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

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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
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"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

[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), Irwin (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

[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 5th day of the month through the 15th, 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 9th 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 ΔSpread 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 ΔSpread 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) $$\%\Delta Notional\ Value_t^1 = \ln\left(\frac{p_t^1 * q_t * m}{p_{t-1}^1 * q_{t-1} * m}\right) * 100$$

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

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):

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

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 (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:

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

where 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):

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

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:

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

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:

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

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:

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

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:

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

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_l=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

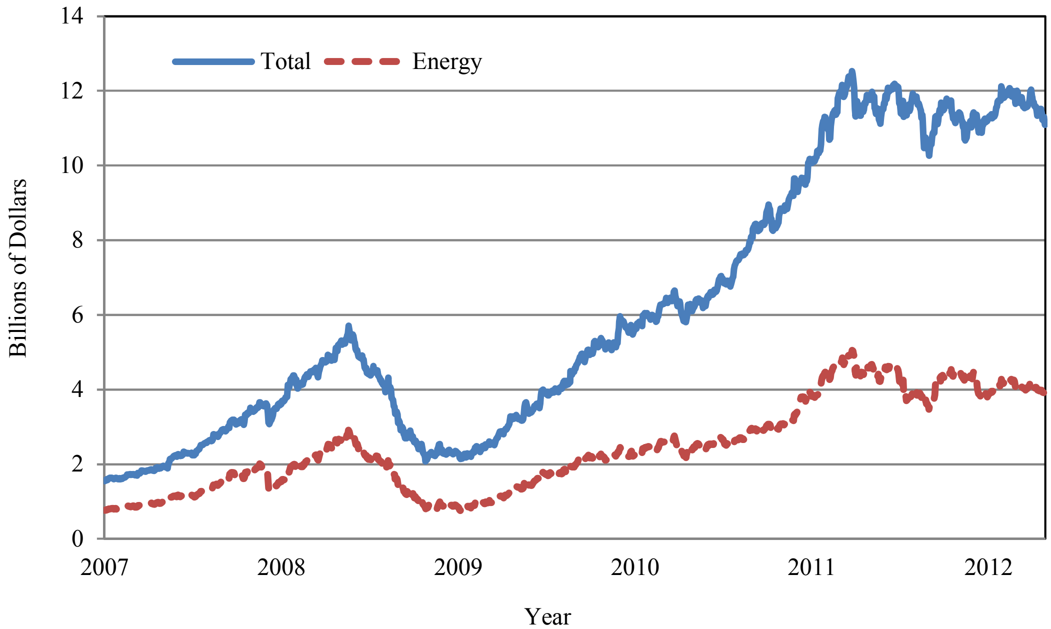
Notes: Buying (selling) is defined as days when the fund is buying (selling) the nearby contract and selling (buying) the deferred contract. The "No Change" column reports the α intercept estimate, the "Buying" column reports the β_1 slope estimate, and the "Selling" column reports the β_2 slope estimate. 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

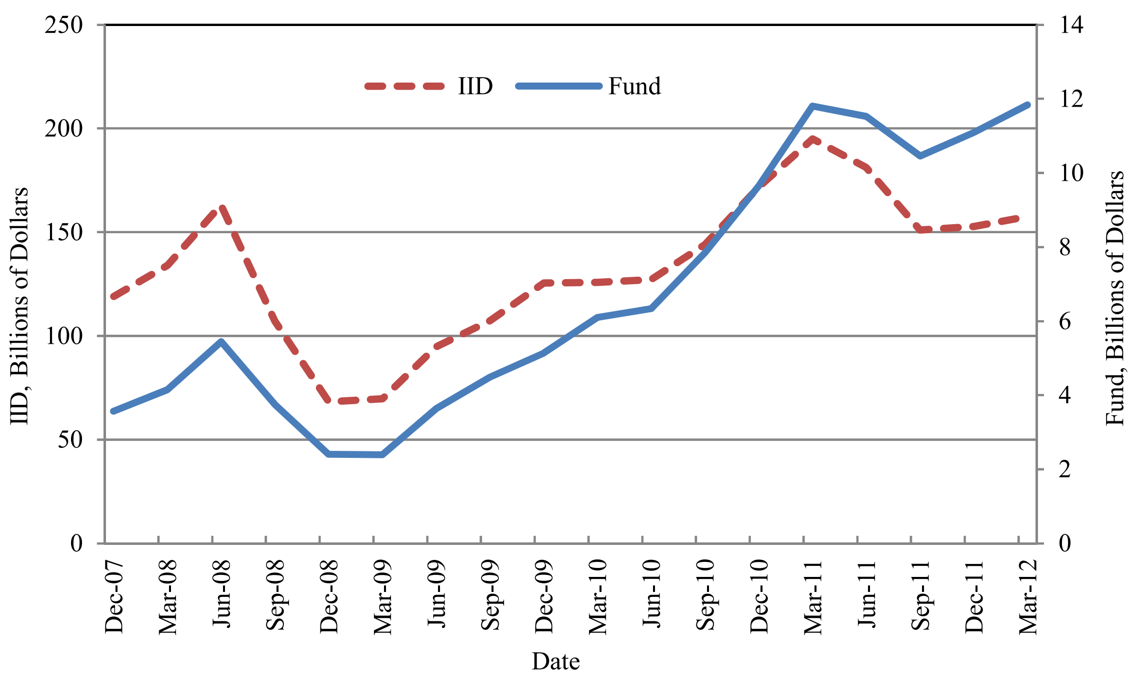
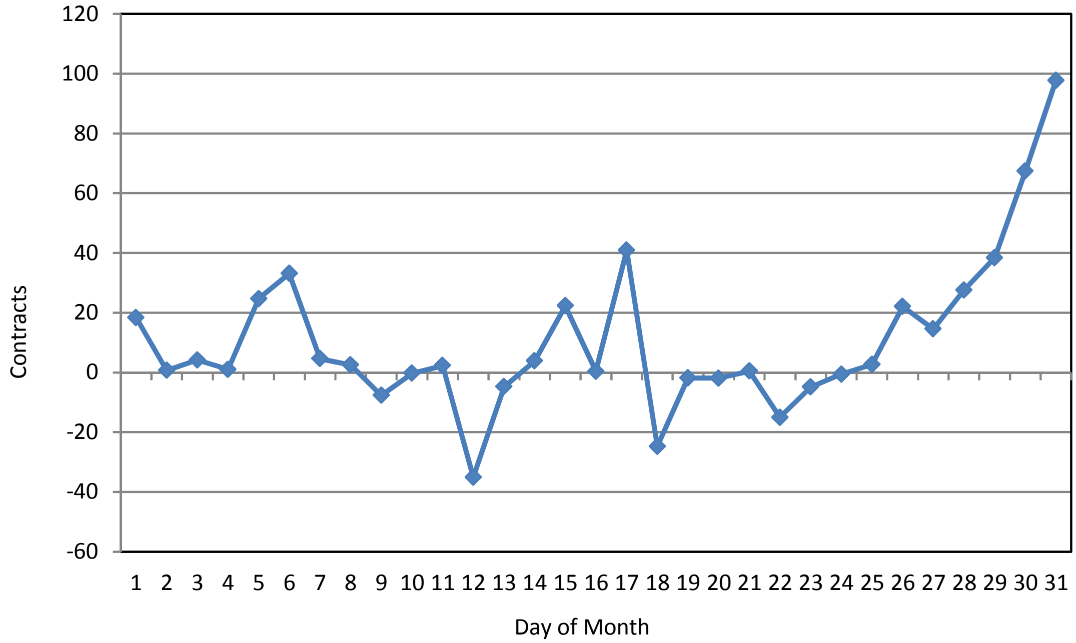


Figure 3. Average Fund Net Position Change by Calendar Day across 4 U.S. Energy Futures Markets, February 13, 2007 – May 30, 2012



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