Do Extreme CIT Position Changes Move Prices in Grain Futures Markets?

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Abstract: *Most previous studies reject the basic tenet of the Masters Hypothesis that financial index investments have pressured agricultural futures prices upward. However, the impact of this investment may be more complicated and nuanced than can be detected by the relatively simple linear Granger causality tests used in many previous studies. Our study applies a new cross-quantilogram (CQ) test to weekly index trader positions and returns in four agricultural futures markets. We find little evidence of significant relationships between extreme index trader position changes and returns.*

Key words: commodity, futures markets, financialization, index investment, directional predictability, Granger causality, quantile

JEL categories: G12, G13, G14, Q02

1. Introduction

A global controversy erupted during the 2007-08 spike in commodity prices about the role of new participants in futures markets—financial index investors. A variety of commodity investment instruments typically are lumped together under the heading “financial index investment” (Engelke and Yuen, 2008). Regardless of the form, these investments have the common goal of providing financial investors with long exposure to returns from a basket of commodity futures. The surge in financial index investment led to widespread charges that the investment wave caused irrational and gross mispricing across a wide range of commodities. This has been labeled the “Masters Hypothesis”, which according to Sanders and Irwin (2017), has the following tenets: 1) financial index investors were directly responsible for driving commodity futures prices higher; 2) the deviations of futures prices from fundamental value were economically very large; and 3) the impact was pervasive across commodity futures markets. These claims have been used to justify the need for tighter regulations on speculation in commodity futures markets around the world.

Some studies find evidence in support of the Masters Hypothesis in agricultural futures markets (e.g., Mayer, 2012; Gilbert and Pfuderer, 2014; Tadesse et al., 2014). However, a much longer list of studies fails to find a significant price impact of commodity index traders (CITs). Many of these studies use linear Granger causality tests between weekly futures returns and CIT positions reported by the U.S. Commodity Futures Trading Commission (CFTC). Noteworthy examples include Stoll and Whaley (2010), Sanders and Irwin (2011), Aulerich, Irwin, and Garcia (2014), Lehecka (2015), and Hamilton and Wu (2015). Over a wide range of markets, data, and methods, these studies find, at best, very limited evidence of a direct link between CIT positions and returns in agricultural futures markets.

Despite the weight of the evidence against the Masters Hypothesis, it continues to resonate with a number of market participants, civic organizations, and policymakers. This may reflect the fact that the impact of financial index investment in agricultural futures markets is more complicated and nuanced than can be detected by relatively simple linear Granger causality tests commonly used in prior literature. Instead of the linear causality at the mean, the relationship between index investment and futures prices may be non-linear and/or hidden in the tails of the data. As noted by Lee and Yang (2012), some statistical relationships may fail to present at the mean of the data but can show up in the tails of the distribution.

To date, only two studies in the CIT literature have used statistical tests to detect these more subtle relationships. Palazzi et al. (2020) applied non-linear Granger causality tests to CIT positions and returns in 12 agricultural futures markets, finding that the more sophisticated non-linear causality test also failed to find evidence of a significant relationship. Algieri, Kalkuhl, and Koch (2017) estimate a multinomial logit model to investigate which factors are associated with the propagation of extreme events in agricultural futures markets, and once again, do not find evidence of an impact of CIT positions. However, neither of these studies analyzed the relationship across different quantiles of the distributions. Given that the discussion on the Master Hypothesis mostly centers around episodes with significant upward price movements, there is clearly a need for additional research to investigate whether the linkage between CIT positions and prices differs under various pricing scenarios.

Our study applies a recently-developed cross-quantilogram (CQ) test to examine the impact of CIT positions on returns in four agricultural futures markets. Han et al. (2016) developed the CQ test to thoroughly analyze the causal relationship between two series in all parts of their distributions, especially the tail quantiles. This test has several advantages, as it: i) captures the lead-lag relationships across all parts of distributions; ii) does not require moment conditions; iii) only requires the time series to be stationary; and iv) includes long lags in the model specification to avoid concerns about degrees-of-freedom. The CQ test has been applied under a variety of contexts, including the spillovers between the U.S. and Chinese agricultural futures markets (Jiang et al., 2016), the spillover of spot gold prices to U.S. stock prices (Baumöhl and Lyócsa, 2017), the quantile dependence and predictability between various energy prices (Scarcioffolo and Etienne, 2021), among others. To the best of our knowledge, the present study is the first to apply the CQ test to analyze the price impact of CIT positions in any type of commodity futures market.

The data for the study consists of weekly CIT positions and returns from January 6, 2004 through December 31, 2019 for Chicago Board of Trade (CBOT) corn, wheat, soybeans, and Kansas City Board of Trade (KCBOT) wheat. We first conduct three types of linear causality tests to provide a baseline for the relationship between CIT positions and prices movements. We fail to reject the null of no causality in most of the cases, across the different tests, measures of position pressure, or the sample period considered. Next, we apply the CQ test of directional predictability in the tails of the distributions of the CIT positions and price movements. Similar to the linear tests, we find very little evidence of a directional relationship in the extremes of the distributions. Our results add to the growing evidence that the Masters Hypothesis is not a useful description of the price impact of CITs in agricultural futures markets.

2. Data

2.1 Commodity index trader positions

The Supplemental Commitment of Traders (SCOT) report published by the CFTC provides weekly CIT positions for CBOT corn, CBOT wheat, CBOT soybeans, and KCBOT wheat. Every

Friday at 3:30 p.m. Eastern time, the CFTC publishes SCOT reports in conjunction with the traditional Commitments of Traders (COT) report. CIT positions in the SCOT report are released as the number of long and short contracts held by index traders as of the previous Tuesday's market settlement. One potential issue with the CIT position data is the internal netting of positions by swap dealers that offer index products to investors. In some markets, short swap positions for certain commodity products tend to offset long swap positions associated with commodity index investments. Fortunately, previous research shows that netting of swap activity is minimal in agricultural markets, and therefore, CIT positions in the SCOT report are generally regarded as accurate measures of aggregate CIT positions (Irwin and Sanders, 2012; Sanders and Irwin, 2013).

The CIT position data are publically available starting from January 2006. Previous studies argue that using post-2006 data may lead to biased results because the buildup of CIT positions in grain futures markets was concentrated in the previous two years (Sanders and Irwin, 2011; Irwin and Sanders, 2011). The CFTC collected additional data for selected grain futures markets over 2004-2005 at the request of the U.S. Senate Permanent Subcommittee on Investigations (USS/PSI, 2009) and the additional data is used for this study. Specifically, weekly CIT positions for the four grain futures markets are available from January 6, 2004 to December 31, 2019, for a total of 853 weekly observations for each market.

We consider two widely used measures that directly reflect the "weight" of index positions in grain futures markets. To start, we compute the net long CIT position for a given market as:

$$CIT\ Net\ Long_t = CITL_t - CITS_t, \tag{1}$$

where $CITL_t$ and $CITS_t$ are the numbers of long and short contracts held by CITs at week t, respectively. In general, CITs hold relatively small short positions in grain futures markets, so the difference between long and net long positions is not large. The first measure of CIT pressure is the change in CIT net positions for a given market:

$$\Delta CIT\ Net\ Long_t = (CITL_t - CITS_t) - (CITL_{t-1} - CITS_{t-1}). \quad (2)$$

The second measure of pressure is the weekly percentage growth of CIT net long positions, defined as,

$$\%CIT\ Net\ Long_t = \frac{(CITL_t - CITS_t) - (CITL_{t-1} - CITS_{t-1})}{(CITL_{t-1} - CITS_{t-1})}. \quad (3)$$

Descriptive statistics for the two measures of index position pressure are presented in Table 1. For net long positions, distributions for all four commodities are left-skewed. They each have positive kurtosis, indicating heavy-tailed distributions. The Jarque-Bera (JB) test suggests that none of the series are normally distributed. The two index position measures both have heavy tails. Augmented Dickey-Fuller (ADF) tests results are not surprising, indicating that CIT net long positions are non-stationary, while the change in net long positions and percent growth in positions are stationary.

2.2 Futures prices and returns

We collect nearby futures prices and compute weekly returns (percentage change in prices) for each of the four markets. To avoid inconsistency in price series when contract rollover occurs, we always calculate returns using the same nearest-to-expiration contract. Since the CFTC compiles the data for SCOT reports as of Tuesday each week, we use Tuesday's closing price to represent the price observation for a week.

Descriptive statistics for futures prices and returns are also presented in Table 1. All nearby futures prices are right-skewed with heavy tails, and non-normally distributed. For return distributions, corn and soybeans are left-skewed, and the two wheat markets are right-skewed. All returns have heavy tails and the JB test suggests none of them are normally distributed. ADF test results suggest that nearby futures prices are non-stationary while returns are stationary.

2.3 Sample break

As noted above, our data covers index trader positions and nearby futures prices from the beginning of 2004 to the end of 2019. Figure 1 plots the total notional value of CIT positions summed across the four grain markets. Notional value for a given week is computed by multiplying the CIT position in a market by the corresponding nearby futures price, and after adjusting for contract size, summing across the four markets. We also include the stages of "financialization," recently proposed by Irwin, Sanders, and Yan (2022), that overlap with the sample period for this study. The first is the growth stage of financialization from 2004 to 2011, during which we observe a rapid increase in commodity index investment. Two spikes in the notional value of CIT positions are observed during the growth stage, one in 2007-2008, and the other one in 2010-2011. These peaks are between $35 and $40 billion. The second stage is the post-financialization period from 2012 to 2019, where we observe CIT notional value decreasing steadily to around $15 billion in the last three years of the sample. If price pressure from CITs exists, it would make the most sense for it to be evident in the growth stage. In the statistical analysis that follows, we report results for the full sample and the two sub-samples based on the growth stages of financialization. This accounts for the very different structural dynamics of index investment before and after 2011.

3. Linear Tests

Plots of CIT positions and futures prices for the four commodities are shown in Figure 2. The plots confirm no contemporaneous increase in futures prices during the large build-up of index traders' positions during 2004-05. Thereafter, if anything, there appears to be a negative relationship between CIT positions and futures prices. Of course, graphical evidence like this is only suggestive. It is important to test for direct statistical links between CIT positions and prices. We begin with the standard linear Granger causality test that has been used in numerous studies in the literature on CIT positions and movements in agricultural futures prices. While these tests have been conducted numerous times in the past, we include them here to provide a benchmark using the same data for the later CQ tests.

3.1 Linear Granger causality tests

In the widely-used linear causality framework (Granger, 1980), a time-series regression is used to determine if one series is useful in forecasting another, or simply, "Granger causing." The specification of the test for returns and CIT pressure in grain futures markets is shown below for a given market:

$$Return_t = \alpha_t + \sum_{i=1}^{m} \gamma_i \, Return_{t-i} + \sum_{j=1}^{n} \beta_j \, \Delta Position_{t-j} + \epsilon_t \quad (4)$$

where $Return_t$ is the log-difference in nearby weekly futures prices for a given market at time t, and $\Delta Position_t$ is the measure of CIT pressure in the same market. All series are stationary (see Table 1). The null hypothesis is that all β_j are jointly zero, suggesting that CIT positions do not Granger-cause returns. Alternatively, if CIT pressure indeed drives up futures prices, then β_j will be greater than zero. The optimal lag order based on Akaike Information Criterion (AIC) is one for both returns and the growth of positions ($m=1, n=1$) for each of the four grain futures markets.

The results of the linear Granger causality test estimated over the full sample period and two subsample periods are presented in Table 2. For the full sample period (2004 -2019), in only two out of the eight cases the null hypothesis of no Granger-causality is rejected at the 5% significance level. Both cases are in the CBOT wheat market. Note that the direction of the estimated relationship is negative, suggesting that lagged changes in CIT positions negatively correlate with price changes, just the opposite of that implied by the Masters price pressure hypothesis. In the first subsample (2004 - 2011) or the growth stage of financialization, in all eight cases we fail to reject no Granger-causality from positions to returns at the 5% significance level. In the second subsample from 2012 to 2019, i.e., the post-financialization stage, significant directional predictability from positions to returns is once again only found for the CBOT wheat market. The estimated directional impact is negative.

3.2 Augmented Granger causality tests

The second set of tests in the linear Granger causality framework is the augmented test of Toda and Yamamoto (1995). This method estimates a VAR model in levels to detect the dynamic causal relationship between two processes that may be integrated or cointegrated of arbitrary order. When two time series are cointegrated or are not strictly stationary, the traditional Granger causality test may detect a spurious relationship, invalidating the results. To avoid such inconsistency, the Toda and Yamamoto (1995) test for Granger causality in a VAR model that accounts for cointegration and stationarity. The model is specified below for a given market:

$$\begin{bmatrix} Price_t \\ Position_t \end{bmatrix} = \sum_{i=1}^{p+d_{max}} \begin{bmatrix} \gamma_{1,i} & \gamma_{2,i} \\ \gamma_{3,i} & \gamma_{4,i} \end{bmatrix} \begin{bmatrix} Price_{t-i} \\ Position_{t-i} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + t \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{bmatrix}, \tag{5}$$

where $Price_t$ is the nearby futures price and $Position_t$ is the net long CIT position. We conduct the augmented Granger Causality test in the following steps: i) each series is tested for the order of integration using the ADF test; ii) determine the value d_{max}, which is the maximum order of integration of two series; iii) set up the VAR model and use the AIC to determine the optimal lags p for the system; iv) use the augmented lag $p + d_{max}$ to estimate the VAR system; and v) apply the Wald test to determine if the position coefficients are significantly different from zero.

Augmented GC test results are presented in Table 3. Note that only one set of results is presented since this test is based on the level of net long CIT positions instead of the change or percent growth in positions. We focus on the direction from index positions to futures prices as the VAR model avoids invalid estimates when two series have different integration orders. We first estimate $d_{max} = 1$ based on the ADF test. Then to determine the lag orders of the VAR model, we use AIC to find the appropriate lags with a maximum lag order of 20 lags and select two lags for the bivariate VAR model. As shown in Table 3, we fail to reject the null of no causality in all cases when utilizing the augmented Granger causality test.

3.3 Long-horizon regression tests

Both the standard and augmented Granger causality tests are designed to detect relationships between weekly CIT positions and returns. Such tests may have low power when detecting relationships over longer horizons (e.g., Summers 1986). Index trader positions may flow in "waves" that build up slowly that eventually push up prices, and then fade slowly as the process is reversed (Sanders and Irwin, 2011). In this situation, horizons longer than a week may be needed to fully capture the relationship between CIT position pressure and futures returns. We follow Sanders and Irwin (2014, 2016) and implement the long-horizon framework developed by Valkanov (2003). The model is defined for a given market as:

$$\sum_{i=0}^{k-1} Return_{t+i} = \alpha + \beta \sum_{i=0}^{k-1} \Delta Position_{t+i-1} + \epsilon_t \tag{6}$$

where all variables are the same as before. To obtain the estimated coefficients, we run an OLS regression of the long-horizon dependent variable on the long-horizon independent variable. Once the horizon k is determined, the dependent variable is the sum of futures returns from t to $t + k - 1$, and the independent variable is the sum of growth/change in CIT positions from $t - 1$ to $t + k$. In essence, equation (6) is an OLS regression of a *k*-period moving sum of the dependent variable at time *t* against a *k*-period moving sum of the independent variable in the previous period, time *t*-1. If the estimated β is positive, this indicates a fads-style model where prices tend to increase slowly over a relatively long period after widespread index fund buying. To be consistent with previous studies, we choose $k = 4$ and $k = 12$ to represent monthly and quarterly time horizons using the weekly data (Singleton, 2014; Hamilton and Wu, 2015; Sanders and Irwin, 2014, 2016).

Valkanov (2003) demonstrates that the OLS slope estimator in (6) is consistent and converges at a high rate as the sample size increases. However, this specification obviously creates an overlapping horizon problem for testing. Valkanov shows that Newey-West *t*-statistics do not converge to well-defined distributions and suggests using the re-scaled *t*-statistic, $t/\sqrt{T}$, along with simulated critical values for inference. Valkanov also demonstrates that the re-scaled *t*-statistic generally is the most powerful among several alternative long-horizon test statistics. Valkanov (2003) provides the simulated critical values for the re-scaled statistic under various scenarios. For sample size $T = 750$, and two nuisance parameters $c = 0$ and $\delta = 0$, the critical values at the 5% significance level at two tails are $(-0.672, 0.727)$.

We report the estimated OLS slope coefficients and the rescaled t-statistics for the Valkanov test at the monthly and quarterly horizons in Table 4. When we compare the test statistics with provided critical values, there is no single case where the rescaled t-statistics are outside the range of the critical values. Once again, estimation results from this linear test suggest no evidence that CIT positions pressure grain futures prices upward.

4. Cross-Quantilogram (CQ) Tests

In the previous section, we conducted three linear causality tests to provide a comprehensive baseline for the relationship between CIT positions and futures prices movements. We fail to reject the null of no causality in most cases, for different testing methods, measures of position pressure, and the sample period considered. These findings are consistent with most prior studies that use similar linear tests (e.g., Stoll and Whaley, 2010; Sanders and Irwin, 2011; Hamilton and Wu, 2015; Lehecka, 2015).

As noted earlier, a concern with these findings is that the relationship between CIT positions and returns may be more subtle and difficult to detect than is possible with linear tests. In particular, linear tests may fail to detect a causal relationship hidden in the tails of the distribution (Lee and Yang, 2012). To address this limitation, we apply the recently developed CQ test to investigate the directional predictability from the change in CIT net long positions to futures returns in the four grain futures markets. We also apply the CQ test to examine the directional impact of futures returns to the change in CIT net long positions.

Linton and Whang (2007) introduced the quantilogram, which measures the directional predictability of a stationary time-series based on different parts of the distribution of a time-series variable. The quantilogram method provides estimates of sample lead-lag correlation of quantiles and a Box-Pierce-type statistic that aggregates the individual correlations across lags. Based on the concept of the quantilogram for a single series, Han et al. (2016) developed the cross-quantilogram (CQ) to measure the directional predictability of a pair of stationary times-series in all parts of the distributions and a Box-Ljung version of a portmanteau test for overall directional predictability. According to Han et al. (2016), the CQ method has several advantages, as it: i) captures the directional lead-lag relationships across all parts of distributions; ii) does not require moment conditions of series; iii) only requires the time series to be stationary; and iv) includes long lags in the model specification to avoid concerns about degrees-of-freedom.

Specifically, for two strictly stationary time-series variables, $x_{1,t}$ and $x_{2,t}$, we define their cumulative distribution as $F_i\ (\cdot)$, and their density function as $f_i\ (\cdot)$. Next, we define the quantile function of each series as $q_i\ (\alpha_i) = inf(v\colon F_i(v) \geq \alpha_i)\,, \forall \alpha_i \in (0,1)$ for $\alpha \equiv (\alpha_1, \alpha_2)^T$. This quantile function returns the minimum quantile of x_i for the probability at α_i. The CQ for quantile α and lag k is specified as:

$$\rho_\alpha(k) = \frac{E[\psi_{\alpha_1}(x_{1,t}-q_{1,t}(\alpha_1))\psi_{\alpha_2}(x_{2,t-k}-q_{2,t-k}(\alpha_2))}{\sqrt{E[\psi^2_{\alpha_1}(x_{1,t}-q_{1,t}(\alpha_1))]}\sqrt{E[\psi^2_{\alpha_2}(x_{2,t-k}-q_{2,t-k}(\alpha_2))]}} \tag{6}$$

where $\psi_{\alpha_i}(u) \equiv 1(u < 0) - \alpha_i$ is a check function that captures the direction of deviation for a given quantile; $k = 0, \pm1, \pm2,$ .... Inside the check function, $\{1\big[[x_{i,t} \le q_{i,t}(\cdot)]\big]\}$ is an indicator function, also known as the quantile-hit or quantile-exceedance process in the literature, that takes on a value of one when $[x_{i,t} \le q_{i,t}(\cdot)]$ and zero otherwise. The $\psi_{\alpha_i}(\cdot)$ function transforms the indicator observations into a sorted sequence for a given quantile level. When an observation is smaller or equal to a given quantile, $\psi_{\alpha_i}(\cdot)$ returns $1 - \alpha_i$; whereas when an observation is greater than a given quantile, $\psi_{\alpha_i}(\cdot)$ returns $-\alpha_i$. In essence, the CQ is the cross-correlation of two quantile-hit processes (Han et al., 2016).

Empirically, we have two series of interests—the change in CIT net long positions and returns. We denote these two stationary time series as $\{x_{1,t}, x_{2,t}\}_{t=1}^{T}$, respectively. First, we estimate the unconditional quantile functions $\hat{q}_i(\cdot)$ for each series by solving for the following minimization functions:

$$\hat{q}_i(\alpha_i) = \underset{v_i \in \mathbb{R}}{\operatorname{argmin}} \sum_{t=1}^{T} \pi_{\alpha_i}(x_{i,t} - v_i) \tag{7}$$

where $\pi_{\alpha_i}(u) \equiv u(\alpha_i - 1[u < 0]), i = 1, 2$. For a set of quantiles of two series $\{\hat{q}_{1,t}(\alpha_1), \hat{q}_{2,t-k}(\alpha_2)\}$, the sample CQ is defined:

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \psi_{\alpha_1}(x_{1,t}-\hat{q}_{1,t}(\alpha_1))\psi_{\alpha_2}(x_{2,t-k}-\hat{q}_{2,t-k}(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha_1}(x_{1,t}-\hat{q}_{1,t}(\alpha_1))}\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha_2}(x_{2,t-k}-\hat{q}_{2,t-k}(\alpha_2))}} \tag{8}$$

where $k = 0, \pm1, \pm2,$ ...The CQ estimates, $\hat{\rho}_\alpha(k)$, capture the directional predictability between two series at a given quantile set $\{\alpha_1, \alpha_2\}$. Further, $\hat{\rho}_\alpha(k) \in [-1,1]$. For example, when $\hat{\rho}_\alpha(1) =$

0, this indicates that when the change in CIT net long positions at time t is above or below the quantile $\hat{q}_{2,t-1}(\alpha_2)$ there is no correlation with returns at time $t+1$ being above or below the quantile $\hat{q}_{1,t}(\alpha_1)$. When $\hat{\rho}_\alpha(1) > 0$, it suggests there is directional predictability between the change in CIT net long positions at time t and returns at time $t+1$, given the two series hit in the quantiles of α_1 and α_2.

An example for corn over the full sample period is presented in Figure 3 to help illustrate how CQ statistics are computed. This plot shows an example for a pair of observations that both hit the quantile with $\alpha_1 = \alpha_2 = 0.1$. On September 27, 2011, the change in corn CIT net long positions is -15,920 contracts and hits in the 0.1 quantile for position changes. One week later on October 4, 2011 we observe a corn return of -10.41% and it hits in the 0.1 quantile for returns as well. The arrow shows that when changes in CIT net long positions are below the 0.1 quantile, it is followed by a return one week later that is also below its 0.1 quantile. This type of comparison is repeated for all observations to compute a CQ statistic for $\alpha_1 = \alpha_2 = 0.1$.

To test for the directional predictability of two series in different quantiles up to k lags, we follow the quantile version of the portmanteau statistical test proposed by Han et al. (2016). To test if there is overall directional predictability from $x_{2,t-k}$ to $x_{1,t}$, for $k \in \{1,2,\dots,p\}$, the null hypothesis is $H_0\colon \rho_\alpha(1) = \rho_\alpha(2) = \cdots = \rho_\alpha(p) = 0$, against the alternative hypothesis $H_a\colon \rho_\alpha(k) \neq 0$. The test statistics is:

$$\hat{Q}_\alpha^{(p)} = \frac{T(T+2)\sum_{k=1}^{p}\hat{\rho}_\alpha^2(k)}{T-k} \tag{9}$$

where $\hat{Q}_\alpha^{(p)}$ is the portmanteau test statistic for overall directional predictability. 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 (Han et al., 2016).

The cross-quantilograms (CQ) for the full sample period are presented in Figures 4 through 7 for CBOT corn, CBOT soybeans, CBOT wheat, and KCBOT wheat, respectfully.[1] We consider four quantiles for both returns and CIT positions: 0.10, 0.25, 0.75, 0.90, resulting in 16 pairs of CQ results for each commodity. These four quantiles represent extreme large decreases, large decreases, large increases, and extreme large increases for the two series. Within each figure, there are 16 subplots that visualize how returns in extreme quantiles respond to the dynamics of lagged extreme changes in CIT net long quantiles. These plots are organized in four panels: (a)–(d), where each panel presents the estimated sample CQ estimates from one of the four quantiles of position changes to all four extreme levels of returns.

Consider Figure 4(a) as an example. Here, the four CQ estimates for the lagged changes in CIT net long positions at the extreme low quantile ($\alpha_2 = 0.1$) and returns at the extreme low ($\alpha_1 = 0.10$), low ($\alpha_1 = 0.25$), high ($\alpha_1 = 0.75$), and extreme high ($\alpha_1 = 0.90$) quantiles for corn over the full sample period are presented. The black bar is the estimated sample CQ statistic at lag k, i.e., $\hat{\rho}_\alpha(k)$. The null hypothesis is that at lag k there is no predictability from the large negative movements in CIT position changes to large movements in futures returns. The red-dashed lines represent the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates. We include 13 lags as this is approximately the same quarterly horizon we used in the long-horizon linear tests in the previous section.

[1] To save space, we only discuss the CQ estimates for the full sample period and the change in CIT net long positions in the paper. Results for all other tests, including two subsample periods are presented in the Online Appendix. These results do not differ materially from the full sample results presented here.

Caution is needed when interpreting the sign of the CQ estimates. For CIT position changes in the two low quantiles ($\alpha_2 = 0.1$ or 0.25) and returns in two low quantiles ($\alpha_1 = 0.1$ or 0.25), which corresponds to the top row of plots in Figures 4-7, a positive CQ estimate suggests that a large drop in CIT net long positions are likely to predict large decreases in futures prices; on the other hand, when the sign is negative, a large drop in CIT net positions are less likely to predict a subsequent large decrease in futures prices. Meanwhile, for CIT position changes in the two low quantiles and returns in two high quantiles ($\alpha_1 = 0.75$ or 0.9), a positive CQ estimate (as plotted in the second row of Figures 4-7) suggests when a large drop in CIT net positions occurs, the likelihood of predicting a large increase in futures prices is low; whereas when CQ estimate is negative, the likelihood of predicting a large price increase is high.

CQ test statistic is mostly non-significant in panels (a) and (b) of Figures 4-7. This suggests that over a 13-week horizon, whether CIT position changes are smaller or greater than the 0.1 or 0.25 quantiles cannot predict returns located in either the left (quantiles 0.1 and 0.25) or right tails (quantiles 0.75 and 0.9) of the distribution. For the few cases where the CQ estimates are significant, empirical evidence for different commodity markets is mixed. For example, during the full sample period in the soybean market, we observe that large decreases in CIT net long positions positively predict large decreases in returns. By contrast, in the CBOT wheat market we observe that large CIT net long decreases are followed by large increases in returns.

Panels (c) and (d) in Figures 4-7 plot the CQ estimates when the lagged CIT positions are in the two high quantiles (0.75 and 0.9). For returns located in the two low quantiles, i.e., $\alpha_1 = 0.1$ or 0.25, a positive CQ estimate suggests that a large increase in CIT net positions is less likely to predict a large drop in futures prices, whereas a negative estimate suggests that a large increase in CIT net long positions is more likely to be followed by large decreases in futures prices. For returns in two high quantiles ($\alpha_1 = 0.75$, $\alpha_1 = 0.9$), when CQ estimates are positive, it indicates that when CIT net long positions exceed high quantiles, they are likely to predict returns located in high quantiles. Meanwhile, a negative CQ estimate suggests that a large increase in CIT net long positions is less likely to predict returns with a large increase. For most cases when CIT positions experience a substantial increase, there is no significant directional predictability from the change in CIT net long positions to returns. Taken together, Figures 4-7 suggest that there are no systematic lead-lag relationships from CIT positions to futures prices when both series are in extreme quantiles.

The portmanteau test statistics for directional predictability from changes in CIT net long positions to returns are presented in Table 5, covering the full sample period and two subsample periods. As noted earlier, the portmanteau test is an omnibus test that aggregates the CQ test statistics from 1 to 13 lags for each pair of quantiles of the two series. During the full sample period, only one case out of 64 has a significant relationship from positions to returns. For the first and second subsamples, there are six and two cases, respectively, out of 64 that fail to reject the null hypothesis of no directional predictability. In total, there are only 9 cases out of 192 (or 4.7%) with a significant portmanteau statistic, slightly less than the number of significant test statistics one would expect at random for a 5% significance level.

For the cases with a significant portmanteau statistic in Table 5, the dominant sign of the underlying CQ estimates over the 1-13 lags is reported in parentheses. Dominance is defined as the sign that appeared more frequently for the 13 estimates. We do this to aid in interpreting these few cases with overall significance. With one exception, the dominant sign is consistent with CIT position changes having the price pressure impact expected under the Masters Hypothesis. For example, during the growth stage of financialization (panel B), the portmanteau statistic for soybeans is significant for $\alpha_1 = \alpha_2 = 0.1$ and the dominant sign is positive. This implies that large decreases in CIT positions directionally predict large decreases in soybean returns. The one exception is CBOT wheat futures during the post-financialization period (panel C) and $\alpha_1 = 0.1, \alpha_2 = 0.75$. Here, the dominant sign is negative, implying that large decreases in CIT positions tend to directionally predict large increases in wheat returns. It is important to emphasize that the number of significant cases, regardless of the dominant sign, is basically what one would expect based on random chance.

As the final part of the analysis, we examine the direction of predictability of futures returns to CIT positions. There is a documented tendency for large non-commercial speculators in agricultural futures markets to be trend-followers (Sanders, Irwin, and Merrin, 2009). That is, positions of large speculators in agricultural futures markets tend to increase after futures prices increase, and *vice versa*. The available evidence for CITs is not as strong. For instance, Auerlich, Irwin, and Garcia (2014) find a significant but small impact of past returns on daily CIT positions in 12 agricultural markets, but this disappears when the analysis is limited to roll windows. Lehecka (2015) analyzes weekly CIT positions in the same 12 agricultural futures markets and reports that past returns do not significantly impact CIT positions.

The portmanteau test statistics for directional predictability from returns to CIT net position changes are presented in Table 6 for the full and two subsample periods.[4] During the full sample period, only two cases out of 64 have a significant relationship from positions to returns. For the first and second subsample periods, there are five and three cases, respectively, out of 64 that fail to reject the null hypothesis of no directional predictability. In total, there are only 10 cases out of 192 with a significant portmanteau statistic. Mirroring the results for positions leading returns, this

[4] Results for the percentage changes in CIT net long positions are included in the Online Appendix.

is only 5.2% of the total cases, slightly greater than the number of significant test statistics one would expect at random for a 5% significance level. Furthermore, in the 10 significant cases, only five show evidence that CIT net long positions have a large decrease following a drop in futures prices. The above results provide scant support for the idea that extreme CIT position changes have a trend-following component. This is actually not all that surprising given that financial index investment is motivated by long-term investment objectives rather than short-term trading (e.g., Stoll and Whaley, 2010).

5. Conclusions

The price impact of financial index investment in agricultural futures markets continues to be a concern to many market participants, civic organizations, and policymakers. The concern that waves of financial index investment have led to irrational and gross mispricing in agricultural futures markets has been labeled the "Masters Hypothesis." While the bulk of the evidence suggests this hypothesis is not well-founded, it's also possible that the impact of index investment in agricultural futures markets is more complicated and nuanced than can be detected by relatively simple linear causality tests used in many studies. The relationship between index investment and futures prices may be non-linear and/or hidden in the tails of the data. The purpose of this study was to use the cross-quantilogram (CQ) test recently developed by Han et al. (2016) to examine whether predictability exists between the change in commodity index trader (CIT) positions and returns in the tails of the distributions for four agricultural futures markets. In addition to making no assumptions of the distributions of the data, the CQ test is able to determine if there is a causal relationship between two series in all parts of the distributions of the series, especially the tail quantiles.

The data for the study consists of weekly CIT positions and returns from January 6, 2004 through December 31, 2019 for Chicago Board of Trade (CBOT) corn, CBOT wheat, CBOT soybeans, and Kansas City Board of Trade (KCBOT) wheat. We first conduct three types of linear causality tests to provide a comprehensive baseline for the relationship between CIT positions and agricultural futures prices movements. The null of no causality was not rejected in the majority of the cases across the different tests, measures of position pressure, or the sample period considered. Next, we apply the CQ test to the same data to determine if there is a relationship between the tails of the distributions of index positions and price movements. Consistent with the standard linear causality tests, we find no evidence of a relationship between index positions and returns.

Commodity markets continue to attract investors who seek to diversify their portfolios and hedge against inflation. Given the increasing complexity of global commodity markets, concerns remain on the role that different types of traders play in shaping commodity prices. The present paper adds to the growing evidence that the Masters Hypothesis is not a useful description of the price impact of CITs in agricultural futures markets, even when prices underwent extreme movements. Future studies may wish to examine other types of traders on both the long- and short-term pricing of commodity markets.

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Table 1: Summary statistics for weekly commodity index traders (CIT) positions and nearby futures prices in four grain futures markets, January 6, 2004 to December 31, 2019

Commodity (units)	obs	Min	Max	Mean	Std. Dev	Skewness	Kurtosis	JB Test	ADF Test
Panel A: CIT Net Long Positions (number of contracts)									
CBOT Corn	835	64646	503937	332391	85529	-0.822	3.561	105.074***	-2.700
CBOT Soybean	835	27101	201251	128727	36529	-0.848	3.804	122.643***	-3.036
CBOT Wheat	835	33696	229565	149459	42852	-0.258	2.564	15.885***	-3.093
KCBOT Wheat	835	12055	66592	37162	12303	-0.242	2.187	31.173***	-3.413**
Panel B: Change in CIT Net Long Positions (number of contracts)									
CBOT Corn	834	-44788	60317	213	9195	0.291	8.569	1089.39***	-12.535***
CBOT Soybean	834	-23250	27251	138	4520	-0.218	9.125	1310.35***	-13.138***
CBOT Wheat	834	-33227	15010	85	3862	-0.660	10.635	2086.52***	-13.451***
KCBOT Wheat	834	-6400	14342	45	1641	0.812	12.361	3136.5***	-14.525***
Panel C: Percent Change in CIT Net Long Positions (%)									
CBOT Corn	834	-14.007	21.958	0.159	3.052	0.516	9.622	1560.83***	-12.807***
CBOT Soybean	834	-20.146	23.204	0.197	3.697	0.342	10.090	1762.9***	-12.903***
CBOT Wheat	834	-20.405	14.166	0.136	2.811	-0.206	9.132	1312.65***	-13.884***
KCBOT Wheat	834	-19.574	26.412	0.165	4.223	0.473	8.231	981.879***	-14.155***
Panel D: Price ($/bushel)									
CBOT Corn	835	1.863	8.313	4.154	1.459	0.856	3.061	101.998***	-1.969
CBOT Soybean	835	5.035	17.683	10.157	2.753	0.237	2.447	18.468***	-2.100
CBOT Wheat	835	2.898	12.230	5.468	1.616	0.822	3.548	104.553***	-2.627
KCBOT Wheat	835	3.170	12.610	5.729	1.764	0.819	3.087	93.69***	-2.409
Panel E: Return (%)									
CBOT Corn	835	-16.493	18.410	-0.151	3.954	-0.002	5.183	165.606***	-13.441***
CBOT Soybean	835	-15.668	11.337	0.064	3.365	-0.233	4.128	51.802***	-14.239***
CBOT Wheat	835	-17.625	16.837	-0.225	4.330	0.204	4.048	43.955***	-14.166***
KCBOT Wheat	835	-16.373	16.215	-0.169	4.131	0.126	3.782	23.448***	-14.393***

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

Table 2: Granger causality test results for weekly commodity index traders (CIT) positions and nearby futures prices in four grain futures markets, January 6, 2004 to December 31, 2019

Commodity	F-statistic		
	Full Sample	2004-2011	2011-2019
Panel A: dependent variable: returns, independent variable: growth in CIT net long positions			
CBOT corn	1.976	3.471	0.017
	(0.160)	(0.063)	(0.895)
CBOT soybean	0.214	0.942	0.020
	(0.644)	(0.332)	(0.888)
CBOT wheat	5.366*	2.044	3.931*
	(0.021)	(0.154)	(0.048)
KCBOT wheat	0.235	0.453	0.061
	(0.628)	(0.501)	(0.805)
Panel B: dependent variable: returns, independent variable: percentage growth in CIT net long positions			
CBOT corn	1.004	1.977	0.003
	(0.317)	(0.160)	(0.959)
CBOT soybean	0.042	0.106	0.000
	(0.837)	(0.745)	(0.993)
CBOT wheat	6.201*	2.572	4.365*
	(0.013)	(0.110)	(0.037)
KCBOT wheat	0.121	0.116	0.034
	(0.728)	(0.734)	(0.854)

Notes: * indicates statistical significance at 5%. F-test statistics are reported in the table, with the corresponding p-values in the parenthesis below. The full sample period consists of 834 weekly observations. For the growth stage of financialization, there are 416 weekly observations from January 13 to December 27, 2011. The post-financialization period runs from January 3, 2012 to December 31, 2019, resulting in weekly observations. The null hypothesis is that there is no Granger causality from CIT position changes to futures returns. The estimated coefficients associated with the position variable are negative for cases with significant test statistics.

Table 3: Augmented Granger causality test results for weekly commodity index traders (CIT) positions and nearby futures prices in four grain futures markets, January 6, 2004 to December 31, 2019

Commodity	Wald statistic		
	Full Sample	2004-2011	2011-2019
Dependent variable: CIT Net Long Positions, independent variable: price			
CBOT corn	1.758	4.590	0.649
	(0.415)	(0.101)	(0.723)
CBOT soybean	0.159	1.954	1.163
	(0.923)	(0.376)	(0.559)
CBOT wheat	2.229	1.992	5.838
	(0.328)	(0.369)	(0.054)
KCBOT wheat	3.356	1.436	3.403
	(0.187)	(0.488)	(0.182)

Notes: * indicates statistical significance at 5%. Wald test statistics are reported in the table, with the corresponding p-values are in the parenthesis below. The full sample period consists of 834 weekly observations. For the growth stage of financialization, there are 416 weekly observations from January 13 to December 27, 2011. The post-financialization period runs from January 3, 2012 to December 31, 2019, resulting in weekly observations. The null hypothesis is that there is no Granger causality from CIT position changes to futures returns.

Table 4: Long-horizon regression tests for weekly commodity index traders (CIT) positions and nearby futures prices in four grain futures markets, January 6, 2004 to December 31, 2019

Commodity	Full Sample		2004-2011		2011-2019	
Horizon (k)	Slope	Rescaled t-statistic	Slope	Rescaled t-statistic	Slope	Rescaled t-statistic
Panel A: dependent variable: returns, independent variable: CIT Net Long Change						
CBOT corn						
Monthly (k=4)	0.0000289	0.0825	0.0000337	0.0557	0.0000237	0.0615
Quarterly (k=12)	0.0000498	0.156	0.0000660	0.129	0.0000248	0.0653
CBOT soybean						
Monthly (k=4)	0.000150	0.252	0.000366	0.295	0.0000613	0.107
Quarterly (k=12)	0.000238	0.440	0.000507	0.520	0.0000928	0.170
CBOT wheat						
Monthly (k=4)	0.0000106	0.0110	-0.0000346	-0.0218	0.0000547	0.0473
Quarterly (k=12)	0.0000333	0.0400	-0.0000395	-0.0308	0.000135	0.118
KCBOT wheat						
Monthly (k=4)	0.000476	0.222	0.000622	0.126	0.000426	0.199
Quarterly (k=12)	0.000468	0.204	0.000452	0.0962	0.000452	0.201
Panel B: dependent variable: returns, independent variable: CIT Net Long Pct Change						
CBOT corn						
Monthly (k=4)	0.000282	0.0988	0.000614	0.0673	0.000175	0.0720
Quarterly (k=12)	0.000238	0.178	0.000595	0.139	0.0000486	0.0932
CBOT soybean						
Monthly (k=4)	0.000232	0.248	0.000629	0.257	0.000105	0.109
Quarterly (k=12)	0.000143	0.447	0.000753	0.459	-0.000176	0.168
CBOT wheat						
Monthly (k=4)	0.000487	0.0183	0.000907	-0.0214	0.000354	0.0556
Quarterly (k=12)	0.000485	0.0640	0.000842	-0.0239	0.000303	0.161
KCBOT wheat						
Monthly (k=4)	0.000476	0.229	0.000622	0.129	0.000426	0.200
Quarterly (k=12)	0.000468	0.252	0.000452	0.143	0.000452	0.215

Notes: * indicates statistical significance at 5%. Critical values for the rescaled t-statistics shown in the table (-0.672, 0.727) are available in Valkanov (2003) table 4 for case 2, $c = 0$, $\delta = 0$, $T = 750$. The full sample period consists of 834 weekly observations. For the growth stage of financialization, there are 416 weekly observations from January 13 to December 27, 2011. The post-financialization period runs from January 3, 2012 to December 31, 2019, resulting in weekly observations. The null hypothesis is that there is no Granger causality from CIT position changes to futures returns.

Table 5: Cross-quantilogram portmanteau test results for weekly commodity index traders (CIT) positions and nearby futures prices in four grain futures markets, positions leading returns, January 6, 2004 to December 31, 2019

Dependent variable: returns, independent variable: CIT Net Long Change									
	Returns Quantile Level					Returns Quantile Level			
CIT Net Long Change Quantile Level	0.1	0.25	0.75	0.9	CIT Net Long Change Quantile Level	0.1	0.25	0.75	0.9
Full sample: 2004 - 2019									
Panel A: CBOT Corn					Panel B: CBOT Soybean				
0.1	14.696	8.382	16.902	13.818	0.1	16.027	21.238	20.012	17.588
0.25	6.558	13.742	8.83	16.982	0.25	16.350	21.836	17.382	10.200
0.75	9.044	10.408	15.002	19.715	0.75	12.115	13.051	12.311	10.016
0.9	14.793	9.388	11.803	7.915	0.9	17.077	15.167	23.623	6.825
Panel C: CBOT Wheat					Panel D: KCBOT Wheat				
0.1	26.306	20.02	22.123	31.059	0.1	12.627	8.782	22.295	14.923
0.25	19.723	14.367	31.918*(-)	26.411	0.25	10.151	9.578	5.167	4.548
0.75	20.299	7.924	19.906	11.742	0.75	15.508	8.598	11.476	5.327
0.9	24.085	8.181	27.142	7.944	0.9	31.224	8.386	13.363	9.604
Growth stage of financialization: 2004 - 2011									
Panel A: CBOT Corn					Panel B: CBOT Soybean				
0.1	33.952	21.98	16.405	21.96	0.1	61.417*(+)	36.780*(+)	13.836	28.311
0.25	11.059	17.225	22.603	18.313	0.25	31.591	27.531	14.437	22.619
0.75	14.251	7.82	17.027	36.734*(+)	0.75	16.737	23.009	9.837	18.608
0.9	19.438	14.157	11.508	14.341	0.9	12.425	17.715	12.694	5.516
Panel C: CBOT Wheat					Panel D: KCBOT Wheat				
0.1	24.058	33.127*(+)	18.146	24.211	0.1	11.996	9.92	23.353	20.377
0.25	35.379	38.026*(+)	41.714*(-)	31.944	0.25	12.105	17.746	8.849	9.176
0.75	12.972	11.383	10.239	12.092	0.75	12.846	14.904	11.813	7.952
0.9	21.654	10.602	25.324	7.375	0.9	13.178	9.455	11.749	10.329
Post-financialization stage: 2012 - 2019									
Panel A: CBOT Corn					Panel B: CBOT Soybean				
0.1	16.443	14.257	17.503	11.078	0.1	18.461	21.019	8.895	9.584
0.25	13.724	16.065	7.057	4.225	0.25	15.887	16.915	16.198	18.809
0.75	12.124	15.192	14.21	16.211	0.75	12.85	6.735	6.562	7.078
0.9	7.149	11.058	15.096	12.283	0.9	9.699	11.842	17.141	10.333
Panel C: CBOT Wheat					Panel D: KCBOT Wheat				
0.1	19.802	34.054*(-)	26.624	29.637	0.1	15.054	15.226	26.481	34.934
0.25	11.049	18.288	30.470*(-)	12.305	0.25	14.334	11.551	21.385	19.391
0.75	10.592	12.088	14.66	15.66	0.75	31.934	7.347	9.162	12.869
0.9	11.031	9.163	12.301	19.458	0.9	21.349	10.567	9.73	19.403

Notes: * indicates statistical significance at 5%. Box-Ljung test statistics for 13 lags are in the table. The sign (+/-) next to the test statistics indicates the dominant sign of the underlying CQ estimates for the Box-Ljung test statistics.

Table 6. Cross-quantilogram portmanteau test results for weekly commodity index traders (CIT) positions and nearby futures prices in four grain futures markets, returns leading positions, January 6, 2004 to December 31, 2019

Dependent variable: CIT Net Long Change, independent variable: returns									
	CIT Net Long Change Quantile Level					CIT Net Long Change Quantile Level			
Returns Quantile Level	0.1	0.25	0.75	0.9	Returns Quantile Level	0.1	0.25	0.75	0.9
Full sample: 2004 - 2019									
Panel A: CBOT Corn					Panel B: CBOT Soybean				
0.1	10.965	15.793	17.586	30.847 *(+)	0.1	19.468	16.947	24.280 *(+)	9.061
0.25	18.625	17.175	17.414	22.69	0.25	13.381	18.636	18.341	11.876
0.75	16.102	18.174	7.292	7.666	0.75	17.855	13.487	21.334	12.803
0.9	15.922	17.321	12.7	11.683	0.9	14.016	8.316	8.761	8.494
Panel C: CBOT Wheat					Panel D: KCBOT Wheat				
0.1	28.253	17.624	12.26	9.607	0.1	15.269	12.492	20.846	15.167
0.25	11.002	22.932	17.1	17.531	0.25	15.087	23.241	15.497	14.437
0.75	24.846	13.878	13.715	10.709	0.75	17.181	17.759	15.269	7.543
0.9	31.025	18.937	8.128	20.215	0.9	14.654	14.634	17.523	8.096
Growth stage of financialization: 2004 - 2011									
Panel A: CBOT Corn					Panel B: CBOT Soybean				
0.1	9.129	8.654	13.778	23.934 *(+)	0.1	57.767 *(+)	49.56 *(+)	18.089	4.943
0.25	21.342	9.917	14.718	19.629	0.25	28.917	26.240	23.573	15.417
0.75	11.98	14.241	7.379	8.12	0.75	32.921 *(-)	17.368	15.897	7.270
0.9	16.692	6.971	18.737	13.692	0.9	20.317	7.457	8.127	12.885
Panel C: CBOT Wheat					Panel D: KCBOT Wheat				
0.1	12.513	14.255	27.695	20.689	0.1	13.91	8.621	17.088	15.278
0.25	6.569	19.882	24.256	25.37	0.25	13.87	16.705	12.767	9.107
0.75	37.02 *(-)	25.503	16.24	17.313	0.75	19.317	19.617	13.947	10.424
0.9	21.543	23.11	21.714	30.078	0.9	15.731	17.396	11.868	11.472
Post-financialization stage: 2012 - 2019									
Panel A: CBOT Corn					Panel B: CBOT Soybean				
0.1	11.470	8.762	13.696	11.082	0.1	29.250 *(-)	36.448 *(-)	14.505	6.986
0.25	11.396	9.172	19.546	14.857	0.25	11.194	23.157	18.155	9.767
0.75	13.891	17.085	6.331	6.407	0.75	11.551	11.793	23.743	16.455
0.9	19.059	20.057	9.893	16.304	0.9	13.258	9.55	20.099	20.056
Panel C: CBOT Wheat					Panel D: KCBOT Wheat				
0.1	31.157	23.023	12.623	12.714	0.1	16.593	11.461	24.700	20.069
0.25	13.377	27.779 *(+)	20.501	15.769	0.25	21.15	8.219	17.220	27.112
0.75	12.473	24.576	16.978	8.097	0.75	29.309	16.392	13.124	11.271
0.9	28.042	19.352	15.083	11.494	0.9	17.361	19.085	8.303	11.376

Notes: * indicates statistical significance at 5%. Box-Ljung test statistics for 13 lags are in the table. The sign (+/-) next to the test statistics indicates the dominant sign of the underlying CQ estimates for the Box-Ljung test statistics.

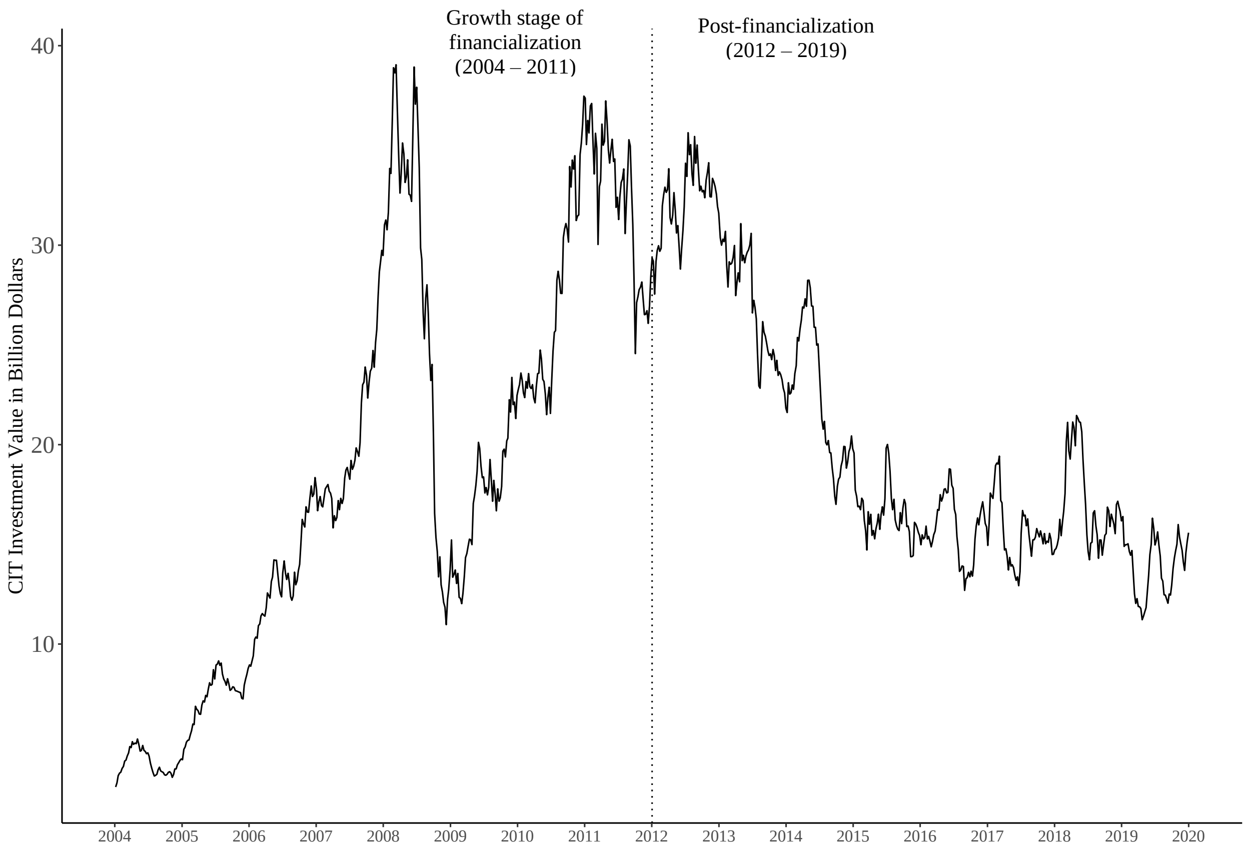


Figure 1. Notional value of commodity index investment in four grain futures markets

Notes: The notional value of commodity index investment is calculated using the index positions retrieved from SCOT report and corresponding nearby futures prices during the sample period. The growth stage of financialization and the post-financialization stage is defined following Irwin, Sanders, and Yan (2022).

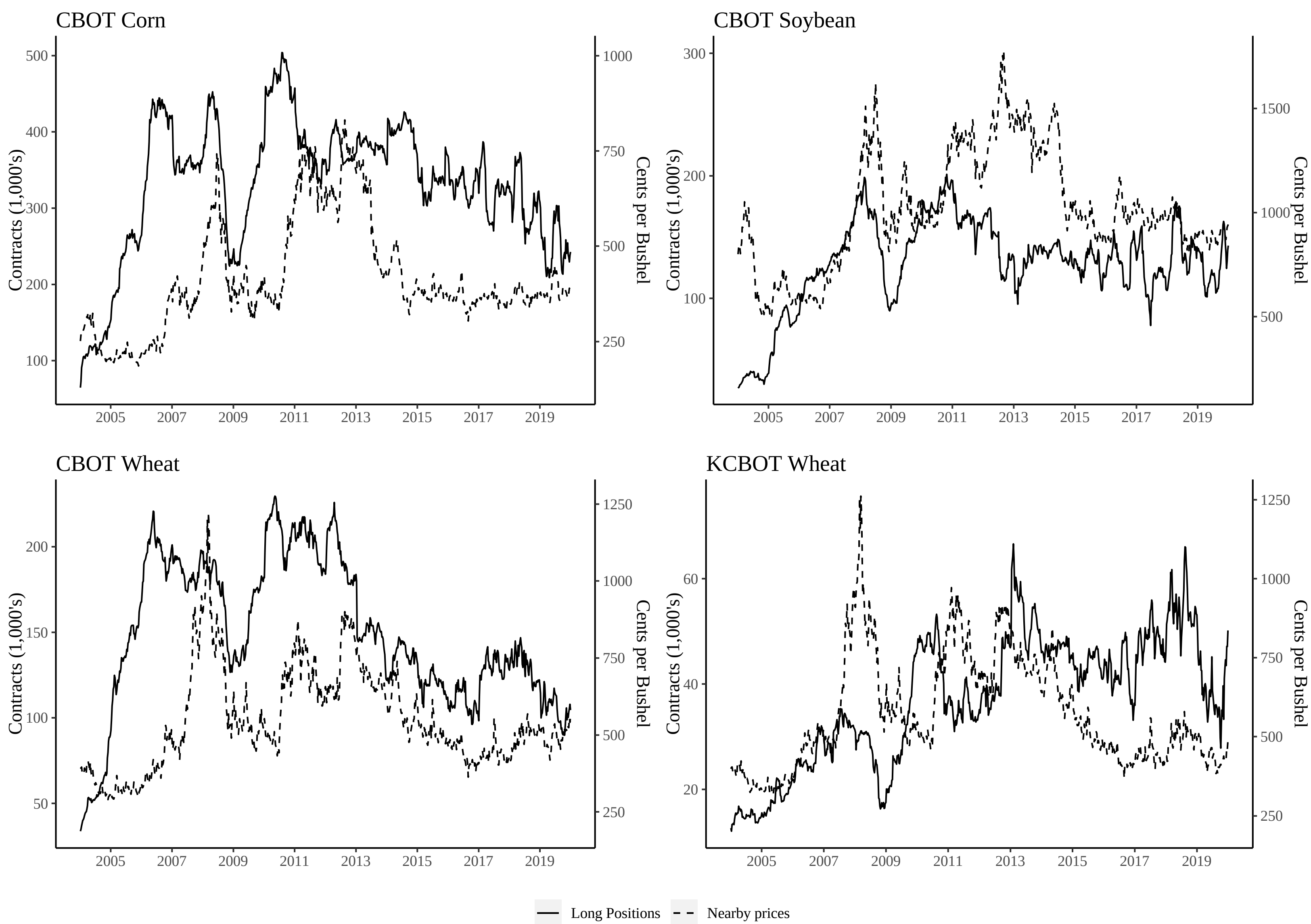


Figure 2. Weekly commodity index trader positions and nearby futures prices of CBOT corn, soybean, wheat, and KCBOT wheat, January 2004 to December 2019

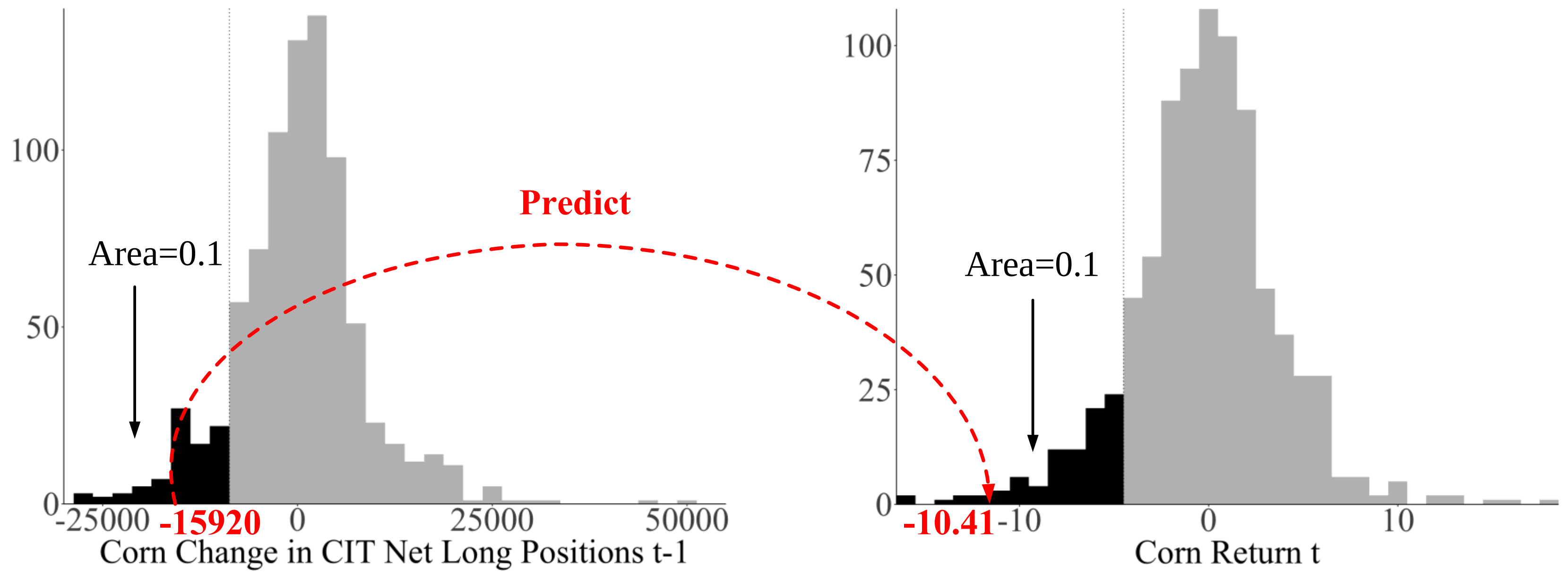
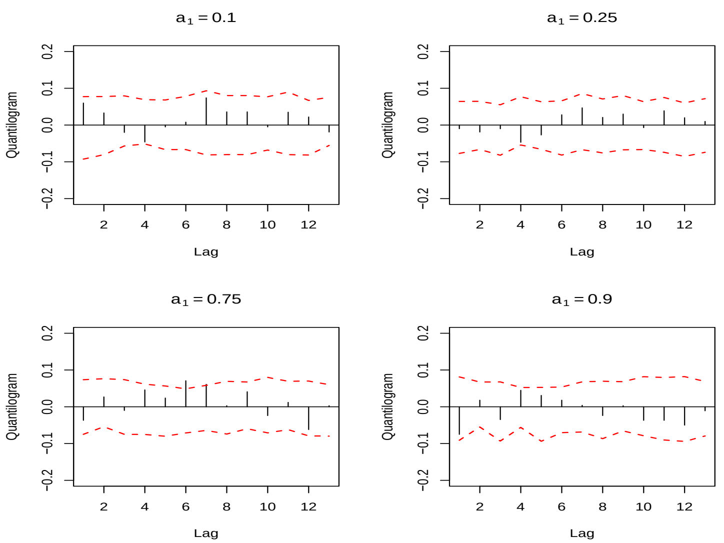
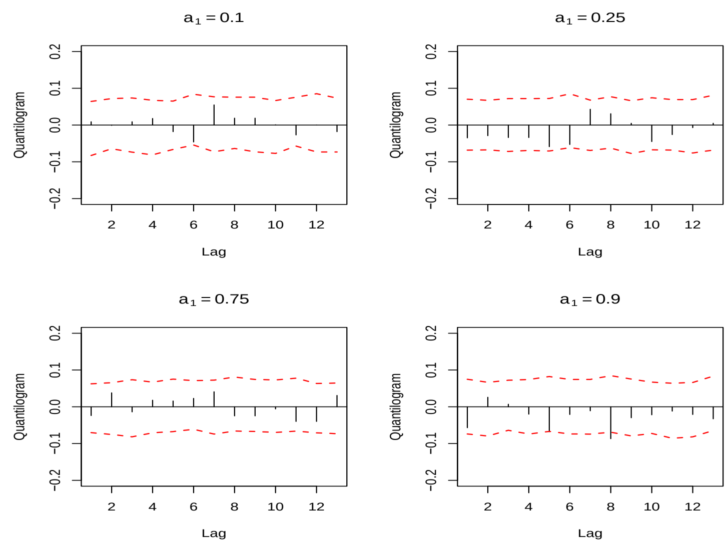


Figure 3. Illustration of the lead-lag dependence from CIT net long position changes at $t-1$ to futures returns at t when both are in the low quantile of 0.1, full sample period in the corn market

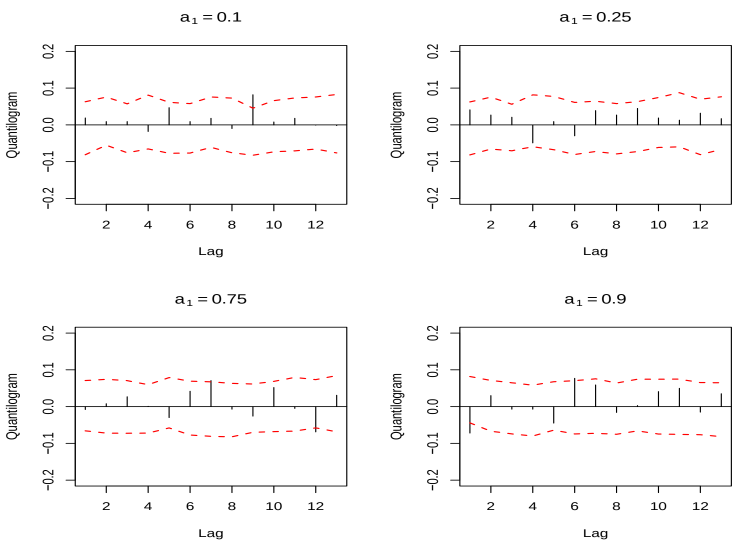
Notes: On September 27, 2011, the change in corn CIT net long positions is -15,920 contracts and hits in the 0.1 quantile for position changes. One week later on October 4, 2011 we observe a corn return of -10.41% and it hits in the 0.1 quantile for returns as well. The arrow shows that when changes in CIT net long positions are below the 0.1 quantile, it is followed by a return one week later that is also below its 0.1 quantile. This type of comparison is repeated for all observations to compute a CQ statistic for $\alpha_1 = \alpha_2 = 0.1$.



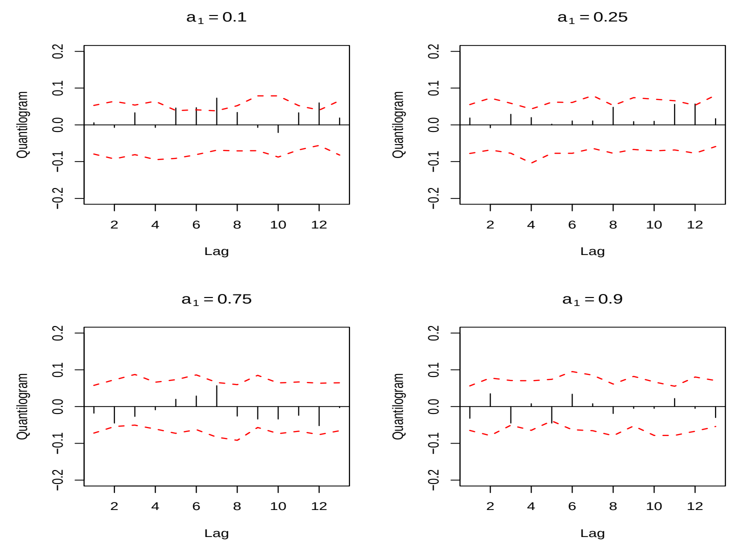
(a) Position change at quantile level 0.1



(b) Position change at quantile level 0.25

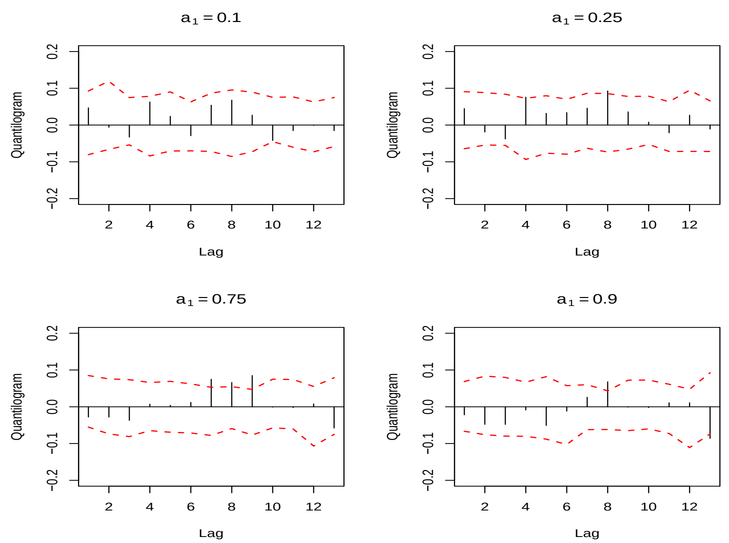


(c) Position change at quantile level 0.75

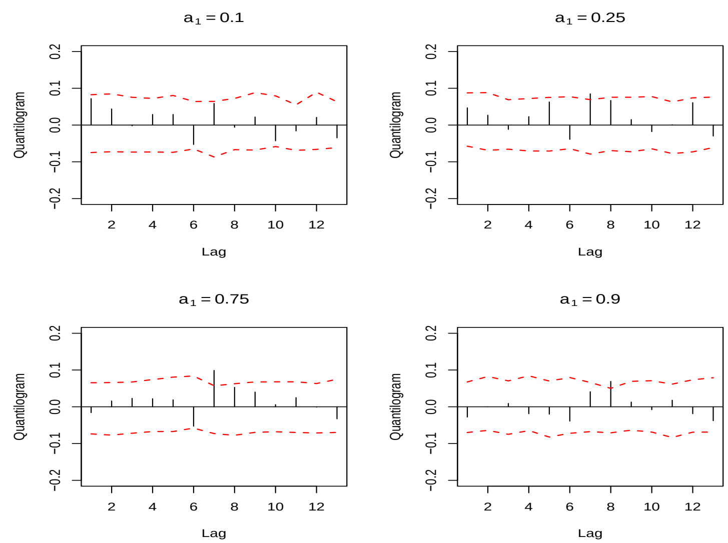


(d) Position change at quantile level 0.9

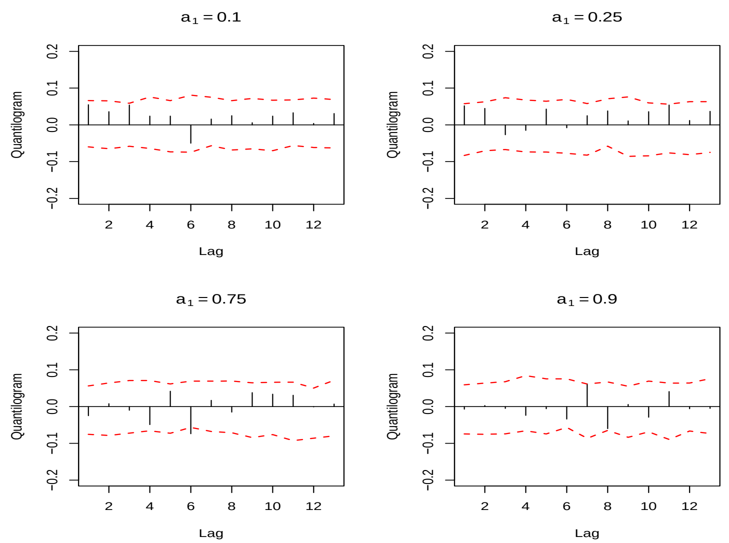
Figure 4. Cross-quantilogram from changes in CIT net long positions to returns in the CBOT corn futures market, 2004 – 2019



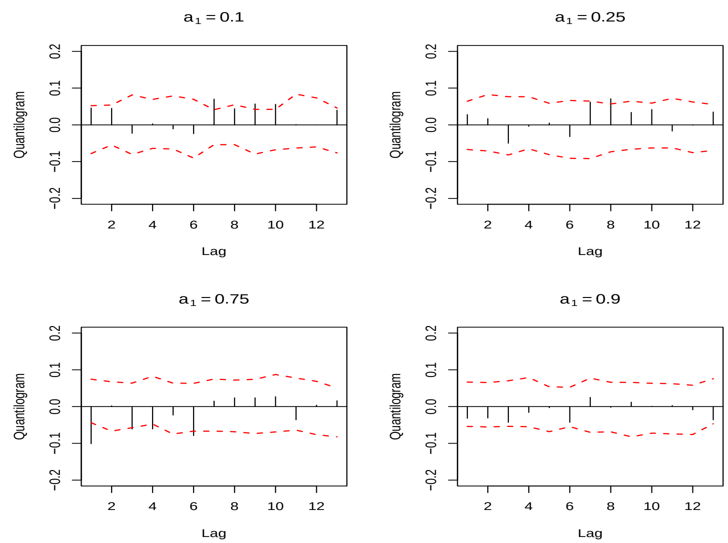
(a) Position change at quantile level 0.1



(b) Position change at quantile level 0.25

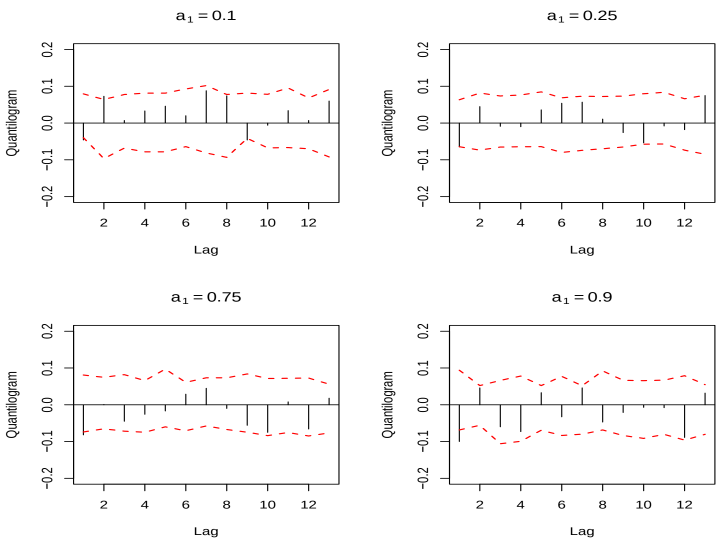


(c) Position change at quantile level 0.75

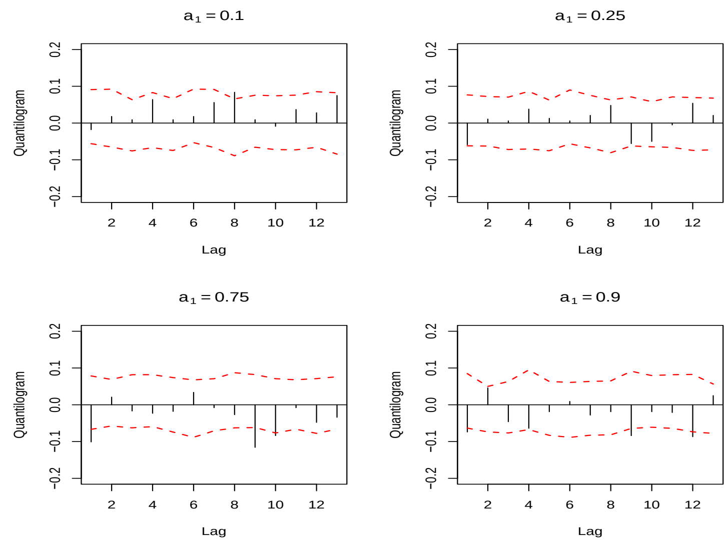


(d) Position change at quantile level 0.9

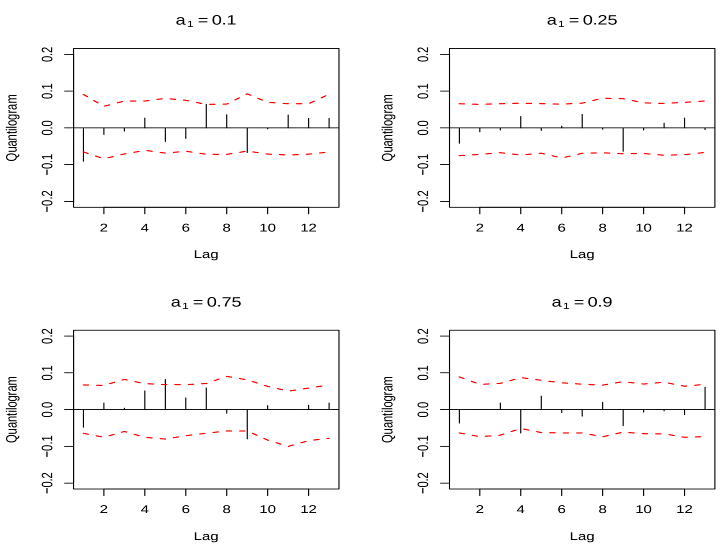
Figure 5. Cross-quantilogram from changes in CIT net long positions to returns in the CBOT soybean futures market, 2004 – 2019



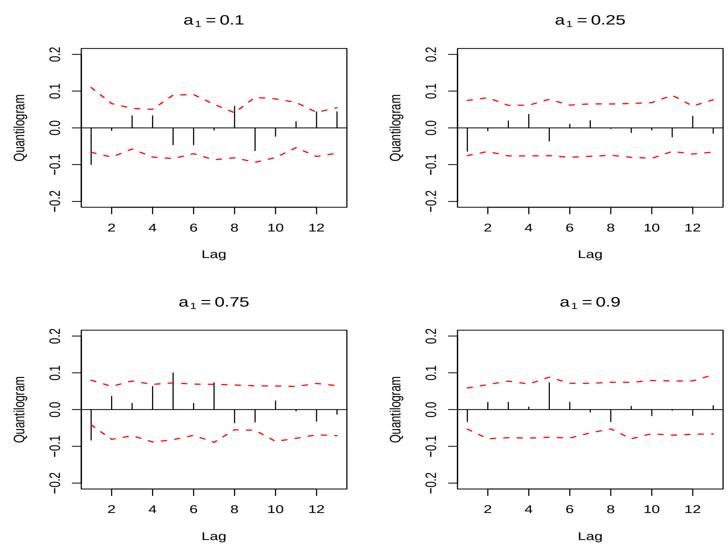
(a) Position change at quantile level 0.1



(b) Position change at quantile level 0.25

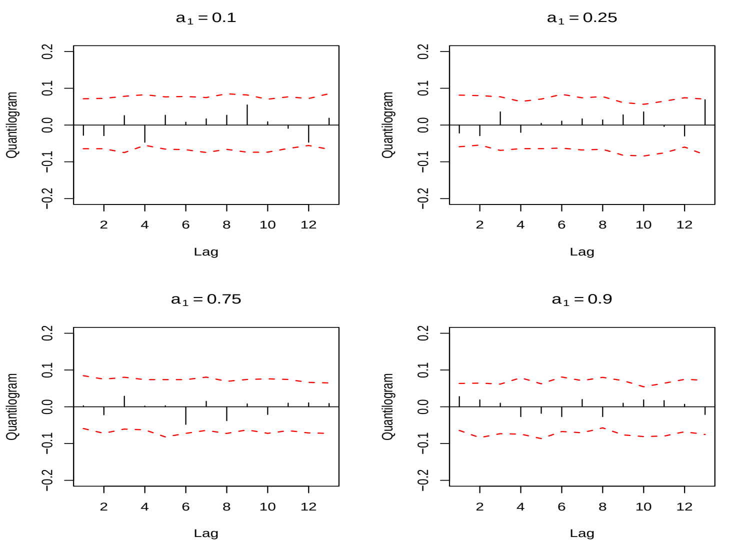


(c) Position change at quantile level 0.75

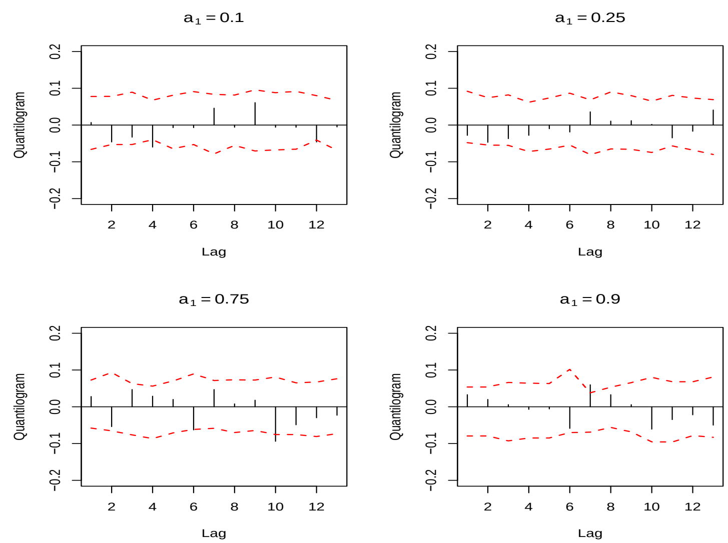


(d) Position change at quantile level 0.9

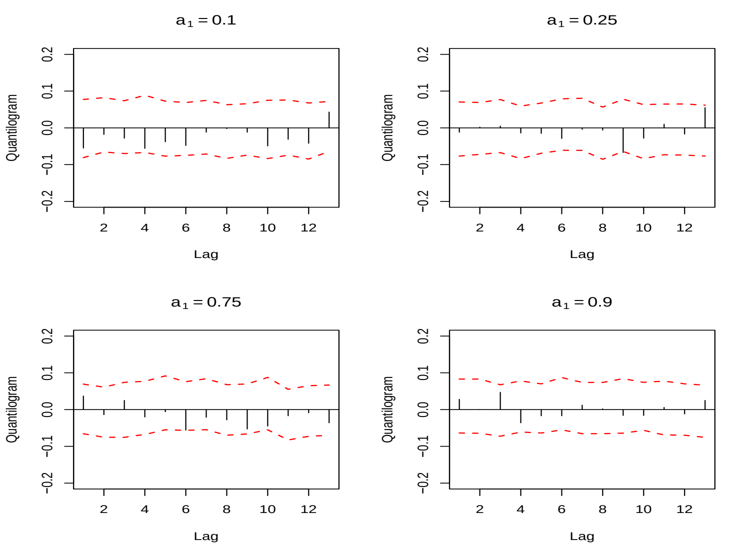
Figure 6. Cross-quantilogram from changes in CIT net long positions to returns in the CBOT wheat futures market, 2004 – 2019



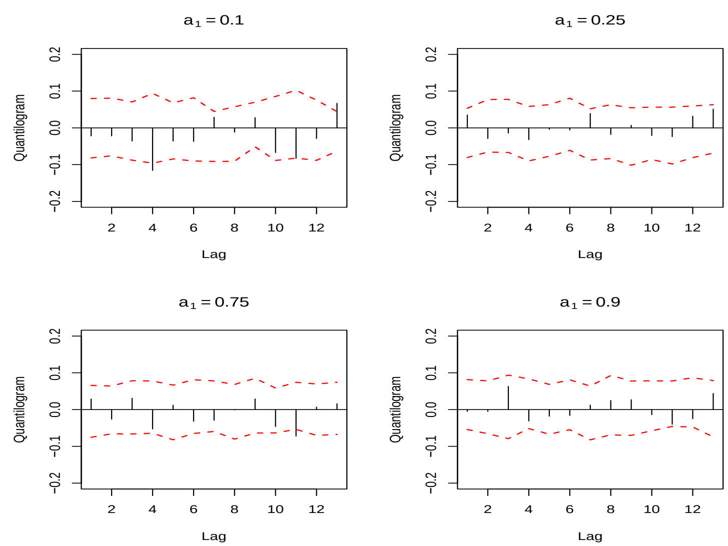
(a) Position change at quantile level 0.1



(b) Position change at quantile level 0.25



(c) Position change at quantile level 0.75



(d) Position change at quantile level 0.9

Figure 7. Cross-quantilogram from changes in CIT net long positions to returns in the KCBOT wheat futures market, 2004 – 2019