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RELATIONSHIP BETWEEN SPOT AND FUTURES PRICES: THE CASE OF GLOBAL FOOD COMMODITIES

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ABSTRACT

Global debates about determining the direction of relationship between commodity futures and spot prices reflect the importance of this issue. Resolving the debate will guide different economic agents to make correct decisions. The aim of this paper is to empirically investigate the direction of relationship between food spot and futures prices using different methodologies so as to resolve the debate. In addition, it is important to know which market could cause price volatilities to the other market, and thus, addressing price volatilities in a correct way. The paper conducts linear and non-linear Granger causality tests along with cointegration and error correction model and concludes with mixed findings. Specifically, linear and nonlinear Granger causality tests found evidence that food futures prices cause food spot prices. This suggests that food futures markets lead the price discovery process, and hence, the direction of information flows goes from food futures markets to food spot markets, and accordingly, any price volatilities in futures markets lead to price volatilities in spot markets. In contrast, the cointegration and error correction model found evidence that food spot prices cause food futures prices. This suggests that food spot markets lead the price discovery process, and hence, the direction of information flows goes from food spot markets to food futures markets, and accordingly any price volatilities in food spot markets lead to price volatilities in futures markets. Based on these differences in the obtained results, the current paper suggests the cointegration and error correction model is preferable since it provides a more formal framework for examining the short-run dynamics and testing for the equilibrium relationship among economic variables. Special attention to alternative instruments, such as the implementation of a global virtual reserve, should be highlighted so as to minimize speculative attacks and avoid excessive spikes of prices in spot and futures markets. This implies the importance of adopting the possible protectionist measures by developing countries in order to hedge against the negative reflections of global food price volatility.

Key words: Food markets, futures prices, spot prices, causality tests, cointegration analysis

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INTRODUCTION

Determining the relationship between futures and spot prices and its trend still represents a debatable issue. It helps in revealing whether futures markets or spot markets lead price discovery process, and hence, determining which market dominates price movements. If the futures price causes the spot price, this means that any volatility in futures prices will lead to volatilities in spot prices. In contrast, if the spot price causes the futures price, this means that any volatilities in spot prices will lead to volatilities in futures prices [1,2]. Determining the direction of the relationship is important since production and consumption decisions depend on efficient price signals from the markets. Also, determining causality supports both producers and consumers to establish the most appropriate hedging strategy to be adopted [3,4]. Furthermore, it should support policymakers to know which market could cause price volatility to the other market, and hence helping them to direct their best efforts on regulating prices so as to avoid food crises. In addition, this enables policymakers to establish the most appropriate hedging strategies to be adopted so as to improve the macroeconomic policies through recognizing commodity prices as leading indicators of inflation [5,6].

Financial theories have interpreted the interaction between spot and futures prices without offering any information about the direction of causality between these prices. This has motivated studies to search empirically for the direction of causality.

In an attempt to empirically reveal the direction of relationship between food futures and spot prices, the current paper uses three different methodologies. Using different methodologies will provide the opportunity to make a comparison between results, and hence attempt to resolve the debate of this issue. The paper proceeds as follows. First, a literature review is presented. Second, the data and variables included in the analysis are described. Third, Granger causality tests followed by cointegration and error correction model (ECM) are conducted. Finally, conclusions and policy implications are interpreted.

LITERARURE REVIEW

Theoretically, the most common financial theories in interpreting an explicit relationship between futures and spot prices are the non-arbitrage theory (cost-of-carry model) and asset pricing theory. According to the non-arbitrage theory, futures price must hold the following condition in order to avoid arbitrage opportunities:

$$\mathbf{F_{t,T} = (1 + r_T)S_t - \left(C_{t,T} - K_T\right)} \qquad \mathbf{(1)}$$

where $F_{t,T}$ represents futures price of a commodity at time t for delivery at time t+T, S_t represents spot price at time t, r_T represents the risk-free T-period interest rate, $C_{t,T}$ represents the capitalized flow of marginal convenience yield[1] and K_T represents the per-

[1] Convenience yield is considered as a common term used in the theory of storage and many related pricing models. The term "yield" implies a return to the owner of inventory derived from the flow of services yielded by a unit of inventory over a given time period [9]. The concept of convenience yield captures the

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unit cost of physical storage. As a result, the cost-of-carry model emphasizes that the futures price should depend upon the spot price and cost of carrying or storing the underlying commodity from now until the delivery time.

Based on the non-arbitrage theory, the asset pricing theory establishes a relationship between futures price and expected future spot price based on information set I_t, $E_t(S_{t+T})$. Futures price is given by the following expression [7]:

$$\mathbf{F_{t,T} = E_t(S_{t+T}) - (R_T - r_T)P_t} \qquad (2)$$

where R_T represents the risk-adjusted discount rate, and $(R_T - r_T)$ represents the risk premium. In this case, the future price is a biased estimate of the future spot price because of the risk premium. More specifically, the future price should typically be lower than the expected future spot price because of the positive risk premium $(R_T > r_T)$ [7,8].

Although the financial theories indicate an explicit relationship between futures and spot prices, they do not provide any information about the direction of causality between these prices. As a result, some studies were motivated to search empirically for the direction of causality between these prices.

Determining whether futures or spot commodity markets lead the price discovery process, and hence, determining the direction of causality between futures and spot prices, constitutes a well-established analysis method in empirical finance, which has successfully been applied to a wide range of financial markets. Theoretically, Yang and Leatham [11] provide three interpretations for the argument that commodity futures markets are expected to lead the price discovery process; (i) transaction costs are typically lower in an active futures market than in a spot market, which provides a greater incentive to search more for better information, (ii) futures markets attract more speculation and these added speculations are expected to improve the amount of information reflected in the spot price, (iii) in processing the information, speculators must take into consideration the responses of all participants to the prices implied by any information, and hence, improving the rationality of market prices. In contrast, Garbade and Silber [12] conclude that the price discovery process in futures markets depend upon whether information flows is actually reflected first in changes in futures prices or in spot prices. Therefore, the direction of information flows between spot and futures prices ultimately becomes an empirical issue.

On one side of the debate, some studies investigate the price discovery process between agricultural spot and futures markets through testing the unbiasedness of the hypothesis that futures prices are an unbiased predictor of spot prices. For instance, Beck [13] shows that the hypothesis that futures prices are unbiased predictors of spot prices is a joint hypothesis such that markets are efficient and risk premiums are absent. He conducts cointegration techniques to test the efficiency and unbiasedness hypothesis in five

idea that there is an inherent benefit derived from the holding of inventories through time. For instance, in the event of large demand shocks for a commodity, having inventories on hand to sell at higher prices provides a different benefit from that of reducing future price volatility through hedging [7,10].

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commodity markets including Chicago Board of Trade (CBOT) corn and soybeans over the period (1966-1986). The results suggest that all five markets were sometimes inefficient but no market was inefficient always. Moreover, rejection of the unbiasedness hypothesis was nearly always caused by market inefficiency rather than the presence of the risk premium. Yang and Leatham [11] conduct cointegration analysis and error correction models to test the hypothesis of unbiasedness in U.S. wheat futures markets over the period (1993-1995). The results support their argument. McKenzie and Holt [14] examine markets' efficiency and unbiasedness in four agricultural futures markets (live cattle, hogs, corn, soybean meal) using cointegration and error correction models with GQARCH-in-mean processes over the period (1966- 2000). Their results suggest that futures markets are both efficient and unbiased in the long run.

On the other side of the debate, other studies have argued that cointegration between spot and futures prices is expected to be found for non-storable commodities but not for storable commodities. This could be due to a misspecification problem; that is, the exclusion of possible non-stationary elements of the cost of carrying, particularly, stochastic interest rates in the co-integration system. Their empirical results and their explanations may strengthen the argument that the futures pricing role does not serve well for the price discovery of commodity futures markets (see, for instance, Brenner and Kroner [15]; Zapata and Fortenbery [16]). Yang *et al*. [17] examine the price discovery process of futures markets for storable and non-storable agricultural commodities through testing the unbiasedness hypothesis using cointegration analysis over the period (1992-1998). Their results suggest cointegration for non-storable commodities, and hence, the usefulness of non-storable future markets in predicting future spot prices. In contrast, no cointegration has been found for storable commodities. They conclude that these results have several important implications for commodity production decision making, commodity hedging, and commodity price forecasting. Pederzoli and Torricelli [18] examine the predictive ability of futures prices on the underlying spot prices in corn spot and futures markets over the period (1998-2011) using cointegration and error correction models. They conclude that, although the results suggest no evidence of efficiency and unbiasedness, the futures corn price turns out to be the best predictor of the spot price if compared with the most used alternatives.

Chinn and Coibion [19] examine whether future prices are: (1), unbiased and/or (2), accurate predictors of future spot prices in agricultural, energy, precious and base metal markets over the period (1990-2012) using simple regression and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) tests. Their results suggest that there are significant differences in unbiasedness across market groups. These differences in unbiasedness reflect differences in forecasting ability. There is no evidence supporting the unbiasedness for precious and base metals and they are poor predictors of subsequent price changes. Energy and agricultural futures markets can generally be characterized as unbiased predictors of future spot prices. Moreover, there is little evidence that these differences reflect liquidity conditions across markets. Dimpfl *et al.* [20] examine the relationship between spot and futures prices of wheat, corn, soybeans, soybean meal, soybean oil, feed cattle, and lean hogs to test which markets lead price discovery process in these commodities. Using cointegration analysis over the period

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(1992-2014), they have found evidence that the prices of these commodities are almost uniquely formed in spot market.

Another group of studies investigates the impact of speculation in futures markets on spot price volatility. Peck [21] has theoretically argued that commodity futures markets could reduce price volatility by facilitating the markets for storage. Bohl and Stephan [22] investigate the impact of growing market shares of futures speculators on spot price volatility in six commodity markets including CBOT wheat, corn, and soybeans, over the period (1992-2008). Using AR-GARCH model, they have found no evidence that futures speculation impacted spot markets. Therefore, they have concluded that the financialization of commodity markets does not make them more volatile. Kim [23] conducts a similar model but investigate the impact in 14 agricultural and energy commodity markets over the period (1992-2012). The results suggest no evidence that futures speculators destabilize commodity spot markets[2].

Conversely, other studies have provided a theoretical explanation supporting the impact of futures speculation on spot price volatility using theoretical models. These studies have argued that once badly informed speculators trade in the commodity futures market to harness lower transaction costs, the benefits of these markets diminish. Stein [24] emphasizes that informed speculators can destabilize spot market for storable commodities. De Long *et al*. [25] have argued that the psychological beliefs of traders can move prices away from their fundamental value. Chari *et al.* [26] and Shalen [27] argue that trading in commodity futures markets could destabilize spot markets when there is information asymmetry in futures markets[3].

DATA

Regarding futures prices, the current paper is based on the prices of CBOT. CBOT is one of the most important global food futures markets. The time series data source of futures prices was obtained from the historical end-of-day dataset of the Chicago Mercantile Exchange Group (CME Data Mine). Regarding spot prices, the time series data source was obtained from the World Bank International Commodity Prices database. Particular focus has been directed to the analysis of food commodities (wheat, corn, and soybeans) because of their importance both globally and locally. First, globally, these commodities are considered the most important in terms of trading volume, especially in CBOT. Second, locally, especially for developing countries, any spikes in international prices will be reflected negatively on the local prices. The considered specific food commodities are U.S. No. 2 soft red winter wheat, No. 2 yellow corn and No. 1 yellow soybeans[4]. The time span of the analysis is from January, 2010 to December, 2018,

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[2] For further discussions, see for instance, Buyuksahin and Harris [4]; Aulerich *et al*. [28]; Brunetti *et al*. [29]

[3] For further discussions see, for instance, Knittel and Pindyck [30]; Sockin and Xiong [31]; Banerjee and Jagannathan [32]; Basak and Pavlova [33]; Cortazar *et al*. [34]

[4] A special focus has been given to these commodities as they are the most globally traded since they are considered as staple food, especially for developing countries

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resulting in 108 monthly observations for each of the three markets. All prices are in U.S. dollars per ton (US$/T).

Since the original analysis of the current paper focuses on the relationship between spot and futures prices of wheat, corn, and soybeans, a descriptive analysis of the relationship was initially performed.

Table 1 presents summary statistics for means and standard deviations of wheat, corn and soybeans spot and futures prices over the period (2010-2018). First, regarding means, wheat and soybeans markets exhibit strong backwardation—that is, the average spot price is higher than the average futures price. Specifically, the average spot price of wheat was 19.20$ higher per ton than the futures price while the average spot price of soybeans was 47.18$ higher per ton than the future price over the period. In contrast, for corn, the average future price is higher than the average spot price. Specifically, the average futures price of corn was 23.66$ higher per ton than the spot price over the period. Second, regarding standard deviations, as shown from the table, the spot price of wheat is more volatile than the future price. In contrast, the futures prices of corn and soybeans are more volatile than the spot prices[5].

The relationship between spot and futures prices is summarized graphically in figures (1-3). For the three markets, there is large price volatility over the entire period of the analysis. The volatility measure here is the standard deviation of prices for each month in the sample period. However, it is unclear whether volatilities in spot markets reflect volatilities in futures market or conversely. For instance regarding wheat, the monthly standard deviation for spot price in June 2012 was 1.3, while for futures price, it was 29.4. In the following month, the spot price was 51.9, while the futures price was 34.7. The monthly standard deviation for spot price in July 2018 was 0.6, while for futures price, it was 13.6. In the following month, spot price was 7.4, while the futures price was 2.07. Regarding corn, the monthly standard deviation for spot price in July 2013 was 13.3, while for futures price, it was 62.4. In the following month, the spot price was 28.8, while the futures price was 1.9. The monthly standard deviation for the spot price in July 2016 was 12.8, while for futures price, it was 8.4. In the following month, the spot price was 8.2, while the futures price was 11.4. The same pattern of these monthly changes in prices and standard deviations is noticed for soybeans as well.

[5] Mean measure is the average prices over the period. Volatility measure is the standard deviation of prices over the period

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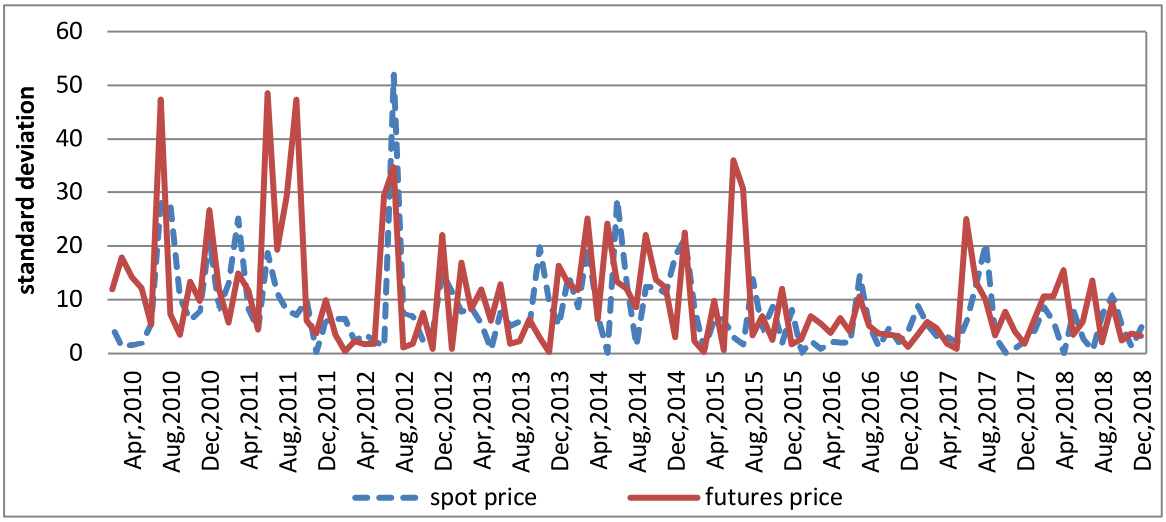

Figure 1: Monthly Volatility in Wheat Spot and Futures Prices, 2010–2018
Sources: World Bank International Commodity Prices Database, Chicago Mercantile Exchange Group end-of-day dataset (CME Data Mine), based on own authors' calculation

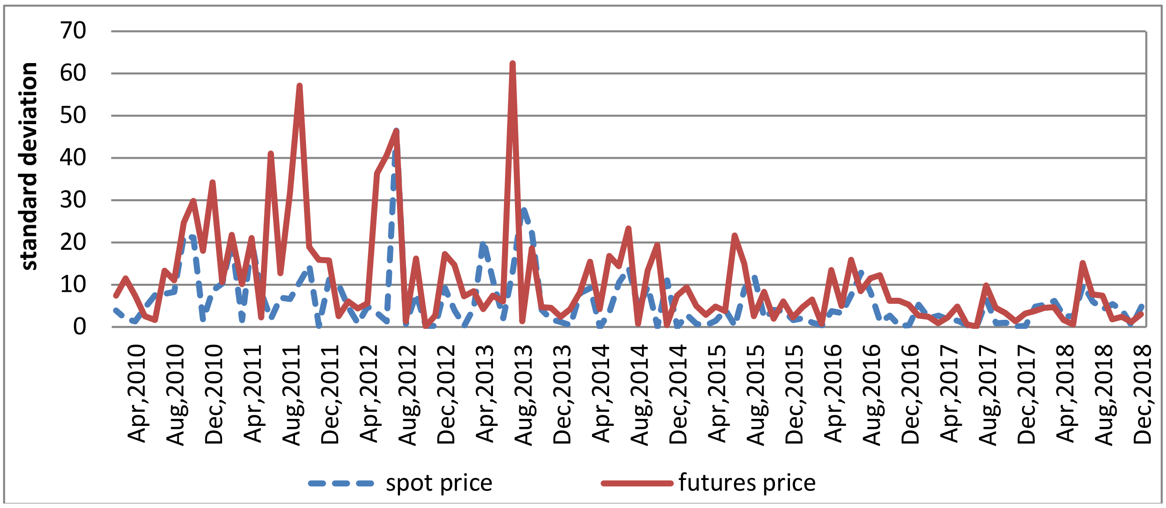

Figure 2: Monthly Volatility in Corn Spot and Futures Prices, 2010–2018
Sources: World Bank International Commodity Prices Database, Chicago Mercantile Exchange Group end-of-day dataset (CME Data Mine), based on own authors' calculation

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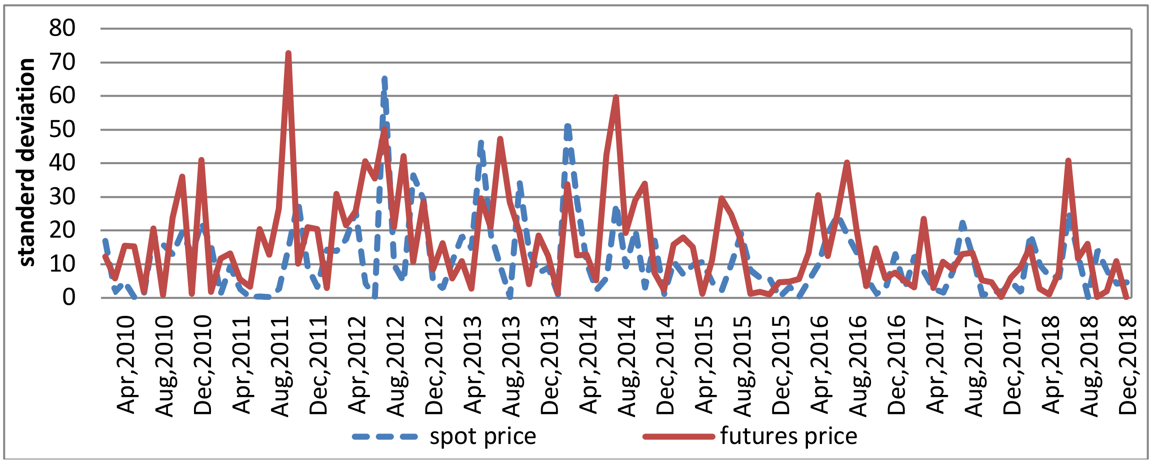

Figure 3: Monthly Volatility in Soybeans Spot and Futures Prices, 2010-2018
Sources: World Bank International Commodity Prices Database, Chicago Mercantile Exchange Group end-of-day dataset (CME Data Mine), based on own authors' calculation

ECONOMETRIC METHODOLOGY

Based on the debate about determining the direction of the relationship between commodity futures and spot prices, as discussed in the literature review section, this paper attempts to resolve this debate using three different methodologies. Empirical methodologies are differ in their statistical powers depending on the conditioning variables incorporated within the models, and hence, using different methodologies is useful in making comparisons among the results. Below, we describe each of these empirical approaches.

Granger Causality Tests

Granger causality tests are conducted with the aim of determining the direction of causality between spot and futures prices in food commodity markets. Specifically, these tests allow us to examine whether changes in futures prices lead to changes in spot prices or the changes in spot prices lead to changes in futures prices. Subsequently, the direction of information flows between food spot and futures markets could be determined, deciding on which market leads to the price discovery process.

Conducting causality tests requires the time series used to be stationary. Thus, stationarity assumption was checked first and tested using Augmented Dickey-Fuller (ADF) and Phillip – Perron (PP) tests.

Table 2 outlines the results of both ADF and PP tests. The results indicate that the logs of spot and future prices of the three commodities are not stationary for all significance levels. However, after taking the difference of log variables, they became stationary at 1 percent significance level for the three commodities. For spot volatility, it is clear that they are stationary at 10 percent significance level in corn commodity, and at 5 percent significance level in the other commodities. For futures volatility, it is clear that they are

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stationary at 5 percent significance level in corn commodity and at 1 percent significance level in the other commodities.

Linear Granger Causality Tests

Linear Granger causality test investigates whether futures price volatility causes spot price volatility or whether spot price volatility causes futures price volatility.

Let VS represent spot price volatility and VF represent futures price volatility. Linear Granger causality test probes whether futures volatility Granger-causes spot volatility (that is if volatility in spot market at time t is related to past volatility in futures market, conditional on past spot volatility) or whether spot volatility Granger-causes futures volatility. Specifically, the test estimates the following regression model for each commodity.

$$\mathbf{VS_t = \alpha_0 + \sum_{K=1}^{P} \beta_{1K} VS_{t-K} + \sum_{K=1}^{P} \beta_{2K} VF_{t-K} + \varepsilon_t} \qquad (3)$$

In this model, $\mathrm{VS_t}$ is the explained variable and it tests whether $\mathrm{VF_t}$ does not Granger-cause $\mathrm{VS_t}$. A similar model is conducted but in case of $\mathrm{VF_t}$ as the explained variable to test whether $\mathrm{VS_t}$ does not Granger-cause $\mathrm{VF_t}$.

Table 3 presents the results of linear Granger causality tests. The higher part of the table documents F-statistic for the null hypothesis that futures price volatility does not Granger-cause spot price volatility, while the lower part documents F-statistic for the null hypothesis that spot price volatility does not Granger-cause futures price volatility. As shown from the higher part, the null hypothesis is rejected at the 1 percent significance level for all of the three commodities. In contrast, the lower part of the table shows that the null hypothesis is not rejected for wheat and corn commodities but is rejected for soybeans commodity at the 5 percent significance level. The results generally suggest that futures price volatility Granger-cause spot price volatility.

Non-linear Granger Causality Tests

Although linear causality tests have high power in identifying linear causal links, their power against non-linear causal links might be low [35]. Non-linear dynamic links might arise when, for instance, allowing for heterogeneous market traders or different types of risk-averse agents in spot and futures markets. Taking into consideration that linear causality tests might overlook non-linear dynamic links between spot and futures prices, the paper involves non-linear (non-parametric) causality tests with the aim of determining the non-linear dynamic links between spot and futures prices.

Non-linear Granger causality tests proposed by Diks and Panchenko are conducted on spot and futures price volatility of each commodity so as to uncover potential non-linear dynamic links between food spot and futures markets [36]. The tests are applied using vector autoregressive (VAR) model. Specifically, compared with equation (3) where the null hypothesis is $H_0: VS_t \,\big|\, (VF_{t-k}, VS_{t-k})$, the non-linear null hypothesis become $H_0: VS_t \,\big|\, (VF_{t-k}, S_{t-k}) \sim VS_t \,\big|\, VS_{t-k}$.

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Table 4 shows the results of the non-linear Granger causality tests. The higher part of the table documents F-statistic for the null hypothesis that futures price volatility does not Granger-cause spot price volatility, while the lower part documents F-statistic for the null hypothesis that spot price volatility does not Granger-cause futures price volatility. As noticed from the higher part, the null hypothesis is rejected at the 1 percent significance level for all of the three commodities. The lower part of the table shows that the null hypothesis is not rejected for wheat and corn commodities but is rejected for soybeans commodity at the 5 percent significance level. Depending on the results of wheat and corn commodities, as they are considered the most important commodities that are traded in CBOT compared with soybeans commodity, it could be generally concluded that the results suggest that futures price volatility Granger-cause spot price volatility.

It can, therefore, be concluded that linear and non-linear Granger causality tests have found evidence that futures prices cause spot prices in food commodity markets. This suggests that food futures markets lead the price discovery process, and hence, the direction of information flows goes from food futures markets to food spot markets.

Cointegration and Error Correction Model

Markets' efficiency hypothesis suggests that futures prices equal expected future spot prices plus or minus a (constant or time-varying) risk premium, whereas futures prices are unbiased predictors of future spot prices only if markets are efficient and there is no risk premium. In other words, testing for unbiasedness of futures prices is equivalent to testing the joint hypothesis of efficiency and risk neutrality. Thus, this part investigates the direction of causality between spot and futures prices through examining the hypothesis of market unbiasedness and efficiency using the cointegration analysis. Specifically, it examines whether futures prices are an unbiased predictor of spot prices. The markets' unbiasedness and efficiency requires testing the joint hypothesis of α=0 (where α denotes the risk premium) and β=1 (where β denotes markets' efficiency) in the following regression equation [18]:

$$S_t - S_{t-k} = \alpha + \beta(F_{t-k} - S_{t-k}) + \varepsilon_t \qquad (4)$$

where S_t denotes spot prices at time t, S_{t-k} denotes spot prices at time t-k, F_{t-k} denotes futures prices at time t-k, and ε_t denotes the error term.

The current paper would agree with the paper of McKenzie and Holt who emphasize that testing the joint hypothesis does not allow distinguishing between the two concepts. Rejection of the joint null may be due to markets' inefficiency (β≠1), or to a constant risk premium even in the presence of markets' efficiency (α≠0 and β=1) or to a time-varying risk premium that rejected unbiasedness of futures prices [14]. Moreover, taking into consideration that markets may be efficient and unbiased in the long run but may present inefficiencies and pricing biases in the short run, two different types of econometric analyses are conducted. First, examining the long run unbiasedness and efficiency-based on cointegration analysis. Second, examining the short run unbiasedness and efficiency-based on an error correction model (ECM).

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Cointegration Analysis

According to the previous results of the ADF and PP tests which showed that the time series of spot and future prices were stationary at the 1 percent significance level for the three commodities, after taking the difference of logs, the cointegration analysis will be conducted using the difference of logs as price changes.

To check for cointegration of spot and futures prices, the Johansen test is conducted. The test estimates the following regression model:

$$\boldsymbol{S_t = \alpha + \beta F_{t-1}} + \varepsilon_t \qquad (\mathbf{5})$$

where: $\alpha \; and \; \beta$ denotes the cointegration parameters.

According to Akaike information criterion (AIC), the appropriate lag length for wheat commodity is lag 3, while the appropriate lag length for corn and soybeans commodities is lag 2. Taking into consideration the appropriate lag lengths and the constant in the cointegration relationship, the results presented in table 5 could be obtained.

The hypothesis of long run market efficiency requires α=0 and β=1. The results of The Johansen tests, which are presented in table 5, proves that there is a cointegration vector in the three commodities. in other words, there is a long-run relationship between spot and futures prices. Thus, markets' efficiency in the long run cannot be rejected.

Table 6 presents the results of examining the unbiasedness of futures price as a predictor of spot prices under the restrictions of α=0 and β=1 as stated in equation (5). The restrictions are tested separately and jointly. Regarding wheat and corn commodities, it is clear that the null $\alpha = 0$ is rejected, and hence, the possibility of a constant positive risk-premium could not be rejected. The joint null (α=0; β=1) is rejected also, and hence, this implies rejection of unbiasedness of the food commodity futures markets. Regarding soybeans commodity, the null α=0 is not rejected, and hence, the possibility of a constant positive risk-premium was rejected. The joint null (α=0; β=1) is not rejected also, and hence, this implies acceptance of unbiasedness of the food commodity futures markets.

Depending on the results of wheat and corn commodities, as they are considered the most important commodities, which are traded in CBOT compared with soybeans commodity, it can be generally concluded that cointegration tests have rejected the hypothesis of unbiasedness of food commodity futures markets. Specifically, cointegration tests have proved that food spot markets lead the price discovery process, and hence, the direction of information flows is from food spot markets to food futures markets. These findings are consistent with the results of previous studies (Yang *et al.* [17]; Pederzoli & Torricelli [18]; Dimpfl *et al.* [20]).

Error Correction Model

Error correction model is conducted to assess the short-run futures markets' efficiency. The model estimates the following equation:

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$$\Delta s_t = -\rho u_{t-1} + \beta \Delta F_{t-1} + \sum_{i=2}^{m} \beta_i \Delta F_{t-i} + \sum_{j=1}^{k} \psi_j \Delta s_{t-j} + \nu_t \qquad (6)$$

where: $\Delta s_t = s_t - s_{t-1}$, $\Delta F_{t-1} = F_{t-1} - F_{t-2}$, u_{t-1} is the lagged value of error correction term and ν_t is a white noise error term.

The model was estimated with the difference of the appropriate lag length of Δs_t and ΔF_{t-1}. Since the appropriate lag length for corn and soybeans commodities is 2, it will be 1 for the difference, while for wheat commodity, the appropriate lag length is 3 and hence, it will be 2 for the difference.

Table 7 presents the results of the ECM estimation. Regarding wheat and corn commodities, the coefficient ρ of u_{t-1} is significant while the coefficient β of $\Delta \boldsymbol{F}_{t-1}$ is not significant. This means that the futures price is not significantly affecting the spot price, a result which is contrary to the hypothesis of futures markets' efficiency. In contrast, regarding soybeans commodity, the coefficient ρ of u_{t-1} is not significant while the coefficient β of $\Delta \boldsymbol{F}_{t-1}$ is significant. This means that the futures price is significantly affecting the spot price, a result which is consistent with the hypothesis of futures markets' efficiency. The results regarding corn commodity are consistent with the results of previous studies (McKenzie and Holt [14]; Pederzoli & Torricelli [18]).

The accuracy of the model was checked to determine its validity. The two tests used for that purpose are the heteroscedasticity test and the residual autocorrelation test. The heteroscedasticity test has a null hypothesis of "No heteroscedasticity". The model is accurate if this null hypothesis is not rejected. The residual autocorrelations test has a null hypothesis of "No residual autocorrelations". The model is accurate if this null hypothesis is not rejected. Results regarding heteroscedasticity test are presented in table 8, while results regarding autocorrelations test are clarified through figures 4-6.

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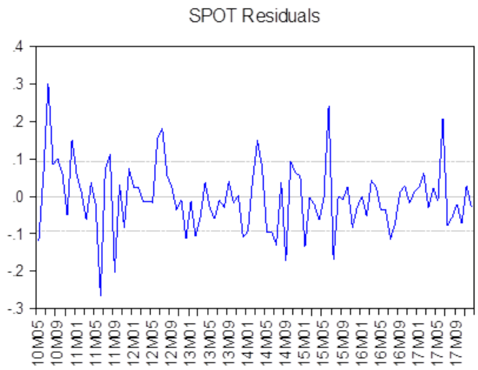

Figure 4: Wheat

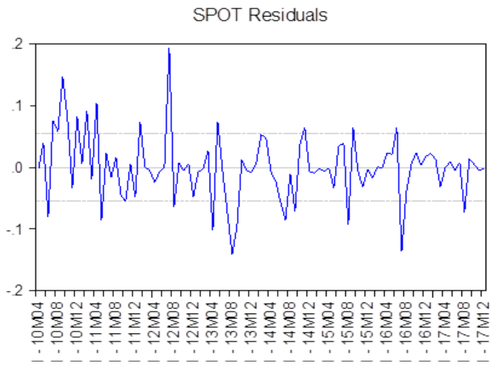

Figure 5: Corn

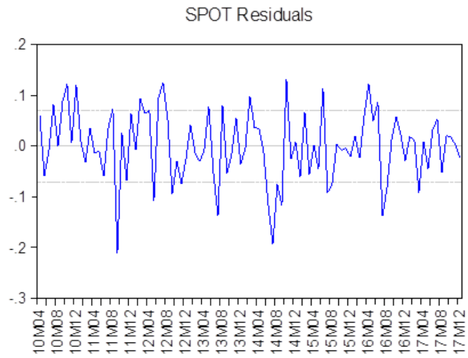

Figure 6: Soybeans

H_0: No residual autocorrelations up to lag h

Figures 4-6: (VEC) Residual Tests for Autocorrelations

Table 8 summarizes the results of test accuracy of the ECM. The results suggest that the null hypothesis is not rejected for all of the three commodities. This suggests that the model is correctly specified. Moreover, as shown in figures 4-6, the residuals of VEC is almost white noise, which supports the accuracy of the model. The test of serial autocorrelation supports that there is no autocorrelation for the residuals for all lags.
As such, it can be concluded that both the cointegration and ECM models have found the evidence that spot prices cause futures prices in major food commodity markets. This suggests that food spot markets lead the price discovery process, and hence, the direction of information flows is expected to go from food spot markets to food futures markets.

CONCLUSION

Financial theories in interpreting the relationship between spot and futures prices do not offer any information about the direction of causality between these prices. Therefore, the aim of the paper was to empirically investigate the direction of causality between spot and future prices of global food commodities (wheat, corn, soybeans). The paper has used three different empirical approaches in an attempt to resolve the debate of the direction of causality.

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Granger causality tests have found evidence that futures prices cause spot prices, and hence, this suggests that food commodity futures markets lead the price discovery process. In contrast, cointegration and error correction models have found evidence against the unbiasedness and efficiency of futures markets. Specifically, the tests suggest that futures prices are biased to spot prices, and hence, this proves that food commodity spot markets lead the price discovery process. These findings have, thus, indicated an important result that the direction of causality cannot be determined decisively. Accordingly, the current paper suggests the cointegration and error correction model is preferable since it provides a more formal framework for examining the short-run dynamics and testing for the equilibrium relationship among economic variables. Thus, it can be concluded that food spot prices cause food futures prices, and hence, any price volatilities in food spot markets lead to price volatilities in food future markets.

Based on the above conclusions, the paper highlights three relevant policy implications: (i) the regulations proposed on organizing global food markets in order to avoid price volatility, should be directed to both food spot and futures markets, (ii) alternative instruments, such as the implementation of a global virtual reserve, should be highlighted so as to minimize speculative attacks and avoid excessive spikes in prices of the spot and futures markets[6] (iii) Since developing countries, especially importing and low-income countries, depend on basic and traditional food commodities (such as wheat, corn and soybeans) as staple foods, they could be sensitive to any rise in global food prices that can negatively affect their local prices. Accordingly, these countries should use all possible protectionist measures in order to hedge against the negative reflections of global food price volatility.

[6] Speculative attacks and excessive spikes in prices of spot and futures markets could be a result of external factors impacts (such as bad weather and natural disasters). In this case, implementation of a global virtual reserve could cover the quantity demanded of commodities without affecting the prices in the markets. For further discussions regarding this point see, for instance, Braun and Torero [37]; Braun and Torero [38]

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May 2020
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Table 1: Means and Standard Deviations, January 2010 to December 2018

commodity	mean		standard deviation	
	spot	futures	spot	futures
wheat	233.07	213.86	50.11	48.99
corn	208.46	231.64	59.86	72.14
soybeans	466.86	419.76	82.73	83.66

Sources: World Bank International Commodity Prices Database, Chicago Mercantile Exchange Group end-of-day dataset (CME Data Mine), Based on own calculation

Table 2: Results of Augmented Dickey-fuller (ADF) and Phillips – Perron (PP) Tests

variables	*Wheat*		*Corn*		*Soybeans*	
	ADF	PP	ADF	PP	ADF	PP
Log spot price	1.5	1.7	0.6	1.0	0.7	1.0
Log futures price	3.2	2.4	1.4	1.4	1.9	1.9
difference of log spot price	54.3***	54.0***	44.2***	44.4***	52.6***	52.2***
difference of log futures price	73.3***	74.6***	71.2***	70.9***	65.7***	65.7***
Spot volatility	7.7**	7.7**	3.9*	4.9*	7.4**	8.9**
Futures volatility	12.6***	13.0***	8.9**	8.6**	13.9***	14.3***

*10%, **5%, ***1% significance. T-statistic reported.
Note: The ADF tests include an intercept. The appropriate lag lengths were selected according to the Schwartz Bayesian criterion

Table 3: Results of Linear Granger Causality Tests, January 2010 to December 2018

Lags	Ho : futures price volatility does not Granger-cause spot price volatility		
	Wheat	Corn	Soybeans
1	50.6***	59.5***	10.0***
2	24.9***	26.7***	17.4***
Lags	**Ho : spot price volatility does not Granger-cause futures price volatility**		
	Wheat	Corn	Soybeans
1	0.69	1.2	5.8**
2	0.3	0.16	4.1**

*10%, **5%, ***1% significance. Granger causality F-statistic documented

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Volume 20 No. 3 May 2020
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ISSN 1684 5374

Table 4: Results of Non-linear Granger Causality Tests, January 2010 to December 2018

Lags	H_o : futures price volatility does not Granger-cause spot price volatility		
	Wheat	Corn	Soybeans
1	50.6***	59.5***	10.0***
2	49.8***	57.4***	34.9***
Lags	**H_o : spot price volatility does not Granger-cause futures price volatility**		
	Wheat	Corn	Soybeans
1	0.7	1.2	5.8**
2	0.6	0.3	8.3**

* 10%, ** 5%, *** 1% significance. Granger causality F-statistic documented

Table 5: Results of Johansen Trace and the Maximal Eigenvalue Tests, January 2010 to December 2018

Rank	Eigen value	Trace test	p-value	Max test	p-value
Wheat					
r=0	0.16	20.9	0.0069	18.2	0.0112
r=1	0.03	2.7	0.1019	2.7	0.1019
Corn					
r=0	0.15	20.2	0.0092	17.5	0.0151
r=1	0.03	2.7	0.1005	2.7	0.1005
Soybeans					
r=0	0.23	30	0.0002	27.3	0.0003
r=1	0.03	2.7	0.1004	2.7	0.1004

Table 6: Results of Examining the Unbiasedness under the Restrictions of α=0 and β=1

	Restrictions	Test statistic	P-value
Wheat	$\alpha = 0$	9.25	0.0024
	$\beta = 1;\ \alpha = 0$	9.25	0.0024
Corn	$\alpha = 0$	7.38	0.0066
	$\beta = 1;\ \alpha = 0$	7.38	0.0066
Soybeans	$\alpha = 0$	0.49	0.4829
	$\beta = 1;\ \alpha = 0$	0.49	0.4829

ajfand SCHOLARLY, PEER REVIEWED
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Volume 20 No. 3
May 2020
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Table 7: Results of the ECM Estimation

		Coefficients	Test statistics	P-value
Wheat	u_{t-1}	-0.52	-3.21	0.001
	ΔF_{t-1}	0.08	0.58	0.603
	ΔF_{t-2}	-0.14	-1.34	0.180
	Δs_{t-1}	0.023	0.14	0.888
	Δs_{t-2}	0.096	0.16	0.873
	Log likelihood		162.97	
	AIC		-2.99	
	SC		-2.84	
Corn	u_{t-1}	-0.44	-3.77	0.0002
	ΔF_{t-1}	0.13	1.54	0.1236
	Δs_{t-1}	-0.01	-0.15	0.8808
	Log likelihood	183.12		
	AIC	-3.38		
	SC	-3.28		
Soybeans	u_{t-1}	-0.071	-0.83	0.4065
	ΔF_{t-1}	0.316	4.38	0.0001
	Δs_{t-1}	-0.032	-0.34	0.7339
	Log likelihood	196.48		
	AIC	-3.63		
	SC	-3.53		

Table 8: Results of the Heteroscedasticity Test

	P-value
Wheat	0.4605
Corn	0.4821
Soybeans	0.9745

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Volume 20 No. 3
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