Evaluation of Volatility Spillovers and Quantile Hedging: a closer look to Brazilian agricultural markets

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Abstract
We evaluate the volatility spillovers among coffee, ethanol, soybeans, reformulated blendstock for oxygenate blending (RBOB) futures prices, and Brazilian spot prices from 2010 to 2020. Using the Diebold and Yilmaz volatility spillover analytical framework (DY), we estimate the total volatility spillover, the gross and net directional volatility spillover. We also analyze the optimal hedge ratio applying the linear quantile regression (QR) model, comparing the optimal hedge ratios with the minimum variance (MV) and error correction model (ECM). Results show an increasing trend in the total volatility spillover index, suggesting an increase in the Brazilian market's connectedness. In addition, we identify quantile ranges where the QR hedge is economical and statistically significant, particularly for extreme spot prices, lower-and-upper quantiles. The knowledge of the volatility spillover effect in agricultural commodity markets may provide additional information for efficient resource allocation decisions about harvesting, output, storage, commercialization, and hedging.

Keywords*: Volatility spillover; Brazilian agricultural commodity; commodity futures markets; optimal hedging; quantile regression; minimum variance; error correction model.*

1. Introduction

Understanding the volatility spillover effects on asset prices is crucial to grasp the financial markets' dynamic pricing information. Pricing information outlines additional inputs for the agents' decision-making process in an increasingly connected market. For example, volatility spillover information may help develop public policy recommendations, optimize trading strategies, and improve risk management effectiveness.

The volatility spillover in agricultural commodity markets may distinguish from additional information input for efficient resource allocation decisions about harvesting, output, storage, commercialization, and hedging. To enhance the allocative decisions, large agricultural commodity players and policymakers may benefit from the volatility spillover analysis of prices and returns (Balcilar & Bekun, 2020; Fasanya & Odudu, 2020). Therefore, the volatility spillover analysis may upgrade the risk management price for the Brazilian agricultural commodity markets. Notably, agricultural commodity domestic futures markets show thinness and low liquidity, expressing low hedging and portfolio diversification capacity.

We evaluate the Brazilian volatility spillovers in the agricultural commodity between spot markets and futures markets. We also assess the hedging of Brazilian commodity price risk using the US futures markets, applying the linear quantile regression (QR) model; then, we compare the QR optimal hedge ratios with mainstream methods of optimal hedge estimation, minimum variance (MV), and error correction models (ECM) to identify the best temporal hedging strategy, weekly or monthly.

Specifically, survey questions are i. to compute the total volatility spillover, the directional spillover *to* and *from*, and the net pairwise volatility spillover, applying the Diebold and Yilmaz (2009, 2012; 2014) framework (DY) for the Brazilian coffee, ethanol, soybeans, and reformulated blendstock for oxygenate blending (RBOB spot and futures markets; and, ii. to estimate the quantile regression (QR) optimal hedge ratios of the Brazilian agricultural commodity; iv. and finally, to compare the QR optimal hedge ratios with mainstream methods of optimal hedge estimation, minimum variance (MV) and error correction models (ECM).

The next section outlines the literature on volatility spillover and hedging. Section 3 discusses the methods and data, particularly the Diebold and Yilmaz (2009, 2012) framework (DY) and the MV, ECM, and QR optimal hedge methodology. The results and discussion section show the main research findings. Last, the conclusion section synthesizes the research results pointing out future research topics.

2. Literature review

2.1. Volatility spillover literature

The literature about volatility spillover is vast, particularly research after the 2008 financial crisis. The Diebold and Yilmaz (2009, 2012, and 2014) (DY) model is widely used to examine the volatility connectedness and the spillover effects among markets. Thus, we present the main DY approach to measure the spillover effect as well as a summary of the literature on volatility spillover.

Diebold and Yilmaz (2009) composed a measure of interdependence of asset returns and volatilities, examining the *return spillovers* and the *volatility spillovers*. The framework facilitates the analysis of non-crisis and crisis periods, including trends and bursts in the spillover effect. Their study used nineteen global equity markets from 1990 to 2009, showing divergent behavior in the dynamics of return spillovers vs. volatility spillovers- return spillovers demonstrated a smooth increasing trend but no bursts.

Later on, Diebold and Yilmaz (2012) proposed a different approach using a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering. The authors examined daily volatility spillovers across US stock, bond, foreign exchange, and commodities markets, showing that significant volatility fluctuations in all four markets during the sample and cross-market volatility spillovers were limited until the global financial crisis began in 2007. Spillovers from the stock market to other markets increased after the Lehman Brothers' collapse in September 2008.

Diebold and Yılmaz (2014) evaluated the connectedness measures composed from parts of variance decompositions, showing useful connectedness measures. The authors analyzed the daily time-varying connectedness of major US financial institutions' stock return volatilities in recent years, including the financial crisis of 2007–2008.

Table 1. Summary of the literature on volatility spillover in commodities markets

Authors	Period	Asset	Findings
Chevallier and Ielpo (2013)	1995–2012	Standart assets, commodities, and currencies	Commodities exhibited weaker volatility spillover
Antonakakis and Kizys (2015)	1987-2014	Gold, silver, platinum, CHF/USD, and GBP/USD exchange rates	Gold, silver, platinum, CHF/USD, and GBP/USD were net transmitters of returns spillovers
Diebold, Liu, and Yilmaz (2017)	2011-2016	Nineteen commodities.	The energy sector was the highest contributor to other commodities. Energy, industrial metals, and precious metals were highly connected
Zhang and Broadstock (2020)	1982-2017	Beverage, fertilizer, food, metal, precious metals, raw materials, and oil	Food commodities contributed to the system dynamic more than 80% after 2008
Dahl, Oglend, and Yahya (2020)	1986-2016	Crude oil and agricultural commodities	Crude oil became net receiver after 2006, and during periods of financial turmoil, evidence of bidirectional spillover between crude oil and agricultural commodities.
Yoon, Al Mamun, Uddin, and Kang (2019)	1999-2016	Stock, bond, currency, and commodities	US stock market was the largest contributor of return spillover in the Asia-Pacific.
Balcilar and Bekun (2020)	2006-2016	Cocoa, banana, groundnut, soybeans, barley, maize, sorghum, rice, wheat, CPI, NOIL, and NEER.	Banana, cocoa, groundnut, maize, soybeans, and wheat were net transmitters of spillovers.
Fasanya and Odudu (2020)	1980-2017	Wheat, rice, soybeans, groundnut, and palm oil	Interdependence among agricultural commodities in Nigeria

2.2. Quantile regression literature

Johnson (1960) identified that the theory of hedging and speculation was inadequate for certain market practices. The complexity of the trader's action to distinguish between hedging and speculation is a challenge in formulating a specific model. Thus, a stream of literature seeks to discuss the theory of hedging and speculation, presenting a reformulated concept of hedging and building a model that clarifies hedging and speculation concepts, contributing to a better understanding of certain market phenomena. For instance, Hung, Chiu, and Lee (2006) derive a new mean-risk hedge ratio based on the concept of Value at Risk (VaR). The proposed zero-VaR hedge ratio has an analytical solution, and it converges to the MV hedge ratio under a simple martingale process or normality. A bivariate constant correlation GARCH(1,1) model with an error correction term is employed to estimate expected returns and time-varying volatilities of the spot and futures in the S&P 500 index. Empirical results indicate that the joint normality and martingale process does not hold for S&P 500 futures, and the conventional minimum variance hedge is inappropriate for a hedger who only cares about downside risk, showing an alternative hedging method for a practitioner to use the concept of Value-at-Risk to reflect the risk-averse level.

Reboredo (2013) assessed the role of gold as a safe haven or hedge against the US dollar (USD) using copulas to characterize average and extreme market dependence between gold and the USD. For a wide set of currencies, empirical evidence distinguished positive and significant average dependence between gold and USD depreciation, consistent with the fact that gold can act as a hedge against USD rate movements. Symmetric tail dependence between gold and USD exchange rates indicated that gold could be a safe haven against extreme USD rate movements.

Shrestha, Subramaniam, Peranginangin, and Philip (2018) estimated the minimum variance (MV) and quantile hedge ratios for three energy-related commodities, crude oil, heating oil, and natural gas. For crude oil and heating oil, the quantile hedge ratios had an inverted U-shape, using daily data. However, for natural gas, the quantile hedge ratios were mostly below the MV hedge ratio, which is significantly lower than the naïve hedge ratio. The behavior of hedge ratios for daily data was consistent with empirical results, which suggest that price discovery mostly takes place in the futures market for natural gas.

Troster, Bouri, and Roubaud (2019) performed a quantile regression analysis of *flights-to-safety* with the implied market volatilities of stock, gold, gold-mining, and silver. The authors found unidirectional causality running from the stock market's volatility to gold, gold-mining, and silver volatilities.

While the quantile hedge ratio in the low-volatility state is relatively flat, in the high-volatility state, the quantile hedge varies with the spot return distribution and displays a U-type relationship. Moreover, the U shape is more prominent for agricultural futures and less prominent for others. Also, by comparing hedging effectiveness, the quantile hedge strategy is more effective than the no-hedge strategy and the hedging strategy derived from error correction models.

In conclusion, the specific contribution of the research is the application of the quantile regression (QR) framework to estimate the optimal hedging ratios of relevant Brazilian agricultural commodity groups, using the US futures markets, compared to traditional hedge approaches of minimum variance (MV) and error-correction model (ECM). To the best of our knowledge, it is the first analysis of the research problem.

3. Methodology and data

3.1. Spillover approach

The section identifies the research methods and data. We use the Diebold and Yilmaz (2009, 2012, and 2014) framework (DY) to compute the volatility spillover index among twelve Brazilian commodity spot markets and international commodity and financial futures markets. In particular, the index derives from the variance decomposition of an *n*-variable vector autoregression (VAR) model used to calculate the total spillovers in a simple VAR, with Cholesky factor orthogonalization.

Next, the DY approach generates the directional spillovers in a generalized VAR framework eliminating the ordering results' dependence. As such, a covariance stationary *n*-variable VAR (*p*):

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \qquad \text{Eq. 1}$$

where: $\varepsilon \sim (0, \Sigma)$ = vector of i.i.d. disturbances.

The moving average representation is: $x_t = \sum_{i=0}^{\infty} \mathrm{A}_i \varepsilon_{t-i}$, with the n x n coefficient matrices expressing $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, and $A_0 = n$ x n identity matrix, with $A_i = 0$ for $i < 0$. Specifically, the DY approach calculates the variance decomposition, expressing each variable's forecast error variances in system shocks. Therefore, the variance decomposition demonstrates the fraction of the h-step-ahead error variance in forecasting x_i resulting from shocks to x_j, for all $j \neq i$, for each i.

The DY index uses the VAR framework of Koop, Pesaran, and Porter (1996) and Pesaran and Shin (1998) (KPSS), resulting in variance decompositions that order invariant. As such, the shocks to each variable are not orthogonal, and the sum of the contributions to the variance of the forecast error, the row sum of the parts of the variance decomposition table, cannot be equal to one.

Next, we define the own variance shares as the fractions of the h-step-ahead error variances in forecasting xi resulting in shocks to x_i, for $i = 1, 2, \ldots, n$, and cross variance shares, or spillovers, as the fractions of the h-step-ahead error variances in forecasting x_i relating to shocks to x_j, for $i, j = 1, 2, \ldots, n$, such that $i \neq j$. Defining the KPSS h-step-ahead forecast error variance decompositions by $\theta_{ij}^{g}(h)$, for $h = 1, 2, \ldots$, then:

$$\theta_{ij}^{g}(h) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma A_h' e_j\right)} \qquad \text{Eq. 2}$$

where: Σ = variance matrix for the error vector e; σ_{ij} = standard deviation of the error term for the j-th equation; and, ε_i = selection vector, with one as the i-th element, and zeros otherwise.

To estimate the total volatility spillover index, we use the volatility contributions from the KPSS variance decomposition. The total spillover index demonstrates the contribution of spillovers of volatility shocks of the asset classes to the total forecast error variance:

$$S^{g}(h) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{n} \tilde{\theta}_{ij}^{g}(h)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^{g}(h)} \cdot 100 = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{n} \tilde{\theta}_{ij}^{g}(h)}{n} \cdot 100 \qquad \text{Eq. 3}$$

The DY framework estimates the net volatility spillover from market i to all other markets j, the difference between the gross volatility shocks transmitted to and received from all other markets, as:

$$S_i^{g}(h) = S_{i\to j}^{g}(h) - S_{i\leftarrow j}^{g}(h) \qquad \text{Eq. 4}$$

Last, we compute the net pairwise volatility spillovers between markets i and j, the difference between the gross volatility shocks transmitted from market i to market j, and the shocks transmitted from j to i:

$$S_{ij}^{g}(h) = \left(\frac{\tilde{\theta}_{ji}^{g}(h)}{\sum_{i,k=1}^{n} \tilde{\theta}_{ik}^{g}(h)} - \frac{\tilde{\theta}_{ij}^{g}(h)}{\sum_{j,k=1}^{n} \tilde{\theta}_{jk}^{g}(h)}\right) \cdot 100 \qquad \text{Eq. 5}$$

$$= \left(\frac{\tilde{\theta}_{ji}^{g}(h) - \tilde{\theta}_{ij}^{g}(h)}{n}\right) \cdot 100$$

To estimate the volatility values, we model the weekly log returns: $r_t^i = \log\left(\frac{P_t^i}{P_{t-1}^i}\right)$, where r_t^i = weekly log return of commodity i, week t, and P_t^i = price of commodity i, week t. Thus, we apply a standard *GARCH* (*1,1*) model on the weekly log returns, r_t^i, taking the square root of the resulting variance to calculate the weekly volatility of commodity i on week t, σ_t^i.

3.2. The Minimum Variance Optimal Hedge Ratio (MV)

To explain the minimum variance optimal hedge ratio (MV) calculation, we define S_t and F_t as the spot and futures prices at time t. The returns on the spot and futures hedgers' portfolio are expressed as:

$$\Delta S_t = ln(S_t) - ln(S_{t-1}), \text{ and} \quad \text{Eq. 6}$$
$$\Delta F_t = ln(F_t) - ln(F_{t-1})$$

The return on the hedged portfolio: $R_{Ht} = \Delta S_t - H\Delta F_{t,}$, where: H = hedge ratio.

We estimate the MV hedge ratio, H_{MV}, by minimizing the variance of R_H with relation to H:

$$H_{MV} = \frac{Cov(\Delta S_t, \Delta F_t)}{Var(\Delta F_t)} \quad \text{Eq. 7}$$

The MV hedge ratio, Equation 1, can be estimated using the coefficient in a linear regression of spot on futures returns, illustrating the conventional approach to estimate the MV hedge ratio. The linear regression equation expression is:

$$\Delta S_t = \alpha + \beta\Delta F_t + \varepsilon_t \quad \text{Eq. 8}$$

where: H_{MV} = estimation of the MV optimal hedge ratio, the estimation of the slope coefficient, β.

3.3. The Error-Correction Model Optimal Hedge Ratio (ECM)

However, the linear regression MV optimal hedge estimation, Equation 8, does not employ the cointegrating equation between the ΔS_t and ΔF_t returns (Engle and Granger, 1987). If two-time series are cointegrated, then Equation 8 is spurious, so the estimated optimal hedge ratio β can be biased.

In the presence of a cointegrating relationship between two-time series, particularly the spot and futures prices, we can apply the error correction model (ECM) to calculate the optimal hedge ratio:

$$\Delta S_t = \alpha + \beta \Delta F_t + \gamma u_{t-1} + \sum_{i=1}^{m} \phi_{S_i} \Delta S_{t-i} + \sum_{i=1}^{m} \phi_{F_j} \Delta S_{t-j} + \varepsilon_t \qquad \text{Eq. 9}$$

Where: u_t is the residual from the cointegrating regression: $\Delta(S_t) = \alpha + \gamma \Delta (Ft) + u_t$. We use the Akaike information criterion (AIC) to estimate the lag-length of Equation 9.

3.4. The Quantile Regression Optimal Hedge Ratio (QR)

Koenker and Bassett (1978) formulate the semi-parametric quantile regression method. The objective is to identify the relationship between the quantile of the dependent variable's conditional distribution and the registered covariates. Thus, we define the linear regression estimators of Equation 2 expressing the spot (S_t), and futures (F_t) returns as:

$Y_t = \Delta S_t,\ t = 1, \ldots, T$, and
$X_t = \Delta F_t,\ t = 1, \ldots, T.$

We estimate the linear regression of the parameter vector [α,β] as:

$$[\hat{\alpha}, \hat{\beta}] = \underset{\alpha, \beta}{arg\ min} \sum_{t=1}^{T} [y_t - \mu_t(x_t; \alpha, \beta)]^2,\ \ \mu_t(x_t; \alpha, \beta) = \alpha + \beta x_t, \qquad \text{Eq. 10}$$

where: $\mu_t(\,)$ = the sample estimator of the conditional expectation function under the linear model, $E(y_t|x_t) = \mu_t(x_t; \alpha, \beta) = \alpha + \beta x_t$. As such, the linear regression estimator indicates dependence on the average relationship between y_t and x_t.

The MV quantile regression hedge ratio (H_{QR}) and its H_{QR} effectiveness show economic validity compared with the MV and ECM optimal hedges, H_{MV} and H_{ECM}. The difference between hedge ratio values does not express under-hedging or over-hedging for short and long hedgers. For example, if the hedger uses the MV ratio, H_{MV}, and $H_{QR} < H_{MV}$ with the realized spot price in the lower quantiles, *1%*-to-*10%*, the MV hedge identifies over-hedging. In contrast, if the realized spot categorizes in the higher quantiles, *90%*-to-*99%*, the MV hedge identifies under-hedging. The example is positive for short hedgers but deleterious for long hedgers.

Notably, it benefits the short hedgers because they choose over-hedging when they need protection from the futures contract and under hedged when they do not need protection from the futures contracts. Specifically, the efficient scenario for an MV hedger identifies the case where $\beta = \beta(\tau), \tau \in [0,1]$. In this scenario, both long and short hedgers are hedged despite the realization of the spot prices.

In conclusion, the estimation of $\beta(\tau)$ for different values of τ aids the identification of the different scenarios for the future price constellation. Besides, the estimation of $\beta(\tau)$ for different hedge-structure allows the identification of whether $\beta(\tau)$ depends on time horizons. The research estimates the QR optimal hedging ratios for fifteen quantiles, *1%, 2%, 5%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 95%, 98%* and *99%,* and the MV and ECM hedge ratios for weekly and monthly data.

3.5. Data

We use weekly and monthly data for the following spot and futures prices series, encompassing three Brazilian commodity groups, softs, grains and oilseeds, and energy (see the descriptive statistics in appendix A.1.) from September 2010 to March 2020.

We estimate the QR, MV, and ECM optimal hedge ratio for each group, using different contracts: i. the softs group, we use the CEPEA/ESALQ Arabica Coffee as spot price and the July 2020 ICE coffee weekly futures price series; ii. energy group, we apply the CEPEA/ESALQ São Paulo Hydrate Ethanol Fuel Indicator as the spot price. As the future price, we use the May 2020 CME Ethanol futures prices and the May 2020 CME reformulated blendstock for oxygenate blending (RBOB) gasoline futures prices. We also compare both ethanol and RBOB futures optimal hedge ratios set - QR, MV, and ECM; for the grains and oilseeds group, we use the ESALQ/BM&FBOVESPA Paranaguá Soybeans spot prices, and the futures prices, we use the March 2020 CME soybeans weekly prices. We justify using the March 2020 soybeans futures contracts by its synchronicity with the Brazilian soybeans harvest season.

4. Empirical results and discussion

We divide this section between the spillover and the hedge ratio analysis. The first section shows the volatility spillover results for the Brazilian agricultural commodity markets, coffee, ethanol, soybeans, and RBOB weekly log returns. Then, we investigate the minimum variance (MV), the error-correction model (ECM), and the quantile regression (QR) hedges for coffee, ethanol, RBOB, and soybeans, comparing the results for weekly and monthly data.

To use the regression models, we compute the Phillips-Perron (PP), and the Augmented Dickey-Fuller (ADF) tests with constant and trend for the coffee, ethanol, and soybeans spot and futures prices and RBOB futures prices, in levels and first differences. PP and ADF unit root tests[1] reject the hypothesis of no unit root for the prices in levels. The only exception is the ethanol spot and future prices in levels showing the acceptance of the no unit root hypothesis in the level series within the 1%-to-5% statistical significance range. Therefore, except for the weekly ethanol prices, we estimate the optimal hedge ratios using the first differences.

4.1. Spillover

Table 2 shows the results of gross directional spillovers. The results are based on VAR with max lags of 5 and generalized variance decomposition of 10th day-ahead volatility forecast errors (Diebold & Yilmaz, 2012).

The rows sums represent the contributions 'From Others,' the sum of the columns as the contribution 'TO Others.' The total volatility spillover index is found in the lower right corner with a 41.6%. The coffee futures prices express the highest contribution from others, 59.32%, followed by coffee futures (46.52%), while the coffee RBOB shows the lowest contribution, 29.14%. Accounting for the net spillover, we find the largest spillover effect from the soybean futures prices (SOY_F: 82.51-38.70 = 43.81%) and from others to the Ethanol spot price (ETH_S: 11.09-36.86 = -25.77%). Notably, there was an abrupt spike in 2020, highlighting the volatility spillover increase due to the Pandemic situation (See fig.1).

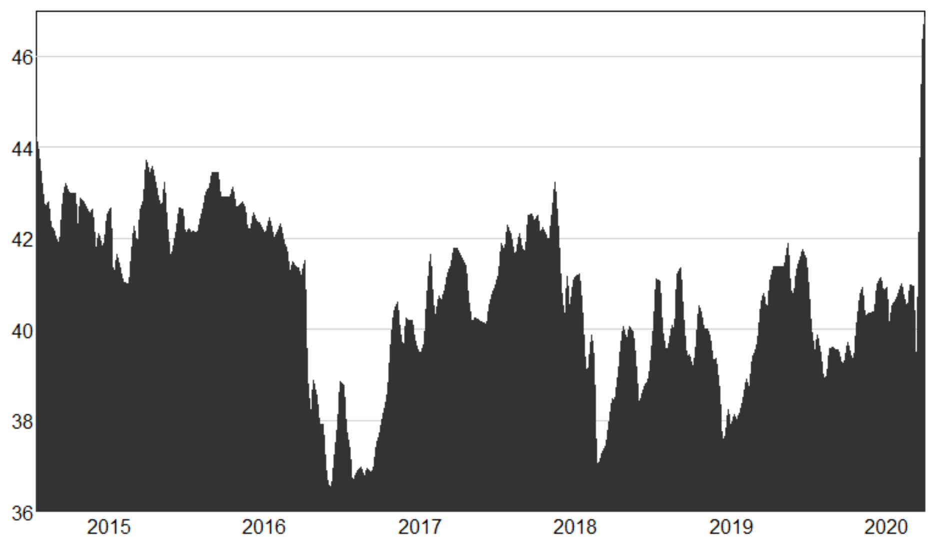
[1] For conciseness, the results are not reported here. However, they are available upon request.

Tab. 2. Volatility spillover (connectedness) for weekly log returns Spillover (Connectedness)

	ETH_F	**ETH_S**	**COFFEE_F**	**COFFEE_S**	**SOY_S**	**SOY_F**	**RBOB**	**FROM Others**
ETH_F	62.29	0.78	5.18	3.84	2.33	23.32	2.25	37.71
ETH_S	10.90	63.14	4.59	9.30	0.59	8.15	3.33	36.86
COFFEE_F	5.57	2.07	53.48	31.04	1.98	5.57	0.29	46.52
COFFEE_S	6.22	2.47	41.54	40.68	1.63	7.16	0.29	59.32
SOY_S	8.64	1.19	1.49	1.74	57.07	29.14	0.72	42.93
SOY_F	14.38	0.10	2.19	2.16	19.37	61.30	0.50	38.70
Rbob	9.16	4.48	0.81	2.50	3.04	9.16	70.86	29.14
Directional TO Others	54.87	11.09	55.80	50.59	28.94	82.51	7.37	
Directional Including Own	117.16	74.23	109.28	91.27	86.01	143.81	78.24	Total Spillover **41.6%**

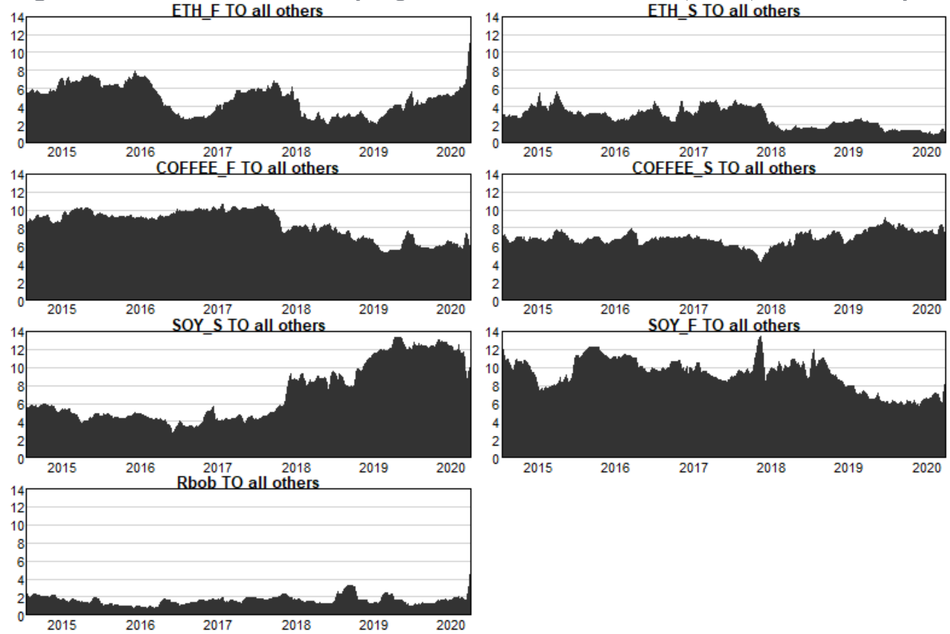
Obs.: F = futures prices; S = spot prices. ETH stands for Ethanol, and SOY for soybeans.

Fig.1. Total Volatility Spillover (Connectedness): coffee, ethanol, soybean, and RBOB.



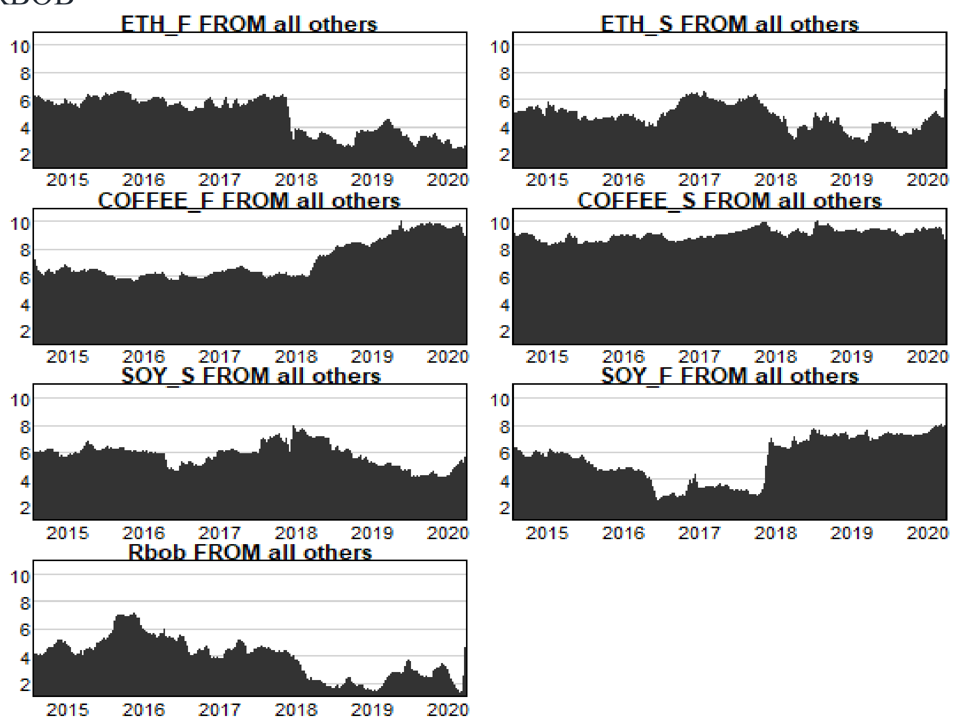
The total spillover shows the volatility from all commodities analyzed in our study. Nonetheless, we are also interested in understanding the directional spillover information. Thus, we estimate and plot the $S^{g}_{i\leftarrow j}(h)$ 'Directional TO Others' row, and the $S^{g}_{i\rightarrow j}(h)$ directional 'From Others' column. Fig. 3. depicts the directional spillover to others; among the commodities, either soybean future and spot are the greatest gross contributor to other markets. Fig. 4 illustrates the directional volatility spillovers from others to all the involved variables. The spillover from other to coffee futures price appears to be increasing over time, while the coffee spot remains steady.

Fig. 2. Directional Volatility Spillovers, TO ethanol (ETH), coffee, soybean (SOY), and RBOB



Obs.: F = futures prices; S = spot prices.

Fig. 3. Directional Volatility Spillovers, FROM ethanol (ETH), coffee, soybean (SOY), and RBOB



Obs.: F = futures prices; S = spot prices

We also provide the net pairwise combination of the involved variables (Equation 4). Thus, the plot in Appendix A.2. shows how much each commodity contributes to the volatility in other markets. The soybean spillover dynamic emphasizes the impacts of the US growth rate, the increase of the Brazilian agricultural commodity exports, especially to China, and the commodity markets' financialization.

The directional volatility spillovers for the Brazilian agricultural commodity spot futures markets show an idiosyncratic volatility pattern for each Brazilian commodity group. The DY framework indicates different volatility regimes, coupled with the price level analysis, can help understand the market pricing dynamics and trends. Therefore, the DY volatility spillover describes a helpful approach to upgrade informational inputs about volatility patterns in domestic and international markets, formulating more efficient resource allocation decisions. In particular, the knowledge of the volatility spillover dynamics for the Brazilian agricultural commodity spot markets can result in increased competitiveness and informed production, storage, commercialization, and hedging decisions.

4.2. Optimal hedge ratio analysis

The section outlines the research results in Table 3., illustrating the findings from the minimum variance (MV), the error-correction model (ECM), and the quantile regression (QR) hedges for coffee, ethanol, RBOB, and soybeans, comparing the results for weekly and monthly data. Particularly, spot prices indicate the Brazilian commodity markets, and futures prices show the US futures markets, including RBOB futures prices.

Appendix A.3. depicts the quantiles of the normal distribution of the variables in levels and first differences. We identify a different pattern in the quantile distributions among level and first difference series - steeper inclination and higher differences among values; and lower tendency and smaller differences. Since we compare spot prices of Brazilian agricultural commodities with US agricultural futures markets, differences in the harvest season, contract specification, informational richness, market depth, and hedgers' behavior may explain the results.

We employ three approaches to estimate the optimal hedge ratios, MV, ECM, and QR, for the weekly and monthly data first differences of spot and futures prices, except for the ethanol spot and futures, where the prices are in levels. Appendix A.4. shows the optimal hedge ratio plots.

Tab. 3. Quantile Regressions, Minimum Variance, and Error-Correction Model Optimal Hedge Ratios

	Quantiles															MV	ECM
	0,01	**0,02**	**0,05**	**0,1**	**0,2**	**0,3**	**0,4**	**0,5**	**0,6**	**0,7**	**0,8**	**0,9**	**0,95**	**0,98**	**0,99**		
COFFEE WEEKLY	0,515	0,541	0,554	0,606	0,553	0,568	0,578	0,572	0,544	0,554	0,536	0,594	0,632	0,83	0,779	0,554	0,577
COFFEE MONTHLY	0,47	0,699	0,649	0,716	0,751	0,677	0,619	0,658	0,604	0,581	0,565	0,697	0,657	0,557	0,481	0,643	0,645
ETHANOL WEEKLY	0,629	0,594	0,514	0,532	0,64	0,679	0,726	0,799	0,799	0,801	0,786	0,826	1,02	1,92	1,64	0,746	0,747
ETHANOL MONTHLY	-0,192	0,057	0,397	0,509	0,201	0,173	0,109	0,056	0,107	0,169	0,172	0,196	0,005	0,049	0,28	0,218	0,177
RBOB WEEKLY	0,074	0,211	0,041	0,149	0,099	0,9	0,114	0,092	0,096	0,108	0,145	0,154	0,138	0,177	0,37	0,107	0,116
RBOB MONTHLY	-0,877	-0,148	0,32	0,055	0,139	0,099	0,135	0,161	0,137	0,144	0,208	-0,011	0,001	0,283	0,569	0,111	0,096
SOY WEEKLY	0,186	0,33	0,378	0,421	0,33	0,35	0,358	0,343	0,314	0,261	0,263	0,261	0,27	0,34	0,335	0,317	0,315
SOY MONTHLY	3,006	0,445	0,272	0,472	0,408	0,429	0,399	0,382	0,358	0,283	0,311	0,398	0,425	0,7	0,779	0,413	0,411

Source: Research results.

The coffee optimal hedge ratios, the weekly QR hedge ratio values are slightly lower than the MV ratios for the lower quantiles, with a similar pattern for the ECM ratios, except for the mid-upper quantiles of the last. For the *90%* and upper quantiles, both the MV and ECM coffee hedge ratios illustrate lower values than the QR. For example, the QR hedge ratios for coffee at 1%, 50%, and 90% quantiles are 0.515, 0.572, and 0.594, respectively, and the MV and ECM ratios are 0.554 *0.577*, respectively.

Comparing the monthly coffee QR and the MV and ECM optimal hedge ratios shows approximately similar inverted U shapes, except for differences in the *50%*-to-*80%* quantiles. The results align with Lien, Shrestha, and Wu (2016), identifying that the inverted U shape QR optimal hedge ratios are most prominent for agricultural commodities.

We distinguish different patterns to compare the weekly ethanol QR, MV, and ECM optimal hedge ratios. The QR hedge values are lower than the *40%* quantile, increasing the positive difference slightly up to *90%*, with spikes for the upper quantiles. For example, the QR hedge ratios for ethanol at *1%*, *50%,* and *90%* quantiles are *0.629*, *0.799*, and *0.826*, respectively, and the MV and ECM ratios are *0.746* and *0.747,* respectively.

Besides, we recognize skewed inverted U shapes, except for positive differences in the 5%-to-20% and 99% quantiles, comparing the monthly ethanol QR and the MV and ECM optimal hedge ratios. Particularly, the QR hedge ratio for the *1%* quantile is negative, *-0.192*, a spurious value. The results align with Lien, Shrestha, and Wu (2016), who identify that the inverted U shape QR optimal hedge ratios are common for agricultural commodities.

We analyze the weekly ethanol spot and the RBOB futures prices QR, MV, and ECM optimal hedge ratios. Comparing both the MV and ECM with the QR hedge ratios, we distinguish a similar whipsaw pattern. Up to the *2%* quantile, the QR ratios are higher than the MV and ECM values, lowering around the *5%* quantile. For example, the QR hedge ratios for ethanol and RBOB at *1%*, *50%,* and *90%* quantiles are *0.074*, *0.092*, and *0.154*, respectively, and the MV and ECM ratios are *0.107* and *0.116,* respectively. Furthermore, comparing the monthly ethanol and RBOB QR and the MV and ECM optimal hedge ratios, we recognize skewed S shapes, with positive differences in the *1%*-to-*2%* and the *90%*-to-*95%* quantiles differing from the Lien, Shrestha, and Wu (2016) findings.

The soybeans optimal hedge ratios show that the weekly QR hedge ratio values are lower than the MV ratios for the *1%*-to-*2%* quantiles, with a similar pattern for the ECM ratios. For the *2%*-to-*60%* quantiles, the QR values are higher than both the MV and ECM hedge ratios. Further, the *60%-to-98%* quantiles the MV and ECM hedge values are higher than the QR values, and the *98%* and upper quantiles, both the MV and ECM soybeans hedge ratios illustrate lower values than the QR. For example, the QR hedge ratios for soybeans at 1%, 50%, and 90% quantiles are 0.186, 0.343, and 0.261, respectively, and the MV and ECM ratios are 0.317 *0.315,* respectively. Additionally, comparing the monthly soybeans QR, the MV and ECM optimal hedge ratios show approximately similar U shapes, except for differences in the *1%*-to-*2%* and the upper *95%* quantiles. The results do not align with Lien, Shrestha, and Wu (2016), identifying the most prominent inverted U shape QR optimal hedge ratios for agricultural commodities. Specifically, Appendix A.4. illustrates the plot of the two comparative panels. A visual inspection identifies the differences.

4.3. Robustness test

We estimate the *t*-test of the difference between the QR, MV, and ECM hedge ratios mean, weekly and monthly data (See Appendix A.5. and A.6.) as a robustness test.

Appendix A.5. shows the difference between the QR hedge ratio and the MV ratio means. Mostly, the QR means are statistically different from the MV hedge ratios, with 1%-to-5% statistical significance levels. Furthermore, the 50% quantile mean difference shows no statistical significance for weekly and monthly data.

We find similar results in Appendix A.6. Thus, the QR means are statistically different from the ECM hedge ratios, with 1%-to-5% statistical significance levels. Furthermore, the 50% quantile mean difference shows no statistical significance for weekly and monthly data. As such, we validate the inverted U-shaped format for the difference between the QR and the MV and ECM hedge ratios, in line with Lien, Shrestha, and Wu (2016).

Using a cost-benefit analysis, the QR hedge ratio (HQR) translates economic significance when the quantile values are lower than the MV and ECM hedge ratios, HMV and HECM. Therefore, depending on the commodity market and the monthly timeframe, the HQR can be more efficient than the HMV and HECM.

In conclusion, the quantile regression behavior demonstrates the spot price reacts slowly to changes in the market fundamentals, stocks, production, consumption, price shocks, and the futures price changes almost in real-time. For instance, if the spot price demonstrates a large shift in fundamentals, it may not fully adjust quickly to the change in one week, while the futures price reacts almost instantaneously. In contrast, the monthly spot and futures price series, lasting 4-weeks, incorporate the same set of informational inputs and converge with small differentials.

The literature on hedging distinguishes different causes for the results, e.g., transaction costs, liquidity, exchange margins, and leverage (Fleming, Ostdiek, & Whaley, 1996; Lien et al., 2016; Silvapulle & Moosa, 1999).

5. Conclusion and further research

Our study analyzed the volatility spillovers between the Brazilian agricultural commodity spot prices and futures markets. We computed the total volatility spillover, the directional spillover to and from commodities, and the net pairwise volatility spillover, applying the Diebold and Yilmaz (2009, 2012, and 2014) framework (DY). Understanding the volatility spillover gives information about the market dynamic. In this sense, we evaluate optimal hedging using the linear quantile regression (QR) model. Specifically, we estimated the quantile regression (QR) optimal hedge ratios for groups of relevant Brazilian agricultural commodity groups, softs (coffee), grain and oilseeds (soybeans), and energy (ethanol and RBOB) using the US futures markets. Further, we compared the QR optimal hedge ratios with mainstream methods of optimal hedge estimation, minimum variance (MV), and error correction models (ECM), summarizing the research results to identify the best temporal hedging strategy, weekly or monthly.

The recent increase in total spillover effects reveals the impact of the COVID pandemic. Furthermore, the pairwise spillovers expose the effects of the rise in the Brazilian agricultural commodity exports, especially soybean exports to China, and positive informational richness among the agents, hedgers, speculators, and traders. The DY volatility spillover framework demonstrates the usefulness of estimating the dynamic relationships among the variables. The DY framework outline illustrates a systematic application to examine volatility spillover dynamics in the Brazilian agricultural commodity spot markets, regional and national, for example, to analyze the soybeans market volatility spillover between Mato Grosso and Paraná.

The optimal hedging results show that spot prices tend to adjust longer than one week, while futures prices react promptly to a change in fundamentals. In contrast, the spot and futures prices series incorporate the same set of informational inputs and converge with small differentials. The use of the QR optimal hedge ratios for the commodities spot prices in the US futures markets can result in positive economic gains and more efficient resource allocation.

Further research could deepen the study of the volatility spillover effects between food prices and commodities futures markets and whether using futures contracts could reduce the food volatility price. Understanding the price dynamics is of paramount importance not only to policymakers to design policies to alleviate the spike in food prices but to farmers, consumers, and countries since high volatility could jeopardize agricultural investment, input allocation, mainly when there is no mechanism to share risk (i.e., futures contracts).

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Appendix

A. 1. Descriptive statistics. Coffee, ethanol, soybeans spot and futures prices, gasoline futures prices. Weekly and monthly values, levels, and first differences.

Weekly

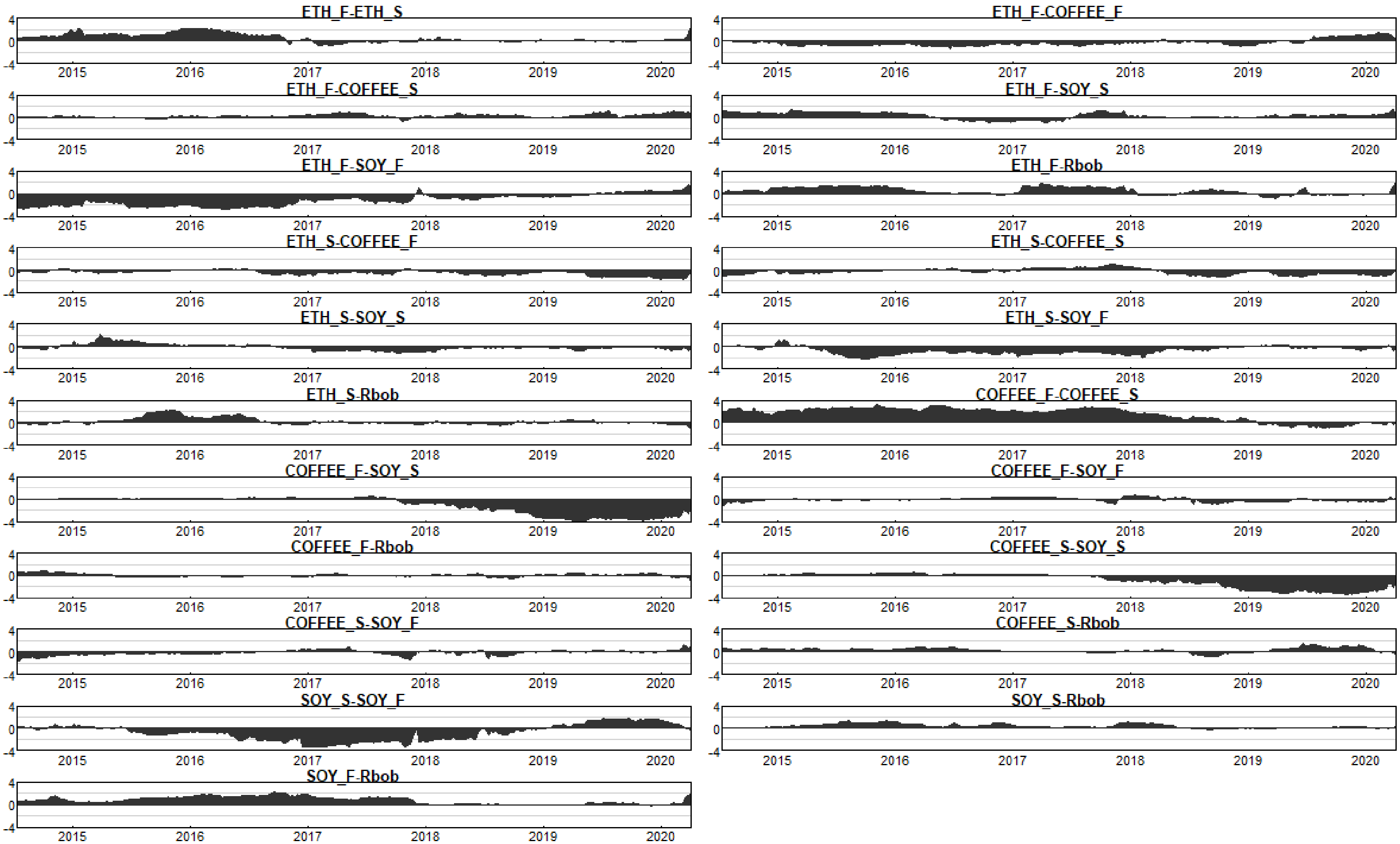
Statistics	$Coffee_F$	$D(Coffee_F)$	$Coffee_S$	$D(Coffee_S)$	Soy_F	$D(Soy_F)$	Soy_S	$D(Soy_S)$	ETH_F	$D(ETH_F)$	ETH_S	$D(ETH_S)$	$RBOB_F$	$D(RBOB_F)$
Mean	155.02	-0.14	162.79	-0.17	24.35	-0.01	26.19	-0.01	0.47	0.00	0.52	0.00	0.59	0.00
Median	139.13	-0.43	144.39	-0.63	22.66	0.02	24.16	0.01	0.41	0.00	0.50	0.00	0.54	0.00
Maximum	299.85	27.00	341.76	26.94	37.54	2.35	45.00	2.62	0.72	0.07	0.98	0.09	0.89	0.06
Minimum	89.00	-27.95	95.47	-21.71	18.55	-6.08	18.70	-6.81	0.23	-0.13	0.30	-0.19	0.16	-0.12
Std. Dev.	46.09	6.62	57.20	5.80	4.40	0.74	5.30	0.68	0.11	0.02	0.10	0.02	0.15	0.02
Skewness	1.14	0.22	1.40	0.37	0.66	-1.92	0.88	-2.11	0.76	-1.20	0.98	-1.69	0.14	-1.35
Kurtosis	3.53	5.09	4.26	5.53	2.27	16.77	3.33	24.87	2.15	11.45	4.53	18.32	1.83	8.21
JB	114	94	196	145	47	4239	67	10289	63	1599	128	5109	30	714
Prob	-	-	-	-	-	-	-	-	-	-	-	-	-	-
ObS.	498	498	498	498	498	498	498	498	498	498	498	498	498	498

Monthly

Statistics	$Coffee_F$	$D(Coffee_F)$	$Coffee_S$	$D(Coffee_S)$	Soy_F	$D(Soy_F)$	Soy_S	$D(Soy_S)$	ETH_F	$D(ETH_F)$	ETH_S	$D(ETH_S)$	$RBOB_F$	$D(RBOB_F)$
Mean	214.72	-0.28	241.39	-0.20	29.79	0.06	31.80	0.06	0.62	0.00	0.64	0.00	0.74	0.00
Median	210.30	-0.25	242.50	-0.90	29.82	0.13	30.46	0.13	0.62	0.00	0.64	0.00	0.75	0.00
Maximum	299.85	24.75	341.76	17.91	37.54	2.35	45.00	2.62	0.72	0.07	0.98	0.09	0.89	0.06
Minimum	148.95	-27.95	161.93	-18.18	23.70	-2.72	25.27	-6.81	0.50	-0.08	0.49	-0.19	0.57	-0.10
Std. Dev.	42.07	8.13	55.07	7.50	2.73	0.92	4.57	1.00	0.05	0.02	0.10	0.03	0.07	0.03
Skewness	0.14	0.01	0.20	0.01	0.34	-0.40	1.10	-2.78	-0.21	-0.43	0.78	-2.11	-0.12	-1.30
Kurtosis	1.76	3.95	1.62	2.88	3.24	2.89	3.61	20.79	2.77	4.38	3.55	16.29	2.88	6.66
JB	8	5	11	0	3	3	27	1,781	1	13	14	997	0	103
Prob	0.02	0.10	0.01	0.96	0.27	0.19	-	-	0.56	-	-	-	0.83	-
ObS.	123	123	123	123	123	123	123	123	123	123	123	123	123	123

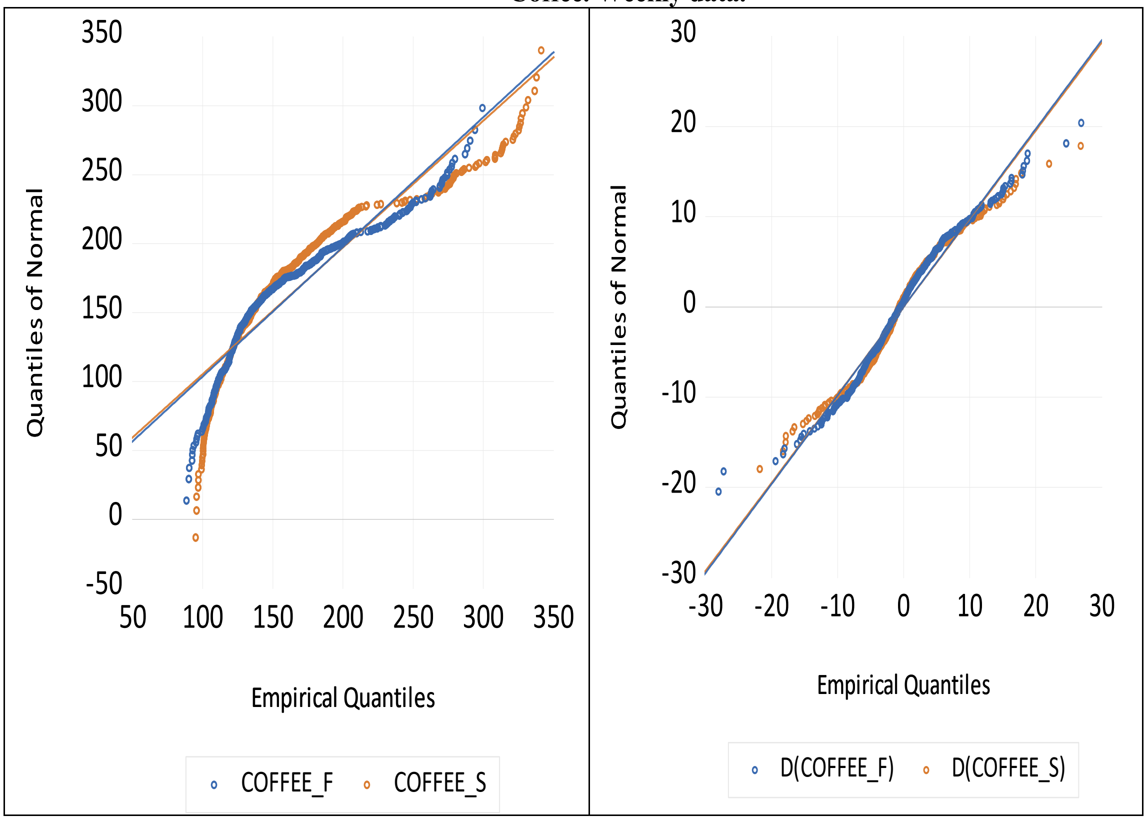
Source: Research results. Obs.: D(.) = first difference; F = futures prices; S = spot prices.

A.2. Net Pairwise Volatility Spillovers (ethanol, soybeans, coffee, and RBOB)

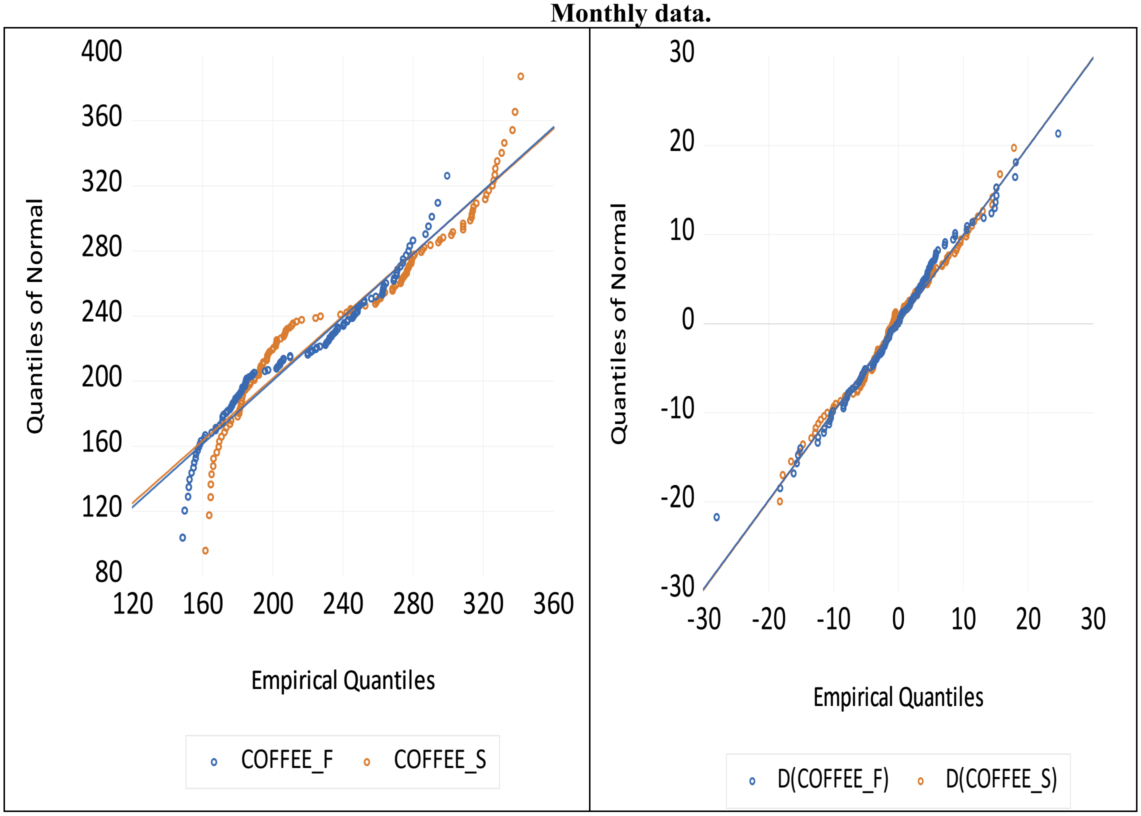


A.3.A. Quantile graphs

Coffee. Weekly data.



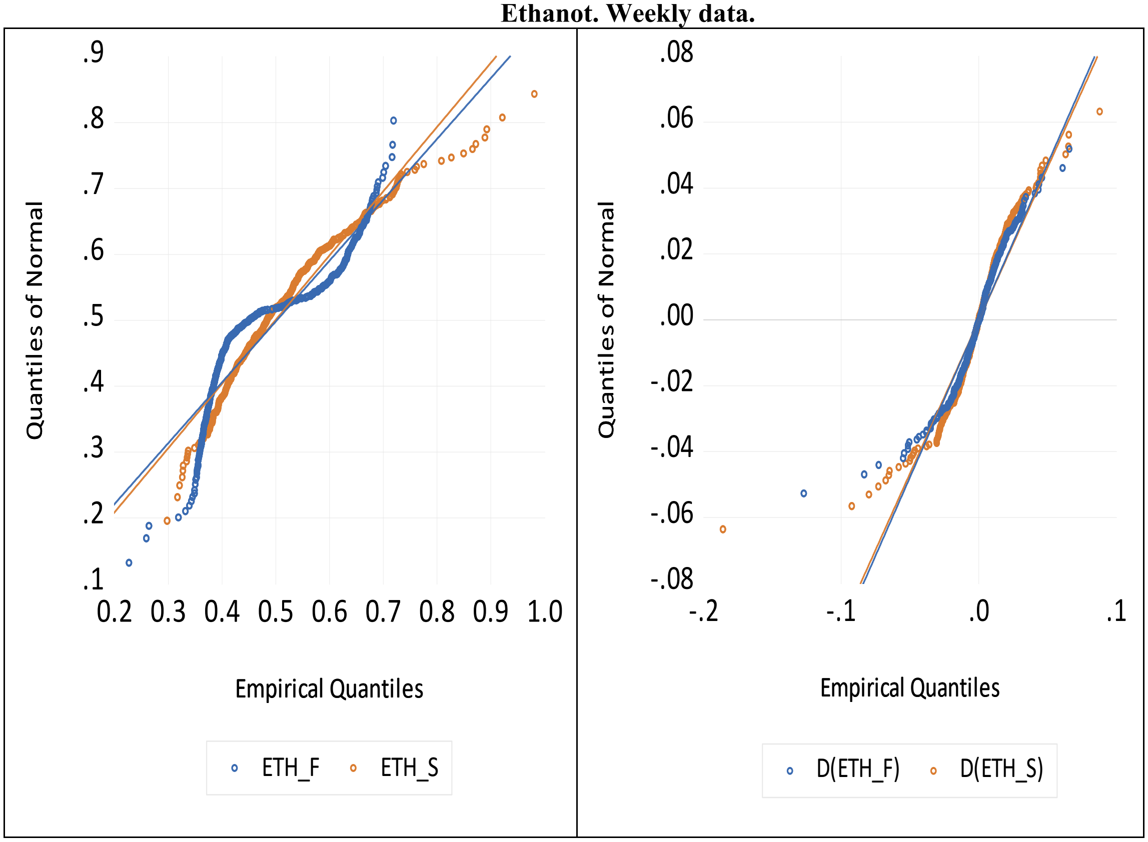
Monthly data.



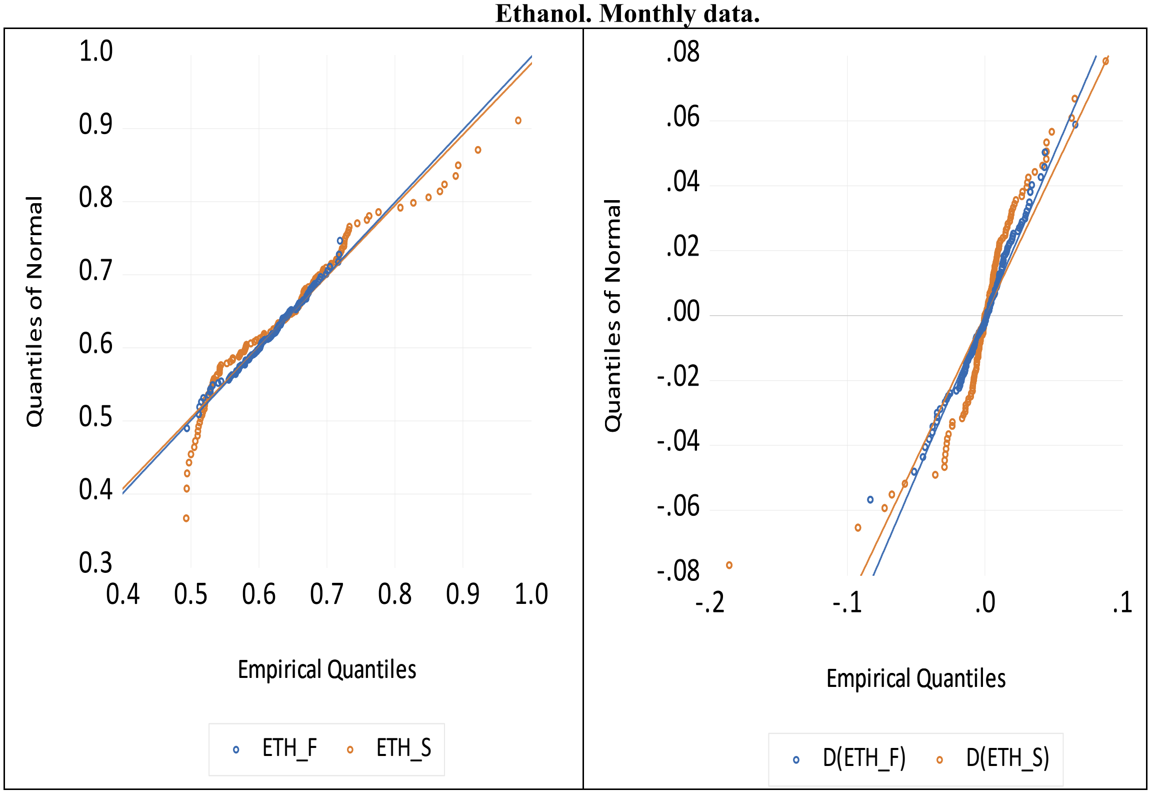
Source: Research results.

A.3.B. Quantile graphs. Cont.

Ethanot. Weekly data.



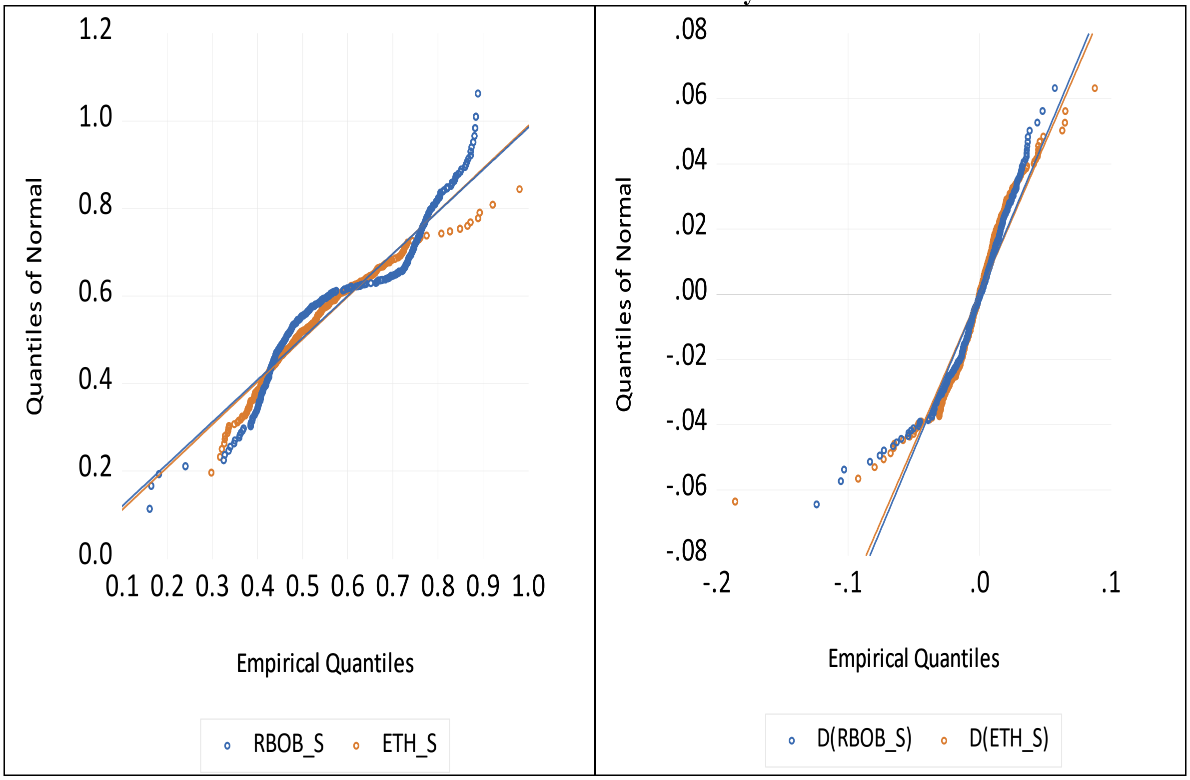
Ethanol. Monthly data.



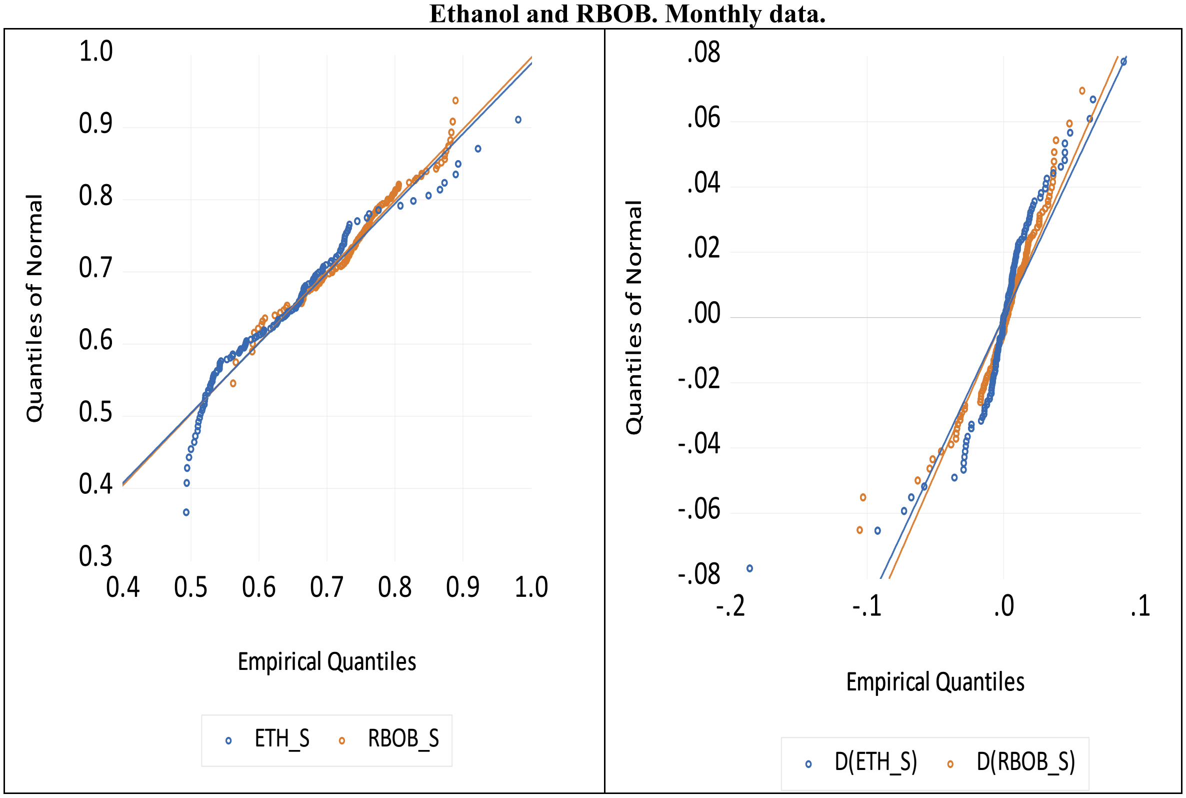
Source: Research results.

A.3.C. Quantile graphs. Cont.

Ethanot and RBOB. Weekly data.



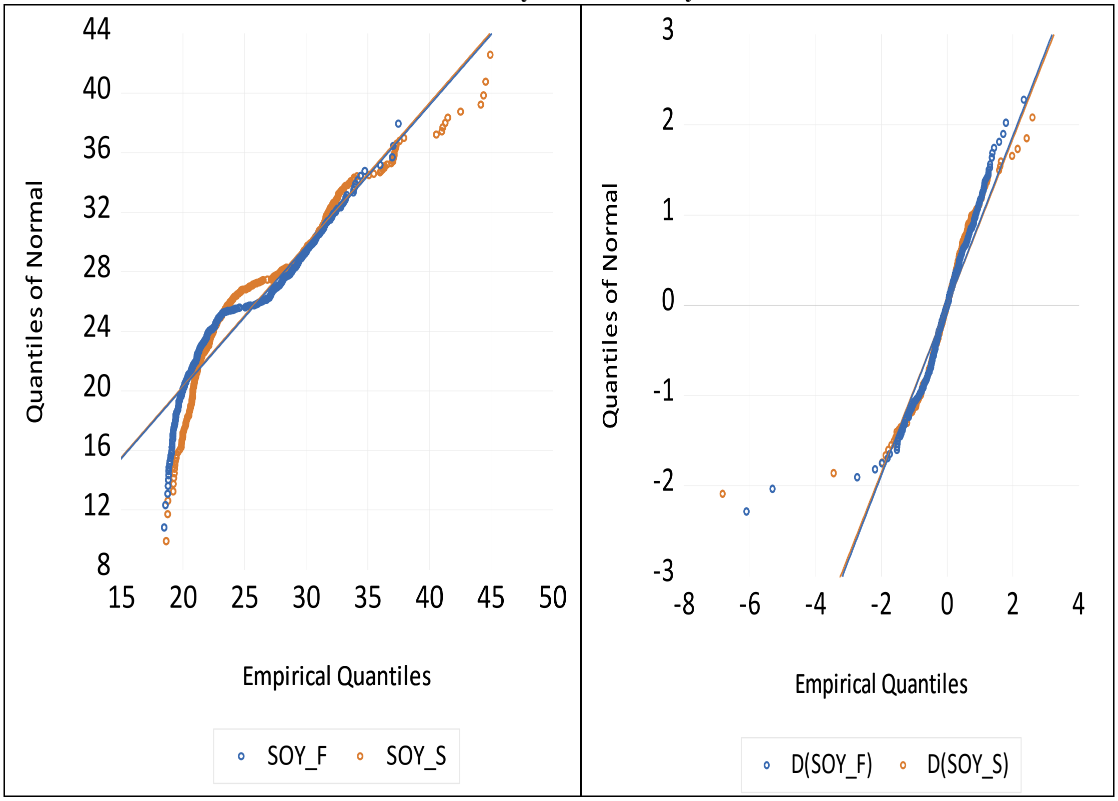
Ethanol and RBOB. Monthly data.



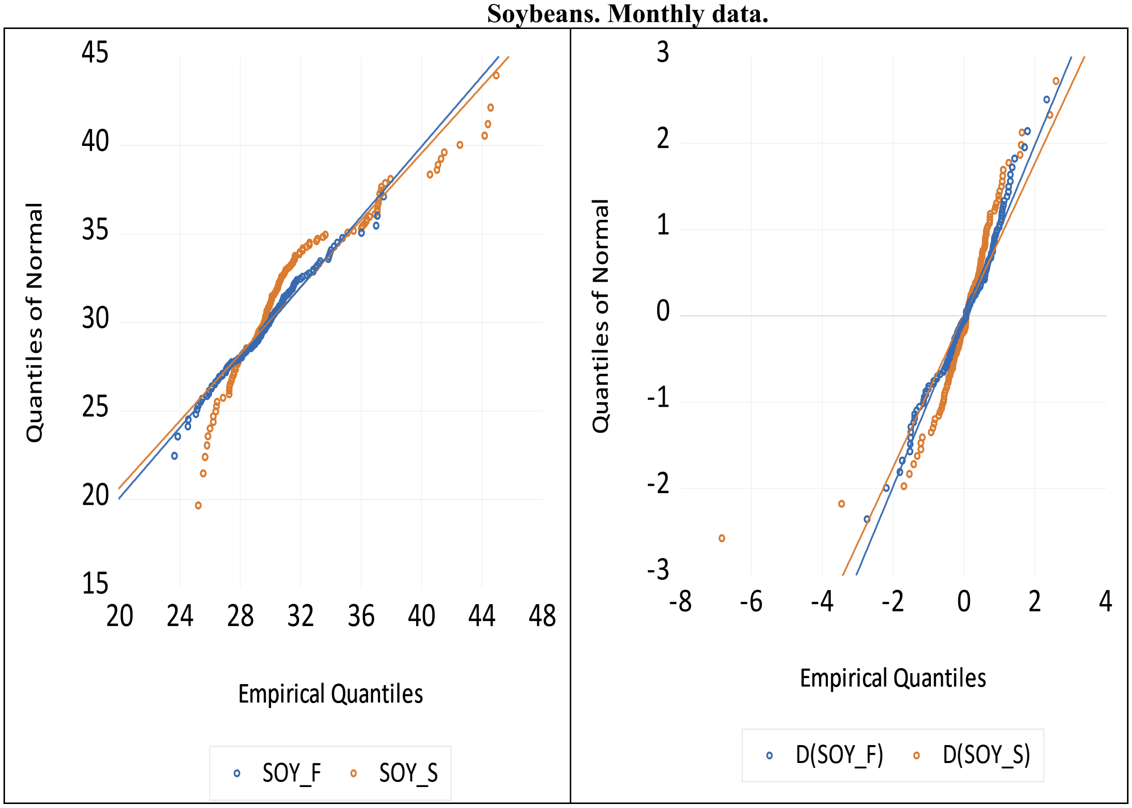
Source: Research results.

A.3.D. Quantile graphs. Cont.

Soybeans. Weekly data.

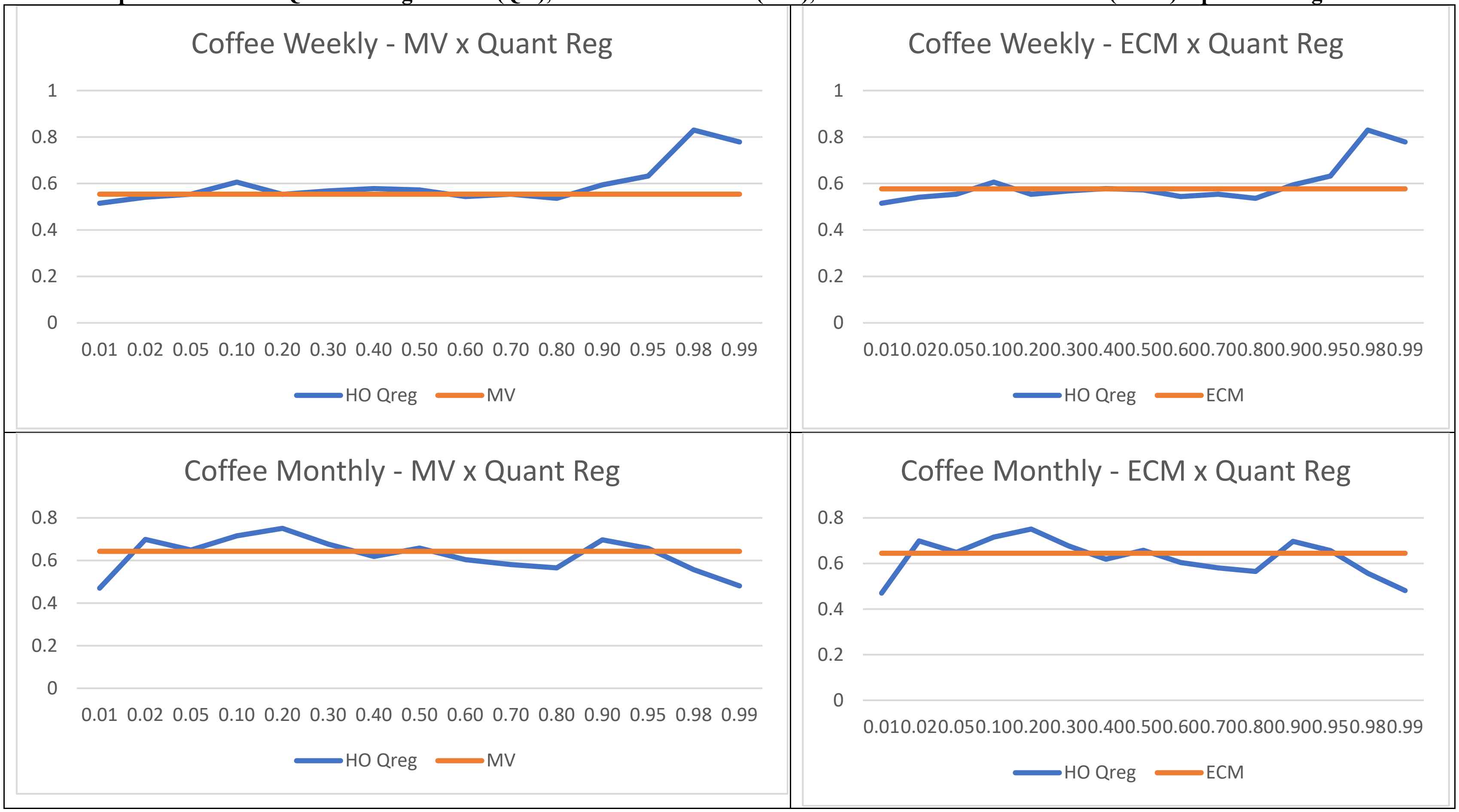


Soybeans. Monthly data.



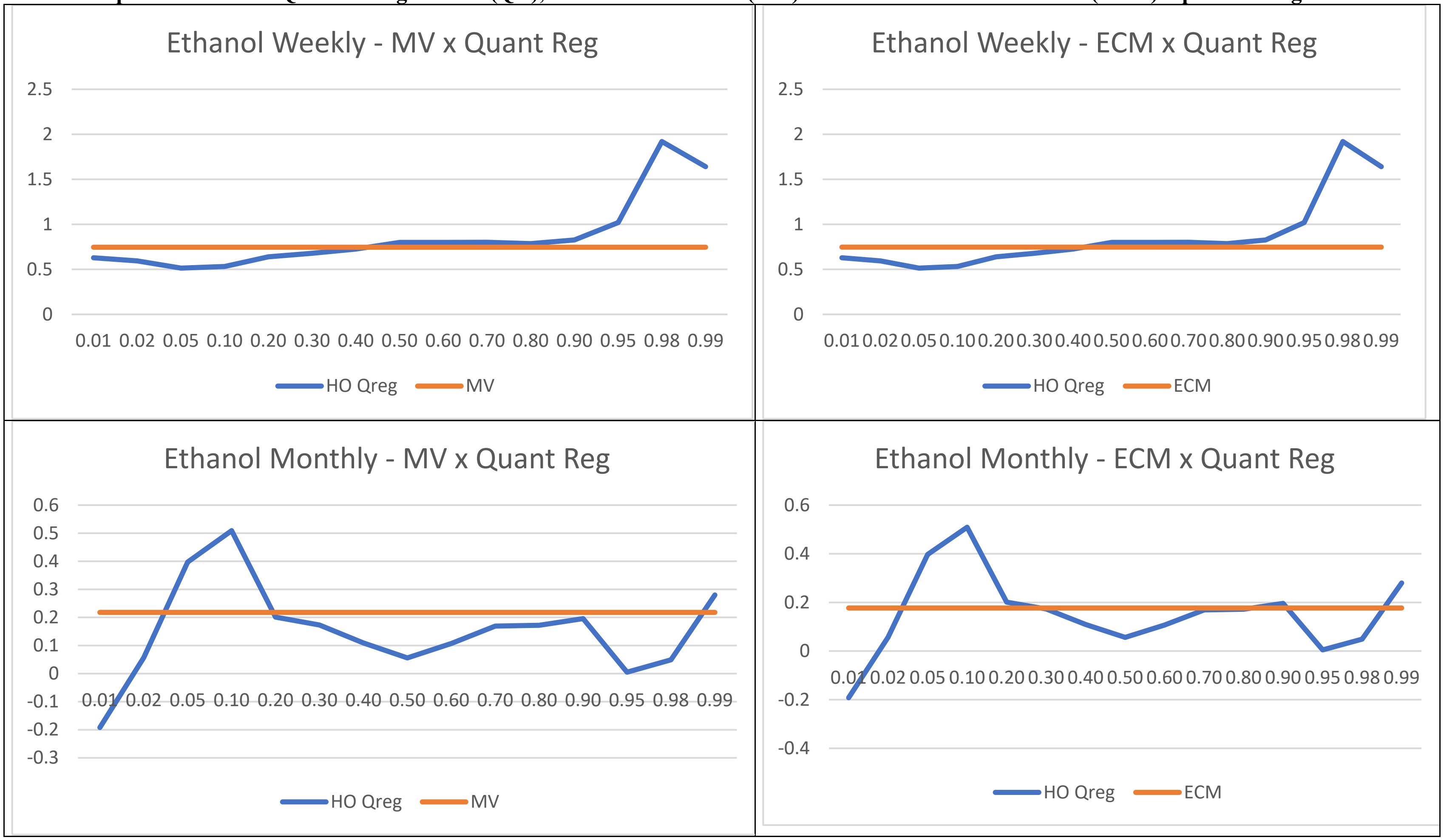
Source: Research results.

A.4.A. Comparison between Quantile Regressions (QR), Minimum Variance (MV), and Error-Correction Model (ECM) Optimal Hedges.



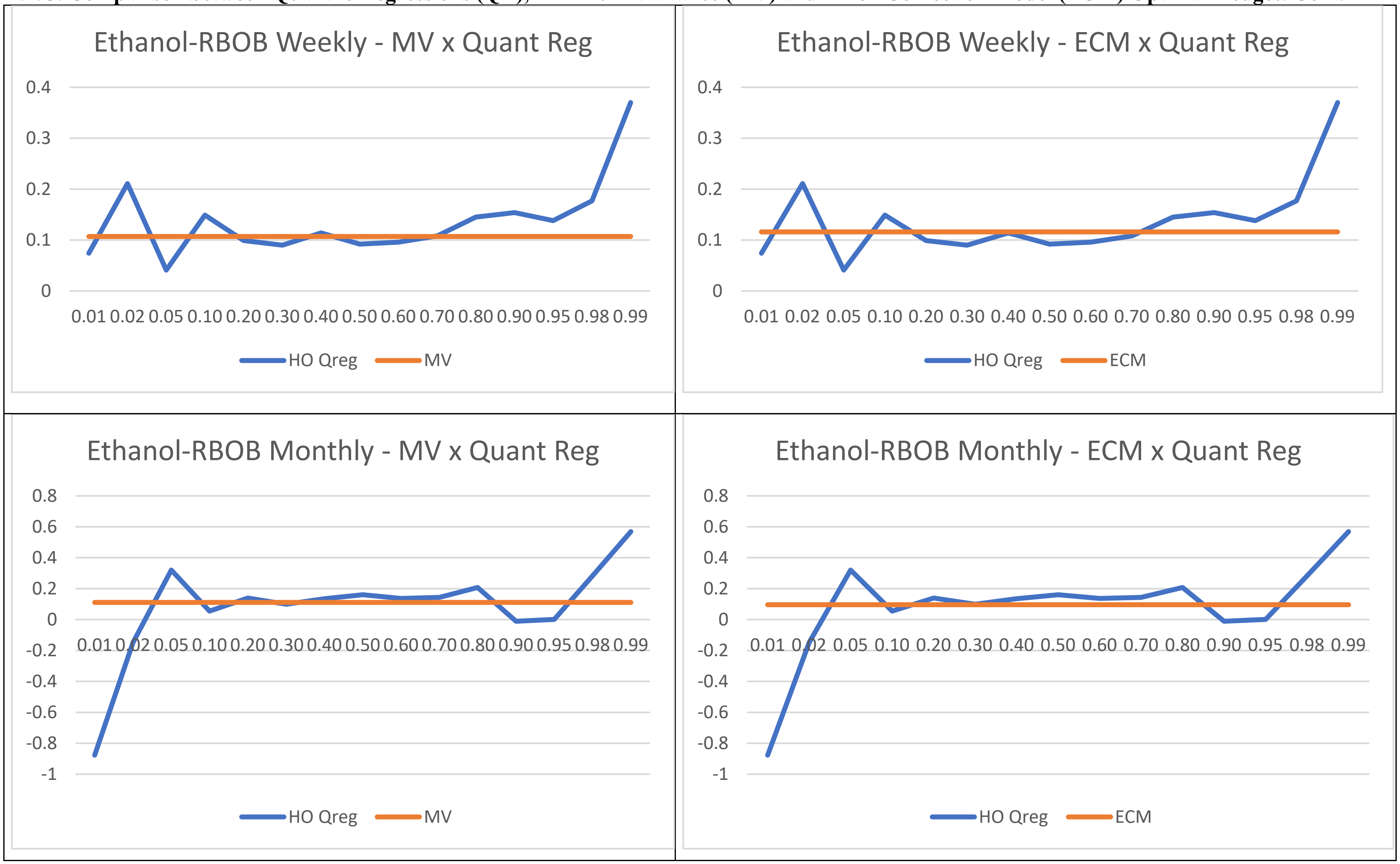
Source: Research results.

A.4.B. Comparison between Quantile Regressions (QR), Minimum Variance (MV) and Error-Correction Model (ECM) Optimal Hedges. Cont.



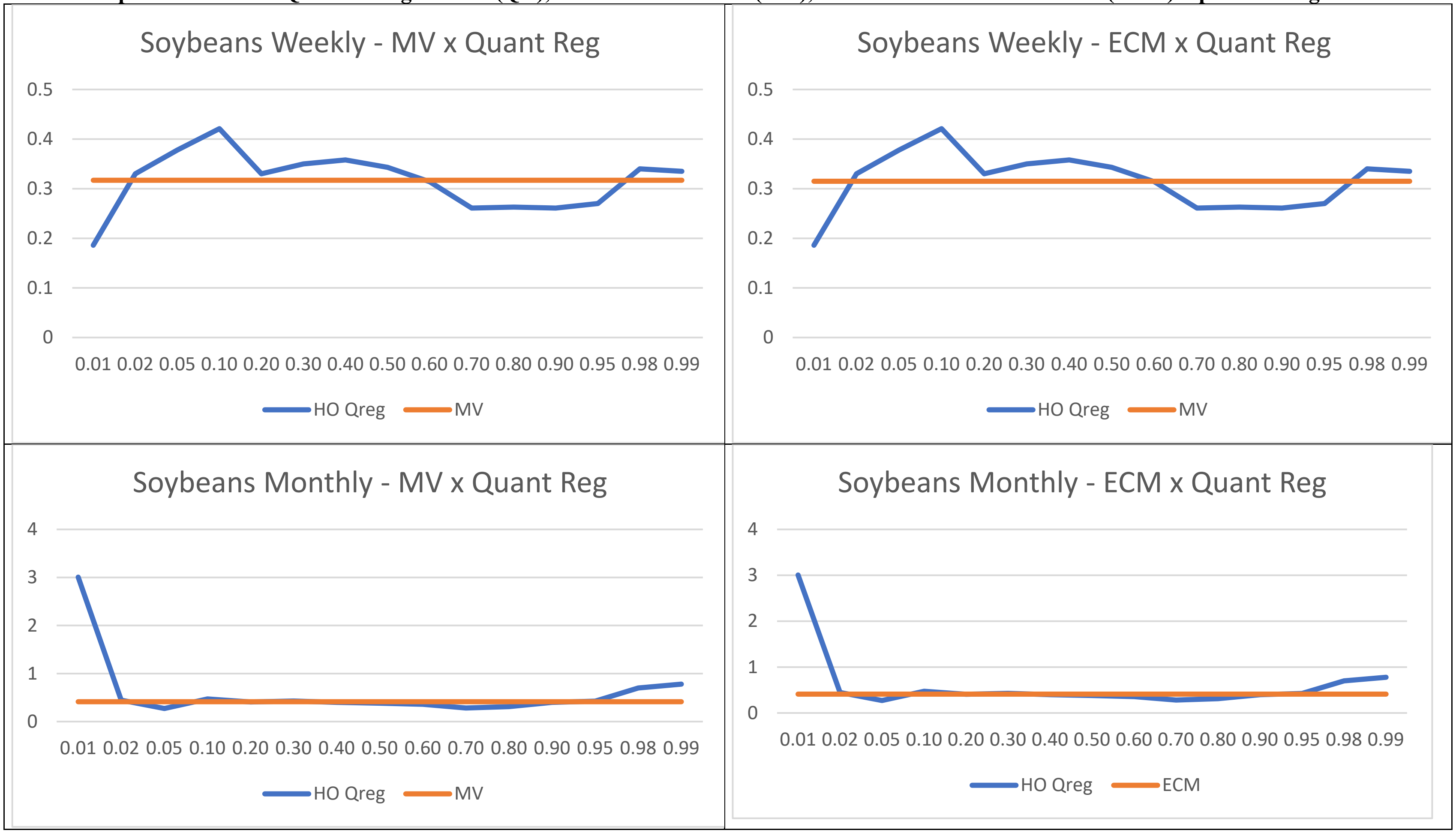
Source: Research results.

A.4.C. Comparison between Quantile Regressions (QR), Minimum Variance (MV) and Error-Correction Model (ECM) Optimal Hedges. Cont.



Source: Research results.

A.4.D. Comparison between Quantile Regressions (QR), Minimum Variance (MV), and Error-Correction Model (ECM) Optimal Hedges. Cont.



Source: Research results.

A.5. Test of Difference Between Quantile Hedge Ratio and Minimum Variance Hedge. Weekly and Monthly Data.

Quantiles	0.01	0.05	0.10	0.50	0.90	0.95	0.99
COFFEE WEEKLY	6.182*	3.504*	2.407*	0,111	-2,534*	-3.700*	-6.013*
COFFEE MONTHLY	6.805*	4.230*	2.914*	0.078	-3.553*	-4.399*	-6.517*
ETHANOL WEEKLY	6.182*	0.013*	0.010*	-0.0003	-0.010*	-0.014*	-0.024*
ETHANOL MONTHLY	0.045*	0.020*	0.012*	-0.0003	-0.014*	-0.022*	-0.038*
RBOB WEEKLY	0.032*	0.014*	0.009*	-0.0004	-0.009*	-0.013*	-0.028*
RBOB MONTHLY	0.082*	0.020*	0.013*	-0.0003	-0.014*	-0.022*	-0.036*
SOY WEEKLY	0.033**	0.422*	0.313*	-0.015	-0.313*	-0.432*	-0.729*
SOY MONTHLY	2.837*	0.570*	0.354*	-0.005	-0.433*	-0.586*	-0.962*

Source: Research results.

A.6. Test of Difference Between Quantile Hedge Ratio and Error Correction Model Hedge. Weekly and Monthly Data.

	Quantiles						
COFFEE WEEKLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	6.184*	3.506*	2.408*	0.113	-2.533*	-3.700*	-6.013*
COFFEE MONTHLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	6.816*	4.234*	2.917*	0.083	-3.550*	-4.394*	-6.507*
ETHANOL WEEKLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	6.184*	0.013*	0.010*	-0.0003	-0.010*	-0.014*	-0.024*
ETHANOL MONTHLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	0.044*	0.020*	0.012*	-0.0003	-0.015*	-0.022*	-0.038*
RBOB WEEKLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	0.032*	0.014*	0.009*	-0.0004	-0.009	-0.013*	-0.028*
RBOB MONTHLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	0.082*	0.020*	0.013*	-0.0004	-0.014*	-0.022*	-0.037*
SOY WEEKLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	0.033**	0.422*	0.313*	-0.015	-0.313*	-0.433*	-0.730*
SOY MONTHLY	**0.01**	**0.05**	**0.10**	**0.50**	**0.90**	**0.95**	**0.99**
	2.850*	0.565*	0.355*	-0.006	-0.433*	-0.586*	-0.960*

Source: Research results.