NCCC-134
APPLIED COMMODITY PRICE ANALYSIS, FORECASTING AND MARKET RISK MANAGEMENT

Do Extreme CIT Position Levels Have Market Impacts in Grain Futures Markets?

by

Jiarui Li, Scott H. Irwin, and Xiaoli L. Etienne

Suggested citation format:
Li, J., S. H. Irwin, and X. L. Etienne. 2021. "Do Extreme CIT Position Levels Have Market Impacts in Grain Futures Markets?" Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. [http://www.farmdoc.illinois.edu/nccc134].

Do Extreme CIT Position Levels Have Market Impacts in Grain Futures Markets?

Jiarui Li, Scott H. Irwin, and Xiaoli L. Etienne*

Paper prepared for the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2021.

* Jiarui Li is a PhD candidate in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign. Scott H. Irwin is the Laurence J. Norton Chair of Agricultural Marketing and professor in the Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign. Xiaoli L. Etienne is an Associate Professor in the Division of Resource Economics and Management at the West Virginia University.

Do Extreme CIT Positions Have Market Impacts in Grain Futures Markets?

The "Masters Hypothesis" argues that the growing buying pressure from commodity index funds since 2000 drove up food and energy prices. A group of studies use linear Granger causality tests to examine the relationship between the speculative pressure and futures prices in agricultural futures markets. Some of them find little evidence to support the Masters Hypothesis, however, some of them find significant statistical links between the two series. We add the results from the quantile Granger causality test and the newly developed quantile dependence measure called cross-quantilogram to the standard linear Granger causality tests. Our findings suggest from 2004 to 2019, both extreme quantiles and the mean frameworks do not provide any supporting evidence for the Masters Hypothesis.

Key words: Agriculture; Commodity; Futures markets; Index investment; Masters Hypothesis

Introduction

From early 2000, with the financialization of the commodity markets, billions of dollars flushed into the markets. Meanwhile commodity prices exploded around 2004, along with the increase in food prices. Critics linked these two events together; and they blamed index funds and index traders' speculative activities for raising the grain commodities prices. The idea that speculative pressure drives up commodity prices was very popular. Michael Masters, a hedge fund manager is a leading proponent for this view. He argues that the speculative pressure comes from the massive demand from the index funds and such demand-side pressure causes the price bubbles in commodities markets. Irwin and Sanders summarize his argument and term it as the "Masters Hypothesis" (2012a).

Along the trend of the financialization of the commodities markets, there are a series of studies investigating the empirical relationship between index positions and commodity prices and testing the Masters Hypothesis. However, these studies' findings are divided. Some find that there is little evidence in support of the Masters Hypothesis. For example, Aulerich et al. (2013) apply the Granger causality tests on 12 agricultural commodities during the period when these commodities index positions had rapid growth. They do not find any statistical link between the positions and futures returns. Gilbert (2010a), Gilbert and Pfuderer (2014) find no causality between speculations and returns for either grain or livestock markets. Etienne et al. (2018) apply the structural vector autoregressive model on four different measures of speculations for corn, and they find corn's prices are largely impacted by fundamental factors. Lehecka (2015) applies the Toda and Yamamoto Granger causality model and he shows speculative measures do not account for the behavior of prices. Capelle-Blancard and Coulibaly (2011) use the innovative seemingly unrelated regression system to show that after control the correlation between different markets, index investments cannot explain the increasing prices in agricultural commodity prices.

However, some studies have opposite conclusions and they show index funds are the cause of the increase in commodity prices. For example, Robles et al. (2009) use the Granger causality test and they show that the speculative pressures increase the spot prices of agricultural commodities.

Gilbert (2010b), Gilbert and Pfuderer (2012) find significant relationship bewteen index positions and an index of food price changes and food price returns in less liquid agricultural markets (soybean oil, feeder cattle, live cattle, and lean hogs).

The above literature uses linear Granger causality tests with conditional mean regression models. The limitation of the linear framework is that for causal relations lie in the tails of the distributions, they do not have the power to detect them. As both CIT positions pressure and futures returns have heavy tails, information in tails are worth investigating as Lee and Yang (2012) argue that for some relationships fail to present in mean, they might be available in tails.

In this study, we apply both linear-based Granger causality methods and quantile-based Granger causality methods to test for the Masters Hypothesis using commodity index traders (CIT) weekly positions and corresponding nearby futures prices for corn, soybean, CBOT wheat, and KCBT wheat futures markets from 2004 to 2019. We first want to confirm the findings of prior studies by checking the causal relationship in mean. Then with quantile-based methods, we want to explore if such causal relations are available in extreme quantiles.

The first quantile-based method is the quantile Granger causality test where we can estimate the quantile causal effects with quantile regressions. This method detects the two variables causal relations by focusing on both series lower and upper quantiles, which helps us to see how the large increase or decrease in returns respond to the corresponding large increase or decrease in index positions. The second method is a newly developed approach named cross-quantilogram (CQ). This method has the following benefits. First, in contrast to previous studies looking into causal linkage and focusing on conditional mean of two series, CQ captures the lead-lag relationships across all parts of distributions. This approach extends the discussion by focusing on extremely large positions where the markets believe have the most valuable insider information; and returns from the extremely negative to the extremely positive values that reflect futures prices movements from two directions. Another advantage of the CQ approach is that it does not require moment conditions as it focuses on quantile hits, and for time series variables, which usually have heavy tails, this method is applicable to them (Fama 1965). This also means CQ does not need the time series to meet a specific distributional assumption. CQ only requires the time series to test causality to be stationary. Also, CQ approach includes very long lags in the causality test, which means we can cover the complete life cycle of futures contract without concerns about degree-of-freedom. This paper is the first to apply CQ to test for the Masters Hypothesis.

The remaining parts of the paper is organized as follows. The second section discusses the methodologies to test the causal relationship between positions pressure and futures returns. The third section introduces the dataset we use. The fourth section presents the empirical results and discusses if our results are in line with previous literatures findings. The fifth section concludes the paper and provides some thoughts for the future work.

Methodology

Standard Granger Causality

The first set of tests we apply for the Masters Hypothesis is the standard Granger Causality (GC) test (Granger, 1980). The specification of the test is shown as below:

(1) $$Return_t = \alpha_t + \sum_{i=1}^{m} \gamma_i \, Return_{t-i} + \sum_{j=1}^{n} \beta_j \, \Delta Position_{t-j} + \epsilon_t$$

where $Return_t$ is the log-difference in nearby weekly futures prices for a given market at time t, and $Position_t$ is the measure of CIT net long positions in the same market. The null hypothesis of the standard GC test is that β_j is zero, suggesting that CIT positions do not Granger-cause futures returns. And to show if CIT net long positions indeed drive up the futures prices, the alternative hypothesis is β_j is greater than zero.

To decide how many lagged periods we need to set up for both returns and positions in the model, we apply the Akaike Information Criterion (AIC) for the model selection. The lag orders for both returns and positions is one from the AIC estimates (m=1, n=1).

But we should be skeptical about the standard GC test results, as this test may omit the true driver for both variables of interests in our model; also, this test is based on the assumption that the relationship between the two variables should be linear, otherwise the test results are not revealing the true Granger causality from one to another (Irwin, 2013).

Augmented Granger Causality

The second set of the tests is the augmented GC test that applies the VAR model to detect the dynamic causal relationship between two cointegrated time series variables. When two time series are cointegrated, or when they are not strictly stationary, traditional GC test tends to conclude with a spurious relationship, and the results are not valid (Granger 1980, Engle and Granger 1987). To avoid the inaccurate test results, we follow Toda and Yamamoto (1995)'s procedure to test for Granger causality in the VAR models that take care of the cointegration and stationarity. This model's Chi-square distribution hold asymptotically. The model is specified as below:

(2) $$\begin{bmatrix} Return_t \\ \Delta Position_t \end{bmatrix} = \sum_{i=1}^{p+d_{max}} \begin{bmatrix} \gamma_{1,i} & \gamma_{2,i} \\ \gamma_{3,i} & \gamma_{4,i} \end{bmatrix} \begin{bmatrix} Return_{t-i} \\ \Delta Position_{t-i} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + t \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}.$$

The augmented Granger Causality procedure has the following steps: first, test for each series order of integrations using Augmented Dickey-Fuller (ADF) test and determine the value of d_{max}. d_{max} is the maximum order of integration of two series; second, set up the VAR model and use the AIC to determine the optimal lags p for the system; third, use the augmented lags $p + d_{max}$ to the VAR system and apply the Wald-test to check if the coefficients before the bivariate vector of price and position are jointly zero.

The augmented GC framework includes the constant terms α_1 and α_2, the linear time trend β_1 and β_2, along with the error term $\epsilon_{1,t}$ and $\epsilon_{2,t}$. The null hypothesis of the augmented GC test is that $\gamma_{2,i}$ or $\gamma_{3,i}$ = 0, for all $i = 1,2,3, \dots p$, indicating that CIT net long positions do not Granger-cause futures returns or the other way around.

Quantile Granger Causality

The third set of the test is the quantile GC test proposed by Lee and Yang (2012); and by Chuang, Kuan and Lin (2009). The quantile GC framework is a non-parametric approach that captures the causal relationship at different quantile levels. The traditional GC test only looks at one part of the conditional distribution: mean; however, information is also available in different quantiles (Troster, 2016). Evidence has found that conditional mean causal relationships between money and income relationship is not significant, whereas, their relationship is significant in tail quantiles (Lee and Yang, 2012).

For a given quantile level τ, if x does not Granger cause y, then we have:

$$(3) \qquad Q_{y_t}(\tau|(\mathcal{Y},\mathcal{X})_{t-1}) = Q_{y_t}(\tau|\mathcal{Y}_{t-1}), \forall\, \tau \in (0,1)$$

where $Q_{y_t}(\tau|\mathcal{F})$ is the τ-th quantile of $F_{y_t}(\cdot\,|\mathcal{F})$, and $F_{y_t}(\cdot\,|\mathcal{F})$ is the conditional distribution of y_t. The Granger causality test in quantiles is based on the quantile regression developed by Koenker and Bassett (1978). To test the Granger causality from CIT positions pressure to futures returns in selected conditional quantile levels, we specify the relationship as follows:

$$(4) \qquad Return_t = \alpha_{1,t} + \sum_{i=1}^{m} \gamma_{1,i}\,(\tau) Return_{t-i} + \sum_{j=1}^{n} \beta_{1,j}\,(\tau)\, \Delta Position_{t-j} + \epsilon_{1,t}(\tau).$$

The null hypothesis of no Granger causality from CIT net long positions is that $\beta_{1,j}(\tau) = 0$, for all $j = 1,2,3, \dots p$. As the quantile framework has the asymptotic normality, we can use the Wald statistics to check the significance of the entire parameter process $\beta_{1,j}(\tau)$. We also use the AIC for model selection, and the AIC estimates return a one-lag period for both series (m=1, n=1).

Cross-Quantilogram

The last methodology is the cross-quantilogram (CQ) proposed by Han et al. (2016) that has the following advantages: CQ captures the directional lead-lag relationships across all parts of distributions; CQ does not require moment conditions; CQ only requires the time series to be stationary; and CQ includes long lags, avoid concerns about degree-of-freedom.

Suppose we have two time series $x_{1,t}$ and $x_{2,t}$, and they are both strictly stationary. Their cumulative distribution is $F_i\,(\cdot)$, and their density function is $f_i\,(\cdot)$. We define the quantile function of each series as $q_i\,(\alpha_i) = \inf(v\colon F_i(v) \geq \alpha_i)\,, \forall \alpha_i \in (0,1)$. This quantile function returns the minimum quantile of x_i for the probability at α_i. CQ model is specified as below:

$$(5) \qquad \rho_\alpha(k) = \frac{E[\psi_{\alpha_1}(x_{1,t}-q_1(\alpha_1))\psi_{\alpha_2}(x_{2,t-k}-q_2(\alpha_2))]}{\sqrt{E[\psi^2_{\alpha_1}(x_{1,t}-q_1(\alpha_1))]}\sqrt{E[\psi^2_{\alpha_2}(x_{2,t-k}-q_2(\alpha_2))]}}$$

where $\psi_{\alpha_i}(u) \equiv 1(u < 0) - \alpha_i$ is a check function that captures the direction of deviation from a given quantile; $k = 0, \pm 1, \pm 2, \dots$. For the CQ model, $\psi_{\alpha_i}(\cdot)$ indicates that at time t, if our observed time series value is smaller than a given quantile level, $\psi_{\alpha_i}(\cdot)$ returns $-\alpha_i$; on the other hand, if our observed value is greater than the given quantile level, $\psi_{\alpha_i}(\cdot)$ returns $1 - \alpha_i$, which is greater than 0. This can be summarized as $\{1\left[x_{i,t} < q_i(\cdot)\right] - \alpha_i\}$ to represent the quantile-hit or the quantile-exceedance process (Han et al., 2014), where $1[\cdot]$ is an indicator function.

Suppose we observed two empirical sample time series specified as $\{x_{1,t}, x_{2,t}\}_{t=1}^{T}$. First, we need to estimate the unconditional quantile functions $\widehat{q_\iota}(\cdot)$ by solving for the following minimization functions:

(6) $\hat{q}_i(\alpha_i) = \underset{v_i \in \mathbb{R}}{\text{argmin}} \sum_{t=1}^{T} \pi_{\alpha_i}(x_{i,t} - v_i)$

where $\pi_{\alpha_i}(u) \equiv u(\alpha_i - 1[u < 0]), i = 1, 2$. Then for a set of quantiles $\{\alpha_1, \alpha_2\}$, we can plug in the estimated quantile function $\hat{q}_i(\alpha_i)$, and the sample cross-quantilogram is:

(7) $\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \psi_{\alpha_1}(x_{1,t} - \hat{q}_1(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - \hat{q}_2(\alpha_2))]}{\sqrt{\sum_{t=k+1}^{T} \psi_{\alpha_1}^2(x_{1,t} - \hat{q}_1(\alpha_1))}\sqrt{\sum_{t=k+1}^{T} \psi_{\alpha_2}^2(x_{2,t-k} - \hat{q}_2(\alpha_2))}}$

where $k = 0, \pm 1, \pm 2, \ldots$(Han et al., 2016). The cross-quantilogram statistics $\hat{\rho}_\alpha(k)$ captures the directional predictability between two series at a given quantile set. $\hat{\rho}_\alpha(k) \in [-1,1]$, and when $\hat{\rho}_\alpha(k) = 0$, this suggests that there is no directional predictability between two series. To test the predictability from one time series to another, from one lag to k lags, we follow the quantile version of the Ljung-Box-Pierce statistic test proposed by Han et al. (2016). To test if there is any directional predictability from $x_{2,t}$ to $x_{1,t}$, for $k \in \{1, 2, \ldots, p\}$, the null hypothesis is H_0: $\rho_\alpha(1) = \rho_\alpha(2) = \cdots = \rho_\alpha(p) = 0$, against the alternative hypothesis H_a: $\rho_\alpha(k) \neq 0$. The test statistics is:

(8) $\hat{Q}_a^{(p)} = \frac{T(T+2)\sum_{k=1}^{p} \hat{\rho}_\alpha^2(k)}{T-k}$

where $\hat{Q}_a^{(p)}$ is the portmanteau test statistics for our directional predictability hypothesis. The corresponding critical values for the portmanteau test (Han et al., 2016) are derived from the stationary bootstrap of Politis and Romano (1994). The stationary bootstrap is a block bootstrap procedure and the length of each block is randomly determined. The strength of the block bootstrap is that it can reach a high convergence rate using nonparametric estimation to find critical values regardless of the distribution. The stationary bootstrap constructs confidence interval for each estimated the statistic of p cross-quantilograms $\{\rho_\alpha(1), \ \rho_\alpha(2), \ \ldots, \ \rho_\alpha(p)\}$ (Han et al., 2016).

Data

Supplemental Commitments of Traders (SCOT) Report

This paper uses the SCOT report published by the Commodity Futures Trading Commission (CFTC) to collect the commodity index traders' positions of Chicago Board of Trade (CBOT) corn, CBOT wheat, CBOT soybeans, and Kansas City Board of Trade (KCBT) wheat.

SCOT reports are published every Friday at 3:30 p.m. Eastern time by CFTC and the historical data are available back to 2006. SCOT are available to the public as the response to complaints that the legacy Commitments of Traders (COT) were not accurate for classifying commercials and noncommercial. As more index funds flow into the market since 2000, if a long-only index fund hedges its positions with swap dealers in the futures market, this fund may be classified as commercials, but the purpose of such hedging has speculative behavior (CFTC, 2006). With the SCOT reports, we can look into the category of index traders and avoid the uncertainties from classifying positions with different underlying purpose.

In the SCOT reports, four categories' positions add up to the market's open interests, and these categories' relationship are specified as below:

(9) $NCL^{-CITL} + NCS^{-CITS} + 2NCSP + CL^{-CITL} + CS^{-CITS} + CITL + CITS + NRL + NRS = 2 \cdot TOI$

where NCL^{-CITL} (NCS^{-CITS}) and CL^{-CITL} (CS^{-CITS}) are noncommercial long (short) and commercial long (short) positions after removing the long (short) positions of index traders. $CITL$ ($CITS$) are index traders long (short) positions. NRL (NRS) are nonreporting long (short) positions. $NCSP$ are the positions of noncommercial spreading positions.

CFTC provides additional data from 2004 to 2005 as a response to the observation that before 2006 there had been position buildup in index traders' positions (Aulerich et al., 2013; Brunetti and Reiffen, 2012; Sanders et al., 2010; Sanders and Irwin, 2011). Our study includes index traders' positions from January 6, 2004 to December 31, 2019, with 853 weekly observations for each of the four markets.

Following Irwin's (2013) measure of CIT positions that directly reflect the "weight" of index positions as the drive for futures prices, we use CIT net long positions to calculate the pressure of index positions. There are two ways to measure index positions pressure. First, we use the change in net long positions. Second, we use the percentage change in net long positions.

The descriptive statistics for CIT net long positions and the two measures of index positions pressure are included in Table 1. All of the series are stationary based on the Augmented Dickey-Fuller (ADF) test, except for corn's CIT net long positions. For net long positions, four commodities are all left-skewed. They all have positive Kurtosis, indicating they all have heavy-tailed distribution. The Jarque-Bera (JB) test's null hypothesis is that a series has normal distribution. We can observe that four series reject the null hypothesis, suggesting none of them are normally distributed. For the two measures of index positions pressure, most of them are right-skewed and have heavy tails. The JB test suggest non-normal distribution for all of them.

Futures Returns

For the four markets of interests, the futures returns are the percentage change in nearby futures prices. To avoid the inconsistency in price series with contract rollovers, we calculate the return using the same nearest-to-expiration contract. Nearby futures are the nearest-to-expiration contract, the expiration month is not included. Since CFTC compilate the data for Friday's SCOT report on Tuesday, we use Tuesday's closing price to represent the price observation for each week.

The descriptive statistics for returns are presented in Table 1. For all of the four commodities, their returns are stationary. Corn and soybean's returns are left-skewed, and two wheat commodities are right-skewed. All series have heavy tails and the JB test suggest none of them are normally distributed.

The contemporaneous relationship between CIT positions and futures prices for four commodities are summarized in Figure 1. Take corn as an example, since 2006 it does seem like futures prices are following the build-up of index traders' positions. But if we look into the periods of 2004-2006, futures prices are relatively stable compared to the rising patterns of index positions. Whether it is the index positions driving up grain futures prices or it is mere coincidence, we need more formal statistical tests to unravel the relationship between CIT positions and futures prices.

Results and Discussion

Standard Granger Causality Test Results

Standard Granger Causality (GC) test results are summarized in Table 2. The results suggest that 2004-2009 positions do not Granger cause future returns for all of the four commodities except CBOT wheat. However, when we look into the coefficients before the positions, they are negative. This means that even though in CBOT wheat futures market, index trader' positions do Granger cause returns, but it fails to drive up the future prices.

Augmented Granger Causality Test Results

Augmented GC test results are also included in Table 2. The results are similar to standard GC test that all but CBOT wheat have no causal effects from CIT positions to prices from 2004 to 2019. For CBOT wheat, even though the test results suggest positions Granger cause returns, the coefficients before positions are all negative. Our findings fail to support Masters Hypothesis, and we find that although CIT positions have causal effects on futures prices, they do not drive up the prices.

Quantile Granger Causality Test results

We use quantile GC test to detect the causality relationship in quantiles between CIT positions and grain futures prices. We consider four pairs of quantile levels for the CIT position pressures and corresponding futures returns: 0.1, 0.25, 0.75, 0.9, as both series have heavy tails. These four quantile levels capture the information in both upper and lower tails. The Wald-test statistics and p-values are presented in Table 3, for observations from 2004 to 2019. The test results suggest that in general, CIT positions pressures fail to Granger cause futures returns over the tail regions, which means the increasing CIT positions do not Granger cause the inflation in futures prices.

For each measure of CIT positions pressures, for all of the four commodities, we have 16 pairs between the pressure and returns. For both the changes in index traders' net longs and percentage change in net longs, there are only 5 out of 16 cases that have significant causal relationships. For example, when corn's positions pressures and returns are both in 0.9 quantiles, we fail to reject the null hypothesis that there are no causal effects from positions to prices. We also find similar significant causalities from positions to prices for soybeans in 0.1 and 0.25 quantiles, CBOT wheat for all quantiles. However, we further find the estimated coefficients before positions are all negative. This suggest that even though there are significant causal effects from CIT positions to prices in some commodities' futures markets, positions do not positively cause the increase of futures prices.

Cross-Quantilogram Results

The cross-quantilogram (CQ) results for each of the four grain futures markets are presented in Figures 2 – 5. For each commodity, there are 16 pairs of cross-quantilogram results. This is because like what we have in the quantile GC test, we are interested in the tail regions of each heavy-tailed series. We set up four quantiles for CIT positions pressure and each commodity's futures returns, i.e. 0,1, 0.25, 0.75, 0.9. These four quantiles represent the extremely low, low, high, and extremely high values in positions pressure and returns. An advantage of CQ is that it detects the dynamics of the Granger causality from a series to another, which means that for a given quantile of positions pressure, we can measure the pairs between this given quantile of pressure and the four extreme levels of returns. CQ helps us to complete the discussion of Granger causality by assessing the relationship of two series in tails; and CQ extends the test for Masters Hypothesis by not limiting to series conditional mean and using a linear framework, instead it looks into the tail quantiles of the CIT pressure and corresponding futures returns respective distribution.

For each commodity, we have 16 subplots that represent the 16 pairs between the four quantile levels of CIT positions pressure and returns. This makes it possible for us to observe how large movements in returns react to the large movements in CIT positions pressures. These subplots are organized in four parts: (a) – (d), where each part represents the estimated sample CQ between a given quantile of CIT positions pressure and four quantiles of returns, from the extremely large decrease in returns to the extremely large increase in returns. The positions pressure is the change in CIT net long positions and for (a) – (d), pressure quantile is 0.1, 0.25, 0.75, 0.9 respectively*. For each subplot, the black bar is the estimated sample CQ at different lag k, i.e., $\hat{\rho}_\alpha(k)$. The red-dashed lines represent the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates. We include 13 lags as it is the largest lag order reported by AIC.

For CIT positions pressure in low quantiles, i.e., large decrease in CIT net long positions, in long term, most of the estimated CQ statistics are insignificant in CBOT wheat market, indicating that large decrease in CIT net longs do not Granger cause large movements in returns. For corn, soybean and KCBT wheat markets, we observe some cases that large increase in returns follow the large decrease in pressure. These results suggest Granger causality, but the relationship is opposite to the argument of the Masters Hypothesis. Here the large decrease in index net long positions do not Granger cause great negative returns, showing futures prices do not move along and follow the movements of CIT net long positions. In short term, there are some significantly negative CQ statistics for KCBT wheat large increase in returns, which fails to support the Masters Hypothesis.

For CIT positions pressure in high quantiles, i.e., large increase in CIT net long positions, in long term, the majority of the estimated CQ statistics are not significant. In corn and soybean futures markets, we observe a few significantly positive CQ statistics for returns in left tails; and significantly negative CQ statistics for returns in right tails. These findings all indicate the negative causal relationship between the increase in large CIT net long positions and the increase in large futures prices. There are only a few cases in CBOT wheat and KCBT wheat markets, where we observe significantly positive CQ statistics for returns in 0.75 and 0.9 quantiles, and significantly negative CQ statistics for returns in 0.1 quantiles. In short term, all of the significant

* To save space we do not include the results for the percentage change in CIT net long positions. Results are available upon request.

CQ statistics show negative directional dependence between two variables for all the pairs of quantile levels.

The portmanteau test statistics are summarized in Table 4. It tests on the futures returns' directional dependence on CIT net long positions pressure for events up to 13 lags for each pair of quantile levels. The test results confirm the insignificance of the quantile correlation for each of the four commodities. The test statistics are significant in 6 out of 64 cases, meaning in general we fail to find any supporting statistical links between the two variables.

Discussion

We use the linear Granger causality models as the benchmark to compare with the two non-parametric quantile models that focus on the tails of time series distributions. With the linear models we do not find any causal relationships from CIT positions pressure to returns. Our findings are consistent with the findings from prior studies (Lehecka, 2015; Irwin, 2013). Then with both quantile Granger causality test and cross-quantilogram, we can detect the causal relationship between two variables in different quantiles which could not be detected with the linear frameworks. Especially for pressure and returns that both have heavy tails, these two methods circumvent the limitations of the linear models which only focus on the conditional mean of the distribution.

After testing the quantile dependence relationship between the two variables, we do not find any supporting statistical evidence for the hypothesis that CIT net long positions create buying pressure and drive up food prices. The results from quantile Granger causality test suggest that there is no dependence relationship from both lower and upper levels of quantiles. And the test results from cross-quantilogram further suggest that no matter it is in long term or short term, large movements in CIT net long positions do not Granger cause large movements in futures prices. In summary, all the tests results suggest index traders do not affect commodity futures prices. The quantile-based causality approaches complement the evidence that are in contrast to the Masters Hypothesis by showing there is no Granger causality in tail quantiles of both positions pressure and returns. Index traders are more like trend-followers in the markets and the comovement of two series are likely to be caused by another factor or just mere coincidence.

Conclusions

This paper uses two standard linear Granger causality tests and two quantile Granger causality methods to test for the hypothesis that if there is any causal relationship from CIT net long positions to futures prices in mean and in the extreme quantile levels for four grain futures markets. We first apply the linear methods to show that in mean, two series do not have any relationships, or they only have significantly negative relationship. We also apply the quantile-based methods to first show that when two series are both in low and upper quantiles, there is no causal relationship from CIT positions to prices. Then we apply the cross-quantilogram to test that at a given tail quantile of positions pressure, there is no causal relationship from it to returns in both lower and upper quantiles.

Our findings provide more evidence to show that Masters Hypothesis is not valid in grain futures markets and our findings are in line with the arguments that index investments are not the cause for the bubbles in food prices (Irwin and Sanders, 2012b). We show that not only in means but also in tail quantiles of these two series, there is no relationships or there is only negative relationship. However, there are still some rare cases, like in CBOT wheat and KCBT wheat futures markets, where we find some positive dependence from large increase in positions to large increase in returns. This might be caused by structural break around 2010 when futures prices started to drop as we can observe in Figure 1. We can split our dataset into two parts, one is before 2010 and the other one is after 2010. Then we can re-run the tests and see if such rare cases are still available.

Table 1. Summary Statistics

	Obs (n)	Min	Max	Mean	Std. Dev	Skewness	Kurtosis	JB Test	ADF Test
Return									
Corn	835	-16.493	18.410	-0.151	3.954	-0.004	5.179	165.166***	-8.348***
Soybean	835	-15.668	11.337	0.064	3.365	-0.235	4.131	52.179***	-8.272***
CBOT Wheat	835	-17.625	16.837	-0.225	4.330	0.203	4.032	42.835***	-9.751***
KCBT Wheat	835	-16.373	16.215	-0.169	4.131	0.124	3.771	22.803***	-9.323***
CIT Net Long Positions									
Corn	835	64646	503937	332391	85528.832	-0.822	3.561	105.074***	-2.950
Soybean	835	27101	201251	128727	36529.416	-0.848	3.804	122.643***	-3.203*
CBOT Wheat	835	33696	229565	149459	42851.531	-0.258	2.564	15.885***	-3.142*
KCBT Wheat	835	12055	66592	37162	12302.797	-0.242	2.187	31.173***	-3.156*
Change in CIT Net Long Positions									
Corn	834	-44788	60317	213	9194.862	0.291	8.569	1089.385***	-7.83**
Soybean	834	-23250	27251	138	4519.885	-0.218	9.125	1310.348***	-8.619**
CBOT Wheat	834	-33227	15010	85	3862.276	-0.660	10.635	2086.522***	-7.958**
KCBT Wheat	834	-6400	14342	45	1641.455	0.812	12.361	3136.496***	-9.543**
Percentage (%) Change in CIT Net Long Positions									
Corn	834	-14.007	21.958	0.159	3.052	0.516	9.622	1560.829***	-8.161**
Soybean	834	-20.146	23.204	0.197	3.697	0.342	10.090	1762.903***	-8.289**
CBOT Wheat	834	-20.405	14.166	0.136	2.811	-0.206	9.132	1312.645***	-7.468**
KCBT Wheat	834	-19.574	26.412	0.165	4.223	0.473	8.231	981.879***	-9.010**

Notes: *, **, and *** are the significance level at 10%, 5%, and 1% respectively. Skewness measures the symmetry of a series' distribution, when it is negative, it indicates the distribution is left-skewed; whereas when it is positive, it indicates the distribution is right-skewed. Kurtosis measures the tail shape of the distribution, when it is negative, it indicates thin-tailed distribution; whereas when it is positive, it indicates heavy-tailed distribution. Jarque-Bera (JB) test is a "goodness of fit" test to check if a series has normal distribution. The null hypothesis is that a series has normal distribution. Augmented Dickey-Fuller (ADF) test is to check if a series has unit root. The null hypothesis is that a series has unit root.

Table 2. Granger Causality Test Results and Augmented Granger Causality Test Results

	From Positions to Price	
	Standard GC	Augmented GC
	2004-2019	
Panel A: Change in CIT Net Long		
corn	-	-
soybean	-	-
CBOT wheat	**	**
KCBT wheat	-	-
Panel B: % Change in CIT Net Long		
corn	-	-
soybean	-	-
CBOT wheat	**	**
KCBT wheat	-	-

Notes: *, **, and *** are the significance level at 10%, 5%, and 1% respectively. "-" indicates there is no causality from index traders' positions to returns. For significant test results, the coefficients before positions are all negative.

Table 3. Granger Causality Test in Quantiles

	From Positions to Returns			
Quantile Levels	0.1	0.15	0.75	0.9
Panel A: Change in CIT Net Long	2004-2019			
Corn	0.045	0.517	1.185	14.600***
	(0.841)	(0.480)	(0.264)	(0.000)
Soybean	19.970**	11.372**	1.542	0.116
	(0.015)	(0.026)	(0.147)	(0.720)
CBOT Wheat	2.129*	3.082**	7.842***	6.103**
	(0.094)	(0.032)	(0.001)	(0.016)
KCBT Wheat	0.533	0.067	0.069	0.556
	(0.485)	(0.801)	(0.778)	(0.431)
Panel B: % Change in CIT Net Long				
Corn	0.022	0.001	0.639	12.400***
	(0.886)	(0.973)	(0.493)	(0.000)
Soybean	3.150***	3.408	1.425	0.003
	(0.000)	(0.136)	(0.196)	(0.954)
CBOT Wheat	1.744	3.270**	7.780***	10.000***
	(0.133)	(0.032)	(0.002)	(0.002)
KCBT Wheat	1.364	0.066	0.070	0.121
	(0.228)	(0.801)	(0.776)	(0.715)

Notes: *, **, and *** are the significance level at 10%, 5%, and 1% respectively. p-values are in the parenthesis. For significant test results, the coefficients before positions are all negative.

Table 4. Portmanteau Test Statistics with 13 Lags in Four Grain Futures Markets

Panel A: CBOT Corn

	Return Quantile Level			
CIT Net Long Change Quantile	Q_0.1	Q_0.25	Q_0.75	Q_0.9
Q_0.1	16.027	21.238	20.012	17.588
Q_0.25	16.350	21.836	17.382	10.200
Q_0.75	12.115	13.051	12.311	10.016
Q_0.9	17.077	15.167	23.623	6.825
CIT Net Long % change Quantile				
Q_0.1	17.781	27.351	17.276	16.189
Q_0.25	16.252	24.919	16.868	9.707
Q_0.75	9.017	9.851	14.836	7.184
Q_0.9	6.466	9.726	25.169 **	8.330

Panel B: CBOT Soybean

	Return Quantile Level			
CIT Net Long Change Quantile	Q_0.1	Q_0.25	Q_0.75	Q_0.9
Q_0.1	16.027	21.238	20.012	17.588
Q_0.25	16.350	21.836	17.382	10.200
Q_0.75	12.115	13.051	12.311	10.016
Q_0.9	17.077	15.167	23.623	6.825
CIT Net Long % change Quantile				
Q_0.1	17.781	27.351 **	17.276	16.189
Q_0.25	16.252	24.919	16.868	9.707
Q_0.75	9.017	9.851	14.836	7.184
Q_0.9	6.466	9.726	25.169 **	8.330

Panel C: CBOT Wheat

	Return Quantile Level			
CIT Net Long Change Quantile	Q_0.1	Q_0.25	Q_0.75	Q_0.9
Q_0.1	26.306	20.020	22.123	31.059
Q_0.25	19.723	14.367	31.918 **	26.411
Q_0.75	20.299	7.924	19.906	11.742
Q_0.9	24.085	8.181	27.142 **	7.944
CIT Net Long % change Quantile				
Q_0.1	24.993	15.293	30.04 **	27.164 **
Q_0.25	21.599	8.025	20.952	15.213
Q_0.75	22.950	8.332	18.689	15.004
Q_0.9	22.762	8.352	20.317	6.549

Panel D: KCBT Wheat

	Return Quantile Level			
CIT Net Long Change Quantile	Q_0.1	Q_0.25	Q_0.75	Q_0.9
Q_0.1	12.627	8.782	22.295	14.923
Q_0.25	10.151	9.578	5.167	4.548
Q_0.75	15.508	8.598	11.476	5.327
Q_0.9	31.224	8.386	13.363	9.604
CIT Net Long % change Quantile				
Q_0.1	9.100	6.357	15.009	20.261
Q_0.25	11.800	11.192	9.117	6.000
Q_0.75	24.987	7.593	8.607	7.656
Q_0.9	26.697	9.761	6.963	9.431

Notes: *, **, and *** are the significance level at 10%, 5%, and 1% respectively.

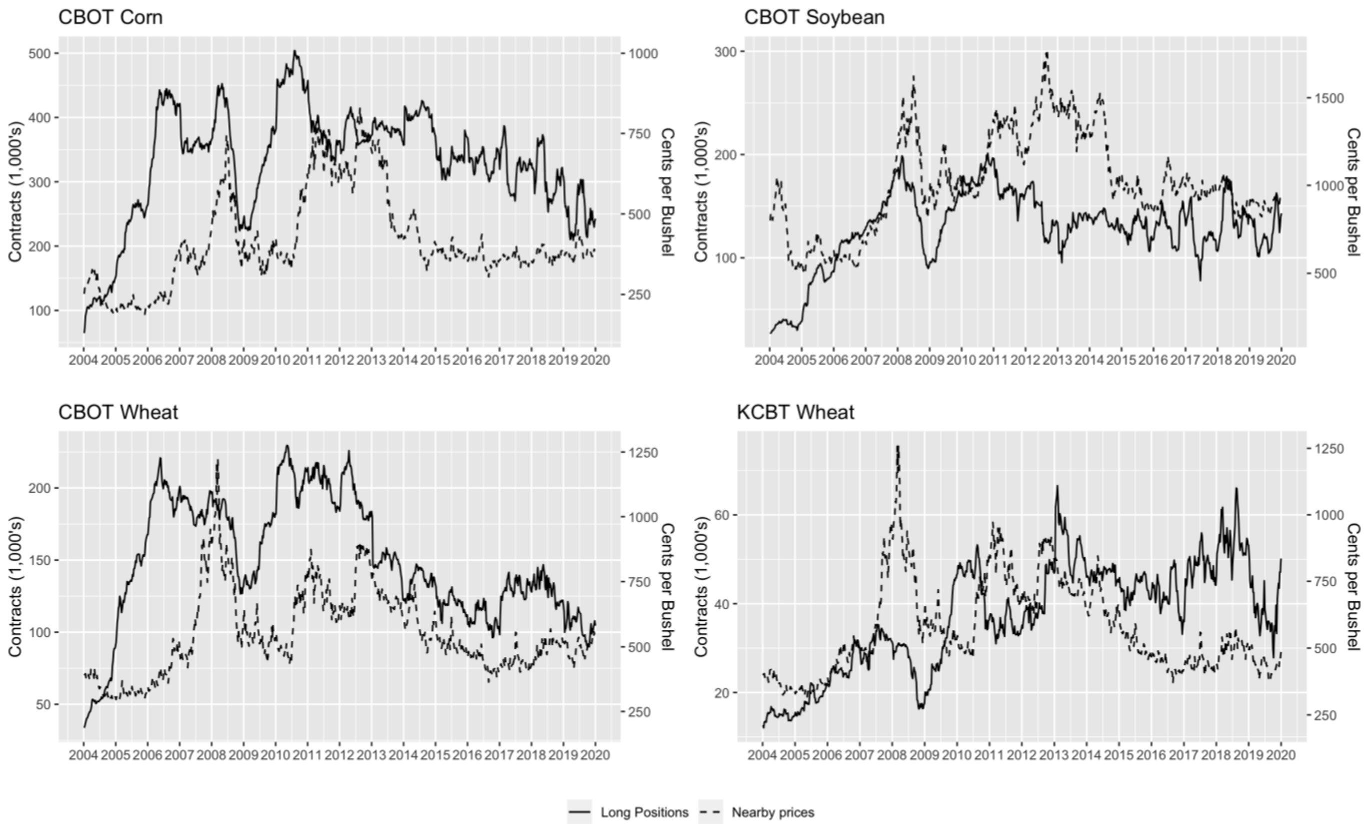

Figure 1. Weekly commodity index trader positions and nearby futures prices of CBOT corn, soybean, wheat, and KCBT wheat, January 2004 to December 2019

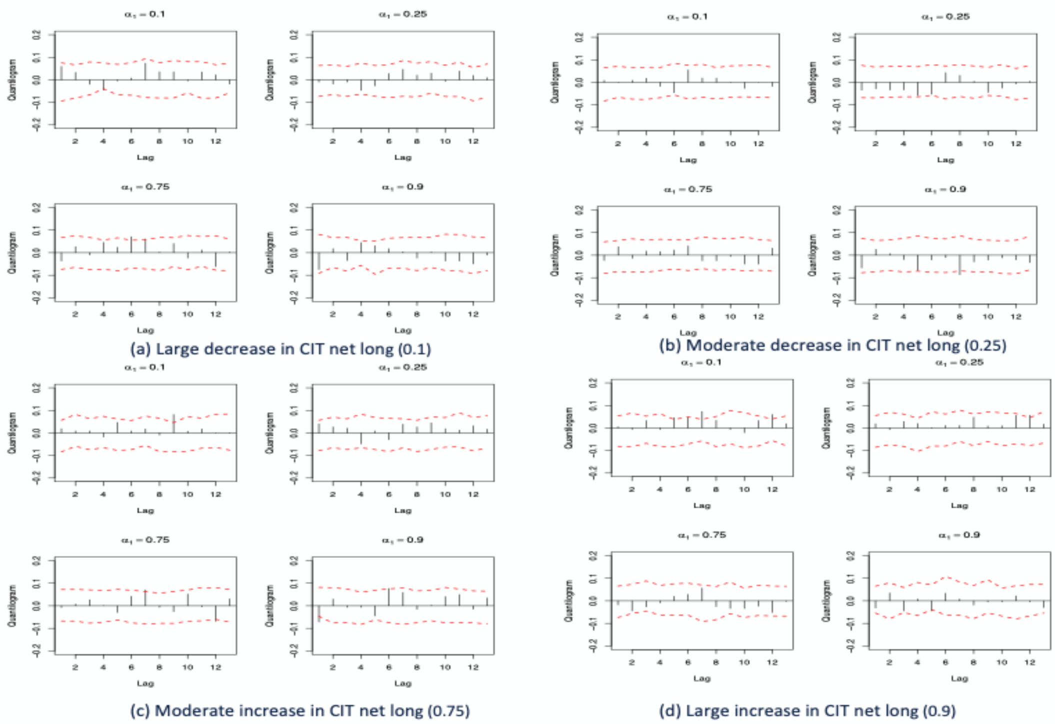

Figure 2. Cross-Quantilogram from Changes in CIT Net Long Positions to Returns in **Corn** Futures Market

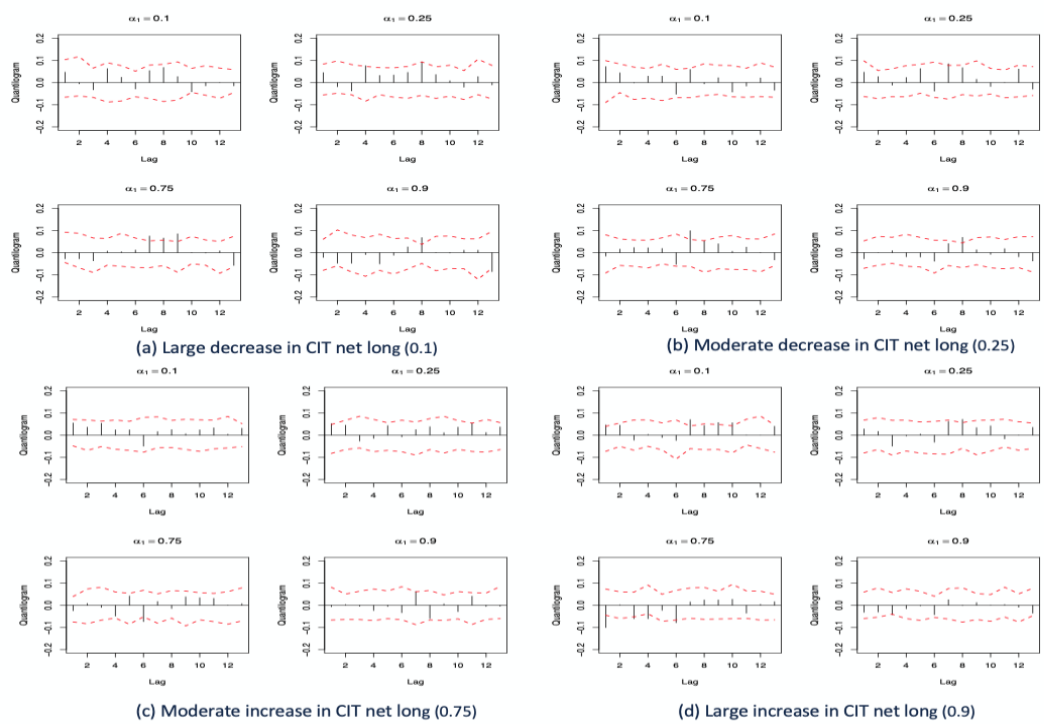

Figure 3. Cross-Quantilogram from Changes in CIT Net Long Positions to Returns in **Soybean** Futures Market

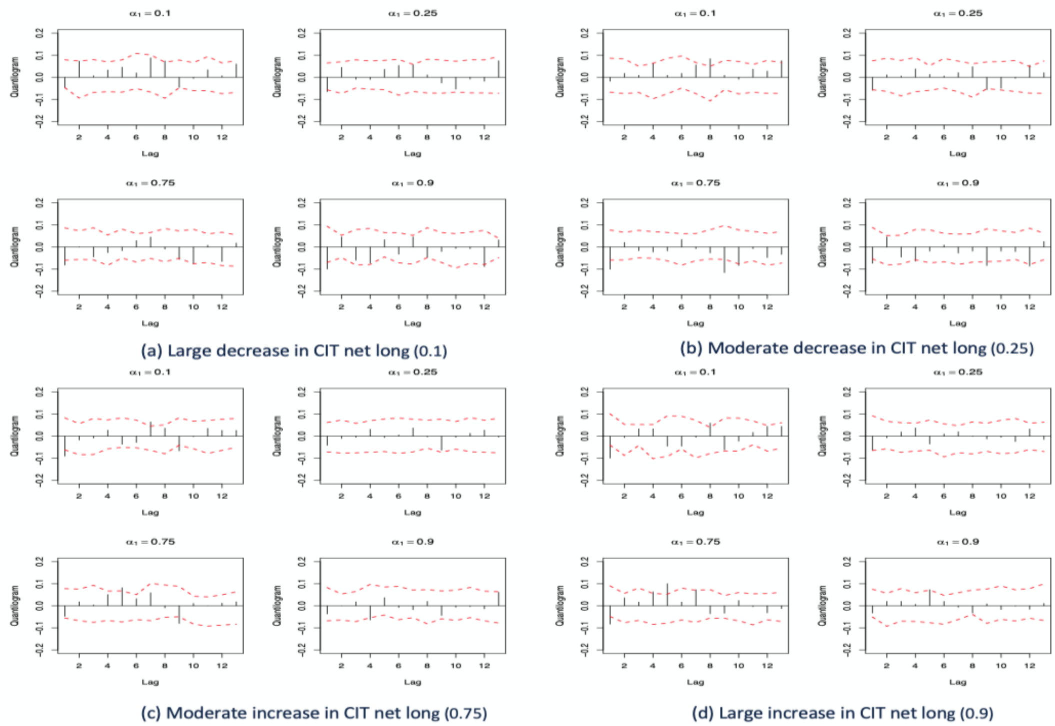

Figure 4. Cross-Quantilogram from Changes in CIT Net Long Positions to Returns in **CBOT Wheat** Futures Market

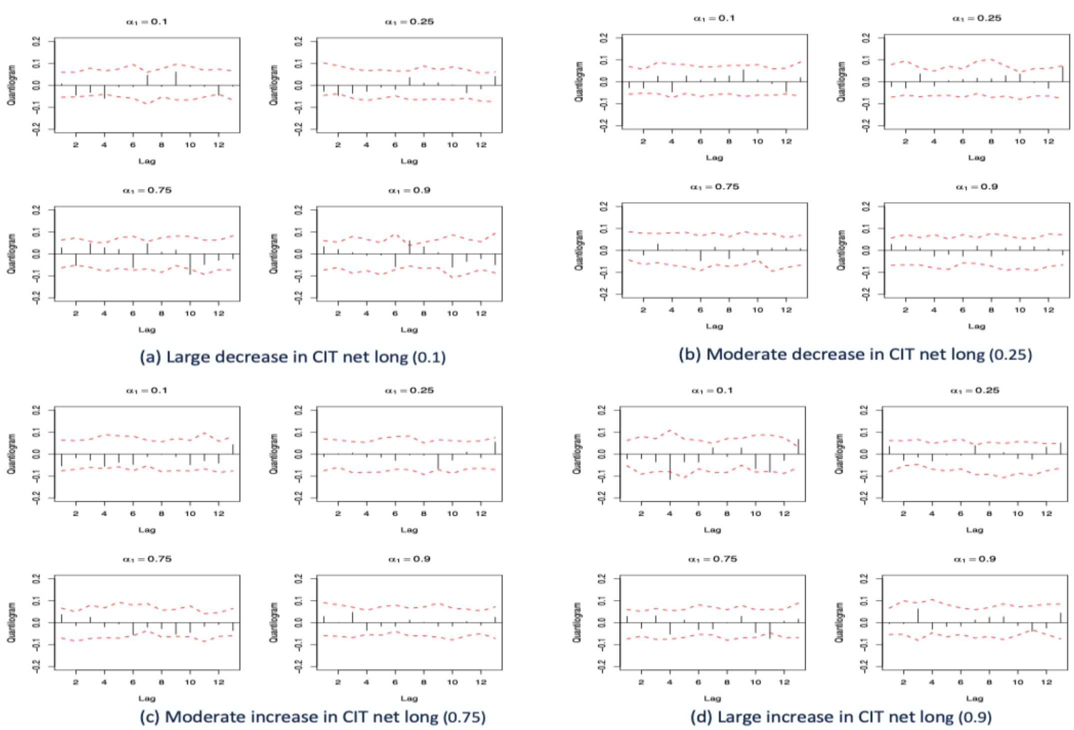

Figure 5. Cross-Quantilogram from Changes in CIT Net Long Positions to Returns in **KCBT Wheat** Futures Market

Preferences

Aulerich, N. M., Irwin, S. H., & Garcia, P. (2014). Bubbles, food prices, and speculation: evidence from the CFTC's daily large trader data files. *The economics of food price volatility* (pp. 211-253). University of Chicago Press.

Brunetti, C., & Reiffen, D. (2014). Commodity index trading and hedging costs. *Journal of Financial Markets*, 21, 153-180.

Capelle-Blancard, G., & Coulibaly, D. (2011). Index trading and agricultural commodity prices: A panel Granger causality Analysis. *International Economics*, *126–127*, 51–71. https://doi.org/10.1016/S2110-7017(13)60036-0.

CFTC (2006). Comprehensive review of the commitments of traders reporting program. Washington, DC. https://www.cftc.gov/foia/fedreg06/foi060621a.htm. Accessed 20 Dec 2020.

Chuang, C. C., Kuan, C. M., & Lin, H. Y. (2009). Causality in quantiles and dynamic stock return–volume relations. *Journal of Banking & Finance*, 33(7), 1351-1360.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 251-276.

Etienne, X. L., Irwin, S. H., & Garcia, P. (2018). Speculation and corn prices. *Applied Economics*, 50(44), 4724-4744.

Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, 38(1), 34-105.

Gilbert, C. L. (2010a). Speculative influences on commodity futures prices 2006-2008. Geneva, Switzerland: United Nations Conference on Trade and Development.

Gilbert, C. L. (2010b). How to understand high food prices. *Journal of Agricultural Economics, 61(2)*, 398–425. https://doi.org/10.1111/j.1477-9552.2010.00248.x.

Gilbert, C. L., & Pfuderer, S. (2012). Index funds do impact agricultural prices. *Money, macro and finance study group workshop on commodity markets, London.*

Gilbert, C. L., & Pfuderer, S. (2014). *The financialization of food commodity markets.* In Handbook on Food. Edward Elgar Publishing.

Granger, C. W. J. (1980). Testing for causality. A personal viewpoint. *Journal of Economic Dynamics and Control, 2(C),* 329–352. https://doi.org/10.1016/0165-1889(80)90069-X.

Han, H., Linton, O., Oka, T., and Whang, Y.-J. (2016). The cross-quantilogram: measuring quantile dependence and testing directional predictability between time series. *Journal of Econometrics, 193(1):*251–270.

Irwin, S. H. (2013). Commodity index investment and food prices: Does the "masters hypothesis" explain recent price spikes? *Agricultural Economics, 44(SUPPL1)*, 29–41. https://doi.org/10.1111/agec.12048.

Irwin, S.H., Sanders, D.R. (2012a). Testing the Masters hypothesis in commodity futures markets. *Energy Econ*. 34, 256–269.

Irwin, S. H., & Sanders, D. R. (2012b). Financialization and structural change in commodity futures markets. *Journal of agricultural and applied economics*, 44(1379-2016-113661), 371-396.

Lee, T.-H., Yang, W. (2012). Money-income Granger-causality in quantiles. *Advances in Econometrics 30*:383–407.

Lehecka, G. V. (2015). Do hedging and speculative pressures drive commodity prices, or the other way round? *Empirical Economics*, *49(2)*, 575–603. https://link.springer.com/article/10.1007%2Fs00181-014-0886-7

Politis, D. N., & Romano, J. P. (1994). The stationary bootstrap. *Journal of the American Statistical association*, 89(428), 1303-1313.

Robles, M., Torero, M., & Braun, J. von. (2009). *When speculation matters: International food policy research institute, issue brief 57. IFPRI - issue brief*. International Food Policy Research Institute. Retrieved from https://www.cabdirect.org/cabdirect/abstract/20093129784.

Sanders, D. R., Irwin, S. H., & Merrin, R. P. (2010). The adequacy of speculation in agricultural futures markets: too much of a good thing? *Applied Economic Perspectives and Policy*, 32(1), 77-94.

Sanders, D.R., Irwin, S.H. (2011). New evidence on the impact of index funds in U.S. grain futures markets. *Can. J. Agric. Econ. 59*, 519–32.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, *66(1–2)*, 225–250. https://doi.org/10.1016/0304-4076(94)01616-8.

Troster, V. (2018). Testing for Granger-causality in quantiles, *Econometric Reviews*, *37:8*, 850-866, DOI: 10.1080/07474938.2016.1172400