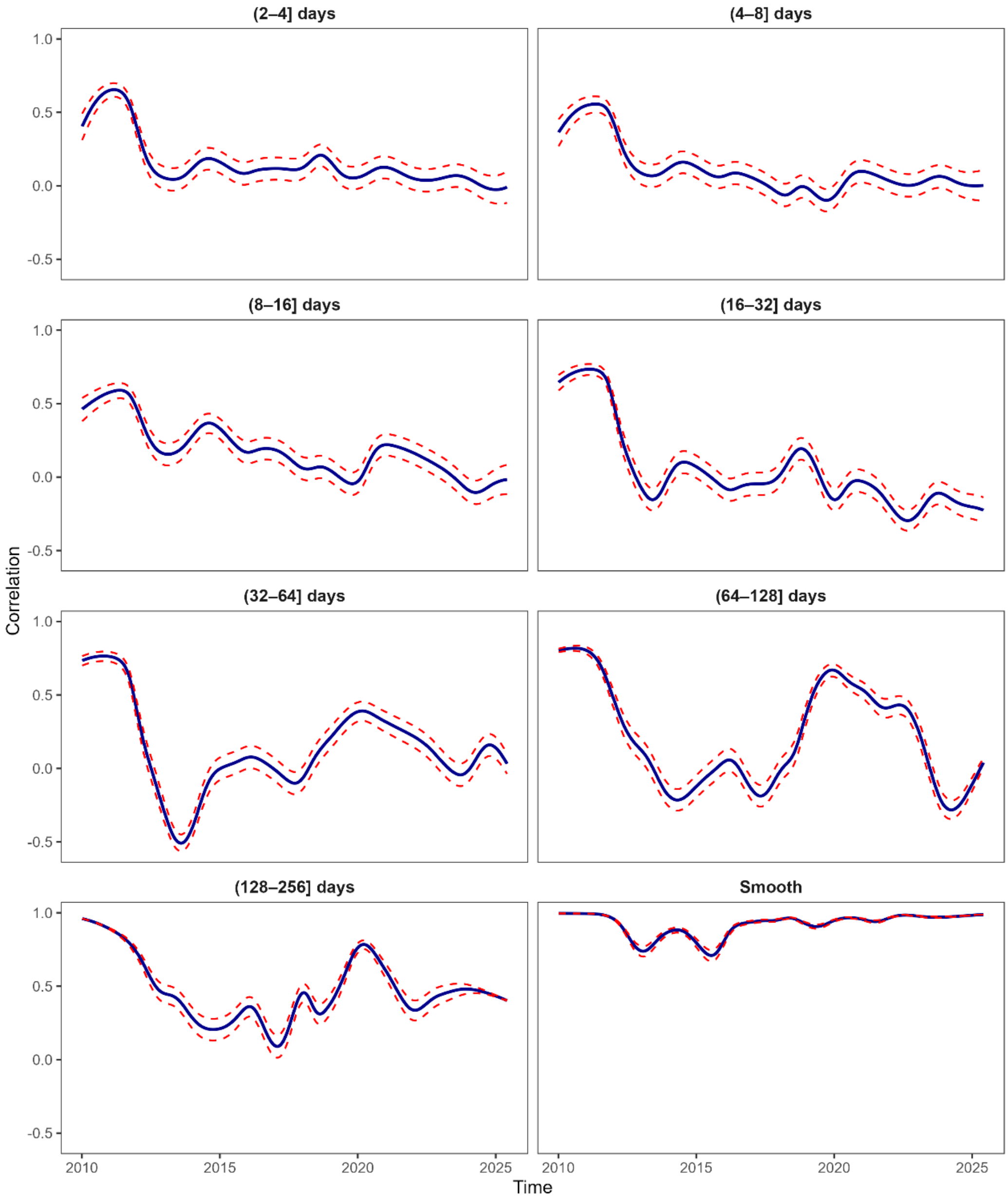
4.3. The WLMC coefficients for realized volatility

The realized volatility (RV), measured here by the daily squared returns (Andersen & Bollerslev, 1998), contains key information about the historical price fluctuations of an asset. As such, it is employed by investors for risk assessment, portfolio optimization, option pricing, and forecasting. Figure 9 plots the dynamic multiscale structure of connectedness for the pair (oil RV and meal RV). For timescales up to 1 month, the correlations exhibit downward trends; there is also a large number of weak and/or negative and statistically significant values (especially in the most recent periods). For the timescales (32,64] and (64,128], the correlations do not show any clear trend (relatively long periods of positive and statistically significant values alternate with relatively long periods of negative and statistically significant values). For the timescale [128-256], all correlations are positive and statistically significant; small at the middle of the sample and large at the beginning and at the end. In the long run, the RV correlations are close to 1. Figure 10 shows the time-varying and multiscale correlation coefficients for the pair (oil RV and soybeans RV). The connectedness pattern is very similar to that for the pair (oil RV and meal RV). Figure 11 plots the WLMC results for the pair (meal RV and soybeans RV). All correlations are positive and statistically significant; only at the (16-64] timescale there is a clear downward trend. The values for the long run are very close to 1. From the visual comparison of Figures 9 to 11, it follows that the RV link between meal and soybeans is far stronger relative to those for the other two pairs.

Figure 12 presents the WLMC coefficients from the joint (trivariate) analysis. All correlations are positive and statistically significant; there is some evidence of decreasing intensity in co-volatility at the small and medium timescales. Interestingly, the average values of correlations at the small timescales are larger than those at the medium ones. The joint analysis shows that there is considerable synchronisation of turbulent and tranquil periods across the three markets of the US soybean complex.

Figure 13 shows the relevant heatmap of the dominant variable(s). For the majority of time period-frequency combinations, the RV of soybeans dominates. Nevertheless, in a sizable part of combinations in the second half of the sample, the RV of meal price appears to be driven by the RVs of oil and soybean prices.

Figure 9. WLM Correlations for soybean oil and soybean meal realized volatility

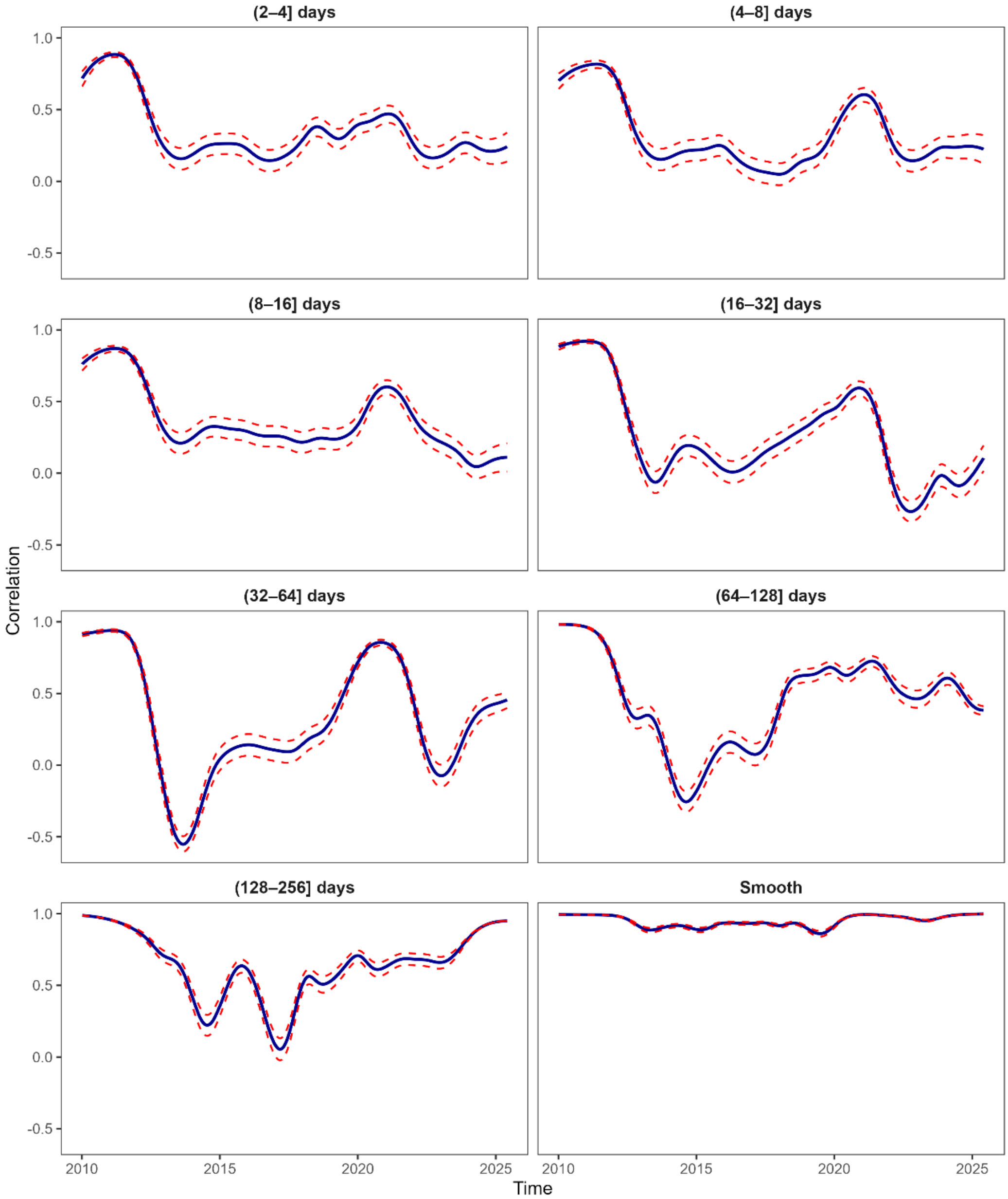


5. Conclusions

The pattern (sign and intensity) of price links in the soybeans complex is of interest to industry stakeholders, futures markets participants, and research economists. To investigate this, the present work employs daily futures prices of soybeans, soybean meal, and soybean oil from 2010 to 2025, as well as the WLMC approach, which allows joint (multivariate) associations to be time-varying and frequency-dependent. The analysis considers both price returns and realized volatility.

The empirical results suggest: The three price returns series maintain a time-varying, frequency-dependent, and positive connectedness that tends to increase with the time horizon. However, despite the very large timescales, the degree of market integration is not perfect. This, in turn, implies that, although the crush spread is to a certain extent self-hedged, soybean processors may still need to hedge at the smaller time scales by assuming opposite positions on the cash and futures markets.

Figure 10. WLM Correlations for soybeans and soybean oil realized volatility



Most of the scale-specific links among the three return series exhibit downward trends. There are two possible explanations for this dynamic pattern. First, it is the rising influence of noise traders and speculators on the futures markets' outcomes. Second, it is the uneven growth in the demand for meals and oil. The weakening of price connections over time may raise concerns for policymakers, as it could undermine the desirable property of self-hedged profits.

(c) The vertical price links tend to be more pronounced than the horizontal ones.

(d) Almost invariably, the stochastic process maximizing the multiscale correlation coefficients in the complex is the input (soybeans) returns, implying that the information in the US soybean complex is likely to be transmitted upstream rather than downstream. The demand-driven vertical market integration is consistent with Verleger's (1982) hypothesis.

(e) The dynamics and the multiscale pattern of the RV connectedness provide considerable evidence that the markets in the US soybean complex are likely to share tumultuous and calm periods (i.e., they exhibit co-volatility). The RV of soybean prices is, under most time-frequency combinations, the dominant process in the system (suggesting the market of soybeans is a recipient of instability or tranquility from the other two markets).

The application of the WLMC approach has provided certain useful insights about The nature and the dynamics of price and volatility linkages in the US soybean complex. Nevertheless, as noted by Polanco-Martinez (2023), the WLM correlation coefficients may be influenced by the presence of delayed dependencies. Therefore, one potential avenue for future research is to extend the WLMC approach to account for lagged effects. Another avenue may consider price links in the US soybean industry using alternative tools (such as Generalized Forecast Errors, Variance Decomposition, and Multifractal Correlations). In any case, additional work on this elaborate topic is certainly warranted.

Figure 11. WLM Correlations for soybeans and soybean meal realized volatility

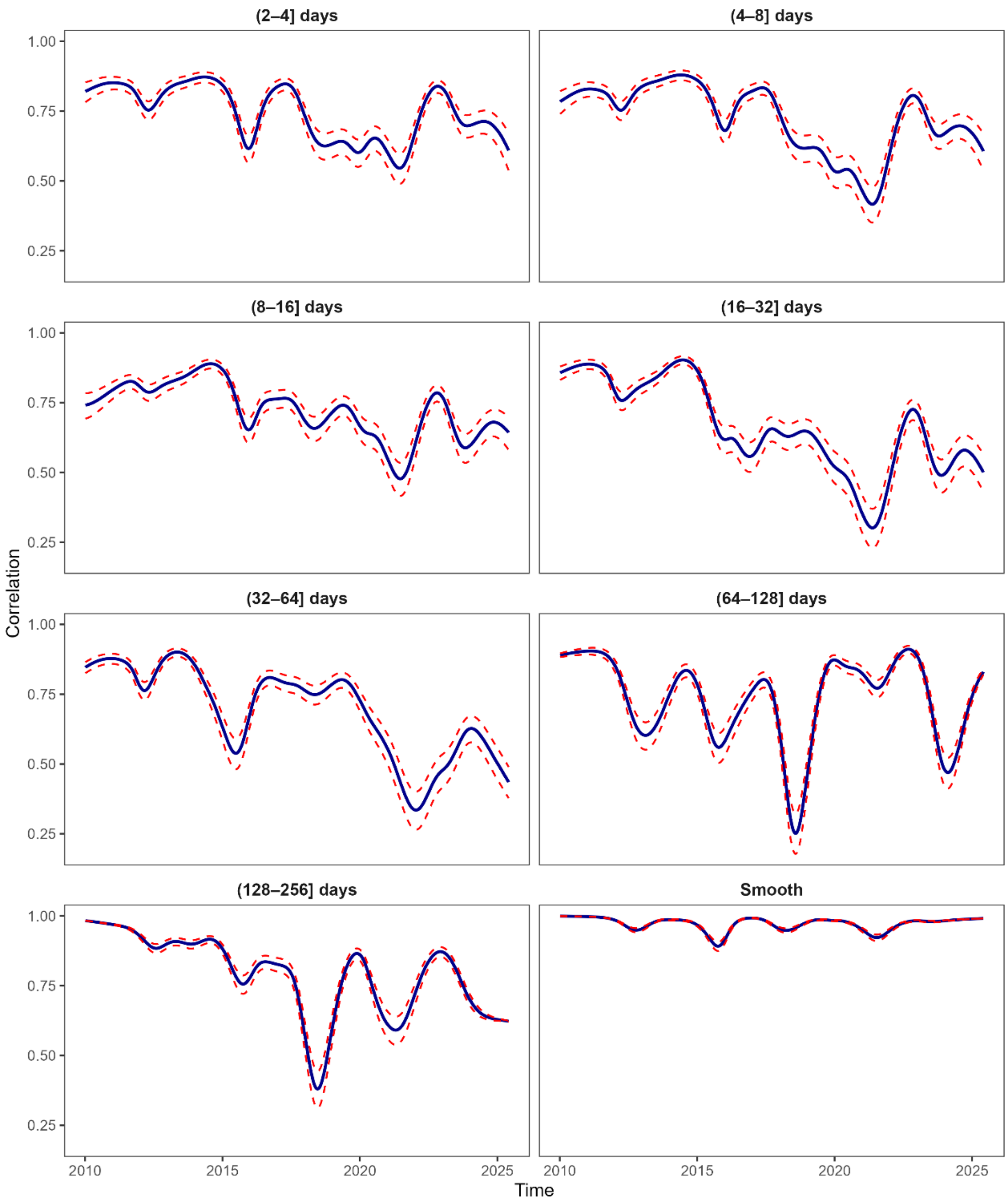


Figure 12. WLM Correlations for soybeans, soybean oil, and soybean meal realized volatility

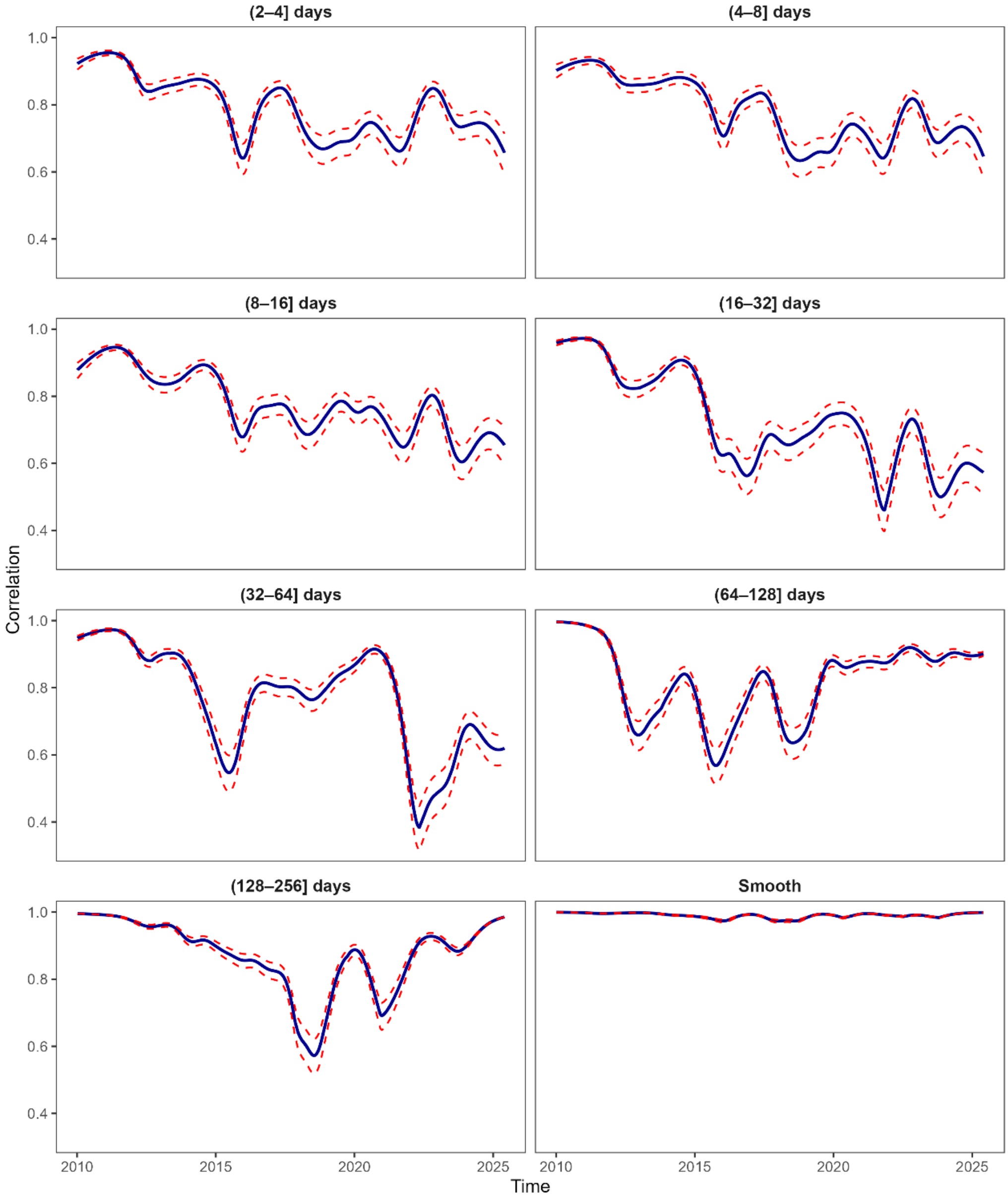
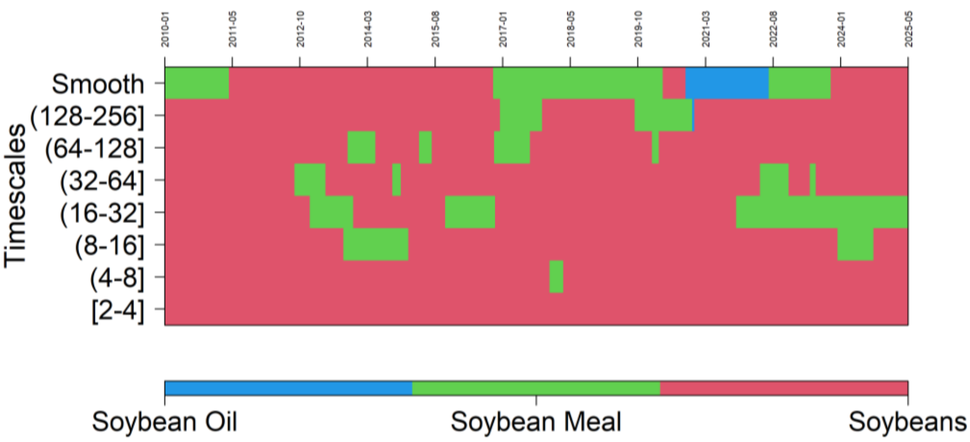


Figure 13. The heatmap of dominant variable(s): Soybeans, soybean oil, and soybean meal realized volatility



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Appendix A

Table A.1 (a). KPSS test results

Price levels (in natural logs)	With constant	With a deterministic trend
Soybeans	1.319	1.331
Soybean Meal	0.667	0.666
Soybean Oil	1.935	2.183
Price returns		
Soybeans	0.072	0.073
Soybean Meal	0.033	0.049
Soybean Oil	0.082	0.093

Note: At the 5 per cent level, the critical values are 0.463 and 0.146 for the model with a constant and the model with a deterministic trend, respectively

Table A.1 (b). Hadri's test results

Price levels (in natural logs)	With constant	With a deterministic trend
z test (p-value)	472.8 (0.00)	1585.1 (0.00)
Price returns		
z test (p-value)	-1.13 (0.87)	-0.25 (0.6)

Note: Alternative hypothesis: at least one series has a unit root

Table A.2. Returns. Descriptive statistics

Commodity	Mean	SD	Max	Min	Skewness	Kurtosis	Normality
Soybean Oil	0	0.015	0.073	-0.095	-0.200 (0.000)	5.230 (0.000)	0.981 (0.000)
Soybean Meal	0	0.018	0.103	-0.186	-1.415 (0.000)	17.473 (0.000)	0.895 (0.000)
Soybeans	0	0.014	0.064	-0.111	-0.811 (0.000)	9.201 (0.000)	0.947 (0.000)

Note: p-values in parentheses.

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