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Abstract

The purpose of this paper is to assess whether index investment Granger causes grain futures price movements during explosive periods. A forward and backward recursive procedure developed by Phillips, Shi, and Yu (2012) is used to detect and date-stamp explosive periods in in the price of corn, soybean, and wheat futures traded on the CBOT, as well as wheat futures traded on the KCBT between January 2004 and February 2012. The statistical tests indicate that most of these grain futures markets experienced explosive periods between the end of 2007 and first half of 2008, as well as in the second half of 2010. If CITs are indeed responsible for the sharp price fluctuations as claimed by Masters (2008, 2009) and others, they are mostly likely to have led the price movement during these explosive periods. Using dummy variables to reflect the explosive periods identified with the PSY procedure, we investigate the relationship between commodity index (CIT) positions and changes in futures prices. We find that no Granger causality can be established from changes in CITs net long positions to returns in corn, soybeans, and KC wheat futures in either explosive or non-explosive periods, consistent with the results from the traditional Granger causality test. For wheat futures traded on the CBOT, estimation results show that CITs Granger cause returns in explosive and non-explosive periods. Examination of the impulse response function, however, suggests that the effect is relatively small and dissipates quickly. Overall, the results from the modified Granger causality test differentiating explosive from non-explosive periods provide additional evidence that CITs are mostly likely not responsible for the large price movement observed in grain futures between January 2004 and February 2012.

Key words: explosive periods, multiple regime switching, date-stamping, price explosiveness, index investment, grain futures, Granger causality

Introduction

The recent large fluctuations in grain futures prices have generated a great deal of concern in commodity markets and led many to wonder who or what is at fault. Some blame speculators for the rise in prices, especially commodity index traders (CITs) who trade weighted baskets of commodities in the futures markets (e.g. Masters 2008; Masters 2009; Masters and White 2008; USS/PSI 2009.) CITs have been accused of artificially raising commodity futures prices by pouring massive funds into markets and thereby creating buy-side pressure. In response to these concerns, regulatory efforts have centered on setting speculative position limits. For instance, the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act granted the U.S. Commodity Futures and Trading Commission (CFTC) the authority to set aggregate speculative position limits on futures and swap positions in all non-exempt 'physical commodity markets' in the U.S.

Concerns over the role of speculative activities are not without theoretical grounds. Shleifer and Summers (1990), De Long et al. (1990), and others find that speculation can drive prices away from fundamental values and thus result in speculative bubbles. For CITs, given that investment activities are carried out for the purpose of portfolio diversifications, their positions are sometimes considered "…insensitive to the supply and demand fundamentals" (Masters and White, 2008, p.29). Irwin and Sanders (2012) argue that under this scenario CITs could impact futures prices under three scenarios: (1) when commodity futures markets are not sufficiently liquid to absorb the large order flow of index funds; (2) when index investors are noise traders and their positions are large enough to make arbitrage risky; and (3) when other traders in commodity futures markets mistakenly see the large order flow of index funds on the long side as a reflection of valuable private information and create added buy-side pressure.

Whether CITs and other speculators created a bubble during the peak of commodity price spikes between 2006 and 2008, as well as between 2010 and 2011, is ultimately an empirical question. Arguments against CITs have mainly relied on the observation that the period of commodity price boom (2006-2008) coincides with the period when CITs held large long positions in the futures markets (e.g., Masters 2008). On the other hand, statistical testing concerning the role of index investment has mainly focused on finding statistical links between commodity futures price movements and market positions held by CITs. Granger causality tests have been widely used to establish lead and lag relationships between price changes and investment activities of CITs in commodity futures markets (e.g., Gilbert 2010a; Gilbert 2010b; Stoll and Whaley 2010; Sanders and Irwin 2011a 2011b; Büyüksahin and Harris 2011; Brunetti, Büyüksahin, and Harris 2011), and in general, limited evidence of a statistical causal linkage has been established from index investment to market price movements in various agricultural and energy futures markets.

Previous research relating index investment with large commodity price movement can be criticized on at least two fronts. First, the studies do not provide a precise definition of what constitutes a price spike, at best referring to it qualitatively as a long period of run-up in commodity prices. The historical price data indicate that both nominal and deflated cash prices for almost all commodities are characterized by occasional booms and sharp busts. Numerical simulations of a dynamic rational expectations storage model by Wright and Williams (1991) also demonstrate the boom-and-bust pattern in commodity prices in the presence of supply shocks. Nonetheless, it is not clear exactly which episodes should be considered "abnormal" or "explosive" and therefore of special concern to market participants and policy makers. It is important to distinguish between explosive and non-explosive periods to avoid misleading conclusions.

A second problem is a direct consequence of lacking a clear definition of what constitutes "explosive" periods. Specifically, previous studies usually fail to provide an accurate measure of when the price spikes start and end. Empirical studies to date have mostly relied on comparing the pattern of index investment with the price movement over an *ad hoc* sample period. For instance, the Granger causality analysis conducted by various researchers have either chosen a period that covers the period with large price volatilities, e.g. 2006-2011, or simply included the period whenever index investment data are available. Admittedly, studies that fall into these categories can be useful when investigating the correlation between price movement and index investment. Yet, to obtain more precise conclusions, the behavior of index investment during the explosive periods must be examined, which requires the origination and termination dates of the sub-periods with explosive price behavior be measured accurately and at a relative high frequency.

The purpose of this paper is to assess whether index investment Granger causes grain futures price movements during explosive periods. A forward and backward recursive procedure developed by Phillips, Shi, and Yu (2012) is used to detect and date-stamp explosive periods in the grain markets. If CITs are indeed responsible for the sharp price fluctuations as claimed by Masters (2008, 2009) and others, they are mostly likely to have led the price movement during these explosive periods. We then introduce a dummy variable into the regression model to identify the explosive periods and a create interaction term between this dummy variable and the CIT position changes. The modified Granger causality test provides only limited evidence supporting the argument that speculators were important drivers of price movements in grain futures markets, especially during the explosive periods examined.

Testing for Explosive Price Behavior

The PSY Detection and Date-stamping Procedure

The econometrics field has developed numerous methods to identify structural breaks and regime switching. However, the complexity of the nonlinear structure usually involved in the data generating process makes obtaining a robust measure of the timing of the transition difficult. Previous methods only serve to confirm whether a known single break point has occurred (the Chow test) or to find only one unknown break point (the Zivot and Andrews (2002) structural break test). Phillips, Wu and Yu (2011, PWY hereinafter), and Phillips and Yu (2011, PY hereinafter) recently proposed a powerful testing procedure based on forward, recursively calculated Augmented Dickey-Fuller (ADF) test statistics to detect the existence of one single explosive period and find its origination and termination dates. Homm and Breitung (2011) show that in various simulations the PWY procedure performs satisfactorily against other recursive procedures and is particularly effective as a real-time detection algorithm for explosive market behavior.

Though the PWY procedure was originally designed for detecting single explosive periods, Phillips, Shi, and Yu (2012, PSY hereinafter) have advanced this technique by providing a limit theory of multiple regime switching tests and developed a consistent, real-time date-stamping algorithm for multiple explosive periods.[1] In numerous simulation studies, they show that the test statistic possesses good discriminatory power and not only can consistently detect the existence of multiple explosive periods of a price series, but can also locate their origination and collapse dates. Similar to the PWY procedure, an important advantage of the PSY procedure is that it can serve as a real time surveillance tool to monitor the price behavior since its date-stamping strategy is developed in a forward recursive framework. In the realm of commodity futures markets, policy makers could benefit from knowing *in real-time* whether prices are behaving in an explosive manner.

The underlying assumption of PSY's procedure is that outside of explosive periods, the asset price follows a random walk process. When the price P_t becomes explosive, the random walk assumption no longer holds. Assume there has been two explosive sub-periods in commodity futures prices with the first one being $B_1 = [\tau_{1e}, \tau_{1f}]$ and the second $B_2 = [\tau_{2e}, \tau_{2f}]$, where τ_{1e},

τ_{1f}, τ_{2e}, τ_{2f} are the origination and termination dates of each episode, respectively. Such a data generating process can be represented as:

$$P_t = P_{t-1}1\{t \in N_0\} + \delta_T P_{t-1}1\{t \in B_1 \cup B_2\} + \left(\sum_{k=\tau_{1f}+1}^{t} \varepsilon_k + P^*_{\tau_{1f}}\right)1\{t \in N_1\}$$
$$+ \left(\sum_{l=\tau_{2f}+1}^{t} \varepsilon_k + P^*_{\tau_{2f}}\right)1\{t \in N_2\} + \varepsilon_t 1\{t \in N_0 \cup B_1 \cup B_2\}, \tag{1}$$

where $1\{.\}$ is the indicator function such that $1\{.\} = 1$ when the conditions in the bracket hold and 0 otherwise, δ_T is a parameter greater than 1, ε_k is an iid normally distributed error term, and $N_0 = [1, \tau_{1e})$, $N_1 = (\tau_{1f}, \tau_{2e})$, and $N_2 = (\tau_{2f}, \tau]$ are three non-explosive sub-periods. The price series first behaves as a random walk until date τ_{1e-1}, after which it becomes explosive and eventually collapses at date τ_{1f}. It then continues its pure random walk path until date τ_{2e-1}, and starts to expand again until date τ_{2f}. The price then reverts back to its random walk path until the end of sample period τ.

Equation (1) implies that to obtain an accurate measure of the start and end dates of price explosiveness, the testing procedure first needs to distinguish the explosive behavior of a price series at τ_{1e} from its non-explosive behavior at τ_{1e-1}. Similarly at τ_{1f}, the testing procedure must be capable of identifying the transition from an explosive path to a random walk. This can be accomplished using either PWY's or PY's forward recursive testing procedures based on the ADF test statistics. PWY and PY show that when the prices start to explode, their testing procedures can successfully detect such regime switching. This is due to their sensitivity of different signals. For example, if explosive behavior is not observed at τ_{1f}, the coefficient estimate is biased downward toward stationarity, enabling the PWY and PY procedures to successfully detect termination dates.

Nevertheless, results from the PWY and PY procedures can be severely biased when the underlying data generating process contains multiple explosive episodes, especially when the first explosive sub-period is longer than the following one. In this case, because the PWY and PY procedures use a single starting point for the entire testing process, signals from the first explosive episode is mixed with the second one. Often the downward bias from the first explosive sub-period can contaminate the ability of successful detection of the following explosive period. To remedy this, PSY propose to use a generalized forward recursive framework consisting of two test steps: detection and date-stamping. Defining the estimation start and end points r_1 and r_2, respectively, their estimation equation becomes:

$$\Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} \gamma^i_{r_1,r_2} \Delta P_{t-i} + \varepsilon_t, \tag{2}$$

where $\Delta P_t = P_t - P_{t-1}$, k is the lag order, and $\varepsilon_t \sim iid\ N(0, \sigma^2_{r_1,r_2})$.

The ADF *t* statistic corresponding to this estimation equation is $ADF_{r_1,r_2} = \frac{\beta_{r_1,r_2}}{se(\beta_{r_1,r_2})}$. The varying window size of the regression r_w is a function of r_1 and r_2 such that $r_w = r_2 - r_1 + 1$. Defining r_{w_0} to be the minimum window size required to estimate equation (2) and a fixed ending point r_2, the starting point r_1 can vary between the first observation to observation $r_2 - r_{w_0} + 1$. By varying the starting point r_1 there are $[r_2 - r_{w_0} + 1]$ ADF t statistics for any fixed ending point r_2. Let $SADF_{r_2}$ be the maximum of those $[r_2 - r_{w_0} + 1]$ ADF t statistics such that $SADF_{r_2} = sup_{r_1 \in [1, r_2 - r_{w_0} + 1]}\{ADF_{r_1,r_2}\}$. Now allow the ending point r_2 to vary between r_{w_0} and τ, the last data point included in the estimation; we then obtain $[\tau - r_{w_0} + 1]$ $SADF_{r_2}$ statistics. Denote the maximum of $SADF_{r_2}$ as $GSADF_{\tau}^{r_{w_0}}$ such that

$$GSADF_{\tau}^{r_{w_0}} = sup_{r_2 \in [r_{w_0}, \tau]} \left\{ sup_{r_1 \in [1, r_2 - r_{w_0} + 1]} \left(ADF_{r_1,r_2} \right) \right\}. \tag{3}$$

Then, the existence of an explosive period is confirmed if $GSADF_{\tau}^{r_{w_0}} > cv_{\tau, r_{w_0}}^{\rho}$, where $cv_{\tau, r_{w_0}}^{\rho}$ is the $100\rho\%$ critical values based on τ observations and a minimum window size r_{w_0}. The GSADF test statistic is essentially a rolling window ADF test with a double-sup selection criterion, in which both the starting and ending points of the estimation vary. In various simulation studies, PSY show that the GSADF test possesses good discriminatory power in detecting whether a time series has experienced explosiveness over the entire sample period.

The second step is to locate the specific explosive periods by comparing the $SADF_{r_2}$ test statistics and their respective critical values.[2] While the GSADF test can detect explosive periods over the entire sample period, the SADF test aims to identify the origination and termination dates of explosive periods on a recursive basis. The estimated origination and ending dates of the first explosive episode are specified as:

$$\begin{aligned} \widetilde{r_{1e}} &= inf_{r_2 \in [r_{w_0}, n]} \left\{ r_2 : SADF_{r_2} > cv_{r_2}^{\rho} \right\}, \quad \text{and} \\ \widetilde{r_{1f}} &= inf_{r_2 \in [\widetilde{r_{1e}} + h, n]} \left\{ r_2 : SADF_{r_2} < cv_{r_2}^{\rho} \right\}, \end{aligned} \tag{4}$$

where $cv_{r_2}^{\rho}$ is the $100\rho\%$ critical values based on r_2 observations. Similarly, the estimated origination and collapse dates of the second explosive episode can be defined as:

$$\begin{aligned} \widetilde{r_{2e}} &= inf_{r_2 \in [\widetilde{r_{1f}}, n]} \left\{ r_2 : SADF_{r_2} > cv_{r_2}^{\rho} \right\}, \quad \text{and} \\ \widetilde{r_{2f}} &= inf_{r_2 \in [\widetilde{r_{2e}} + h, n]} \left\{ r_2 : SADF_{r_2} < cv_{r_2}^{\rho} \right\}. \end{aligned} \tag{5}$$

In essence, the origination date is defined as the first date that the sup test statistics $SADF_{r_2}$ exceeds the corresponding critical value, and it terminates as soon as it falls below the corresponding critical values. The recursive framework allows the SADF procedure to be a real-time date-stamping algorithm. PSY obtained the asymptotic distribution of SADF test statistic and proved that under various scenarios, the SADF test can consistently detect the start and end dates of explosive periods and outperforms the date-stamping strategy proposed by PWY.[3]

The PSY procedures rely on the assumption that, absent explosive periods, the price series follows a random walk. This suggests that when applying the PSY procedure to a specific market during a non-explosive period, the price series should follow a random walk. Here, we use nearby futures prices to detect the price explosiveness in the grain market when applying the GSADF testing and SADF date-stamping procedures. Nearby futures are used because it is well-known that CITs tend to concentrate their trading activities in the most liquid and shortest maturity contracts (Stoll and Whaley 2010; Büyüksahin and Harris 2011; Sanders and Irwin 2011a,b).

Also note in equations (4) and (5) when defining the end dates of the explosive periods, the price explosiveness needs to last at least h periods to be considered economically meaningful. In this paper, h is set to two weeks, or ten business days. In a competitive futures market, all the information available is reflected in futures quotes, and market participants can generally react quickly to any new information. Any speculator-driven price movement away from prices based on fundamentals may only be short-lived. It is thus expected that if there is any imbalance in the futures market, it should disappear within a short time period. In an earlier study, Gilbert (2010b) adopted the same criterion when applying the PWY procedure on various daily commodity futures price series and only found explosive periods with copper and soybeans.[4]

Futures Price Data

The price data used are weekly prices of corn, soybean, and wheat futures traded at the Chicago Board of Trade (CBOT), as well as hard red winter wheat futures traded at the Kansas City Board of Trade (KCBT). Weekly prices are used in order to match the weekly reporting frequency of CIT positions available from the CFTC. In non-delivery months, the weekly price refers to the closing Tuesday price of the nearby futures contract. On the last business day before delivery months the data are switched to the next-to-expire contract. Returns are defined as the difference between the price logarithms: $\log(P_t) - \log(P_{t-1})$. For a given roll date, note that P_{t-1} refers to the price of the same futures contract as P_t but on the previous Tuesday. This ensures that the returns are always constructed using prices from the same contract. The sample period examined is January 2004 to February 2012, resulting in 426 weekly observations for each commodity. The resulting sample includes sub-periods when commodity prices were low and stable (2004 - mid 2006), booming (mid 2006 - mid 2008), sharply dropping (mid 2008 - end of 2008), and booming again (2009 - 2012).[5]

The nearby corn, soybean, wheat, and KC wheat futures prices are plotted in Figure 1. Over the first sub-period (2004 - mid 2006), corn prices centered near $2/bu. and for the two wheat futures mean prices were upwards of $3/bu. Though the soybean price falls into a wider range, it fluctuates around $6/bu. for much of the sample. The prices of all four commodities increased substantially in the second sub-period (mid 2006 - mid 2008). The futures prices of corn and soybean first peaked in July 2008, while CBOT and KC wheat prices reached the sample maximums about four months earlier in March 2008. Compared to the lowest price in the first sub-period, the prices of corn approximately quadrupled in the second sub-period, and the prices of soybeans and two wheat futures increased more than 200%. The commodity prices then plummeted in the second half of 2008, particularly in September with the onset of the financial crisis and the “Great Recession.” The prices of corn and soybeans dropped 50% to below $3.5/bu.

and \$9/bu. in December 2008, respectively. The price decrease was also significant in two wheat futures as their prices plummeted from over \$12/bu. at the peak in March 2008 to \$5.50/bu. in October 2008.

In the last sub-period (2009 - 2012), prices began to rise again, sparking a new round of discussions about food prices and speculative behavior. Nevertheless, the prices of two wheat futures did not reach their mid-2008 highs. By contrast, corn and soybean prices as of February 2012 were very close to their 2008 peak prices This price behavior suggests that corn and soybean futures are more likely to have experienced price explosiveness starting in late 2010 compared to the two wheat futures.

PSY Testing Results

As a first step in determining the existence of explosive periods and locating their exact origination and termination dates, the lag order in the estimation equation (2) must be specified. Phillips and Yu (2009) show the asymptotic distributions of the test statistics remain the same when a low lag order is used. PY used a lag order of zero when conducting the forward recursive analysis with initialization of the first observation. PSY further demonstrate that adding lag orders can potentially bias the estimation results and recommend obtaining the ADF test statistics with a lag order of zero. In this study, we employ the testing strategy recommended by PSY and set the lag order to zero ($k = 0$ in equation (2)). The initial start-up sample for the generalized forward recursive analysis contains 20 observations (the first 20 weeks of the data: $r_1 = 1$ and $r_2 = 20$), or almost 5% of the total sample. The minimum window size is 20 observations as well.[6] For instance, to obtain the SADF test statistics for a fixed ending data point 21 ($r_2 = 21$), two regressions are estimated where the first starts with observation 1 ($r_1 = 1$) and the second with observation 2 ($r_1 = 2$). $SADF_{26}$ is then set to the larger ADF *t* statistics calculated from those two regressions. Correspondingly, the generalized test statistic $GSADF_{426}^{21}$ is the largest $SADF_{r_2}$ test statistic obtained, where r_2 varies from 21 to 426.

Table 1 presents the critical values of the GSADF test statistic obtained from 5000 Monte Carlo replications with a sample size of 426 and a minimum window size of 20, as well as the respective GSADF test statistic for each commodity. The GSADF statistics for soybeans, CBOT wheat, and KCBT wheat futures are 4.5, 4.01, and 4.14, respectively. All of them exceed the 1% right-tail critical values (i.e. 4.5>3.23, 4.01>3.23, and 4.14>3.23), giving strong evidence of explosive periods in soybean and wheat futures. Moreover, based on the GSADF statistics, the null hypothesis that there had been no explosive periods can also be rejected for corn futures at the 5% confidence level, as the test statistic is larger than the 5% right-tail critical value (3.12>2.63). In other words, based on the ex-post GSADF test, there were explosive periods in corn futures from 2004 to 2012. The results from the GSADF test thus suggest that price explosiveness was a component of grain futures prices for at least some time periods.

To locate the start and end dates of the explosive periods, the $SADF_{r_2}$ series are compared to the 5% critical value series ($cv_{r_2}^{95\%}$), which are obtained as a by-product when simulating the critical values for the GSADF test statistic. Figure 2 plots the $SADF_{r_2}$ test statistics and their respective critical values. Table 2 further summarizes the explosive periods identified by the SADF procedure. Not surprisingly, all four grain futures have experienced several periods of market explosiveness between 2004 and 2011, with most of the explosive periods observed between the end of 2006 and mid-2008 when commodity prices hit record highs. For corn and soybeans, 51 and 52 weeks of prices during this period are explosive (i.e., non-random walk), respectively. Out of the 426 weeks studied, explosive prices occurred in the corn and soybean futures about 12% of the time. For CBOT and KCBT wheat futures, the prices were explosive about 8% of the time during this period (37 and 34 weeks, respectively). Results from the SADF date-stamping algorithm thus further strengthen the conclusion drawn from the ex-post GSADF detecting test.

In addition to the 2006-2008 price spikes, another 2-4 weeks of price explosiveness are observed in the second half of 2010 in all four commodities. However, though the price levels are high between 2009 and 2012, not nearly as many explosive periods were confirmed during this time frame compared to the 2006-2008 price booms. Table 2 and Figure 2 also suggest the explosive periods identified in the CBOT and KC wheat futures are almost identical. Corn and soybean explosive periods also exhibit a very high degree of similarity. Both commodities experienced 2-4 weeks of explosiveness in July and August 2004 which are not found in two wheat futures, and the start and end dates of the explosive periods identified during the unprecedented price boom of 2008 line up quite closely as well. This is not surprising given that corn and soybeans are competing crops usually grown in the same region, are likely affected by similar weather shocks, and are both used as feed in the production of livestock.

Despite the similarities of price explosiveness, the origination and conclusion dates of the explosive periods are not exactly the same across commodities, suggesting that commodity-specific factors may have driven the price explosiveness in addition to general macroeconomic factors. For instance, explosive periods occurred first in corn and wheat futures during the price boom period (2006 - mid 2008) on 10/17/2006 which lasted for two weeks. Corn prices were explosive again in November 2006 which lasted into January 2007. In contrast, soybean prices did not drift away from a random walk until February 2007. For KC wheat futures, prices first became explosive even later (August 2007). In addition, there were about nine months of non-explosiveness in corn futures before explosive behavior appeared again in January 2008. In the meantime soybean, wheat, and KC wheat futures prices became explosive. Overall, these dissimilarities among grain futures call for careful identification of specific factors that may have driven individual price explosiveness.

Granger Causality Tests

Returns and Index Investment Position Data

Having identified the explosive periods in grain futures, the next step is to examine the behavior of returns in relation to positions during explosive and non-explosive periods. For index investment activities, we use the Supplemental Commitments of Traders (SCOT) report prepared by the CFTC. The SCOT reports are available publically starting in January 2006 and include the positions held by commercials, non-commercials, CITs, and non-reporting traders. The CIT positions are drawn from both the commercial and non-commercial positions in the legacy Commitments of Traders (COT) reports. The CFTC did collect additional data for CBOT corn, soybean and wheat futures and KCBOT wheat futures over 2004-2005 at the request of the U.S.

Senate Permanent Subcommittee on Investigations (USS/PSI, 2009) and these data are also used in the present analysis. Consequently, the same 426 observations are available for the Granger tests as in the previous PSY tests.

Table 3 reports descriptive statistics for the SCOT data during both explosive and non-explosive periods. CIT investment activities are measured by their net long positions (i.e., number of long contract minus number of short contract held by CITs). During explosive periods, returns range from 0.55% in soybean futures to 1.02% in KC wheat futures, while during non-explosive periods returns are slightly negative, ranging from -0.18% in wheat to -0.05% in soybeans. This pattern is not surprising given that most of the explosive periods occurred during periods of increasing prices and are thus likely to exhibit positive returns. Though the standard deviations of returns are comparable in both periods, the distributions are less dispersed in the explosive periods for all four markets (i.e., the ranges of values are much smaller). If in fact CITs are responsible for the explosive periods, CITs' net long positions did not increase as much as one would expect at those times. Corn markets experienced the largest increase, from about 328,000 to 400,000 – a 29% increase. For CBOT wheat futures, CITs net long positions only increased about 19,000 contracts in the explosive periods, or an 11% increase. Given that CITs investment activities are relatively stable in explosive and non-explosive periods, casting blame on the CITs for price explosiveness may be difficult to substantiate.

The unconditional contemporaneous correlations between returns and CITs investment activities are quite different in explosive and non-explosive periods (see Table 3). Returns and CITs net long positions are generally only weakly correlated in non-explosive periods, with the correlation coefficient ranging from 0.03 in KC wheat to 0.10 in corn. The contemporaneous link between returns and CITs net long positions significantly strengthened during explosive periods. For instance, the correlation coefficients increased to 0.33 and 0.31 in soybean and wheat futures, both of which are statistically significant as well. Nevertheless, correlation does not establish temporal causality or lead/lag relation since it only indicates the degree of a contemporaneous linkage.

To further investigate the behavior of index investment, we plot CIT net long positions along with the explosive periods identified by the PSY procedure in Figure 3. As can be seen in the figure, some correspondence between the peaks of CIT positions and price explosiveness is observed in corn and soybean futures, especially during the explosive periods found in 2008. However, while CITs held large net long positions between 2010 and 2011, corn and soybean futures prices are mostly non-explosive during this period. The relation of CITs and price explosiveness becomes even less clear when analyzing the two wheat futures. While CITs net long positions significantly increased For KC wheat after 2009, there are only four explosive weeks in total between 2009 and 2012. Net long positions held by CITs have been relatively stable over the entire sample period in CBOT wheat futures, while most of the explosive periods occurred between 2007 and 2008. Overall, it is difficult to visually distinguish a consistent pattern between CITs net long positions and explosive periods.

Traditional and Modified Granger Causality Tests

To formally test the causal and lead/lag relationship between returns and index investment, we conduct the traditional Granger causality test under a bivariate vector autoregression (VAR) framework, as well as a modified Granger causality test that incorporates the price explosiveness interaction terms. The traditional Granger causality test ignores any price explosiveness in the sample periods and treats the entire dataset as one stable regime, while in the modified Granger causality test, the causality between returns and CIT positions is allowed to change during explosive periods. A comparison of the two tests can potentially reveal the importance of precisely identifying explosive periods, enabling us to more accurately assess the role of index investment in grain futures markets.

The traditional Granger causality test starts with a bivariate VAR model:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + e_t, \tag{6}$$

where y_t=[returns$_t$,, CIT$_t$]$'$, p is the maximum lag order used in the VAR model, A_0 is a 2×1 vector of constants, $A_1, A_2, \ldots, A_p$ are 2×2 matrices, and e_t is a 2×1 vector of error terms. The lag order p in Equation (6) is first selected using the Akaike information criterion (AIC) and the resulting VAR model is tested for autocorrelations using the Lagrange-multiplier (LM) test. If we fail to pass the LM test, added lags are incorporated into the VAR system until no residual autocorrelation is found. To account for potential heteroscedasticity, robust standard errors are used in each individual equation.

Panel A of Table 4 reports the p-values from the traditional Granger causality test. The lag structure is rather simple for all commodities except corn. It can be seen that CITs did not Granger cause returns in any of the four grain futures markets, while returns did Granger cause CITs investment activities in all the markets except KC wheat. The results from the traditional Granger causality test are consistent with previous studies using various sample periods.

To investigate whether the causality between returns and index investment differ in explosive and non-explosive periods, we introduce a dummy variable that indicates when the prices are explosive as defined by the PSY procedure and include the interactions between the dummy and trading activities as well as returns in the Granger causality test. Specifically, we construct the following modified Granger causality test:

$$\text{Returns}_t = a_0 + \sum_{i=1}^{p} a_i \text{Returns}_{t-i} + \sum_{i=1}^{p} b_i\, \text{CIT}_{t-i} + \sum_{i=1}^{p} c_i\, [\text{CIT}_{t-i} * D_{t-i}] + e, \tag{7}$$

$$\text{CIT}_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \text{CIT}_{t-i} + \sum_{i=1}^{p} \beta_i\, \text{Returns}_{t-i} + \sum_{i=1}^{p} \gamma_i\, [\text{Returns}_{t-i} * D_{t-i}] + \varepsilon, \tag{8}$$

where D, the dummy variable, indicates price explosiveness and $i = 1, \ldots, p$ is the lag structure. Following the same lag structure used in the traditional Granger causality test, the residuals from Equations (7) and (8) are tested for serial correlations. If autocorrelation is found, more lag terms are added to the individual equation until no autocorrelation exists. Each equation is estimated using robust standard errors. Unlike the traditional Granger causality test, the lag structures are allowed to vary in different equations within an individual market. However, within a specific equation a fixed lag order is used for all the right-hand side variables. Granger causality is found if the joint null hypothesis of zero coefficients is rejected for CITs or returns in either explosive or non-explosive periods. The modification as specified in Equations (7) and (8) essentially enables us to detect any possible shifts in causal relationship in explosive periods compared to when the prices follow a random walk. If the relationship is constant over the sample period, we would expect the joint hypothesis for the interaction terms with CITs or returns to be not rejected.

Panel B of Table 4 reports the *p*-values from the modified Granger causality test. The lag structure is found to be the same as in the traditional Granger causality test. In corn, soybeans, and KC wheat futures markets, no causal relationship can be established from changes in CITs investment activities to returns in either explosive or non-explosive periods as all the p-values are larger than 0.10. However, statistical significance is found in the wheat futures traded on CBOT. More specifically, CITs did Granger cause returns in wheat futures in both explosive and non-explosive periods, and this causality has changed in explosive periods as well. This causal relationship is not found while using the traditional Granger causality that ignores price explosiveness. The causality from returns to CITs investment activities, on the other hand, is very much like the results from the traditional Granger causality test. Returns Granger caused index-investment in both explosive and non-explosive periods in all grain futures markets except KC wheat, and this causality is largely invariant to price explosiveness.

Since Granger causality is found from CITs to returns in wheat futures traded on CBOT, we need to evaluate the overall magnitude of CIT position changes on returns. We construct the impulse response functions (IRFs) for the return equations when the prices are explosive. Specifically, using the lag operator and assuming $D_{t-i} = 1$ for $= 1, \ldots, p$, Equation (7) can be re-written as

$$(1 - L - L^2 - \cdots - L^p)\mathrm{Returns}_t = a_0 + \sum_{i=1}^{p}(b_i + c_i)\,\mathrm{CIT}_{t-i} + \mathrm{e}. \tag{9}$$

Thus, the overall magnitude of effects from lagged changes in CIT net long positions on returns is equal to $(1 - \sum_{i=1}^{p} L^i)^{-1} \sum_{i=1}^{p}(b_i + c_i)L^i\,\mathrm{CIT}_t$. We assume the impulse equals one standard deviation of the changes in CIT net long positions during the explosive periods, and the impulse occurred in period 1. The corresponding responses of returns in wheat futures traded on CBOT are plotted in Figures 4. As can be seen in the plot, a one standard deviation (about 3.87 thousand contracts) increase in CIT net long position in period 1 would increase returns in wheat futures by 0.79% in period 2. Given that the standard deviation of returns in wheat futures during explosive periods is 2.52%, this is a rather moderate, if not small, increase (30% of the standard deviation of returns). In addition, starting from period 3, the response of returns essentially dies out and is indistinguishable from zero. The IRFs thus indicate that though there is causality from CITs to returns in wheat futures traded on CBOT in explosive periods, the magnitude of effect is moderate and dissipates quickly.

Summary and Conclusions

Precisely defining explosive periods of market price behavior is an essential first step when investigating concerns about commodity prices. Studies seeking to untangle the factors driving recent food price fluctuations can especially benefit from such a precise measure. The importance of this argument emerges when investigating the controversy surrounding the role of commodity index investment in futures markets. Most of the existing evidence against CITs relies on the argument that CITs held large positions between 2006 and 2008, as well as between 2010 and 2012 when prices reached historical highs in many commodity markets.

In this paper, we define the explosive periods in commodity futures market as periods when price fails to follow a random walk. We use the multiple-regime switching testing procedure developed by Phillips, Shi, and Yu (2012) (PSY) to identify explosive periods in the prices of corn, soybeans, and wheat futures traded on the CBOT, as well as wheat futures traded on the KCBT between January 2004 and February 2012. The findings indicate that most these grain futures markets experienced explosive periods between the end of 2007 and first half of 2008, as well as in the second half of 2010. In corn and soybean futures, prices were explosive about 12% of the time. For the two wheat futures, the number is slightly lower – the prices were explosive about 8% of the time.

Using dummy variables to reflect the explosive periods identified with the PSY procedure, we investigate the relationship between CIT positions and changes in futures prices. Dummy variable interaction terms to allow for differential effects during the explosive periods are included in a modified Granger causality framework. While the standard Granger causality test can only examine causality over the entire sample period without differentiating explosive and non-explosive periods, the modified Granger causality test allows causality to differ when prices are explosive.

We find that no Granger causality can be established from changes in CITs net long positions to returns in corn, soybeans, and KC wheat futures in either explosive or non-explosive periods, consistent with the results from the traditional Granger causality test. For wheat futures traded on CBOT, estimation results show that CITs Granger cause returns in explosive and non-explosive periods. Examination of the impulse response function, however, suggests that the effect is relatively small to moderate and dissipates quickly. For example, a one standard deviation increase in CIT net long positions in (explosive) period 1 only increases the returns in wheat futures in period 2 by 0.79%.

If price explosiveness is ignored in the traditional Granger causality test then a statistically significant effect of CITs on returns in CBOT wheat is missed. Nonetheless, this finding does not change the overall tenor of the results. The results from the modified Granger causality test differentiating explosive from non-explosive periods provide additional evidence that CITs are mostly likely not responsible for the large price movement observed in grain futures between January 2004 and February 2012.

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Endnotes

[1] Though the PWY, PY, and PSY procedures are designed to detect rational speculative bubbles, the procedures are used here to detect the existence of explosive periods. The rational bubble literature is based on an observed price series and a well-specified fundamental series. However, it is hard to obtain the fundamental value of commodities. Applying the PSY procedure to commodity prices thus serves to better diagnose price explosiveness.

[2] Such a date stamping strategy is referred to as the BSADF (backward sup ADF) test by PSY. For simplicity, it is referred to as the SADF test here. Note that this test is different from what PWY refer to as SADF.

[3] The PSY date-stamping procedure only date-stamps the start and end dates of explosive periods. It does not indicate how explosive, or the magnitude of price explosiveness during the explosive periods.

[4] Different values of h are specified, and as we show later in Table 3, these different values mostly affect explosive periods identified before 2006. Explosive periods found after 2006 are nearly unaffected.

[5] To account for any potential inflation effects, the nominal futures prices are adjusted by the CPI collected by the US Bureau of Labor Statistics. Given that the CPI ranges from the mid-180s at the beginning of 2004 to the upper-220s in 2012, real futures prices are somewhat smoother than the nominal prices. Nevertheless, the nominal price and real price series yield very similar results when conducting the PSY procedure and for brevity, only results using the nominal futures prices are discussed.

[6] The minimum window size is chosen so that the chance of finding explosive periods is maximized and there are a sufficient number of observations to estimate equation (2).

Table 1. GSADF Testing Results

Panel A. Critical Values for GSADF Test		
90%	2.35	
95%	2.63	
99%	3.23	
Panel B. GSADF Test Statistics for Weekly Grain Futures Prices (Jan 2004 - Feb 2012)		
Corn	3.12	**
Soybeans	4.50	***
Wheat	4.01	***
KC Wheat	4.14	***

*Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, respectively.*

Table 2. SADF Date-Stamping Results

Commodity	Explosive Periods	Length (weeks)
Corn	7/27/2004 - 8/10/2004	2
	10/17/2006 - 10/31/2006	2
	11/7/2006 - 1/9/2007	9
	1/16/2007 - 3/27/2007	10
	1/8/2008 - 1/22/2008	2
	1/29/2008 - 2/12/2008	2
	2/19/2008 - 7/22/2008	22
	9/14/2010 - 9/28/2010	2
	Total	51 (11.97%)
Soybeans	7/27/2004 - 8/24/2004	4
	2/13/2007 - 3/6/2007	3
	9/11/2007 - 4/1/2008	29
	4/8/2008 - 4/29/2008	3
	5/13/2008 - 7/22/2008	10
	10/26/2010 - 11/16/2010	3
	Total	52 (12.21%)
Wheat	10/17/2006 - 10/31/2006	2
	8/7/2007 - 11/13/2007	14
	11/20/2007 - 4/1/2008	19
	8/3/2010 - 8/17/2010	2
	Total	37 (8.69%)
KC Wheat	8/28/2007 - 11/13/2007	11
	11/20/2007 - 4/1/2008	19
	8/3/2010 - 8/17/2010	2
	9/7/2010 - 9/21/2010	2
	Total	34 (7.98%)

Table 3. Descriptive Statistics for Returns and CIT Net Long Positions (1,000 contracts)

	Panel A: Corn			
	Explosive (N=51)		*Non-Explosive (N=356)*	
	Returns	CIT	Returns	CIT
Mean	0.62%	400	-0.15%	328
St. Dev.	1.97%	69	2.06%	100
Min	-3.61%	113	-7.16%	108
Max	6.64%	495	8.00%	504
Correlation	0.217		0.0967*	
	Panel B: Soybeans			
	Explosive (N=52)		*Non-Explosive (N=355)*	
	Returns	CIT	Returns	CIT
Mean	0.55%	163	-0.05%	126
St. Dev.	1.74%	40	1.69%	44
Min	-3.72%	35	-6.80%	30
Max	4.24%	201	4.92%	198
Correlation	0.328**		0.0516	
	Panel C: Wheat			
	Explosive (N=37)		*Non-Explosive (N=370)*	
	Returns	CIT	Returns	CIT
Mean	0.85%	188	-0.18%	169
St. Dev.	2.52%	8	2.04%	44
Min	-4.80%	175	-7.65%	50
Max	6.36%	209	5.69%	230
Correlation	0.307*		0.0489	
	Panel D: KC Wheat			
	Explosive (N=34)		*Non-Explosive (N=373)*	
	Returns	CIT	Returns	CIT
Mean	1.02%	34	-0.10%	29
St. Dev.	2.42%	6	1.86%	10
Min	-3.76%	28	-7.11%	14
Max	6.42%	53	4.91%	53
Correlation	0.251		0.0309	

*Notes: Correlation refers to the correlation between returns and CIT net long positions; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, respectively.*

Table 4. Granger Causality Test Results

Panel A. Traditional Granger Causality Test

	Lag	*CITs Granger Cause Returns*	*Returns Granger Cause CITs*
Corn	(4,4)	0.22	0.02
Soybeans	(1,1)	0.43	0.07
Wheat	(1,1)	0.27	0.02
KC Wheat	(1,1)	0.62	0.59

Panel B. Modified Granger Causality Test

		CITs Granger Cause Returns			*Returns Granger Cause CITs*		
	Lag	Non-Explosive	Explosive	Combined	Non-Explosive	Explosive	Combined
Corn	(4,4)	0.25	0.59	0.22	0.02	0.97	0.13
Soybeans	(1,1)	0.89	0.18	0.34	0.02	0.05	0.03
Wheat	(1,1)	0.04	0.05	0.04	0.04	0.38	0.02
KC Wheat	(1,1)	0.92	0.18	0.38	0.81	0.65	0.91

Note: The table reports the p-values of Granger causality tests

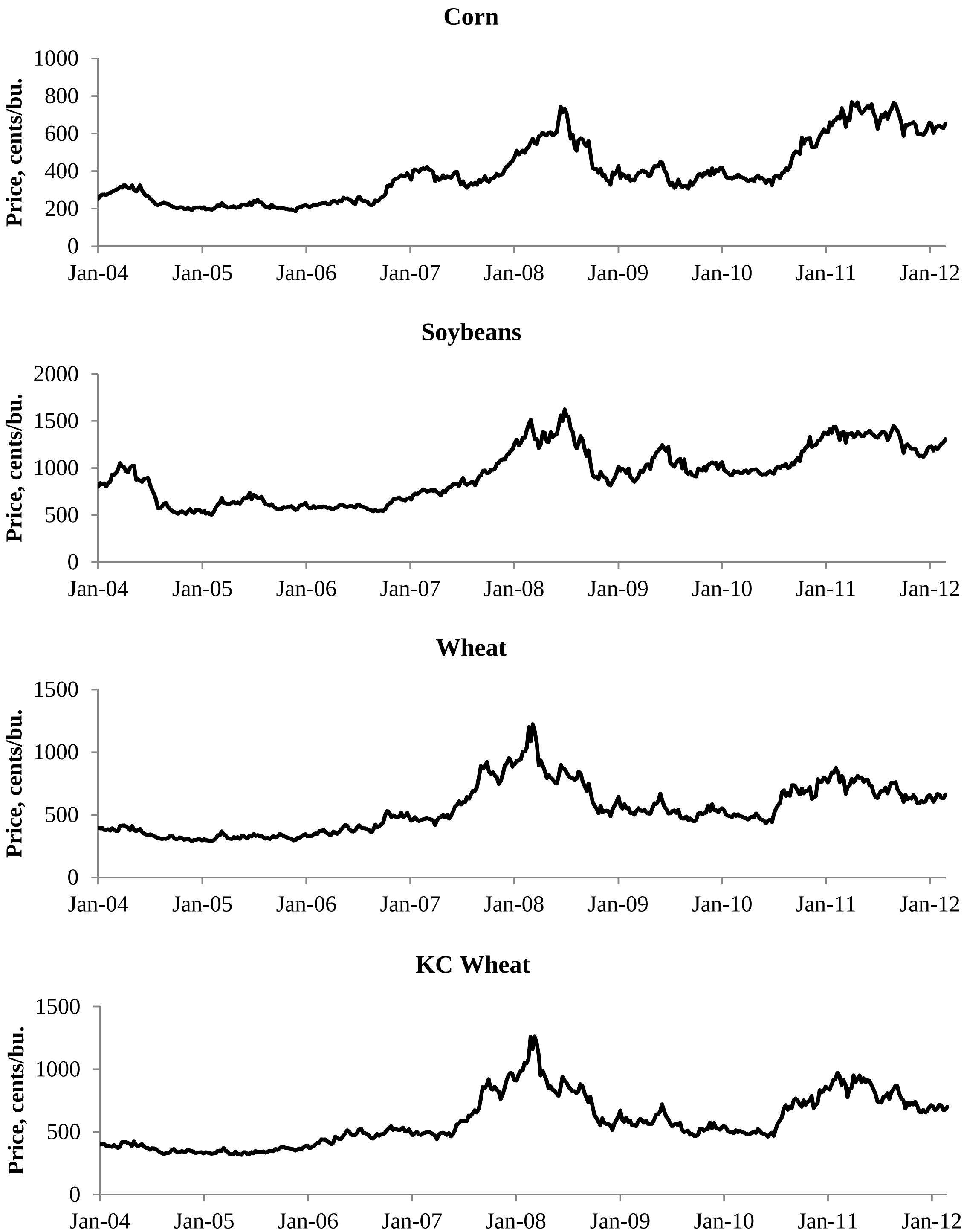

Figure 1. Weekly Nearby Futures Prices of Grains (Jan 2004 - Feb 2012)

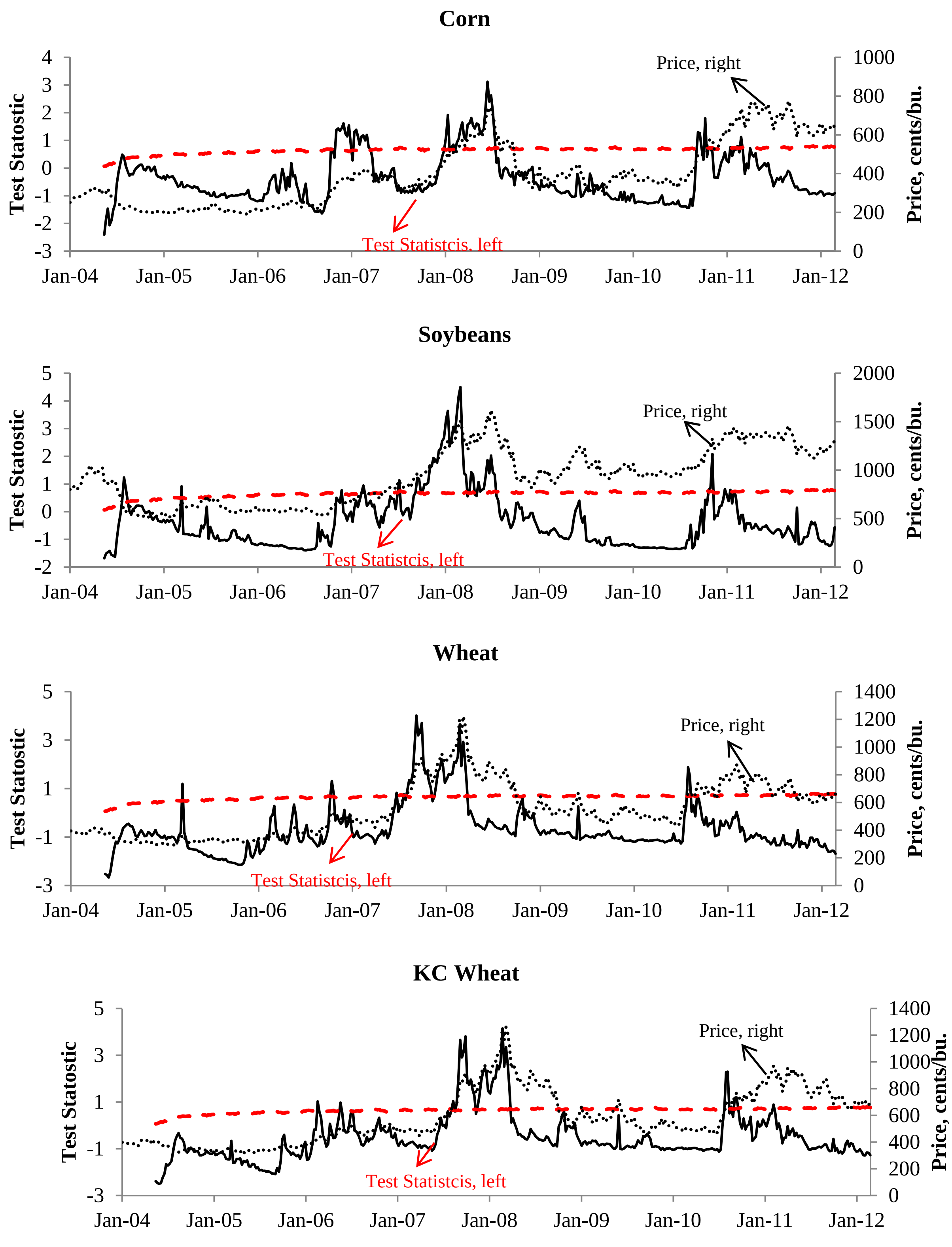

Figure 2. PSY Date-Stamping Results of Corn, Soybeans, Wheat and Kansas Wheat

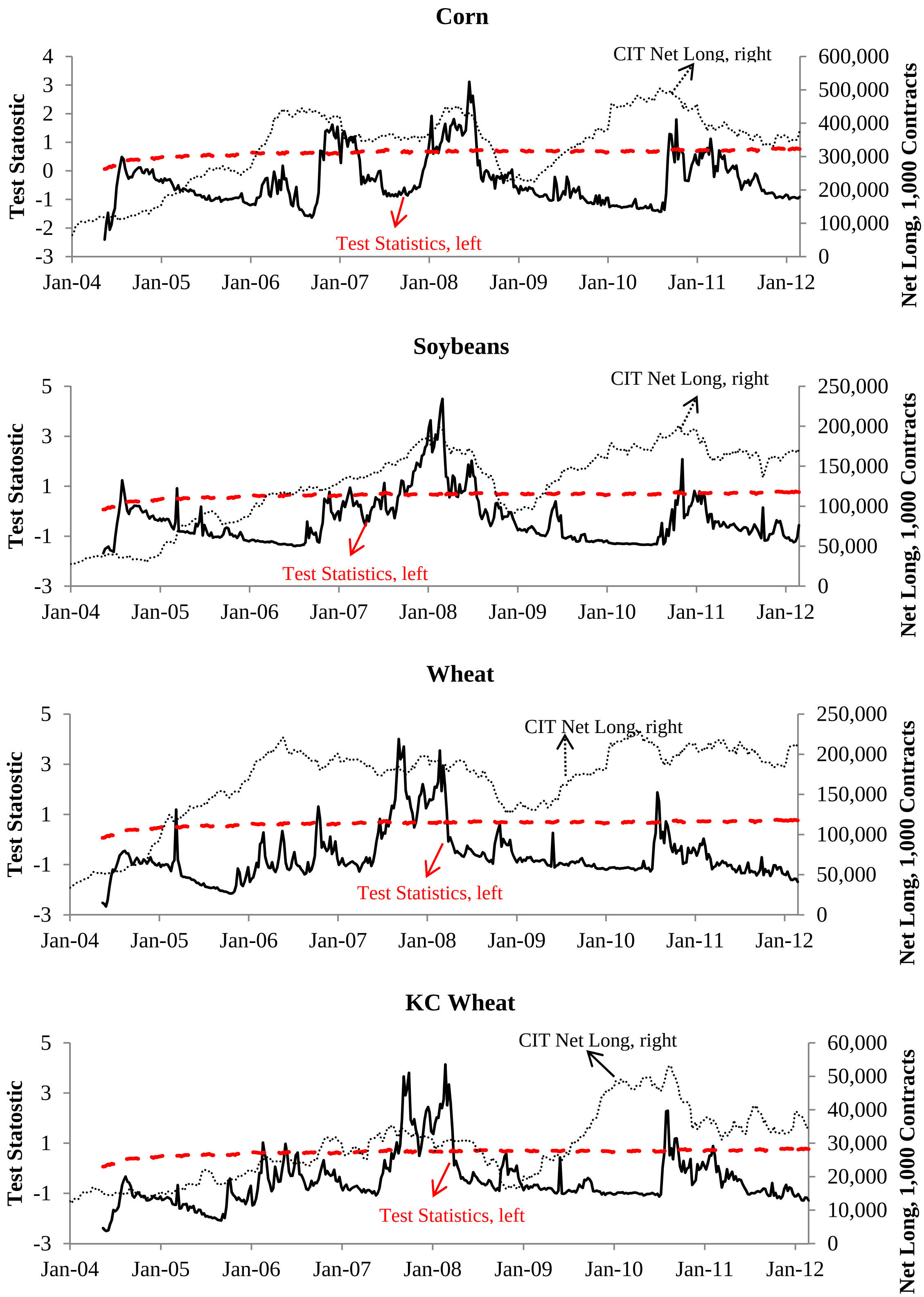

Figure 3. Explosive Periods and CIT Net Long Positions

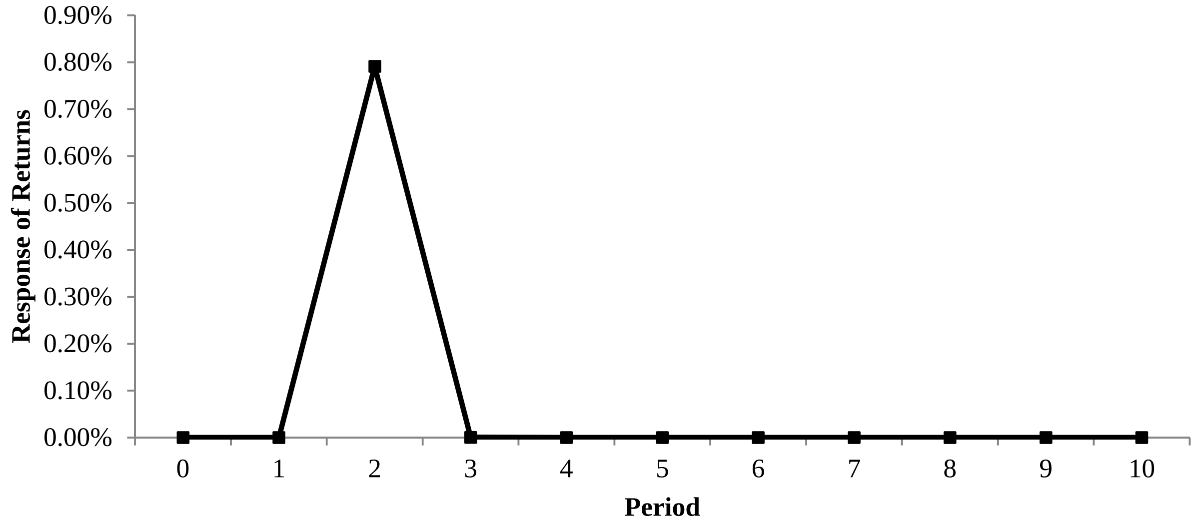

Figure 4. Response of Returns to a One Standard Deviation Increase in the Changes of CIT Net Long Positions at Period 1 in Wheat Futures