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The Impact of Index Funds in Commodity Futures Markets: *A Systems Approach*

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Investment in long-only commodity index funds soared over the last five years. Some refer to this surge and its attendant impacts as the *financialization* of commodity futures markets. In view of the scale of this investment—in excess of $250 billion in 2008—it is not surprising that a worldwide debate has ensued about the role of index funds in commodity futures markets. On one side, championed by Masters [2008], are those who declare that the "wall" of investment money works to drive prices away from fundamental value. Others (e.g., Krugman [2008]; and Irwin, Sanders, and Merrin [2009]) are dismissive of the notion that commodities are mispriced in liquid and efficient markets and point out logical inconsistencies in the bubble argument and several contradictory facts.

Several studies have been completed recently in an attempt to sort out which side of the index fund debate is correct. A few conclude that commodity index funds have impacted commodity futures prices (e.g., Gilbert [2009; 2010]; Einloth [2009]; and Tang and Xiong [2010]). Irwin and Sanders [2011] argue that the data and methods used in these studies are subject to a number of important criticisms that limit the degree of confidence one can place in the results. Most studies find little or no evidence of a relationship between index fund positions and movements in commodity futures prices (e.g., Buyuksahin and Harris [2009]; Stoll and Whaley [2010]; Sanders and Irwin [2010; 2011]). However, a concern with these studies is the power of the time-series statistical tests used, which may lack the statistical power necessary to reject the null hypothesis, because the dependent variable—the change in futures prices—is extremely volatile. Another issue is that direct tests of the relationship between index fund positions and price movements in energy futures markets have been hampered by the lack of publically available data on positions of index funds in these markets.

The objective of this research is to provide new empirical evidence on the market impact of commodity index funds that addresses the deficiencies found in previous studies. Our empirical analysis uses new data from the Commodity Futures Trading Commission (CFTC) contained in the "Disaggregated Commitments of Traders" (DCOT) report. This report includes data on the positions held by swap dealers—which are assumed to reflect index-type investments since much of the commodity index-based investment is delivered through swaps[1]—in a variety of markets including energy futures markets. We focus on a group of 14 grain, livestock, soft, and energy futures markets. Bivariate Granger causality tests are used to investigate lead–lag dynamics between index fund positions and futures returns (price changes) or price volatility in each commodity futures market. In addition, a new systems approach to testing

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lead–lag dynamics is introduced and applied. The systems approach improves the power of statistical tests by taking into account the contemporaneous correlation of model residuals across markets and allows a test of the overall impact of index funds across markets.

DISAGGREGATED COMMITMENTS OF TRADERS REPORT

The CFTC has long had a large trader reporting system for the purpose of detecting and deterring futures and options market manipulation (Fenton and Martinaitas [2005]). Positions must be reported to the CFTC on a daily basis if they meet or exceed reporting levels. A weekly snapshot of the position data is compiled in aggregate form and released to the general public as the "Commitment of Traders" report (COT). The COT pools traders into two broad categories (commercial and noncommercial), all contract maturities are aggregated into one open-interest exhibit, and the report is released each Friday with the data as of the end-of-day on the preceding Tuesday.

In response to requests for more information about the composition of open interest, the CFTC began publishing the DCOT report in September 2009 and ultimately provided historical data back to June 2006 (CFTC [2009]).[2] The DCOT reports breaks down combined futures and delta-adjusted options total open interest (TOI) as follows in Equation 1:

$$\underbrace{[SDL + SDS + 2(SDSP)] + [MML + MMS + 2(MMSP)] + [PML+PMS] + [ORL + ORS + 2(ORSP)]}_{\text{Reporting}} + \underbrace{[NRL + NRS]}_{\text{Non-Reporting}} = 2(TOI), \quad (1)$$

where reporting traders (those traders with positions over a specific size) are disaggregated into processors and merchants (PM), swap dealers (SD), managed money (MM), and other reportables (OR). Positions are divided into long (L), short (S), and spreading (SP) as indicated by the corresponding suffixes. For example, the SDL, SDS, and SDSP are the swap dealers' long, short, and spreading positions, respectively. Spreading positions are simply offsetting long and short positions in the same market, but with different contract months and are largely considered market neutral.

Swap dealers (SD) are defined by the CFTC as those traders who deal primarily in swaps and hedge those transactions in the futures market. Processors and merchants (PM) include traditional commercial users—processors, and producers of the commodity who are actively engaged in the physical markets and are using the futures to hedge associated price risks. Managed money (MM) represents positions held by commodity trading advisors, commodity pool operators, and hedge funds,[3] who manage and conduct futures trading on the behalf of clients. Other reportable (OR) are noncommercial traders who are large enough to report, but do not fit into one of the other categories.

It is important, especially for the energy futures markets, to understand the manner in which index fund positions are categorized in DCOT reports. The first notable point is that pension and other investment funds that place index investment directly into the futures markets rather than going through a swap dealer are classified as managed money (MM) or other reportables (OR) in the DCOT. At least in agricultural futures markets, this leakage into other categories is rather small; Sanders, Irwin, and Merrin [2010] show that nearly 85% of index positions are held by swap dealers in these markets. Of potentially greater concern, a swap dealer's position in the futures market may represent a variety of over-the-counter (OTC) positions. That is, how active are the swap dealers in nonindex-related swaps? Calculations by the CFTC [2008] suggest that for commodities, such as wheat, over 90% of the swap dealer long positions represent index traders; whereas, in crude oil it may be as low as 41%. The difference between the two extremes reflects the amount of nonindex-related OTC or swap trading. Wheat, for example, has very little OTC trading other than positions reflecting index-related positions. Conversely, crude oil has very active OTC markets used by index funds, hedgers, and other speculators. Therefore, a swap dealers' overall long position will reflect a mix of index, hedging, and other speculative positions.

Swap dealers net these various positions internally (offset long and short positions on their own books), and then look to lay off the residual risk in the futures market. As a result, a swap dealer's long position in the futures market may represent only a portion of the overall index investments to which they are party (see Exhibit 1 for a hypothetical example).

Certainly, it can be argued that the net position—representing the residual component, which must be

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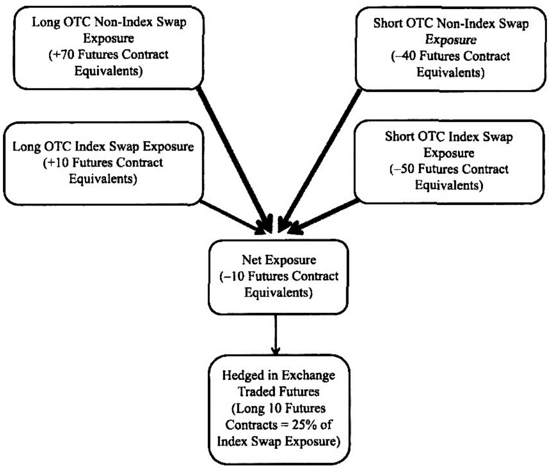
Exhibit 1

A Hypothetical Example of Swap Dealers Hedging Activities



hedged in the commodity futures market—is most likely to impact prices. Regardless, a large portion of swap dealer trading represents commodity index investors, making their positions a useful measure of their direct trading activity in commodity futures markets (Buyuksahin and Harris [2009]). Indeed, in agricultural markets, Irwin and Sanders [2010] demonstrate a high correlation between net long positions held by swap dealers and those reported for index investors, suggesting that swap dealer positions are an acceptable, if imperfect, proxy for index trader positions in time-series tests.

The DCOT swap dealer position data are available weekly (reflecting Tuesday's closing positions) from June 13, 2006 through December 29, 2009, resulting in 186 observations for empirical work. The data are collected for 14 grain, livestock, soft, and energy futures markets: Chicago Board of Trade (CBOT) corn, CBOT soybeans, CBOT soybean oil, CBOT wheat, Kansas City Board of Trade (KCBOT) wheat, New York Board of Trade (NYBOT) cotton, Chicago Mercantile Exchange (CME) live cattle, CME feeder cattle, CME lean hogs, NYBOT coffee, NYBOT sugar, NYBOT cocoa, New York Mercantile Exchange (NYMEX) crude oil, and NYMEX natural gas. For these markets, weekly returns are calculated using nearby futures contracts adjusting for contract rollovers as shown in Equation 2:

$$R_t = \ln \frac{p_t}{p_{t-1}} \cdot 100 \qquad (2)$$

where p_t is the futures price of the nearest-to-expiration contract on Tuesday of each week corresponding with the DCOT as-of position dates. In order to avoid distortions associated with contract rollovers, p_{t-1} in the log relative price return is always calculated using futures prices for the same nearest-to-expiration contract as p_t. Rollover dates for the 12 agricultural commodities occur on or before the first of the delivery month, such that no return is calculated using prices during the delivery month. For the energy markets, the rollover occurs on or before the 16th of the month preceding the delivery month, also avoiding any issues associated with delivery intentions.

Two measures of volatility are computed for use in the empirical tests. First, a forward-looking volatility measure, or implied volatility, is extracted from the options quotes for each market. Implied volatility is provided by CRB online quote services and is calculated in the following manner:

> This volatility is measured by entering the prices of options premiums into an options-pricing model, then solving for volatility. The implied volatility value is based on the mean of the two nearest-the-money calls and the two nearest-the-money puts using the Black options-pricing model. This value is the market's estimate of how volatile the underlying futures will be from the present until the option's expiration. (CRB [2010]).

While this method of deriving the market's implied volatility assumes that Black's pricing model is correct, it is a commonly accepted method of calculating the volatility implied in the options markets and is generally regarded as providing reasonably efficient volatility estimates (e.g., Hull [2000] p. 255). The resulting volatility is expressed as an annualized percentage.

In Equation 3, actual or realized market volatility is calculated using the high–low range estimator originally developed by Parkinson [1980] and widely used by financial analysts (e.g., Sitmo [2010])[4]:

$$\sigma_t = \sqrt{\frac{Z}{n 4 \ln 2} \sum_{i=1}^{n} \left(\ln \frac{H_i}{L_i} \right)^2} \qquad (3)$$

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where Z is equal to 52 in order to annualize the volatility estimate, n is equal to 1 week, and H_i and L_i are the high and low prices for the week. Specifically, H_i and L_i are extracted from the daily highs and lows of the nearest-to-expiration futures contract recorded from Wednesday through Tuesday (inclusive) corresponding with the DCOT as-of position dates. The same contract rollover rules are used for computing realized volatility and returns.

Prior to formal statistical modeling, it is important to determine if the series in question are stationary (fixed mean and variance). If not, then tests of statistical significance may be invalid (Enders [1995] p. 216). Here, we follow the standard testing procedure popularized by Dickey and Fuller to test the null hypothesis of a unit root. The results suggest that returns and volatility are stationary, while the swap dealer positions need to be differenced to be stationary. So, in the following time-series models, the swap dealer positions will be differenced, while returns and volatility will be used in levels to achieved balanced regression equations (same order of integration on the right and left side of the equations).

EMPIRICAL METHODS AND RESULTS

Arguments that index funds impact commodity prices focus primarily on the role of long-only index funds that purchase commodity futures as an asset class. Indeed, Masters and White [2008] suggest that this is essentially a demand shift that pushes up prices. In a demand framework, the relevant measure of positions is that of quantity. Therefore, the analysis that follows concentrates on swap dealers' net positions (long positions–short positions) reported in the DCOT report as a proxy for their overall buying or demand.[5]

The summary statistics for DCOT swap dealers net long positions are shown in Exhibit 2. They indicate the size of index positions had a wide range over the sample period. For instance, in the corn futures market the swap dealer position had a maximum of 430,100 contracts and a minimum of 163,606 for a range of over 100%. In the sugar, cocoa, crude oil, and natural gas markets the effect of swap dealer netting is seen in the occurrence of a net short position (the minimum net long position is negative). This confirms that the swap dealer positions in these markets contain positions other than those held by long-only index funds.

EXHIBIT 2

Summary Statistics, Net Long Position Held by Swap Dealers (number of contracts), June 2006 to December 2009

Market	Mean	Maximum	Minimum	St. Dev.
Corn	313,172	430,100	163,606	77,941
Soybeans	121,557	193,888	73,898	27,892
Soybean Oil	61,453	89,502	27,442	16,234
CBOT Wheat	142,550	189,217	91,681	25,373
KCBOT Wheat	22,073	33,863	9,952	6,906
Cotton	72,092	118,380	42,637	16,797
Live Cattle	88,844	128,967	65,368	16,351
Feeder Cattle	4,161	6,723	1,730	1,194
Lean Hogs	69,149	114,377	36,326	16,858
Coffee	37,179	56,959	21,667	8,718
Sugar	132,099	271,255	–32,149	81,371
Cocoa	8,380	16,474	–5,103	4,763
Crude Oil	40,912	106,176	–10,534	27,504
Natural Gas	49,018	253,500	–67,553	78,063

To gauge the relative size of the swap dealer positions in each market, the percentage of the long-side of each market held by swap dealers is also tabulated. The summary statistics for percentage of long positions are provided in Exhibit 3. The percentage of long positions held by DCOT swap dealers can vary over a wide range. In cotton, the average is 31.1%, but it ranges from a maximum of 41.9% to a minimum of 22.1%. Likewise, in CBOT wheat, live cattle, and lean hogs the swap dealers (index positions) can be at times over 40% of the long side of the market. Even the energy markets show relatively high maximum levels, with the percentage of long positions for swap dealers having a maximum of 45.0% in crude oil and 38.6% in natural gas. It is often these

EXHIBIT 3

Summary Statistics, Percentage of Long Positions Held by Swap Dealers, June 2006 to December 2009

Market	Mean	Maximum	Minimum	St. Dev.
Corn	22.5	29.0	17.0	2.4
Soybeans	23.7	28.2	19.8	1.6
Soybean Oil	23.9	30.5	17.4	2.9
CBOT Wheat	37.4	44.5	31.5	2.9
KCBOT Wheat	18.4	24.6	11.4	3.2
Cotton	31.1	41.9	22.1	4.7
Live Cattle	33.7	41.0	27.4	4.0
Feeder Cattle	15.6	22.2	10.1	2.9
Lean Hogs	36.0	42.6	26.7	3.4
Coffee	24.0	36.8	17.6	4.7
Sugar	25.9	34.2	20.5	3.7
Cocoa	14.6	23.8	9.8	3.4
Crude Oil	37.5	45.0	30.4	4.2
Natural Gas	30.2	38.6	22.3	5.1

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large relative position sizes that spawn accusations of price influence. But, clearly, both the net positions (Exhibit 2) and the percentage of the long positions held (Exhibit 3) can swing over wide ranges. The important question is whether these swings in positions affect prices.

Hamilton [1994] suggests the direct, or bivariate, Granger test for examining the lead–lag or causal relationship between two series. Granger causality is a standard linear technique for determining whether one time series is useful in forecasting another. In our case, the time series of interest are market measures of returns (R), implied volatility (IV), and realized volatility (RV). The causal variable is the net swap dealer position (NET). As an example, consider the causal relationship between market returns and net positions. Under the null hypothesis that index traders' net position does not Granger cause market returns, the following linear regression (Equation 4) is estimated for each market (k) over time (t):

$$R_{t,k} = \alpha_k + \sum_{i=1}^{m} \gamma_{i,k} R_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} \Delta NET_{t-j,k} + \varepsilon_{t,k} \quad (4)$$

where the lag structure (m, n) for each market is determined by a search procedure over $m = 4$ and $n = 4$ using OLS and choosing the model that minimizes the Schwartz criteria to avoid overparmeterization (Enders [1995] p. 88). 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.

Previous time-series studies of lead–lag relationships between index fund market participation and commodity futures returns conduct tests market-by-market when data on multiple markets are available (e.g., Stoll and Whaley [2010]; Sanders and Irwin [2011]). As noted earlier, standard time-series approaches can be criticized for a lack of statistical power when the dependent variable demonstrates extreme volatility such as that observed for market returns. Summers [1986] demonstrates that traditional time-series tests may also have low statistical power against a random walk null hypothesis if the true data-generating process is driven by fad or sentiment. Researchers have proposed alternative, more powerful time-series tests (e.g., Jegadeesh [1991]) and they have been applied in previous work on the market impact of commodity index funds; however, they can still suffer from a lack of robustness under the alternative hypothesis (see Daniel [2001]).

In this research, the power of causality tests based on Equation (4) is increased by modeling the K markets as a system of seemingly unrelated regressions. Since the error term, $\varepsilon_{t,k}$, in Equation (4) 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).[6] Previous researchers have used the SUR framework to increase the power of market efficiency tests in foreign exchange markets (Frankel [1980]; Bilson [1981]). 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 ($\varepsilon_{t,k}$) and with the number of equations. Harvey also points out additional efficiency gains by imposing the constraint of equal parameters across equations, where appropriate. Moreover, estimating Equation (3) as a system of K regressions also allows for a more complete set of hypothesis tests.

Traditional bivariate causality in a single market, k, is tested under the null hypothesis in Equation (4) that traders' net positions (NET) cannot be used to predict (do not lead) market returns: $H_0{:}\beta_{j,k} = 0$ for all j. A rejection of this null hypothesis, using an F-test of the stated restriction, provides direct evidence that trader positions are indeed useful for forecasting returns in that market. In order to gauge the aggregate impact of trader positions in that market, the null hypothesis that $\Sigma_{j=1}^{n} \beta_{j,k} = 0$ in each k market will reveal the cumulative directional impact of traders positions on returns, if any. Clearly, in the event that the lag structure is $n = 1$, then the test of null hypothesis that $\Sigma_{j=1}^{n}\beta_{j,k} = 0$ is equivalent to a simple test on the parameter restriction that $\beta_{1,k} = 0$.

When estimated as a system of K equations in a SUR framework, Equation (4) allows for the testing of systematic or aggregate impacts across all markets. To further increase the efficiency gains, coefficients are restricted across market equations where appropriate (see Harvey [1991] p. 69). Specifically, the strategy for selecting the restricted SUR model follows the sequential testing procedure outlined by Harvey (p. 186) where the most general model is first estimated (no crossmarket parameter restrictions). Then, using a Wald test, the hypothesis of equal parameter estimates is tested across markets. When the null of equal parameter estimates is not rejected, then the restriction is placed on the model. Specifically, all K models are first estimated as a SUR system using the lag structure chosen with the OLS search procedure. Second,

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for each estimated parameter the null hypothesis that the cross-equation parameters are equivalent is tested (e.g., $\gamma_{1,1} = \gamma_{1,2} = \cdots = \gamma_{1,K}$). If we fail to reject the null hypothesis at the 10% level, then that parameter restriction is imposed resulting in a pooled estimate or single parameter across equations (e.g., $\gamma_{1}.$). A 10% significance level is used (instead of 5%) to be somewhat conservative in the imposition of parameter restrictions. By pooling parameters—when we fail to reject that they are equivalent—the number of parameter estimates is decreased and statistical efficiency is further enhanced.

To illustrate, consider again Equation (4) and two extreme examples. First, the most restrictive case, where the null of equivalency across markets is not rejected for all parameters. In this case, the parameter estimates are all pooled. Then, causality testing proceeds using the pooled parameter under the null, $H_0{:}\beta_{j}. = 0$ for all j (where $j.$ represents a parameter common across the K markets). Rejection of the null hypothesis suggests that positions lead returns across the system (all markets jointly). Additionally, the aggregate impact that $\Sigma_{j=1}^{n}\beta_{j}. = 0$ can be tested for the system as a whole. In this most restrictive case, there are no tests for individual markets as the pooled result applies equally to all markets.

At the other extreme, assume that we reject the null hypothesis of equal crossmarket parameters in all cases. This is the least restrictive case where none of the parameter estimates are pooled and individual coefficients are estimated for all K markets. In this case, the null hypothesis is tested for each k under the null, $H_0{:}\beta_{j,k} = 0$ for all j, as well as the aggregate impact, $\Sigma_{j=1}^{n}\beta_{j,k} = 0$, is tested for each k market. Moreover, the SUR estimation allows for the testing of systemwide causality, $H_0{:}\beta_{j,k} = 0$ for all j and k, and for the systematic impact across markets, $\Sigma_{k=1}^{K}\Sigma_{j=1}^{n}\beta_{j,k} = 0$. This is an important improvement over a strictly market-by-market OLS approach to causality testing, because it allows for broader statements about systematic impacts.

The first set of empirical causality tests focus on the null hypothesis that net positions do not lead returns. In this case, the independent variable in Equation (4) is market returns (R) and the explanatory variable is the change in the net position (ΔNET). Exhibit 4 shows the SUR test results for the null hypothesis that the swap dealer positions do not lead returns for each market.

In every market, except live cattle, changes in net swap dealer positions enter the model specification with the minimum lag structure of $n = 1$. The testing of parameter restrictions was unable to reject that the $\beta_{1,k}$ coefficients were equivalent across markets, k, which results in a pooled estimation of $\beta_{1}.$, across all K markets. As a consequence, all the markets for which $n = 1$ have the same causality test result where $\beta_1 = -0.0018$ and it is not statistically different from zero. The $\beta_{2,k}$ was only specified and estimated for live cattle. So, this market generates an incremental result, but also fails to reject the null of no causality (p-value = 0.2994). In this particular system, there is a common β_1 and a single $\beta_{2,k}$ estimated for live cattle. Therefore, the test for systemwide causality ($\beta_{1}. = \beta_{2,k} = 0$) happens to be equivalent to the test for just the live cattle market. So, the system results likewise

EXHIBIT 4

Granger Causality Test Results for DCOT Net Swap Dealer Net Positions Do Not Lead Returns, June 2006 to December 2009

$R_{t,k} = \alpha_k + \sum_{i=1}^{m}\gamma_{i,k}R_{t-i,k} + \sum_{j=1}^{n}\beta_{j,k}\Delta NET_{t-j,k} + \varepsilon_{t,k}$ for each market, k, and time, t.

Market, k	m, n	p-value $\beta_j = 0, \forall j$	Estimate $\Sigma\beta_j$	p-value $\Sigma\beta_j = 0$
Corn	1,1	0.1694	–0.0018	
Soybeans	1,1	0.1694	–0.0018	
Soybean Oil	1,1	0.1694	–0.0018	
CBOT Wheat	1,1	0.1694	–0.0018	
KCBOT Wheat	1,1	0.1694	–0.0018	
Cotton	1,1	0.1694	–0.0018	
Live Cattle	2,2	0.2994	–0.0017	0.6868
Feeder Cattle	2,1	0.1694	–0.0018	
Lean Hogs	1,1	0.1694	–0.0018	
Coffee	1,1	0.1694	–0.0018	
Sugar	1,1	0.1694	–0.0018	
Cocoa	1,1	0.1694	–0.0018	
Crude Oil	1,1	0.1694	–0.0018	
Natural Gas	3,1	0.1694	–0.0018	
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\Sigma\Sigma\beta_{j,k}$	p-value $\Sigma\Sigma\beta_{j,k} = 0$
System		0.2994	0.0017	0.6868

Notes: $\Sigma\beta_j$ values are taken to the 10^5 power. The models are estimated across the K markets as an SUR system. Wald tests could not reject the following crossmarket coefficient restrictions: $\alpha_1 = \alpha_2 = \cdots = \alpha_K$; $\gamma_{2,1} = \gamma_{2,2} = \cdots = \gamma_{2,K}$; $\beta_{1,1} = \beta_{1,2} = \cdots = \beta_{1,K}$ for all K markets. These restrictions are imposed on the system and the common coefficients are estimated as a single pooled parameter across all K markets.

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show a cumulative impact that is not statistically different from zero. In total, there is no evidence that the net positions held by DCOT swap dealers lead market returns.[7]

The second set of causality tests focus on the linkage between net positions and market volatility. While there is a growing body of empirical work on the impact of trader positions on returns, there is less empirical evidence with regard to trader positions and market volatility. Granger causality tests are run in a similar fashion to those used to test the linkages between positions and returns. Equation (5) is used to test the null hypothesis that net trader positions (*NET*) do not lead implied volatility (*IV*) in an SUR framework:

$$IV_{t,k} = \alpha_k + \sum_{i=1}^{m} \gamma_{i,k} IV_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} \Delta NET_{t-j,k} + \varepsilon_{t,k} \quad (5)$$

The results for estimating Equation(5) are shown in Exhibit 5, where the null of equal coefficients on lagged positions is not rejected.[8] Therefore, individual $\beta_{j,k}$ coefficients are estimated for each market, *k*. In the system, there are two rejections of the no causality null hypothesis at the 5% level across the 14 markets. The null hypothesis of no causality is rejected at the 5% level for soybeans and also for natural gas. The estimated direction of the impact is negative in both markets, suggesting that larger swap dealer positions actually lead to lower implied volatility. The two individual market rejections result in a rejection of the null hypothesis of no causality for the system (p-value = 0.0005). However, the mixed signs on the coefficients result in a cumulative directional impact (–4.0300) that is not statistically different from zero (p-value = 0.5821), suggesting that while there are market specific impacts (soybeans and natural gas) there is not a pervasive directional impact across the system of markets.

The prior set of tests focused on implied or forward-looking volatility. Granger causality tests are also performed to see if positions lead actual or realized volatility (*RV*) as measured by Parkinson's high–low estimator in Equation (6):

$$RV_{t,k} = \alpha_k + \sum_{i=1}^{m} \gamma_{i,k} RV_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} \Delta NET_{t-j,k} + \varepsilon_{t,k} \quad (6)$$

Exhibit 6 presents the estimates and hypothesis tests associated with Equation (6). Again, individual $\beta_{j,k}$ coefficients are estimated for each market, *k*. The SUR system rejects the null of no causality in soybeans and cocoa at the 5% level. Coffee is the only market with two lags of positions and it has a negative cumulative impact (p-value = 0.0581). Causality is also tested for the system as a whole utilizing the pooled estimation. The null of no causality across the market system is rejected at the 5% level and the cumulative impact is systematically negative (p-value = 0.0131).

The results in Exhibits 4 and 5 are reasonably consistent in suggesting that higher levels of index trader or swap dealer participation in the markets are associated with lower levels of volatility in subsequent weeks. While there are some significant individual market findings, the strongest results are manifest in the systemwide rejections. Specifically, in Exhibit 6, a negative leading relationship is suggested between index trader positions and realized volatility across all markets.

EXHIBIT 5

Granger Causality Test Results for DCOT Swap Dealers Net Positions Do Not Lead Implied Volatility, June 2006 to December 2009

$IV_{t,k} = \alpha_k + \sum_{i=1}^{m} \gamma_{i,k} IV_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} \Delta NET_{t-j,k} + \varepsilon_{t,k}$ for each market, *k*, and time, *t*.

Market	*m, n*	*p*-value $\beta_j = 0, \forall j$	Estimate $\Sigma\beta_j$	*p*-value $\Sigma\beta_j = 0$
Corn	1,1	0.1822	–0.3630	
Soybeans	3,1	0.0000	–2.9400	
Soybean Oil	4,1	0.1688	–1.0500	
CBOT Wheat	2,1	0.2661	0.6510	
KCBOT Wheat	2,1	0.8405	–0.3430	
Cotton	3,1	0.1614	2.6000	
Live Cattle	3,1	0.9342	0.0538	
Feeder Cattle	1,1	0.3466	–3.1100	
Lean Hogs	1,1	0.5871	2.5700	
Coffee	2,1	0.2567	–2.8600	
Sugar	2,1	0.3046	–0.6420	
Cocoa	2,1	0.2979	1.9600	
Crude Oil	4,1	0.5051	0.2700	
Natural Gas	1,1	0.0045	–0.8260	
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\Sigma\Sigma\beta_{j,k}$	*p*-value $\Sigma\Sigma\beta_{j,k} = 0$
System		0.0005	–4.0300	0.5821

Notes: $\Sigma\ \beta_j$ values are taken to the 10^5 power. The models are estimated across the K markets as an SUR system. Wald tests could not reject the following crossmarket coefficient restrictions: $\gamma_{2,1} = \gamma_{2,2} = \cdots = \gamma_{2,K}$; $\gamma_{4,1} = \gamma_{4,2} = \cdots = \gamma_{4,K}$ for all K markets. These restrictions are imposed on the system and the common coefficients are estimated as a single pooled parameter across all K markets.

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EXHIBIT 6

Granger Causality Test Results for DCOT Swap Dealer Net Positions Do Not Lead Realized Volatility, June 2006 to December 2009

$RV_{t,k} = \alpha_k + \sum_{i=1}^{m} \gamma_{i,k} RV_{t-i,k} + \sum_{j=1}^{n} \beta_{j,k} \Delta NET_{t-j,k} + \varepsilon_{t,k}$ for each market, k, and time, t.

Market	m, n	p-value $\beta_j = 0, \forall j$	Estimate $\Sigma\beta_j$	p-value $\Sigma\beta_j = 0$
Corn	2,1	0.8258	0.2000	
Soybeans	4,1	0.0242	–3.3700	
Soybean Oil	2,1	0.5347	–0.9500	
CBOT Wheat	2,1	0.6975	0.4370	
KCBOT Wheat	3,1	0.1308	–5.5000	
Cotton	3,1	0.9358	0.2340	
Live Cattle	3,1	0.0600	–2.4600	
Feeder Cattle	3,1	0.5317	–5.8200	
Lean Hogs	3,1	0.1531	3.7900	
Coffee	1,2	0.1568	–11.8200	0.0581
Sugar	3,1	0.8018	–0.3200	
Cocoa	4,1	0.0420	–12.0300	
Crude Oil	3,1	0.0889	1.0500	
Natural Gas	1,1	0.5975	0.4610	
		p-value $\beta_{j,k} = 0, \forall j,k$	Estimate $\Sigma\Sigma\beta_{j,k}$	p-value $\Sigma\Sigma\beta_{j,k} = 0$
System		0.0408	–36.1000	0.0131

Notes: $\Sigma\beta_j$ values are taken to the 10^5 power. The models are estimated across the K markets as an SUR system. Wald tests could not reject the following crossmarket coefficient restrictions: $\gamma_{3,1} = \gamma_{3,2} = \cdots = \gamma_{23,K}$ for all K markets. These restrictions are imposed on the system and the common coefficients are estimated as a single pooled parameter across all K markets.

Some care must be taken when interpreting causality results (see Newbold [1982]). The lead–lag relationship does not necessarily imply that index trader positions have some dampening impact on implied volatility. It may simply indicate that larger index fund or swap dealer positions coincide with other fundamental factors that portend lower volatility levels. Still, the results provide evidence that is contrary to popular notions that index investments exacerbate market volatility. Importantly, the results for market returns show no evidence linking futures prices to index investments suggesting that there is not a mechanism by which these market participants could create a price bubble.

SUMMARY AND CONCLUSIONS

Money flowing into the commodities markets as an alternative investment increased rapidly from 2004 through 2008. At the same time, commodity prices also increased rather dramatically with a number of commodity prices hitting all-time highs in the first half of 2008. Not surprisingly, this tandem of events brought commodity index funds under intense scrutiny and a worldwide debate ensued as to the role of index funds in commodity futures markets. Those who believe index funds were responsible for a bubble in commodity futures prices (e.g., Masters [2008]) make what seems like an obvious argument—the sheer size of index investment overwhelmed the normal functioning of these markets. Importantly, an empirical linkage must be made between commodity index fund positions and prices or there is no obvious mechanism by which a bubble can form. Therefore, continued empirical tests are an important element of this debate.

Our empirical analysis relies on data compiled by the CFTC in the "Disaggregated Commitments of Traders" report. In particular, the positions held by swap dealers are assumed to reflect index-type investments. The data are used to test if index funds impact either returns or price volatility across 14 grain, livestock, soft, and energy futures markets. The sample period begins on June 13, 2006, and ends on December 29, 2009, yielding a total of 186 weekly observations for analysis. Bivariate Granger causality tests are used to investigate lead–lag dynamics between index fund positions and futures returns (price changes) or price volatility in each commodity futures market. In addition, a new systems approach to testing lead–lag dynamics is introduced and applied. The systems approach improves the power of statistical tests by taking into account the contemporaneous correlation of model residuals across markets and allows a test of the overall impact of index funds across markets.

Examination of the data characteristics and subsequent empirical modeling lead to the following general conclusions. First, there is no convincing evidence that positions held by index traders (as represented by swap dealers) impact market returns. The system of Granger-style causality tests fails to reject the null hypothesis that that trader positions do not lead market returns. Hence, there is no evidence of a linkage between index trader positions in commodity futures markets and price levels. Second, larger net long positions by index traders lead to lower market volatility in a Granger sense. There is a consistent tendency to reject the null hypothesis that index trader positions do not lead market volatility. The direction of the impact is routinely negative. While index

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positions lead to lower volatility in a statistical sense, it is possible that trader positions coincide with some other fundamental variable that is actually causing the lower market volatility. Still, this result is contrary to popular notions about index traders increasing market volatility.

The policy implications of the results are straightforward: current regulatory proposals to limit speculation—especially on the part of index funds—are not justified and likely will do more harm than good. In particular, limiting the participation of index fund investors would rob the commodity futures markets of an important source of liquidity and risk-absorption capacity at a time when both are in high demand. Most likely, increased U.S. regulation will force commodity index funds off-shore to rapidly growing international futures markets that have a lower regulatory burden. Or, more ominously, tighter position limits on speculation in commodity futures markets combined with the removal of hedge exemptions could force commodity index funds into thinly traded cash markets, where truly chaotic results could follow.

ENDNOTES

The authors are indebted to Hongxia Jiao for her assistance in collecting the data for this study.

[1]See CFTC [2008].

[2]Since 2007, the CFTC has also released the, "Supplemental Commodity Index Traders," (CIT) reports, which break out the positions of index traders for 12 agricultural markets. See Irwin and Sanders [2010] for a detailed comparison of the CIT and DCOT reports.

[3]Funds that identify themselves as hedge funds may be registered with the CFTC and, thus, technically would be more accurately described as CTAs. Registration requirements can be found at www.NFA.futures.org/NFA-registration/CTA/index.html.

[4]See Spurgin [2001] for a discussion of bias and efficiency of Parkinson estimators.

[5]We tested other position measures including the percentage of long positions as shown in Exhibit 3. The empirical results were generally not sensitive to the position measure and the results presented here are representative of those found for all of the position measures. For a more thorough description of the relevant position measures, see Irwin and Sanders [2010].

[6]The correlation matrix of residuals for the OLS estimates of (4) showed correlation coefficients ranging from a high of 0.96 (CBOT wheat and KCBOT wheat) to a low of −0.12 (corn and feeder cattle) with an average of 0.28.

[7]We also ran Granger causality tests using index trader positions for 12 agricultural futures markets found in CFTC "Supplemental" (CIT) reports. Similar hypothesis test results were found using the CIT data. See Irwin and Sanders [2010].

[8]Equations (5) and (6) were also estimated with monthly dummy variables to test for seasonality in volatility. For this sample period, the null hypothesis of equal volatility across months was not rejected, so the monthly dummy variables were not included in the final model specifications.

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The Journal of Alternative Investments

Market Distress

The Role of Speculators During Times of Financial Distress 10

Naomi E. Boyd, Jeffrey H. Harris, and Arkadiusz Nowak

One of the best-known and largest hedge fund failures was the 2006 failure of Amaranth Advisors, LLC. The authors use detailed, trader-level data to examine the role of speculators during times of financial distress—in this case, the failure of Amaranth. They find that speculators served as a stabilizing force during the period by maintaining or increasing long positions, even while prices fell. The authors develop two testable propositions regarding liquidation versus transfer of positions and conclude that the probability of transfer was more likely for distant contract expirations and for contracts more dominantly held by the distressed trader. The article also examines the role of speculators in providing liquidity and mitigating the effects of liquidity risk by evaluating the change in the number of traders, the size and time between trades, and a Herfindahl measure of speculative trader concentration during the crisis period.

Market Manipulation

Squeeze Play: *The Dynamics of the Manipulation End Game* 26

Craig Pirrong

This article considers one of the most significant regulatory concerns facing derivatives markets: the case of market manipulation by means of a corner, or "squeeze." There are many famous examples of squeezes dating back to the very origins of derivatives trading and extending to the present day. These manipulations distort prices by moving them away from the supply- and demand-driven equilibrium, which limits the effectiveness of the market as a venue for price discovery and effective hedging. Unfortunately, the dynamics of trading as a contract nears expiration have not been modeled extensively. As a result, the existing literature cannot capture many of the interesting actions and interactions observed during actual squeezes. This article fills that void by examining the effects of asymmetrical information on the trading strategies of large longs and shorts as a contract approaches expiration. It provides insight into the mechanism of real-world corners and squeezes and the associated price movements around expiration that are not driven by supply and demand.

Impact of Index Funds

The Impact of Index Funds in Commodity Futures Markets: *A Systems Approach* 40

Dwight R. Sanders and Scott H. Irwin

This article addresses the debate regarding the role of index funds in commodity futures markets. Many have argued that index funds are speculators that are responsible for bubbles in commodity futures prices. The argument is based on the premise that the sheer size of index investment can overwhelm the normal functioning of these markets. Importantly, an empirical linkage must be made between commodity index fund positions and prices, or there is no obvious mechanism by which a bubble can form. The authors' empirical analysis uses new data from the U.S. Commodity Futures Trading Commission contained in the "Disaggregated Commitments of Traders" report. Granger-style causality regressions provide no convincing evidence that positions held by swap dealers impact market returns. Surprisingly, the results do suggest that larger commodity index positions are associated with declining market volatility, although these results may be market specific.

Commodity Index Investing: *Speculation or Diversification?* 50

Hans R. Stoll and Robert E. Whaley

A number of seemingly unrelated commodities experienced simultaneous price spikes in 2007 and 2008. Congress

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