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Article

Sign and size asymmetries between futures and spot prices in the markets of agricultural commodities

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Abstract: The goal of the present article is to examine asymmetries in sign and size among spot and futures prices in the markets of agricultural commodities of corn, hard red wheat, and soybeans. Daily observations of spot and futures prices for the three agricultural commodities and the econometric tool of local linear regressions have been utilized. The empirical results were obtained for the period between January 2000 and the end of March 2025. The empirical results reveal evidence of asymmetric dependence in sign and size, at the very extremes of the distribution, under extreme negative changes for the commodity of corn and under extreme positive changes for the commodity of soybeans. Accordingly, extreme price increases/decreases of different signs but of the same absolute magnitude are transmitted from futures to spot prices with different intensity. Moreover, large price shocks in value are transmitted from futures to spot prices more forcefully compared to smaller ones. Evidence of sign and size asymmetries might greatly help diversify the traders' investment risk.

Keywords: asymmetries; prices; futures; agricultural commodities; investors

JEL classification: G15, C12, C14

1. Introduction

Perhaps, more than any other category of commodities, agricultural futures play the most vital role in our everyday life. The most pronounced economic impact of the agricultural futures markets is the significant influence they exercise on the spot market prices. Market reports for the agricultural futures market constitute an essential part for traders and speculators in determining spot prices based on the fundamental reports (Miljkovic et al., 2024). Asymmetries between futures and spot prices can impact the stability, transparency, and efficiency of markets (Singbo & Sossou, 2024). Policymakers, regulators, central banks, and governments must carefully monitor these price discrepancies as they can have direct effects on market behavior, inflation expectations, and broader economic stability (Biswal & Jain, 2019). The stability of agricultural prices is crucial, especially for developing countries, where the population spends a significant amount of their income on food. Through agricultural futures markets, governments can hedge the risk and provide stability for the prices of farm products and commodities. In addition, fiscal funds can be utilized to stabilize the prices of agricultural commodities (Chen et al., 2021).

Economic crises in the past years have caused the prices of agricultural products to skyrocket, and some have suspected foul play from speculators (Baines, 2017; Conrad, 2023; Han, 2024). The most recent case is the ongoing conflict between Russia and Ukraine that has led to inflated prices in many agricultural commodities (Arndt et al., 2023; Kornher et al., 2024). Furthermore, economists predict that the recently imposed US tariffs will trigger retaliation countermeasures by the top importers of U.S. farm products and prompt wild swings in commodity markets.

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High prices and volatility in world food prices have strengthened the attention of policymakers to agriculture and fueled the debate about the future reliability of world markets as a source for food. The role of speculators in the markets of agricultural commodities has been the subject of many discussions. Policy makers, politicians, and traders have feared that speculation could impair the efficiency of futures markets and, as a consequence, affect the spot prices of agricultural commodities. The price linkage among futures and spot prices for a commodity is essential when utilizing the futures market in order to hedge against price uncertainty (Banerjee et al., 2024). With the employment of futures markets to secure future prices for their commodities, market participants can be protected from adverse movements in spot prices. Futures markets enable farmers to secure a price for their products far in advance. This fact can help plan and budget with more security and minimize risk. Risk hedging, futures markets, and agricultural risk management are very well connected. Futures markets gather information on the supply side and the demand side of agricultural commodities. Communicating price information from the futures markets to the spot markets is called price discovery.

Broadly speaking, spot prices and futures prices refer to different markets across time horizons, where the demand and supply have not remained the same. Information contained in the prices of futures contracts can be used by producers and investors. Producers may base their production on the futures contract prices in order to hedge against possible risks, and traders can use futures contracts as a benchmark to price their commodities. The market efficiency hypothesis states that futures and spot prices must encompass new information because they both reflect the value of the underlying commodity. In reality, commodity markets are not perfect. The presence of transaction costs can cause one market to adjust faster to new information than the other market. Finding the direction of the linkage is crucial because decisions regarding production and consumption depend on efficient price signaling.

Causality between futures and spot markets has been studied extensively, as it can guide investors and assist in discovering arbitrage opportunities between the two types of prices. The overwhelming majority of the empirical results in the finance literature reveal that price shocks originate from the futures markets (Joseph et al., 2014; Jena et al., 2018; Hernandez et al., 2010; Samak et al., 2020; Xu et al., 2019; Bohl et al., 2020; Ameur et al., 2022; Penone et al., 2022; Kaur, 2023). Nonetheless, on a few occasions, there is evidence that price shocks originate from the spot markets (Srinivasan, 2012; Samak et al., 2020; Szczepanska Przekota, 2022), and evidence of bidirectional causality (Dash & Andrews, 2010; Chen & Tongurai, 2022; Qin et al., 2023; Narayanasamy et al., 2023; Fang et al., 2024) was fully identified.

The most common methodological approaches used are linear and non-linear Granger causality tests, cointegration tests (Hernandez et al., 2010; Samak et al., 2020), vector error correction models (Xu et al., 2019), GARCH models (Shihabudheen & Padhi, 2010; Srinivasan, 2012; Meyer & Von Cramon-Taubadel, 2004), and Var and copula approaches (Dai et al., 2023; Li & Chavas, 2023).

The majority of the previous research has focused mainly on whether price discovery takes place in the futures market or in the spot market. The present article revisits the relationship between futures prices and spot prices for the agricultural commodities of corn, soybeans, and hard red wheat, and tests for sign and size asymmetric dependence between these two prices. The asymmetries between futures and spot prices can have significant policy implications, particularly in financial markets, commodities trading, and macroeconomic stability (De Jong et al., 2022). In addition, contrary to earlier studies, this article focuses on the contemporaneous relationship between the two prices and not on the lag-lead one.

Corn, soybeans, and hard red wheat are the three largest crops in the U.S. (Fousekis, 2023). Furthermore, corn and soybeans are very significant in terms of food supply (food and feed) and in terms of non-food materials from renewable fuels to bio-based plastics.

This study is undertaken in two steps. In the first step, it adopts the majority of the findings of the relevant literature and assumes that agricultural futures prices lead spot prices. Across different agricultural commodities, most of the studies have concluded that futures markets dominate the price discovery process (Hernandez et al., 2010; Xu et al., 2019; Bohl et al., 2020). In the second step, the econometric tool of local regression is employed. Local regression has three distinct advantages: (a) it allows "the data to speak for itself"; (b) it requires only some degree of smoothness; and (c) it obtains the regression line directly instead of inferring its shape from estimated coefficients at a small number of points. Accordingly, local regression can capture complex patterns in the data, without requiring a specific functional form or distributional assumptions. In addition, it is resilient against inaccuracies in the functional structure and capable of managing outliers and disturbances within the data that are common problems in real-world data. Unlike (a)symmetric GARCH models and Vector Error Correction Models, local regression adjusts to specific characteristics within the data without relying on a singular overall model for the entire dataset. After it obtains the non-parametric fit, the present study performs tests for linearity and for sign and size symmetry.

The three most recent empirical works have examined asymmetries in agricultural commodities and provide theoretical and empirical grounds for comparison with the present study. The first one, by Dai et al. (2023), employed a combination of the Copula-CoVaR approach and the ARMA-GARCH-skewed Student-t model to investigate the tail dependence structure and extreme risk spillover effects between the international agricultural futures and spot markets, selecting the agricultural commodities of soybeans, corn, wheat and rice) as examples. Their empirical findings revealed that the tail dependence structures for the four futures-spot pairs are distinct, and each of them exhibits a certain degree of asymmetry. The downside risk spillover effects for both soybeans and maize are significantly stronger than their corresponding upside risk spillover effects. On the other hand, there is no significant strength difference between the two risk spillover effects for wheat and rice.

The second one, by Li and Chavas (2023), investigated the role of futures markets and their dynamic effects on the stability of commodity prices. Their analysis was based on combining two econometric approaches: a quantile vector autoregression (QVAR) model of the marginal distributions of futures and spot prices and a copula of their joint distribution. The commodities examined were the US soybean and corn markets. The econometric investigation revealed the presence of nonlinear cointegration relationships between futures and spot prices.

The third one, by Mao et al. (2024), used price data for corn and soybeans in China and identified the exact bubble dates for the futures and spot markets. The corresponding futures prices dominated the process of price discovery. Results indicated asynchronous price bubbles between these two markets and nonlinear transmission effects between the futures and spot prices.

To the best of our knowledge, this is the first work to account for sign and size asymmetries between futures and spot prices for agricultural commodities. The empirical findings of the study are in agreement with the findings of nonlinearities and asymmetries in the most recent studies by Dai et al. (2023), by Li and Chavas (2023) and by Mao et al. (2024). In addition, the evidence of symmetry for the case of hard red wheat agrees with the findings by Dai et al. (2023).

The empirical results of asymmetries, for the commodities of corn and soybeans, can be employed by policymakers to prevent or minimize the effects of future crises in the agricultural sector. Governments and regulatory bodies may need to implement mechanisms to improve transparency and information dissemination to ensure more accurate pricing. For example, regulators could enforce better reporting standards for market participants, especially in commodity markets where futures markets often serve as an early indicator of expected supply-demand imbalances. Central banks and monetary authorities may need to account for futures market trends in their economic models and policy decisions. For example, suppose the futures market signals potential price increases in commodities like food or energy. In that case, central banks may take preemptive actions by adjusting interest rates or using other monetary tools. Governments in these countries may need to work on strategic reserves or adjust fiscal policy to buffer against future price hikes. Trade policy might also be influenced by futures-spot price asymmetries, especially when dealing with critical goods like food and agricultural commodities.

This paper is structured as follows: Section 2 presents the methodology, Section 3 presents the data, Section 4 presents the empirical results, Section 5 presents the discussion, and Section 6 presents the conclusions.

2. Methodology

2.1. Local linear regression

In the following equation

$$y_i = \mu_u + \epsilon_i = E(y_i | x_i = u) + \epsilon_i \quad (1)$$

y is the dependent variable, x is the independent variable, u are focal point, μ is the conditional mean function and ϵ_i The error component whose mean is zero.

The conditional mean function μ can be captured by a p-degree (p ≥1) Taylor series expansion as

$$\mu_u = \beta_0 + \beta_1(x-u) + \cdots + \beta_p(x-u)^p =< \beta, B(x-u) > \quad (2)$$

where β are the coefficients and B(●) are the functions that fit the model. The minimization of the following equation estimates the coefficients in equation (2):

$$\sum_{i=1}^{N} w_i(x)(y_i -< \beta, B(x-u) >)^2 \quad (3)$$

where $w_i(x) = W[(x-u)/h(x)]$, and h(x) is the bandwidth. The local estimate of μ(u) is the first part of vector β, which is μ(u) =< β, B(0) >= β0.

The second component of vector b gives the local slope estimate:

$$s(u) =< \beta, B'(0) >= \beta_1 \quad (4)$$

The vector gives the fitted values:

$$M = \Theta y \quad (5)$$

where Θ is the projection matrix, and the equivalent number of parameters is $DF_{np} = tr(\Theta\Theta^{\intercal})$; the residuals degrees of freedom are DFres = (n -1) - DFnp. If we connect the estimates of the local regressions at every focal point, we obtain the non-parametric fit. Equation (5) provides the test statistic (Fousekis, 2015, 2020) to test the linearity of the relationship between the dependent and the independent variable. Equations (1) to (4) describe the unrestricted relationship and the relationship expressed by the standard linear model. $Y_i = a + bx_i + e_i$, It is the restricted one.

$$F = \frac{(RSS_R - RSS_U)/(DF_{np} - 2)}{RSS_U / DF_{res}} \quad (6)$$

where RSSR is the residual sum of squares from the restricted model and RSSU is the residual sum of squares from the unrestricted model. Under the null hypothesis of linearity, the statistic in equation (6) follows the F-distribution with (DFnp - 2) and DFres degrees of freedom. The null hypothesis is rejected for large values of the test statistic.

2.2. Sign and size symmetry tests

Let's consider two shocks of opposite sign but of similar magnitude, and *sk* and *s-k* are the respective local slopes in the non-parametric fit. AWald-type test (Fousekis & Tzaferi, 2020) is utilized to test if sk = s-k. The present work uses the following statistics:

$$\Phi = (R\Lambda)'(RV_{\Lambda}R')^{-1}(R\Lambda) \quad (7)$$

If asymmetry is present (H0), Φ has an x2 distribution with one (1) degree of freedom. R is the vector with restrictions imposed, the estimate for the bootstrap is L = (sk, s-k), and VΛ is the relevant variance-covariance matrix. The same test is employed to test the symmetry hypothesis under shocks of the same sign but of different magnitude, namely, k and m. These two shocks have local slopes equal to sk and sm (Patton, 2013; Fousekis, 2020). In order to obtain empirical results for non-parametric regression, we have to choose the correct bandwidth. In the case where the bandwidth is small, a large variance is produced. On the other hand, when the bandwidth is big, over-smoothing is the result, and the bias is large. In the present study, the nearest neighborhood bandwidth is employed, where each smoothing window has the same percentage (w) of observations. The best global goodness of fit is achieved for the value of w that minimizes the Generalized Cross Validation (GCV) criterion in equation (7):

$$GCV = N\frac{\sum_{i=1}^{N}\left(Y_i-\hat{\mu}(x_i)\right)^2}{\left(N-DF_{np}\right)^2} \quad (8)$$

3. Data

The data are daily observations of spot and futures prices for corn, soybeans, and hard red wheat from January 2000 to the end of March 2025. The source of the data is QUANDL—CORE FINANCIAL DATA (2025).

Table 1 presents summary statistics and tests on the distribution of spot and futures price log-returns. Hard red wheat exhibits negative and statistically significant skewness, indicating a few very large negative shocks. Corn and Soybeans exhibit positive skewness. All three series show excess kurtosis, indicating a broad distribution (i.e., one with fat tails). The excess kurtosis is most notable for the Hard red wheat. The null hypothesis of normality is strongly rejected in all cases.

Table 1. Summary statistics on spot and futures price returns

Commodity	Mean	Max	Min	Skewness (p-val)	Kurtosis (p-val)	Normality (p-val)
Spot:						
Corn	-0.0002	0.1918	-0.1997	0.1435 (<0.01)	6.2012 (<0.01)	0.9889 (<0.01)
Hard Red Wheat	-0.0002	0.1576	-0.3572	-4.4356 (<0.01)	82.3367 (<0.01)	0.6876 (<0.01)
Soybeans	-0.0003	0.1533	-0.1341	0.6777 (<0.01)	8.3579 (<0.01)	0.9981 (<0.01)
Futures:						
Corn	-0.0002	0.4567	-0.1139	0.5112 (<0.01)	13.4358 (<0.01)	0.9778 (<0.01)
Hard Red Wheat	-0.0003	0.5436	-0.3779	-2.4213 (<0.01)	93.4348 (<0.01)	0.6891 (<0.01)
Soybeans	-0.0003	0.3459	-0.1987	0.9123 (<0.01)	17.4333 (<0.01)	0.9224 (<0.01)

The Kwiatkowski–Phillips–Schmidt–Shi (KPSS) (Kwiatkowski et al., 1992) test has been employed to examine whether the price levels and the logarithmic changes of spot prices and futures prices contain unit roots. The null hypothesis tests for weak stationarity or a non-unit root. Table 2 presents the results. All price levels contain unit roots in both spot and futures prices. On the other hand, logarithmic changes, for all six series, are weakly stationary.

Table 2. KPSS unit root tests

Commodity	Price Levels	Log Returns
Spot prices:		
Corn	0.835	0.042
Hard red wheat	0.587	0.033
Soybeans	0.222	0.045
Futures prices:		
Corn	0.352	0.044
Hard red wheat	0.813	0.032
Soybeans	0.345	0.047

Note: The tests were carried out with a deterministic trend in the auxiliary regression; the critical values are 0.216, 0.146, and 0.119 at the 1%, 5%, and 10% levels, respectively.

To corroborate the results of the KPSS tests, the Ng and Perron (2001) tests were employed to determine the logarithmic changes of the spot and futures prices. In the Ng–Perron tests, the null hypothesis of non-stationarity is rejected if the test statistic is algebraically smaller than the critical value. Table 3 presents the results. The results show that for all six variables, the null hypothesis of non-stationarity in the logarithmic changes is rejected at any conventional significance level. Hence, according to the KPSS and the Ng-Perron tests, we conclude that the logarithmic changes of spot prices and futures prices are I(1).

Table 3. Ng and Perron (2001) unit root tests on the logarithmic changes

Commodity	Lag	MZ_a	MZ_t	MSB	MPT
Spot prices:					
Corn	3	-26.88	-3.72	0.077	1.22
Hard red wheat	1	-28.22	-3.77	0.122	1.98
Soybeans	2	-25.98	-3.52	0.111	3.98
Futures prices:					
Corn	0	-34.44	-3.89	1.133	2.56
Hard red wheat	2	-26.44	-3.92	0.091	3.41
Soybeans	3	-29.43	-4.01	1.145	3.62
Critical values					
1%		-23.80	-3.42	0.143	4.03
5%		-17.30	-2.91	0.168	5.48
10%		-14.20	-2.62	0.185	6.67

Note: Critical values are taken from Table 1 of Ng and Perron (2001). Lags are selected according to modified Akaike information.

4. Empirical models and results

4.1. Linearity tests

For the null hypothesis of global linearity, the empirical values of the F-statistic and their associated p-values are reported in Table 4. The p-values for all market pairs are well above the conventional levels of statistical significance. More specifically, the empirical F-value for Corn is 1.912, with a p-value equal to 0.234. For Hard red wheat, the F-statistic assumes the value of 0.248. The p-value is 0.911. Lastly, for Soybeans, the value of the F-statistic is 1.192, and the p-value is equal to 0.337. We conclude, therefore, that the null hypothesis of global linearity between the spot and the futures prices is consistent with the real-world data.

Table 4. Test for global linearity

Commodity	Value of F-statistic	p-value
Corn	1.912	0.234
Hard red wheat	0.248	0.911
Soybean	1.192	0.337

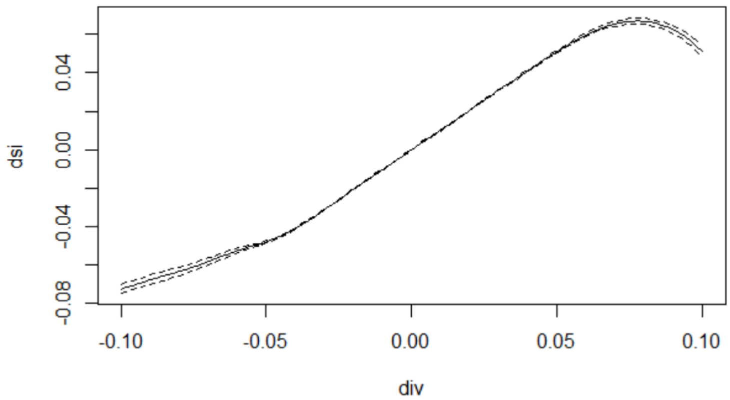
4.2. Empirical results for sign and symmetry tests

4.2.1. Corn

Panels (a) and (b), in Figure 1, present the fits for Corn and the associated slopes. Visual inspection indicates a positive relationship, linearity (with possible nonlinearities at the extremes), and evidence of asymmetry with respect to sign. In addition, the careful observation of the slope shows that, around the tails, spot market returns are not so responsive to changes in futures changes.

Figure 1. Corn

(a) Non-parametric fit



(b) Slope profile

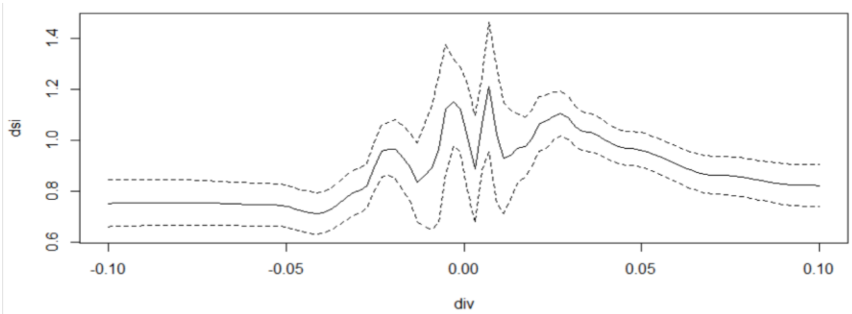


Table 5 presents the empirical estimates of the slopes and the results of the tests for symmetry. The symmetry tests have been contacted for the vector of stock returns (-0.04, -0.02, - 0.01, -0.005, 0.005, 0.01, 0.02, and 0.04) that, roughly, correspond to the quantiles (1%, 5%, 10%, 25%, 50%, 75%, 95%, and 99%) of the futures returns (div) distribution. At the very extremes of the distribution (1% and 5% quantiles), sign symmetry is rejected at the 5% significance level. The numerical values of the differences are -0.171 and -0.201, for the 1% and 5% quantiles, respectively. Results reveal evidence of asymmetric dependence concerning the sign (negative vs positive changes) but only at the extremes. One possible explanation is that traders and investors who have placed long positions react differently from those with short positions. Price increases benefit long positions but harm short positions, and vice versa. In the case of corn, traders with short positions have a more sizable reaction. Size symmetry cannot be rejected in all cases, except for negative changes between 1% and 25% and 5% and 25%. Both tests provide evidence of asymmetries in sign and size at the extremes.

Table 5: Asymmetry tests between futures prices and spot prices for Corn

a) Slopes at specific futures returns:									
Quantile	1%	5%	10%	25%	50%	75%	90%	95%	99%
Estimated value	0.774	0.757	0.937	0.979	1.084	1.115	1.048	0.958	0.945
p-value	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

b) Sign asymmetry:			
1% - 99%	5% - 95%	10% - 90%	25% - 75%
-0.171 (0.032)	-0.201 (0.042)	-0.111 (0.822)	-0.136 (0.713)

c) Size asymmetry under negative returns				
50% - 10%	50% - 25%	50% - 5%	50% - 1%	25% - 10%
0.147 (0.5333)	0.105 (0.899)	0.327 (0.089)	0.310 (0.065)	0.042 (0.445)
25% - 5%	25% - 1%	10% - 5%	10% - 1%	5% - 1%
0.222 (0.087)	0.205 (0.059)	0.180 (0.445)	0.163 (0.553)	-0.0177 (0.989)

d) Size asymmetry under positive returns				
50% - 75%	50% - 90%	50% - 95%	50% - 99%	75% - 90%
-0.031 (0.912)	0.036 (0.899)	0.126 (0.158)	0.139 (0.268)	0.067 (0.938)
75% - 95%	75% - 99%	90% - 95%	90% - 99%	95% - 99%
0.157 (0.575)	0.170 (0.089)	0.090 (0.789)	0.103 (0.777)	0.013 (0.645)

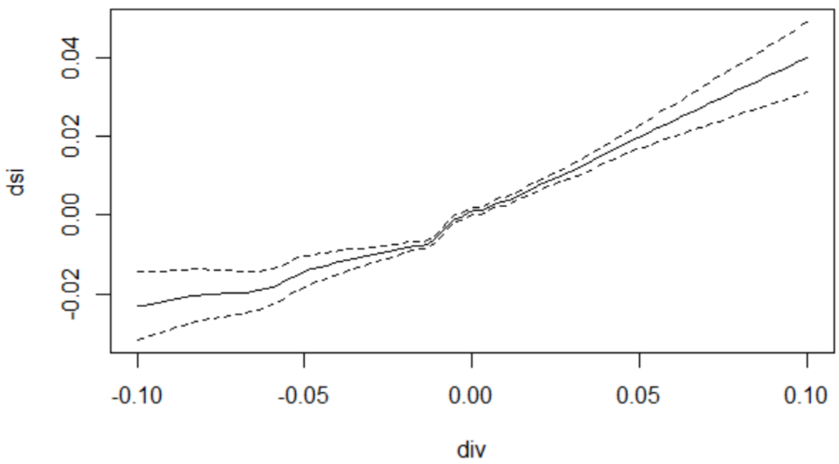
Note: In parentheses, the present study reports the p-values estimated after 3000 replications using Politis and Romano's (1994) block bootstrap method.

4.2.2. Hard red wheat

Figure 2, panels (a) and (b), show the diagrams for Hard red wheat. We observe a positive relationship and a strong linear relationship. The slope profile provides evidence that at the tails as well as in the middle of the distribution, spot market returns are not so responsive when futures prices increase or decrease.

Figure 2: Hard Red Wheat

(a) Non-parametric fit



(b) Slope profile

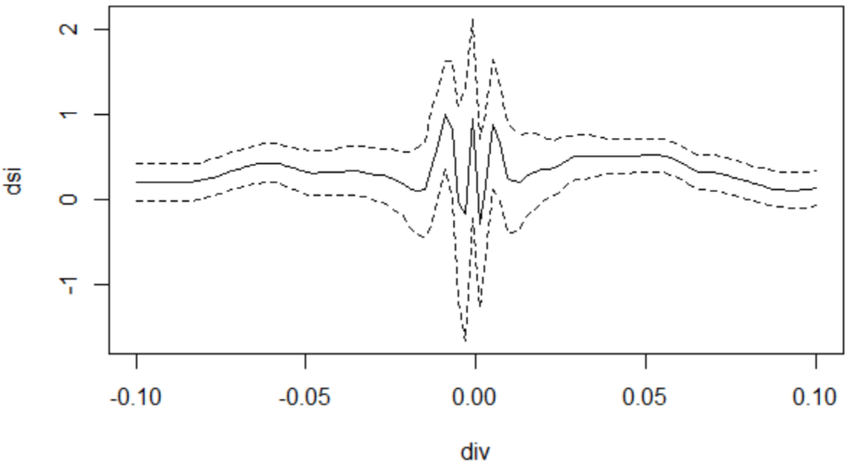


Table 6. Asymmetry tests between futures prices and spot prices for Hard red wheat

a) Slopes at specific futures returns				
Quantile	1%	5%	10%	25%
Estimated values	0.392	0.375	0.342	0.395
	(<0.01)	(<0.01)	(<0.01)	(<0.01)
Quantile	50%	75%	90%	95%	99%
Estimated values	0.402	0.418	0.428	0.427	0.420
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
b) Sign asymmetry				
1%-99%	5%-95%	10%-90%	25%-75%	
-0.028 (0.877)	-0.052 (0.788)	-0.086 (0.957)	-0.023 (0.978)	
c) Size asymmetry under negative returns				
50%-10%	50%-25%	50%-5%	50%-1%	25%-10%
0.060 (0.989)	0.007 (0.891)	0.027 (0.989)	0.010 (0.988)	0.053 (0.967)
25%-5%	25%-1%	10%-5%	10%-1%	5%-1%
0.020 (0.952)	0.003 (0.978)	-0.033 (0.898)	-0.050(0.892)	-0.017(0.928)
d Size asymmetry under positive returns				
50%-75%	50%-90%	50%-95%	50%-99%	75%-90%
-0.016 (0.922)	-0.026 (0.888)	-0.025 (0.983)	-0.018(0.933)	-0.010(0.945)
75%-95%	75%-99%	90%-95%	90%-99%	95%-99%
-0.009 (0.978)	-0.002(0.945)	0.008 (0.989)	0.008(0.968)	0.007(0.988)

Note: In parentheses, the present study reports the p-values estimated after 3000 replications with the block bootstrap method by Politis and Romano (1994).

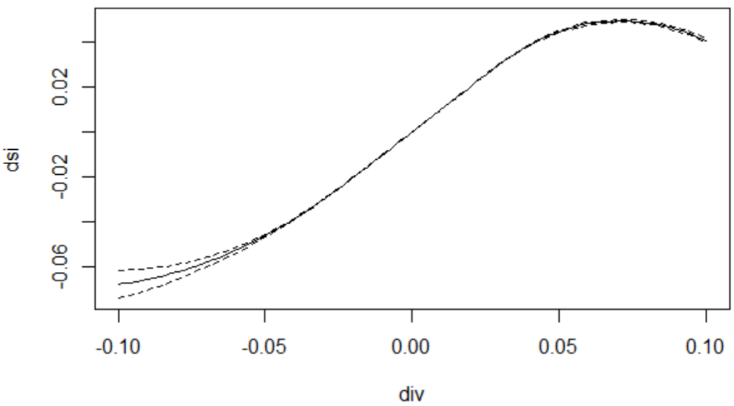
4.2.3. Soybeans

In Figure 3, panels (a) and (b) present the diagrams for Soybeans. We observe a positive relationship and linearity, with some non-linearities at the extremes. The slope profile provides evidence that close to the tails, spot market returns are more sensitive to changes in futures returns.

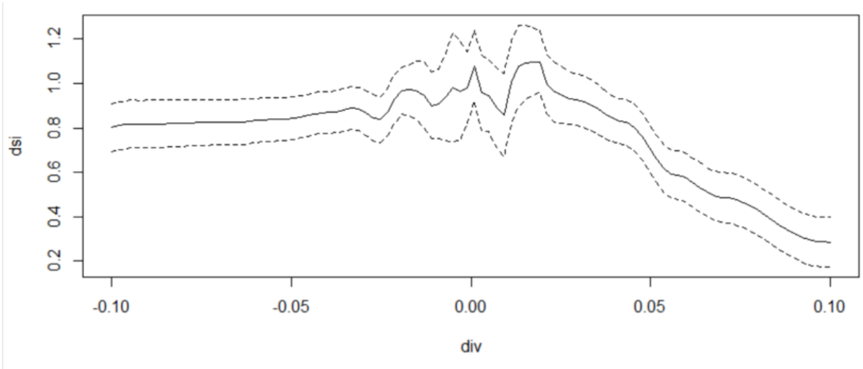
The empirical results of Table 7 reveal that, at the very extremes of the distribution (1% and 5% quantiles), symmetry concerning sign can be rejected at the 10% significance level. In addition, the numerical values of the differences are 0.236 and 0.135, for the 1% and 5% quantiles, respectively. Regarding soybeans, traders and investors appear to have a more intense and diverse reaction to positive changes in the futures prices than to negative changes. Unlike corn, one can suggest that extreme price increases in futures prices cause a more sizable reaction to traders with long positions than investors with short positions (and their reaction under extreme negative changes to futures prices). Size symmetry cannot be rejected in all cases, except for positive changes between 1% and 25% and 5% and 25%, under positive returns.

Figure 3. Soybeans

(a) Non-parametric fit



(b) Slope profile



4.3. Asymmetries between futures and spot prices in corn and soybeans

Asymmetries between futures and spot prices, for the agricultural commodities of corn and soybeans, might result from storage costs, seasonality, hedging behavior, and logistical constraints (Zhu, 2021; Tonin et al., 2020). Storage costs might fluctuate and as a result demand for silo space might be higher before harvest. Pre-harvest and post-harvest dynamics can be a decisive factor. Before harvest, spot prices may rise due to tight supply, while futures prices reflect expected future supply. After harvest, spot prices drop due to increased supply, but futures may remain elevated if future demand is strong. Weather shocks and export bans can asymmetrically impact spot and futures prices.

Hedgers (farmers and processors) may cause temporary imbalances. If farmers hedge heavily, futures prices may be depressed relative to spot prices. If processors hedge aggressively, futures may rise faster than spot (Cheng & Xiong, 2014). If traders expect higher future production (due to farmers planting more corn), futures may rise less sharply than spot prices. Soybean oil and palm oil constitute the two largest vegetable oils. The strength and the pattern of the contemporaneous association between the two prices are behind the soybean-palm oil spread that determines whether switching from one vegetable oil to the other is beneficial. At the same time, traders watch the soybean-palm oil spread closely in commodity futures markets to exploit profit opportunities. The weak linkages are behind the wide fluctuations of the soybean-palm oil spread, which, in turn, justify hedging from soybean oil processors and might cause divergence between futures and spot prices (Fousekis, 2023).

Table 7. Asymmetry tests between futures prices and spot prices for Soybeans

a) Slopes at specific futures returns					
Quantile	1%	5%	10%	25%	
Estimated values	0.845	0.841	0.842	0.867	
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	
Quantile	50%	75%	90%	95%	99%
Estimated values	0.879	0.886	0.849	0.706	0.609
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
b) Sign asymmetry					
1%-99%	5%-95%	10%-90%	25%-75%		
0.236 (0.068)	0.135 (0.087)	-0.007 (0.978)	-0.019(0.859)		
c) Size asymmetry under negative returns					
50%-10%	50%-25%	50%-5%	50%-1%	25%-10%	
0.037 (0.782)	0.012(0.75)	0.038 (0.755)	0.034 (0.732)	0.025 (0.902)	
25%-5%	25%-1%	10%-5%	10%-1%	5%-1%	
0.026 (0.888)	0.022(0.898)	0.001 (0.925)	-0.003 (0.977)	-0.004(0.955)	
c) Size asymmetry under positive returns					
50%-75%	50%-90%	50%-95%	50%-99%	75%-90%	
-0.007 (0.952)	0.030(0.922)	0.173 (0.088)	0.270(0.059)	0.037(0.943)	
75%-95%	75%-99%	90%-95%	90%-99%	95%-99%	
0.180 (0.084)	0.277(0.059)	0.143(0.074)	0.240(0.028)	0.097(0.599)	

Note: In parentheses, the present study reports the p-values estimated after 3000 replications with the block bootstrap method by Politis and Romano (1994).

Transportation and logistical constraints widen when transportation bottlenecks (e.g., rail delays, port congestion) prevent arbitrage. Regional shortages can cause spot prices to diverge from futures (OIS Arvis et al., 2010). Lastly, corn and soybeans are used in the production of biofuel. Ethanol biofuel is made from corn by breaking down the kernel starch into sugar and then fermenting it into a liquid. Soybean oil is a major feedstock in the production of biodiesel. Biofuel demand, especially for ethanol, which consumes approximately 40% of U.S. corn, creates particular pricing dynamics between spot and futures markets (Carter et al., 2012). The impact is often asymmetric, meaning spot and futures prices don't move in lockstep. When ethanol demand surges (due to policy changes like higher Renewable Fuel Standard mandates or rising crude oil prices), spot corn prices can spike quickly because Ethanol plants compete directly with feed/food buyers for immediate supply. Short-term storage/ transport constraints prevent rapid adjustments (Peddyreddy, 2023). For example, in 2021-2022, high oil prices boosted ethanol demand, tightening near-term corn supply, and lifting spot prices faster than futures. In Tables 5, 6, and 7, the p-values were estimated after 3000 replications using Politis and Romano's block bootstrap method (1994). The present study performed robustness tests to check the validity of the estimation results. Lagged values of the spot and futures prices were introduced. The new estimates, except in the size of the coefficients, confirmed the initial results, namely, the sign of the coefficients and the asymmetries.

5. Discussion

According to the empirical results of the present work, for the commodities of corn and soybeans, there is evidence of asymmetric dependence in sign, namely, price crashes (booms) in the futures markets are transmitted with different intensity to spot prices as price booms (crashes) do.

The empirical findings of the study are in agreement with the findings of nonlinearities and asymmetries in the most recent studies by Dai et al. (2023), by Li and Chavas (2023), and by Mao et al. (2024). In addition, the evidence of symmetry for the hard red wheat case agrees with the findings by Dai et al. (2023). The work by Dai et al. (2023), for the commodities of soybeans, corn, wheat, and rice, revealed that the tail dependence structures for the four futures-spot pairs are distinct, and each exhibits a certain degree of asymmetry. On the other hand, there is no significant strength difference between the two risk spillover effects for wheat and rice. Li and Chavas (2023) suggested the presence of nonlinear cointegration relationships between futures and spot prices for the commodities examined, US soybean and corn. Mao et al. (2024) used price data for corn and soybeans in China, and their findings indicated asynchronous price bubbles between these two markets and nonlinear transmission effects between the futures and spot prices.

Asymmetries between futures and spot prices may signal a lack of perfect information in the market, which can lead to inefficiencies in price discovery (Theissen, 2016). Governments and regulatory bodies may need to implement mechanisms to improve transparency and information dissemination to ensure more accurate pricing. For example, regulators could enforce better reporting standards for market participants, especially in commodity markets where futures markets often serve as an early indicator of expected supply-demand imbalances.

Futures markets, quite often, are driven by speculation, leading to price divergences and asymmetries between futures and spot prices. This can distort the real-time supply and demand dynamics, particularly if speculators are influencing futures prices and, as a result, spot prices. Contango (futures price > spot price) or backwardation (futures price < spot price) could signal expectations of future scarcity or surplus. Speculative bubbles can form if futures prices are significantly disconnected from spot prices, especially if speculative activity becomes detached from fundamental factors (Mao et al., 2024). Governments may regulate speculative activity, particularly in markets prone to high volatility (e.g., oil, agricultural products). This could involve measures such as: i) position limits for large traders in futures markets to reduce the risk of excessive speculation, ii) margin requirements that limit leverage, ensuring that futures contracts are not used in excessively risky ways, and iii) market surveillance to detect signs of manipulation or unusual trading activity.

Futures contracts are used for hedging purposes by producers, consumers, and traders to mitigate the risk of price fluctuations (Lou, 2024). An imbalance between futures and spot prices can impact the effectiveness of hedging strategies (Norwood et al., 2021). Producers and consumers in commodity markets might use futures to lock prices for future delivery. If futures prices deviate too much from spot prices, it could signal risks to those who depend on futures for risk management. For example, a significant divergence between futures and spot prices could indicate that hedging costs are becoming more expensive or that risk management strategies might not align well with actual market conditions. Governments and regulators might focus on ensuring that futures markets remain useful and efficient tools for hedgers. This could involve: a) ensuring liquidity in the futures market to prevent large price swings that could discourage hedging, and b) monitoring and adjusting margin requirements or other risk management tools to keep hedging accessible for smaller producers or consumers.

Asymmetries in futures and spot prices can also have broader economic implications. A prolonged period of contango in commodity markets (corn or soybeans) could signal future price increases, which could spill over into inflation expectations. Increased food prices have inflationary effects due to their high participation in the consumer price index. Given the economic impact of futures prices on spot prices, one could expect an increase in the consumer price index (Evans et al., 2011). Futures prices often reflect expectations about future supply and demand conditions. If futures prices are much higher than spot prices, it may signal that market participants expect future shortages, which can influence inflation expectations. The mode and the structure of price linkages between futures and spot prices are something that domestic policy makers have to take into account in order to control prices. Central banks might use futures and spot price data to gauge future inflationary pressures and adjust monetary policy accordingly. Central banks and monetary authorities may need to account for futures market trends in their economic models and policy decisions. For example, suppose the futures market signals potential price increases in commodities like food or energy. In that case, central banks may take preemptive actions by adjusting interest rates or using other monetary tools.

In a globalized economy, futures and spot price asymmetries in one market can spill over into others, especially if countries rely heavily on imported commodities or have exposure to global futures markets (Dai et al., 2023). For example, suppose futures prices for a commodity (corn) are much higher than the spot price. In that case, it might signal future supply constraints, which could impact countries that depend heavily on that commodity. Countries with large import dependencies may find that futures price movements influence domestic inflation or cost-of-living adjustments. Governments in these countries may need to work on strategic reserves or adjust fiscal policy to buffer against future price hikes. Trade policy might also be influenced by futures-spot price asymmetries, especially when dealing with critical goods like energy, food, and metals.

European Union policy strategists may also utilize the empirical results of this work, namely the asymmetric dependence between futures and spot prices of corn and soybeans and the symmetric dependence in the commodity of hard red wheat. Integration and stability of prices within the European Union have been important for many years. European policy makers can suggest the release or withdrawal of commodity stocks (increase or decrease supply) and stabilize prices accordingly.

6. Conclusion

The motivation of the present study has been to examine for sign and size asymmetries spot and futures prices in the markets of agricultural commodities. This has been examined using daily data from the commodities of corn, hard red wheat and soybeans. A non-parametric analysis has been applied.

The analysis is performed in two stages. In the first stage, the regression fits and the local slopes for each pair are obtained. In stage two, statistical tests are utilized in order to evaluate formally if non-linearities are present as well as the presence of sign and size asymmetries.

The empirical results indicate that there are sign and size asymmetries between futures and spot prices in the agricultural commodities of corn and soybeans. These asymmetries might be the result of storage costs, seasonality, hedging behavior, and logistical constraints.

Future works on the subject may involve the explicit study of the Covid-19 effects on the sign and asymmetric dependence between futures and spot prices. One possible suggestion is to collect data on the spot and futures prices of the agricultural futures, before and after the pandemic, and subsequently obtain empirical results for these two separate periods. The statistical analysis will provide us with useful information regarding the economic impact of the coronavirus pandemic.

Supplementary Materials: Please refer to any additional supplementary material available online: online appendices, datasets, codes, etc.

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