Journal of Agricultural and Resource Economics 42(1):45–67 ISSN 1068-5502

New Evidence that Index Traders Did Not Drive Bubbles in Grain Futures Markets

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

This paper analyzes the price impact of financial index investments in grain futures markets during bubble and non-bubble periods over January 2004–June 2015. A recursive bubble-testing procedure is used to detect and date-stamp bubble periods in corn, soybean, and wheat markets. Granger causality tests are used to investigate the lead-lag dynamics between index-trader positions and weekly returns (price changes). Overall, the findings provide little support for the dual claims that (i) grain futures prices recently experienced large and long-lasting bubbles and (ii) index investment was a primary driver of those bubbles.

Key words: index investment, prices, speculation

Introduction

Food commodity prices increased rapidly after 2006, punctuated by large spikes in 2007–2008 and again in 2010–2011. Effective policy responses to rising and volatile food commodity prices require careful assessment of the underlying causes. Much recent attention has been directed toward the trading activities of a new type of participant in commodity futures markets—commodity index traders (CITs). Hedge fund manager Michael Masters has played a leading role in raising concerns, testifying numerous times before the U.S. Congress and Commodity Futures Trading Commission (CFTC) that unprecedented buying pressure from index investments created a series of massive bubbles in commodity futures prices (Masters, 2008, 2009). These bubbles were then transmitted to spot prices through arbitrage links between futures and spot prices, with the end result that commodity prices far exceeded fundamental values. Irwin and Sanders (2012) use the term "Masters Hypothesis" as a shorthand label for this argument.

Several prominent international development and civic organizations have expressed support for the Masters Hypothesis (e.g., de Schutter, 2010; Herman, Kelly, and Nash, 2011; Robles, Torero, and von Braun, 2009). This statement from Joachim von Braun, director of Germany's Center for Development Research is representative of the level of concern in these organizations: "We have good analysis that speculation played a role in 2007 and 2008. . . Speculation did matter and it did amplify, that debate can be put to rest. These spikes are not a nuisance, they kill. They've killed thousands of people" (as quoted in Ruitenberg, 2010).

Gilbert and Pfuderer (2014) and Sanders and Irwin (2016) summarize various mechanisms through which index-trading activities could affect commodity prices and drive prices away from fundamentals. First, in an illiquid market where the short-run elasticity of supply of counterparty positions is low, it is possible for prices to temporarily deviate from fundamental values when there

Xiaoli L. Etienne is an assistant professor in the Division of Resource Economics and Management at West Virginia University. 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, both in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign.
The authors would like to thank the two anonymous reviewers for their valuable suggestions that have helped to improve the quality of the paper.

Review coordinated by Hikaru Hanawa Peterson.

is a large demand for counterparty positions (e.g., high demand for short positions due to index buying). Second, if index traders have unpredictable market positions, then the large-scale entry of index funds may create "noise trader risk," making arbitrage against their positions difficult. Prices may be pushed away from fundamentals in such circumstances (see de Long et al., 1990). Third, in futures trading, information is revealed through trading activities. Other traders in futures markets may associate index buying with valuable private information and revise their own demands upward, which—in turn—could push prices higher (Sockin and Xiong). Sanders and Irwin (2016) argue that none of these theoretical explanations for price impacts of index activities are very compelling given the widely-known reasons for index trading in commodity markets (i.e., portfolio diversification, inflation hedges, and capturing long-run risk premiums).

In practice, whether financial index investments created large bubbles in the agricultural markets during the price spikes of 2007–2008 and 2010–2011 is ultimately an empirical question. To date, research has mainly focused on testing statistical links between price movements and index investment activities in agricultural futures market, using either time-series regression tests, such as Granger causality tests (e.g., Brunetti, Büyükşahin, and Harris, 2016; Büyükşahin and Harris, 2011; Capelle-Blancard and Coulibaly, 2011; Gilbert, 2010a,b; Hamilton and Wu, 2015; Sanders and Irwin, 2011a,b; Stoll and Whaley, 2010), cross-sectional regression tests (e.g., Irwin and Sanders, 2012; Sanders and Irwin, 2010), or conditional correlation tests (e.g., Büyükşahin and Robe, 2014; Tang and Xiong, 2012). While most studies have failed to establish a causal link between index positions and price changes in agricultural futures markets, some studies report evidence of an impact; a few cases report a very large impact.[1] For example, Tang and Xiong (2012) find that prices of non-energy commodities in two popular commodity indices have become significantly correlated with oil prices since 2006. They attribute this pattern and the resulting elevated price volatility to commodity financialization brought about by increasing participation of index traders. Mayer (2012) and Gilbert and Pfuderer (2014) find that index-trader positions have a price impact for some agricultural commodities during certain periods. Lagi et al. (2015) develop a highly stylized dynamic model of food prices and assert that only two variables—corn ethanol and speculation—are needed to explain recent price spikes. In particular, their results imply that speculation by index funds inflated food commodity prices in 2007–2008 by about 80% relative to fundamental value.

Several recent studies conduct direct tests for bubbles in agricultural markets using the statistical framework developed by Phillips, Wu, and Yu (2011); Phillips and Yu (2011); and Phillips, Shi, and Yu (2015). In this framework, the normal behavior of a price series is assumed to be a random walk, and an abnormal (bubble) period is defined as an episode in which the price series demonstrates an explosive root (autoregressive root greater than unity). The question then boils down to distinguishing bubble and non-bubble periods in a given price series (i.e., finding structural time-series breaks, see Gilbert, 2010b; Phillips and Yu, 2011; Gutierrez, 2013; Areal, Balcombe, and Rapsomanikis, 2014; Etienne, Irwin, and Garcia, 2014, 2015a,b). Overall, while the majority of these studies find prices to be explosive (e.g., bubbles) during some periods in some markets, bubbles only represent a small portion of price behavior since 2004; most price spikes appear to be non-bubbles.

In sum, the empirical literature on index investment and agricultural futures prices has largely developed along two separate tracks—one that focuses on the price impact of index positions in futures markets and another that directly tests for bubbles in agricultural futures prices. It is natural to ask whether valuable insights can be gained by bringing these two streams of literature together. The study by Robles, Torero, and von Braun (2009) (later cited in von Braun and Torero, 2009) is instructive in this regard. The authors conduct Granger causality tests based on a thirty-month rolling window and find a statistically significant impact of speculation during 2006–2008—but not before or after—in various agricultural markets. These authors conclude that "the overall evidence points to the following interpretation: *before and after the food crisis, speculation activity had no*

[1] Cheng and Xiong (2014), Fattouh, Kilian, and Mahadeva (2013), Irwin (2013), Irwin and Sanders (2011), Will et al. (2013), and Will et al. (2016) provide surveys of this rapidly expanding literature.

effect on spot prices formation while during the crisis it did. This is not to say that before and after the crisis speculation was not present, it was (probably to a less extent) but did not Granger cause spot prices" (von Braun and Torero, 2009, p. 9, emphasis original). This focuses attention squarely on the key policy issues: (i) Were recent spikes in grain futures prices large bubbles? and (ii) Was index investment the main driver of those bubbles? Policy makers could be misinformed about the market impact of financial index investments if a differential effect during price spikes is ignored or inaccurately measured.

The purpose of this paper is to analyze the differential price impact of index investment in grain futures markets during explosive and non-explosive periods of price behavior. Our study is the first to use recently developed econometric tests to rigorously date-stamp bubbles and non-bubbles when analyzing the price impact of index investment. We focus on grain markets because these markets have been at the forefront of concerns about the effect of index investment on food commodity prices and some studies have reported empirical evidence of a pronounced index-trading impact during recent price spikes. The specific markets analyzed are corn, soybeans, and wheat traded at the Chicago Board of Trade (CBOT) and wheat traded at the Kansas City Board of Trade (KCBT) between January 2004 and June 2015.

In the first part of the analysis, we use the bubble-testing procedure developed by Phillips, Shi, and Yu (2015) to date-stamp explosive periods in the four grain futures markets. In the second part, we use Granger causality tests to investigate lead-lag dynamics between index-trader positions and weekly returns (price changes) in the four markets. We introduce a dummy variable into the Granger regressions and create interaction terms between this dummy variable and index positions during explosive and non-explosive periods. We further examine whether the estimated lead-lag dynamics are sensitive to adding the positions of other traders (i.e., commercial and non-commercial traders) in the Granger causality test. We then conduct a battery of sensitivity analyses to determine whether our results are robust to different bubble specifications and datasets. Overall, the findings provide little support for the dual claims that grain futures prices recently experienced large and long-lasting bubbles and that index investment was a primary driver of those bubbles.

Testing for Bubbles

Distinguishing explosive (bubble) episodes from their non-explosive counterparts essentially involves determining when regime switching or structural breaks occur in a data series. Here, the multiple-bubble-testing procedure developed by Phillips, Shi, and Yu (2015) is used to date-stamp bubble periods in grain futures markets. Specifically, given a price sequence $\{P_t\}$ with a sample size of T, we consider the following estimation equation:

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

where $\Delta P_t = P_t - P_{t-1}$, k is the lag order, $\varepsilon \sim IID(0,\sigma^2_{r_1,r_2})$, and r_1 and r_2 are the starting and ending points of the sample being estimated, where $r_1 \in [1, r_2 - r_{w_0} + 1]$ and $r_2 \in [r_{w_0}, T]$ and r_{w_0} is the minimum window size required for regression. The ADF t-statistic corresponding to this equation is $ADF_{r_1,r_2} = \frac{\beta_{r_1,r_2}}{se(\beta_{r_1,r_2})}$. For every ending point r_2 we define $SADF_{r_2} = Sup_{r_1 \in [1, r_2 - r_{w_0} + 1]} ADF_{r_1,r_2}$. The starting and ending dates of explosive periods can thus be estimated using equations (2) and (3):

(2) $$\widetilde{r_{1e}} = inf_{r_2 \in [r_{w_0}, T]} \{r_2 : SADF_{r_2} > cv^{\rho}_{r_2}\}$$

and

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

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. To account for potential small-sample bias and conditional heteroskedasticity of grain futures prices, we follow Etienne, Irwin, and Garcia (2014, 2015a,b) and use the recursive wild bootstrap procedure of Gonçalves and Kilian (2004) to obtain critical values for the SADF statistics. In addition to the voluminous evidence on time-varying price volatility in commodity markets, the use of the wild bootstrap for inference is supported by recent theoretical simulation results in Harvey et al. (2016). We set the minimum bubble length, h, to 3 so that potential bubble periods are not missed.[2]

We collect futures prices for corn, soybeans, and wheat traded on the Chicago Board of Trade (CBOT) and hard red winter wheat traded on the Kansas City Board of Trade (KCBT) from January 2004 to June 2015. Etienne, Irwin, and Garcia (2015a) demonstrate that the use of futures prices for individual contracts versus a single series of rolling nearby contract prices impacts PSY bubble test results. Both cash and nearby futures prices for seasonally produced and storable commodities may spike upward dramatically as stocks are drawn down to very low levels and the market faces the full inelasticity of consumption demand (Wright and Williams, 1991). As such, bubble tests applied to cash or rolling nearby futures may not be able to disentangle price changes due to a true bubble component from the impact of a stockout or near stockout on prices. Etienne, Irwin, and Garcia (2015a) also note that a rolling nearby price series is constructed by stringing together the last two to three months of adjacent futures contracts as if the data were truly drawn from one continuous contract; this creates the potential for large price jumps and discontinuities at the points where the different contracts are spliced together, particularly for storable commodities. Prices from individual futures contracts for a storable commodity should behave as a random walk under fairly general conditions (e.g., Fama and French, 1987; Tomek, 1997) and by definition do not have to be spliced together, thus avoiding the potentially serious jumps and discontinuity problems discussed above.

Consequently, we examine one contract each year for each commodity, typically the contract with the highest trading volume (i.e., the December contract for corn, the November contract for soybeans, and the July contract for the two wheat futures price series). To avoid potentially double-counting bubbles, we let each price sequence start thirteen months before the contract expiration date and end on the last trading day of the month before the contract expires. These two guidelines result in a thirteen-month sample period for each contract.

Phillips, Wu, and Yu (2011) show that the PSY testing framework and its earlier versions are compatible with a number of explanations for market exuberance, including the rational bubble literature, herd behavior, and exuberant and rational responses to economic fundamentals. In particular, they show that under the rational bubble theory—which decomposes observed prices into a fundamental and bubble component—if the fundamental values are non-explosive then the explosive behavior detected in observed prices should provide sufficient evidence for the presence of bubbles in the market. In the context of the present paper, if we assume market efficiency and that the fundamental prices of these agricultural commodities follow a random walk (or non-explosive) process, explosive prices can be viewed as indicating a bubble in the market. However, Bobenrieth, Bobenrieth, and Wright (2013) argue that explosive periods in grains can also emerge when inventories are low as a rational response to economic fundamentals. As a result, we stress that the definition of bubble in the current paper is rather broad, referring to any period when prices deviate from random walk behavior. While this definition of a bubble has no direct implication for volatility, it should be clear that volatility can increase as bubbles arise.

[2] Phillips, Wu, and Yu (2011) suggest the minimum bubble length should be $\log(n)$, where n is sample size. This implies a minimum bubble length of five days in the present paper, since each daily individual futures price series consists of about 270 observations. However, we follow the $h = 3$ rule, which is more sensitive for detecting bubble episodes and factors that influence their appearance. More discussion of the difference in bubble testing results using the three-day and five-day criteria is presented in Etienne, Irwin, and Garcia (2014). In the Granger causally test, we conduct sensitivity analysis using different minimum bubble lengths and find the results to be insensitive to the value of h used.

Table 1. Number of Bubble Days in Grain Futures Prices, January 2004–June 2015

Year	Corn	Soybeans	Wheat	KC Wheat
2004	33	29	0	0
2005	5	19	3	0
2006	29	18	3	4
2007	21	20	8	17
2008	22	39	21	29
2009	15	12	7	0
2010	9	11	8	4
2011	4	11	17	13
2012	27	6	9	10
2013	0	6	4	28
2014	56	32	25	27
2015	3	0	0	0
Sum	224	203	105	132
	(7.75%)	(7.02%)	(3.63%)	(4.57%)

Notes: Corn, soybeans, and wheat are traded at the Chicago Board of Trade (CBOT) and KC wheat is traded at the Kansas City Board of Trade (KCBT). Bubbles were identified using the PSY method with 90% critical values from a recursive wild bootstrap procedure. Explosive prices need to last at least three business days to be defined as part of a bubble. Numbers in parentheses are the percentage of days with bubbles.

Before delving into the testing results, it is useful to identify terms. We use the term "spike" as a generic descriptor of large upward or downward price movements. We refer to "explosive behavior" or "price explosiveness" when the SADF test statistic goes above its corresponding critical value. Since we set the minimum bubble length, h, to be three days, a "bubble period" or "bubble" is an episode with three consecutive days of "explosive prices." Additionally, we refer to any day during a "bubble period" as a "bubble day."

Table 1 presents the total number of days experiencing bubbles using the PSY date-stamping procedure. To allow a relatively expansive definition of bubble periods, 90% critical values obtained from recursive wild bootstraps are used. It appears that all four grain futures markets experienced multiple bubbles, with most appearing between 2006 and 2008 when grain prices hit record highs. For corn and soybeans, 224 and 203 days, respectively, out of the twelve years (about 7% of the sample) contain bubbles. CBOT and KCBT wheat contracts had 105 and 132 bubble days, respectively, or 3–4% of the sample for these markets. These findings are consistent with those of Etienne, Irwin, and Garcia (2014, 2015b) and others: while bubbles do exist, they represent only a small portion of price behavior in agricultural commodity markets, the prices of which tend to largely follow a random walk process.[3]

Bubbles are typically associated with high and volatile prices. However, the PSY bubble testing results suggest that this is not necessarily the case. We find 33 and 29 days with bubbles during 2004 in the corn and soybean markets, a time when prices were relatively stable. In fact, the number of bubble days found in 2004 is comparable to the far more volatile 2007–2008 period for the two markets considered. While counterintuitive, recall that under the PSY framework bubbles are defined as any price behavior that deviates from a random walk, which is not directly related to price volatility. Non-bubble periods may have large price volatility if the variance of the random disturbance in equation (1) is sufficiently large. Equivalently, when the autoregressive coefficient in equation (1) exhibits only mild explosiveness (slightly above 1) and the variance of the error term is small, the price change during a bubble period may turn out to be small. Results in table 1 clearly indicate that caution should be taken when equating volatile prices with bubbles.

Table 2 provides more details regarding the length and magnitude of the bubbles detected in the four markets during the sample period. As suggested by previous studies (e.g., Etienne, Irwin, and

[3] Because we use 90% critical values when date-stamping bubbles, the total percentage of sample periods with bubbles reported in table 1 is higher than that reported in Etienne, Irwin, and Garcia (2014, 2015b), who used 95% critical values.

Table 2. Bubble Length and Price Changes During Bubble Episodes, January 2004–June 2015

Panel A. Frequency of Bubble Lengths

	≤ 5 days	≤ 10 days	≤ 15 days	>15 days	Total Episodes	Avg. Length (days)	Longest Bubble Episode
Corn	13	10	1	4	28	8.00	12/10/2007–1/17/2008 (27 days)
Soybeans	17	13	2	1	33	6.15	12/20/2007–1/18/2008 (20 days)
Wheat	14	2	0	2	18	5.83	10/6/2008–10/28/2008 (17 days)
KC Wheat	20	4	1	1	26	5.08	10/3/208–10/28/2008 (18 days)

Panel B. Price Change During Bubble Episodes

	Positive Bubbles				Negative Bubbles			
	Episodes	Avg. Length (days)	% ΔP Start to Peak	% ΔP Peak to End	Episodes	Avg. Length (days)	% ΔP Start to Trough	% ΔP Trough to End
Corn	16	7.63	2.36	-0.29	12	8.50	-1.95	0.38
Soybeans	22	6.73	1.69	-0.23	11	5.00	-1.03	0.24
Wheat	7	4.43	2.34	-0.14	11	6.73	-1.94	0.28
KC Wheat	11	4.00	2.04	-0.12	15	5.87	-1.78	0.13

Notes: Bubble days were identified using the PSY method with 90% critical values from a recursive wild bootstrap procedure. Explosive prices need to last at least three business days to be defined as part of a bubble. Numbers in parentheses are the percentage of days with bubbles. Percentage price changes are measured by log price differences.

Garcia, 2014), bubbles in these markets tend to be short-lived, with an average length of five (KCBT wheat) to eight (corn) days (panel A). The longest bubble episode lasted 27 days in the corn market, followed by 20 days in soybeans, 18 days in KCBT wheat, and 17 days in CBOT wheat. All four of these episodes occurred in 2007–2008, when the four markets experienced dramatic price variations. While we do find several long bubbles (e.g., longer than three weeks), they appear to account for only a small portion of overall bubble episodes, typically less than 10% of the total number.

To estimate the magnitude of bubbles, we use the "event study" approach suggested by Etienne, Irwin, and Garcia (2014) to calculate price changes during the detected explosive episodes. Positive (negative) bubbles are defined as episodes when the average price during the bubble episode is higher (lower) than the price at bubble origination. The price change from the origination date of the bubble to peak (trough) for positive (negative) bubbles is an indicator of bubble magnitude, while the price change from peak (trough) to the end of the bubble period is an indicator of price correction during the bubble. Panel B of table 2 shows that a surprisingly large number of explosive periods occurred during the sample period when prices were downward-trending. While receiving far less attention in the literature compared to positive bubbles, the prevalence of negative bubbles in grain markets clearly suggests that more research is needed to understand their nature and causes. We find that for positive (negative) bubbles, the average price change from bubble origination to peak (trough) is about 2% (1%). The price correction from the optimum to end is less than 1% for both positive and negative bubbles. Overall, bubbles occurring in the four grain markets are not only short-lived but also of small magnitude.

Given that 2006–2008 experienced dramatic price spikes of considerable concern to policy makers and market participants, we provide in table 3 details on the specific explosive episodes identified by the PSY procedure during these three years. As can be seen, more than 30% of the total bubbles identified during the 2004–2015 period in the four markets occurred between 2006 and 2008. However, even during periods with such dramatic volatility, bubbles occurred only about 10% of the time in the corn and soybean markets between 2006 and 2008. For CBOT and KCBT wheat markets, the percentages are even lower—4.3% and 6.6% for wheat traded on the CBOT and KCBT, respectively.

Table 3. Bubble Periods for Grain Futures Prices, January 2006–December 2008

			Positive Bubbles		Negative Bubbles	
	Bubble Periods	**Length (Days)**	**% Δ*P* Start to Peak**	**% Δ*P* Peak to End**	**% Δ*P* Start to Trough**	**% Δ*P* Trough to End**
Corn	10/12/06–10/19/06	6	3.19	−0.68		
	10/23/06–10/30/06	6	1.90	−0.39		
	11/01/06–11/09/06	7	3.05	−0.95		
	11/22/06–11/30/06	6	1.67	0.00		
	12/26/06–1/02/07	5	0.38	0.00		
	6/12/07–6/18/07	5	1.96	−0.08		
	12/10/07–1/17/08	27	8.15	−0.78		
	6/10/08–6/18/08	7	4.53	0.00		
	7/21/08–7/23/08	3			−1.29	0.00
	Total days	72 (9.56%)	3.10	−0.36	−1.29	0.00
Soybeans	8/16/06–8/22/06	5			−0.35	0.14
	8/25/06–8/29/06	3			−0.47	0.00
	9/11/06–9/13/06	3			−0.48	0.16
	10/23/06–10/31/06	7	1.54	−0.65		
	11/14/07–11/28/07	10	1.18	−0.42		
	12/10/07–12/12/07	3	0.37	0.00		
	12/20/07–1/18/08	20	7.63	−1.02		
	2/22/08–2/26/08	3	1.13	0.00		
	2/28/08–3/03/08	3	0.71	0.00		
	6/06/08–6/20/08	10	3.30	−1.25		
	6/26/08–7/03/08	6	1.89	0.00		
	12/26/08–1/06/09	7	2.39	0.00		
	Total days	80 (10.24%)	2.24	−0.37	−0.43	0.10
Wheat	5/16/06–5/18/06	3	2.05	−0.46		
	6/13/07–6/15/07	3	1.23	0.00		
	12/04/07–12/10/07	5	2.72	0.00		
	9/09/08–9/12/08	4			−0.79	0.00
	10/06/08–10/28/08	17			−5.90	0.00
	Total days	32 (4.26%)	2.00	−0.15	−3.34	0.00
KC Wheat	8/17/06–8/22/06	4			−0.72	0.00
	3/30/07–4/03/07	3			−1.56	0.00
	6/12/07–6/15/07	4	3.07	−0.27		
	9/27/07–10/01/07	3	1.40	0.00		
	11/27/07–11/30/07	4	2.45	0.00		
	12/06/07–12/10/07	3	2.36	0.00		
	2/05/08–2/11/08	5	2.95	−0.48		
	9/09/08–9/16/08	6			−2.56	0.00
	10/03/08–10/28/08	18			−8.48	0.63
	Total days	50 (6.64%)	2.45	−0.15	−3.33	0.16

Notes: Bubble days were identified using the PSY method with 90% critical values from a recursive wild bootstrap procedure. Explosive prices need to last at least three business days to be defined as part of a bubble. Numbers in parentheses are the percentage of days with bubbles. Percentage price changes are measured by log price differences.

The specific bubble periods detected by the PSY procedure in 2006–2008 largely coincide with episodes of large observed price volatility in these markets. Bubbles are found when the prices sharply increased from below \$3.00/bushel in October 2006 to almost \$4.00/bushel in January 2007 in the corn market and from about \$11.00/bushel in November 2007 to \$15/bushel in March 2008 in the soybean market. However, no bubbles are found when the two wheat prices peaked in March 2008, and corn prices retain their random walk behavior between the end of June and the beginning of July 2008, when record high prices were observed. Both corn and soybeans have one relatively long positive bubble episode between December 2007 and January 2008, lasting 27 and 20 business days, respectively. Regardless, the price rise in each episode is moderate, about 8%, and the subsequent correction is only about 1%. The price rise during all other positive bubbles in 2006–2008 is considerably smaller.

Overall, we find explosive prices in only a small portion of the sample period. Even during the volatile periods of 2006–2008, the percentage of days with bubbles is much lower than many anticipated. Results in this section stand in sharp contrast to the belief that speculative bubbles were the main driver of the recent spike in commodity markets, as argued by a number of hedge fund managers, commodity end-users, policy makers, and some researchers (e.g., Masters, 2008, 2009; U.S. Senate, Permanent Subcommittee on Investigations, 2009; Baffes and Haniotis, 2010; de Schutter, 2010).

Traditional and Modified Granger Causality Tests

As identified earlier, a main tool used in the existing literature to test for the price impact of index-trading activities is Granger causality, which investigates the lead-lag relationship between price changes and index-trading activities. In this section, we follow this literature but make an important modification to conventional Granger-style tests. In the traditional Granger causality test, data are often treated as one stable regime, ignoring any bubble behavior in the sample period. We relax this assumption and allow the relationship between returns and trading positions to change in different regimes by adding bubble interaction terms in the regression equation. A comparison of the modified and traditional tests can potentially reveal the importance of precisely identifying bubble periods, enabling us to more accurately assess the role of index investments in grain markets.

The use of Granger causality tests is motivated in several ways. First, the key idea behind the Masters Hypothesis is that a "wave" of financial index investments artificially inflated prices in agricultural futures markets. If the Masters Hypothesis holds, the flow of index-trader positions should systematically precede changes in commodity prices (i.e., index-trader positions should contain a predictive component to futures returns). Singleton (2014) argues that information on CIT positions could help to predict future price changes for at least three reasons: (i) CIT flows could lead to subsequent price changes to balance supply of and demand for positions in the futures market; (ii) the risk premium of investors in futures trading may be affected by information contained in the CIT flows; and (iii) some financial institutions may revise their trading strategies based on order-flow information. The price impacts of CIT activities are likely to manifest over a timeframe of weeks, as changing the allocation of capital to commodity, drawing information from past price changes, and revising beliefs about future fundamental factors typically occur on a weekly or monthly basis.

Second, the CIT position data we use for Granger causality tests is from the CFTC's *Supplemental Commitments of Traders* (SCOT) reports. The SCOT report is released each Friday in conjunction with the legacy *Commitments of Traders* (COT) report and shows the combined futures and options contract positions as of Tuesday's market close. Under the weak-form Efficient Market Hypothesis (EMH), information on CIT activities should not impact price changes prior to the publication of the SCOT report (Friday). This suggests that as long as Tuesday's price (the date that the SCOT report is compiled) is used, the price impact of CIT trading activities in contemporaneous time should be low. Instead, information on CIT activities, as soon as it becomes available, may induce subsequent changes in trading strategies of other traders, affecting prices in future periods.[4] Previous studies show little price impact of index-trading activities on a daily basis prior to the public release of the SCOT data. For instance, Sanders and Irwin (2016) find that the return on the day after the compilation of SCOT reports (Wednesday, which is prior to its publication date) is not affected by CIT trading activities.

Finally, Hamilton and Wu (2015) derive a model of futures price arbitrage in commodity markets, showing that if the large net long positions of index funds changes the risk premium that compensates traders taking the opposite position, then the positions of index traders should help predict excess returns for the contracts in which they actively participate. The key hypothesis behind this model is that risk-averse arbitrageurs who expect to close their positions in a later period should be compensated with a risk premium for taking the opposite position of index traders. If this hypothesis holds, positions of index traders in previous periods should be correlated with the risk premium demanded by arbitrageurs, which in turn correlates with subsequent price changes. Hamilton and Wu (2015) suggest that this framework essentially provides a theoretical justification for the use of Granger causality tests.

As noted above, the PSY date-stamping results are based on daily prices for individual futures contracts. Etienne, Irwin, and Garcia (2014, 2015a,b) argue that daily deviations from a random walk for individual futures contracts provide the most reliable approach for detecting explosive price movements. However, index-trader position data from the CFTC are only available on a weekly basis. For this reason, a weekly return series must be constructed for use in Granger causality tests. One possibility is to generate weekly returns based on individual futures contract prices, but this is problematic because the number of weekly observations available for each contract would be quite limited. Instead, we use a continuous series of weekly nearby returns over 2004–2015 for the Granger causality tests. As our goal is to determine the price impacts of index traders during explosive and non-explosive periods, the bubble-testing analyses we conduct using daily individual futures contract prices should be viewed as a tool to detect the periods of potential concern to policy makers. Given the arbitrage link between different futures contracts in storable commodities, using returns based on nearby prices is unlikely to materially change the estimation results relative to a different method of constructing the return series for Granger causality tests. Additionally, if CITs were to have a price impact on futures prices, their impact should be largest on nearby prices, as they tend to concentrate their trading activities in the most liquid and shortest maturity contracts (e.g., Stoll and Whaley, 2010).

To obtain a measure of bubble episodes at the weekly frequency, we map the daily bubble sequences based on the PSY test to a weekly frequency by relying on the rule that a week is considered a bubble week if it contained at least one bubble day.[5] For example, consider an eight-day bubble period that included four business days in one week and four business days in the next. Our rule would classify both weeks as bubble weeks. The weekly prices are the closing Tuesday price of the nearby futures contract since index-trader positions available in CFTC reports refer to Tuesday positions. Observations are switched to the next-to-expire contract on the last business day before the start of the delivery month.

[4] Although contemporaneous correlations between index trading and price changes may exist, these should not be confused with contemporaneous causality. A significant contemporaneous correlation may exist due to the existence of common driving factors rather than the causality between these two variables. However, as shown in table 4, with the exception of corn, the contemporaneous correlation between index trading and returns is not statistically significant in either bubble or non-bubble periods, further weakening the notion that prices should be contemporaneously affected by index-trading activities (on a weekly basis). Sanders and Irwin (2016) report that contemporaneous correlations between index net positions and price changes do not exist consistently over time.

[5] More specifically, a "bubble day" refers to a day that falls in a "bubble episode" with at least three consecutive days of explosive prices. If we only find explosive prices during one day of the week in a five-day period (week) using the daily individual futures contract price series, this date will not be considered a "bubble day" unless: (i) it is a Monday and the two business days prior to this date also contain explosive prices, or (ii) it is a Friday and the following two business days also contain explosive prices. In other words, a "bubble day" needs to fall during a bubble episode with at least three consecutive days of explosive prices.

Since our main interest is the impact of index investments on price movements, we only report the one-way causality from index positions to returns.[6] The first specification is

$$R_{t,k} = \alpha_k + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \varepsilon_{t,k}, \tag{4}$$

where $R_{t,k}$ is the weekly return $[R_{t,k} = (\ln P_{t,k} - \ln P_{t-1,k}) \times 100]$ for week t in market k and $X_{t,k}$ is the change in index positions. When calculating returns on contract roll dates, $P_{t-1,k}$ refers to the price of the same futures contract as $P_{t,k}$ on the previous Tuesday. The lag structure, (I, J), for each market is determined using a search procedure over a maximum of five lags and selecting the model that minimizes the Schwartz criteria to avoid over-parameterization (Enders, 1995, p. 88). The resulting equations are tested for autocorrelation using the Lagrange-multiplier (LM) test, and lags are added to the equation to eliminate remaining autocorrelation. Causality from index investments to returns is established if the joint hypothesis that $\beta_{j,k} = 0$ for any j in market k is rejected.

To investigate whether the causality between returns and index positions differs in bubble and non-bubble periods, we introduce a dummy variable (D) that indicates bubble periods based on testing results from the PSY procedure. Interaction terms between the dummy and index investments are included in the Granger causality test. Equation (5) provides the "modified Granger causality test":

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \sum_{j=1}^{J} \theta_{j,k} (X_{t-j,k} \times D_{t-j,k}) + \varepsilon_{t,k}, \tag{5}$$

The inclusion of the dummy variable essentially enables us to detect possible shifts in the causal relationship in bubble periods compared to non-bubble periods. If index positions help predict price changes during bubble periods, we would expect the null hypothesis that $\beta_j + \theta_j = 0$ to be rejected for any j in market k.

Traditional and modified Granger causality tests are conducted using position data from the SCOT reports. Irwin and Sanders (2012) show that the measurement errors with aggregate CIT positions are likely rather small and support the widespread view that CIT data provide valuable information about index trader activity in agricultural futures markets. The publicly available SCOT reports start in January 2006. The CFTC collected additional data for CBOT corn, soybean, and wheat futures and KC wheat futures contracts for 2004–2005 at the request of the U.S. Senate Permanent Subcommittee on Investigations (U.S. Senate, Permanent Subcommittee on Investigations, 2009), and these data are also included in the present analysis.

To extend the model to a multivariate framework, positions of additional traders (commercial and non-commercial) and their interaction terms are included in equations (4) and (5). The multivariate analysis may be more powerful than bivariate analysis if the variation in returns is related to the dynamic interaction of multiple types of traders rather than index traders alone (Brunetti, Büyükşahin, and Harris, 2016). If the regressions in equations (4) and (5) are estimated on a market-by-market basis, the power of standard statistical tests might be compromised due to the existence of contemporaneously correlated error terms across markets (Aulerich, Irwin, and Garcia, 2013; Capelle-Blancard and Coulibaly, 2011; Sanders and Irwin, 2011b). We thus model the K markets as a system under Zellner's Seemingly Unrelated Regression (SUR) framework which accounts for correlations across error terms. The SUR estimation allows for system-wide causality to be tested (e.g., $\beta_{j,k} = 0$ for all j and k in equation 4), an improvement over a strictly market-by-market estimation framework.

---

[6] Results of causality from returns to index net long positions are in general consistent with previous studies in that returns have some tendency to lead index-trader position changes (e.g., Aulerich, Irwin, and Garcia, 2013). These results are available from the authors upon request.

Table 4. Descriptive Statistics for Weekly Returns and Trader Positions from CFTC Supplemental Commitment of Traders (SCOT) Reports for Grain Futures Markets, January 2004–June 2015

Panel A: Corn	Bubble (N=68)					Non-Bubble (N=532)				
	Mean	SD	Min	Max	Corr	Mean	SD	Min	Max	Corr
Return (%)	0.18	2.27	−5.32	6.64		−0.07	1.83	−7.16	8.00	
Comm	−343.10	195.20	−749.59	6.55	−0.49**	−319.74	178.72	−760.38	14.98	−0.11**
NonComm	114.68	126.36	−157.75	357.45	0.50**	76.29	130.26	−240.85	372.76	0.11**
CIT	331.59	118.60	72.86	494.62	0.16	343.34	92.46	64.65	503.94	0.06
Panel B: Soybeans	**Bubble (N=63)**					**Non-Bubble (N=537)**				
	Mean	SD	Min	Max	Corr	Mean	SD	Min	Max	Corr
Return (%)	0.73	1.80	−3.72	4.90		−0.02	1.55	−6.80	4.92	
Comm	−167.50	111.90	−355.46	84.45	−0.32**	−140.64	95.51	−362.00	65.60	−0.13**
NonComm	69.81	74.39	−86.23	221.42	0.33**	45.51	65.50	−92.99	224.82	0.13**
CIT	126.39	51.73	27.10	198.71	0.10	128.81	40.23	27.70	201.25	0.07
Panel C: Wheat	**Bubble (N=33)**					**Non-Bubble (N=567)**				
	Mean	SD	Min	Max	Corr	Mean	SD	Min	Max	Corr
Return (%)	−0.39	2.59	−5.20	5.80		−0.06	1.94	−7.65	7.14	
Comm	−104.59	55.34	−199.90	−7.15	−0.65**	−111.38	47.29	−213.49	−2.03	−0.07
NonComm	−45.20	35.13	−103.32	13.12	0.61**	−32.85	31.35	−110.79	40.40	0.07
CIT	170.13	28.99	120.10	216.19	0.55**	161.01	45.08	33.70	229.57	0.03
Panel D: KC Wheat	**Bubble (N=45)**					**Non-Bubble (N=555)**				
	Mean	SD	Min	Max	Corr	Mean	SD	Min	Max	Corr
Return (%)	−0.27	2.22	−5.04	4.68		−0.00	1.79	−7.11	6.42	
Comm	−43.03	21.71	−89.14	−7.77	−0.68**	−40.86	24.10	−112.01	7.64	−0.09**
NonComm	13.05	18.76	−14.60	49.41	0.60**	13.07	21.42	−40.16	67.79	0.08
CIT	38.10	12.52	16.29	63.73	0.22	33.45	12.23	12.06	66.59	−0.00

Notes: Corn, soybeans, and wheat are traded at the Chicago Board of Trade (CBOT) and KC wheat is traded at the Kansas City Board of Trade (KCBT). SD is the standard deviation. Comm and NonComm refer to commercial and non-commercial traders, and CIT to commodity index traders. Net positions of traders are reported in thousands of contracts. Corr is the correlation between returns and trader positions. Double asterisks (**) indicate statistical significance at the 5% level.

Table 5. Bivariate Granger Causality Test Results for Grain Futures Markets, Weekly *Supplemental Commitment of Traders* (SCOT) Positions, January 2004–June 2015

Panel A. Traditional Bivariate Granger Causality Test

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \varepsilon_{t,k}$$

		p-value	**Estimate**
Market k	i, j	$\beta_j = 0,\ \forall j$	β_j
Corn	1,1	0.012**	−0.016
Soybeans	1,1	0.685	0.006
Wheat	1,1	0.787	0.002
KC Wheat	1,1	0.300	−0.019

	p-value	**Breusch-Pagan test of independence**	
	$\beta_{j,k} = 0,\ \forall j, k$	**chi2(6)**	**p-value**
System	0.088	1,413.450	0.0000**

Panel B. Modified Bivariate Granger Causality Test

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \sum_{j=1}^{J} (\theta_{j,k} X_{t-j,k} \times D_{t-j,k}) + \varepsilon_{t,k}$$

		p-value				**Estimate**	
Market k	i, j	$\beta_j = 0,\ \forall j$	$\theta_j = 0,\ \forall j$	$\beta_j = \theta_j = 0,\ \forall j$	$\beta_j + \theta_j = 0,\ \forall j$	β_j	θ_j
Corn	1,1	0.015**	0.911	0.046**	0.596	−0.016	0.003
Soybeans	1,1	0.552	0.487	0.720	0.602	0.009	−0.032
Wheat	1,1	0.882	0.342	0.584	0.305	0.001	0.026
KC Wheat	1,1	0.180	0.140	0.212	0.263	−0.026	0.097

	p-value			**Breusch-Pagan test of independence**	
	$\beta_{j,k} = 0,\ \forall j, k$	$\theta_{j,k} = 0,\ \forall j, k$	$\beta_{j,k} + \theta_{j,k} = 0,\ \forall j, k$	**chi2(6)**	**p-value**
System	0.071	0.548	0.664	1,412.527	0.0000**

Notes: Corn, soybeans, and wheat are traded at the Chicago Board of Trade (CBOT) and KC wheat is traded at the Kansas City Board of Trade (KCBT). R is nearby return (%), X is change in CIT net positions (1,000 contracts), and D is a dummy variable indicating bubble periods. Double asterisks (**) indicate statistical significance at the 5% level.

One potential question regarding the Granger causality test is that it may appear to be inappropriate to perform statistical inference for regressions during bubble periods. This should not be a substantive problem, because bubbles in prices do not imply bubbles in returns, which is the left-side variable in equations (4) and (5). In fact, prices need to increase at an increasing ratio for returns to be explosive. This can be seen in a straightforward manner: assume $P_{t+1} = \rho_1 P_t + \epsilon_1$ and $P_{t+2} = \rho_2 P_{t+1} + \epsilon_2$, where $\rho_1 > 1$, $\rho_2 > 1$, and ϵ_1 and ϵ_2 are IID mean zero error terms. Then returns can be calculated as $R_t = \log(P_{t+1}/P_t) = \log(\rho_1 + \epsilon_1/P_t)$ and $R_{t+1} = \log(P_{t+2}/P_{t+1}) = \log(\rho_2 + \epsilon_2/P_{t+1})$. If returns are explosive, then $R_{t+1} = \mu_1 R_t + \varepsilon_1$ and $\mu_1 > 1$. Taking expectations gives $E[R_{t+1}] = \mu_1 E[R_t]$. Since $\mu_1 > 1$, we have $E[\log(\rho_2 + \epsilon_2/P_{t+1})] > E[\log(\rho_1 + \epsilon_1/P_t)]$, or $\rho_2 > \rho_1$. The implication is that price needs to grow at an ever-increasing rate for *returns* to be explosive in a bubble episode. This is contrasted with the assumption of the PSY test that the explosive price component during bubble periods is constant. To corroborate these arguments, we also conducted PSY tests on the return series for each individual futures contract and the weekly nearby contract and found no statistically significant evidence of bubble periods in any of the four grain markets.

Results from the SCOT Position Data

Descriptive statistics for the SCOT data are presented in table 4. Commercial traders, non-commercial traders, and CIT investment activities are measured by their net long positions (i.e., number of long contract minus number of short contract). As noted, bubble weeks are periods with at least one day experiencing bubbles during that week as identified by 90% critical values in the daily individual futures contract prices (as shown in tables 1–3). Table 4 shows that average returns range from −0.39% in CBOT wheat to 0.73% in soybeans during bubble periods, while during non-bubble periods average returns are all negative, ranging from −0.06% in CBOT wheat to −0.00% in KCBT wheat. The average returns during bubbles and non-bubbles are not statistically different for all markets except soybeans. However, the variances of returns during bubble and non-bubble periods are significantly different for all markets but KCBT wheat.[7]

If index traders are in fact responsible for price behavior during bubble periods, one would expect CIT net long positions to increase significantly during these time periods. However, the data in table 4 suggest otherwise. The KCBT wheat market experienced the largest increase, from about 33 to 38 thousand contracts, or a 14% increase. For the other three markets, CIT net positions either remained at a similar level (CBOT wheat) or slightly decreased (corn and soybeans) in bubble periods. Given that CIT positions are relatively stable in bubble and non-bubble periods, it would be surprising to find little if any relationship between the positions and subsequent market returns. With the exception of KCBT wheat, no significant difference is found for CIT net long positions between bubble and non-bubble periods. In contrast, non-commercial traders experienced a much more significant increase in their net long positions during bubble episodes in both percentage and absolute value terms. For instance, non-commercial net positions in the corn market increased by 38 thousand contracts, representing an increase of over 50% from non-bubble to bubble periods.

The unconditional contemporaneous correlations between returns and investment activities are rather different in bubble and non-bubble periods. Returns and CIT net positions are generally only weakly correlated in non-bubble periods, with the correlation coefficient ranging from −0.00 in KCBT wheat to 0.06 in corn. This contemporaneous link strengthened during bubble periods, increasing to 0.16, 0.10, 0.55, and 0.22 in corn, soybeans, CBOT wheat, and KCBT wheat markets, respectively. However, the contemporaneous correlation coefficient is statistically significant only in the CBOT wheat market during bubble periods. This suggests that the contemporaneous price effect of index traders, if they exist, should be rather weak. By contrast, the contemporaneous correlations between commercial or non-commercial trading activities and returns are mostly statistically significant. Nevertheless, correlation is not temporal causality since it only measures a contemporaneous link.

To further investigate the behavior of index investments, we plot CIT net positions along with the bubble periods (i.e., the vertical lines) in figure 1. Some correspondence between the peaks of CIT positions and price bubbles is observed in corn and soybean markets, especially during the bubble periods found in 2008, when prices spiked. However, when CITs held large net positions in 2005–2006 and later in 2010–2011, corn and soybean prices were mostly non-bubble. The relationship between CIT net positions and bubble occurrences becomes even less clear when analyzing the two wheat futures markets. While CIT net long positions significantly increased for KC wheat after 2008, only a combined six weeks are identified as bubbles from 2009 to 2011. Net positions held by CITs were high between 2009 and 2012 in CBOT wheat, yet only a few bubbles existed during this period. It also appears that many of the bubble periods occur as index traders reduce their net long positions. Overall, it is difficult to see a consistent pattern between CIT net positions and price movements in bubble periods.

Table 5 reports the p-values for the traditional and modified bivariate Granger causality tests between returns and CIT positions as well as the Breusch-Pagan cross-sectional dependence test

[7] When variances of returns and net positions between bubbles and non-bubbles are found to be statistically different, we use the Welch's two-sample test, which accounts for unequal variances to test for the difference in means.

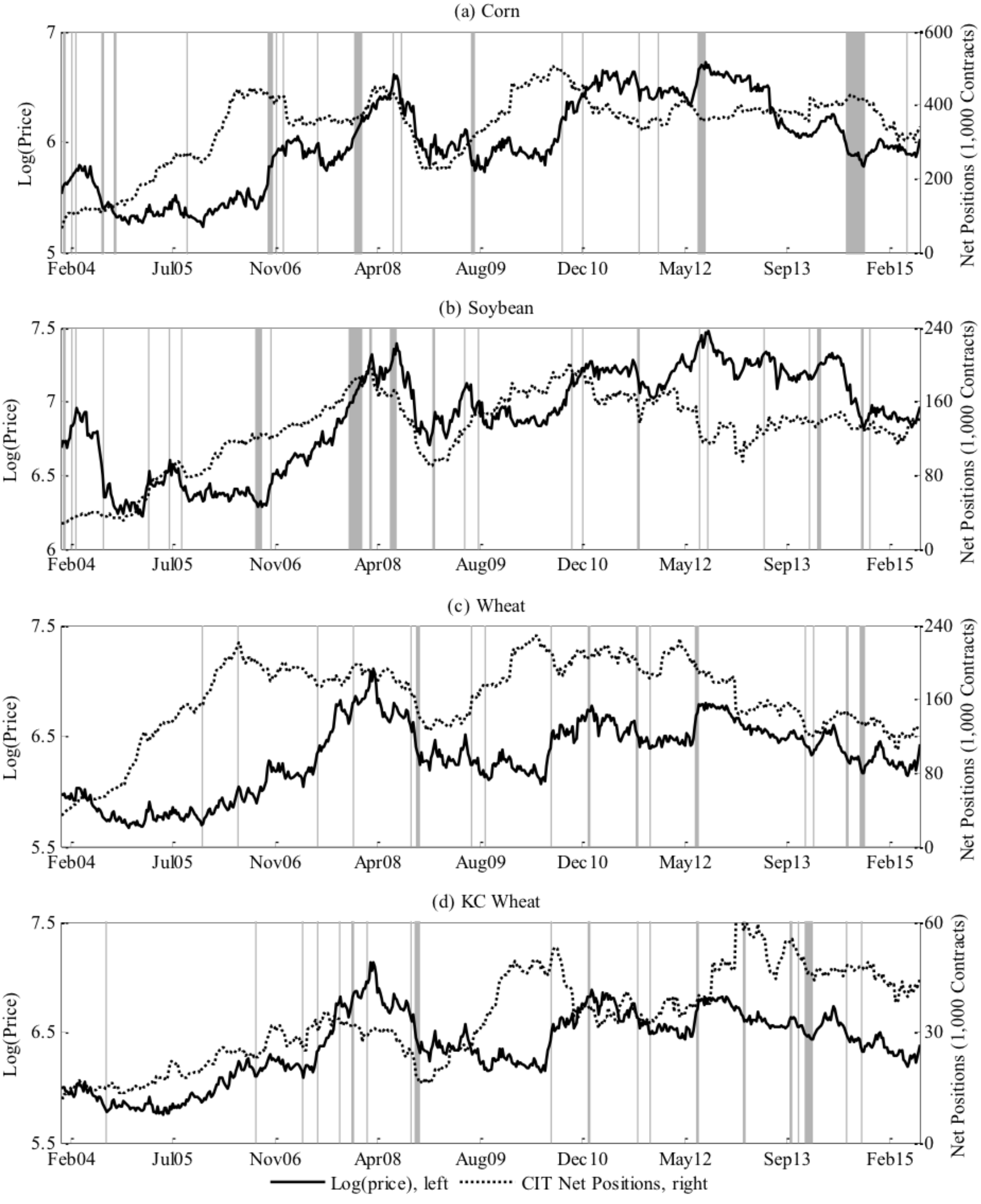

Figure 1. Bubble Periods and Commodity Index Trader (CIT) Net Long Positions in Grain Futures Markets, January 2004–June 2015

Notes: Vertical lines identify bubble periods.

statistic. Consistent with the bulk of previous studies, changes in net long positions are used in the estimation. There is a clear, strong correlation across the four markets as the Breusch-Pagan test rejects the null of no cross-sectional dependence in the returns at the 1% level of significance, supporting the use of SUR. The traditional Granger test (panel A) indicates that CITs did not Granger cause returns in soybean and the two wheat markets but did have an effect on corn price returns. However, the estimated coefficient β_1 in the corn equation is negative and small in magnitude, the opposite of the notion that index investments created a massive bubble in commodity futures markets (e.g., Masters, 2008, 2009). System-wide, the null of no CIT impact across all four markets is not rejected. Results from the traditional bivariate causality tests are consistent with most previous studies (e.g., Aulerich, Irwin, and Garcia, 2013; Brunetti, Büyükşahin, and Harris, 2016; Hamilton and Wu, 2015; Lehecka, 2015; Sanders and Irwin, 2011a,b; Stoll and Whaley, 2010).

In the modified analysis (panel B, table 5), no causal relationship can be established from CIT net position changes to returns in either bubble or non-bubble periods in any market except corn. For corn, CIT net positions has a significant price dampening effect during non-bubble periods but not during bubbles. In contrast to Robles, Torero, and von Braun (2009) and von Braun and Torero (2009), the modified test suggests that CITs do not have differential price impacts in “spike” versus “non-spike” periods in most of the markets. The system-wide null of no CIT impact across all markets in bubble periods is also not rejected for the modified test.

Table 6 reports results for the multivariate Granger causality tests between returns and CIT net position changes in each market. Changes in net positions of commercial and non-commercial traders are added to each equation to account for effects from other traders. Statistical significance is not evident at the 5% level for the traditional Granger causality test in any of the markets except corn or system-wide (panel A). Similar results are found in the modified multivariate Granger test (panel B), where we do not find any price impact of CIT activities in bubble and non-bubble periods in soybean and the two wheat markets. The only exception is the corn equation, where we find significant price impact during non-explosive periods but not during explosive periods. However, the estimated effect is negative as both coefficients (β and θ) are negative. Tests (not reported) for the null hypothesis that commercial or non-commercial traders do not cause returns are not rejected for the four markets.

Table 3 suggests that some bubbles occur shortly after the ending of the previous bubble. These bubbles may come from one longer bubble period. We therefore combine two bubbles as one single bubble episode if the second bubble occurred within five business days of the ending of the first one. As can be seen in panel A of table 7, regression results using these longer bubble periods are virtually identical to those results presented in tables 5 and 6, again suggesting that CIT trading activities had little price impact during either bubble or non-bubble periods.

As noted earlier, our PSY testing results could be affected the critical values and minimum bubble length used to date-stamp bubbles. To assess whether our Granger causality test results are sensitive to the parameters used in the PSY procedure, we conduct robustness checks assuming alternative minimum bubble lengths and critical values. As can be seen in table 7 panels B–D, regardless of the minimum bubble lengths (one, five, seven days) used, we fail to establish a causal link between index net position changes and returns during either bubble or non-bubble periods for soybean and the two wheat markets. For corn, we find that index net position changes do have a negative effect during bubble periods—the same conclusion as when the minimum bubble length is three days.[8] Additionally, panel E of table 7 indicates that when the more restrictive 95% critical values are imposed, we fail to identify any statistical significance in any of the markets except for corn. Our results appear to be robust to the minimum bubble length and critical values used when detecting bubbles.[9]

Additional Robustness Checks

In mapping bubble testing results from the daily individual futures prices to a weekly frequency, we define a week as containing bubbles if any day during the week falls during a bubble episode. This

[8] We also consider minimum bubble lengths of two, four, six, and ten days, and the results remain unchanged.

[9] Additionally, we define the entire calendar period of 2006–2008 as a bubble period, independent of any formal bubble testing. This is the most prolonged grain-price spike in the sample period; approximately the same spike period was investigated by Robles, Torero, and von Braun (2009) and von Braun and Torero (2009). With the exception of corn, we do not find any differential impact in 2006–2008 compared to other periods for any of the other three markets. The estimated effect of CIT activities is again negative in the corn equation.

Table 6. Multivariate Granger Causality Test Results for Grain Futures Markets, Weekly *Supplemental Commitment of Traders* (SCOT) Positions, January 2004–June 2015

Panel A. Traditional Multivariate Granger Causality Test

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \boldsymbol{B}_k \boldsymbol{Z}_k + \varepsilon_{t,k}$$

		p-value	Estimate
Market k	i, j	$\beta_j = 0, \ \forall j$	β_j
Corn	1,1	0.033**	−0.019
Soybeans	1,1	0.912	0.002
Wheat	1,1	0.361	0.011
KC Wheat	1,1	0.511	−0.016

	p-value	Breusch-Pagan test of independence	
	$\beta_{j,k} = 0, \ \forall j, k$	chi2(6)	p-value
System	0.194	1,399.095	0.0000**

Panel B. Modified Multivariate Granger Causality Test

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \sum_{j=1}^{J} (\theta_{j,k} X_{t-j,k} \times D_{t-j,k}) + \boldsymbol{B}_k \boldsymbol{Z}_k + \boldsymbol{C}_k (\boldsymbol{Z}_k \times \boldsymbol{D}_k) + \varepsilon_{t,k}$$

		p-value				Estimate	
Market k	i, j	$\beta_j = 0, \ \forall j$	$\theta_j = 0, \ \forall j$	$\beta_j = \theta_j = 0, \ \forall j$	$\beta_j + \theta_j = 0, \ \forall j$	β_j	θ_j
Corn	1,1	0.037**	0.907	0.092	0.468	−0.020	−0.004
Soybeans	1,1	0.909	0.387	0.678	0.382	0.002	−0.059
Wheat	1,1	0.479	0.993	0.765	0.856	0.010	0.001
KC Wheat	1,1	0.428	0.426	0.661	0.653	−0.023	0.073

	p-value			Breusch-Pagan test of independence	
	$\beta_{j,k} = 0, \ \forall j, k$	$\theta_{j,k} = 0, \ \forall j, k$	$\beta_{j,k} + \theta_{j,k} = 0, \ \forall j, k$	chi2(6)	p-value
System	0.229	0.883	0.820	1,346.600	0.0000**

Notes: Corn, soybeans, and wheat are traded at the Chicago Board of Trade (CBOT) and KC wheat is traded at the Kansas City Board of Trade (KCBT). R is nearby return (%), X is change in CIT net positions (1,000 contracts), D is a dummy variable indicating bubble periods, and $\boldsymbol{Z}$ is a matrix that includes lagged positions of commercial and non-commercial traders. Double asterisks (**) indicate statistical significance at the 5% level.

could mask the differential price impact during weeks containing different numbers of bubble days. To test this hypothesis, we define separate dummies for bubble weeks with one, two, three, four, and five bubble days found in the daily individual futures contract price series and re-estimate the Granger causality tests. Table 8 panel A suggests that CIT net positions do not Granger cause returns during any of the bubble weeks, regardless of how many bubble days they contain. Our results are insensitive to whether we differentiate the numbers of bubble days found for a week or assume all weeks with at least one bubble days to be bubble weeks.

The results in tables 2 and 3 show that not all bubble episodes occurred during periods with upward-trending prices; as an additional robustness check we differentiate between positive and negative bubbles. Regression results with separate dummies for positive and negative bubbles are presented in panel B of table 8. Again, with the exception of corn during non-bubble periods, CIT activities have no price effect during either bubble or non-bubble periods. The only statistically significant coefficient estimate is again negative, suggesting a small dampening effect of CIT net positions on corn futures prices in positive bubble periods.

Table 7. Modified Multivariate Granger Causality Test Results for Grain Futures Markets Based on Alternative Minimum Bubble Lengths and Critical Values, Weekly *Supplemental Commitment of Traders* (SCOT) Positions, January 2004–June 2015

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \sum_{j=1}^{J} (\theta_{j,k} X_{t-j,k} \times D_{t-j,k}) + \boldsymbol{B}_k \boldsymbol{Z}_k + \boldsymbol{C}_k (\boldsymbol{Z}_k \times \boldsymbol{D}_k) + \varepsilon_{t,k}$$

	p-value				Estimate	
Market k	$\beta_j = 0,\ \forall j$	$\theta_j = 0,\ \forall j$	$\beta_j = \theta_j = 0,\ \forall j$	$\beta_j + \theta_j = 0,\ \forall j$	β_j	θ_j
Panel A. Merging Adjacent Bubbles, Minimum Bubble Length = 3 Days, Critical Values = 90%						
Corn	0.046**	0.899	0.112	0.515	–0.020	0.003
Soybeans	0.727	0.286	0.565	0.312	0.008	–0.063
Wheat	0.403	0.907	0.663	0.730	0.122	0.007
KC Wheat	0.474	0.741	0.767	0.900	–0.021	0.033
Panel B. Minimum Bubble Length = 1 Day, Critical Values = 90%						
Corn	0.061	0.804	0.102	0.280	–0.019	–0.006
Soybeans	0.788	0.401	0.700	0.424	0.006	–0.046
Wheat	0.374	0.982	0.648	0.769	0.013	–0.001
KC Wheat	0.397	0.619	0.683	0.823	–0.014	0.043
Panel C. Minimum Bubble Length = 5 Days, Critical Values = 90%						
Corn	0.039**	0.837	0.114	0.747	–0.020	0.008
Soybeans	0.927	0.360	0.647	0.353	0.002	–0.066
Wheat	0.418	0.674	0.692	0.774	0.011	–0.034
KC Wheat	0.506	0.928	0.801	0.974	–0.019	0.014
Panel D. Minimum Bubble Length = 7 Days, Critical Values = 90%						
Corn	0.032**	0.902	0.096	0.706	–0.020	0.005
Soybeans	0.938	0.898	0.986	0.883	–0.002	–0.130
Wheat	0.406	0.386	0.529	0.444	0.011	–0.092
KC Wheat	0.556	0.764	0.784	0.715	–0.016	–0.078
Panel E. Minimum Bubble Length = 1 Day, Critical Values = 95%						
Corn	0.030**	0.587	0.094	0.890	–0.021	0.017
Soybeans	0.761	0.365	0.661	0.391	0.006	–0.076
Wheat	0.350	0.918	0.621	0.776	0.013	0.007
KC Wheat	0.361	0.692	0.649	0.856	–0.025	0.045

Notes: $\boldsymbol{R}$ is nearby return (%), $\boldsymbol{X}$ is change in CIT net positions (1,000 contracts), $\boldsymbol{D}$ is a dummy variable for bubbles, and $\boldsymbol{Z}$ is a matrix that includes lagged positions of commercial and non-commercial traders. In Panel A, two bubble periods are merged into one if the second occurred within five days of the end of the first in the daily individual futures contract. The new bubble periods are then mapped to the nearby frequency. Double asterisks (**) indicate statistical significance at the 5% level.

A further robustness check for the modified Granger test uses positions from the CFTC's *Disaggregated Commitment of Traders* (DCOT) reports. The DCOT reports were first published in September 2009 and later extended back to June 2006, yielding 473 observations. Traders are separated into five categories: producers and merchants, swap dealers, managed money, other reportables, and non-reportables. According to the CFTC, a swap dealer primarily deals in swaps and uses the futures markets to manage or hedge the associated risks. Irwin and Sanders (2012) show that aggregate swap dealer positions in agricultural futures markets have a moderately high correlation

Table 8. Robustness Checks of Multivariate Granger Causality Tests for Grain Futures Markets

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \sum_{j=1}^{J} (\theta_{j,k} X_{t-j,k} \times D_{t-j,k}) + \boldsymbol{B}_k \boldsymbol{Z}_k + \boldsymbol{C}_k (\boldsymbol{Z}_k \times \boldsymbol{D}_k) + \varepsilon_{t,k}$$

Panel A. Differentiating between Number of Bubble Days Found during a Week, Weekly SCOT (Dummy $i = i$ days within the week fall in a bubble period, the base group is no bubble, i=1,. . . ,5), 01/2004–06/2015

	p-value					
Market k	$\beta_j = 0,\ \forall j$	$\beta_j + \theta_j^1 = 0,\ \forall j$	$\beta_j + \theta_j^2 = 0,\ \forall j$	$\beta_j + \theta_j^3 = 0,\ \forall j$	$\beta_j + \theta_j^4 = 0,\ \forall j$	$\beta_j + \theta_j^5 = 0,\ \forall j$
Corn	0.038**	0.643	0.056	0.974	0.595	0.828
Soybeans	0.933	0.479	0.570	0.570	0.691	0.400
Wheat	0.572	0.495	0.729	0.446	0.360	0.995
KC Wheat	0.459	0.543	0.165	0.638	0.790	0.503

Panel B. Differentiating between Positive and Negative Bubbles, Weekly SCOT (Dummy 1= Positive Bubbles, Dummy 2= Negative Bubbles), 01/2004–06/2015

	p-value					Estimate		
Market k	$\beta_j = 0,\ \forall j$	$\theta_J^P 0,\ \forall j$	$\theta_j^N = 0,\ \forall j$	$\beta_j + \theta_J^P = 0,\ \forall j$	$\beta_j + \theta_J^N = 0,\ \forall j$	$\beta_{j,k}$	$\theta_{j,k}^P$	$\beta_{j,k}^N$
Corn	0.035**	0.644	0.519	0.986	0.291	−0.020	0.021	−0.033
Soybeans	0.930	0.772	0.256	0.783	0.255	0.002	−0.024	−0.136
Wheat	0.502	0.844	0.911	0.907	0.780	0.010	−0.011	0.008
KC Wheat	0.419	0.582	0.300	0.520	0.380	−0.024	−0.134	0.140

Panel C. Granger Causality Test with Weekly DCOT (Dummy=Bubbles), 06/2006–06/2015

	p-value				Estimate	
Market k	$\beta_j = 0,\ \forall j$	$\theta_j = 0,\ \forall j$	$\beta_j = \theta_j = 0,\ \forall j$	$\beta_j + \theta_j = 0,\ \forall j$	β_j	θ_j
Corn	0.026	0.834	0.055	0.319	−0.025	−0.007
Soybeans	0.990	0.545	0.818	0.527	−0.000	−0.044
Wheat	0.272	0.933	0.520	0.751	0.017	0.006
KC Wheat	0.422	0.898	0.680	0.722	−0.025	−0.015

Notes: $\boldsymbol{R}$ is nearby return (%) and X is change in net index investment positions in 1,000 contracts. For panels C–E, D is a dummy indicating bubble periods. For pD is a [2X1] vector of dummies indicating positive and negative bubbles. For panel A, D is a [5X1] vector of dummies indicating number of bubble days found for the week. $\boldsymbol{Z}$ is a matrix that includes lagged net positions of other traders. Double asterisks (**) indicate statistical significance at the 5% level.

Table 9. Modified Bivariate Granger Causality Test Results for Grain Futures Markets with Alternate Weekly Speculative Measures, January 2004–June 2015

$$R_{t,k} = \alpha_{t,k} + \sum_{i=1}^{I} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{J} \beta_{j,k} X_{t-j,k} + \sum_{j=1}^{J} (\theta_{j,k} X_{t-j,k} \times D_{t-j,k}) + \varepsilon_{t,k}$$

Market k	$\beta_j =$ 0, $\forall j$	$\beta_j + \theta_j =$ 0, $\forall j$	$\beta_j =$ 0, $\forall j$	$\beta_j + \theta_j =$ 0, $\forall j$	$\beta_j =$ 0, $\forall j$	$\beta_j + \theta_j =$ 0, $\forall j$
Panel A. Results using Working's *T* Index						
	Working's *T* Using COT		**Working's *T* Using SCOT**		**Working's *T* Using SCOT Adjusted for Non-Reportables**	
Corn	0.182	0.286	0.383	0.617	0.431	0.683
Soybeans	0.180	0.169	0.412	0.375	0.343	0.312
Wheat	0.728	0.550	0.737	0.633	0.524	0.376
KC Wheat	0.212	0.250	0.213	0.289	0.385	0.465
Panel B. Results using Tadesse et al. *ESV* Measure						
	***ESV* Using COT**		***ESV* Using SCOT**		***ESV* Using SCOT Adjusted for Non-Reportables**	
Corn	0.185	0.099	0.098	0.023**	0.129	0.024**
Soybeans	0.817	0.528	0.662	0.628	0.744	0.700
Wheat	0.139	0.418	0.260	0.967	0.213	0.907
KC Wheat	0.683	0.720	0.870	0.781	0.962	0.851

Notes: Corn, soybeans, and wheat are traded at the Chicago Board of Trade (CBOT) and KC wheat is traded at the Kansas City Board of Trade (KCBT). R is nearby return (%), X is the speculative measure, and D is a dummy variable indicating bubble periods. ESV and Working's T are defined as in equations (6) and (7). ESV and Working's T using COT, SCOT, and SCOT adjusted for non-reportables refer to the index values calculated using the CFTC legacy Commitment of Traders (COT) reports without adjusting for non-reportable positions, the CFTC Supplemental Commitment of Traders (SCOT) reports without adjusting for non-reportable positions, and the CFTC SCOT reports adjusting for non-reportable positions, respectively. Double asterisks (**) indicate statistical significance at the 5% level.

with quarterly benchmark positions available from the CFTC beginning at the end of 2007. Results of the modified Granger causality tests on the DCOT data are reported in panel C of table 8. Again, we do not find any statistical significance in soybean and wheat markets during either bubble or non-bubble periods. Swap dealer activities only negatively affect corn price returns during non-bubble periods and have no effect during bubble periods. The system-wide null of no swap dealer impact across all four grain markets is not rejected either. Clearly, evidence supporting the argument that index investment activities were the main driver of grain price spikes is sparse at best.

As a final robustness check, we test whether more general measures of speculative activities predict returns in grain futures markets during bubble and non-bubble periods. The two additional measures are Tadesse et al.'s 2014) measure of excessive open interest of speculative futures (ESV) and Working's T as developed in Working (1960). These measures are defined as:

$$ESV = (SL - SS) - (HL - HS) \tag{6}$$

$$T = \begin{cases} 1 + \frac{SS}{HL+HS} & \text{if} \quad HS \geq HL, \text{ or} \\ 1 + \frac{SL}{HL+HS} & \text{if} \quad HS < HL. \end{cases} \tag{7}$$

In equations (6) and (7), SL and SS are long and short positions held by speculators and HL and HS long and short positions of hedgers. We compute three versions of indexes for each measure using (i) COT data, (ii) SCOT data unadjusted for non-reportable positions, and (iii) SCOT data adjusted for non-reportable positions. Results from the modified bivariate Granger causality test using the alternative speculative measures are presented in table 9. As can be seen in the table, no significant effect is observed for most of the speculative measures during bubble or non-bubble periods, providing further evidence that speculative activities are unlikely to be the driver of price movements in commodity markets.

Summary and Conclusions

This paper analyzed the market impact of financial index investments in grain futures markets during bubble and non-bubble periods of price behavior. The specific markets analyzed include corn, soybeans, and wheat traded at the Chicago Board of Trade (CBOT) and wheat traded at the Kansas City Board of Trade (KCBT) between January 2004 and June 2015.We focused on this problem because grain futures markets are at the forefront of concerns about the effect of index investments on food commodity prices and some studies report empirical evidence of a pronounced index-trading impact during recent price spikes. Policy makers could potentially be misinformed about the market impact of financial index investments if this differential effect during bubble and non-bubble periods is ignored or inaccurately measured.

We used a recursive bubble-testing procedure developed by Phillips, Shi, and Yu (2015) to detect and date-stamp bubble periods in the four markets. Defining explosive periods using critical values at the 90% level, our findings indicated that all four grain futures markets experienced multiple bubbles during the sample period. However, bubbles only represented a small portion of price behavior. Only 7% of the sample period exhibited bubble behavior in corn and soybeans. The proportion was even lower in the two wheat markets—prices were explosive 3–4% of the time. Even during the volatile period of 2006–2008, we found that prices deviated from a random walk only 4–10% of the time in the four markets. The bubble-testing results stand in sharp contrast with the view that speculative bubbles were the main driver of the 2006–2008 spike in commodity markets, as argued by a number of hedge fund managers, commodity end users, policy makers, and some researchers (e.g., Masters, 2008, 2009; U.S. Senate, Permanent Subcommittee on Investigations, 2009; Baffes and Haniotis, 2010; de Schutter, 2010).

Granger causality tests were used to investigate lead-lag dynamics between index-trader positions and weekly nearby returns (price changes) in the four markets. We introduced a dummy variable into the Granger regressions and created interaction terms between this dummy variable and index positions to distinguish bubble and non-bubble periods. This was the first study to examine the causal links from index investments to agricultural futures price changes while allowing for differential impacts during rigorously date-stamped bubble regimes. With the exception of corn, we found no evidence that index positions Granger caused returns in any of the other three futures markets during bubble or non-bubble periods. We did find significant impact in the corn market for some specifications, but the coefficient estimates are all negative and of small magnitude.

We conducted additional robustness checks, including (i) merging adjacent bubbles into one bubble, (ii) using alternative minimum bubble lengths and critical values when date-stamping bubbles, (iii) differentiating between bubble days found during a week, (iv) differentiating between positive and negative bubbles, v) considering a different CFTC position dataset (i.e., the DCOT data), and vi) using the Working's T and Tadesse et al.'s (2014) ESV index as more general measures of speculative activities. With a few exceptions, we failed to find any statistical significance in the robustness checks.

Overall, our findings provide little support for the dual claims that grain futures prices recently experienced large and long-lasting bubbles and that index investment was a primary driver of these bubbles. In other words, buying pressure from financial index investors, or speculators in general, did not cause massive bubbles or extreme price movements in agricultural futures markets during recent years. It follows that new limits on speculation in agricultural futures markets are not grounded in well-established empirical findings and could impede the price-discovery and risk-shifting functions in these important markets. Neither is there a need to consider caps on trading in "extreme" market situations or a Tobin tax on agricultural futures trading as suggested by Tadesse et al. (2014).

While we do not find evidence that index-trading behavior caused price bubbles in the grain markets, like other recent studies, we do find evidence of what might best be described as multiple "micro-bubbles" in these markets. A relevant question is what drove agricultural futures price movements during the bubble and non-bubble periods and, further, which factors played a differential role in these two regimes. The study by Etienne, Irwin, and Garcia (2015b) indicates that market supply and demand conditions may be important in explaining price dynamics during bubble episodes. However, these authors only investigated the probability of bubble occurrence, not the magnitude of price movements during bubble episodes. Determining which factors are the primary drivers of agricultural commodity price movements during bubble and non-bubble periods remains an important direction for future research.

[Received January 2016; final revision received August 2016.]

References

Areal, F., K. Balcombe, and G. Rapsomanikis. "Testing for Bubbles in Agricultural Commodity Markets." ESA Working Paper 14–07, Rome, 2014. Available online at http://www.fao.org/3/a-i3869e.pdf.

Aulerich, N. M., S. H. Irwin, and P. Garcia. "Bubbles, Food Prices, and Speculation: Evidence from the CFTC's Daily Lee Trader Data Files." Working Paper 19065, National Bureau of Economic Research, Washington, DC, 2013.

Baffes, J., and T. Haniotis. "Placing the 2006/08 Commodity Price Boom into Perspective." Policy Research Working Paper 5371, World Bank, Washington, DC, 2010. Available online at http://papers.ssrn.com/abstract=1646794.

Bobenrieth, E., J. Bobenrieth, and B. Wright. "Bubble Troubles? Rational Storage, Mean Reversion and Runs in Commodity Prices." Working paper, Washington, DC, 2013. Available online at http://www.nber.org/chapters/c12812.

Brunetti, C., B. Büyükşahin, and J. H. Harris. "Speculators, Prices and Market Volatility." *Financial and Quantitative Economics* forthcoming(2016).

Büyükşahin, B., and J. H. Harris. "Do Speculators Drive Crude Oil Futures Prices?" *Energy Journal* 32(2011):167–202.

Büyükşahin, B., and M. A. Robe. "Speculators, Commodities and Cross-Market Linkages." *Journal of International Money and Finance* 42(2014):38–70. doi: 10.1016/j.jimonfin.2013.08.004.

Capelle-Blancard, G., and D. Coulibaly. "Index Trading and Agricultural Commodity Prices: A Panel Granger Causality Analysis1." *International Economics* 126–127(2011):51–71. doi: 10.1016/S2110-7017(13)60036-0.

Cheng, I.-H., and W. Xiong. "Financialization of Commodity Markets." *Annual Review of Financial Economics* 6(2014):419–441. doi: 10.1146/annurev-financial-110613-034432.

de Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldman. "Noise Trader Risk in Financial Markets." *Journal of Political Economy* 98(1990):703–738. doi: 10.1086/261703.

de Schutter, O. "Food Commodities Speculation and Food Price Crises: Regulation to Reduce the Risks of Price Volatility." Briefing Note 02, United Nations Special Raporteur on the Right to Food, Louvain-la-Neuve, Belgium, 2010. Available online at http://www.srfood.org/images/stories/pdf/otherdocuments/20102309_briefing_note_02_en_ok.pdf.

Enders, W. *Applied Econometric Time Series*. New York: Wiley, 1995.

Etienne, X. L., S. H. Irwin, and P. Garcia. "Bubbles in Food Commodity Markets: Four Decades of Evidence." *Journal of International Money and Finance* 42(2014):129–155. doi: 10.1016/j.jimonfin.2013.08.008.

———. "$25 Spring Wheat Was a Bubble, Right?" *Agricultural Finance Review* 75(2015a):114–132. doi: 10.1108/AFR-12-2014-0042.

———. "Price Explosiveness, Speculation, and Grain Futures Prices." *American Journal of Agricultural Economics* 97(2015b):65–87. doi: 10.1093/ajae/aau069.

Fama, E. F., and K. R. French. "Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage." *Journal of Business* 60(1987):55–73.

Fattouh, B., L. Kilian, and L. Mahadeva. "The Role of Speculation in Oil Markets: What Have We Learned So Far?" *Energy Journal* 34(2013):7–33.

Gilbert, C. L. "How to Understand High Food Prices." *Journal of Agricultural Economics* 61(2010a):398–425. doi: 10.1111/j.1477-9552.2010.00248.x.

———. "Speculative Influences on Commodity Futures Prices 2006–2008." United Nations Conference on Trade and Development Discussion Paper 197, United Nations, Geneva, Switzerland, 2010b. Available online at http://unctad.org/en/Docs/osgdp20101_en.pdf.

Gilbert, C. L., and S. Pfuderer. "The Role of Index Trading in Price Formation in the Grains and Oilseeds Markets." *Journal of Agricultural Economics* 65(2014):303–322. doi: 10.1111/1477-9552.12068.

Gonçalves, S., and L. Kilian. "Bootstrapping Autoregressions with Conditional Heteroskedasticity of Unknown Form." *Journal of Econometrics* 123(2004):89–120. doi: 10.1016/j.jeconom.2003.10.030.

Gutierrez, L. "Speculative Bubbles in Agricultural Commodity Markets." *European Review of Agricultural Economics* 40(2013):217âĂŞ–238. doi: 10.1093/erae/jbs017.

Hamilton, J. D., and J. C. Wu. "Effects of Index-Fund Investing on Commodity Futures Prices." *International Economic Review* 56(2015):187–205. doi: 10.1111/iere.12099.

Harvey, D. I., S. J. Leybourne, R. Sollis, and A. R. Taylor. "Tests for Explosive Financial Bubbles in the Presence of Non-Stationary Volatility." *Journal of Empirical Finance* 38(2016):548–574. doi: 10.1016/j.jempfin.2015.09.002.

Herman, M.-O., R. Kelly, and R. Nash. "Not a Game: Speculation vs Food Security." Issue Briefing 3, Oxfam International, Oxford, 2011. Available online at https://www.oxfam.org/en/research/not-game-speculation-vs-food-security.

Irwin, S. H. "Commodity Index Investment and Food Prices: Does the "Masters Hypothesis" Explain Recent Price Spikes?" *Agricultural Economics* 44(2013):29–41. doi: 10.1111/agec.12048.

Irwin, S. H., and D. R. Sanders. "Index Funds, Financialization, and Commodity Futures Markets." *Applied Economic Perspectives and Policy* 33(2011):1–31. doi: 10.1093/aepp/ppq032.

———. "Testing the Masters Hypothesis in commodity futures markets." *Energy Economics* 34(2012):256–269. doi: 10.1016/j.eneco.2011.10.008.

Lagi, M., Y. Bar-Yam, K. Z. Bertrand, and Y. Bar-Yam. "Accurate Market Price Formation Model with Both Supply-Demand and Trend-Following for Global Food Prices Providing Policy Recommendations." *Proceedings of the National Academy of Sciences* 112(2015):E6119–E6128. doi: 10.1073/pnas.1413108112.

Lehecka, G. V. "Do Hedging and Speculative Pressures Drive Commodity Prices, or the Other Way Round?" *Empirical Economics* 49(2015):575–603. doi: 10.1007/s00181-014-0886-7.

Masters, M. W. *Testimony before the Committee on Homeland Security and Governmental Affairs*. Washington, DC, 2008. Available online at http://www.hsgac.senate.gov/imo/media/doc/052008Masters.pdf?attempt=2.

———. *Testimony before the Commodities Futures Trading Commission*. Washington, DC, 2009. Available online at http://www.cftc.gov/idc/groups/public/@newsroom/documents/file/hearing080509_masters.pdf.

Mayer, J. "The Growing Financialisation of Commodity Markets: Divergences between Index Investors and Money Managers." *Journal of Development Studies* 48(2012):751–767. doi: 10.1080/00220388.2011.649261.

Phillips, P. C. B., S. Shi, and J. Yu. “Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500.” *International Economic Review* 56(2015):1043–1078. doi: 10.1111/iere.12132.

Phillips, P. C. B., Y. Wu, and J. Yu. “Explosive Behavior in the 1990s NASDAQ: When did Exuberance Escalate Asset Values?” *International Economic Review* 52(2011):201–226. doi: 10.1111/j.1468-2354.2010.00625.x.

Phillips, P. C. B., and J. Yu. “Dating the Timeline of Financial Bubbles During the Subprime Crisis.” *Quantitative Economics* 2(2011):455–491. doi: 10.3982/QE82.

Robles, M., M. Torero, and J. von Braun. “When Speculation Matters.” Issue Brief 57, International Food Policy Research Institute, Washington, DC, 2009. Available online at http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/32141.

Ruitenberg, R. “Global Food Reserve Needed to Stabilize Prices, Researchers Say.” 2010. Available online at http://www.bloomberg.com/apps/news?pid=newsarchive&sid=au9X.0u6VpF0.

Sanders, D. R., and S. H. Irwin. “A Speculative Bubble in Commodity Futures Prices? Cross-Sectional Evidence.” *Agricultural Economics* 41(2010):25–32. doi: 10.1111/j.1574-0862.2009.00422.x.

———. “The Impact of Index Funds in Commodity Futures Markets: A Systems Approach.” *Journal of Alternative Investments* 14(2011a):40–49. doi: 10.3905/jai.2011.14.1.040.

———. “New Evidence on the Impact of Index Funds in U.S. Grain Futures Markets.” *Canadian Journal of Agricultural Economics* 59(2011b):519–532. doi: 10.1111/j.1744-7976.2011.01226.x.

———. “Bubbles, Froth and Facts: Another Look at the Masters Hypothesis in Commodity Futures Markets.” *Journal of Agricultural Economics* forthcoming(2016). doi: 10.1111/1477-9552.12191.

Singleton, K. J. “Investor Flows and the 2008 Boom/Bust in Oil Prices.” *Management Science* 60(2014):300âĂŞ–318. doi: 10.1287/mnsc.2013.1756.

Sockin, M., and W. Xiong ().

Stoll, H. R., and R. E. Whaley. “Commodity Index Investing and Commodity Futures Prices.” *Journal of Applied Finance* 20(2010):7–46.

Tadesse, G., B. Algieri, M. Kalkuhl, and J. von Braun. “Drivers and Triggers of International Food Price Spikes and Volatility.” *Food Policy* 47(2014):117–128. doi: 10.1016/j.foodpol.2013.08.014.

Tang, K., and W. Xiong. “Index Investment and the Financialization of Commodities.” *Financial Analysts Journal* 68(2012):54–74. doi: 10.2469/faj.v68.n6.5.

Tomek, W. G. “Commodity Futures Prices as Forecasts.” *Review of Agricultural Economics* 19(1997):23–44. doi: 10.2307/1349677.

U.S. Senate, Permanent Subcommittee on Investigations. *Excessive Speculation in the Wheat Market*. Washington, DC, 2009. Available online at http://www.hsgac.senate.gov/imo/media/doc/REPORTExcessiveSpecullationintheWheatMarketwoexhibitschartsJune2409.pdf.

von Braun, J., and M. Torero. *The Grain Markets International (Virtual) Reserves Proposal: Addressing Questions and Comments*. Washington, DC, 2009.

Will, M. G., S. Prehn, I. Pies, and T. Glauben. “Is Financial Speculation with Agricultural Commodities Harmful or Helpful?” Discussion Paper 2012–27, Martin Luther University, Halle, Wittenberg, 2013.

———. “Is Fnancial Speculation with Agricultural Commodities Harmful or Helpful? A Literature Review of Empirical Research.” *Journal of Alternative Investments* 18(2016):84–102. doi: 10.3905/jai.2016.18.3.084.

Working, H. “Speculation on Hedging Markets.” *Food Research Institute Studies* 2(1960):185–220.

Wright, B. D., and J. C. Williams. *Storage and Commodity Markets*. Cambridge: Cambridge University Press, 1991.