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Re: Position limits and Aggregation of Positions

We are submitting the following comments on the Commission's Notice of Proposed Rulemaking (NOPR) for Position Limits for Derivatives and Aggregation of Positions issued as appeared in the Federal Register (Federal Register Release: 79 FR 30762).

We have jointly and separately published a number of academic studies on commodity futures markets. In particular, we have conducted several studies in recent years on the possible impact of speculation, and index funds in particular, on commodity futures prices. Attached are two such manuscripts that are relevant to the Commission's consideration of expanded position limits on derivatives and in particular limits on combined futures positions.

Both manuscripts use the detailed daily position data—futures and swaps—provided by a large private index fund to examine any potential impact of position changes on futures market prices. The data provide a new look at the issue of linkages between index fund positions and prices because it is available at a higher frequency and covers more markets than those studies that rely on the Commission's *Index Investment Data*, *Disaggregated Commitments of Traders*, or *Supplemental Commitments of Traders* reports. In particular, the data used in the analysis looks at the fund's aggregate futures position—all contract months combined in both the futures and swaps market—and any potential linkage to price changes. The empirical results show no causal linkages running from aggregate or total positions to changes in futures prices. This result has particular relevance for consideration of "all month" or "combined" position limits.

The first manuscript, "The 'Necessity' of New Position Limits in Agricultural Futures Markets: The Verdict from Daily Firm-Level Position Data," directly looks at the concept of "necessity" and "excessive speculation" as it appears in the Commodity Exchange Act (CEA). In particular, an economist's reading of the CEA suggests a high hurdle for imposing speculative position limits. First, the speculation must be "causing" the price fluctuations which suggests a temporal ordering from speculation to the price changes. Second, the price changes must be "sudden" or "unreasonable" or "unwarranted." This description precludes speculation that warrants price changes—that is, informed speculation. So, not only must empirical "causation" be established from speculative positions to price changes, but it must also be shown that the speculation is not bringing important new information to the market in a price discovery role.

In this first manuscript the focus is on the firm-level position data across 13 U.S. agricultural futures markets. The firm-level data are shown to be representative of the overall index fund industry. Empirical tests fail to find any evidence linking the firm's trading with market returns. Thus, there is no support for the "necessity" of position limits across futures contracts.

The second manuscript, "Energy Futures Prices and Commodity Index Investment: New Evidence from Firm-Level Position Data," examines the potential price impact on four energy futures markets. Simple correlation tests, difference-in-means tests, and Granger causality tests generally fail to reject the null hypothesis that changes in the fund's positions are unrelated to subsequent returns in the four energy futures markets. We also fail to find any evidence that commodity index positions are related to price movements in the energy futures market using long-horizon regression specifications. Overall, the empirical tests in this study fail to find compelling evidence of predictive links between commodity index investment and changes in energy futures prices.

The results of these studies, and others, generally fail the first hurdle in establishing "necessity" of position limits. That is, there is no convincing evidence that index fund positions cause price fluctuations. Therefore, new or expanded limits on speculative positions on in commodity futures markets are unnecessary.

We appreciate the opportunity to comment. If we can provide further information or feedback to the Commission, please don't hesitate to contact either one of us.

Sincerely,

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The 'Necessity' of New Position Limits in Agricultural Futures Markets:
The Verdict from Daily Firm-Level Position Data

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The ‘Necessity’ of New Position Limits in Agricultural Futures Markets: The Verdict from Daily Firm-Level Position Data

Abstract: Regulators are proposing new position limits in U.S. commodity futures markets while the actual impact of long-only index funds on futures prices continues to be debated. Researchers have noted the data limitations—frequency and market breadth—associated with using data compiled by the U.S. Commodity Futures Trading Commission (CFTC). This research addresses these shortfalls by using daily position data for a specific long-only index fund. The empirical analysis focuses on the firm-level position data across 13 U.S. agricultural futures markets. The firm-level data are shown to be representative of the overall index fund industry. Empirical tests fail to find any evidence linking the firm’s trading with market returns. However, there does appear to be a consistent negative relationship between the firm’s roll transactions and changes in calendar price spreads. Notably, the direction of this impact is opposite of price-pressure hypothesis. The results of this study, and others, indicate that a clear verdict can be reached—new limits on speculation in agricultural futures markets are unnecessary.

JEL categories: D84; G12; G13; G14; Q13; Q41

Key words: Agricultural; Bubble; Commodity; Futures market; Index funds; Michael Masters; Price; Speculation

The 'Necessity' of New Position Limits in Agricultural Futures Markets: The Verdict from Daily Firm-Level Position Data

Excessive speculation…causing sudden or unreasonable fluctuations or unwarranted changes in the price of such commodity, is an undue and unnecessary burden on interstate commerce in such commodity. For the purpose of diminishing, eliminating, or preventing such burden, the Commission shall…fix such limits on the amounts of trading…as the Commission finds are necessary to diminish, eliminate, or prevent such burden. Commodity Exchange Act, 1936.

Introduction

Corn, soybeans, and wheat futures prices set new nominal price records in 2007-2008. The rapid increase in commodity prices coincided with the emergence of new financial vehicles that provided investors exposure to indices that track returns in commodity futures markets. These financial investments are packaged in a variety forms that provide the investor with long-only exposure to an index of commodity prices. Not surprisingly, concerns soon emerged among market participants, regulators, and civic organizations that the inflows into new commodity index investments were driving increases in commodity prices. This notion is most commonly associated with hedge fund manager Michael W. Masters and is often referred to as the "Masters Hypothesis" (Irwin and Sanders 2012). The Masters Hypothesis essentially argues that unprecedented buying pressure from index investors created massive bubbles in commodity futures prices. In turn, these bubbles were transmitted to spot prices through arbitrage linkages between futures and spot prices. The end result was that commodity prices—and the prices of staple food and energy products—exceeded values warranted by traditional supply and demand factors.

Policymakers and other advocates were quick to adopt Masters-like arguments after the 2007-2008 price spikes and pushed for regulations to limit commodity index activity. As a result, the 2010 *Dodd–Frank Wall Street Reform and Consumer Protection Act* (*Dodd-Frank*) laid the groundwork for more restrictive speculative limits on commodity futures positions. The Commodity Futures Trading Commission's (CFTC) first attempt at position limits under *Dodd-Frank* was vacated in 2012 by U.S. District Court Judge Robert Wilkins on grounds that the CFTC in essence did not establish the "necessity" of the limits as required by the 1936 Commodity Exchange Act (CEA). That is, the CFTC did not show that excessive speculation was causing unwarranted changes in commodity prices (Young, Donley, and Gagoomal 2012). CFTC Commissioner Scott D. O'Malia laid bare the essence of the court's decision: "…the court explicitly stated that the statute unambiguously requires a finding of necessity before establishing position limits" (O'Malia 2012). As shown in the opening quote to this article, "necessity" refers to original language in the CEA which grants the CFTC the ability to fix position limits that are "necessary" to prevent excessive speculation "causing sudden or unreasonable fluctuations or unwarranted changes in the price of [a] commodity." The CFTC skirted this issue in the proposed rulemaking, claiming essentially that *Dodd-Frank* requires them to implement the new rules irrespective of the "necessary" conditions in the original CEA. Federal Judge Robert Wilkins clearly disagreed with this omission and indicated that the "necessity" finding was in fact required (Young, Donley, and Gagoomal 2012).

Undeterred, the CFTC both appealed the Court decision and simultaneously formulated new position limit rules in 2013 (Miedema 2013). While the CFTC ultimately dropped the appeal, the CFTC Commissioners approved the new position limit rules in November 2013 (Michaels 2013). How successful the CFTC will be in establishing the "necessity" described in the CEA and required by the U.S. District court remains to be seen. An economist's interpretation of "excessive speculation" as outlined in the CEA represents a high hurdle indeed. First, the speculation must be "causing" the price fluctuations. Second, the price changes must be “sudden” or “unreasonable” or “unwarranted.” This definition of excessive speculation seemingly excludes speculation that cannot be shown to *cause* price changes which implies a temporal ordering. Likewise, the CEA description precludes speculation that warrants price changes—that is, informed speculation.

Given the important policy implications and the world-wide nature of the debate, it should come as no surprise that a number of recent academic studies investigate the empirical relationship between commodity index positions and price movements in commodity futures markets. Some find evidence of a positive impact (e.g., Gilbert 2010) but most do not (e.g., Stoll and Whaley 2010). Extensive reviews of this rapidly expanding literature are provided by Irwin and Sanders (2011), Will et al. (2012), Fattouh, Kilian, and Mahadeva (2013), Irwin (2013), and Cheng and Xiong (2013).

Most prior research relies on data compiled by the CFTC through the *Large Trader Reporting System* (LTRS). These data are made available through two widely used reports, the *Supplemental Commitment of Traders* (SCOT) and the *Disaggregated Commitment of Traders* (DCOT) report. Prior work that uses these CFTC data suffers from limitations in terms of both the frequency of the data and the availability of data across markets. For example, the SCOT data are relatively accurate measures of commodity index positions (Irwin and Sanders 2012), but are only available at weekly intervals for 12 agricultural futures markets and exclude important energy and metal futures markets. The DCOT data nets on- and off-exchange index positions, and may therefore substantially underestimate index positions in some markets, especially energy and metals markets (Irwin and Sanders 2012). Compiled independently of the LTRS, the CFTC also publishes the *Index Investment Data* (IID) report. The IID are available for all major futures markets and considered the most accurate data available on index positions;

but historical data are available only at quarterly and monthly frequencies which severely limits the number of observations available for statistical tests. Some authors (e.g., Singleton 2013) have attempted to circumvent these issues by imputing positions for the energy markets from the positions reported for agricultural markets in the *SCOT* report. Sanders and Irwin (2013) demonstrate how this data mapping process can lead to unreliable position data and potentially misleading empirical results, which highlights the need for more detailed data.

In this article, we bring new data to bear on the debate over the impact of index funds on commodity futures prices. Specifically, daily futures and swaps positions are obtained for a major commodity index fund. The data set spans 22 U.S. futures markets from October 1, 2007 through May 30, 2012, or a total of 1,176 daily observations for each market.[1] In this paper, we focus on 13 agricultural futures markets where new position limits have been proposed.[2] The daily positions provide for a data set that is unique in understanding the trading patterns and potential market impact of index traders. Moreover, the data include positions in both futures and swaps markets which are not available in either the SCOT or DCOT reports. Causal linkages between index positions and price changes, if they exist, may be more evident in these data covering both futures and swaps markets.

Position Data

The position data are collected from a large investment company (the "Fund") that offers several commodity investment programs. The majority of the Fund's commodity investments are held in a relatively fixed basket of commodity futures to replicate a proprietary index. Detailed data on actual positions held by the Fund in U.S. futures markets are available for 22 U.S. futures markets. The empirical analysis presented here focuses on 13 key agricultural markets: Chicago Board of Trade (CBOT) corn, CBOT soybean oil, CBOT soybeans, CBOT soybean meal, CBOT

Wheat, Intercontinental Exchange (ICE) cocoa, ICE Cotton, ICE Sugar, ICE coffee, Chicago Mercantile Exchange (CME) Feeder Cattle, CME live cattle, CME lean hogs, and Kansas City Board of Trade (KCBOT) wheat. For each of these 13 markets, complete position data are available for 1,176 days from October 1, 2007 through May 30, 2012.[3]

The position data for the Fund includes futures positions for each market by calendar month contract. In addition to the direct futures positions, "look alike" swap positions are held in corn, CBOT wheat, soybeans, soybean oil, and cotton. These swaps are constructed to precisely mirror a particular exchange traded futures contract. The swap positions are smaller than the direct futures positions held in these markets. For example, in corn, the swap position averaged 4,613 contracts from February 14, 2011 to January 17, 2012. Over that same time period, the direct futures position was an average of 18,365 contracts. So, the swap position represented 20% of the total position. Comparable calculations show that when swap positions are held, the percent of the total position was 8% for soybean oil, 7% for CBOT wheat, 24% for cotton, and 21% for soybeans. Swap positions were not continuously held in these markets. For instance, on the last day of the data set, May 30, 2012, swap positions were only held in three of the five markets. When analyzing the potential impact of positions on market returns, the swap positions are combined with the futures positions to arrive at a total or aggregate position for each market. Notably, this is an improvement over studies that use firm-level daily position data from the CFTC's non-public LTRS (e.g., Buyuksahin, and Harris 2011; Aulerich, Irwin, and Garcia 2013), which does not record swaps positions and therefore may not accurately reflect total commodity exposure (Irwin and Sanders 2012; Sanders and Irwin 2013). The data set did not include any instances of a short total position in any market. So, the total position in each market is long-only.

This unique data set also provides the ability to distinguish between trading that represents new investment in the Fund and trading that represents roll transactions. Changes in the aggregate long position held by the fund clearly represent outright buying or selling. However, there are also days with active trading but no change in the overall long position within a market. On those days, the Fund is “rolling” or transferring long market positions from one calendar maturity month to another. The normal roll transaction is selling nearby contracts and simultaneously buying the next listed contract; thereby, the long position in the nearby contract is transferred to the next active contract.

From the detailed position data, a series is created that represents the number of contracts that are “rolled” between futures contracts within a market. For example, if the aggregate long position increases by 100 contracts and a total of 100 contracts was traded across calendar months, then there were no roll transactions and the net new investment is represented by the aggregate increase of 100 contracts. If, however, the aggregate long position increases by 100 contracts and 300 contracts trade across the calendar months, then 100 of the contracts traded were to establish the new position and 200 total trades (100 sells and 100 buys) represented the rolling or moving of 100 positions across calendar months. The size of “roll transactions” will be used to analyze the impact on futures spreads. The ability to precisely identify roll transactions for the Fund is a potential improvement over prior research, which has mostly relied on assumed roll “windows” or aggregate position size as an indicator (Stoll and Whaley 2010; Aulerich, Irwin, and Garcia 2013). The data set here provides a detailed and direct measure of rolling activity.

Position Trends and Characteristics

Figure 1 shows the notional value of Fund positions in all 22 U.S. markets that are actively traded. Notional value is simply the net position of the Fund multiplied by the relevant futures contract price. The total position size (futures plus swaps) grows from under $4.0 billion in 2007 to $12.0 billion in 2011 and then stabilizes between $10.0 and $12.0 billion. As a standard of comparison, the total positions held by the Fund are compared to those reported in the CFTC's IID report. In Figure 2, the total notional value of index positions for U.S. markets reported in the IID are plotted alongside those held by the Fund for each quarter-end from December 31, 2007 to March 30, 2012. Over the sample period, the Fund's total position and that reported in the IID have a positive correlation of 0.86 in levels and 0.97 in differences. The Fund has grown more rapidly than the industry, with the Fund's portion of the industry increasing from 3.0% in late 2007 to a high of 7.6% in 2012.

The Fund's holding on a market-by-market basis are also compared to the 21 markets in the IID that coincide with those traded by the Fund. The percent of index positions held in each market are shown for April 30, 2012 in table 1. With regard to allocation across markets, the Fund's holdings are not markedly different from that found in the IID. The top eight holdings for both the Fund and the industry (IID) are the same and account for over 70% of both the Fund and IID investment allocation. The Fund's agricultural holdings are also compared to those reported in the SCOT report for the nearest date available, May 1, 2012 (table 2). On this date, the top five agricultural markets are the same and make up over 70% of the holdings in the 12 SCOT agricultural markets. Notably, across markets in tables 1 and 2, the Fund's holdings are fairly consistent at just under 10% of the industry holdings in each market. The exceptions are feeder cattle and soybean meal, which are not included in some of the more popular commodity indices (e.g., S&P GSCI). Overall, the Fund's allocation across markets and aggregate investment flow through time do not differ substantially from that observed for the industry as a whole. In that regard, the Fund's position data should be representative of industry participation and activity in the agricultural futures markets.

The position characteristics for calendar year 2011 are presented in table 3 along with a comparison to statistics for each futures market. The first column shows the average position size in contracts. The largest number of contracts was held in the corn futures market at 22,495 contracts, which represents 1.6% of the open interest in that market. The Fund's position averages 2.7% of the open interest across the 14 markets in table 3. The largest relative position is held in MGEX wheat at 5.6% of the open interest (on average) in 2011. The Fund is not an active trader from an outright buying or selling perspective. In 2011, the number of days with a position change in CBOT wheat was 129 out of 252 possible trading days, or 51%. So, while trading may occur in bursts, it averages about every other day in CBOT wheat. Position changes are most frequent in corn (161 days) and least common in MGEX wheat (69 days). The relative amount of trading across markets is roughly proportional to the position size in each market which reflects a more frequent need to re-balance larger positions.

The third column in table 3 presents the absolute average daily change in the position for each market in 2011. Since changes in net positions are relatively infrequent, the average is only calculated for days on which there is a change in the position. The change in the aggregate position in each market represents the minimum amount of trading that must have occurred on that day in that market. So, if the net position in a market increases from 1,000 contracts to 1,200 contracts, then a minimum of 200 contracts were bought that day (although not necessarily at the same time). Conversations with Fund management suggest that most trading occurs at the end of the day near the closing price. For 2011, the average change in positions across all markets is 58 contracts. The largest is in corn at 244 contracts followed by soybeans (133) and sugar (80). Relative to the average daily volume in each market, the average change in the Fund's position is very small—averaging just 0.1% of daily trading volume across markets. The maximum or largest position change for each market is also shown in table 3 (column 4). Clearly, the Fund does have days with heavy trading. This is especially noteworthy in cotton where the Fund traded 1,209 contracts in a single day which represents 5.8% of the average daily trading volume for cotton (20,984). Likewise, in MGEX wheat the Fund's maximum position change (243) represents 3.5% of average daily volume (6,874). Still, even the maximum position changes are generally a small portion of trading volume and average just 1.3% across all markets. It is important to note that the trading does appear to be clustered. The pattern of trading through the month is illustrated in figure 3, where a majority of the activity occurs at the end of the month when new inflows are most likely to occur.

Further evidence on the characteristics of the Fund's positions is provided in table 4, which shows the Fund's position size along with the average index trader as reported in the SCOT report. The average SCOT index trader's position is calculated as the net long index position in each market divided by the number of reporting long index traders in that market. As a comparison, the average corn position size in 2011 was 22,493 contracts for the Fund, which was larger than that held by the average SCOT index trader (13,484). Indeed, the Fund's average position size is larger than the average index trader in every market except CBOT wheat, where the Fund increases overall wheat exposure by using the CBOT, KCBOT, and MGEX wheat contracts. Interestingly, in only two markets—cotton and sugar—does the Fund's week-to-week position change exceed that of the average SCOT index trader. Among index traders, the Fund is a relatively large market participant.

The position data confirm the idea that index traders in general, and the Fund in particular, are not overly active on a daily basis in terms of outright buying and selling. That is, the change in the aggregate position is relatively small while the overall position is relatively large. Not surprisingly then, the Fund must make fairly large, yet somewhat infrequent, transactions to roll or switch long positions from the nearby expiring futures contract to the next.

The frequency and size or the Fund's roll transactions are shown table 5. On average, the fund is active rolling futures positions 70 days per year, or 28% of the trading days. Rolling occurs most frequently in corn (on 96 days) and is least frequent in cocoa (on 37 days). The average roll transactions shifts 5.4% of the position across futures contracts. Given the overall position size that must be rolled, the size of roll transactions are relatively large with the largest relative roll size in cocoa (301 contracts, 11.5% of position), soybean meal (479 contracts, 11.1% of position) and MGEX wheat (319 contracts, 10.5% of position). The maximum roll transactions are indeed quite large with both MGEX wheat and cocoa having maximums that are over 60% of the average position size. Across markets, the average maximum roll is 32.6% of the position size which suggests that nearly one-third of the position is sometimes rolled in a single day.

As shown in figure 4, the Fund rolls positions primarily between the 8th and 15th day of the calendar month which is consistent with the rest of the industry (Aulerich, Irwin, and Garcia 2013). Notably, the size of the roll transaction in each market is larger than changes in the outright position which makes investigating the impact of rolling on market spreads particularly interesting with this data set.

Empirical Methods and Results

To match up with the Fund's (long) positions, daily log relative returns, R_t, are calculated using nearby futures contracts adjusting appropriately for contract roll-overs as follows:

(1) $$R_t^1 = \ln\left(\frac{p_t^1}{p_{t-1}^1}\right) * 100$$

where, p_t^1 is the futures price of the first listed or nearest-to-expiration contract on each trading day. In order to avoid distortions associated with contract rollovers, p_t^1 in the log relative price return always reflects the same nearest-to-expiration contract as p_{t-1}^1. Roll-over dates for the 13 markets are set on the 15th of the month prior to the delivery month. The rolling patterns observed in the position data did not appear to be standard across all markets. However, the majority of contract switching generally occurs in the days around the 15th of the month prior to delivery as shown in figure 4.

Returns for the second or next active futures contract are also calculated as follows:

(2) $$R_t^2 = \ln\left(\frac{p_t^2}{p_{t-1}^2}\right) * 100$$

where p_t^2 is the settlement price of the second or next actively listed energy futures contract on each trading day. For example, if the nearby return in crude oil is calculated using the March futures, then the second listed contract return is calculated using the April contract. The same conventions as described above for switching contracts are used to create a series of daily returns (R_t^2) for the second listed contract for each market.

While some prior researchers have used various absolute measures of the spread between the first and second contract—e.g., differences, price ratios, or percent of full carry—these measures can be problematic as it is difficult to account for differing storage costs and term structures across markets. Therefore, tests for the impacts of rolling activity focus on a more direct measure of changes in the spread, which is the simple difference in the return between the first and the second listed contracts:

(3) $$\Delta Spread_t = R_t^1 - R_t^2.$$

Note that $\Delta Spread_t = R_t^1 - R_t^2 = \ln\left(\frac{p_t^1}{p_{t-1}^1}\right) - \ln\left(\frac{p_t^2}{p_{t-1}^2}\right) = \ln\left(\frac{p_t^1}{p_t^2}\right) - \ln\left(\frac{p_{t-1}^1}{p_{t-1}^2}\right)$ is equivalent to the log relative change in the price ratio or slope of the futures curve on day *t* (correctly adjusted for contract switching). As such, it accurately captures the relative movement in the nearby and second-listed futures contracts. The *ΔSpread* variable is stationary for all 13 markets. Additionally, the average correlation coefficient across markets for R_t^1, R_t^2 is 0.98; so, using the *ΔSpread* variable substantially reduces the variance of the dependent variable in regression models and increases statistical power in time-series tests.

Correlation Coefficients

As a first step in testing for possible market impacts, Pearson correlation coefficients are calculated between the change in positions and market returns on the same day (contemporaneous correlation). The lagged correlation is calculated between the change in the net position and the market return the following day. The Pearson correlation coefficients are calculated over 1,176 data points in each market. So, the correlations have a standard error of $\sqrt[2]{\frac{1}{n-3}}$ or 0.0292 and any correlation that is greater than 0.057 (1.96 x 0.0292) in absolute value is statistically different from zero (5% level, two-tailed t-test).

As shown in table 6, the average contemporaneous correlation across markets is positive.[4] But, the relationship is statistically significant in only 2 of the 13 markets (feeder cattle and lean hogs). So, while these two correlations are positive—suggesting that increases in long positions (buying) coincide with upward price movement—they should be interpreted cautiously for a number of reasons. First, the correlations are of a very small magnitude (0.06) and of questionable economic importance. Second, and most important, there are no statistically significant correlations between changes in positions and market returns on the following day. That is, there is no evidence that the buying in these markets precedes a price increase as none of the 1-day lagged correlations are statistically different from zero.

The correlations between roll transactions and spread changes are also shown in table 6. The correlations are calculated in a contemporaneous fashion, as well as with a 1-day lag between the roll position and subsequent spread change. Notably, the average correlation across all markets for both the contemporaneous and lagged correlations is negative. For the contemporaneous correlations, eight correlation coefficients are statistically different from zero at the 5% level and seven of them are negative. Two of the markets—cotton and coffee—continue to show a negative and statistically significant correlation the following day.

The correlation coefficients in table 6 suggest a possible linkage between roll transactions to market spreads. However, the direction of the impact is negative which is the opposite implied by a price pressure effect. Indeed, the negative correlations suggest that when the fund is rolling long positions (selling nearby, buying deferred) the nearby contract's price is actually increasing relative to the deferred contract's price.

Difference-in-Means Test

Another approach to understanding potential market impacts is to test if returns are different following days where there is active buying (increase in long position) or selling (decrease in long position) as compared to days following no activity (no change in the position). The difference-in-mean returns conditioned on market activity can easily be tested within the framework proposed by Cumby and Modest (1987) because the disaggregated position data allows us to precisely divide the sample into trading and non-trading days for a single large entity. The Cumby-Modest regression is:

(4a) $$R_t^1 = \alpha + \beta_1 Buying_{t-1} + \beta_2 Selling_{t-1} + \epsilon_t$$

where $Buying_{t-1}$ = 1 if there is an increase in the long Fund position on day *t-1* (0 otherwise) and $Selling_{t-1}$ = 1 if there is a decrease in the long Fund position on day *t-1* (0 otherwise). In equation (4a) the following day's nearby futures return conditioned on buying ($\alpha + \beta_1$) is statistically different from the unconditional market return (α) if the null hypothesis $\beta_1 = 0$ is rejected using a *t*-test. Likewise, the following day's nearby futures return conditioned on selling ($\alpha + \beta_2$) is statistically different from the unconditional market return (α) if the null hypothesis $\beta_2 = 0$ is rejected. Equation (4a) is estimated for each market individually using OLS and the Newey-West covariance estimator which is consistent under general forms of heteroskedastic and serial correlation. It is also estimated across all markets in a pooled estimation using White's estimator to correct for cross-market heteroskedasticity.

The behavior of spreads following days with active rolling are investigated in a parallel fashion.

(4b) $$\Delta Spread_t = \alpha + \beta_1 Buying_{t-1} + \beta_2 Selling_{t-1} + \epsilon_t$$

where $Buying_{t-1}$ = 1 if positive roll transactions are transacted (buy nearby/sell deferred) on day *t* (0 otherwise) and $Selling_{t-1}$ =1 if negative roll transactions (sell nearby/buy deferred) are transacted on day *t-1* (0 otherwise). In equation (4b), the change in the spread (ΔSpread) conditioned on buying ($\alpha + \beta_1$) is statistically different from the unconditional change in the spread (α) if the null hypothesis that β_1=0 is rejected using a *t*-test. Likewise, the change in the spread conditioned on selling ($\alpha + \beta_2$) is statistically different from the unconditional market return (α) if the null hypothesis that β_2=0 is rejected.

The estimation results for (4a) are presented in table 7 for each market individually as well as a model pooled across all 13 markets. None of the estimated slope coefficients is statistically different from zero at the 5% level. On days following buying and selling, market returns are no different than on days following no change in the position. The result holds true across all individual markets as well as the pooled estimates across markets. The results provide no evidence that market returns are different when conditioned on fund buying or selling.

Table 8 shows the results of estimating (4b) when the change in the spread is conditioned on spread buying or selling the previous day. For individual markets, two of the conditional means are statistically different from the unconditional mean at the 5% level (KCBOT wheat and cotton) and another 2 at the 10% level. Notably, each of these rejections of the null is associated with a negative impact where positive (negative) roll activity is followed by a negative (positive) change in the calendar spreads. The pooled estimation of (4b) shows that on the day after traditional negative roll transactions (sell nearby futures, buy deferred futures), there is a statistically significant and systematic tendency for the nearby contract to gain on the deferred contract by 0.026% (*p*-value = 0.001). Due to the large number of observations in the pooled model, this provides convincing statistical evidence that futures spreads tend to narrow following the Fund's rolling of long positions. This result differs markedly from the accusation that index funds may cause spreads to widen (nearby futures lose relative to deferred futures). Instead, it suggests the opposite; the market moves towards the Fund's spread trades.

It is also worth noting that the magnitude is generally small from a return perspective. Consider the results for CBOT wheat spreads in table 8, where the mean change in the nearby-deferred spread on days with spread selling, or negative roll transactions, was 0.02%. Since the average wheat market prices was \$6.70 per bushel over the sample, two basis points represents less than one-quarter of a cent. The impact on a single day—while statistically significant—may be smaller than the bid-ask spread for most markets. An exception is cotton, where the impact of 0.00115% on a \$0.8688 per pound item is \$0.001 or \$50 per contract. It is also important to remember that the coefficients in table 8 reflect one-day impacts. The total economic importance would clearly be greater over a 5-day rolling window as depicted in figure 4.

Granger Causality Tests

Following prior researchers (e.g., Stoll and Whaley 2010), we consider the causal relationship between market returns and the change in Fund positions. Under the null hypothesis that changes in positions do not Granger cause market returns, the following linear regression is estimated for each market:

(5a) $$R_t^1 = \alpha + \sum_{i=1}^{m} \gamma_i \ R_{t-i}^1 + \sum_{j=1}^{n} \beta_j \, \Delta Position_{t-j} + \epsilon_t$$

where return variables are defined as before and $\Delta Position_{t-j}$ is the change in the Fund long position (all contracts) for the market on day *t-j*. The lag structure (*m*,*n*) for each market is determined by a search procedure over *m* = 30 and *n* = 30 using OLS and choosing the model that minimizes the Schwartz criteria to avoid over-parameterization. If the OLS residuals demonstrate serial correlation (Breusch-Godfrey Lagrange multiplier test), additional lags of the dependent variable are added until the null of no serial correlation cannot be rejected.

Traditional bivariate causality in a single market, *k*, is tested under the null hypothesis in (5a) that changes in positions cannot be used to predict (do not lead) market returns: $H_0 : \beta_j = 0$ for all *j*. A rejection of this null hypothesis, using an *F*-test of the stated restriction provides direct evidence that position changes are indeed useful for forecasting returns in that market. For each market, $\sum_{j=1}^{n} \beta_j$ is calculated as an indicator of the direction of market impact.

Following the lead of Capelle-Blancard and Coulibaly (2011), equation (5a) is also pooled and modeled as a system of seemingly unrelated regressions (SUR). Since the error term, ε_t, in (5a) is correlated across markets the power of causality tests can be increased by employing a GLS estimator within Zellner's seemingly unrelated regression (SUR) framework (see Harvey, 1991, p. 66). Under the SUR approach, GLS parameter estimates are the best linear unbiased coefficient estimates. The efficiency gains over OLS estimates increase with the correlation between the residuals across markets and with the number of equations. To specifically test for a systematic impact across markets, common coefficients are specified for β_j on the lagged position variables across markets.[5]

Using the same specification procedure, an analogous model is estimated and used to test for causality running from the Fund’s roll activity to changes in futures market spreads:

(5b) $$\Delta Spread_t = \alpha_k + \sum_{i=1}^{m} \gamma_i \, \Delta Spread_{t-i} + \sum_{j=1}^{n} \beta_j \, Roll_{t-j} + \epsilon_t$$

where $Roll_{t-j}$ represents the rolling of positions across calendar months. The standard roll of selling nearby and buying deferred contracts is recorded as a negative quantity (e.g., -500 contracts). The null of no causality is tested again as $H_0 : \beta_j = 0$ for all j.

Table 9 shows the test results for the individual markets examining both returns (5a) and spreads (5b). Focusing on the estimations for returns (5a), the (*m*,*n*) lag structure that minimized the SIC was somewhat trivial with only the soybean meal model containing more than one lag of the position variable. The *p*-values for the null hypothesis of no causality $H_0 : \beta_j = 0$ for all j in (5a) indicates that the null hypothesis is not rejected for any market. The magnitude of the estimated slope coefficients are noticeably small in absolute terms and not statistically different from zero. It is then not surprising that the common coefficients on lagged position changes in the pooled model are not statistically different from zero across this group of markets. Again, there is no evidence of a systematic impact from the Fund's change in position to market returns.

Table 9 also shows the results for estimating equation (5b) and testing for causality between the Fund's rolling activity and changes in calendar spreads. There is again some evidence of a causality running from roll transactions to spreads. In particular, the null hypothesis is rejected at the 5% level for two markets (KCBOT wheat and coffee) and at the 10% level for two markets (cotton and live cattle). Importantly, the direction of the impact is negative in these four markets as well as two markets of marginal significance (CBOT wheat and cocoa). Given the number of marginally significant rejections in individual markets and the consistency of the signs, it is not surprising that the pooled model rejects the null of no causality with a *p*-value of 0.0215. The common coefficient suggest a very small negative impact where a -100 contract traditional roll increases the nearby-deferred calendar spread by 0.0019%. While statistically significant, by itself, this would seem to be of doubtful economic importance. Still, the Fund's rolling activity occurs over roughly 5 days (figure 4) and the maximum roll within a market is often in excess of 1,000 contract per day. So, the cumulative impact may indeed by of economic significance.

Figure 5 graphically depicts the average daily roll and average daily change in the futures spread across calendar days for cotton. The negative relationship documented in tables 6, 8, and 9 for cotton are very apparent in the figure. Notably, the direction of this leading relationship is the opposite of what would be found if the Fund's trading were "pushing around" the spreads. Indeed, the overall spread analysis and results indicate that the Fund is rolling positions when the market gives them the opportunity or is moving "toward their trade." This result is consistent with the empirical findings of Aulerich, Irwin, and Garcia (2012). It is also consistent with a "sunshine trading" effect (Admati and Pfleiderer 1991), where large traders essentially preannounce their intentions and thereby attract potential counterparties, increase liquidity, and lower trading costs (Bessembinder, et al. 2012).

Long Horizon Tests

The previous three tests are designed to detect the relationship, if any, between daily position changes and returns. Those tests are important because of the uniqueness of this daily data set. However, these tests may have low power to reject the null hypothesis for two reasons. First, the dependent variable in the regressions—the change in commodity futures prices—is well-known to be highly volatile. Second, index positions may flow in "waves" that build slowly, pushing prices higher, and then fading slowly (e.g., Summers 1986). In this scenario, horizons longer than a day may be necessary to capture the predictive component of index fund positions. Consequently, we implement the long-horizon regression model as described by Valkanov (2003):

(6) $$\sum_{i=0}^{m-1} R_{t+i}^{1} = \alpha + \beta \sum_{i=0}^{k-1} \Delta Position_{t+i-1} + \epsilon_{t+1}$$

where all variables are defined as before. In essence, equation (6) is an OLS regression of a *k*-period moving sum of the dependent variable at time *t* against an *m*-period moving sum of the independent variable in the previous period, time *t*-1. If the estimated β is positive (negative), then it indicates a fads-style model where prices tend to increase (decrease) slowly over a relatively long time period after widespread index fund buying (selling). The fads stylization captured in (6)—with a positive β—is consistent with the Masters Hypothesis that position changes can drive bubble-like price behavior in commodity futures prices.

The long-horizon regression (6) is estimated using the underlying dependent variable of returns and the independent variable of change in positions.[6] Both of these variables are stationary, so the sums are also stationary. Valkanov (2003) demonstrates that the OLS slope estimator in this specification is consistent and converges at a high rate of T. The specification in (6) clearly creates an overlapping horizon problem for inference. 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.

Recently, Singleton (2013) and Hamilton and Wu (2013) use a variation of this model where m=1 and k=13 weeks. Singleton refers to the 13-week position change as the "flow" of investment funds and finds considerable predictability between the imputed measure of investment flows and crude oil futures returns. Hamilton and Wu (2013) find that the impact is isolated to crude oil, appears to be sensitive to the lag-length chosen, and does not hold up out-of-sample. As a first step in testing for long-run relationships, we mirror the weekly data frequency used by Hamilton and Wu (2013) by setting m=5 and k=65 days which essentially equals the 1-week returns and 13-week investment flow identified by Singleton (2013). Additional long-horizon regressions (6) are estimated over alternative horizons of m=k=20, 60, 120, and 240 trading days, which approximately correspond to monthly, quarterly, semi-annual, and yearly time horizons. The estimated OLS β coefficients for (6) are shown in table 10 along with the re-scaled t-statistic. Critical values for the rescaled t-statistic (-0.563, 0.595) are taken from Valkanov's (2003) Table 4 for Case 2 and c = -5.0, δ = 0.00, T = 750, and tail values representing the 10% significance level. These represent a conservative case that, if anything, favors a rejection of the null hypothesis that the slope equals zero.

The Singleton case (m=5, k=65) is shown in the first set of columns. The estimated slope coefficients for this case are noticeably small and the rescaled t-statistics do not exceed Valkanov's critical values for any of the markets. Likewise, in all of the other cases (m=k=20, 60, 120, 240) not a single estimated slope coefficient is statistically different from zero. Moreover, among the 65 slope coefficients estimated 25 (39%) are negative and 40 (61%) are positive, so there is little consistency with regard to the direction of any impact. These results are similar to those reported by Hamilton and Wu (2013) for agricultural markets and provide no evidence that the Fund's market positions impact commodity futures returns over longer horizons. Importantly, the results also indicate that the failure to detect causal linkages between Fund position changes and price changes in earlier tests was likely not due to problems with the statistical power of the tests.

Summary and Conclusions

After the experience of recent spikes in commodity prices, policymakers are considering additional speculative position limits and other restrictions on futures market participation. Empirical studies examining the linkages between futures market activity and price fluctuations are an important input to the regulatory process. This study brings fresh data to the debate regarding the price impact of long-only index investment in commodity futures markets. Here, high frequency daily position data for 13 agricultural futures and swaps markets are available from a representative large commodity index fund ("the Fund") from October 1, 2007 through May 30, 2012. The empirical results provide a unique look at potential market linkages that may not be captured with the more aggregate data sets available from the U.S. Commodity Futures Trading Commission (CFTC).

A battery of statistical tests found no causal relationship between the Fund's outright buying and selling and market returns. Simple correlation tests and Granger causality tests uniformly fail to reject the null hypothesis that changes in positions do not lead market returns in any individual market or across the system of markets. Difference-in-means tests show no statistical difference in market returns on the days after the Fund trades compared to days following no trading. Long-horizon regressions find no evidence that changes in Fund positions exert longer-term pressure on returns in any of the 13 markets. There were no tell-tale signs of any causal linkages between fund position changes and price changes.

Statistically significant findings are documented between the Fund's rolling of long positions across calendar months and changes in futures price spreads. That is, there was consistent evidence of a negative relationships between roll transactions and the change in the nearby-deferred futures spread. In particular, the nearby futures spread narrowed (nearby futures return was greater than the deferred futures return) on days following roll transactions (selling nearby, buying deferred). The result shows up consistently across different statistical tests including Pearson correlation coefficients, difference-in-means tests, and Granger causality tests. Importantly, the directional result is consistently negative across all of the tests. The negative relationship is inconsistent with a price pressure hypothesis but is much more consistent with a "sunshine trading" effect, where liquidity is actually increased by index fund rolling activity.

In sum, the results of this study add to the growing body of literature showing that buying pressure from index funds was not one of the main drivers of the spikes in food commodity prices in recent years. The results presented here are especially compelling because they are based on daily position data that does not suffer from several of the criticisms that have been leveled against the more commonly used weekly aggregate position data from the CFTC. In particular, the data allow for detailed tests over daily horizons with 13 different agricultural markets and includes both futures and swaps positions.

The empirical evidence presented here and found in prior studies should be relevant inputs into the CFTC's rule-making process. The CEA sets what appears to be a high bar for justifying position limits. First, it must be demonstrated that position limits are "necessary" to prevent excessive speculation from "causing sudden or unreasonable fluctuations or unwarranted changes in the price of [a] commodity." Second, position limits must be "appropriate" in their balance between the prevention of excessive speculation and market manipulation with ensuring sufficient market liquidity and price discovery (Young, Gagoomal, and Kearns 2012). The necessary empirical evidence linking "excessive speculation" to "unwarranted price changes" is scant. In a comprehensive review, Will, et al. (2012, p. 18) concluded that "…most empirical studies are unable to confirm that financial speculation has led to an increase in the price levels of agricultural commodities." From a more legal perspective, Notini (2013, p.3) argues that "The CFTC ignored modern commenter-submitted studies that refute a connection between speculation and price swings. If the CFTC had considered these studies, it might have concluded that the connection between excessive speculation and drastic price movement is an unjustified theory…" The research presented here bolsters that conclusion. While no single empirical study is entirely conclusive, the body of empirical evidence is quite convincing. At this point in the policy debate, there is very little evidence that long-only index funds or other speculators are "causing…unwarranted fluctuations in price." Thus, a clear verdict can be reached—new limits on speculation in agricultural futures markets are unnecessary.

End Notes

[1] The proprietary data for this research were provided under the stipulation that it be kept confidential. For simplification, the index fund will simply be referred to as the "Fund" and detailed position data or statistics that might compromise confidentiality are not presented.

[2]This article focuses on the 13 agricultural markets because they are of most interest to readers of *Applied Economic Perspectives and Policy* and it facilitates a comparison to the 12 agricultural markets included in the CFTC's *Supplemental Commitments of Traders* (SCOT) report. Sanders and Irwin (2014) use the firm-level data set to examine similar issues in the energy markets.

[3] Data are also available for Minneapolis Grain Exchange (MGEX) wheat. However, the series doesn't start until October 30, 2009 and is excluded from the time series models. However, it is included in the tables displaying summary statistics for calendar year 2011.

[4] In table 6 and following tables the markets are ordered in a fashion that groups like markets (grains, livestock, and softs).

[5] Sanders and Irwin (2011) suggest a more rigorous systems approach to estimating (5a) and (5b). However, the independent variables only enter the specification at very short lags (m=1, n=1) in this case making the systems estimation somewhat trivial.

[6] The long-horizon regressions specified in (6) are not estimated for spreads as most price-spreads are bound by storage-related arbitrage conditions. Therefore, it doesn't make much intuitive or economic sense to test for longer-term "bubbles" in spread relationships.

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Table 1. Notional Values and Market Allocations of Fund and *Index Investment Data* (IID), April 30, 2012

Market	Fund	% Allocation	($ Billions) IID	% Allocation	Fund % of IID
Crude Oil	2.239	19%	38.400	25%	5.8%
Gold	1.508	13%	17.400	11%	8.7%
Soybeans	0.961	8%	13.800	9%	7.0%
Copper	0.823	7%	6.300	4%	13.1%
Natural Gas	0.804	7%	9.700	6%	8.3%
Corn	0.764	6%	11.900	8%	6.4%
Heating Oil	0.594	5%	7.800	5%	7.6%
RBOB Gasoline	0.567	5%	9.500	6%	6.0%
Live Cattle	0.544	5%	5.600	4%	9.7%
Sugar	0.497	4%	6.500	4%	7.6%
Silver	0.472	4%	5.100	3%	9.3%
CBOT Wheat	0.431	4%	7.000	4%	6.2%
Cotton	0.308	3%	3.400	2%	9.1%
Soybean Oil	0.299	3%	3.700	2%	8.1%
Lean Hogs	0.278	2%	3.100	2%	9.0%
Coffee	0.266	2%	2.900	2%	9.2%
Soybean Meal	0.184	2%	0.800	1%	23.0%
KCBOT Wheat	0.097	1%	1.300	1%	7.4%
Feeder Cattle	0.091	1%	0.600	0%	15.2%
Platinum	0.076	1%	0.600	0%	12.6%
Cocoa	0.063	1%	0.800	1%	7.9%
Total	**11.865**	**100%**	**156.200**	**100%**	**7.6%**

Notes: Positions for the industry are based on *Index Investments Data* (IID) reports from the U.S. Commodity Futures Trading Commission (CFTC). Allocations and totals only reflect the U.S. markets displayed in the table.

Table 2. Notional Values and Market Allocations of Fund and *Supplemental Commitment of Traders* (SCOT), May 1, 2012

Market	($ Millions) Fund	% Allocation	($ Millions) SCOT	% Allocation	Fund % of SCOT
Soybeans	1,030	22%	11,582	20%	8.9%
Corn	882	19%	13,560	23%	6.5%
Live Cattle	535	11%	5,344	9%	10.0%
Sugar	493	10%	5,943	10%	8.3%
CBOT Wheat	407	9%	6,817	12%	6.0%
Cotton	306	6%	3,255	6%	9.4%
Soybean Oil	293	6%	3,245	6%	9.0%
Lean Hogs	280	6%	3,126	5%	9.0%
Coffee	270	6%	2,633	5%	10.2%
KCBT Wheat	94	2%	1,143	2%	8.2%
Feeder Cattle	89	2%	550	1%	16.2%
Cocoa	67	1%	837	1%	8.0%
Total	**4,746**	**100%**	**58,034**	**100%**	**8.2%**

Note: Table 2 does not include Fund data for soybean meal because it is not included in the SCOT report.

Table 3. Fund Position Levels and Characteristics, Calendar Year 2011

	-----Fund-----				-----Futures Market-----		-----Fund's % of Market-----		
Market	**Average Position Size**	**Days Position Change**	**Average Position Change**	**Maximum Position Change**	**Average Open Interest**	**Average Daily Volume**	**Position Size**	**Average Change**	**Maximum Change**
Corn	22,495	161	244	905	1,385,738	313,511	1.6%	0.1%	0.3%
Soybeans	10,851	150	133	625	578,431	179,142	1.9%	0.1%	0.3%
CBOT Wheat	5,428	129	36	258	449,685	96,362	1.2%	0.0%	0.3%
KCBOT Wheat	4,892	98	22	245	174,531	21,807	2.8%	0.1%	1.1%
MGEX Wheat	3,039	69	25	243	54,307	6,874	5.6%	0.4%	3.5%
Soybean Meal	6,508	117	40	209	204,162	67,144	3.2%	0.1%	0.3%
Soybean Oil	4,302	79	46	590	322,936	95,859	1.3%	0.0%	0.6%
Cotton	4,314	123	68	1,209	161,690	20,984	2.7%	0.3%	5.8%
Live Cattle	11,684	154	34	383	337,577	53,701	3.5%	0.1%	0.7%
Feeder Cattle	1,441	70	8	62	39,196	6,271	3.7%	0.1%	1.0%
Lean Hogs	7,991	153	36	401	240,558	39,563	3.3%	0.1%	1.0%
Coffee	2,844	111	16	120	116,374	20,534	2.4%	0.1%	0.6%
Sugar	15,781	156	80	1,110	581,838	98,033	2.7%	0.1%	1.1%
Cocoa	2,619	73	19	206	165,822	19,635	1.6%	0.1%	1.0%
Average	**7,442**	**117**	**58**	**469**	**343,775**	**74,244**	**2.7%**	**0.1%**	**1.3%**

Note: MGEX wheat is included in the table because complete data were available for 2011. Average position changes and roll size reflect the absolute value of the change to reflect the size (not direction) of the position change. Position changes and roll size are only calculated for the days in which there is a non-zero change or roll.

Table 4. Fund Position Size, Position Change, and the Average Index Trader in the *Supplemental Commitment of Traders* (SCOT) Report, Contracts, Calendar Year 2011.

	-----Fund-----		-----Average SCOT Trader-----	
Market	**Position Size**	**Position Change**	**Position Size**	**Position Change**
Corn	22,493	185	13,484	339
Soybeans	10,853	93	6,254	157
CBOT Wheat	5,426	67	7,150	187
KCBOT Wheat	4,890	40	1,842	66
Soybean Oil	6,503	56	3,813	122
Cotton	4,348	106	2,003	80
Live Cattle	11,685	83	5,517	107
Feeder Cattle	1,441	10	481	21
Lean Hogs	7,985	78	4,079	93
Coffee	2,846	30	1,582	42
Sugar	15,757	215	7,432	206
Cocoa	2,619	26	1,701	80
Average	**8,071**	**82**	**4,612**	**125**

Notes: The data in table 4 are calculated only on weekly (Tuesday) dates that match up with the release of the SCOT report; therefore, they will differ slightly from those compiled from daily data in table 3. Soybean meal and MGEX wheat are not included in this table because it is not part of the SCOT report. SCOT average position data are calculated as the net long position divided by the number of reporting long index traders.

Table 5. Fund Position Levels and Roll Transaction Characteristics, Calendar Year 2011

Market	Futures Position	Number of Days with Roll Transaction	Average Roll Size	Average as a Percent of Position	Maximum Roll Size	Maximum as a Percent of Position
Corn	22,495	96	452	2.0%	3,324	14.8%
Soybeans	10,851	83	352	3.2%	2,926	27.0%
CBOT Wheat	5,428	70	101	1.9%	1,050	19.3%
KCBOT Wheat	4,892	61	330	6.7%	1,594	32.6%
MGEX Wheat	3,039	40	319	10.5%	1,875	61.7%
Soybean Oil	6,508	58	280	4.3%	2,552	39.2%
Soybean Meal	4,302	40	479	11.1%	1,756	40.8%
Cotton	4,314	59	163	3.8%	1,050	24.3%
Live Cattle	11,684	92	346	3.0%	1,160	9.9%
Feeder Cattle	1,441	95	107	7.4%	626	43.4%
Lean Hogs	7,991	85	185	2.3%	1,482	18.5%
Coffee	2,844	72	129	4.5%	1,089	38.3%
Sugar	15,781	96	475	3.0%	2,011	12.7%
Cocoa	2,619	37	301	11.5%	1,919	73.3%
Average	**7,442**	**70**	**287**	**5.4%**	**1,744**	**32.6%**

Note: MGEX wheat is included in the table because complete data were available for 2011. Average position changes and roll size reflect the absolute value of the change to reflect the size (not direction) of the position change. Position changes and roll size are only calculated for the days in which there is a non-zero change or roll.

Table 6. Correlation Coefficients between Daily Returns and Fund Position Changes, October 1, 2007 - May 30, 2012

	Returns		Spreads	
Market	**Contemporaneous**	**1-Day Lag**	**Contemporaneous**	**1-Day Lag**
Corn	0.0051	0.0273	-0.1323	-0.0134
Soybeans	0.0002	0.0124	-0.0475	-0.0314
CBOT Wheat	-0.0550	0.0283	-0.0600	0.0077
KCBOT Wheat	0.0484	0.0146	-0.0309	-0.0241
Soybean Meal	-0.0074	-0.0317	-0.0166	-0.0090
Soybean Oil	0.0273	-0.0069	-0.0133	-0.0133
Cotton	0.0376	0.0454	-0.1512	-0.0971
Live Cattle	0.0322	0.0451	-0.0507	-0.0562
Feeder Cattle	0.0636	0.0545	0.0759	0.0328
Lean Hogs	0.0667	-0.0306	-0.0682	-0.0360
Coffee	-0.0042	0.0440	-0.1040	-0.0794
Sugar	-0.0218	0.0385	-0.1934	0.0011
Cocoa	-0.0046	-0.0223	-0.1146	-0.0396
Average	**0.0145**	**0.0168**	**-0.0698**	**-0.0275**

Notes: Correlations are computed using all 1,176 observations and have a standard error of 0.0292. Gray shading highlights correlations that are statistically different from zero at the 5% level. The "Returns" column reflects the correlation between changes in the Fund position and daily market returns. The "Spreads" columns reflects the correlation between futures spreads and the Fund's roll activity.

Table 7. Cumby-Modest Difference-in-Mean Return Tests for Daily Fund Positions, October 1, 2007 - May 30, 2012

	-----Coefficient Estimates-----						-----Observations-----		
Market	**No Change**	**P-value**	**Buying**	**P-value**	**Selling**	**P-value**	**"no change**	**"buys"**	**"sells"**
Corn	0.077	0.435	-0.068	0.339	-0.084	0.318	531	321	323
Soybeans	0.081	0.335	-0.019	0.425	-0.006	0.544	570	348	257
CBOT Wheat	-0.051	0.601	-0.044	0.969	-0.227	0.339	587	293	295
KCBOT Wheat	-0.074	0.351	0.157	0.205	-0.234	0.350	737	212	226
Soybean Meal	0.122	0.083	-0.092	0.148	-0.031	0.388	794	217	164
Soybean Oil	-0.064	0.369	0.096	0.169	0.092	0.219	742	241	192
Cotton	-0.020	0.831	0.014	0.796	0.028	0.788	619	332	224
Live Cattle	-0.041	0.298	0.044	0.150	-0.087	0.488	512	309	354
Feeder Cattle	-0.015	0.680	0.034	0.482	-0.048	0.670	783	199	193
Lean Hogs	-0.075	0.255	-0.097	0.841	-0.029	0.669	525	349	301
Coffee	0.018	0.812	-0.067	0.568	-0.028	0.725	656	283	236
Sugar	-0.001	0.994	0.049	0.765	0.131	0.492	533	399	243
Cocoa	0.028	0.689	-0.049	0.639	-0.111	0.487	831	193	151
Pooled	0.000	0.997	-0.006	0.928	-0.054	0.433	8,420	3,696	3,159

Notes: Buying (selling) is defined as days when there is an increase (decrease) in the long Fund position. The "No Change" column reports the α intercept estimate, the "Buying" column reports the β_1 slope estimate, and the "Selling" column reports the β_2 slope estimate. The pooled model is estimated across all markets.

Table 8. Cumby-Modest Difference-in-Mean Spread Tests for Daily Fund Positions, October 1, 2007 - May 30, 2012

	-----Coefficient Estimates-----						-----Observations-----		
Market	**No Roll**	**P-value**	**Buying**	**P-value**	**Selling**	**P-value**	**"no roll"**	**"buys"**	**"sells"**
Corn	-0.013	0.112	0.021	0.532	-0.021	0.765	870	18	287
Soybeans	0.004	0.573	-0.038	0.210	0.002	0.838	889	14	272
CBOT Wheat	-0.026	0.007	-0.038	0.753	0.020	0.063	917	18	240
KCBOT Wheat	-0.017	0.024	-0.050	0.012	0.000	0.274	969	2	204
Soybean Meal	0.012	0.162	0.051	0.572	0.004	0.699	1,054	3	118
Soybean Oil	-0.001	0.466	0.017	0.439	-0.001	0.938	999	12	164
Cotton	-0.022	0.233	-0.054	0.721	0.115	0.002	928	13	234
Live Cattle	-0.019	0.038	0.056	0.545	0.017	0.077	829	6	340
Feeder Cattle	-0.009	0.196	0.199	0.462	-0.012	0.843	884	2	289
Lean Hogs	-0.008	0.698	-0.316	0.175	0.033	0.356	834	11	330
Coffee	-0.006	0.005	-0.006	0.975	0.004	0.229	969	10	196
Sugar	-0.021	0.260	0.046	0.618	0.001	0.553	880	11	284
Cocoa	-0.011	0.051	-0.025	0.632	0.058	0.147	1,022	12	141
Pooled	-0.010	0.004	-0.019	0.551	0.026	0.001	12,044	132	3,099

Notes: Buying (selling) is defined as days when the Fund is buying (selling) the nearby contract and selling (buying) he deferred contract. The “No Change” column reports the α intercept estimate, the “Buying” column reports the β_1 slope estimate, and the “Selling” column reports the β_2 slope estimate. The pooled model is estimated across all markets.

Table 9. Granger Causality Tests that Fund Position Changes Lead Market Returns, October 1, 2007 - May 30, 2012

	-------Returns------			-------Spreads------		
		p-value	Estimate		*p*-value	Estimate
Market	***m,n***	$\beta_j=0, \forall j$	$\sum \beta_j$	***m,n***	$\beta_j=0, \forall j$	$\sum \beta_j$
Corn	1,1	0.4043	0.0425	1,1	0.7969	0.0003
Soybeans	1,1	0.7831	0.0216	2,1	0.7778	-0.0004
CBOT Wheat	1,1	0.5883	0.0461	1,1	0.1255	-0.0041
KCBOT Wheat	1,1	0.5713	0.0461	12,1	0.0008	-0.0063
Soybean Meal	1,2	0.3895	-0.0658	2,1	0.6171	0.0011
Soybean Oil	1,1	0.7289	-0.0357	6,1	0.2343	-0.0007
Cotton	1,1	0.1789	0.1000	1,1	0.0686	-0.0390
Live Cattle	1,1	0.1591	0.0347	1,1	0.0587	-0.0052
Feeder Cattle	1,1	0.2467	0.1877	1,1	0.2305	0.0083
Lean Hogs	1,1	0.2337	-0.0494	4,1	0.1757	-0.0126
Coffee	1,1	0.1334	0.2868	1,1	0.0179	-0.0047
Sugar	2,1	0.0980	0.0908	2,1	0.7503	-0.0020
Cocoa	1,1	0.4482	-0.1577	1,2	0.1026	-0.0144
Pooled	2,2	0.6478	0.0054	12,2	0.0215	-0.0019

Notes: The estimated coefficients are scaled by 100. The pooled model is estimated across the 13 markets as an SUR system restricting the β_j, slope parameters to be equal across markets. These restrictions are imposed on the system and the common coefficients are estimated as a single pooled parameter across all 13 markets.

Table 10. Long-Horizon Regression Tests that Daily Fund Position Changes Impact Returns, October 1, 2007 - May 30, 2012

	m=5, k=65		m=k=20		m=k=60		m=k=120		m=k=240	
Market	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**
Corn	0.0004	0.03	0.0021	0.04	0.0045	0.05	0.0087	0.08	0.0120	0.11
Soybeans	0.0005	0.02	0.0006	0.01	0.0045	0.03	0.0049	0.02	0.0047	0.03
CBOT Wheat	0.0001	0.02	0.0002	0.01	0.0013	0.04	0.0006	0.01	-0.0020	-0.03
KCBOT Wheat	0.0009	0.05	0.0017	0.03	0.0031	0.04	0.0043	0.04	0.0114	0.07
Soybean Meal	-0.0004	-0.01	-0.0047	-0.06	-0.0034	-0.02	-0.0001	0.00	0.0056	0.04
Soybean Oil	-0.0002	-0.01	0.0014	0.02	0.0003	0.00	-0.0062	-0.03	-0.0126	-0.09
Cotton	-0.0013	-0.04	0.0013	0.01	-0.0047	-0.02	-0.0072	-0.02	-0.0058	-0.01
Live Cattle	0.0001	0.03	0.0011	0.04	0.0015	0.04	0.0018	0.04	0.0018	0.04
Feeder Cattle	0.0000	0.00	-0.0001	0.00	0.0023	0.02	0.0042	0.02	0.0061	0.03
Lean Hogs	0.0001	0.01	0.0013	0.04	-0.0004	0.00	0.0003	0.00	0.0051	0.04
Coffee	-0.0014	-0.03	-0.0057	-0.05	-0.0112	-0.04	-0.0092	-0.02	-0.0046	-0.01
Sugar	0.0000	0.00	-0.0003	-0.01	0.0029	0.03	0.0057	0.05	0.0059	0.12
Cocoa	0.0001	0.00	-0.0045	-0.02	-0.0072	-0.04	0.0005	0.00	-0.0034	-0.03

Note: This table reports the results of estimating long-horizon regressions between average daily returns and average daily positions held by The Fund. Critical values for the rescaled t-statistic (-0.563,0.595) are taken from Valkanov's (2003) Table 4 for Case 2 and c = -5.0, δ = 0.00, T = 750, and tail values representing the 10% significance level.

Figure 1. Daily Total Fund Notional Value for 22 U.S. Commodity Futures Markets, October 1, 2007 - May 30, 2012

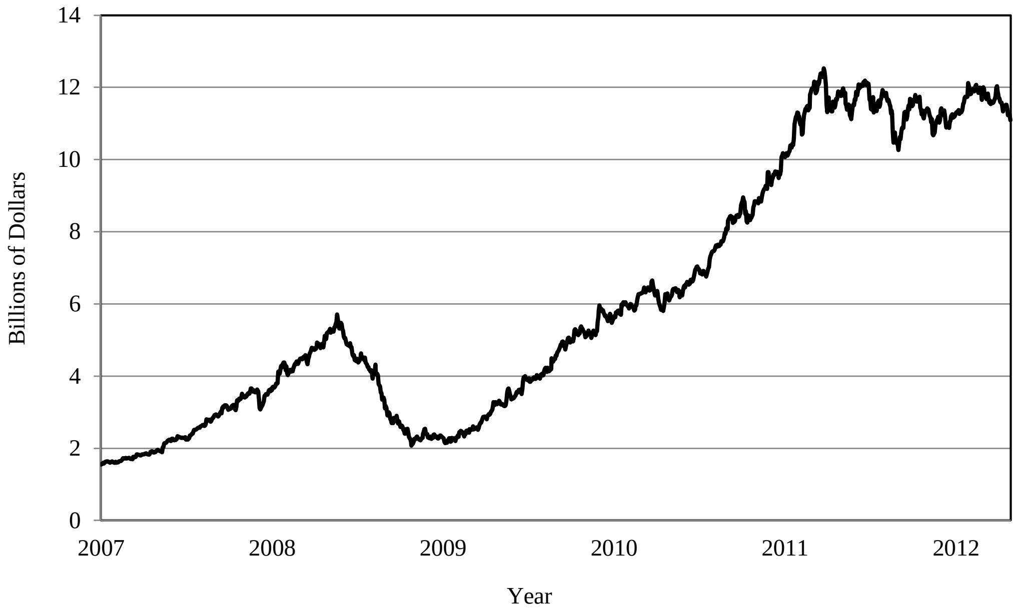


Figure 2. Comparison of Quarterly Fund and Total Index Investment Data (IID) Notional Value for 21 U.S. Commodity Futures Markets, December 2007 - March 2012

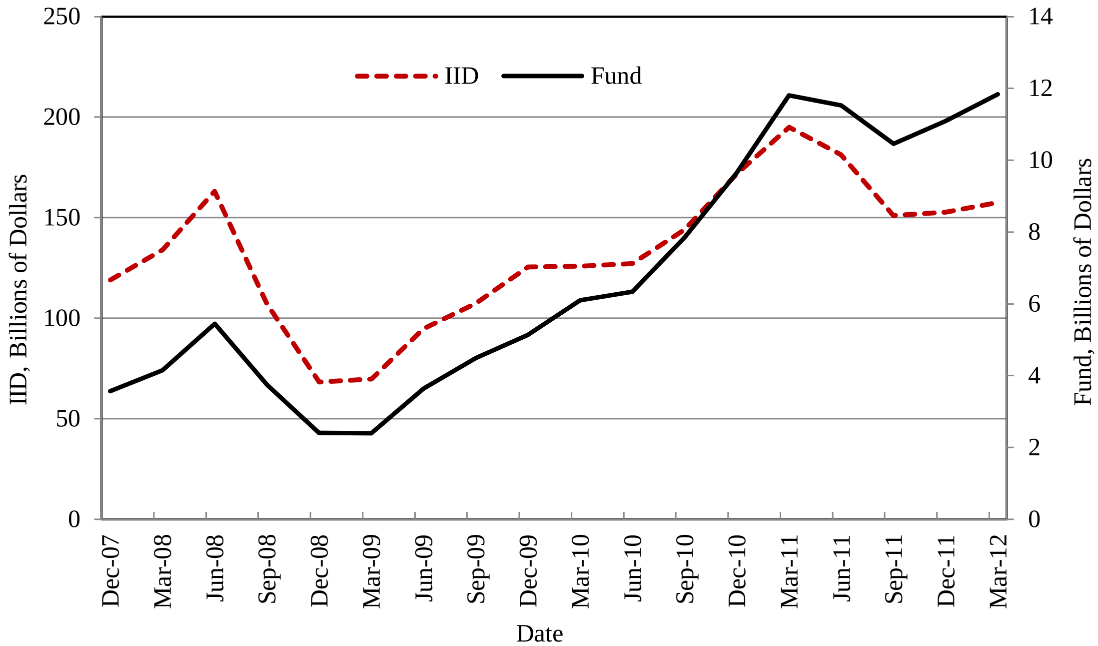


Figure 3. Average Fund Net Position Change by Calendar Day within the Month, 13 U.S. Agricultural Futures Markets, October 1, 2007 - May 30, 2012

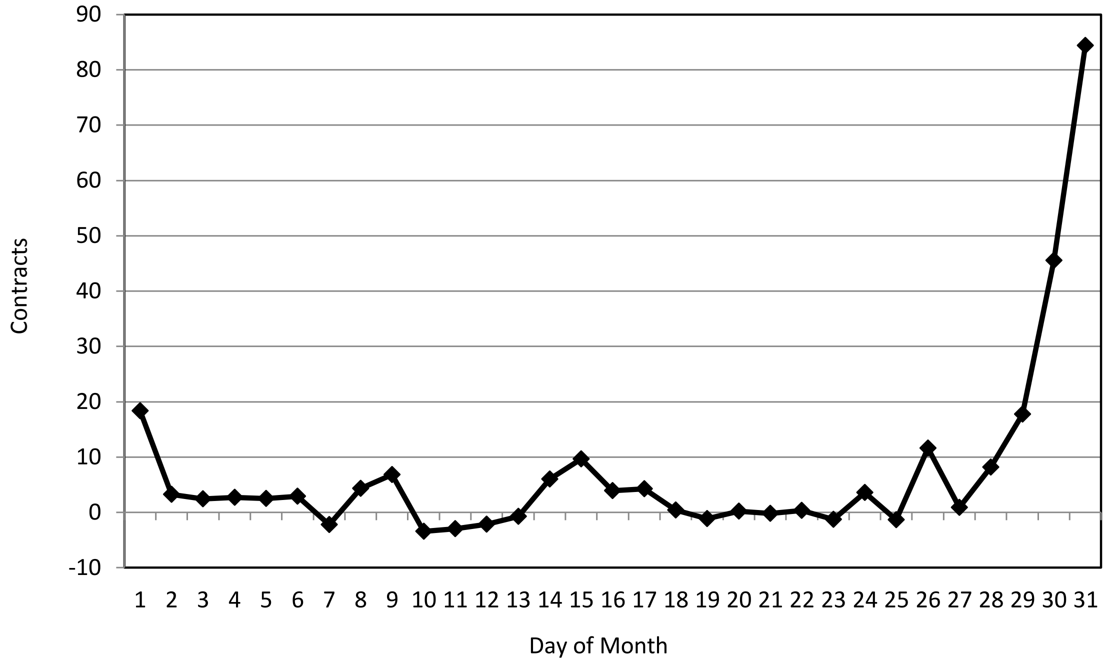


Figure 4. Average Fund Roll Position Change by Calendar Day within the Month, 13 U.S. Agricultural Futures Markets, October 1, 2007 - May 30, 2012

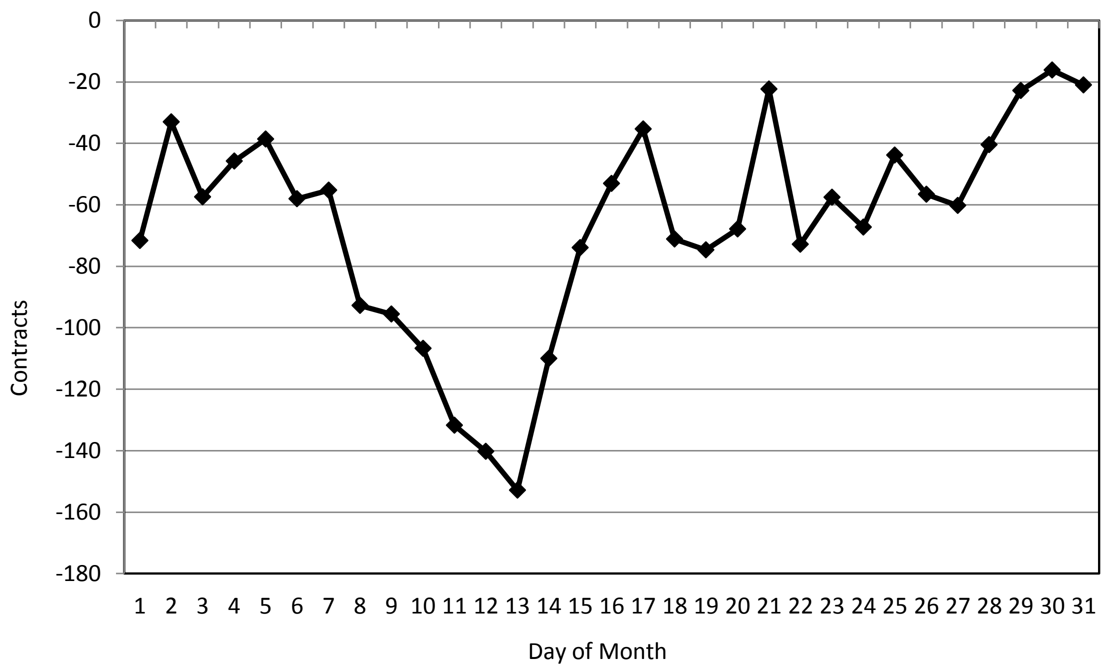
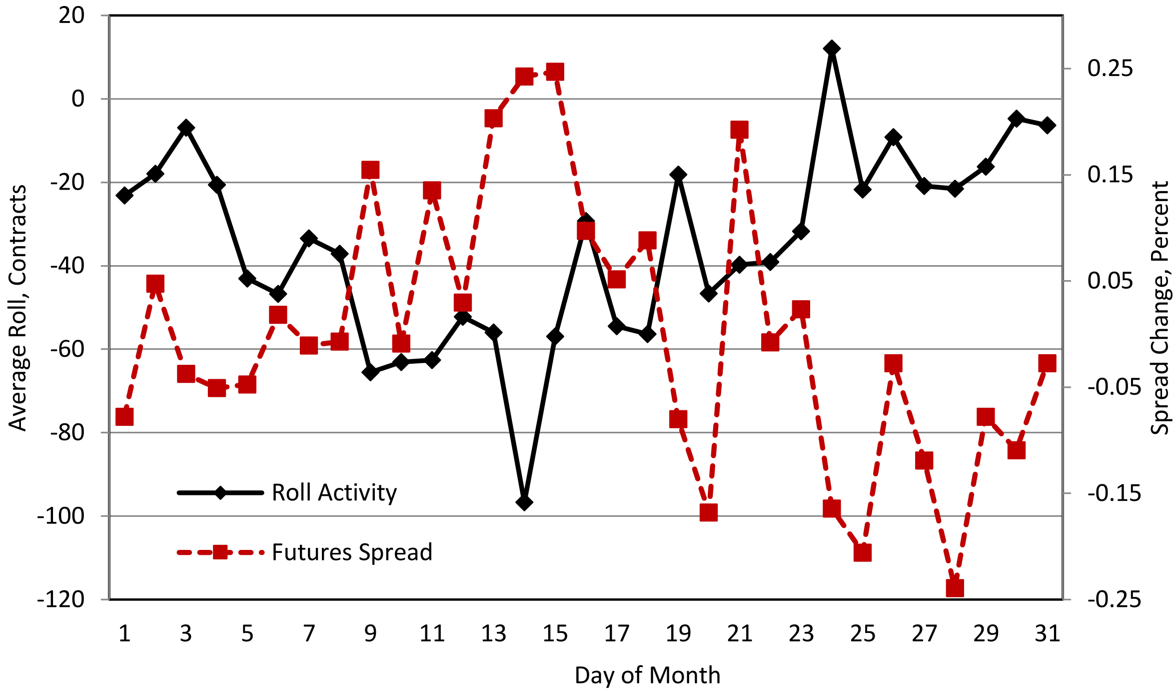


Figure 5. Average Fund Roll Position by Calendar Day within the Month and the Average Change in the Nearby Calendar Spread, Cotton, October 1, 2007 - May 30, 2012



Energy Futures Prices and Commodity Index Investment:
New Evidence from Firm-Level Position Data

by

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Energy Futures Prices and Commodity Index Investment:
New Evidence from Firm-Level Position Data

Abstract: This study brings fresh data to the highly-charged debate about the price impact of long-only index investment in energy futures markets. We use high frequency daily position data for NYMEX crude oil, heating oil, RBOB gasoline, and natural gas that are available from a representative large commodity index fund ("the Fund") from February 13, 2007 through May 30, 2012. Simple correlation tests, difference-in-means tests, and Granger causality tests generally fail to reject the null hypothesis that changes in Fund positions are unrelated to subsequent returns in all four energy futures markets. We also fail to find any evidence that commodity index positions are related to price movements in the WTI crude oil futures market using Singleton's (2013) long-horizon regression specification. Our results suggest Singleton's original finding of significant impacts and high levels of predictability are simply an artifact of the method used to impute crude oil positions of index investors in a particular sample period. Overall, the empirical tests in this study fail to find compelling evidence of predictive links between commodity index investment and changes in energy futures prices.

JEL categories: D84; G12; G13; G14; Q13; Q41
Key words: Bubble, Commodity; Futures market; Index funds; Michael Masters; Energy prices

**Energy Futures Prices and Commodity Index Investment:
New Evidence from Firm-Level Position Data**

"a flood of dumb money…billions of dollars of investment interest in oil, entering the game…in the form of commodity index funds…I began to refer to these overwhelming influences on price as 'Oil's Endless Bid.'" (Dicker, 2011, p. vii).

1. Introduction

The above quote from Dicker's (2011) book, "Oil's Endless Bid," summarizes the commonly held belief that a "flood of dumb money" in the form of long-only index investment has had an exceptionally large impact on energy futures prices. A fairly recent phenomenon, long-only commodity index investments are packaged in a variety forms but share a common goal—provide investors with long-only exposure to returns from an index of commodity prices.[1] The market impact of index investment is most commonly associated with the rapid rise in crude oil futures prices during 2007-2008. Hedge fund manager Michael W. Masters is frequently associated with the argument that unprecedented buying pressure from index investors created a massive bubble in crude oil futures prices during 2007-2008, and this bubble was transmitted to spot oil prices through arbitrage linkages between futures and spot prices (e.g., Masters and White, 2008). The end result was that crude oil futures and spot prices purportedly far exceeded fundamental values. Irwin and Sanders (2012a) use the term "Masters Hypothesis" as a short-hand label for this explanation of the 2007-2008 spike in crude oil prices and commodity prices in general.

Given the important implications of Masters-style arguments for analysis and regulation of energy futures markets, it should come as no surprise that a veritable flood of academic

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[1] Commodity index investors may enter directly into over-the-counter (OTC) contracts with swap dealers to gain the desired exposure to returns from a particular index of commodity prices. Some firms also offer investment funds whose returns are tied to a commodity index. Exchange-traded funds (ETFs) and structured notes (ETNs) also have been developed that track commodity indexes. See Engelke and Yuen (2008), Stoll and Whaley (2010), and Irwin and Sanders (2011) for further details on commodity index investments.

studies on the subject has appeared in recent years. The main objective of these studies is to investigate whether there is a significant empirical relationship between commodity index positions and price movements in energy futures markets. Most studies do not find evidence of a positive impact. For example, Buyuksahin and Harris (2011) conduct a battery of time-series statistical tests and do not find a link between swap dealers positions (a proxy for commodity index fund positions) and subsequent returns in crude oil futures. However, some studies, most notably Singleton (2013), report surprisingly high levels of predictability in energy futures markets using an estimate of money flows into commodity index investments.[2] Extensive reviews of this rapidly expanding literature are provided by Irwin and Sanders (2011), Will et al. (2012), Fattouh, Kilian, and Mahadeva (2013), and Cheng and Xiong (2013).

Previous empirical studies on the market impact of index investment rely mainly on aggregate position data compiled and made available to the public by the U.S. Commodity Futures Trading Commission (CFTC). These data are available in three CFTC reports, the *Supplemental Commitment of Traders* (SCOT), the *Disaggregated Commitment of Traders* (DCOT) report, and the *Index Investment Data* (IID) report. Prior work that uses CFTC data suffers from limitations on both the frequency of the data and the availability of data across markets. The SCOT data are relatively accurate measures of commodity index positions (Irwin and Sanders, 2012a); but, the data are only available for 12 agricultural futures markets which

[2] A significant relationship may reflect the impact of commodity index investment on the price of risk, or risk premiums, in futures markets. In the theoretical models of Hamilton and Wu (2011, 2013), Brunetti and Reiffen (2012), Etula (2013), and Acharya, Lochstoer, and Ramadorai (2013) competition from index investment reduces the risk premium that accrues to long position holders. Irwin and Sanders (2012b) note this has the net effect of lowering the cost of hedging to traditional physical market participants. An exception is the theoretical model of Cheng, Kirilenko, and Xiong (2012), where index investors reduce long positions in times of financial stress. Alternatively, a significant relationship may reflect the bubble impact of index investment under the Masters Hypothesis. So, the flow of index investment under the risk premium framework impacts prices in energy futures markets, but this reflects a rational re-pricing of risk, whereas the same flow of index investment under the Masters Hypothesis leads to irrational price bubbles.

excludes important energy and metal futures markets. The IID are available for all major futures markets, including crude oil; but, historical data are available at quarterly and monthly frequencies which limits the number of observations available for time-series statistical tests. The DCOT data nets on- and off-exchange index positions, and therefore, may substantially underestimate index positions in some markets (Irwin and Sanders, 2012a). The limitations of the CFTC data are most severe for key energy markets such as WTI crude oil futures. Some researchers (e.g., Singleton, 2013; Hamilton and Wu, 2013) address these issues by imputing positions for the energy markets from the positions reported for 12 agricultural markets in the SCOT report. Sanders and Irwin (2013) demonstrate how this data mapping process can lead to unreliable position data and potentially misleading empirical results. This discussion highlights the need for data on index positions in energy futures markets that is available at a high frequency (at least daily) and incorporates both on- and off-exchange positions.

In this article, we address these data concerns by using detailed data on the positions held by a large commodity index fund. Specifically, daily futures positions in four major U.S. energy futures markets—WTI crude oil, heating oil, RBOB gasoline, and natural gas— are available for analysis. The sample includes 1,331 daily observations from 2007 through 2012 for each market.[3] Importantly, the data set spans the controversial spike in crude oil prices during 2007-2008. To the best of our knowledge, this is the first study of energy futures markets (or any commodity futures market) to have access to the detailed trading records of a large index fund. This new firm-level data set provides a potentially more informative measure of index investment patterns in energy futures markets than either swap dealer positions from the DCOT

[3] The proprietary data for this research were provided under the stipulation that it be kept confidential. For simplification, the index fund will simply be referred to as the "Fund" and detailed position data or statistics that might compromise confidentiality are not presented. Upon request, the authors will provide readers directions for requesting permission to use the data.

or positions estimated via a data mapping algorithm. Linkages between index positions and price changes in energy futures markets, if they exist, may be more evident using these relatively high frequency daily position data. A number of statistical tests, including market timing tests, Granger causality tests, and long-horizon regression tests, are used to examine the impact of index fund position changes on returns in the four energy futures markets. In addition, we test whether the rolling of fund positions across contract maturity months has an impact on term spreads.

2. Firm-Level Data on Fund Positions

The position data used in this study is from a large investment company (the “Fund”) that offers several commodity investment programs to sophisticated customers with minimum initial investments ranging up to $100 million. The majority of the Fund’s commodity investments are held in a relatively fixed basket of commodity futures to replicate a proprietary index that has weightings constrained by both sector and commodity. Detailed data on actual positions held by the Fund in U.S. futures markets are available for 22 U.S. futures markets; but, here, we concentrate on four important energy markets: New York Mercantile Exchange (NYMEX) crude oil, Heating Oil, RBOB Gasoline, and natural gas. Complete daily data are available from February 13, 2007 through May 30, 2012 providing for a total of 1,331 observations.

The position data for the Fund include contracts held in each futures market by futures maturity month. Swap positions are also reported; but, the Fund did not hold swaps or other off-exchange derivatives in the energy futures markets during the sample period. The data set did not include any instances of a short total position in any of the four energy futures markets. So, the total position in each market is long-only.[4]

2.1. Position Trends and Characteristics

Figure 1 shows the notional value of Fund positions in the 22 U.S. markets that are actively traded. Notional value is simply the sum of the position in each contract times the settlement price of that specific futures contract**.** The total notional value (futures plus swaps) grows from under $2 billion in 2007 to just over $12 billion in 2011. After a very consistent growth path—interrupted only by the 2008-2009 recession—the total notional value has been fairly stable between $10 and $12 billion since January 2011. Figure 1 also shows the total notional value in just the four energy futures markets. The growth pattern for energy and non-energy markets is similar before the 2008-2009 recession, but diverged thereafter. From 2009 to 2012, the notional value of fund positions in energy futures markets increased by 174% while the non-energy futures markets increased by 265%. This divergence highlights why attempts to infer index holdings in energy markets from non-energy markets may generate large over-estimates (Sanders and Irwin, 2013).

As a standard of comparison, the total positions held by the Fund are compared to those reported in the CFTC's IID report. In figure 2, the total notional value of index positions for 21 U.S. markets reported in the IID are plotted alongside those held by the Fund for each quarter-end from December 31, 2007 to March 30, 2012. Over the sample period, the Fund's total

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[4] The daily data file did contain what appeared to be an aggregation or clerical error on a single day in May of 2007 where long positions across all markets declined by more than 70% for a single day. On the very next day, the market positions were back to the level of two days prior. No other trading day in the entire data set showed a change in notional value of more than 24%. Given the high likelihood of a data error for this date, the data on that one day are replaced with the positions on the prior trading day. This data correction eliminates the impact of a one-day outlier on the results and should have no meaningful impact on tests for systematic and longer-term market impacts.

notional position and that reported in the IID have a positive correlation of 0.86 in levels and 0.97 in percent changes. While fluctuations in the Fund's total position generally mirror those experienced by the industry, including the rapid growth from 2009-2010 and a leveling off of positions in 2011-2012, the Fund has nonetheless garnered a larger percentage of total index investment in U.S. futures markets over time. The Fund's portion of the industry's total positions ranges from a low of 3.0% in late 2007 to a recent high of 7.5% in 2012.

The Fund's holdings on a market-by-market basis are also compared to the 21 markets in the IID that coincide with those traded by the Fund. The percent of index positions held in each market are shown for a representative date in table 1. With regard to allocation across markets, the Fund's holdings are not markedly different from that found in the IID. On April 29, 2011, the top five holdings for both the Fund and the industry (IID) were of the same ordinal rank: #1-crude oil, #2-gold, #3-natural gas, #4-corn, and #5-soybeans. These five markets represent 55% of the Fund's investment on this date and 59% of the IID total. Two of the top five holdings are in energy markets (crude oil and natural gas). The Fund had 41% of its holdings in the four energy futures markets while the IID showed an industry allocation of 46% to those markets. Overall, the Fund's allocation across markets and investment flow through time do not differ substantially from that observed as a whole in the commodity index investment industry. In that regard, the Fund's position data should be representative of industry participation and activity in commodity futures markets.

A summary of the Fund's energy futures market positions are provided in table 2 which shows the position characteristics for individual energy markets for the complete calendar years of 2008 through 2011. The data in table 2 illustrate the growth in the Fund's overall energy positions and relative position size across the energy markets. As shown in panel A, the Fund held an average of 24,992 crude oil futures contracts in calendar year 2011. However, changes in the position are on average a relatively small 111 contracts (panel B). Position changes occur on 177 of the 252 trading days (panel C).

The change in the aggregate position in each market represents the minimum amount of trading that occurred on that day. So, if the net position in a market increases from 1,000 contracts to 1,200 contracts, then a minimum of 200 contracts were bought that day (although not necessarily at the same time). The actual trade for the day could have been larger if there were any positions that were both entered and exited during the day. However, communication with the Fund managers suggests that most all trading occurs near the close of trading and contracts are rarely entered and exited on the same trading day. Figure 3 shows the average net position change across the energy markets by calendar day. Not surprisingly, the majority of the activity occurs around the end of the month when new inflows are most likely to occur.

The position data confirm the idea that index traders in general, and the Fund in particular, are not particularly active on a daily basis in terms of outright buying and selling. That is, the change in the aggregate position is fairly small even though the overall position is relatively large. Trade activity tends to be concentrated toward the end of the month as the Fund adjusts to new money inflows and rebalances the portfolio.

2.2. Position Rolling

A novel feature of the dataset is the ability to precisely distinguish positions that represent new investment in the Fund versus roll transactions. The Fund's aggregate position in each market changes when there are either net inflows or outflows from their investment funds. On those days, the Fund buys (inflows) or sells (outflows) accordingly. Days in which there is a change in the aggregate long position represent days in which the Fund is active in the marketplace with outright buying or selling. A roll transaction is defined as trading across futures contract maturity months within a particular market with no change in the aggregate position. A roll transaction is conducted in order to move market positions from one calendar maturity month to another. The common roll transaction is to sell nearby contracts in which there is an established long position and buy the next listed contract. Thereby, the long position is continually maintained, but it is "rolled" from the nearby contract to the next active contract.

As an example, if the aggregate long position increases by 500 contracts and there were 500 contracts traded across calendar months, then there were no roll transactions and the net new investment is represented by the aggregate increase of 500 contracts. If, however, the aggregate long position increases by 500 contracts and 1,500 contracts trade across the calendar months, then there was a roll transaction. Specifically, 500 of the contracts traded were to establish the new position and 1,000 total trades (500 sells and 500 buys) represented the rolling or moving of 500 positions across calendar months. If the roll involves selling nearby and buying deferred contracts, then it is recorded as a negative quantity (e.g., -500 contracts). This would represent the classic rolling of long positions from nearby to deferred contracts. Instances where long positions are moved from deferred contracts to the nearby contract are recorded as a positive roll transaction (+500).

Most roll transactions are the traditional rolling of established long positions—sell nearby and buy deferred. However, all four energy markets exhibited both long and short rolling activity. In order to keep the tracking of roll activity manageable, the roll quantity is always calculated relative to the nearby contract. Rolling is only recorded in- and out- of the nearby contract and positions are assumed to flow generically into the next listed contract. That is, there was no attempt to segregate positions that might have been rolled into the second, third, or fourth deferred contract months. Instead, if the roll was -500 contracts then it was simply recorded as selling 500 nearby contracts and buying 500 deferred contracts. A cross-check on this method revealed that the vast majority of rolled positions were simply moved ahead to the next most active energy futures contract.

Although position changes for the fund tend to be somewhat small (table 2, panel B), the large overall position sizes require an active rolling of positions. The size and frequency of rolling are shown in table 2, panels D and E. In 2011, the number of days in which contracts are rolled is greatest in crude oil (131) and RBOB gasoline (119). Since the NYMEX energy futures have a contract listed for each of the 12 calendar months, this suggests that the position is rolled each month over the course of roughly 10 days. This tendency is illustrated in figure 4 which shows roll activity across the days of the month. For the energy markets, rolling tends to occur in the 10 days from roughly the 5^{th} day of the month through the 15^{th}, much like the rest of the commodity index fund industry (Aulerich, Irwin, and Garcia, 2013). This is similar to funds tracking the popular S&P GSCI where positions are rolled (the "Goldman roll") from the 5th through the 9^{th} trading day of the month prior to expiration.

The size of the average daily roll transaction is shown in Panel D of table 2. Comparing the 2011 data in table 2, we can see that the average change in the position size (Panel B) is smaller in every market than the average roll transaction (Panel D). For 2011 in crude oil, the average change in the position size is 111 contracts while the average roll transaction is 710 contracts. Based on the relatively larger daily transaction sizes associated with rolling positions across contract months, if there is a market impact due to index trading activity it may be more likely to be found in calendar spread relationships than in outright market prices (Stoll and Whaley, 2010).

3. Empirical Methods and Results

3.1. Calculation of Returns, Spread Changes, and Notional Value

Daily returns are calculated using nearby futures contracts adjusting for contract roll-overs as follows:

(1) $$R_t^1 = \ln\left(\frac{p_t^1}{p_{t-1}^1}\right) * 100$$

where p_t^1 is the settlement price of the first listed or nearest-to-expiration energy futures contract on each trading day. In order to avoid distortions associated with contract rollovers, p_t^1 always reflects the same nearest-to-expiration contract as p_{t-1}^1. Roll-over dates for the markets are set on the 15th of the month prior to the delivery month. This is consistent with the majority of the contract switching in the energy markets which occurs before the 15th of the month prior to delivery (see figure 4).

Returns for the second or next active futures contract are also calculated as follows:

(2) $$R_t^2 = \ln\left(\frac{p_t^2}{p_{t-1}^2}\right) * 100$$

where p_t^2 is the settlement price of the second or next actively listed energy futures contract on each trading day. For example, if the nearby return in crude oil is calculated using the March futures, then the second listed contract return is calculated using the April contract. The same conventions as described above for switching contracts are used to create a series of daily returns (R_t^2) for the second listed contract for each market.

While some prior researchers have used various absolute measures of the spread between the first and second contract—e.g., differences, price ratios, or percent of full carry—these measures can be problematic. For example, our preliminary tests indicated that non-stationarity was an issue with time series on the spread levels or absolute price differences between contract months. Besides these statistical issues, it is difficult to account for differing storage costs and term structures across markets. Therefore, tests for the impacts of rolling activity focus on a more direct measure of changes in the spread, which is the simple difference in the return between the first and the second listed contracts:

(3) $$\Delta Spread_t = R_t^1 - R_t^2.$$

Note that $\Delta Spread_t = R_t^1 - R_t^2 = \ln\left(\frac{p_t^1}{p_{t-1}^1}\right) - \ln\left(\frac{p_t^2}{p_{t-1}^2}\right) = \ln\left(\frac{p_t^1}{p_t^2}\right) - \ln\left(\frac{p_{t-1}^1}{p_{t-1}^2}\right)$ is equivalent to the log relative change in the price ratio or slope of the futures curve on day *t* (correctly adjusted for contract switching). As such, it accurately captures the relative movement in the nearby and second-listed futures contracts. The *Δ*Spread variable is stationary for all markets. Additionally, the average correlation coefficient across markets for R_t^1, R_t^2 is over 0.99; so, using the *Δ*Spread variable substantially reduces the variance of the dependent variable in regression models and increases statistical power in time series tests.

In most empirical tests, Fund trading activity is specified as the change in aggregate position size:

(4) $$\Delta Position_t = q_t - q_{t-1}$$

where q_t is the total number of long contracts held in a given energy futures market on day *t*. Positions generally are held in the first listed or nearest-to-expiration energy futures contracts. Regardless, the total position on each day is aggregated across all contract maturity months. For some empirical tests, the notional value of Fund positions is examined. The notional value at time *t* is simply price (*p*) times position size (*qm*), where *m* is the number of units per contract:

(5a) $$Notional\ Value_t^1 = p_t^1 * q_t * m,$$ and

$$(5b) \qquad \%\Delta Notional\ Value_t^1 = \ln\left(\frac{p_t^1 * q_t * m}{p_{t-1}^1 * q_{t-1} * m}\right) * 100$$

$$= \left[\ln\left(\frac{p_t^1}{p_{t-1}^1}\right) + \ln\left(\frac{q_t}{q_{t-1}}\right)\right] * 100 = \left[R_t^1 + \ln\left(\frac{q_t}{q_{t-1}}\right)\right] * 100.$$

So, the percent change in notional value at time *t* is just the percent change in price or market return plus the percent change in the number of contracts held. This makes notional value a somewhat imprecise measure of commodity investments as it combines price and quantity impacts. That is, notional value of a position can increase (decrease) when no new positions actually enter (exit) the market simply due to a change in the market price (R_t^1). As a result, notional value by construction is contemporaneously correlated with market prices and cannot be used in any empirical tests that examine contemporaneous relationships. To be consistent with some prior research, notional value will also be used in certain empirical tests; however, it is not the preferred measure and the results must be interpreted with caution. For the majority of empirical tests conducted here the Fund's position is measured as the change in the quantity held (measured in contracts) as this more accurately represents the demand concept of new buying.

3.2. Empirical Analysis of Position Changes and Returns

3.2.1. Correlation Coefficients

As a first step in testing for possible market impacts, Pearson correlation coefficients are calculated between the change in Fund positions and market returns on the same day (contemporaneous correlation). The lagged correlation is calculated between the change in the Fund position and the market return the following day. The unconditional Pearson correlation coefficients are calculated over the 1,330 data points in each market. So, the correlations have a standard error of $\sqrt[2]{\frac{1}{n-3}}$ or 0.0275 and any correlation that is greater than 0.0538 (1.96 x 0.0275) in absolute value is statistically different from zero (5% level, two-tailed *t*-test). Because of the relative infrequency of net positions changes, the correlation coefficients are also estimated only using days when there is a change in the position. For these conditional correlations the number of observations and standard errors vary across markets.

As shown in panel A of table 3, the average unconditional contemporaneous correlation across markets is a small and positive 0.0067. None of the contemporaneous correlations across the individual markets are statistically different from zero at the 5% level. More importantly, there are no statistically significant correlations between changes in positions and market returns on the following day. That is, there is no evidence that the buying in these markets precedes a price increase (or decrease) as none of the 1-day lagged correlations are statistically different from zero. This is true for both the change in the position (contracts) and the change in notional value (panel B). Note that contemporaneous correlations are not computed for notional values due to the natural correlation that stems from the calculation in (4b). The correlations conditioned on a non-zero change in the position show analogous results. There is no evidence of either a contemporaneous or lagged correlation between Fund positions changes and market returns.

3.2.2. Difference-in-Means Test

Another approach to understanding potential market impacts is to test if returns are different following days where there is active buying (increase in long position) or selling (decrease in long position) as compared to days following no activity (no change in the position). The difference in mean returns conditioned on market activity can easily be tested within the framework proposed by Cumby and Modest (1987):

$$R_t^1 = \alpha + \beta_1 Buying_{t-1} + \beta_2 Selling_{t-1} + \epsilon_t \quad (6)$$

where $Buying_{t-1} = 1$ if there is an increase in the long Fund position on day *t-1* (0 otherwise) and $Selling_{t-1} = 1$ if there is a decrease in the long Fund position on day *t-1* (0 otherwise). In equation (6) the following day's nearby futures return conditioned on buying ($\alpha + \beta_1$) is statistically different from the unconditional market return (α) if the null hypothesis $\beta_1 = 0$ is rejected using a *t*-test. Likewise, the following day's nearby futures return conditioned on selling ($\alpha + \beta_2$) is statistically different from the unconditional market return (α) if the null hypothesis $\beta_2 = 0$ is rejected. Equation (6) is estimated for each market individually using OLS. The residuals are tested for serial correlation (Breusch-Godfrey test) and heteroskedasticity (White's test) and the Newey-West covariance estimator is used where appropriate.

While (6) may lack some of the power of alternative specifications due to the binary nature of the independent variables, it also may better capture days where there is heavy index fund buying or selling. The data suggest that the Fund behaves similar to the rest of the industry (see table 1). So, the specification in (6) may accurately identify days with heavy industry activity even though the magnitude of trading for this particular Fund is only a fraction of the industry as a whole. This is the first application to date of a Cumby-Modest type test in the literature on the impact of commodity index investment. The test can be applied here because the disaggregated position data allows us to precisely divide the sample into trading and non-trading days for a single large entity.

The estimation results are presented in table 4. None of the estimated slope coefficients are statistically different from zero at the 5% level. On days following buying and selling, market returns are no different than on days following no change in the position. The only statistically significant coefficient is the intercept term (no position change) for natural gas which is statistically negative and captures the marked decline in natural gas prices over this sample period.

3.2.3. Granger Causality Tests

Following prior researchers (e.g., Stoll and Whaley, 2010; Buyuksahin and Harris, 2011), we consider the "causal" relationship between market returns and the change in Fund positions. Under the null hypothesis that changes in positions do not Granger cause market returns, the following linear regression is estimated for each market:

$$R_t^1 = \alpha + \sum_{i=1}^{m} \gamma_i \ R_{t-i}^1 + \sum_{j=1}^{n} \beta_j \, \Delta Position_{t-j} + \epsilon_t \tag{7}$$

where the return and position variables are defined as before. The lag structure (m,n) for each market is determined by a search procedure over m = 25 and n =25 using OLS and choosing the model that minimizes the Schwartz criteria to avoid over-parmeterization. If the OLS residuals demonstrate serial correlation (Breusch-Godfrey Lagrange multiplier test), additional lags of the dependent variable are added until the null of no serial correlation cannot be rejected. White's test is used to test for heteroskedasticity, and if found, the model is re-estimated using White's heteroskedastic consistent variance-covariance estimator. Traditional bivariate causality is tested under the null hypothesis in (7) that changes in positions cannot be used to predict (do not lead) market returns: $H_0 : \beta_j = 0$ for all j. A rejection of this null hypothesis using an F-test of the stated restriction provides direct evidence that position changes are indeed useful for forecasting returns in that market. Some researchers (e.g., Stoll and Whaley, 2010; Hamilton and Wu, 2013) have suggested that notional value of investments is the important explanatory variable to consider. So, (7) is estimated using both the change in position measured in number of contracts and the log-relative percent change in notional value.

Table 5 shows the test results for the null hypothesis that the position changes do not lead nearby futures returns for each market.[5] The (*m,n*) lag structure that minimized the SIC was a (1,1) for each market except natural gas which specified one more than one additional lag of returns (2,1). Because only a single lag of the change in positions is verified the test for causality is just a *t*-test for $\beta_j = 0$. As shown in panel A of table 5, the null hypothesis that changes in positions (contracts) do not lead returns $H_0 : \beta_j = 0$ for all *j* is not rejected at the 5% level for any market except heating oil. The Granger causality tests using the percent change in notional value as the independent variable (panel B, table 4) are consistent with those shown in panel A. That is, the null hypothesis of no causal relationship from the percent change in notional value to market returns is rejected at the 5% level only for heating oil.

The rejections in heating oil are peculiar, given the much larger positions and activity in crude oil and natural gas. Stability tests of the model—in particular recursive coefficient estimates—point to influential observations on January 18 and 22, 2008. On each of these days, the Fund sold 801contracts of heating oil. On the following days, the nearby heating oil futures price fell by 1.1% and 2.4%, respectively. Oddly, these large transactions bracket the U.S. holiday honoring Martin Luther King, Jr. and trading volumes surrounding the holiday were likely somewhat thin. When these two observations are removed from the sample the Granger causality tests fail to reject the null hypothesis of no causality in heating oil futures with the p-value for the model in contracts at 0.6602 and in notional value at 0.2705. Importantly, this indicates that the result is not indicative of a systematic causal relationship within the data. It does, however, suggest that index funds executing large trades on days with light trading volume—especially around exchange holidays—may well have some isolated market impact.

[5] The four markets were also estimated as a system (see Capelle-Blancard and Coulibaly , 2011). However, the results were nearly identical since market positions enter the specification with just a single lag.

However, this type of market impact may be a rational response to short-term liquidity demands which is distinctly different from an irrational bubble-type of market impact.

3.2.4. Singleton Regression Tests

In a widely-discussed article, Singleton (2013) considers a version of the long-horizon regression model frequently used to test predictability in stock returns (e.g., Boudoukh and Richardson, 1993):

(8) $$R_t^1 = \alpha + \sum_{i=1}^{m} \gamma_i \ R_{t-i}^1 + \beta \sum_{j=1}^{n} \Delta Position_{t-j} + \epsilon_t$$

where positions in (8) enter the model as a moving sum calculated over the most recent *n* observations. The moving sum is, of course, equivalent to the change in the position over the interval between *t-1* and *t-n*. Singleton uses a variation of this model where *m*=1 and *n*=13 weeks. The basic intuition of the long-horizon model is that summing the position variable strengthens the signal in positions about subsequent price movements relative to noise. If the estimated slope coefficient, β, is positive (negative), then it indicates a fads-style model where prices tend to increase (decrease) slowly over a relatively long time period after wide-spread buying. The “fads” stylization captured in (8) is consistent with the popular notion that index investment may flow in “waves” that build slowly, pushing prices higher and then fading slowly (e.g., Summers 1986). In this scenario, horizons longer than a day or even a week may be necessary to capture the predictive component of index fund positions.

Singleton (2013) does not use actual index positions held in crude oil in his empirical tests, but rather he follows Masters and White (2008) and uses an imputed measure based on index positions held in agricultural futures markets. Singleton refers to the 13-week position change as the “flow” of investment funds. Considerable predictability between the imputed measure of investment flows and crude oil returns is found with adjusted R-squared values ranging from 13% up to 31% over a 1-week horizon using data from September 2006 through January 2010 (Singleton, 2013, table 3). Hamilton and Wu (2013) question Singleton's results on several fronts and attempt to replicate them. Using the percent change in the notional value of positions imputed from the SCOT report, Hamilton and Wu (2013) find that the impact is isolated to crude oil, appears to be sensitive to the lag-length chosen and does not hold up out-of-sample.

We estimate the following version of Singleton's model:

$$R_t^1 = \alpha + \gamma R_{t-1}^1 + \beta \Delta Position_{t-1,t-k+1} + \epsilon_t \tag{9}$$

where $\Delta Position_{t-1,t-k+1}$ is the change in the total Fund position (in contracts) over the previous k time periods. This specification is equivalent to setting m=1 and n=k in (8) where the position variable is a k period moving sum of position changes. Singleton emphasizes the importance of a 13-week (65 trading day) investment flow in driving crude oil returns. For the sake of completeness, Singleton's model also is estimated using 30-, 65-, and 130-day changes in both positions and notional value. Our estimation of this model is a clear improvement on prior work because actual Fund position data are available for the energy markets, whereas Singleton as well as Hamilton and Wu (2013) rely on position data imputed from the 12 agricultural markets covered in the SCOT report.

The basic model estimation results for (9) are presented in table 6. Panel A shows the results using the change in position size in contracts as the independent variable and panel B contains the results using the percent change in notional value. In panel A, there are no statistically significant linkages between "flow" as measured by position size and returns. When the model is estimated using notional value as the independent variable (Panel B) a marginally statistically significant slope coefficient is found for crude oil (p-value=0.0853) when *k*=65 days. The estimated slope coefficient for crude oil (*k*=65) is 0.0069 which suggests that a 1% increase in notional value results in a quite small 0.0069% increase in nearby daily crude oil prices.

The regression results for changes in contract positions reported in table 6 stand in sharp contrast to Singleton's, who reports a statistically significant impact from index investor positions and high predictability (high R-squared). Sanders and Irwin (2013) argue that Singleton's results and others based on imputed energy positions may be unreliable due to mapping of index positions held in the 12 SCOT agricultural futures markets to those held in energy markets. This argument is supported by the data graphed in Figure 1, where there does not appear to be a consistent mapping from positions held in non-energy markets to the energy markets. Indeed, for the Fund data examined, the daily correlation between the percent change in notional value for energy and non-energy markets is just 0.57. In this particular data set, inferences about positions held in energy markets based on the other markets certainly could lead to erroneous conclusions.

To further investigate the use of imputed positions, the combined number of contracts held in the 12 SCOT agricultural markets by the Fund is calculated. Only a slight transformation of this variable is needed to replicate the mapping algorithm used by Singleton (2013) and Hamilton and Wu (2013). A version of (9) is then estimated using the actual positions for each energy market along with the combined positions held in the 12 SCOT markets:

$$R_t = \alpha + \gamma R_{t-1} + \beta_1 \Delta Position_{t-1,t-k+1} + \beta_2 \Delta SCOT\ Position_{t-1,t-k+1} + \epsilon_t. \quad (10)$$

where $\Delta Position_{t-1,t-k+1}$ is again the change in the total Fund position (in contracts) over the previous *k* time periods in the specific energy futures market and $\Delta SCOT\ Position_{t-1,t-k+1}$ is the combined positions of the Fund over the previous *k* time periods in the 12 SCOT agricultural futures markets.

The estimation results for equation (10) with k=65 are shown in table 7 panel A and they reveal that the use of SCOT data—and likely any transformation thereof—may produce positive results in the energy markets. Across all four markets there is a clear positive relationship between investment flows in the SCOT market and returns in energy futures. Specifically, the relationship between the SCOT market positions and crude oil returns is statistically different from zero at the 5% level. None of the estimated coefficients for the actual energy market positions are statistically significant. Obviously, it makes little sense for the SCOT positions to impact energy returns when the energy positions themselves do not. As shown in panel B of table 7, when the sample is split into two time periods (2007-2009 and 2010-2012) the positive impact of the SCOT positions is evident only in the first period, which roughly corresponds to the sample period used by Singleton. In the second sample (2010-2012), none of the energy or SCOT position variables is positive and statistically significant at the 5% level.[6]

While the above analysis casts doubt on the reliability of Singleton's original regression results, we did find a marginally significant coefficient in crude oil using positions measured in terms of notional value (Panel B, table 6). It turns out this result has a logical explanation unrelated to index position changes. As we demonstrated earlier (equation 5b), the change in notional value is simply the sum of the log-relative changes in prices and positions. So, notional value really does not add new information to the regression model beyond the change in price, which in turn suggests that the mild rejection found for crude oil in the notional value regression

[6] Heating oil does have a p-value of 0.0432 and a negative coefficient over 2010-2012 (Table 7, Panel B). While significant, the negative sign is opposite of the sign over 2007-2009.

likely stems from the price component of notional value. This can be seen more clearly by separating notional value into its price and position components in the estimated model:

(11) $$R_t^1 = \alpha + \gamma R_{t-1}^1 + \beta_1 \%\Delta Positions_{t-1,t-k+1} + \beta_2 R_{t-1,t-k+1}^1 + \epsilon_t$$

where $\%\Delta Position_{t-1,t-k+1}$ is the percent change in the total Fund position (in contracts) over the previous *k* time periods and $R_{t-1,t-k+1}^1$ is the percent (log-relative) change in the settlement price for the first listed or nearest-to-expiration energy futures contract over the previous *k* time periods. Equation (11) is estimated for k=65 and the results are presented in panel C of table 7.[7] The estimated coefficients on the percent change in contracts (β_1) and percent change in price (β_2) are revealing. None of the estimated coefficients on contract positions is statistically different from zero. In contrast, the estimated coefficients on percent price change are positive and marginally statistically significant for crude oil (p-value=0.1171) and heating oil (p-value=0.0826). The slight positive impact using notional value in table 6 (panel B) is therefore likely due to a unique time-series pattern in returns during the sample period and not related to the actual positions held by the Fund. This result shows how using notional value to test for index investment impacts may commingle a zero quantity-related impact with a positive price-related impact associated with unusual time-series patterns. This is especially true for samples covering tumultuous market action like that seen in crude oil from 2007-2008.

3.2.5. Valkanov Long-Horizon Regression Tests

As in improvement on the long-horizon specification used by Singleton (2013), we estimate the model proposed by Valkanov (2003):

(12) $$\sum_{i=0}^{m-1} R_{t+i}^1 = \alpha + \beta \sum_{i=0}^{k-1} \Delta Position_{t+i-1} + \epsilon_{t+1}$$

[7] The unconditional correlation coefficients reported in Table 3 clearly show that this specification will not suffer from multicollinearity problems.

where all variables are defined as before. In essence, equation (12) is an OLS regression of a *k*-period moving sum of the dependent variable at time *t* against an *m*-period moving sum of the independent variable in the previous period, time *t*-1. If the estimated β is positive (negative), then it indicates a fads-style model where prices tend to increase (decrease) slowly over a relatively long time period after widespread index fund buying (selling). The fads stylization captured in (12)—with a positive β—is consistent with the hypothesis that position changes can drive bubble-like price behavior in commodity futures prices. Valkanov demonstrates that the OLS slope estimator in this specification is consistent and converges at a high rate of *T*. The specification in (12) clearly creates an overlapping horizon problem for inference. 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.

The Valkanov long-horizon regression (12) is estimated using the underlying dependent variable of returns and the independent variable of change in positions. Both of these variables are stationary, so the sums are also stationary. We set m=k in all regressions and alternative horizons of 5-, 30-, 65-, 130-, and 240-trading days are specified in order to bracket the horizons used in the Singleton regressions in table 6. To the best of our knowledge, this is the first application of Valkanov's long-horizon regression test to multi-market index fund positions.[8] The estimated OLS β coefficients for (12) are shown in table 8 along with the re-scaled *t*-statistic. Critical values for the rescaled *t*-statistic (-0.563, 0.595) are taken from Valkanov's (2003) Table 4 for Case 2 and c = -5.0, δ = 0.00, T = 750, and tail values representing the 10%

[8] Irwin and Sanders (2012a) apply the test to the positions of two single-commodity ETFs.

significance level. These represent a conservative case that, if anything, favors a rejection of the null hypothesis that the slope equals zero. The estimated slope coefficients presented in table 8 are noticeably small. For example, at the quarterly horizon (k = 60) none of the estimated slope coefficients exceeds 0.10 (which would suggest that a 1,000 contract increase in positions pushes up price 10 basis points). So, not surprisingly, the rescaled t-statistics do not exceed Valkanov's critical values for a single long-horizon test. There is no evidence that the Fund's market positions impact commodity futures returns over longer horizons.

3.3. Empirical Analysis of Roll Activity and Spreads

3.3.1. Correlation Analysis

Simple correlations between roll transactions and spread changes are shown in Table 9. The correlations are calculated in a contemporaneous fashion as well as with a 1-day lag between the roll position and subsequent spread change. Notably, the average correlation across all markets for both the contemporaneous and lagged correlations is negative. For the contemporaneous correlations—both conditional and unconditional—the correlation coefficients for heating oil and RBOB gasoline are statistically different from zero at the 5% level and negative. None of the correlations are statistically significant when calculated with a 1-day lag.

Some of the correlation coefficients in table 9 may suggest a possible relationship between Fund roll transactions to market spreads. However, the direction of the impact is negative which is opposite of a price pressure effect. That is, roll transactions that involve selling (buying) the nearby contract actually occur in conjunction with the nearby contract increasing (decreasing) in price relative to the deferred contract.

3.3.2. Difference-in-Mean Tests

Another approach to understanding potential market impacts is to test if market returns are different on days following active buying of the spreads (buy nearby/sell deferred) or selling of the spreads (sell nearby/buy deferred) as compared to days with no activity (no rolling). The difference in mean returns, conditioned on market activity, can easily be tested within the same Cumby and Modest (1987) framework used earlier:

(13) $$\Delta Spread_t^1 = \alpha + \beta_1 Buying_{t-1} + \beta_2 Selling_{t-1} + \epsilon_t$$

where $Buying_{t-1}$ = 1 if positive roll transactions are transacted (buy nearby/sell deferred) on day *t* (0 otherwise) and $Selling_{t-1}$ =1 if negative roll transactions (sell nearby/buy deferred) are transacted on day *t-1* (0 otherwise). In equation (13), the change in the spread (ΔSpread) conditioned on buying ($\alpha + \beta_1$) is statistically different from the unconditional change in the spread (α) if the null hypothesis that β_1=0 is rejected using a *t*-test. Likewise, the change in the spread conditioned on selling ($\alpha + \beta_2$) is statistically different from the unconditional market return (α) if the null hypothesis that β_2=0 is rejected. The model is estimated using OLS. The residuals are tested for autocorrelation and heteroskeasticity and the Newey-West estimator is used where appropriate.

The results are presented in table 10 for each market. The only statistically significant coefficient (5% level) is the β_2 for heating oil. The estimated parameter is 0.0131 which suggests that on days following rolls (sell nearby, buy deferred) the spreads decrease by 0.0131 percent. That is, when traditional rolling of long futures position occurs (selling nearby, buying deferred) the nearby contract actually gains on the deferred—the opposite of what one might expect from a market pressure hypothesis.

3.3.3. Granger Causality Tests

Futures spreads and roll transactions are also tested in a Granger causality framework. Under the null hypothesis that roll transactions do not Granger cause changes in the spread, the following linear regression is estimated:

(14) $$\Delta Spread_t^1 = \alpha_k + \sum_{i=1}^{m} \gamma_i \, \Delta Spread_{t-i}^1 + \sum_{j=1}^{n} \beta_j \, Roll_{t-j} + \epsilon_t$$

where $Roll_{t-j}$ represents the rolling of positions across calendar months. Specifically, the classic roll of selling nearby and buying deferred contracts is recorded as a negative quantity (e.g., -500 contracts). The model is specified and estimated with the same procedure used for equation (7). Since conventional roll transactions (sell nearby/buy deferred) are recorded as negative numbers, a positive β_j implies that spreads narrow following such roll transactions. The results are presented in Table 11, with the model specification never including more than a single lag of roll activity. As a consequence, non-causality for each of the markets is simply tested under the null hypothesis that β_1=0 using a *t*-test. Given the lag specification, it is not surprising that we fail to reject the null hypothesis of non-causality in each of the four markets.[9]

The results of the empirical analysis of roll transactions and spreads are curious in that very little evidence of a market impact is found even though roll transactions are typically much larger than outright buying or selling by the Fund (see table 1). When there is a statistically significant finding, it tends to suggest that spreads narrow (nearby futures gain relative to deferred futures) following traditional roll transactions (sell nearby, buy deferred). This is the opposite of a price pressure hypothesis and consistent with a "sunshine trading" effect that reduces transaction costs and draws needed liquidity to the market (Admati and Pfleiderer, 1991; Bessembinder et al., 2012). Interestingly, Aulerich, Irwin, and Garcia (2013) report a similar

[9] Roll transactions and price spread changes are not tested using long-horizon methods. Price spreads are generally limited by arbitrage opportunities across contract months; therefore, there is little reason to suspect that any long-term, bubble-like relationships could occur in the price differences across futures contracts.

tendency for spreads to narrow following index roll transactions in the 12 agricultural SCOT markets.

4. Summary and Conclusions

This study brings fresh data to the highly-charged debate about the price impact of long-only index investment in energy futures markets. Prior empirical studies have been limited to low frequency observations, the narrow cross-section of markets covered by the various reports available from the U.S. Commodity Futures Trading Commission (CFTC), or data that nets on- and off-exchange positions. Some researchers (e.g., Singleton, 2013; Hamilton and Wu, 2013) have relied on position data imputed from agricultural commodities. We use high frequency daily position data for NYMEX crude oil, heating oil, RBOB gasoline, and natural gas that are available from a representative large commodity index fund ("the Fund") from February 13, 2007 through May 30, 2012. Importantly, the data set spans the controversial spike in crude oil prices during 2007-2008. This new firm-level data set provides a potentially more informative measure of index investment patterns in energy futures markets.

The positions held by the Fund are shown to be representative of the commodity index industry as measured by the CFTC's Index Investment Data (IID). Simple correlation tests and difference in means tests fail to reject the null hypothesis that changes in positions are unrelated to subsequent market returns. Similarly, Granger tests fail to demonstrate a systematic causal relationship from Fund positions to market returns. However, the Granger tests do reject the null for heating oil due to what appears to be an isolated incidence of active trading around an exchange holiday.

Market impacts are also tested using the long-horizon regression specification of Singleton (2013). Our regression results for changes in contract positions stand in sharp contrast to Singleton's original results using changes in positions. We find no evidence of a statistically significant impact in any of the four energy futures markets, while he finds a statistically significant impact on crude oil futures prices and high predictability (high R-squared). The explanation for the difference in results is that Singleton used a mapping procedure to estimate crude oil positions based on positions in agricultural markets and this led to erroneous findings. We demonstrate this by regressing returns on the Fund's actual positions in energy futures markets and positions held by the Fund in 12 agricultural futures markets. A statistically significant impact on returns is found for the agricultural market positions but not for energy market positions. Obviously, it makes little sense for the positions in agricultural markets to impact energy returns when the energy positions themselves do not. Furthermore, the impact of agricultural market positions is only significant in the 2007-2009 sub-sample. The findings suggest that Singleton's regression results are simply an artifact of the method used to impute crude oil positions of index investors in a particular sample period. We also estimate the more general long-horizon regression test of Valkonov (2003) and find no evidence that changes in Fund positions exert longer-term pressure on returns in energy futures markets.

Additional tests are conducted to examine the impact of rolling futures positions on price spread behavior. Simple correlations, Granger causality models, and difference-in-means tests are utilized. Generally, the findings only suggest weak linkages between the Fund's roll transaction and price spreads in the energy markets. A statistically significant linkage is found for one market (heating oil) with the difference-in-mean test. In that case, the directional impact is negative, which runs counter to the price pressure hypothesis. The empirical results for roll positions and price spreads generally provide very little evidence that rolling activity impacts spreads in the energy futures markets.

In sum, the results of this study add to the growing body of literature showing that buying pressure from index funds was not one of the main drivers of the spikes in energy futures prices in recent years. The results presented here are particularly compelling because they are based on daily position data that does not suffer from several of the criticisms that have been leveled against the more commonly used weekly aggregate position data available from the CFTC. Likewise, the approach is an improvement over studies that have used index positions in agricultural markets to impute positions in energy markets. The results are especially interesting because we fail to find any evidence that commodity index positions are related to price movements in the WTI crude oil futures market. In practical terms, our results suggest that data on commodity index investment is unlikely to provide useful predictive information to energy market analysts and traders.

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Table 1. Notional Values and Market Allocations of Fund and *Index Investment Data* (IID), April 29, 2011

Market	($ Billions) Fund	% Allocation	($ Billions) IID	% Allocation	Fund % of IID
NYMEX WTI Crude Oil	2.973	24%	53.800	27%	5.5%
NYMEX Gold	1.421	12%	19.200	9%	7.4%
NYMEX Natural Gas	0.823	7%	17.800	9%	4.6%
CBOT Corn	0.814	7%	15.700	8%	5.2%
CBOT Soybeans	0.753	6%	13.500	7%	5.6%
NYMEX Copper	0.691	6%	7.600	4%	9.1%
NYMEX Heating Oil	0.637	5%	10.700	5%	6.0%
NYMEX RBOB Gasoline	0.616	5%	11.800	6%	5.2%
NYMEX Silver	0.605	5%	8.600	4%	7.0%
CME Live Cattle	0.557	5%	6.800	3%	8.2%
ICE Sugar	0.415	3%	6.400	3%	6.5%
ICE Coffee	0.322	3%	5.200	3%	6.2%
ICE Cotton	0.315	3%	4.900	2%	6.4%
CME Lean Hogs	0.292	2%	3.900	2%	7.5%
CBOT Soybean Oil	0.229	2%	3.600	2%	6.4%
CBOT Wheat	0.227	2%	8.600	4%	2.6%
KCBOT Wheat	0.226	2%	1.500	1%	15.1%
CBOT Soybean Meal	0.158	1%	0.800	0%	19.7%
CME Feeder Cattle	0.099	1%	0.700	0%	14.1%
NYMEX Platinum	0.095	1%	0.600	0%	15.8%
ICE Cocoa	0.087	1%	1.300	1%	6.7%
Total	**12.353**	**100%**	**203.000**	**100%**	**6.1%**

Notes: Positions for the industry are based on *Index Investments Data* (IID) reports from the U.S. Commodity Futures Trading Commission (CFTC). Allocations and totals only reflect the U.S. markets displayed in the table. CBOT: Chicago Board of Trade, NYMEX: New York Mercantile Exchange, ICE: Intercontinental Exchange, CME: Chicago Mercantile Exchange, KCBOT: Kansas City Board of Trade.

Table 2. Annual Fund Position Size and Trading Characteristics, 2008-2011

Market	2008	2009	2010	2011
Panel A: Average Total Postion Size (contracts)				
Crude Oil	10,620	13,245	19,365	24,992
Heating Oil	1,738	1,964	3,281	4,588
RBOB Gasoline	2,522	3,248	3,415	4,546
Natural Gas	3,549	4,185	8,628	16,490
Panel B: Average Change in Total Position (contracts)				
Crude Oil	95	103	69	111
Heating Oil	26	18	19	14
RBOB Gasoline	26	27	26	16
Natural Gas	28	62	91	91
Panel C: Number of Days in which Total Position Changes				
Crude Oil	147	178	165	177
Heating Oil	118	121	119	122
RBOB Gasoline	123	131	107	135
Natural Gas	135	137	164	160
Panel D: Average Size of Roll (contracts)				
Crude Oil	868	566	544	710
Heating Oil	167	99	104	85
RBOB Gasoline	283	157	169	190
Natural Gas	290	277	315	502
Panel E: Number of Days on which Rolls Occur				
Crude Oil	78	104	115	131
Heating Oil	49	89	81	98
RBOB Gasoline	44	89	85	119
Natural Gas	58	79	108	77

Note: Data are presented for complete calendar years only.

Table 3. Correlation Coefficients between Daily Returns and Fund Position Changes, February 13, 2007 - May 30, 2012

	Unconditional		Conditional	
Market	**Contemporaneous**	**1-Day Lag**	**Contemporaneous**	**1-Day Lag**
Panel A: Position Changes				
WTI Crude Oil	0.0241	-0.0144	0.0279	-0.0173
Heating Oil	0.0228	0.0316	0.0279	0.0472
RBOB Gasoline	0.0052	0.0057	-0.0014	0.0117
Natural Gas	-0.0255	0.0065	-0.0376	0.0077
Average	**0.0067**	**0.0074**	**0.0042**	**0.0123**
Panel B: Percent Change in Notional Value				
WTI Crude Oil		-0.0143		-0.0081
Heating Oil		0.0172		0.0226
RBOB Gasoline		-0.0243		-0.0228
Natural Gas		-0.0608		-0.0382
Average		**-0.0206**		**-0.0116**

Notes: Unconditional correlations are computed using all 1,330 observations and have a standard error of 0.0275. Conditional correlations use only data points where there is a non-zero change in positions. The number of observations ranges from a low of 658 (RBOB gasoline) to a high of 847 (crude oil). The corresponding standard errors are 0.0391 (RBOB gasoline) and 0.0344 (crude oil). None of the calculated correlation coefficients are statistically different from zero.

Table 4. Cumby-Modest Difference-in-Mean Tests for Daily Fund Positions, February 13, 2007 - May 30, 2012

Market	No Change	p-value	Buying	p-value	Selling	p-value	"buys"	"sells"
Crude Oil	0.0063	0.9562	-0.0637	0.7064	-0.0656	0.6971	420	427
Heating Oil	0.0231	0.7778	0.1404	0.3178	-0.2207	0.1466	354	283
RBOB Gasoline	0.1175	0.2146	-0.1107	0.4728	-0.2303	0.2061	408	249
Natural Gas	-0.2698	0.0196	0.0956	0.6596	0.0060	0.9750	362	420

Notes: Buying (selling) is defined as days when there is an increase (decrease) in the long Fund position. The "No Change" column reports the α intercept estimate, the "Buying" column reports the β_1 slope estimate, and the "Selling" column reports the β_2 slope estimate. The number of "buy" and "sell" observations are reported in the final columns.

Table 5. Granger Causality Tests that Fund Position Changes Lead Market Returns, February 13, 2007 - May 30, 2012

Panel A: Independent Variable: Contracts

Market	*m,n*	β_j	p-value
Crude Oil	1,1	-0.0140	0.6314
Heating Oil	1,1	0.1778	0.0320
RBOB Gasoline	1,1	0.0439	0.8240
Natural Gas	2,1	0.0061	0.7827

Panel B: Independent Variable: Notional Value

Market	*m,n*	β_j	p-value
Crude Oil	1,1	-0.0674	0.9906
Heating Oil	1,1	4.2472	0.0074
RBOB Gasoline	1,1	-0.1531	0.9806
Natural Gas	2,1	-4.0257	0.4201

Notes: The independent variable "contracts" in panel A is the change in the daily position held by the Fund. The estimated coefficients in panel A are scaled by 100. The independent variable "notional value" in panel B is the log-relative percent change in the notional value.

Table 6. Singleton Long-Horizon Regression Tests with Various Lengths of Fund Investment Flows, February 13, 2007 - May 30, 2012

Panel A: Independent Variable: Contracts

	k=30		k=65		k=130	
Market	**Slope Estimate**	**p-value**	**Slope Estimate**	**p-value**	**Slope Estimate**	**p-value**
Crude Oil	0.0024	0.4801	0.0017	0.5330	0.0025	0.2978
Heating Oil	-0.0018	0.9153	-0.0005	0.9699	0.0038	0.7167
RBOB Gasoline	0.0161	0.4360	0.0089	0.5082	0.0113	0.2683
Natural Gas	-0.0015	0.7417	-0.0039	0.1574	-0.0003	0.9014

Panel B: Independent Variable: Notional Value

	k=30		k=65		k=130	
Market	**Slope Estimate**	**p-value**	**Slope Estimate**	**p-value**	**Slope Estimate**	**p-value**
Crude Oil	0.0062	0.2652	0.0069	0.0853	0.0028	0.2891
Heating Oil	0.0022	0.5795	0.0036	0.2228	0.0010	0.6176
RBOB Gasoline	0.0081	0.2152	0.0051	0.2321	0.0015	0.5727
Natural Gas	0.0020	0.6608	0.0028	0.3214	0.0026	0.1982

Notes: The independent variable “contracts” in panel A is the change in the daily position held by the Fund measured in actual contracts. The estimated coefficients in panel A are scaled by 100. The independent variable “notional value” in panel B is the logarithmic percent change in notional value. The model is estimated using White’s heteroskedastic consistent estimator for crude oil, heating oil, and RBOB gasoline. The estimator of Newey-West is used for the natural gas model.

Table 7. Alternative Singleton Long-Horizon Regression Tests with 65-Day Fund Investment Flows, February 13, 2007 - May 30, 2012.

Panel A: Independent Variables: Own Contracts and SCOT Market Contracts (k=65)

Market	Own Position Slope Estimate	p-value	SCOT Position Slope Estimate	p-value
Crude Oil	0.0013	0.6205	0.0038	0.0442
Heating Oil	-0.0029	0.8158	0.0027	0.0636
RBOB Gasoline	0.0030	0.8003	0.0028	0.1278
Natural Gas	-0.0051	0.0777	0.0038	0.0247

Panel B: Independent Variables: Own Contracts and SCOT Market Contracts (k=65)

Market	Own Position Slope Estimate	p-value	SCOT Position Slope Estimate	p-value
Sample: 2007-09				
Crude Oil	-0.014	0.0442	0.0100	0.0005
Heating Oil	-0.020	0.2309	0.0066	0.0022
RBOB Gasoline	-0.011	0.7563	0.0060	0.0347
Natural Gas	0.052	0.1593	0.0010	0.7741
Sample: 2010-12				
Crude Oil	-0.001	0.6174	-0.0025	0.1519
Heating Oil	-0.002	0.9042	-0.0026	0.0432
RBOB Gasoline	-0.010	0.4209	-0.0018	0.2349
Natural Gas	-0.006	0.0772	0.0021	0.2884

Panel C: Independent Variables: Percent Change in Contracts and Returns (k=65)

Market	Contracts Slope Estimate	p-value	Returns Slope Estimate	p-value
Crude Oil	-0.0008	0.8562	0.0083	0.1171
Heating Oil	-0.0021	0.5108	0.0080	0.0826
RBOB Gasoline	0.0017	0.6458	0.0046	0.4119
Natural Gas	0.0008	0.8758	0.0016	0.6723

Notes: The independent variable for positions in panels A and B are the change in the daily position held by the Fund measured in actual contracts and the estimated coefficients are scaled by 100. The model is estimated using White's heteroskedastic consistent estimator for crude oil, heating oil, and RBOB gasoline. The estimator of Newey-West is used for the natural gas model. The specific subsamples in panel B are February 13, 2007 – December 31, 2009 and January 1, 2010 – May 31, 2012. The independent variables in Panel C are the logarithmic percent change in contracts and prices (returns).

Table 8. Valkanov Long-Horizon Regression Tests with Various Lengths of Fund Investment Flows, February 13, 2007 - May 30, 2012

Panel A: Dependet Variable: Contracts

	k=5		k=30		k=65		k=130		k=240	
Market	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**
Crude Oil	0.0256	0.02	0.1682	0.06	0.3086	0.05	0.5362	0.04	0.5081	0.05
Heating Oil	0.1896	0.04	0.5733	0.04	0.9168	0.03	1.0122	0.02	1.5814	0.04
RBOB Gasoline	0.1341	0.02	0.7697	0.03	1.2372	0.03	2.1416	0.05	3.6495	0.08
Natural Gas	-0.0540	-0.05	-0.0951	-0.07	-0.1375	-0.05	-0.1376	-0.02	0.0592	0.01

Panel A: Dependet Variable: Notional Value

	k=5		k=30		k=65		k=130		k=240	
Market	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**	**Slope Estimate**	**Re-scaled t-stat.**
Crude Oil	31.9	0.19	36.8	0.12	50.7	0.10	67.2	0.10	66.0	0.10
Heating Oil	134.8	0.11	163.3	0.09	208.2	0.08	241.3	0.08	224.7	0.11
RBOB Gasoline	179.5	0.27	227.6	0.14	262.8	0.13	280.1	0.15	282.2	0.18
Natural Gas	70.4	0.07	85.6	0.06	106.5	0.08	144.9	0.13	172.2	0.25

Note: This table reports the results of estimating long-horizon regressions between average daily returns and average daily positions held by the Fund. Critical values for the rescaled t-statistic (-0.563,0.595) are taken from Valkanov's (2003) Table 4 for Case 2 and c = -5.0, δ = 0.00, T = 750, and tail values representing the 10% significance level. The independent variable "contracts" in panel A is the change in the daily position held by the Fund. The estimated coefficients in panel A are scaled by 100. The independent variable "notional value" in panel B is the dollar change in the notional value.

Table 9. Correlation Coefficients between Daily Spread Changes and Fund Roll Transactions, February 13, 2007 - May 30, 2012

	Unconditional		Conditional	
Market	**Contemporaneous**	**1-Day Lag**	**Contemporaneous**	**1-Day Lag**
WTI Crude Oil	0.0143	-0.0275	0.0461	-0.0360
Heating Oil	-0.1140*	-0.0318	-0.1460*	0.0008
RBOB Gasoline	-0.1701*	-0.0337	-0.1957*	-0.0433
Natural Gas	-0.0278	0.0315	0.0177	0.0688
Average	**-0.0744**	**-0.0154**	**-0.0695**	**-0.0024**

Note: Unconditional correlations use all data and have 1,331 observations and a standard error of 0.0274. Conditional correlations use only data points where there is a non-zero change in positions. The number of observations ranges from a low of 385 (natural gas) to a high of 513 (crude oil). The corresponding standard errors are 0.0512 (RBOB Gasoline) and 0.0443 (crude oil). Coefficients denoted by an asterisk are statistically different from zero at the 5% level.

Table 10. Cumby-Modest Difference-in-Mean Tests for Spreads based on Daily Fund Rolling of Positions, February 13, 2007 - May 30, 2012

Market	No Change	P-value	Buying	P-value	Selling	P-value	"buys"	"sells"
Crude Oil	-0.0179	0.2633	-0.0030	0.9709	0.0038	0.8859	32	481
Heating Oil	0.0005	0.8963	0.0667	0.0672	0.0131	0.0389	9	383
RBOB Gasoline	0.0047	0.6142	0.0162	0.8618	0.0147	0.3674	10	398
Natural Gas	-0.0204	0.1803	0.0071	0.9400	0.0013	0.9654	19	366

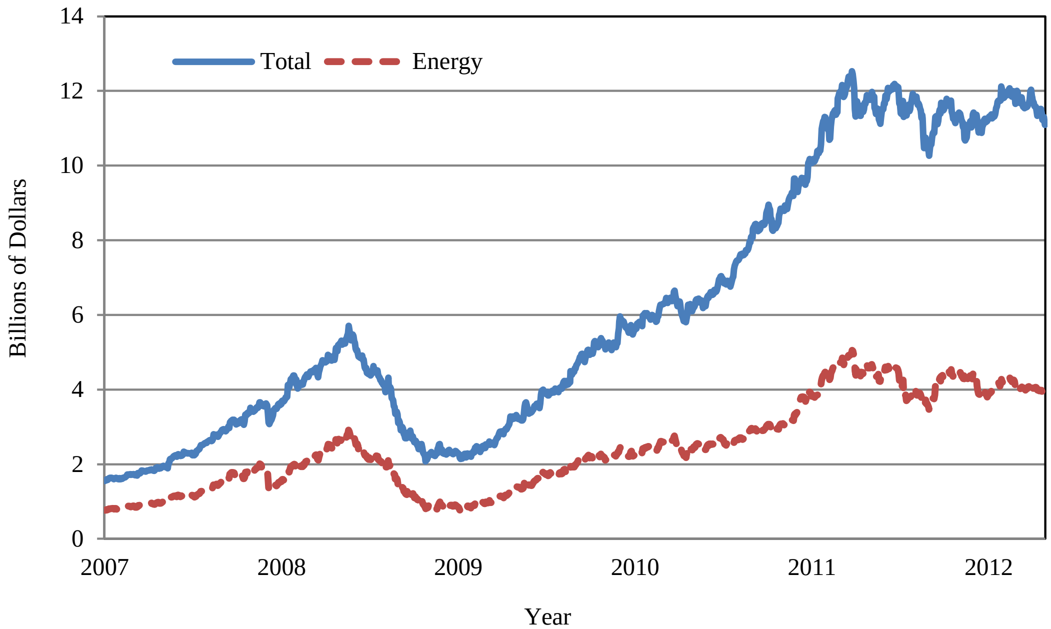
Notes: Buying (selling) is defined as days when the fund is buying (selling) the nearby contract and selling (buying) the deferred contract. The "No Change" column reports the α intercept estimate, the "Buying" column reports the β_1 slope estimate, and the "Selling" column reports the β_2 slope estimate. The number of "buy" and "sell" observations are reported in the final columns.

Table 11. Granger Causality Tests that Fund Rolling Leads Market Spreads, February 13, 2007 - May 30, 2012

Market	*m,n*	β_j	p-value $\beta_j =0$
Crude Oil	18,1	-0.0009	0.7131
Heating Oil	2,1	-0.0027	0.4871
RBOB Gasoline	2,1	-0.0026	0.5748
Natural Gas	1,1	0.0038	0.3024

Notes: The estimated coefficients in panel A are scaled by 100.

Figure 1. Daily Total Fund Notional Value for 22 U.S. Commodity Futures Markets and 4 U.S. Energy Futures Markets, February 2, 2007 – May 30, 2012



Note: The 4 U.S. energy futures markets include: WTI crude oil, heating oil, RBOB gasoline, and natural gas all traded on the New York Mercantile Exchange.

Figure 2. Comparison of Quarterly Fund and Total Index Investment Data (IID) Notional Value for 21 U.S. Commodity Futures Markets, December 2007 - March 2012

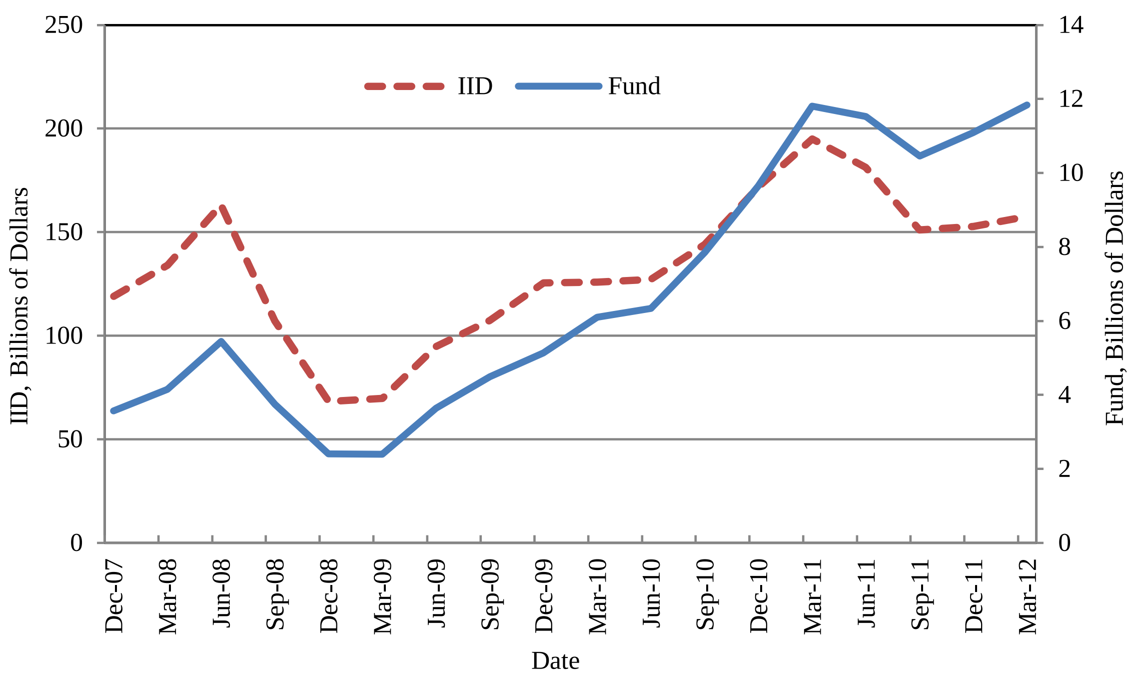
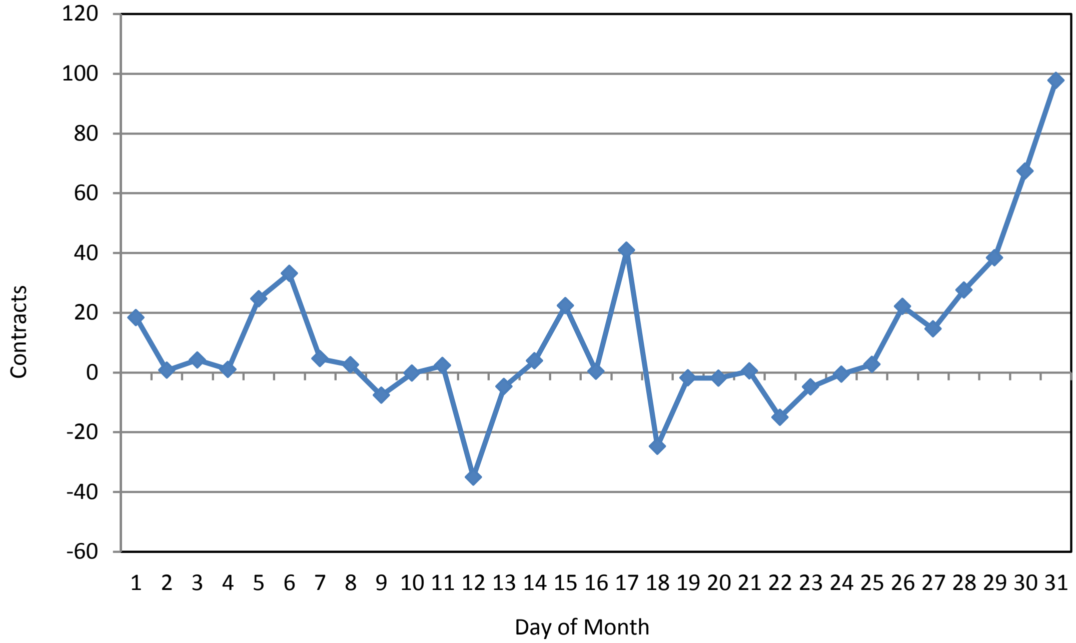


Figure 3. Average Fund Net Position Change by Calendar Day across 4 U.S. Energy Futures Markets, February 13, 2007 – May 30, 2012



Note: The 4 U.S. energy futures markets include: WTI crude oil, heating oil, RBOB gasoline, and natural gas all traded on the New York Mercantile Exchange.

Figure 4. Average Number of Contracts Rolled by Calendar Day across 4 U.S. Energy Futures Markets, 2007-2012