Agricultural Commodity Price Spikes since 2006:
A New Look at the Efficiency of U.S. Futures Markets

Velmurugan P. Shanmugam
Assistant Professor
Department of Commerce
School of Management
Pondicherry University
Puducherry 605014
E-mail: vshanmugan@astate.edu

Bill Hu
Assistant Professor of Finance
College of Business
Arkansas State University
State University, AR 72467
E-Mail: xhu@astate.edu

Cheng-Huei Chiao
Assistant Professor
Craig School of Business
Missouri Western State University
St. Joseph, MO 64507
E-Mail: cchiao@missouriwestern.edu

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Corresponding author: Bill Hu, Phone: (870)9722280, Email: xhu@astate.edu
Velmurugan P. Shanmugam is a visiting Fulbright-Nehru Postdoctoral Research Fellow at Arkansas State University. All errors remain our own.

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Abstract

The U.S. agricultural commodities market has experienced unusual price spikes since 2006. We investigate the interrelationship and direction of information flows between spot and futures prices of 12 agricultural commodities, for a whole period of 1995 to 2011 and two sub-periods, before 2006 and since 2006. We find that cointegration and long-term relationship exist significantly in spot and futures returns for all the commodities, an indication that the commodity futures market is efficient in providing hedge against price risk in respective commodities. The causality tests indicate that futures prices lead changes in spot prices and have stronger ability to predict spot prices in Wheat (CBOT), Corn, Soybean oil, Cotton, Live cattle, Feeder cattle, Cocoa, Sugar, and Coffee. For other commodities, both spot and futures prices are equally responsible for the price discovery process due to information flow from both sides. Finally we document volatility persistence and clustering throughout our study period.

Keywords: Commodity futures; Price spikes; Market efficiency.

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1. Introduction

Since 2006, the U.S. agricultural commodity futures markets have witnessed massive escalations in the number of contracts traded along with price spikes and price distortions, questioning the efficiency of these markets as a device for price discovery and risk reduction. The turbulence in commodities market has off late been disturbing the minds of economists (Stoll & Whaley, 2009, Kaufman, 2010). Many hold the view that the U.S. agricultural commodity futures markets do not perform the role of hedging, causing destabilization of spot prices. Such opinions at times have also been shared by government agencies, believing that the agricultural futures market is not efficient (UNCTAD task force, 2011, United States Senate, 2009). As pointed out in the Third World Network, U.S. commodity futures contracts were useful and affordable as long as futures prices and cash (spot) market prices converge as the contract expiration day approaches. Futures prices help commodities traders to set a benchmark price in the cash market. However, as commodity prices have become more volatile and the convergence less predictable since 2006, has the futures market lost its price discovery and risk management functions?

Lack of convergence between cash and futures contract prices for agricultural commodities may increase the risk of futures-price-based forward contracts for the grain buyers that offer them. These developments are of particular concern to traditional commercial interests — such as grain and oilseed elevators, food processors, grain merchandisers, and other participants in the marketing chain for agricultural products — who are likely to see their costs of operations rise with any decline in the efficiency of the futures market. Agricultural producers are equally concerned because, as grain and oilseed buyers refrain from offering forward contracts, producers are increasingly unable to take advantage of the current high prices (Schnepf, 2008). Therefore there is an apprehension that the U.S agricultural futures market is no longer efficient.

The co-integration between the spot price and futures price is a necessary condition for market efficiency. It ensures that there exists a long-run equilibrium relationship between the two series. The absence of co-integration implies that futures prices provide little information about movement in cash price. Such a futures market is not very efficient (Ali & Gupta, 2011). In case of long term relationship between the spot and futures prices, a change in one variable permanently changes the equilibrium level of another variable. Hence, if the two variables are co-integrated, there exists a long term relationship between them. Under the hypothesis of market efficiency, the market price should fully reflect available information so that there is no strategy from which traders can profit consistently by speculating in the forward or futures market on future levels of the spot price (Lai & Lai, 1991).

In this study, we take a new look at the efficiency of the agricultural commodity market in context of the recent market turmoil. If a market is efficient, Fama (1970) states that prices should always reflect all available information. The only price changes that can occur are the ones that result from new information. An effective futures market should send price signals to the spot market immediately thereby eliminating the chances of making profit from price difference between markets. Therefore both the spot and the futures market fully reflect the available information. Risk reduction or price discovery function of the futures market rests on the fact that the futures market provides a good forecast for the subsequent cash price at maturity. At maturity, the future prices become equivalent to cash prices except for some transaction costs and quality premium. If future prices are a reflection of future demand and supply conditions of the market, they may influence inventory holdings. If futures prices are falling, it indicates that either future demand would fall or future supply would ease. Traders may reduce inventory stock and eventually spot prices decline.

The price discovery role of futures markets assumes that futures markets lead spot markets. However, as sustained by Garbade and Silber (1983), the price discovery function of futures markets hinges on whether new information is actually reflected first in changes in futures markets or in spot markets. Hence, after exploring the existence of co-integration between futures and spot prices, it is imperative to test the causality to assess the direction of relationship (Malliaris & Urrutia, 1998, Silvapulle & Moosa, 1999, Bryant, *et al.*, 2006). These tests allow us to examine the lead-lag direction between changes in the price of futures contracts and changes in spot prices.

Another concern is whether the huge inflow of funds into the agricultural commodity market contributed to the increased volatility in the underlying assets since 2006. OECD (2011) reports that variations in prices become problematic when they are large and cannot be anticipated and, as a result, create a level of uncertainty which increases risks for producers, traders, consumers and governments and may lead to sub-optimal decisions. Although the period since 2006 has been one of extraordinary volatility, there is disagreement about the role of financial speculation as a driver of agricultural commodity price increases and volatility. While high volatility may reduce the hedging effectiveness, speculators may get abnormal royalties leading to ineffectiveness of the market. The U.K. department of environment, food and rural affairs in its report on speculation and food price spikes (2010) has pointed out that greater uncertainty limits opportunities for producers to access credit markets and tends to result in the adoption of low risk production technologies at the expense of innovation and entrepreneurship. The FAO (2009) indicates that high volatility increases the cost of standard price risk management strategies. Further the FAO reported that 2008 agricultural price spikes was accompanied by much higher levels of price volatility in the markets for agricultural commodities such as livestock, vegetable oil and sugar.

The study of market efficiency, causal relationship, and volatility in agricultural commodity futures markets is important to both the government and the producers/marketers. From the government policy point of view, an efficient market means a better alternative to market interventions such as imposing price stabilization policies. For processors and marketers, it provides a reliable forecast of spot prices in the future and allows them to effectively manage risks in the production or marketing process. It is also the interest of international market participants. As U.S. futures markets are matured and established markets unlike agricultural futures markets of countries like China and India, which are in the nascent stage, the efficiency of the U.S. agricultural futures markets are looked upon seriously by growing markets. Hence, this study proceeds with the objective of assessing the cointegration, causal relationship, and volatility of select U.S. agricultural commodity market, with focus on the period of price distortions and to provide policy suggestions based on empirical analysis.

Although recent price spikes in U.S. agricultural commodities have attracted attention from international economists, studies on the efficiency, causal relationships, and volatility of the market in the background of present price distortions, are rare. In addition, economists have studied the emerging lack of convergence between cash and futures prices and have yet to identify any significant causal factor (Irwin, Garcia, &Good, 2007). Most of the existing studies concerning price spikes have been focused either on regulatory requirements, index investments, volatility, and excess speculation. Very few studies have touched upon the efficiency aspect of the agricultural futures market. In such circumstances, a comprehensive study of the dynamics of the efficiency of U.S. agricultural futures markets assumes particular importance. Therefore, the first and foremost contribution of our paper is to document the market efficiency using tests of co-integration, causation, and volatility with Johansen, Granger, and GARCH (1, 1) framework.

2. Literature Review and Hypotheses

The agricultural futures markets serve as a central exchange for both domestic and international information and thus function as a primary mechanism for price discovery and reduce price variability through hedging activities. For many physical commodities, especially agricultural commodities, participants in the cash market base spot and forward prices on the futures prices that are "discovered" in the competitive, open auction market of a futures exchange. The price discovery role is considered an important economic purpose of futures markets (U.S. CFTC, 2011)**.** Regional and local grain elevators rely on futures commodity exchanges for hedging grain purchases and generally set their grain bid prices at a discount to a nearby futures contract in areas of surplus production, or at a premium in deficit production areas. As a result, cash prices and futures contract prices are strongly linked and reflect much of the same information about market conditions (Schnepf, 2008). The co-movement in spot and futures prices provides the theoretical support for hedging, so losses in long futures positions can be offset by gains in short underlying spot market positions, or vice versa (Hull, 2009).

Even though there is abundant research in worldwide commodity futures market in the recent years, there are only few studies focusing on the efficiency & interrelationship between the spot and futures in the U.S agriculture commodity market. Particularly, very few studies used econometric models to study the turbulent period in U.S. agricultural commodities. In addition, existing studies have mainly concentrated on co-integration and causality from the perspective of the impact of fundamental aspects affecting the market, such as biofuel of the U.S. agricultural commodities market. Furthermore, these studies have also differed in terms of the period of the study, frequency of the data used, and commodity products considered for research. Studies that focus to identify the reasons for recent price distortions in the market mostly constrain themselves to check the reason for excess speculation and the impact of commodity index trading in the agriculture futures market. The main literature findings of the recent research on U.S. agricultural commodity market summarized below from the year 1998 to 2011 provide a mixture of aspects highlighted above.

Several studies document market inefficiencies and speculations in commodities. Natanelov *et al*. (2011) find inadequate co-movements of agricultural commodity futures prices and crude oil. However, an analysis of the sub-sample 2006-2007 period reveals that soybean and corn prices are cointegrated with crude oil. The UNCTAD task force on systemic issues and economic cooperation (2011) studies the impact of financialization of commodity futures trading in the background of strong and sustained increase in the primary commodity prices between 2002 and 2008. The study identifies that both the surge in prices and the subsequent sharp corrections affect all major commodity categories (agri and non-agri). The paper calls for better regulation of commodity futures markets and direct interventions in case of destabilizing speculation. Reddy (2005) investigate the determinants that affect the daily returns and volatility in returns of CBOT (Chicago Board of Trade) soybean futures contracts and estimate their effects. The study finds that there is strong evidence of daily, monthly, yearly and volume effects. McKenzie and Holt (2002) analyze the market efficiency in four agricultural commodity futures markets - live cattle, hogs, corn, and soybean meal - using cointegration and error correction models within an ARCH framework. Results indicate each market is unbiased in the long run, although cattle, hogs and corn futures markets exhibit short-run inefficiencies and pricing biases. Results also suggest short-run time-varying risk premiums in cattle and hog futures markets.

In contrast to the market inefficiency literature, many papers argue that the futures market quickly incorporates new information and is thus efficient. Yang and Leatham (1998) find that there is little possibility existing to make speculative profits across U.S. grain markets in the long run and that the unsystematic risk across the grain markets can be reduced by diversified investment portfolios. Stoll and Whaley (2009) study the role of commodity index investing in agriculture futures market. They conclude that commodity index investing is not speculation and it does not cause futures prices to change. Baldi, Vandone, and Peri (2011) investigate the long-run relationship between weekly spot and futures prices for corn for the period January 2004 to September 2006. They conclude that futures markets react more quickly to new or unexpected information than the underlying spot market. Bozic (2011) examines the price discovery, volatility spillovers and adequacy of speculation in cheese spot and futures markets. Bozic finds strong evidence against the hypothesis that excessive speculation is increasing the conditional variance of futures prices. Hernandez and Torero (2010) apply both linear and non-parametric Granger causality tests on the price series of corn, soybean, and wheat to test empirically the direction of information flows between spot and futures prices. They find that price changes in futures markets lead price changes in spot markets more often than the reverse. The study also recommends for a global virtual reserve to prevent disproportionate spikes in grain spot prices.

Although there is considerable amount of work done on the U.S. agricultural commodities market in recent years, none of the studies have concentrated on a comprehensive study on checking the efficiency, causal relationship and volatility aspects between spot and futures prices during period of serious price spikes and distortions. In such circumstances, this study carries a significant importance to check whether U.S. agricultural commodities futures market is efficient in discovering price and minimizing risk with the primary hypothesis that the futures market is not efficient in the sense that there is high level of volatility, absence of long run co-integration relationship and causal relationship among U.S. spot and futures agriculture commodities, since 2006.

3. Data

We study 12 agricultural commodities from all categories which are included in the CFTC COT Supplemental report. Corn, soybeans, wheat, and soybean oil on the CBOT; wheat on the KCBOT; cotton no. 2, coffee C, sugar no. 11, and cocoa on the New York Board of Trade; and live cattle, lean hogs, and feeder cattle on the CME, were taken-up for the study. For examining the efficiency of the futures market and the interdependence, alternatively known as lead-lag relationship, between the underlying spot and futures market of the agricultural commodity sector, the basic data used in this study consist of daily closing prices of the near-month futures contract of the selected (12) agricultural commodities, and their respective spot prices. Since contracts with different maturities are traded every day, the nearby contract is generally the most liquid contract (Crain & Lee, 1996), we retrieve the data from Data Stream for a period of 17 years, starting from Jan-1995 to Nov-2011, for all the commodities except lean hogs, for which the data period is Mar-2002 to Nov-2011, depending on the availability of trading information. Daily return on all the commodities, both in spot and futures market, is the first difference in the log of commodity prices, such that $R_{m,t} = ln(P_{m,t}) - ln(P_{m,t-1})$, where P represents the daily price information of the respective commodities on day t and m represents either the spot market (s) or the futures market (f).

4. Methodology

We first calculate the mean for the price series and adjusted for inflation, on all the 12 agricultural commodities to test the difference in means, in percentage terms, of spot and futures price for each commodity for the overall time period 1995-2011 and two sub-periods, 1995-2005 and 2006-2011, respectively. We also adjust the commodity prices by inflation using the U.S. consumer price index. Since a unit root test is a precondition of co-integration and causality analysis (Ali and Gupta, 2011), next, we conduct unit root tests using autoregressive model to determine whether the returns in both the spot and the futures markets are non-stationary or not. Most of the financial asset price data are non-stationary and typically exhibit a very well-known financial property called random walk, which can be identified through stationarity tests. Stationarity tests are important because regressing one non-stationary series on another may produces spurious results (Mukerjee, 2011). It is also important to establish the number of unit roots that a series contains when testing for co-integration (McKenzie and Holt, 2002). Therefore we apply Augmented Dickey-Fuller (ADF) and non-parametric Phillips-Perron (PP) unit-root tests to both the spot and the futures returns of all the 12 agricultural commodities to determine whether these two time series variables are non-stationary or not. Specifically, we use the following regression equation (Ali and Gupta, 2011):

$$\Delta X_t = b_0 X_{t-1} + \sum_{i=1}^{T} b_i \Delta X_{t-i} + \varepsilon_t \text{ ------------------------------ (1)}$$

where X_t represents the base level of the variables. The null hypothesis of non-stationarity is $b_0 = 0$. If the null hypothesis cannot be rejected at the base level of the series but rejected at the first difference of the series, the series is stationary at the first difference level or I(1). The ADF tests include a constant and the appropriate lag length is selected according to the Aikaike Information Criterion (AIC). Both the log of spot and futures prices of each commodity are I(1).

After establishing the existence of stationarity of the time series data, we proceed with the testing for the existence of long-run equilibrium relationship between the spot and futures prices. The literature survey indicates that several recent studies on the efficiency of the futures market have emphasized the importance of co-integration to support the efficiency of the futures market (Wang and Ke, 2005, Ali and Gupta, 2011). The presence of co-integration ensures long term relationship between spot and futures prices whereas the absence of co-integration shows spot and futures prices drift apart without bound so that the futures price provides little information about the movement of the cash price. We use the Johansen's co-integration tests to assess the long-run relationship among spot and futures prices. Assuming an n-dimensional vector X_t with integration of order I(1), the Johansen's co-integration test estimates a vector autoregressive model. Johansen and Juselius (1990) further improve the model by incorporating an error correction depicted as follows:

$$X_t = \mu + \sum_{i=1}^{p} A_i X_{t-i} + \varepsilon_t \text{------------------------} (2)$$

$$\Delta X_t = \mu + \prod X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \varepsilon_t \text{-----------------} (3)$$

where

$$\prod = \sum_{i=1}^{p} A_i - I \text{ and } \Gamma_i = -\sum_{j=i+1}^{p} A_j$$

where X_t is an n x 1 vector of the *I(1)* variables representing spot (S_t) and futures (F_{t-n}) prices, respectively. μ is a deterministic component which may include a linear trend term, an intercept term, or both. Δ denotes the first difference operator. p is lag length based on the Hannan-Quinn criterion. ε_t is a random error term. If the coefficient matrix Π has reduced rank $r<n$, there exist nxr matrices α and β each with rank r such that $\Pi = \alpha\beta'$ and $\beta' X_t$ is stationary. r is the number of cointegrating relationships. The elements of α are known as the adjustment parameters in the vector error correction model and each column of β is a cointegrating vector. It can be shown that for a given r, the maximum likelihood estimator of β defines the combination of X_{t-1} that yields the r largest canonical correlations of ΔX_t with X_{t-1} after correcting for lagged differences and deterministic variables when present (IMF, 2007). We assume that the cointegrating equation (3) follows linear deterministic trends with a constant intercept. The residual vectors of the above model construct two likelihood ratio tests, namely, the trace test and the maximal eigenvalue test. The trace statistic, J_{trace}, tests the null hypothesis of r cointegrating relations against the alternative of the n cointegrating relations. The maximum eigenvalue statistic , J_{max}, tests the null hypothesis of r conintegrating relations against the alternative of r +1 cointegrating relations. The Johansen likelihood ratio test statistics, J_{trace} and J_{max}, for the null hypothesis that there are at most r cointegrating vectors are given by:

$$J_{trace} = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i) ----------------(4)$$

$$J_{max} = -T \ln(1-\hat{\lambda}_{r+1}) ------------------(5)$$

where T is the sample size and $\hat{\lambda}_i$ is the i^{th} largest canonical correlation. In our test for efficiency of futures market, the null hypothesis should be tested for r = 0 and r = 1. If r = 0 cannot be rejected, we will conclude that there is no cointegration. On the other hand, if r = 0 is rejected, and r = 1 cannot be rejected, we will conclude that there is a cointegration relationship.

We use the linear Granger causality tests over the entire sample period, as well as on sample sub-periods, to analyze the direction and causal relations between futures and spot prices of major agricultural commodities. The linear Granger causality test examines whether past values of one variable can help explain current values of a second variable, conditional on past values of the second variable. Intuitively, it determines whether past values of the first variable contain additional information on the current value of the second variable that is not contained in the past values of the later. If so, the first variable is said to Granger-cause the second variable. We use daily spot return ($R_{s,t}$) and futures return ($R_{f,t}$) because the returns of spot and futures prices are stationary for all the commodities.[1] We evaluate whether futures returns Granger-cause spot returns, whether spot returns Granger-cause futures returns, or both (Hernandez and Torero, 2010). More specifically, we estimate the following regression model for each commodity to analyze the relationship between $R_{s,t}$ and p lagged values of $R_{s,t}$ and $R_{f,t}$

$$R_{s,t} = a_0 + \sum_{k=1}^{p} a_{1k}R_{s,t-k} + \sum_{k=1}^{p} a_{2k}R_{f,t-k} + e_t \quad (6)$$

$$R_{f,t} = a_0 + \sum_{k=1}^{p} a_{1k}R_{f,t-k} + \sum_{k=1}^{p} a_{2k}R_{s,t-k} + e_t \quad (7)$$

We use the F-test to examine the causal relationships between spot and futures returns. The F-statistic for the null hypothesis that the lagged coefficient of $R_{f,t}$ are equal to zero tests whether $R_{f,t}$ Granger-causes $R_{s,t}$ or not. Intuitively, we test whether past futures returns contain additional information on the current spot return. Conversely, $R_{f,t}$ is the dependent variable to test whether $R_{s,t}$ Granger-causes $R_{f,t}$. The critical aspect here is the choice of lags. Insufficient lags yield incorrect test statistics, while too many lags reduce the power of the test. Hence we use Akaike Information Criteria (AIC) to determine the lag structure within each commodity.

[1] The stationarity test results are available upon request.

Lastly, we use the generalized auotregressive conditional heteroscedasticity (GARCH) model to determine the impact of futures on spot price volatility. As simple tests for changes in unconditional variance may be inadequate, researchers (Yang, Balyeat, and Leatham (2005)) have adopted the GARCH model to effectively measure volatility clustering in assets returns. Bollerslev (1986) extends the Engle (1982) ARCH model to the GARCH model which permits for more flexible lag structures. This model suggests that the conditional variance of returns is a linear function of lagged conditional variance terms and past squared error terms. The ARCH group of models has later found extensive use in characterizing time-varying financial market volatility (Ahmad, Shah and Shah, 2010). The ARCH regression model is defined as follows:

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon^2_{t-i}$$

The GARCH (p, q) model (Bollerslev, 1986) is the extension of ARCH model. It is based on the assumption that forecasts of variance changing in time depend on the lagged variance of the asset. An unexpected increase or decrease in the return at time *t* will generate an increase in the expected variability in the next period. By adding one more term to the ARCH specification i.e. $\sum_{i=1}^{q} \beta_i \, \sigma^2_{t-1}$ we get the GARCH model. The GARCH (p, q) model is given by:

$$R_{s,t} = \gamma R_{f,t} + \varepsilon_t \text{ - } (8)$$

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon^2_{t-i} + \sum_{i=1}^{q} \beta_i \, \sigma^2_{t-1} \text{ - - - - - - - } (9)$$

where σ^2_t is conditional variance term for the period t. α_i represents the news coefficient and β_i represents a persistence coefficient. ε^2_{t-i} is an ARCH term and σ^2_{t-1} is a GARCH term. For a GARCH model to be well specified, it is necessary that both α_i and β_i are non-negative. $\alpha_i \geq 0$ and $\beta_i \geq 0$ guarantee that the conditional variance is always positive. Under the GARCH (p, q) model the conditional variance depends on the squared residuals in the previous p periods and the conditional variance in the previous q periods. The order of p and q used in this paper is (1, 1) on the basis of the values of Akaike Information Criteria. In the parenthesis (1, 1), the first term refers to ARCH term and the second term to the GARCH term.

5. Results and Discussion

5.1 Analysis of descriptive statistics

The results and discussion will simultaneously concentrate on the overall period of study and sub-periods. Table 1 reports the mean spot and futures prices for the full period and the two sub-periods. We find that there is significant increase in prices for all commodities for the 2006-2011 period relative to the 1995-2005 period. The price spike ranges from 14.2% for lean hog spot price to 95.35% for sugar futures. There is more than 60 percent increase in both spot and futures prices for commodities CBT wheat, KCBT wheat, corn, soybean, soy oil, cocoa, and sugar. The average price increase is 57.80%, statistically significant at 1 percent level. The increase in commodity prices might be driven by inflation. Therefore we adjust the price series using the U.S. CPI index. We find that the increase in commodity prices is still significant for most of the commodities in this study. Except for cotton and lean hogs, the price increases for the other 10 commodities remain both statistically and economically significant. The average inflation adjusted price increase is 25.90%. Figure 1 illustrates the inflation adjusted spot and futures composites, constructed using the 12 commodities in this study. We can clearly see at least two large price bubbles during the 2006-2011 period. These bubbles coincide with the recent financial crisis. We conjecture that investors turn their attention to commodities after the crash of the equity and real estate markets. In summary, there are significant price spikes for agricultural commodities since 2006.

5.2 Analysis of efficiency of futures market

We use the ADF and PP unit root tests to examine the stationarity of spot and futures prices. We find that both spot and futures price series are not stationary at their levels and become stationary at the first difference.[2] After testing for the pre-condition of the statonarity, we employ cointegration tests to determine the existence of a long-run relationship between the spot and futures prices. Tables 2, 3, and 4 present the cointegration results from the application of the Johansen method of reduced rank regression using the vector error correction model. The Johansen J_{trace} and J_{max} analyses for the period 1995-2011 and 1995 – 2005 (Tables 2 & 3) indicate that the null hypothesis of non-cointegration (r = 0) is rejected at 0.05 level of significance for all the 12 commodities. Table 4 reports the co-integration test results for the sub-period 2006-2011. We obtain the same results for all commodities except coffee. The existence of cointegration confirms the long-term market efficiency. It is apparent that the U.S. agricultural futures markets have enough ability to predict subsequent spot prices, i.e., to discover prices in spot market for these commodities.

5.3 Causality in spot and futures markets

Since cointegration tests indicate only the existence of long-run relationship among spot and futures prices, we further use Granger causality tests to analyze the short-run and the direction of relationship among price series. The results show uni-directional relationship (F → S) for 3 commodities for the period 1995-2011 [wheat (KCBT), soybean (CBOT) & lean hogs (CME)] as shown in Table 5. Granger causality results show uni-directional causality that futures market prices lead the spot prices in 4 commodities for the sub-period 1995-2005 [wheat,

[2] For brevity, we do not include the stationarity test results in our tables. These results are available upon request.

soybean (CBOT), cocoa (ICE), & lean hogs (CME)], as shown in Table 6, and 2 commodities for the sub-period 2006-2011 [soybean (CBT) & lean hogs (CME)], as shown in Table 7. The causality results imply that futures markets in these commodities have stronger ability to discover prices and spot market prices are influenced by the futures market prices, compared to other commodities which show bidirectional relationship (9 commodities in the period 1995-2011, 7 commodities in the sub-period 1995-2005, and 8 commodities during the sub-period 2006-2011) between spot and futures market.

For the purpose of easy comparison on cointegration and causality test results among the three periods, Table 8 summarizes the testing results in a two-by-three matrix based on the cointegration analysis and the causality tests between spot and futures prices of the 12 agricultural commodities. Commodities with cointegration and unidirectional relationship of futures market leading the spot market prices (F → S) have better ability of price discovery compared to commodities with cointegration and bi-directional relationship. The results of this study, in the context of recent price spikes and consequent demand for changes in the existing regulatory framework in U.S, will be useful to exchanges, regulatory authorities, multilateral agencies and the government. The results suggest that since the market is efficient, there is little need for changes in the existing regulations of the agricultural futures market.

5.4 Analysis of volatility during pre and post 2006 period

Now we proceed with testing volatility using GARCH (1, 1) model for all three periods, that is, full period 1995-2011, 1995-2005, and 2006-2011. Table 9 presents the results from GARCH analyses. In the mean equation using spot returns as the dependent variable, if the coefficient (p-value) of futures returns is highly significant, it shows that spot returns will increase with futures returns. As all the coefficients, except lean hogs, of the mean equation in the full period as well as the sub-periods are significant at 0.01 level, we observe that spot returns are positively correlated with the futures returns, and vice versa. Similarly, for the full period and sub-periods, ARCH and GARCH coefficients (α_i and β_i) are highly significant, which means that today's volatility is a function of last period's volatility and last period's squared residuals.

If the coefficient of GARCH (1,1) is close to 1 when spot and futures returns are regressed on each other, it is an indication that large values of σ^2_{t-1} will be followed by large values of σ^2_t and the high volatility existed in the previous period will continue to be high in the current period. For the sub-period 1995-2005, in 5 commodities, soybean, feeder cattle, live cattle, cocoa, and cotton, the β_i coefficients are close to 1. For the sub-period 2006-2011, the β_i coefficients are close to 1 for also 5 commodities, feeder cattle, cocoa, coffee, sugar, and KCBT wheat. The GARCH results suggest volatility clustering in these commodities.

Following Chou (1988), if $\alpha_i + \beta_i$ is close to 1, it demonstrates that volatility shocks are quite persistent. In the sub-period 1995-2006, the coefficients $\alpha_i + \beta_i$ are close to 1 in feeder cattle, live cattle, cocoa, coffee, and KCBT wheat, whereas, $\alpha_i + \beta_i$ is closer to 1 in only 2 commodities, namely, cocoa and coffee, in the later sub-period 2006-2011. These results show that there is no significant increase in volatility in commodities since 2006, even with the flowering of commodity index investments. $\alpha_i + \beta_i > 1$ is the indication that response function of volatility increases with time. In the full period as well as in the sub-periods, $\alpha_i + \beta_i$ is greater than 1 for only two commodities, soy bean and cotton. This means that the response function of volatility in these commodities increases over time. $\alpha_i + \beta_i < 1$ is the indication that response function of volatility shocks decay with time. In the first sub-period, the coefficients $\alpha_i + \beta_i < 1$ in 5 commodities, corn, soy oil, CBT wheat, lean hogs, and sugar, whereas in sub-period 2 , α_i +

$\beta_i < 1$ in 7 commodities, corn , soy oil, CBT wheat, feeder cattle, lean hogs, live cattle, and KCBT wheat. These results show that compared to the sub-period 1995-2005, the response function of volatility shocks decays over time in more commodities in the later sub-period 2006-2011, which is an indication of market efficiency in agricultural commodity futures.

The GARCH framework enables changes in both the level and structure of volatility to be deducted between the 2 sub-periods. An increase in α_i would suggest that news is impounded into prices more rapidly, and a decrease in β_i would suggest that old news has a less persistent effect on prices. Conversely, a reduction in α_i would suggest that news is being impounded into prices more slowly, and an increase in β_i would suggest greater persistence. Comparing the α_i and β_i coefficients in the two sub-periods, we find a decrease in α_i for corn, soy oil, CBT wheat, lean hogs, live cattle, coffee, and KCBT wheat. Therefore the news is impounded into prices more slowly and informational efficiency decreases in the spot market due to the information content in the futures market. In commodities such as soybean, feeder cattle, cocoa, cotton, and sugar, there is an increase in α_i, an indication that news is impounded into prices more rapidly and informational efficiency increases in the spot market due to the information content in the futures prices. With regard to volatility persistence, which measures continuation of existence of volatility, in commodities such as corn, soy oil, soybean, lean hogs, live cattle, and cotton, the old news has less persistence effect on price changes, whereas, in commodities like CBT wheat, feeder cattle, coffee, sugar, and KCBT wheat, old news has greater persistence effect on price changes. Further, if β_i is closer to 1 and α_i is away from 1, it means that the volatility is mainly due to the GARCH term. For the whole period, there is volatility clustering in all commodities except corn and lean hogs, meaning that both spot and futures are responsible for the volatility in the opposite market. Only in the case of corn, the volatility in futures prices is driven by spot prices. With regard to the sub-period 1995-2005, there is volatility clustering in soy bean, feeder cattle, live cattle, cocoa, and cotton. In two commodities, lean hogs and coffee, the volatility in futures prices is driven by spot prices. During the sub-period 2006-2011, there is volatility clustering in feeder cattle, cocoa, coffee, sugar, and wheat. In two commodities, CBT wheat and lean hogs, the volatility in futures prices is driven by spot prices.

In summary, the results of GARCH model reveals that while there is persistence of volatility and volatility clustering throughout the period, there is no specific evidence that volatility has increased significantly in the post 2006 period. It seems that the futures markets perform their prescribed role in increasing the efficiency of the market and providing opportunity for risk mitigation through hedging.

6. Conclusion

In well-established and matured agricultural commodity futures market, such as the U.S. futures market, the markets are expected to perform the role of price discovery and risk management more effectively than other commodity exchanges around the world. We conduct a comprehensive study on the interrelationship between the spot and futures prices of 12 agricultural commodities to understand the dynamics of the co-integration, price causality, and volatility clustering for sub-periods 1995-2005 and 2006-2011. To determine the efficiency of those markets, we compare these two periods which are different by various economical and market conditions. The Johansen's co-integration test on the spot and futures data of the 12 agricultural commodities has shown that the spot and futures markets are co-integrated during the full and sub-periods of study. Therefore the U.S. agricultural commodity futures market is efficient and the agriculture commodity futures exchanges (CBOT, KCBT, CME, & ICE) provide efficient hedge against price risk emerging in respective commodities. The co-integration between spot price and future spot prices is the indication of efficiency and developed nature of the market. The Granger Causality Test results on the direction of flow of information between the spot and futures market show that in majority of the commodities, in the full period as well as the sub-periods of study, there are bi-directional flow of information. Due to information flow from both sides, spot to future markets and future market to spot market, both are equally responsible for the price discovery process. The uni-directional causal relationships exhibited in commodities such as wheat (CBT & KCBT), soybean, lean hogs and cocoa, show that futures market is leading the spot market for these commodities. We further find that there is volatility clustering and persistence throughout the study period, with no abnormality during post 2006 period alone. To be specific, we show that U.S. agricultural commodities markets are highly efficient during the study period, including the period (2006-2011) of price spikes and price distortions. In spite of the above positive indications of market efficiency, the U.S. agriculture commodity market has witnessed massive and prolonged price escalations since 2006. The price spikes may be attributed to other fundamental factors not related to the scope of a futures exchange and call for further research.

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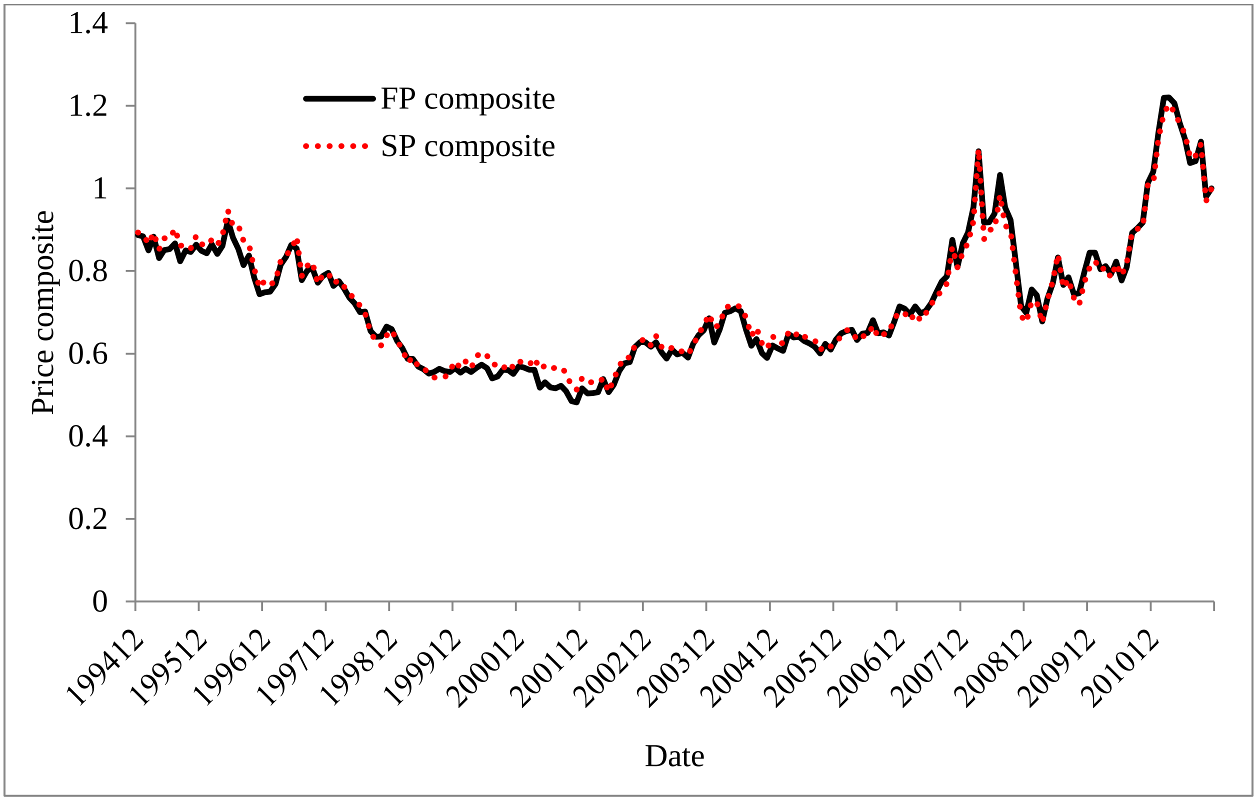

Figure 1 Agricultural commodity futures and spot prices composite (inflation adjusted) over 1995 -2011

We construct the composite using 12 agricultural commodities from all categories, which are included in the CFTC COT Supplemental report. The 12 commodities futures are corn, soybeans, wheat, and soybean oil on the CBOT; wheat on the KCBOT; cotton no. 2, coffee C, sugar no. 11, and cocoa on the New York Board of Trade; and live cattle, lean hogs, and feeder cattle on the CME. We retrieve the daily closing prices of the near-month futures contract of the selected (12) agricultural commodities, denoted as FP, and their respective spot prices, denoted as SP, from Datastream for a period of 17 years, starting from Jan-1995 to Nov-2011, for all the commodities except lean hogs, for which the data period is Mar-2002 to Nov-2011, depending on the availability of trading information. To construct the price composites, we first deflate each time series data by the U.S. Consumer Price Index. We next deflate each inflation adjusted time series by its price in November 2011. Finally, we compute the FP composite by averaging futures prices of the 12 commodities for each trading day. We construct the SP composite in a similar way.

Table 1 Agricultural commodity price hike

We study 12 agricultural commodities from all categories which are included in the CFTC COT Supplemental report. The 12 commodities futures are corn, soybeans, wheat, and soybean oil on the CBT; wheat on the KCBT; cotton no. 2, coffee C, sugar no. 11, and cocoa on the ICE; and live cattle, lean hogs, and feeder cattle on the CME. We retrieve the daily closing prices of the near-month futures contract of the selected (12) agricultural commodities, denoted as *FP*, and their respective spot prices, denoted as *SP*, from Datastream for a period of 17 years, starting from Jan-1995 to Nov-2011, for all the commodities except lean hogs, for which the data period is Mar-2002 to Nov-2011, depending on the availability of trading information. Price for CBT wheat, KCBT wheat, corn, & soybean are in cents per bushel, for soy oil, cotton, lean hogs, live cattle, feeder cattle, sugar & coffee are in cents per pound and for cocoa it is US$ per metric ton. Full refers to the full study period 1995-2011. P1 and P2 refer to the two sub-periods, 1995-2005 and 2006-2011, respectively. * denotes 1% significance level. .

	Without inflation adjustment			With inflation adjustment			(P2/P1 -1)*100%	
Future or Spot Series	Full	P1	P2	Full	P1	P2	without inflation adjustment	with inflation adjustment
CBT_WHEAT _FP	432.81	337.07	612.17	2.29	1.98	2.86	81.62*	44.10*
CBT_Wheat _SP	401.58	327.50	540.37	2.13	1.92	2.52	65.00*	31.07*
KCBT_WHEAT _FP	461.85	359.14	654.25	2.44	2.11	3.05	82.17*	44.64*
KCBT_Wheat_SP	478.11	383.56	655.23	2.53	2.25	3.06	70.83*	36.08*
CBT_CORN_FP	314.46	248.07	438.83	1.66	1.46	2.04	76.90*	39.58*
CBT_Corn No.2 _SP	296.86	234.80	413.12	1.57	1.39	1.92	75.94*	38.44*
CBT_SOYABEANS _FP	745.40	603.99	1010.30	3.94	3.53	4.70	67.27*	32.93*
CBT_Soyabeans_SP	730.18	593.92	985.42	3.86	3.48	4.58	65.92*	31.80*
CBT_SOYABEAN OIL _FP	28.59	22.02	40.90	0.15	0.13	0.19	85.77*	47.36*
CBT_Soya Oil_SP	27.82	21.91	38.89	0.15	0.13	0.18	77.53*	40.99*
CSCE_COTTON #2 _FP	67.28	62.51	76.22	0.36	0.37	0.35	21.94*	-4.63
CSCE_Cotton_SP	64.48	60.19	72.51	0.35	0.36	0.34	20.46*	-6.00
CME_LEAN HOGS_FP	66.74	61.03	70.36	0.33	0.32	0.33	15.30*	1.42*
CME_Lean hogs _SP	63.83	59.68	68.16	0.32	0.33	0.32	14.20*	-2.55
CME_LIVE CATTLE _FP	79.95	71.91	95.00	0.43	0.42	0.44	32.10*	6.56*
CME_Live cattle _SP	79.03	71.36	93.40	0.42	0.41	0.44	30.88*	5.66*
CME_FEEDER CATTLE _FP	91.93	82.03	110.49	0.49	0.47	0.52	34.70*	9.21*
CME_Feeder Cattle _SP	91.73	82.52	108.99	0.49	0.48	0.51	32.08*	7.25*
CSCE_COCOA _FP	1743.52	1369.08	2444.94	9.15	7.97	11.37	78.58*	42.74*
CSCE_Cocoa _SP	1827.37	1450.46	2533.42	9.61	8.46	11.79	74.66*	39.40*
CSCE_SUGAR _FP	11.76	8.83	17.25	0.06	0.05	0.08	95.35*	53.74*
CSCE_Sugar _SP	11.89	9.10	17.10	0.06	0.05	0.08	87.87*	47.73*
CSCE_COFFEE _FP	119.05	102.94	149.21	0.64	0.61	0.69	44.94*	13.01*
CSCE_Coffee _SP	136.80	114.72	178.16	0.73	0.68	0.83	55.30*	21.02*
						Average price hike (%):	57.80	25.90

Table 2 Johansen's cointegration tests for the full period 1995 to 2011

We use the Johansen likelihood ratio test statistics, J_{trace}, and the maximal eigenvalue, J_{max}, to test the null hypothesis that there are at most *r* cointegrating vectors between the commodity futures and spot prices. *, **, and *** denotes significance at 1%, 5%, and 10% level, respectively.

Commodities		**Trace Statistics**		**Max-eigen statistics**		**Cointegration/ Non-cointegration**
		$\mathbf{J}_{trace}$	***p*-value**	$\mathbf{J}_{max}$	***p*-value**	
CBT_CORN	$H_0: r = 0$	38.099*	0.0000	36.625*	0.0000	Cointegration
	$H_0: r \leq 1$	1.473	0.2247	1.473	0.2247	
CBT_SOYOIL	$H_0: r = 0$	17.605**	0.0237	13.817***	0.0587	Cointegration
	$H_0: r \leq 1$	3.787***	0.0516	3.787***	0.0516	
CBT_SOYBEAN	$H_0: r = 0$	74.510*	0.0000	72.001*	0.0000	Cointegration
	$H_0: r \leq 1$	2.509	0.1132	2.509	0.1132	
CBT_WHEAT	$H_0: r = 0$	25.985*	0.0009	21.160*	0.0035	Cointegration
	$H_0: r \leq 1$	4.825**	0.0280	4.825**	0.0280	
CME_FEEDERCATTLE	$H_0: r = 0$	175.584*	0.0001	175.584*	0.0001	Cointegration
	$H_0: r \leq 1$	0.000	0.9918	0.000	0.9918	
CME_LIVECATTLE	$H_0: r = 0$	103.737*	0.0001	102.2567	0.0000	Cointegration
	$H_0: r \leq 1$	1.480	0.2237	1.480	0.2237	
ICE_COCOA	$H_0: r = 0$	101.805*	0.0001	99.124*	0.0000	Cointegration
	$H_0: r \leq 1$	2.680	0.1016	2.680	0.1016	
ICE_COFFEE	$H_0: r = 0$	23.934*	0.0021	22.069*	0.0024	Cointegration
	$H_0: r \leq 1$	1.865	0.1720	1.865	0.1720	
ICE_COTTON	$H_0: r = 0$	141.193*	0.0001	137.553*	0.0001	Cointegration
	$H_0: r \leq 1$	3.6391***	0.0564	3.639***	0.0564	
ICE_SUGAR	$H_0: r = 0$	43.238*	0.0000	41.883*	0.0000	Cointegration
	$H_0: r \leq 1$	1.3549	0.2444	1.354	0.2444	
KCBT_WHEAT	$H_0: r = 0$	20.958*	0.0068	17.995**	0.0123	Cointegration
	$H_0: r \leq 1$	2.962***	0.0852	2.962***	0.0852	
CME_LEANHOGS	$H_0: r = 0$	110.341*	0.0001	103.524*	0.0000	Cointegration
	$H_0: r \leq 1$	6.817*	0.0090	6.817*	0.0090	

Table 3 Johansen's cointegration tests for the sub-period 1995 to 2005

We use the Johansen likelihood ratio test statistics, J_{trace}, and the maximal eigenvalue, J_{max}, to test the null hypothesis that there are at most *r* cointegrating vectors between the commodity futures and spot prices. *, **, and *** denotes significance at 1%, 5%, and 10% level, respectively.

Commodities		**Trace Statistics**		**Max-eigen statistics**		**Cointegration/**
		J_{trace}	***p*-value**	**J_{max}**	***p*-value**	**Non-cointegration**
CBT_CORN	$H_0: r = 0$	66.523*	0.0000	62.437*	0.0000	Cointegration
	$H_0: r \leq 1$	4.085**	0.0432	4.085**	0.0432	
CBT_SOYOIL	$H_0: r = 0$	17.736**	0.0226	13.138***	0.0747	Cointegration
	$H_0: r \leq 1$	4.597**	0.0320	4.597**	0.0320	
CBT_SOYBEAN	$H_0: r = 0$	82.271*	0.0000	76.792*	0.0000	Cointegration
	$H_0: r \leq 1$	5.478**	0.0192	5.478**	0.0192	
CBT_WHEAT	$H_0: r = 0$	26.888*	0.0006	22.053*	0.0024	Cointegration
	$H_0: r \leq 1$	4.834**	0.0279	4.834**	0.0279	
CME_FEEDERCATTLE	$H_0: r = 0$	124.655*	0.0001	124.625*	0.0001	Cointegration
	$H_0: r \leq 1$	0.030	0.8615	0.030	0.8615	
CME_LEANHOGS	$H_0: r = 0$	43.770*	0.0000	40.803*	0.0000	Cointegration
	$H_0: r \leq 1$	2.966***	0.0850	2.966***	0.0850	
CME_LIVECATTLE	$H_0: r = 0$	52.591*	0.0000	49.660*	0.0000	Cointegration
	$H_0: r \leq 1$	2.930***	0.0869	2.930***	0.0869	
ICE_COCOA	$H_0: r = 0$	67.134*	0.0000	62.082*	0.0000	Cointegration
	$H_0: r \leq 1$	5.052**	0.0246	5.052	0.0246	
ICE_COFFEE	$H_0: r = 0$	75.731*	0.0000	70.120*	0.0000	Cointegration
	$H_0: r \leq 1$	5.611**	0.0178	5.611**	0.0178	
ICE_COTTON	$H_0: r = 0$	69.754*	0.0000	66.147*	0.0000	Cointegration
	$H_0: r \leq 1$	3.607***	0.0575	3.607***	0.0575	
ICE_SUGAR	$H_0: r = 0$	43.053*	0.0000	38.098*	0.0000	Cointegration
	$H_0: r \leq 1$	4.954**	0.0260	4.954**	0.0260	
KCBT_WHEAT	$H_0: r = 0$	19.183**	0.0133	15.360**	0.0334	Cointegration
	$H_0: r \leq 1$	3.822***	0.0506	3.822***	0.0506	

Table 4 Johansen's cointegration tests for the sub-period 2006 to 2011

We use the Johansen likelihood ratio test statistics, J_{trace}, and the maximal eigenvalue, J_{max}, to test the null hypothesis that there are at most *r* cointegrating vectors between the commodity futures and spot prices. *, **, and *** denotes significance at 1%, 5%, and 10% level, respectively.

Commodities		**Trace Statistics**		**Max-eigen statistics**		**Cointegration/ Non-cointegration**
		J_{trace}	*p*-value	J_{max}	*p*-value	
CBT_CORN	$H_0: r = 0$	13.826***	0.0878	12.137	0.1056	Cointegration
	$H_0: r \leq 1$	1.689	0.1937	1.689	0.1937	
CBT_SOYOIL	$H_0: r = 0$	12.927	0.1175	7.895	0.3894	Cointegration
	$H_0: r \leq 1$	5.032**	0.0249	5.0316**	0.0249	
CBT_SOYBEAN	$H_0: r = 0$	36.433*	0.0000	33.415*	0.0000	Cointegration
	$H_0: r \leq 1$	3.018***	0.0823	3.018**	0.0823	
CBT_WHEAT	$H_0: r = 0$	16.35**	0.0371	10.304	0.1927	Cointegration
	$H_0: r \leq 1$	6.047	0.0139	6.047**	0.0139	
CME_FEEDERCATTLE	$H_0: r = 0$	164.122*	0.0001	163.962*	0.0001	Cointegration
	$H_0: r \leq 1$	0.160	0.6891	0.160	0.6891	
CME_LEANHOGS	$H_0: r = 0$	105.660*	0.0001	100.786*	0.0000	Cointegration
	$H_0: r \leq 1$	4.872	0.0273	4.872	0.0273	
CME_LIVECATTLE	$H_0: r = 0$	108.315*	0.0001	106.741*	0.0001	Cointegration
	$H_0: r \leq 1$	1.574	0.2095	1.574	0.2095	
ICE_COCOA	$H_0: r = 0$	64.101*	0.0000	60.499*	0.0000	Cointegration
	$H_0: r \leq 1$	3.601	0.0577	3.601***	0.0577	
ICE_COFFEE	$H_0: r = 0$	7.639	0.5047	5.379	0.6934	No-Cointegration
	$H_0: r \leq 1$	2.260	0.1327	2.260	0.1327	
ICE_COTTON	$H_0: r = 0$	99.527*	0.0001	97.995*	0.0000	Cointegration
	$H_0: r \leq 1$	1.532	0.2158	1.531	0.2158	
ICE_SUGAR	$H_0: r = 0$	26.606*	0.0007	25.177*	0.0007	Cointegration
	$H_0: r \leq 1$	1.428	0.2320	1.428	0.2320	
KCBT_WHEAT	$H_0: r = 0$	15.760**	0.0456	11.227	0.1432	Cointegration
	$H_0: r \leq 1$	4.532	0.0332	4.532**	0.0332	

Table 5 Granger causality test statistics: 1995 to 2011

We use the following regression models to estimate for each commodity to analyze the causal relationship between $R_{s,t}$ and p lagged values of $R_{s,t}$ and $R_{f,t}$, where the spot return, $R_{s,t}$, and futures return, $R_{f,t}$, are the first difference in the log spot and futures prices, respectively.

$$R_{s,t} = a_0 + \sum_{k=1}^{p} a_{1k} R_{s,t-k} + \sum_{k=1}^{p} R_{f,t-k} + e_t$$

$$R_{f,t} = a_0 + \sum_{k=1}^{p} a_{1k} R_{f,t-k} + \sum_{k=1}^{p} a_{2k} R_{s,t-k} + e_t$$

Using AIC criteria, the optimal lag structure is p=1. *, **, and *** denotes significance at 1%, 5%, and 10% level, respectively.

Commodities	**Hypothesis**	**F-statistic**	**Probability**	**Direction**	**Relationship**
CBT_CORN	F does not cause S	20.013*	0.000	Bi-directional	F ↔ S
	S does not cause F	8.975*	0.000		
CBT_SOYBEAN_OIL	F does not cause S	17.243*	0.000	Bi-directional	F ↔ S
	S does not cause F	8.516*	0.000		
CBT_SOYBEAN	S does not cause F	1.078	0.340	Uni-directional	F → S
	F does not cause S	48.687*	0.000		
CBT_WHEAT	S does not cause F	5.611*	0.003	Bi-directional	S↔ F
	F does not cause S	17.672*	0.000		
CME_FEEDERCATTLE	F does not cause S	181.567*	0.000	Bi-directional	F ↔ S
	S does not cause F	8.806*	0.000		
CME_LIVECATTLE	S does not cause F	3.323**	0.036	Bi-directional	S↔ F
	F does not cause S	165.025	0.000		
ICE_COCOA	S does not cause F	4.610*	0.010	Bi-directional	S↔ F
	F does not cause S	2561.68*	0.000		
ICE_COFFEE	S does not cause F	15.959*	0.000	Bi-directional	S↔ F
	F does not cause S	1163.40*	0.000		
ICE_COTTON	S does not cause F	17.644*	0.000	Bi-directional	S ↔ F
	F does not cause S	7.587*	0.000		
ICE_SUGAR	S does not cause F	11.134*	0.000	Bi-directional	S ↔ F
	F does not cause S	389.946*	0.000		
KCBT_WHEAT	S does not cause F	0.718	0.487	Uni-directional	F → S
	F does not cause S	31.340*	0.000		
CME_LEANHOGS	F does not cause S	109.366*	0.000	Uni-directional	F → S
	S does not cause F	0.408	0.664		

Table 6 Granger causality test statistics: 1995 to 2005

We use the following regression models to estimate for each commodity to analyze the causal relationship between $R_{s,t}$ and p lagged values of $R_{s,t}$ and $R_{f,t}$, where the spot return, $R_{s,t}$, and futures return, $R_{f,t}$, are the first difference in the log spot and futures prices, respectively.

$$R_{s,t} = a_0 + \sum_{k=1}^{p} a_{1k} R_{s,t-k} + \sum_{k=1}^{p} R_{f,t-k} + e_t$$

$$R_{f,t} = a_0 + \sum_{k=1}^{p} a_{1k} R_{f,t-k} + \sum_{k=1}^{p} a_{2k} R_{s,t-k} + e_t$$

Using AIC criteria, the optimal lag structure is p=1. *, **, and *** denotes significance at 1%, 5%, and 10% level, respectively.

Commodities	Hypothesis	F-statistic	Probability	Direction	Relationship
CBT_CORN	F does not cause S	11.945*	0.000	Bi-directional	F ↔ S
	S does not cause F	5.547*	0.000		
CBT_SOYBEAN_OIL	F does not cause S	5.010*	0.000	Bi-directional	F ↔ S
	S does not cause F	3.0817**	0.015		
CBT_SOYBEAN	S does not cause F	1.556	0.183	Uni-directional	F →S
	F does not cause S	11.976*	0.000		
CBT_WHEAT	S does not cause F	1.474	0.207	Uni-directional	F→ S
	F does not cause S	18.844*	0.000		
CME_FEEDERCATTLE	F does not cause S	61.584*	0.000	Bi-directional	F↔ S
	S does not cause F	8.721*	0.000		
CME_LEANHOGS	F does not cause S	19.235*	0.000	Uni-directional	F → S
	S does not cause F	0.248	0.910		
CME_LIVECATTLE	S does not cause F	2.672**	0.030	Bi-directional	S↔ F
	F does not cause S	72.885*	0.000		
ICE_COCOA	S does not cause F	0.409	0.801	Uni-directional	F→ S
	F does not cause S	481.308*	0.000		
ICE_COFFEE	S does not cause F	7.467*	0.000	Bi-directional	S ↔ F
	F does not cause S	794.345*	0.000		
ICE_COTTON	S does not cause F	3.028**	0.016	Bi-directional	S↔ F
	F does not cause S	5.508*	0.000		
ICE_SUGAR	S does not cause F	1.997***	0.092	Bi-directional	S ↔ F
	F does not cause S	179.983*	0.000		
KCBT_WHEAT	F does not cause S	1.621	0.165	Uni-directional	S → F
	S does not cause F	7.981**	0.000		

Table 7 Granger causality test statistics: 2006-2011

We use the following regression models to estimate for each commodity to analyze the causal relationship between $R_{s,t}$ and p lagged values of $R_{s,t}$ and $R_{f,t}$, where the spot return, $R_{s,t}$, and futures return, $R_{f,t}$, are the first difference in the log spot and futures prices, respectively.

$$R_{s,t} = a_0 + \sum_{k=1}^{p} a_{1k} R_{s,t-k} + \sum_{k=1}^{p} R_{f,t-k} + e_t$$

$$R_{f,t} = a_0 + \sum_{k=1}^{p} a_{1k} R_{f,t-k} + \sum_{k=1}^{p} a_{2k} R_{s,t-k} + e_t$$

Using AIC criteria, the optimal lag structure is p=1. *, **, and *** denotes significance at 1%, 5%, and 10% level, respectively.

Commodities	Hypothesis	F-statistic	Probability	Direction	Relationship
CBT_CORN	F does not cause S	6.799*	0.000	Bi-directional	F ↔ S
	S does not cause F	4.901*	0.000		
CBT_SOYBEAN_OIL	F does not cause S	4.717*	0.000	Bi-directional	F ↔ S
	S does not cause F	3.216**	0.012		
CBT_SOYBEAN	S does not cause F	0.889	0.469	Uni-directional	F →S
	F does not cause S	11.666*	0.000		
CBT_WHEAT	S does not cause F	3.215**	0.0122	Bi-directional	S ↔ F
	F does not cause S	7.514*	0.000		
CME_FEEDERCATTLE	F does not cause S	49.900*	0.000	Bi-directional	F↔ S
	S does not cause F	4.236*	0.002		
CME_LEANHOGS	F does not cause S	35.927*	0.000	Uni-directional	F → S
	S does not cause F	1.825	0.121		
CME_LIVECATTLE	S does not cause F	2.432**	0.045	Bi-directional	S↔ F
	F does not cause S	39.902*	0.000		
ICE_COCOA	S does not cause F	2.202***	0.066	Bi-directional	S↔ F
	F does not cause S	813.666*	0.000		
ICE_COFFEE	S does not cause F	2.341***	0.053	Bi-directional	S ↔ F
	F does not cause S	38.808*	0.000		
ICE_COTTON	S does not cause F	9.213*	0.000	Uni-directional	S → F
	F does not cause S	1.667	0.154		
ICE_SUGAR	S does not cause F	12.075*	0.000	Bi-directional	S ↔ F
	F does not cause S	71.204*	0.000		
KCBT_WHEAT	F does not cause S	0.316	0.867	Uni-directional	S → F
	S does not cause F	7.897*	0.000		

Table 8 Categorization of commodities based on ointegration and Granger causality test results

Causality / Cointegration	**Uni-directional (S → F)***	**Uni-directional (F → S)**	**Bi-directional (F ↔ S)**
Period: 1995 - 2001			
Non-Cointegration	Nil	Nil	Nil
Cointegration	Nil	Wheat (KCBT), Soybean, Lean hogs	Wheat (CBT), Corn, Soybean oil, Cotton, Live cattle, Feeder cattle, Cocoa, Sugar, Coffee
Period: 1995 - 2005			
Non-Cointegration	Nil	Nil	Nil
Cointegration	Wheat (KCBT)	Wheat (CBT), Soybean, Cocoa, Lean hogs	Corn, Soybean oil, Cotton, Live cattle, Feeder cattle, Cocoa, Sugar, Coffee
Period: 2006 - 2011			
Non-Cointegration		Coffee	
Cointegration	Wheat (KCBT), Cotton	Soybean, Lean hogs	Wheat (CBT), Corn, Soybean oil, Live cattle, Feeder cattle, Cocoa, Sugar

Source: compiled from the test result tables for the respective years *F = futures returns S = spot returns

Table 9 GARCH (1. 1) model test for volatility

We use the following GARCH (p, q) models.

Mean equation: $RS_t = \gamma RF_t + \varepsilon_t$

Variance equation: $\sigma^2_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{q} \beta_i \sigma^2_{t-i}$

where σ^2_t is conditional variance term for the period t. γ represents the coefficient of mean equation. α_i represents the news coefficient and β_i represents a persistence coefficient. *, **, and *** denotes significance at 1%, 5%, and 10% level, respectively.

Dependent variable	Mean Eq.	Variance Equation		Mean Eq.	Variance Equation		Mean Eq.	Variance Equation	
	γ	α1	β1	γ	α1	β1	γ	α1	β1
	Full Period 1995 - 2011			Sub Period 1995 - 2005			Sub Period 2006 - 2011		
CBT_Corn Future return	0.919*	0.407*	0.404*	0.868*	0.440*	0.370*	0.940*	0.326*	-0.047*
CBT_Corn Spot return	0.891*	0.429*	0.521*	0.849*	0.459*	0.406*	0.956*	0.339*	0.086*
CBT_Soyoil Future return	0.916*	0.063*	0.923*	0.897*	0.400*	0.251*	0.962*	0.243*	-0.029**
CBT_Soyoil Spot return	0.949*	0.307*	0.514*	0.972*	0.329*	0.280*	0.971*	0.261*	-0.016
CBT_Soybean Future return	0.932*	0.380*	0.778*	0.903*	0.295*	0.815*	0.962*	0.680*	0.629*
CBT_Soybean Spot return	0.905*	0.361*	0.780*	0.870*	0.304*	0.803*	0.936*	0.698*	0.618*
CBT_Wheat Future return	0.686*	0.100*	0.890*	0.673*	0.140*	0.636*	0.804*	0.128*	0.876*
CBT_Wheat Spot return	0.828*	0.214*	0.830*	0.844*	0.354*	0.677*	0.834*	0.367*	-0.005*
CME_Feedercattle Future return	0.050*	0.024*	0.975*	0.039*	0.028*	0.968*	0.400*	0.018*	0.978*
CME_Feedercattle Spot return	0.097*	0.136*	0.860*	0.108*	0.171*	0.838*	0.100*	0.057*	0.872*
CME_Leanhogs Future return	0.039	-0.015*	0.668*	-0.026	-0.012*	0.882*	0.097	-0.011*	0.930*
CME_Leanhogs Spot return	0.005	0.288*	0.642*	-0.022	0.400*	0.636*	0.021	0.242*	0.607*
CME_Livecattle Future return	0.151*	0.014*	0.982*	0.170*	0.015*	0.974*	0.101*	-0.010	0.457
CME_Livecattle Spot return	0.145*	0.022*	0.968*	0.194*	0.058*	0.915*	0.077**	-0.017*	0.576*
ICE_Cocoa Futures return	0.057*	0.032*	0.967*	0.104*	0.037*	0.958*	-0.016	0.025*	0.974*
ICE_Cocoa Spot return	0.061*	0.025*	0.972*	0.101	0.023*	0.969*	0.007	0.035*	0.963*
ICE_Coffee Futures return	0.319*	0.094*	0.899*	0.020*	0.089*	0.908*	0.731*	0.053*	0.945*
ICE_Coffee Spot return	0.521*	0.263*	0.763*	-0.354*	0.371*	0.705*	0.786*	0.074*	0.927*
ICE_Cotton Futures return	0.848*	0.541*	0.754*	0.888*	0.487*	0.764*	0.831*	0.616*	0.738*
ICE_Cotton Spot return	0.796*	0.334*	0.790*	0.808*	0.245*	0.829*	0.820*	3.026*	0.230*
ICE_Sugar Futures return	0.853*	0.276*	0.762*	0.420*	0.234*	0.741*	1.014*	0.301*	0.777*
ICE_Sugar Spot return	0.783*	0.301*	0.728*	0.389*	0.177*	0.622*	0.847*	0.275*	0.778*
KCBT_Wheat Futures return	0.778*	0.308*	0.723*	0.786*	0.337*	0.625*	0.820*	0.205*	0.763*
KCBT_Wheat Spot return	0.846*	0.250*	0.777*	0.861*	0.320*	0.668*	0.970*	0.194*	0.728*