NCCC-134

APPLIED COMMODITY PRICE ANALYSIS, FORECASTING AND MARKET RISK MANAGEMENT

Bubbles in Grain Futures Markets:
When are They Most Likely to Occur?

By

Xiaoli L. Etienne, Scott H. Irwin, and Philip Garcia

Bubbles in Grain Futures Markets: When are They Most Likely to Occur?

Xiaoli L. Etienne, Scott H. Irwin, and Philip Garcia[1]

Paper presented at the NCCC-134 Conference on Applied Commodity Price
Analysis, Forecasting, and Market Risk Management
St. Louis, Missouri, April 22-23, 2013

---

[1] Xiaoli L. Etienne is a PhD student, Scott H. Irwin is the Laurence J. Norton Chair of Agricultural Marketing, and
Philip Garcia is the T.A. Hieronymus Distinguished Chair in Futures Markets, all in the Department of Agricultural
and Consumer Economics, University of Illinois at Urbana-Champaign.

Bubbles in Grain Futures Markets: When are They Most Likely to Occur?

Unprecedented changes in commodity prices since 2004 have had worldwide repercussions, often acting as a destabilizing economic and political influence. In this paper, we use a recently developed multiple bubble testing procedures to detect and date-stamp bubbles in corn, soybean, and wheat futures markets. To account for conditional heteroskedasticity and small sample bias, inferences are derived using a recursive wild bootstrap procedure. We find that the markets experienced price explosiveness about 2% of the time. Using a logit model which accounts for bias due to the rare occurrence of an event, we find that bubbles are more likely to occur in the presence of large aggregate global demand, low stocks to use ratios, and a weak US dollar. While commodity index traders had no effect on the probability of an explosive episode, speculative activity exceeding the minimum level required to absorb hedging activities as measured by the Working's T reduces considerably the probability of a bubble.

Introduction

Since 2004 grain prices have experienced unprecedented large changes. The extreme price fluctuations have had worldwide repercussions, acting as a destabilizing economic and political influence in many countries (e.g., Bellemare 2011). Understanding the driving forces behind these extreme price movements is imperative and has been the subject of much academic debate.

To date, much of the academic debate on recent commodity price volatility has centered on whether fundamentals or speculative activities are to blame. The first stream of research directly tests the effect of index investment activities by financial index traders on commodity price movements, finding little evidence for speculative bubbles caused by index traders in commodity prices (e.g., Stoll and Whaley 2010, Sanders and Irwin 2011, Hamilton and Wu 2013). A closely related area of research examines the co-movements between industrial and non-industrial commodities over time, concluding that the financialization of commodity markets that began after 2004 could explain the large increase in the price volatility of non-energy commodity futures in the US (e.g., Tang and Xiong 2010). A second stream of research attempts to explain commodity price movements through structural models, estimating the relative importance of various possible contributing factors in driving the price volatility (e.g.,Kilian 2009, Carter, Rausser, and Smith 2012, Janzen, Smith, and Carter 2013). With the exception of McPhail, Du, and Muhammad (2012), these structural studies typically find that the price behavior can be largely attributed to either global or market-specific supply/demand conditions.

Another stream of research focuses on directly testing for a bubble component in commodity prices that are potentially unrelated to investment activities of index traders. Research in this category has in general attempted to identify periods when prices deviate away from a random walk and become mildly explosive using recursive testing procedures developed by Phillips, Wu, and Yu (2011), Phillips and Yu (2011), and Phillips, Shi, and Yu (2012). A number of studies have applied these recursive testing procedures to various agricultural markets and found mixed results (Gilbert 2010a, Phillips and Yu 2011, Etienne, Irwin, and Garcia 2012, Gutierrez 2013, Etienne, Irwin, and Garcia 2013). In general, they find that "bubbles", or mildly explosive prices, do exist in grain markets after 2004. However, as Etienne, Irwin, and Garcia (2013) show, bubble episodes only represent a very small portion of the price behavior in agricultural commodity markets. In addition, most bubbles are short-lived, with 80 to 90% lasting fewer than 10 days. These studies, however, have mainly focused on detecting and date-stamping bubbles, without further investigating the underlying causes of these explosive prices.

In this paper we extend the research on bubble testing by examining under what conditions bubbles are more likely to occur in US grain futures markets. We first identify the exact episodes of explosive behavior, including origination and termination dates in corn, soybeans, wheat, and KC wheat futures markets. These explosive episodes are obtained by applying the multiple bubbles testing procedure developed by Phillips, Shi, and Yu (2012) to series of prices for individual futures contracts. To account for potential small sample bias and conditional heteroskedasticity, inferences are derived from the recursive wild bootstrap procedure as discussed in Gonçalves and Kilian (2004). In the presence of explosive behavior, we investigate the relationship of explosive periods to the stocks-to-use ratio, exchange rate, speculative activities in futures markets, and global real economic activity using a rare events logit model. Results suggest that in the presence of low stocks, booming economic growth, and weak US dollar, bubbles are more likely to occur. While commodity index traders do not affect bubble occurrence, more broadly defined speculative activities as measured by Working's T reduces bubble occurrence.

Testing for Bubbles

We use the recursive bubble testing procedure recently developed by Phillips, Shi, and Yu (2012, PSY hereinafter) to date-stamp bubbles in grain futures markets. Specifically, PSY use a generalized framework with variable window widths in the recursive regressions on which the test procedure is based. Defining the estimation start and end points as r_1 and r_2, respectively, the following estimation equation is recursively estimated for a given price sequence $\{P_t\}$:

$$(1) \qquad \Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} \gamma_{r_1,r_2}^i \Delta P_{t-i} + \varepsilon_t,$$

where $\Delta P_t = P_t - P_{t-1}$, k is the lag order, and $\varepsilon_t \sim iid\ N(0, \sigma_{r_1,r_2}^2)$. 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} as the minimum window size required to estimate equation (3) 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 $SADF_{r_2} = Sup_{r_1 \in [1, r_2 - r_{w_0}+1]} ADF_{r_1, r_2}$.[1] Now allow the ending point r_2 to vary between r_{w_0} and T, the last data point included in the estimation; we then obtain $[T - r_{w_0} + 1]$ $SADF_{r_2}$ statistics from a backward-expanding window. These $SADF_{r_2}$ test statistics are then compared to the critical values. The estimated origination and end dates of the first explosive episode are specified by:

(2) $\qquad \widetilde{r_{1e}} = inf_{r_2 \in [r_{w_0}, n]}\{r_2 : SADF_{r_2} > cv_{r_2}^{\rho}\}$ and

(3) $\qquad \widetilde{r_{1f}} = inf_{r_2 \in [\widetilde{r_{1e}}+h, n]}\{r_2 : SADF_{r_2} < cv_{r_2}^{\rho}\}$,

where $cv_{r_2}^{\rho}$ is the 100ρ critical values of the backward-expanding SADF statistic based on r_2 observations and h is the minimum defined length of the bubble episode.

The above testing procedure calls for a well-defined sequence of critical values for the backward SADF test statistic when date-stamping bubbles. To account for conditional heteroskedasticity in the bubble tests and the potential small sample bias, we use the wild bootstrap procedure discussed in Gonçalves and Kilian (2004) when applying the PSY procedure. Gonçalves and Kilian (2004) demonstrate the first-order asymptotic validity of the recursive wild bootstrap procedure for finite-order autoregressions with possible conditionally heteroskedastic errors. Specifically, we use the recursive wild bootstrap method to derive an empirical distribution of the backward SADF test statistic as follows:

1. For each data sequence, we first estimate an autoregressive model under the null hypothesis of no bubble as in equation (3), where $\beta_{r_1, r_2} = 0$. Denote the resulting residuals as $\hat{\varepsilon}_t$ and the estimated autoregressive coefficients as $\hat{\gamma}_{r_1, r_2}^i$.
2. Generate wild bootstrap residuals $\hat{\varepsilon}_t^*$ such that $\hat{\varepsilon}_t^* = \hat{\varepsilon}_t \eta_t$, where η_t is an i.i.d. sequence with zero mean and unit variance. Here we let $\eta_t \sim N(0,1)$.[2]
3. Generate recursive bootstrap samples P_t^* from $P_t^* = P_{t-1}^* + \sum_{i=1}^{k} \hat{\gamma}_{r_1, r_2}^i \Delta P_{t-1}^* + \hat{\varepsilon}_t^*$ for $t = 1, 2, \dots T$. We then calculate the backward SADF values on the bootstrap sample using equation (3) for every ending point given some minimum window size. The White heteroskedasticity-consistent standard error is used while computing the ADF t-statistic.
4. Repeat steps 1 to 3 many times, and obtain the bootstrap distribution of the backward SADF test statistic. Here the number of bootstrap draws is set to 2,000.

In essence, the wild bootstrap sample mimics the pattern of conditional heteroskedasticity in the original data generating process and is thus more effective than the traditional finite sample or standard residual-based bootstrap critical values. The empirical distribution from the wild

bootstrap can then be used to derive inference for the SADF test statistic for the original data calculated using the White standard error. We use the 95% quantile from the wild bootstrap distribution to date-stamp bubbles. Gonçalves and Kilian (2004) argue that that the robust wild bootstrap procedure should be favored in empirical applications over the standard residual-based bootstrap based on an iid error assumption.

Date-Stamping Bubbles in Grain Futures Markets

We consider log futures prices of corn, soybean, and wheat traded on the Chicago Board of Trade (CBOT), as well as the hard red winter wheat futures contract traded on the Kansas City Board of Trade (KCBOT) at the daily frequency. As discussed in Etienne, Irwin, and Garcia (2013), sequences of individual futures contract prices are used instead of rolling nearby futures prices. In the absence of bubbles and assuming rational expectations, no risk premium, and no basis risk, individual futures contract prices should in theory follow a random walk. Consistent with recent work on the latest round of unprecedented price volatility, we choose a sample period from 2004 to 2011. We consider one contract per commodity each year, typically the contract with the highest trading volume. Specifically, these include the December contract for corn, November contract for soybeans, and July contract for two wheat futures. To avoid overlapping bubbles, we limit the sample size of each contract to start on the first day of 13 months before the contract expires, and end on the last trading day of the month before the contract expires. This results in 240-260 observations for each contract. In addition, we set the minimum window size to 20, or roughly one month of data. The minimum bubble length is set to 3 days, or $h = 3$. This is slightly shorter than the 5-6 days as suggested by the log(T) rule of Phillips, Wu, and Yu (2011), but is reasonable given that commodity futures contracts are unlikely to have protracted bubbles because they are finite-horizon instruments with virtually no constraints on short-sales (e.g., Tirole 1982).

For illustration, the PSY testing procedure is presented in figure 1 where we detect and date-stamp bubbles in the 2008 contract prices of four commodities using critical values developed with the recursive wild bootstrap procedure. Date-stamping results are found by comparing the SADF statistic with the 95% critical value sequences. With a minimum bubble length of three days ($h = 3$), three, four, zero, and two bubble episodes are identified in the corn, soybeans, wheat, and KC wheat 2008 contract prices, respectively. Note that there are cases with explosive prices lasting fewer than 3 days, which do not count as bubble episodes.

Table 1 shows the number of days with explosive prices each year for each commodity. Bubbles are most frequent observed in the soybean market, followed by the corn and KC wheat market. For wheat traded on the CBOT, only two bubbles are identified: one in mid-2008 and the other in mid-2010, in total 13 days over the eight years considered. Overall, bubbles are rather rare events in grain futures markets, accounting for only 2.22% of the total price behavior throughout the sample periods for all four commodities considered.

4

Rare Events Logit Model

We turn to analysis of the contributing factors to these bubbles in grain futures markets between 2004 and 2011. This is accomplished through a logit model that deals with binary dependent variables. Consider a conventional logit model, where the dependent variable y follows a Bernoulli distribution and is defined as:

(4)
$$y_t = \begin{cases} 1 & \text{with probability } \pi \text{, bubble occurs} \\ 0 & \text{with probability } 1\text{-}\pi, \text{ no bubbles} \end{cases}.$$

We are interested in estimating the conditional probability of $\Pr(y_t = 1 | X = x_t)$ where x_t is a vector of explanatory variables. The estimation equation may be written as:

(5)
$$logit(\pi) \equiv \ln\left(\frac{\pi}{1-\pi}\right) = X\beta + \varepsilon.$$

This is equivalent to:

(6)
$$\pi = \frac{e^{X\beta}}{1+e^{X\beta}} = \frac{1}{1+e^{-X\beta}} \quad .$$

The maximum likelihood estimator for the conventional logit model is well-known to have finite sample bias but with bias diminishing with larger samples. However, King and Zeng (2001a, b) show that the bias may be amplified in the presence of rare events; i.e., in cases which the number of zeros (nonevents) is dozens to thousands of times more than the number of ones (events) in the dependent variable. Specifically, they demonstrate that in these cases the traditional maximum likelihood estimator $\hat{\beta}$ is a biased estimate of β, and the estimated probability $\hat{\pi}$ is an inferior estimator of true probability even if $\hat{\beta}$ is unbiased. The bias remains significant even in large samples. The basic argument is that while the distribution for nonevents may be well approximated given the large number of zeros available, estimating the distribution of events may be severely inaccurate due to their rarity. This leads to classification errors such that the "cutting point" for distinguishing events from nonevents is biased in the direction of favoring zeros at the expense of ones.

King and Zeng (2001a, b) identify a straightforward procedure to correct the bias in $\hat{\beta}$. Defining the bias-corrected coefficient estimates as $\tilde{\beta}$, then in empirical applications, the following estimates should be calculated:

(7)
$$\tilde{\beta} = \hat{\beta} - (X'WX)^{-1}X'W\xi,$$

where $\xi_i = 0.5Q_{ii}[(1+w_1)\hat{\pi}_i - w_1]$, Q_{ii} are the diagonal elements of $Q = (X'WX)^{-1}X'$, and $W = diag(\hat{\pi}_i(1-\hat{\pi}_i)w_i)$. In essence, the bias term is estimated through a weighted least-square

regression that involves W as the weight. The variance matrix of $\tilde{\beta}$ is $V(\tilde{\beta}) = \left(\frac{n}{n+k}\right)^2 V(\hat{\beta})$. Clearly, the variance of the bias-corrected estimates is always smaller than the variance of original estimate, as $\left(\frac{n}{n+k}\right)^2 < 1$.

The second step in correcting the rare events bias is to correct for the bias in probability calculation. Though estimating the probability using bias-corrected estimate $\tilde{\beta}$ in equation (7) performs better than using MLE estimate $\hat{\beta}$, King and Zeng (2001a, b) argue that $\tilde{\pi}$ is still not optimal since it ignores estimation uncertainty, resulting in too low of a probability for an event. They show that the following probability estimate is less biased for rare events:

(8)
$$Pr(Y_i = 1) \approx \tilde{\pi}_i + C_i = \frac{1}{1+e^{-X\tilde{\beta}}} + C_i, \text{ where}$$

$$C_i = (0.5 - \tilde{\pi}_i)\tilde{\pi}_i(1 - \tilde{\pi}_i)x_0 V(\tilde{\beta})x_0'.$$

Since C_i is positive with rare events data ($\tilde{\pi}_i < 0.5$), the corrected probability will usually be larger than the probability calculated using equation (7). The correction term gets larger as the uncertainty in $\tilde{\beta}$, or $V(\hat{\beta})$ increases.

King and Zeng (2001a,b) show in Monte Carlo experiments that the effect of bias corrections in both coefficient estimates and probability calculation gets larger as the events becomes rarer and the sample size gets smaller. In empirical applications, the bias term can have significant economic implications when sample sizes are sufficiently large. The rare events logit model has for example been widely used in political science to explain wars, presidential elections, epidemiological infections, and especially international relations.

Influencing Factors

In this section, we consider five factors which have been identified as contributing influences to recent increases in volatility that may also affect the occurrence of explosive episodes in grain futures markets. First and foremost is the index trading activities in commodity futures markets. Hedge fund manager Michael W. Masters has testified numerous times (e.g. Masters 2008, 2009) before the U.S. Congress and Commodity Futures Trading Commission (CFTC) that unprecedented buying pressure from index investment created a series of massive bubbles in commodity futures prices. These bubbles were then transmitted to spot prices through arbitrage linkages between futures and spot prices, with an end result that commodity prices far exceeded fundamental values. Irwin and Sanders (2012) use the term "Masters Hypothesis" as a short-hand label for this argument. Several prominent international development organizations (e.g., Robles, Torero, and von Braun 2009, de Schutter 2010, Herman, Kelly, and Nash 2011) have expressed strong support for the Masters Hypothesis. Given the alleged claim that CITs have caused a speculative bubble in commodity markets, it is natural to consider whether CIT trading activities played a role in bubble occurrence. We use the net positions held by commodity index traders to reflect trading activities.

To assess more generally the effect of speculators on bubble occurrence, we also consider an alternative measure of speculative activities in futures market—the Working's speculative T index, which is defined as:

(9) $\qquad T = 1 + SS/(HL + HS)$ if $HS \geq HL$, or

(10) $\qquad T = 1 + SL/(HL + HS)$ if $HS < HL$,

where SL and SS are long and short positions held by speculators, and HL and HS long and short positions of hedgers. The index measures the extent to which speculation is excessive relative to the level of hedging activity in the market. Peck (1980, p. 1037) notes that the speculative index " ...reflects the extent by which the level of speculation exceeds the minimum necessary to absorb long and short hedging, recognizing that long and short hedging positions could not always be expected to offset each other even in markets where these positions were of comparable magnitudes." Peck (1980) finds that the speculative index tends to be lower in grain markets during a more volatile period (1971-1977) compared to an earlier period (1964-1971) when prices were more tranquil. This relationship is confirmed statistically, as Peck (1981) also finds that speculative activities, as measured by Working's T, tend to have a negative effect on the daily trading range of prices, a measure of daily price volatility. More recently, McPhail, Du, and Muhammad (2012) find that while Working's T plays a rather important role in corn price movements between 2000 and 2011, it negatively affects short-run corn prices. However, Du, Yu, and Hayes (2011) show that speculation in crude oil futures (again as measured by Working's T) increases oil price variation.

When constructing Working's T, positions of speculators and hedgers are derived from the non-commercial and commercial trader category of the CFTC *Supplemental Commitment of Trader* (SCOT) report, respectively. The reports reflect combined futures and options positions as of Tuesday's market close, where options are adjusted to the delta-equivalent futures position. Weekly indexes are converted to daily data by assuming constant positions throughout the week. To account for the impact of CIT positions, we add CIT positions from the SCOT report to speculator positions. The SCOT data is publicly available since January 2006. The CFTC collected additional data for CBOT corn, soybean and wheat futures and KC 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. Another problem arises in specifying how to classify the non-reporting traders. Here we follow Sanders, Irwin, and Merrin (2010) and allocate the non-reporting traders' positions to the commercial and non-commercial trader categories using the same ratio as reporting traders.

Apart from speculative activities, we also examine three contributing factors that reflect different market conditions. The first factor is inventory. For storable commodities like grains, the importance of inventory in cash price determination has long been discussed. The annual storage model first introduced by Gustafson (1958) has shown that storage arbitrage can introduce positive autocorrelations in cash prices, which can smooth out price volatility. However, when aggregate stocks are low, the spot prices increase sharply to meet the market clearing condition in the presence of low inventories (Gardner 1979, Wright and Williams 1991, Cafiero and Wright 2011). Wright (2011) finds that annual cash prices and stocks-to-use ratios over the past

7

40 years conform to this relationship and argues that the scarcity argument can explain recent price spikes. Hochman et al. (2011) find that, neglecting inventory demand, prices in 2007 would have been 38% to 52% lower than the observed cash prices in that year. Even though the Gustafson (1958) model was developed for cash prices, the scarcity argument is also relevant to prices in the futures market since the futures price is determined by the current cash price, inventory and interest costs, as well as convenience yield (Working 1949). The inventory data used here are obtained from the World Agricultural Supply and Demand Estimates (WASDE) report released by the USDA. Every month, the WASDE report provides an estimate of the US end-of-marketing-year and world end-of-year stocks for both old and new crops. The estimated stocks-to-use ratio measures the level of carryover stock as a percentage of the total demand to use, and thus closely represents the tightness of the current supply-demand relationship in grain markets. Here we use the estimates for the current marketing year. The monthly estimates are then converted to daily data, which assumes a constant ending stocks-to-use ratio throughout the month.

The second factor that influences market conditions is exchange rate, which may have a strong impact on price behavior. Consider for example that the monthly average exchange rate of US dollar against Euro decreased from 1.13 in January 2000 to 0.75 in December 2004. By July 2008, the Dollar/Euro exchange rate reached a historical low of 0.63. As the US dollar declines in value, the cost of importing products from the US is lower. Since US is a major exporting country of grains, a weak US dollar is likely to increase exports and reduce the amount of available domestic grain, contributing to the commodity price boom observed since 2004. Abbott, Hurt, and Tyner (2008) show that between 2002 and 2007, the trade-weighted US dollar depreciated 22%, while the value of agricultural exports increased 54%, with grain and oilseed exports increasing even more at 63%. They consider the depreciation of the US dollar as the primary driving factor behind the 2008 commodity price spike. Other studies conclude that the falling US dollar played a more minor role. Mitchell (2008) for example, finds that about 20% of the food price increase from January 20002 to February 2008 may be attributed to dollar weakness. In addition, commodity prices are often found to exhibit excess sensitivity to exchange rate movements. Gilbert (2010b) argues that this could be due to either (1) the business cycle component within exchange rates and commodity prices not captured by other demand-side variables, or (2) the causality when constructing exchange rate indexes that run from commodity prices to exchange rate that includes commodity currencies. This research suggests that exchange rates may help contribute to bubbles in grain markets. The daily exchange rate data are obtained from the Federal Reserve Bank of St. Louis, and the trade-weighted U.S. dollar index against major currencies is used. [3]

The last factor we include is the real global economic activity. Many studies suggest that the rapid economic growth in developing countries, notably China and India, is the main driving force of commodity price spike (e.g., von Braun 2008).Though the importance of macroeconomic factors has been asserted, directly incorporation of macroeconomic variables into empirical models has been hindered by the low frequency of macroeconomic indicators, which are typically only available on an annual or quarterly basis (e.g. GDP). In addition, currently available indicators of economic growth tend to be mostly partial measurements for specific regions, unable to reflect global economic activities. Here following Kilian (2009), we use an index based on the dry cargo shipping rate as a measure of global real activity. The

rationality of using this index is that the demand of transport services is primarily determined by the world economic growth (e.g., Klovland 2004). Killian shows that the indicator can capture shifts in the demand for industrial commodities driven by the global business cycle. Unlike other macro-economic indicators that are typically available at an annual or quarterly basis (e.g., GDP), the index can be constructed on a monthly frequency, providing a larger sample size more suitable for evaluating the demand shocks arising from fluctuations in global business cycle.

Estimation Results

As a first step in conducting the empirical analysis, we examine the relationship between explosive prices and the contributing factors considered, as shown in table 2. Notice that explosive prices in corn and soybeans tend to occur when global economics is in a boom phase. By contrast, the average global economic index is lower during bubble episodes for two wheat futures prices. Stocks tend to be lower during bubble periods for corn, soybeans, and KC wheat. For wheat, the difference in stocks between bubble and non-bubble periods is not statistically significant. Exchange rates appear to be lower during explosive periods, consistent with what the theory predicts. For two speculative activity indicators, it appears that Working's T tends to be lower during explosive periods in corn and soybean futures, but higher for two wheat futures. Interestingly, the pattern is completely opposite for CIT net positions, though the difference between explosive and non-explosive periods is statistically insignificant. Overall, when pooled across four commodities, stocks to use ratio, exchange rate, and Working's T are lower during explosive periods, while the real economic growth index and CIT activity tends to be higher when prices are explosive.

To construct a picture of the relationship between bubble episodes and various influencing factors, we plot the values of these five variables along with the explosive periods identified by the PSY procedure. For illustration, we show our results as applied to the corn market in figure 2. Notice that CIT net positions tend to be slightly larger during explosive periods. However, there are periods when CIT held large positions but prices were never explosive (e.g., mid-2010). For Working's T (figure 2(b)), bubbles occur mostly when the level of speculation is low. A similar pattern is observed for ending stocks to use ratio, which tends to be lower than 15% when bubbles occur. For exchange rates and real economic activity, bubbles typically appear when the US dollar is weak and global economic is strong. However, consistent relationships between explosive periods and influencing factors may be difficult to construct based on this simple mapping.

Estimation results from the rare events logit model are presented in table 3, with the measures of speculative activities (i.e. Working's T index and CIT net positions) considered in different models. The models are estimated across four commodities, as estimation bias may be reduced when sample sizes get larger. The results indicate that when global real economics expands, bubbles are more likely to occur. This effect is statistically significant for both models. Stocks to use ratio has a negative impact on the probability of bubble occurrence, consistent with the rational storage model of Gustafson (1958). When inventory level declines, any small demand or supply disruptions may cause large price fluctuations. This amplified effect may thus lead to

overreactions among traders, effectively causing a futures market bubble. Exchange rates tend to negatively affect bubble occurrence as well. As stated previously, weak US dollars may lead to increased exports, reducing grain availability in domestic markets and resulting in an increased probability of bubble occurrence.

For speculative activities, model (1) suggests that CITs did not have any effect on the probability of bubble occurring. This directly contradicts Masters' (2008, 2009) argument that the massive wave of commodity index investments have distorted the underlying supply and demand relationships, leading to a bubble in commodity markets. For the more general measure of speculative activities as measured by Working's T index, model (2) suggests that rather than increasing the probability of bubbles, their occurrence may be reduced when the value of the index increases. This negative effect is statistically significant as well.

We follow King and Zeng (2001a, b) and calculate the probability of bubbles occurring under various conditions. For brevity, we only consider model (2) when speculative activities are represented by Working's T. We first consider the case when all four explanatory variables are at their mean values. The probability is 1.75% when all variables are held to their means, which is slightly less than the 2.22% observed in the actual data. With one standard deviation increase in global economic growth index, the probability of bubble occurrence increases from 1.75% to 2.07%. For ending stocks to use ratio, a one standard deviation increase, or an 11.11% increase from the mean of 18.96%, the probability of bubble occurring is reduced from 1.75% to 1.26%. The effect of exchange rate is similar but with a slightly smaller magnitude, as a one standard deviation increase of exchange rate index is expected to reduce the chance of bubble occurrence from 1.75% to 1.38%.

Perhaps the most surprising result comes from the effect of Working's T index. With one standard deviation increase in the index, the probability of bubble is reduced from 1.75% to 1.09%. This effect appears to be larger than any of the other variables. One explanation may be that as speculative activities increase relative to the minimum level required to absorb the hedging activities, markets benefit from the increased volume and added liquidity, which apparently reduces the likelihood of bubbles in grain markets. However, given that bubbles are rare events during the sample period, the effect of added liquidity may still appear to be small.

Conclusions

This paper investigates under what conditions bubbles are more likely to occur in grain futures markets between 2004 and 2011, a period with unprecedentedly large price volatilities. We apply the multiple bubble testing procedure developed by Phillips, Shi, and Yu (2012) to detect and date-stamp bubbles in corn, soybeans, and wheat markets. To account for potential conditional heterskedasticity and small sample bias, inferences are derived from the recursive wild bootstrap procedure as discussed in Gonçalves and Kilian (2004). We find that overall, about 2.22% of the total sample experienced price explosiveness in grain markets. To examine the effects of various contributing factors on the probability of bubble occurrence, the rare events logit model of King and Zeng (2001a, b) is applied, which accounts for bias induced by events rarity. We find that in

the presence of booming economic growth, low inventory, and weak US dollars, bubbles are more likely to occur. While index traders generally do not affect the probability of bubble occurrence, as the level of speculation exceeding the minimum level required to absorb hedging activities increases, the probability of occurrence is greatly reduced.

The findings in this study are for the most part consistent with previous studies. The rational storage model suggests that prices tend to be high when stocks are low. In the presence of low stocks, any small supply or demand disruptions are likely to trigger large impacts on prices compared to when there is sufficient inventory. A weak US dollar and strong global economic growth may contribute to this price sensitivity by further affecting inventories. Indeed, as argued by Wright (2011), the price behavior over the past few years may not be so unusual as some have suggested, and the main forces of elevated volatility in grain market can be explained using the scarcity argument.

Regarding our findings of speculative activities, it is important to recognize that Working's T is a measure of excess speculative positions relative to the minimum level necessary in the market. It does not imply a level of "excessive" speculative activities in futures market. Working in fact argues that what may be "technically an 'excess' of speculation is economically necessary for a well-functioning market (Working 1960, p.197)." Our results support this argument as increasing speculative activities reduced the probability of bubble occurrence; the added liquidity provided was economically beneficial to the market. These findings are also consistent with those of Peck (1981) and McPhail, Du, and Muhammad (2012) who find that speculative activity can have a negative effect on price volatility and price movements. As for commodity index traders, our findings which are in direct contradiction to Master's claim provide further evidence that CITs were not behind the 2004-2011 grain market bubbles.

References

Abbott, PC, C Hurt, and WE Tyner. 2008. What's driving food prices? *Farm Foundation Issue Report*. Oak Brook, IL.

Bellemare, Marc. 2011. Rising food prices, food price volatility, and political unrest. Working Paper, Sanford School of Public Policy, Duke University.

Cafiero, Carlo, and Brian D Wright. 2011. Can Storage Arbitrage Explain Commodity Price Dynamics? Working Paper.

Carter, Colin, Gordon Rausser, and Aaron Smith. 2012. "The Effect of the US Ethanol Mandate on Corn Prices." Working Paper, Department of Agricultural and Resource Economics, UC Davis.

De Schutter, Olivier. 2010. "Food Commodities Speculation and Food Price Crises: Regulation to reduce the risks of price volatility." *United Nations Special Rapporteur on the Right to Food Briefing Note* no. 2:1-14.

Du, Xiaodong, Cindy L Yu, and Dermot J Hayes. 2011. "Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis." *Energy Economics* no. 33 (3):497-503.

Etienne, Xiaoli L., Scott H Irwin, and Philip Garcia. 2012. Price Explosiveness and Index Trader Behavior in the Corn, Soybean, and Wheat Futures Markets. Paper read at NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, April 16-17, at St. Louis, Missouri.

Etienne, Xiaoli L., Scott H Irwin, and Philip Garcia. 2013. Bubbles in Food Commodity Markets: Four Decades of Evidence. Paper presented at the IMF Conferences on Understanding International Commodity Price Fluctuations, March 20-21, at Washington DC.

Gardner, Bruce L. 1979. *Optimal stockpiling of grain*. Lexington, Magsachusetts: Lexington Books.

Gilbert, Christopher L. 2010a. Speculative influences on commodity futures prices 2006-2008. United Nations Conference on Trade and Development Discussion Paper NO. 197.

Gilbert, Christopher L. 2010b. "How to understand high food prices." *Journal of Agricultural Economics* no. 61 (2):398-425.

Gonçalves, Sílvia, and Lutz Kilian. 2004. "Bootstrapping autoregressions with conditional heteroskedasticity of unknown form." *Journal of Econometrics* no. 123 (1):89-120.

Gustafson, Robert L. 1958. *Carryover levels for grains: A method for determining amounts that are optimal under specified conditions*. Vol. 1178: US Dept. of Agriculture.

Gutierrez, Luciano. 2013. "Speculative bubbles in agricultural commodity markets." *European Review of Agricultural Economics* no. 40 (2):217-238.

Hamilton, James D, and Jing Cynthia Wu. 2013. Effects of index-fund investing on commodity futures prices. Working paper, University of California, San Diego.

Herman, M.O., R. Kelly, and R. Nash. 2011. "Not a Game: Speculation vs. Food Security." Oxfam Issues Briefing, October 3.

Hochman, Gal, Deepak Rajagopal, Govinda R Timilsina, and David Zilberman. 2011. "The role of inventory adjustments in quantifying factors causing food price inflation." World Bank Policy Research Working Paper Series.

Irwin, Scott H, and Dwight R Sanders. 2012. "Testing the Masters Hypothesis in commodity futures markets." *Energy Economics* no. 34 (1):256-269.

Janzen, Joseph P, Aaron D Smith, and Colin A Carter. 2013. Commodity Price Comovement: The Case of Cotton. Working Paper, Department of Agricultural and Resource Economics, UC Davis.

Kilian, Lutz. 2009. "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market." *The American economic review* no. 99 (3):1053-1069.

King, Gary, and Langche Zeng. 2001a. "Explaining rare events in international relations." *International Organization* no. 55 (3):693-715.

King, Gary, and Langche Zeng. 2001b. "Logistic regression in rare events data." *Political analysis* no. 9 (2):137-163.

Klovland, Jan Tore. 2004. *Business cycles, commodity prices and shipping freight rates: Some evidence from the pre-WWI period*: Citeseer.

Masters, Michael W. 2008. Testimony before the Committee on Homeland Security and Governmental Afairs, Unites States Senate.

Masters, Michael W. 2009. Testimony before the Commodities Futures Trading Commission. http://www.cftc.gov/ucm/groups/public/@newsroom/documents/file/hearing080509_masters.pdf.

McPhail, Lihong Lu, Xiaodong Du, and Andrew Muhammad. 2012. "Disentangling Corn Price Volatility: The Role of Global Demand, Speculation, and Energy." *Journal of Agricultural and Applied Economics* no. 44 (3):401-410.

Mitchell, Donald. 2008. A note on rising food prices. In *World Bank Policy Research Working Paper Series No. 4682*.

Peck, Anne E. 1980. "The role of economic analysis in futures market regulation." *American Journal of Agricultural Economics* no. 62 (5):1037-1043.

Peck, Anne E. 1981. "The adequacy of speculation on the wheat, corn, and soybean futures markets." *Research in Domestic and International Agribusiness Management* no. 2:17-29.

Phillips, Peter C.B., Shuping Shi, and Jun Yu. 2012. Testing for multiple bubbles. In *Cowles Foundation Discussion Paer No. 1843*.

Phillips, Peter CB, Yangru Wu, and Jun Yu. 2011. "Explosive Behavior in the 1990s NASDAQ: When did Exuberance Escalate Asset Values?" *International economic review* no. 52 (1):201-226.

Phillips, Peter CB, and Jun Yu. 2011. "Dating the timeline of financial bubbles during the subprime crisis." *Quantitative Economics* no. 2 (3):455-491.

Robles, M, M Torero, and J von Braun. 2009. "When speculation matters." *IFPRI-Issue Brief* (57).

Sanders, Dwight R, and Scott H Irwin. 2011. "The impact of index funds in commodity futures markets: A systems approach." *Journal of Alternative Investments* no. 14 (1):40-49.

Sanders, Dwight R, Scott H Irwin, and Robert P Merrin. 2010. "The adequacy of speculation in agricultural futures markets: Too much of a good thing?" *Applied Economic Perspectives and Policy* no. 32 (1):77-94.

Stoll, Hans R, and Robert E Whaley. 2010. "Commodity index investing and commodity futures prices." *Journal of Applied Finance* no. 20 (1):7-46.

Tang, Ke, and Wei Xiong. 2010. Index investment and financialization of commodities. National Bureau of Economic Research.

Tirole, Jean. 1982. "On the possibility of speculation under rational expectations." *Econometrica* no. 53 (6):1499-1528.

von Braun, Joachim. 2008. High and rising food prices: Why are they rising, who is affected, how are they affected, and what should be done. Paper read at International Food Policy Research Institute (IFPRI), presentation at a US Agency for International Development (USAID) conference on "Addressing the Challenges of a Changing World Food Situation: Preventing Crisis and Leveraging Opportunity," Washington, DC, April 11.

Working, Holbrook. 1949. "The theory of price of storage." *The American Economic Review* no. 39 (6):1254-1262.

Working, Holbrook. 1960. "Speculation on hedging markets." *Food Research Institute Studies* (02).

Wright, Brian D. 2011. "The economics of grain price volatility." *Applied Economic Perspectives and Policy* no. 33 (1):32-58.

Wright, Brian D, and Jeffrey C Williams. 1991. "Storage and commodity markets." *Cambridge, UK: Cambridge University*.

Endnotes

[1] The SADF statistic here is based on a backward-expanding window, different from the SADF statistic in Phillips, Wu, and Yu (2011) and Phillips and Yu (2011) where a forward-expanding window is used.

[2] The results are robust to alternative distributions.

[3] Here major currencies index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. See
http://research.stlouisfed.org/fred2/series/DTWEXM?cid=105 for detail.

Table 1. Number of Days with Explosive Prices by Year for Each Commodity

	Corn	Soybeans	Wheat	KC Wheat	Sum
2004	6	3			9
2005	4	4			8
2006	12	6			18
2007	17	13		6	36
2008	16	26	10	19	71
2009	4	7			11
2010			3	3	6
2011		9		3	12
Sum	**59**	**68**	**13**	**31**	**171**
	(2.98)	(3.47)	(0.69)	(1.65)	(2.22)

Notes: Each explosive episode needs to last at least 3 days to be considered a bubble. Each cell represents the total number of days with bubbles for a given commodity during a given year. Numbers in parentheses are the percentages of days with bubbles during each sample period.

Table 2. Summary Statistics of Explanatory Variables

Variable	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max	Diff b/t Means
		Explosive					**Non-Explosive**				
						Corn					
Real Econ	57	41.5	12.0	18.2	55.6	1922	22.6	21.3	-47.8	57.7	18.8***
Stocks/Use (%)	57	11.5	3.2	7.9	19.4	1922	12.4	5.1	5.0	22.5	-0.9**
Exchange	57	78.0	5.1	71.4	87.9	1922	78.6	5.6	68.0	90.6	-0.6
Working T	57	1.1	0.1	1.0	1.3	1922	1.1	0.1	1.0	1.4	-0.1***
CIT	57	346.3	96.2	90.8	430.5	1922	325.8	110.2	64.6	503.9	20.5
						Soybeans					
Real Econ	66	31.3	29.0	-47.8	57.4	1893	23.1	21.0	-47.8	57.7	8.2**
Stocks/Use (%)	66	7.0	3.9	3.6	18.0	1893	9.8	5.9	3.6	20.5	-2.7***
Exchange	66	75.7	4.7	70.5	86.4	1893	78.8	5.6	68.0	90.6	-3.1***
Working T	66	1.1	0.0	1.1	1.2	1893	1.2	0.1	1.0	1.5	-0.1***
CIT	66	145.5	40.7	31.9	187.4	1893	124.3	48.7	27.1	201.3	21.1***
						Wheat					
Real Econ	13	1.3	4.8	-0.9	15.3	1863	24.7	21.0	-47.8	57.7	-23.4***
Stocks/Use (%)	13	30.8	9.2	26.1	49.8	1863	27.2	9.2	10.1	50.4	3.6
Exchange	13	80.7	3.5	74.9	85.0	1863	79.0	5.4	68.0	90.6	1.7
Working T	13	1.5	0.1	1.3	1.6	1863	1.4	0.1	1.1	1.8	0.2***
CIT	13	156.4	30.2	138.8	209.4	1863	162.5	50.0	33.7	230.0	-6.1
						Kansas Wheat					
Real Econ	31	14.9	24.1	-9.3	57.7	1842	24.7	21.0	-47.8	57.7	-9.8**
Stocks/Use (%)	31	26.3	8.8	13.3	49.8	1842	27.3	9.3	10.1	50.4	-1.0
Exchange	31	77.6	3.9	72.1	85.0	1842	79.0	5.4	68.0	90.6	-1.4*
Working T	31	1.1	0.1	1.1	1.2	1842	1.1	0.1	1.0	1.4	0.0
CIT	31	26.2	11.0	16.3	50.9	1842	28.0	10.1	12.1	53.3	-1.8
						Pooled					
Real Econ	167	29.4	25.2	-47.8	57.7	7520	23.8	21.1	-47.8	57.7	5.6***
Stocks/Use (%)	167	14.0	10.1	3.6	49.8	7520	19.1	11.1	3.6	50.4	-5.1***
Exchange	167	77.2	4.8	70.5	87.9	7520	78.8	5.5	68.0	90.6	-1.6***
Working T	167	1.1	0.1	1.0	1.6	7520	1.2	0.1	1.0	1.8	-0.1***
CIT	167	192.7	134.6	16.3	430.5	7520	161.7	126.3	12.1	504.0	31.0***

Notes: N refers to the number of days with bubbles. The unit for CIT net positions is 1,000 contracts. The last column reports the differences in means between explosive and non-explosive periods for each explanatory variable. One, two, and three asterisks indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3. Results from Rare Events Logit Model

	Pooled	
	(1)	**(2)**
Real Econ	0.010**	0.008**
	(0.00)	(0.00)
Stocks/Use	-0.042***	-0.029***
	(0.01)	(0.01)
CIT	0.000	
	(0.00)	
Exchange	-0.036**	-0.043***
	(0.01)	(0.01)
Working's T		-3.209***
		(1.08)
Constant	-0.628	3.563**
	(1.14)	(1.75)
Sample Size	7687	7687

Notes: The dependent variable takes a value of 1 when bubble occurs, and 0 otherwise. Standard errors in parentheses. One, two, and three asterisks indicate significance at the 1%, 5% and 10% levels, respectively.
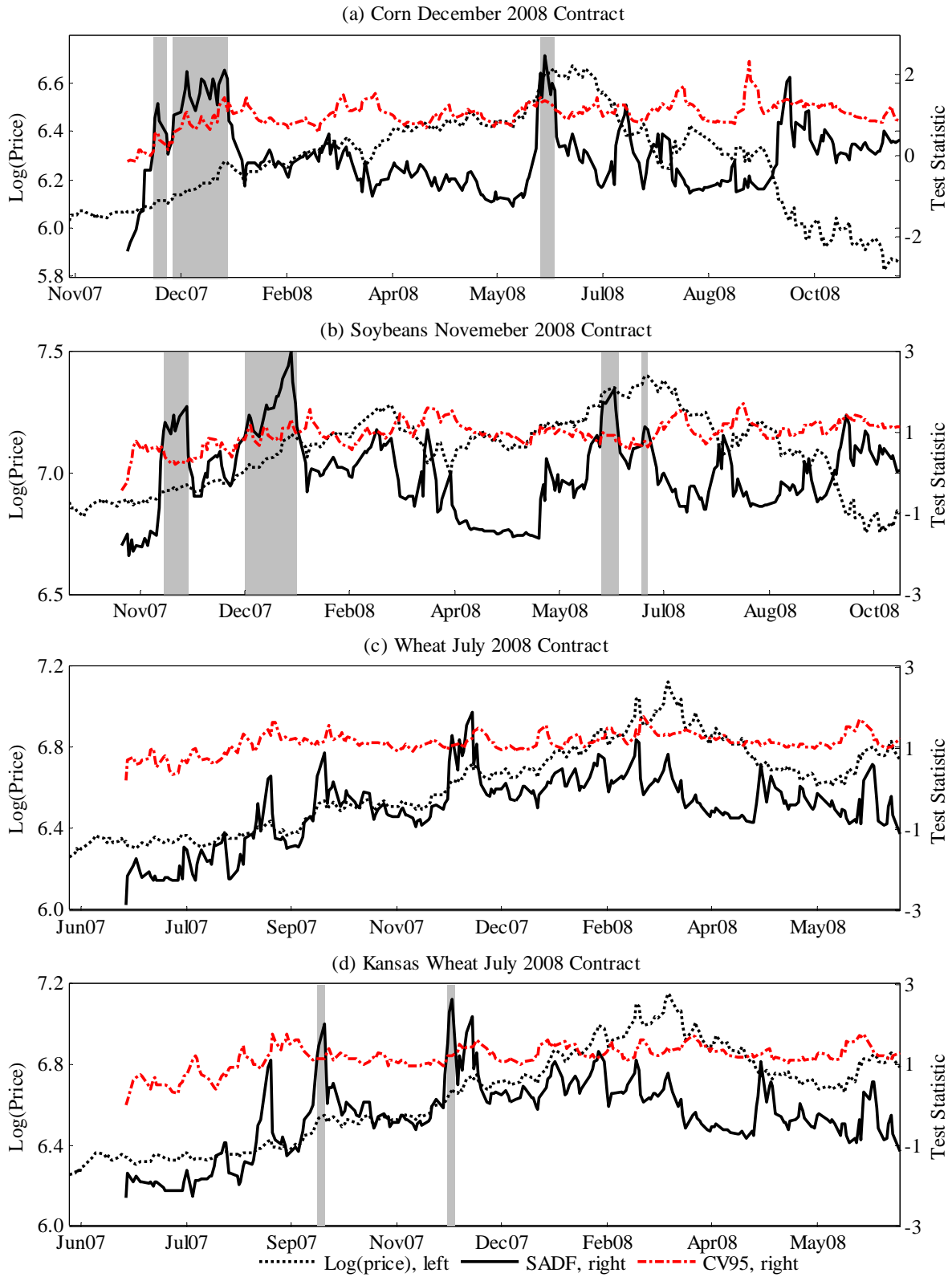
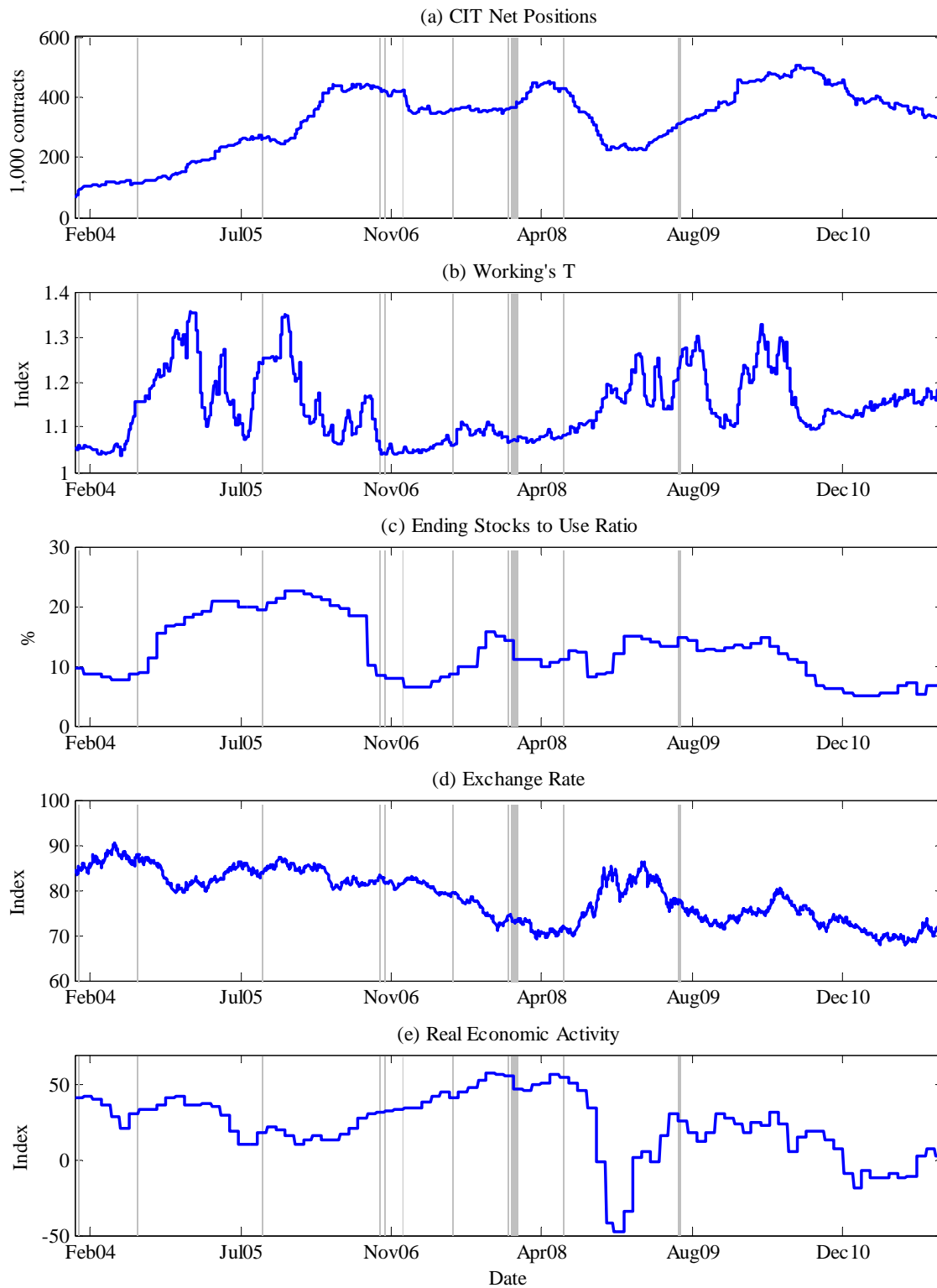**Figure 1. SADF Date-Stamping Results for Grain Futures Contracts in 2008 (h =3 days)**

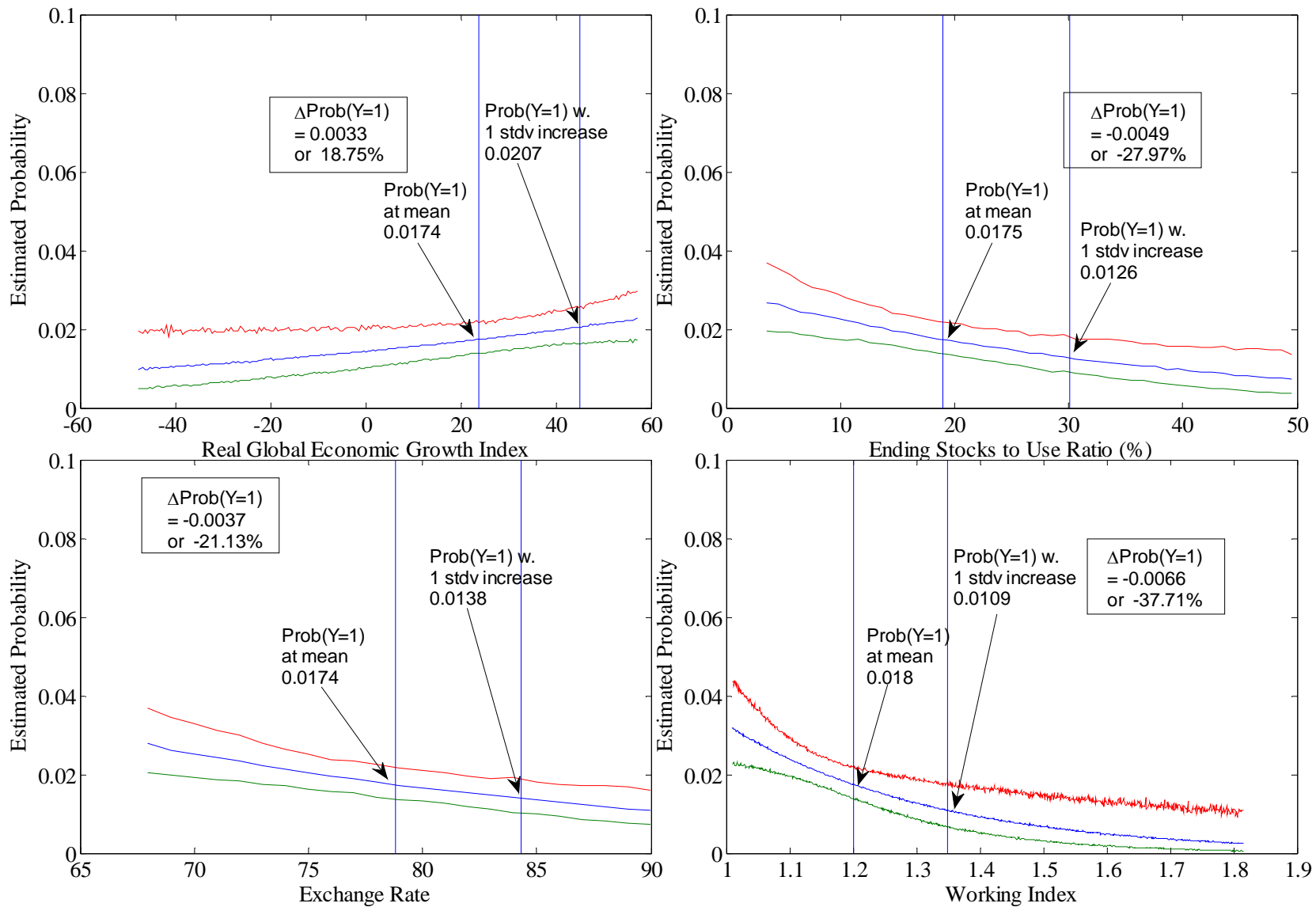**Figure 2. Explosive Episodes in the Corn Futures Market and Influencing Factors, January 2000—November 2011**

21

Figure 1. Effects of Explanatory Variables on Bubble Occurrence