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RESEARCH ARTICLE

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 the influx of financial index investments has pressured agricultural futures prices upwards substantially. However, the impact of index investment activities 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. Overall, we find limited support for a significant relationship between extreme index trader position changes and returns, and even less support that increased index trading activities have pushed commodity prices higher.

Keywords: commodity; directional predictability; financialization; futures markets; Granger causality; index investment; quantile

JEL classifications: G12; G13; G14; Q02

Introduction

A global controversy erupted during the 2007–08 commodity price spike about the role of a new type of participant 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) the influx of financial index investors was 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.[1] These claims have been used to justify the need for tighter regulations on speculation in commodity futures markets around the world.

[1]It is important to distinguish price impacts associated with the order flow of index investment from the impacts under the Masters Hypothesis. The price impact of index order flow is expected to be relatively small and temporary, as the orders consume market liquidity at the time trades are made. In contrast, the price impact under the Masters Hypothesis is very large and long-lasting, essentially a large price bubble lasting many months and possibly even years. See Irwin, Sanders, and Yan (2022) and Yan, Irwin, and Sanders (2022) for studies of the order flow impact of index investment in commodity futures markets.

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

Despite the weight of the evidence against the Masters Hypothesis, it continues to resonate with a number of market participants, civic organizations, and policy makers. For example, CFTC Commissioner Romero recently called for an investigation of the role of "passive investment" in the commodity price spikes of 2021–22 (CFTC, 2022). In a similar vein, U.S. Senators Booker and Warren formally requested the CFTC examine whether "excessive speculation" played a role in driving commodity prices higher (Warren and Booker, 2022). These concerns 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. Lee and Yang (2012) caution that some statistical relationships may fail to present at the mean of the data but can show up in the tails of the distribution.

Evidence of nonlinearity in commodity price fluctuations has been found in various previous studies. Mackey (1989) noted that such nonlinearity might stem from non-linear supply and demand schedules and production plus storage delays. Myers (1994) highlighted that commodity prices tend to present time-varying volatility, with large (small) price changes often followed by subsequent large (small) changes. Deaton and Laroque (1995) simulated commodity prices under the competitive storage framework, noting that prices are non-linear in nature because storage cannot be negative. Commodity prices also exhibit excess kurtosis, where the tails of distributions appear to be much fatter than the normal distribution (Deaton and Laroque, 1995). In particular, because demand is relatively inelastic, commodity prices can jump abruptly above their long-run averages when inventory is low. These conclusions are further illustrated by recent empirical work highlighting the importance of accounting for nonlinearity and analyzing tail behavior in commodity price modeling (Brock et al., 1996; Hsieh, 1989; Hammoudeh et al., 2015; Bouri, Gupta, and Roubaud, 2019; Selmi et al., 2018).

The process of commodity market financialization may have further complicated the underlying data-generating process for commodity prices. Cheng and Xiong (2014) pointed out that financialization has introduced additional risks to the commodity markets. While providing liquidity to hedgers when trading to accommodate hedgers' needs, financial investors sometimes consume liquidity when they trade commodities in response to sudden changes in other markets. Financialization may have also led to information friction in commodity markets, making it more difficult for market participants to distinguish price movements due to noises from those due to changes in fundamentals (Cheng and Xiong, 2014). Irwin and Sanders (2012b) argued that commodity prices were affected by several concurrent structural changes during the growth stage of financialization, such as the transition to electronic trading, easier access to futures markets due to technological advances, and the entry of nontraditional market participants. These changes suggest that the relationship between commodity prices/returns and CIT activities may be more complicated than indicated by previous studies using simple linear Granger causality tests.

To date, only two studies in the literature have used statistical tests to detect CIT's price impact beyond the mean level while accounting for nonlinearity. 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 Masters 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 (1) captures the lead-lag relationships across all parts of distributions; (2) does not require moment conditions; (3) only requires the time series to be stationary; and (4) 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 our knowledge, the present study is the first to apply the CQ test to analyze the price impact of CIT positions in any commodity futures market.

The data for the study consist of weekly CIT positions and prices from 2004 to 2019 for corn, wheat, and soybeans traded on the Chicago Board of Trade (CBOT) and wheat traded on the Kansas City Board of Trade (KCBOT). Price returns and position changes are used in the analysis to obtain stationary time series. We first conduct three linear causality tests to provide a baseline for the relationship between CIT positions and price movements. We fail to reject the null of no causality in most cases, across the different tests used, the measures of position pressure employed, and 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 for various lags. A quantile version of the portmanteau tests is employed to evaluate the overall significance of the CQ test statistics across all lags. Similar to the linear tests, we find limited evidence of a directional relationship in the extreme quantiles of the distributions. Furthermore, in all but one instance where significant price impact is found, the evidence does not support that large CIT position increases drive up commodity prices. Overall, 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. CIT Positions

The *Supplemental Commitment of Traders* (SCOT) report published by the CFTC provides weekly CIT positions for CBOT corn, wheat, soybeans, and KCBOT wheat. Released every Friday at 3:30 p.m. Eastern time, the SCOT report contains the number of long and short contracts held by index traders as of the previous Tuesday's market settlement. The SCOT reports are publicly available starting from January 2006. Previous studies argue that using only post-2006 data may lead to biased results because the build-up of CIT positions in grain markets was concentrated in the previous 2 years (Irwin and Sanders, 2011; Sanders and Irwin, 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 are 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.

One potential issue with the SCOT CIT 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 that the SCOT report provides accurate measures of aggregate CIT positions (Irwin and Sanders, 2012a; Sanders and Irwin, 2013). In Appendix Figure A1, we plot the net long positions in the four markets using the CFTC *Index Investment Data* (IID). Compared to the SCOT, IID represents the most accurate measure of index investment as it summarizes positions before the internal netting of swap activity (Irwin and Sanders, 2012a). However, the IID data are only available quarterly from December 2007 to March 2010 and monthly from March 2010 to October 2015. As can be seen, the net long positions computed from the SCOT report behaved very similarly to that from the IID report during the period when both data sets were available. This suggests that the netting effect from swap dealers is likely minimal and remains so in the latter part of the sample. Overall, the CIT positions from the SCOT data should provide a reasonable approximation of investment trading activities.

Following previous studies, 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. Descriptive statistics for net long positions are presented in Table 1. For all four commodities, the net long positions are left-skewed, each with positive kurtosis, indicating heavy-tailed distributions. The Jarque-Bera (JB) test suggests that none of the series are normally distributed. The Augmented Dickey-Fuller (ADF) test shows that CIT net long positions are non-stationary.

We consider two stationary measures that directly reflect the "pressure" of index positions. The first is the change in CIT net positions for a given market:

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

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

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

As can be seen in Table 1, the two index position measures both have heavy tails, highlighting the importance of considering different parts of distributions when analyzing CITs' price impacts.

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 collected futures closing prices on Tuesdays. Like changes in positions (computed as the difference between positions from the previous Tuesday to the current), we calculate returns over the same period between two consecutive Tuesdays.

Table 1 shows that 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.

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	64,646	503,937	332,391	85,529	−0.822	3.561	105.074***	−2.700
CBOT Soybean	835	27,101	201,251	128,727	36,529	−0.848	3.804	122.643***	−3.036
CBOT Wheat	835	33,696	229,565	149,459	42,852	−0.258	2.564	15.885***	−3.093
KCBOT Wheat	835	12,055	66,592	37,162	12,303	−0.242	2.187	31.173***	−3.413**
Panel B: Change in CIT Net Long Positions (number of contracts)									
CBOT Corn	834	−44,788	60,317	213	9,195	0.291	8.569	1089.39***	−12.535***
CBOT Soybean	834	−23,250	27,251	138	4,520	−0.218	9.125	1310.35***	−13.138***
CBOT Wheat	834	−33,227	15,010	85	3,862	−0.660	10.635	2086.52***	−13.451***
KCBOT Wheat	834	−6400	14,342	45	1,641	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: 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.
** indicates statistical significance at 5%, and *** indicates statistical significance at 1%.

2.3. Sample Break

As noted above, our data cover 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 markets. Notional value for a given week in a given market is computed as CIT position × corresponding nearby futures price × futures contract size (5,000 bushels for all four commodities). We split the full sample into two sub-periods following the stages of "financialization" recently proposed by Irwin, Sanders, and Yan (2022). The first is the growth stage from 2004 to 2011, during which there was a rapid increase in commodity index investment. Two spikes in the CIT notional value were evident, one in 2007–2008 and the other in 2010–2011, with values ranging between \$35 and \$40 billion. The second stage is the post-financialization period from 2012 to 2019, where CIT notional value decreased steadily to around \$15 billion in the last 3 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 subsamples: the growth stage of financialization (2004–2011) and the post-financialization period (2012–2019). This accounts for the very different structural dynamics of index investment before and after 2011.

3. Linear Tests

Figure 2 plots CIT positions and futures prices for the four commodities. As can be seen, there is 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 previous studies on the price impact of CIT. While these tests have been conducted repeatedly 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 is shown below for a given market:

$$\text{Return}_t = \alpha_t + \sum_{i=1}^{m} \gamma_i \text{Return}_{t-i} + \sum_{j=1}^{n} \beta_j \Delta \text{Position}_{t-j} + \epsilon_t \tag{4}$$

where Return_t is the log difference in nearby weekly futures prices for a given market at time t, and $\Delta\text{Position}_t$ is the measure of CIT pressure in the same market. Price returns and changes in positions are used because the level data (prices and CIT positions) are mostly non-stationary (see Table 1). The null hypothesis is that all $\beta_j's$ are jointly zero, suggesting that CIT position changes 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 position changes ($m = 1$, $n = 1$) for each of the four markets.

The results of the linear Granger causality test for the full sample and the two subsample periods are presented in Table 2 Panel A.[2] For the full sample (2004–2019), in only one out of the four cases the null hypothesis of no Granger causality is rejected at the 5% significance level. The case is in the CBOT wheat market. Note that the direction of the estimated relationship is negative, suggesting that lagged CIT position changes negatively correlate with price changes, just the opposite

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

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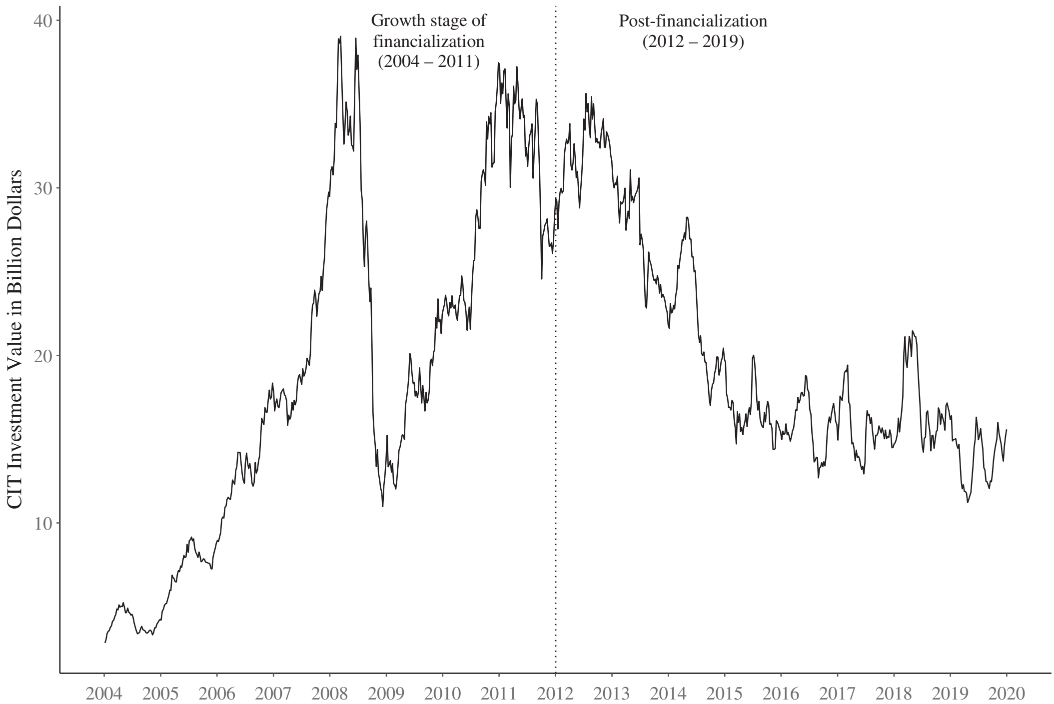

Figure 1. Notional value and equivalent net long positions of commodity index investment in four grain futures markets. Notes: The notional value of commodity index investment is calculated using the index positions retrieved from the SCOT report and corresponding nearby futures prices during the sample period. The growth and post-financialization stages are defined following Irwin, Sanders, and Yan (2022).

of that implied by the Masters price pressure hypothesis. In the first subsample (2004–2011) or the growth stage of financialization, we fail to reject no Granger causality from positions to returns in all eight cases. In the second subsample from 2012 to 2019 (the post-financialization stage), we again found negative predictability from positions to returns for CBOT wheat and no predictability in other markets.

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). When two time series are cointegrated or are not strictly stationary, the traditional Granger causality test may detect a spurious relationship that invalidates the results. To avoid such inconsistency, Toda and Yamamoto (1995) suggest testing for Granger causality in a VAR model that accounts for cointegration and stationarity. Important to note is that the test specifies variables in levels, regardless of their orders of integration. Specifically, we estimate the following:

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

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: (1) each series is tested for the order of integration using the ADF test; (2) determine the value $d_{\max}$, which is the maximum order of integration of two series; (3) set up the VAR model and use the AIC to determine the optimal

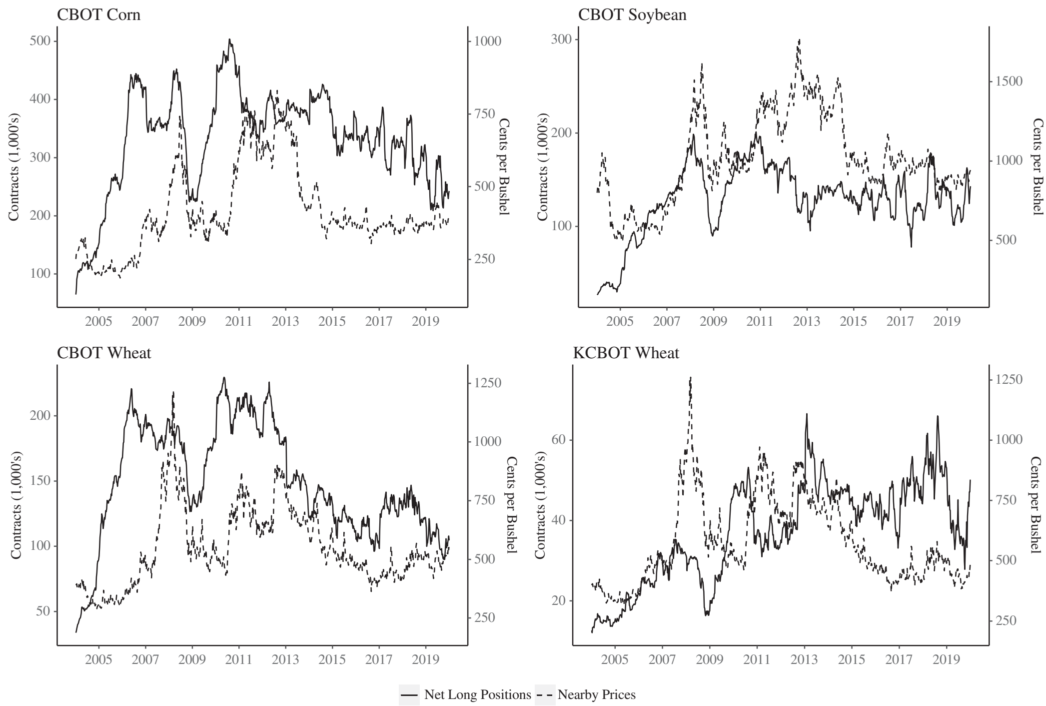

Figure 2. Weekly commodity index trader net long positions and nearby futures prices of CBOT corn, soybean, wheat, and KCBOT wheat, January 2004 to December 2019.

lags p for the system; (4) use the augmented lag $p + d_{\max}$ to estimate the VAR system; and (5) apply the Wald test to determine if the position coefficients differ significantly from zero.

Testing results are presented in Table 2 Panel B. Note that only one set of results is presented since the augmented Granger causality test is based on the level of net long CIT positions instead of the change or percent growth in positions. We set $d_{\max} = 1$ based on the ADF test. We then 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 2 Panel B, we fail to reject the null of no causality from CIT positions to futures prices in any of the markets in either the full or the two subsamples when utilizing the augmented Granger causality test. Results provide strong evidence against the Masters Hypothesis that CIT activities increased futures prices.

3.3. Long-Horizon Regression Tests

Both the standard and augmented Granger causality tests are designed to detect relationships between weekly CIT positions/position changes and prices/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, eventually pushing 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:

$$\sum_{i=0}^{k-1} \text{Return}_{t+i} = \alpha + \beta \sum_{i=0}^{k-1} \Delta\text{Position}_{t+i-1} + \epsilon_t \tag{6}$$

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where all variables are the same as before. 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 $t + k$, with k being the horizon. 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 $(t - 1)$. 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. Following previous studies (Hamilton and Wu, 2015; Sanders and Irwin, 2014, 2016; Singleton, 2014), we choose $k = 4$ and $k = 12$ to represent monthly and quarterly time horizons using the weekly data described in the data section.

Valkanov (2003) demonstrates that the OLS slope estimator in (6) is consistent and converges rapidly as the sample size increases. However, this specification 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 rescaled t-statistic, $t/\sqrt{T}$, along with simulated critical values for inference. Valkanov also demonstrates that the rescaled t-statistic generally is the most powerful among several alternative long-horizon test statistics.

We report the estimated OLS slope coefficients and the rescaled t-statistics for the Valkanov test at the monthly and quarterly horizons in Table 2 Panel C.[3] When we compare the test statistics with provided critical values, all rescaled t-statistics are within the range of the critical values, that is, non-statistically significant. Once again, estimation results from this linear test suggest no evidence that CIT positions pushed grain futures prices upward.

4. CQ Tests

In the previous section, we conducted three linear causality tests to provide a baseline result for the relationship between CIT activities and futures price movements. Consistent with most prior studies that use similar linear tests (e.g., Hamilton and Wu, 2015; Lehecka, 2015; Sanders and Irwin, 2011; Stoll and Whaley, 2010), we fail to reject the null of no causality in most cases.

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 on CIT net long position changes.

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 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 (1) captures the directional lead-lag relationships across all parts of distributions; (2) does not require moment conditions of series; (3) only requires the time series to be stationary; and (4) 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 $q_i\ (\alpha_i) = \inf(v : F_i(v) \geq \alpha_i),\ \forall \alpha_i \in (0, 1)$ for $\alpha \equiv (\alpha_1,\ \alpha_2)^T$. This quantile

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

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Table 2. Summary of three linear Granger causality test results for weekly commodity index traders (CIT) positions/position changes and prices/returns in four grain futures markets, January 6, 2004, to December 31, 2019

	Full Sample	2004–2011	2011–2019
Panel A: Standard Granger Causality Test Results			
Commodity	Dependent variable: returns, independent variable: growth in CIT net long positions		
	F-statistic (*p*-values)		
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: Augmented Granger Causality Test Results			
Commodity	Dependent variable: price, independent variable: CIT net long positions		
	Wald-statistic (*p*-values)		
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)

(*Continued*)

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Table 2. (*Continued*)

	Full Sample		2004–2011		2011–2019	
Panel C: Long-Horizon Regression Test Results						
Commodity	Dependent variable: returns, independent variable: growth in CIT net long positions					
Horizon (k)	Slope	Rescaled t-statistic	Slope	Rescaled t-statistic	Slope	Rescaled t-statistic
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

Notes: 1. Standard Granger causality test results are presented in Panel A. ** indicates statistical significance at 5%. F-test statistics are reported in the table, with the corresponding p-values in the parenthesis below. The null hypothesis is that no Granger causality exists from CIT position changes to futures returns. The estimated coefficients associated with the position variable are negative for cases with significant test statistics.

2. Augmented Granger causality test results are presented in Panel B. ** indicates statistical significance at 5%. Wald test statistics are reported in the table, with the corresponding p-values in the parenthesis below. The null hypothesis is that no Granger causality exists from CIT positions to futures prices.

3. Long-horizon regression test results are presented in Panel C. ** 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 null hypothesis is that no Granger causality exists from CIT position changes to futures returns.

4. The full sample period consists of 835 weekly observations. For the growth stage of financialization, there are 417 weekly observations from January 3 to December 27, 2011. The post-financialization period runs from January 3, 2012, to December 31, 2019, resulting in 418 weekly observations.

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:

$$\rho_\alpha(k) = \frac{E[\psi_{\alpha_1}(x_{1,t} - q_{1,t}(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - q_{2,t-k}(\alpha_2))}{\sqrt{E\left[\psi^2_{\alpha_1}(x_{1,t} - q_{1,t}(\alpha_1))\right]}\sqrt{E\left[\psi^2_{\alpha_2}(x_{2,t-k} - q_{2,t-k}(\alpha_2))\right]}} \tag{7}$$

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; $k = 0, \ \pm 1, \ \pm 2, \ \ldots$. Inside the check function, $\{1[[x_{i,t} \le q_{i,t}(\cdot)]]\}$ 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 stationary series of interests—the change in CIT net long positions and returns.[4] We denote these two time series as $\{x_{1,t}, x_{2,t}\}_{t=1}^T$, respectively. First, we estimate the unconditional quantile functions $\widehat{q_i}(\cdot)$ for each series by solving for the following minimization functions:

$$\widehat{q_i}(\alpha_i) = \text{argmin}_{v_i \in \mathbb{R}} \sum_{t=1}^{T} \pi_{\alpha_i}(x_{i,t} - v_i) \tag{8}$$

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 as:

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^T \psi_{\alpha_1}(x_{1,t} - \hat{q}_{1,t}(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2))}{\sqrt{\sum_{t=k+1}^T \psi^2_{\alpha_1}(x_{1,t} - \hat{q}_{1,t}(\alpha_1))}\sqrt{\sum_{t=k+1}^T \psi^2_{\alpha_2}(x_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2))}} \tag{9}$$

where $k = 0, \ \pm 1, \ \pm 2, \ldots$ 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 of corn over the full sample period is presented in Figure 3 to help illustrate how CQ statistics are computed. This plot shows an example of a pair of observations that both hit the quantile with $\alpha_1 = \alpha_2 = 0.1$. On September 27, 2011, the corn CIT position change 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 hit 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 $k \in \{1, 2, \ldots, p\}$, the null

[4]The CQ test requires that both series be stationary. Prices and CIT net long positions are non-stationary. Therefore, we again use returns and changes in positions in the CQ test.

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hypothesis is $H_0: \rho_\alpha(1) = \rho_\alpha(2) = \ldots = \rho_\alpha(p) = 0$, against the alternative hypothesis $H_a: \rho_\alpha(k) \neq 0$. The test statistic is:

$$\hat{Q}_a^{(p)} = \frac{T(T+2)\sum_{k=1}^{p} \hat{\rho}_\alpha^2(k)}{T-k} \tag{10}$$

where $\hat{Q}_a^{(p)}$ 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 CQs for the full sample period are presented in Figures 4 through 7 for CBOT corn, soybeans, wheat, and KCBOT wheat, respectively.[5] We consider four quantiles for both returns and CIT positions: 0.10, 0.25, 0.75, and 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 these quantiles respond to the dynamics of lagged extreme changes in CIT net long quantiles. These plots are organized into four panels where each panel presents the estimated 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, that is, $\hat{\rho}_\alpha(k)$. 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. In total, there are 218 CQ test statistics for each commodity across various combinations of lags and quantiles.

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 (i.e., extreme low quantile for CIT position changes) is likely to predict large decreases in futures prices (i.e., extreme low quantile for returns); on the other hand, when the sign is negative, a large drop in CIT net positions is less likely to predict a subsequent large decrease in futures prices. Meanwhile, for CIT position changes in the two low quantiles and returns in the 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 (i.e., extreme high quantile for returns) is high.

The 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 in either the left (quantiles 0.1 and 0.25) or right tails (quantiles 0.75 and 0.9) of the distribution for the four markets. 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

[5]To save space, we only discuss the CQ estimates for the full sample period and when CIT pressure is measured by change in 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.

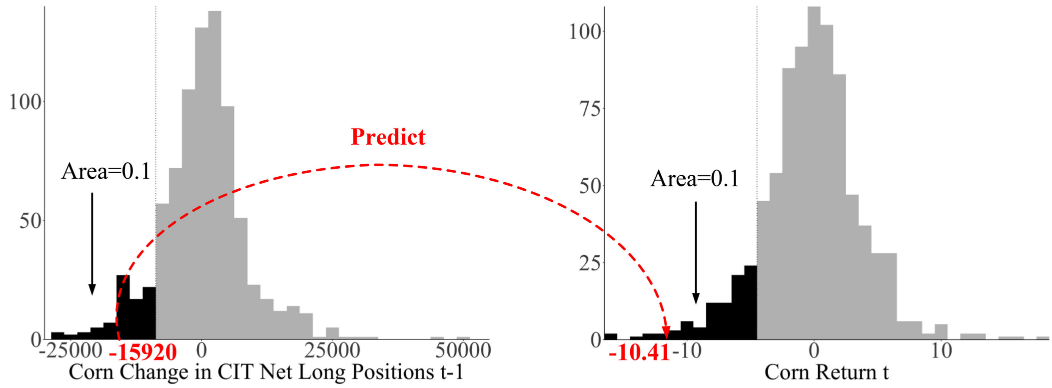

Figure 3. Illustration of the lead-lag dependence from CIT net long position changes at $t-1$ to futures returns at t when both are in the low quantile of 0.1, full sample period in the corn market. Notes: On September 27, 2011, the change in corn CIT net long positions was −15,920 contracts and hits 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 hit 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 $\alpha_1 = \alpha_2 = 0.1$.

long positions positively predict large decreases in returns. Meanwhile, in CBOT wheat we observe that large CIT net position 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, that is, $\alpha_1 = 0.1$ 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 returns. 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 position changes exceed high quantiles, they are likely to predict returns 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.

Overall, across all combinations of quantiles and lags, the ratio of statistically significant CQ test statistics is low for all four commodities, ranging from around 4% for KCBOT wheat to around 10% for CBOT wheat. For those significant cases, there is no clear pattern of the estimated predictability from position changes 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 their extreme quantiles.

The portmanteau test statistics for directional predictability from changes in CIT net long positions to returns are presented in Figure 8. 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. In the plot, the four quantiles of the position change and returns are on the x-axis and y-axis, respectively. Each cell represents the portmanteau test statistics of each quantile combination, with a darker color indicating a larger test value. Boarders around the cell indicate statistical significance at the 5% level. A solid border suggests that for lags from 1 to 13, the underlying CQ estimates have a positive dominant sign, whereas a dashed border indicates a negative dominant sign. 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.

Figure 8 shows that significant predictability from positions to returns only exists in one out of 64 cases for the full sample period. For the first and second subsamples, six and two cases,

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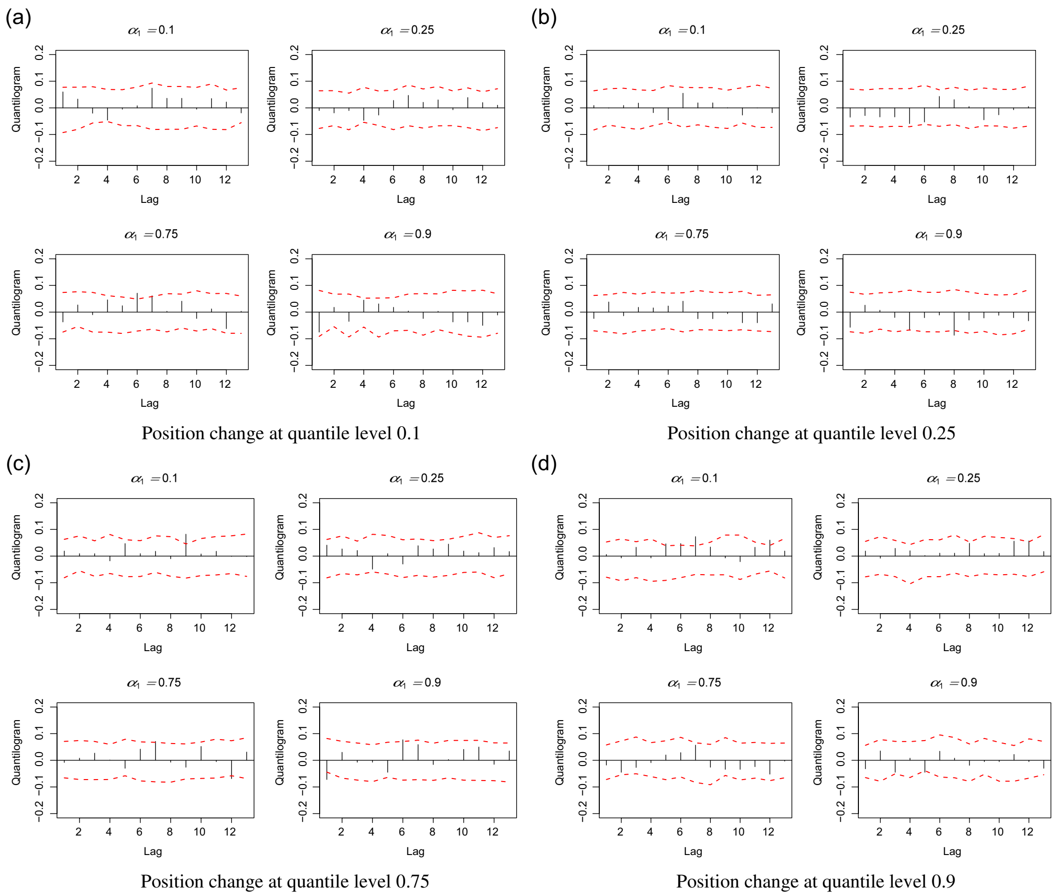

Figure 4. Cross-quantilogram from changes in CIT net long positions to returns in the CBOT corn futures market, 2004–2019. (a) Position change at quantile level 0.1. (b) Position change at quantile level 0.25. (c) Position change at quantile level 0.75. (d) Position change at quantile level 0.9.

respectively, out of 64 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.

We further investigate the dominant sign for the cases with a significant portmanteau statistic in Figure 8. Out of the nine significant cases, in only one instance there is evidence supporting the Masters Hypothesis, that is, that a large increase in the CIT net longs has directional predictability to a large increase in futures returns. This occurred for CBOT corn in subperiod 1 for $\alpha_1 = 0.75$ and $\alpha_2 = 0.9$, where the portmanteau test statistic is significant, and the dominant sign is positive. In all the remaining significant cases the evidence does not support the Masters Hypothesis. For example, during the post-financialization period (Panel C) and $\alpha_1 = 0.75, \alpha_2 = 0.25$ in CBOT wheat market, the dominant sign is negative, implying that large decreases in CIT positions tend to directionally predict large increases in wheat returns. Compared to other markets, CBOT wheat has overall more significant cases, 6 out of 48 in the three sample periods combined. However, none of these six significant cases support the Masters Hypothesis that increased index trading led to higher commodity prices. Overall, we note that the number of significant cases (9 out of 192), regardless of the dominant sign, is basically what one would expect based on random chance and that there is even less evidence supporting the Masters Hypothesis (1 out of 192).

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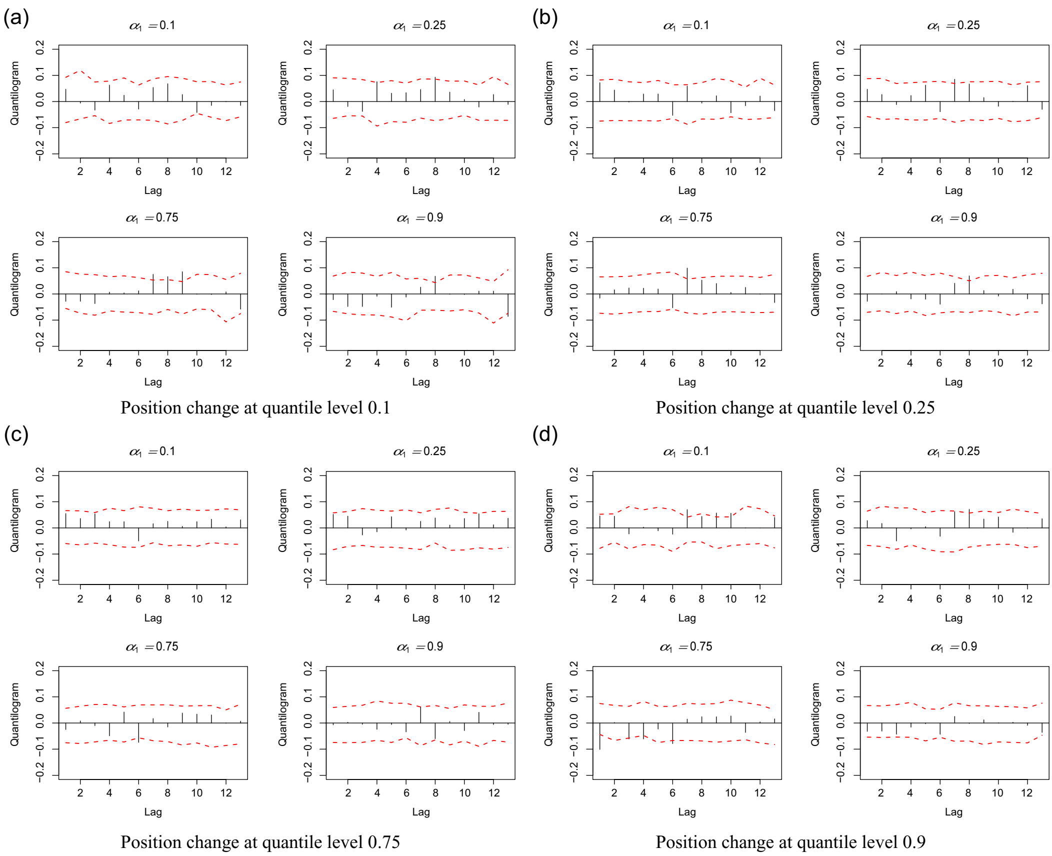

Figure 5. Cross-quantilogram from changes in CIT net long positions to returns in the CBOT soybean futures market, 2004–2019. (a) Position change at quantile level 0.1. (b) Position change at quantile level 0.25. (c) Position change at quantile level 0.75. (d) Position change at quantile level 0.9.

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, the 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, Aulerich, 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 Figure 9 for the full and two subsamples,[6] where returns are on the x-axis and position changes are on the y-axis. During the full sample period, significant causality exists from positions to returns in only 2 out of 64 cases. For the first and second subsamples, 5 and 3 cases, respectively, out of 64 we 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 causality from positions to returns, this 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.

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

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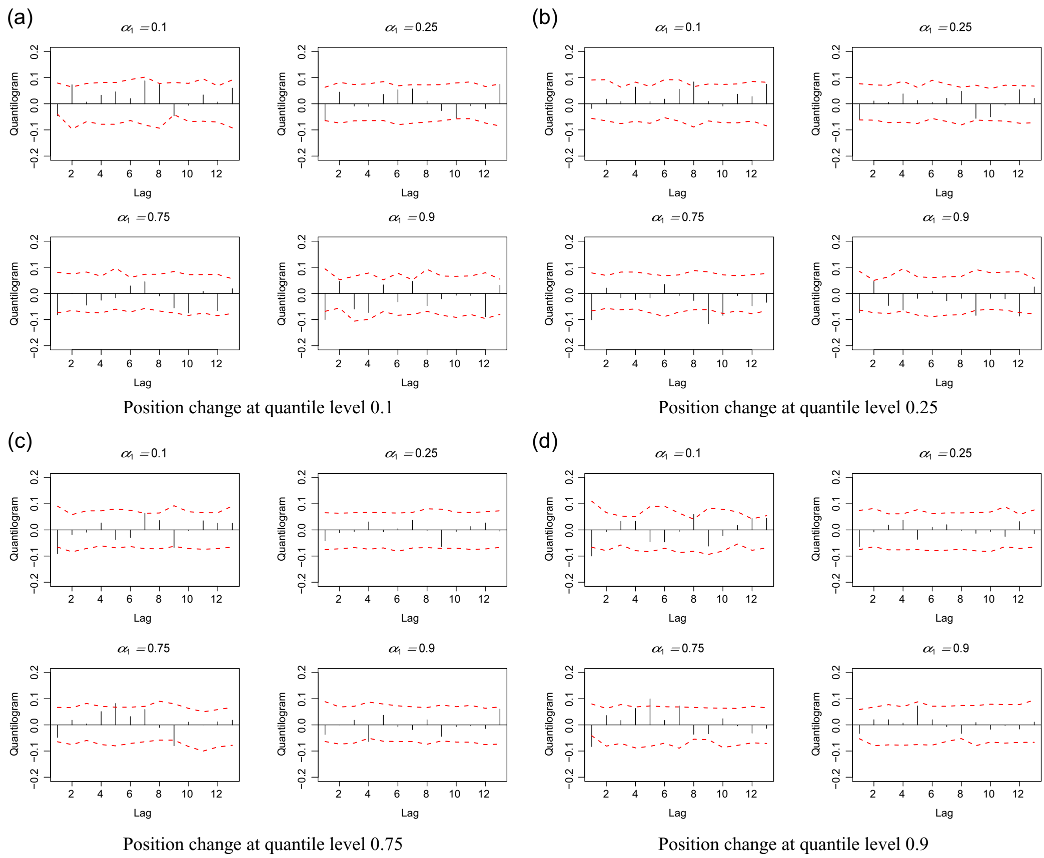

Figure 6. Cross-quantilogram from changes in CIT net long positions to returns in the CBOT wheat futures market, 2004–2019. (a) Position change at quantile level 0.1. (b) Position change at quantile level 0.25. (c) Position change at quantile level 0.75. (d) Position change at quantile level 0.9.

Furthermore, in the 10 significant cases, only 5 show evidence that CIT net long positions significantly decrease following a drop in futures prices. Overall, these results provide scant support for the idea that extreme CIT position changes have a trend-following component.

Our results are consistent with the notion that financial index investment is motivated by long-term investment objectives rather than short-term trading (e.g., Robe and Roberts, 2019; Stoll and Whaley, 2010). Robe and Roberts (2019) used non-public data from 2015 to 2018, including all trader-level futures positions reported to CFTC, to investigate the nature of market participants, the maturity structure of the positions held by different types of traders, and via the main business lines of these traders, their corresponding aggregate position patterns. Similar to our findings, their results show that the main goal of CITs is to have long-term and passive investments for portfolio diversification.

Given the mostly passive nature of index investment, the increasing participation of CITs may have a limited impact on the risk-sharing and information discovery function of futures markets, and further, futures price movements. The longstanding hedging pressure theory suggests speculators take over risks from hedgers and, in return, are compensated for a risk premium. The likelihood that CITs have changed the risk-sharing between hedgers and speculators is low if they do not actively trade commodities for their own needs. Meanwhile, since trading rules for index replication are well-defined and the specific allocation for commodities is also pre-determined

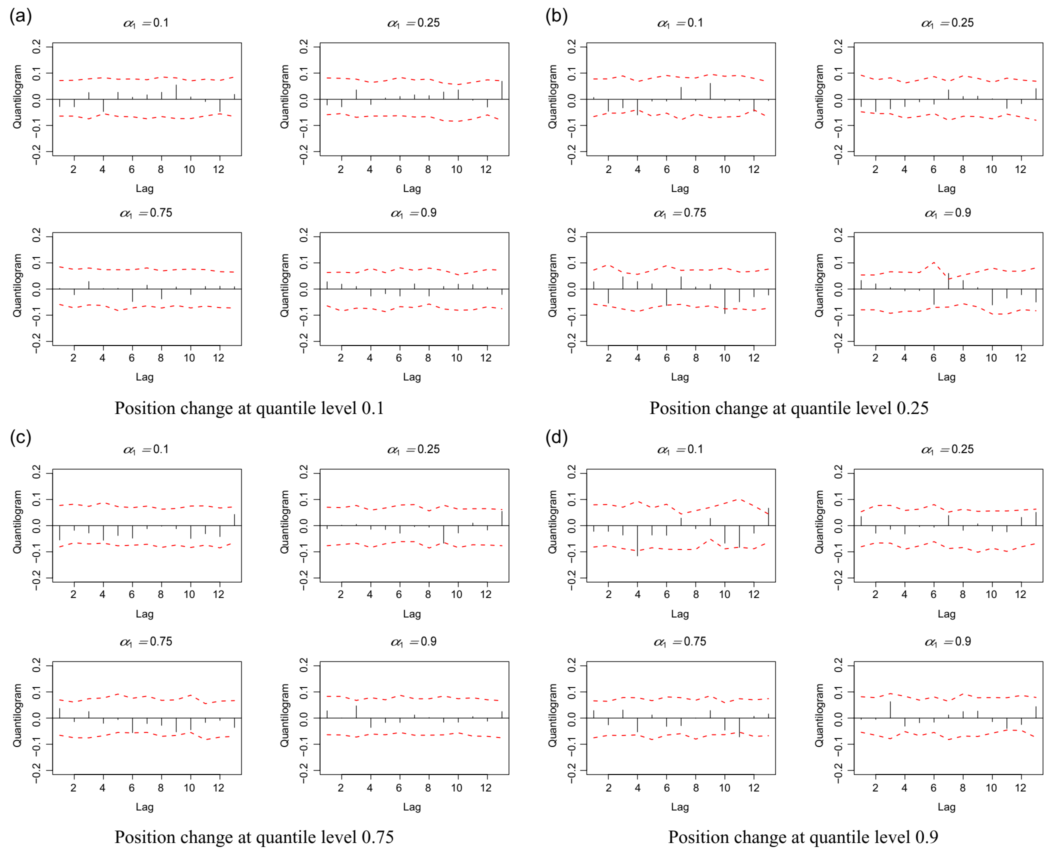

Figure 7. Cross-quantilogram from changes in CIT net long positions to returns in the KCBOT wheat futures market, 2004–2019. (a) Position change at quantile level 0.1. (b) Position change at quantile level 0.25. (c) Position change at quantile level 0.75. (d) Position change at quantile level 0.9.

(Stoll and Whaley, 2010), the presence of index trading may have a limited impact on the price discovery function of futures trading.

5. Conclusions

The price impact of financial index investment in agricultural markets continues to concern many market participants, civic organizations, and policy makers. The concern that influxes of financial index investment drove up agricultural futures markets has been labeled the "Masters Hypothesis." While the bulk of the evidence suggests this hypothesis is not well-founded, the impact of index investment in agricultural futures markets may be more complicated and nuanced than can be detected by relatively simple linear causality tests used in many studies. In particular, 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 CQ test recently developed by Han et al. (2016) to examine whether predictability exists between the change in CIT positions and returns in the tails of the distributions for four agricultural futures markets. In addition to making no assumptions about 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.

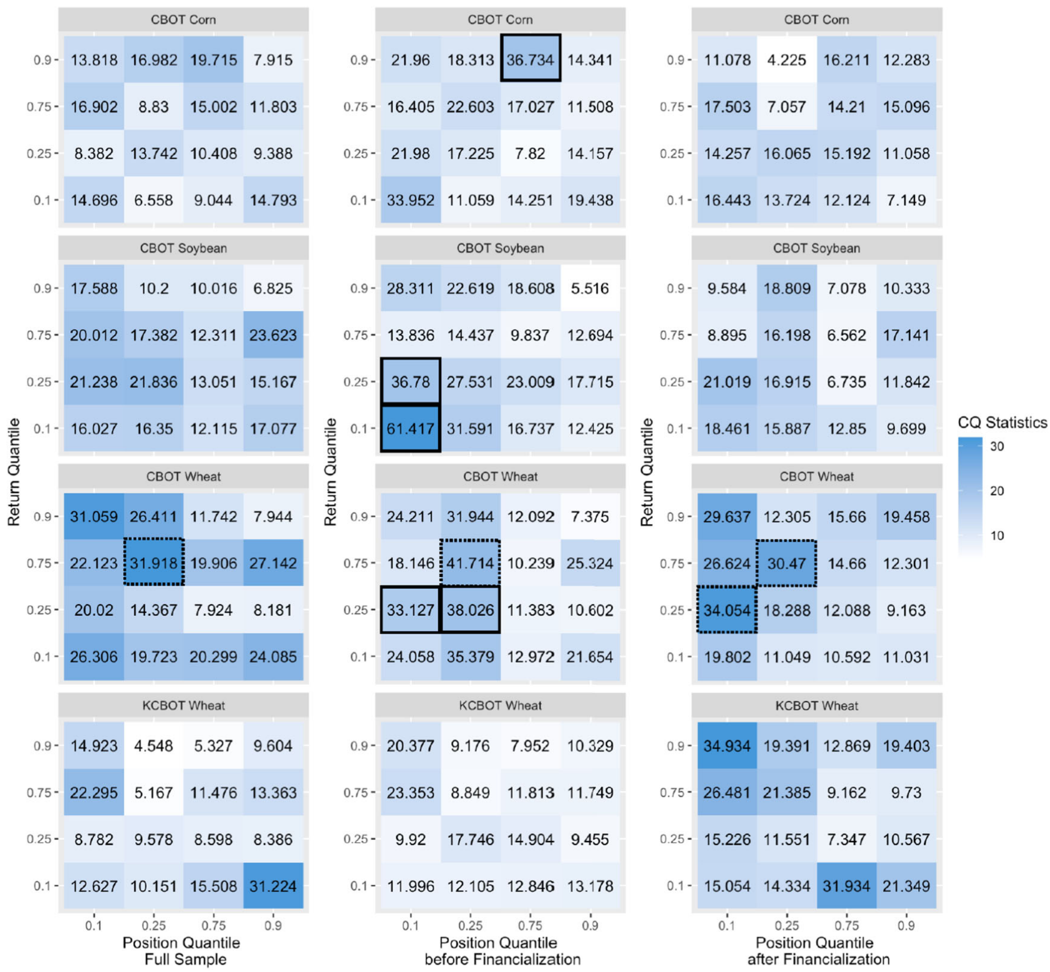

Figure 8. Cross-quantilogram portmanteau test results for weekly commodity index traders (CIT) positions and nearby futures returns in four grain futures markets, positions leading returns, January 6, 2004, to December 31, 2019. Notes: Darker color indicates large portmanteau test statistics. Boarders around a cell suggest the test statistic is significant at 5%. A solid border indicates the dominant sign of the underlying CQ estimates for the Box-Ljung test is positive, whereas a dashed border indicates a negative dominant sign.

Data for the study consist of weekly CIT positions and returns from January 6, 2004, through December 31, 2019, for CBOT corn, wheat, soybeans, and 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 price movements. We fail to reject the null of no causality in most cases across the different tests used, the measures of position pressure employed, and 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 linear causality tests, we find no evidence of directional predictability from CIT position changes to returns in most cases. For the cases where we identify a significant impact, we further evaluate the signs of the estimated coefficient and find that with one exception, they do not support the claim that large CIT position increases have driven up commodity prices. Overall, our results provide only limited support that CIT position changes significantly impact returns. The support is even scanter for the narrower-scope question of whether large CIT position increases drive up futures prices, which is one of the underlying tenets of the Masters hypothesis.

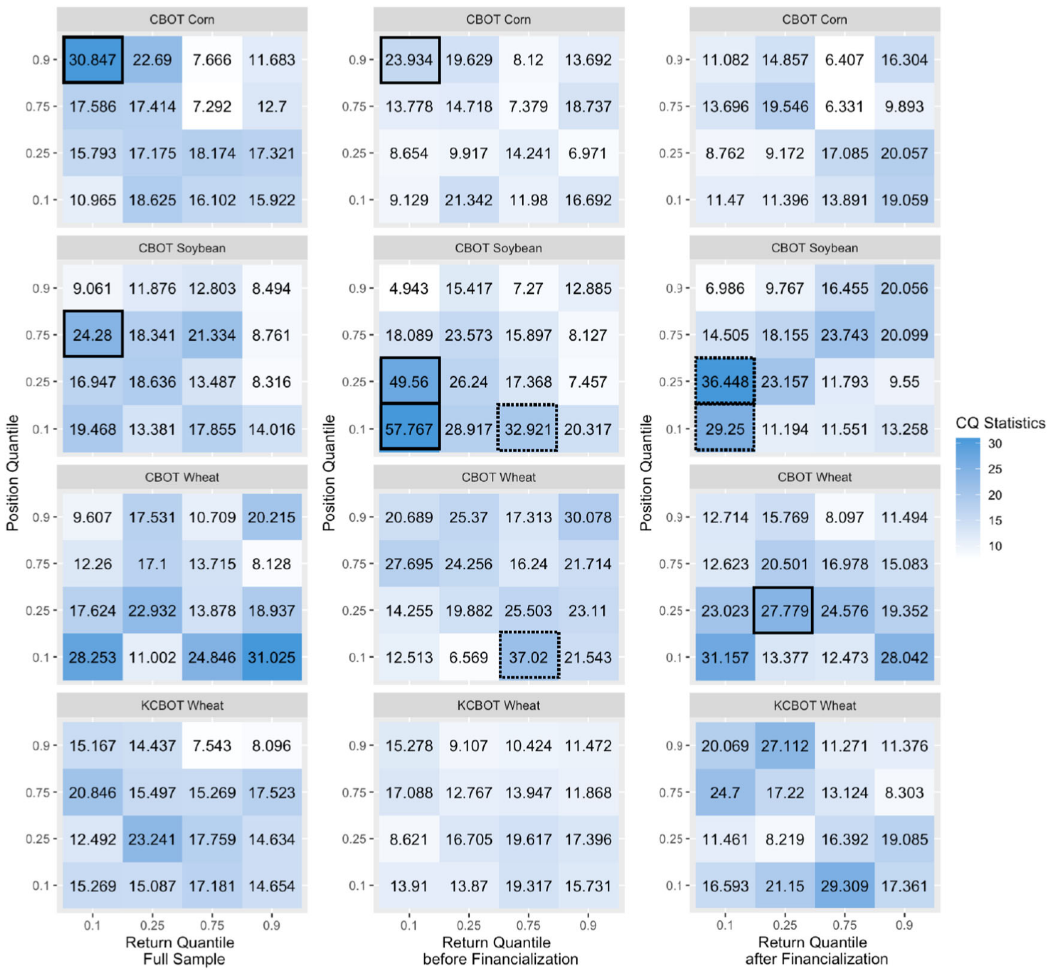

Figure 9. Cross-quantilogram portmanteau test results for weekly commodity index traders (CIT) positions and nearby futures returns in four grain futures markets, returns leading positions, January 6, 2004, to December 31, 2019. Notes: Darker color indicates large portmanteau test statistics. Boarders around a cell suggest the test statistic is significant at 5%. A solid border indicates the dominant sign of the underlying CQ estimates for the Box-Ljung test is positive, whereas a dashed border indicates a negative dominant sign.

One interesting question is why there are more significant cases in CBOT wheat than in the other three markets, especially in the simple linear Granger causality and CQ tests. One possibility is trader composition. Using non-publically available CFTC data for the same four commodities analyzed in the present paper, Robe and Roberts (2019) found that only 19% and 30% of the long and short open interest in the CBOT wheat market were attributed to commercial traders in 2015–2018, respectively, substantially lower than the ratios in the other three markets. Meanwhile, CITs held 43% of long open interest in CBOT wheat, whereas in the other three markets, the ratio ranges from 29% (soybeans) to 36% (corn). Further, the percentages of non-commercial long and short open interests were also the highest in CBOT wheat. These numbers suggest that non-hedgers, including both non-commercial traders and CITs, may play a more important role in CBOT wheat than in the other three grains markets.

For most of the significant cases that show a price impact, test results suggest that increases in CIT net long position changes are associated with lower futures returns, contrary to the

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underlying tenet of the Masters Hypothesis. Robe and Roberts (2019) noted that CITs held a higher share of short open interest than the other three markets. The larger presence of CIT short positions may be one reason for the negative CIT price impact. Our results appear to echo Kang, Rouwenhorst, and Tang (2020) finding that following a position change, commodities that were purchased by non-hedgers underperformed those that were sold by them, while commodities bought by hedgers earned significantly higher returns than those they sold. Kang, Rouwenhorst, and Tang (2020) argue that hedgers earn a risk premium for providing liquidity to non-hedgers, offsetting the liquidity they pay to obtain price insurance.

It is worth noting that the weekly data may affect the accuracy of directional predictability between futures returns and CIT position changes. Previous studies report that using different data frequencies may significantly affect empirical results (Bachmeier and Griffin, 2003; Chua, de Silva, and Suardi, 2017). In our case, weekly CIT data are unable to uncover the impacts of index investments over shorter time intervals, for instance, at a daily horizon. However, previous studies utilizing daily data also fail to find evidence supporting the Masters Hypothesis. For example, using the CFTC *Large Trader Reporting System data*, Aulerich, Irwin, and Garcia (2014) found that daily index investment position changes did not positively affect futures returns in the four grain markets analyzed in the present paper. Sanders and Irwin (2017) examined the correlation between weekly changes in index net long positions and the daily returns on each day in the subsequent week for 12 agricultural commodities, again failing to find support for a positive price impact. Future studies may wish to examine whether the results of the present paper hold for higher-frequency data.

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 about 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. One extension of the paper is to analyze a broader set of commodities, to see whether the same results found in our analyses hold for other commodities that may present different characteristics from grains. Future studies may wish to examine other types of traders on both the long- and short-term pricing of commodity markets.

Supplementary material. To view supplementary material for this article, please visit https://doi.org/10.1017/aae.2022.40

Data statement. The data that support the findings of this study are available in the Open Science Framework at: http://doi.org/10.17605/OSF.IO/KXAV2

Author contributions. Conceptualization: J.L., S.H.I., X.E.; Data curation: J.L., S.H.I.; Formal analysis: J.L., S.H.I., X.E.; Funding Acquisition: S.H.I..; Investigation: J.L., S.H.I., X.E.; Methodology: J.L., S.H.I., X.E.; Project Administration: S.H.I.; Software: J.L.; Supervision: S.H.I., X.E.; Visualization: J.L.; Writing-original draft: J.L.; Writing-review and editing: S.H.I., X.E.

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