Does "Paper Oil" Matter?

Energy Markets' Financialization and Co-Movements with Equity Markets

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Abstract

Using a uniquely comprehensive dataset of trader positions in U.S. energy futures markets, we find considerable changes in the open interest make-up between 2000 and 2010. We document that these changes help predict an important element of the distribution of energy returns. Controlling for macroeconomic and physical-oil market fundamentals, we show that co-movements between energy and stock market returns go up significantly amid increased paper-market activity by hedge funds – especially funds active in both equity and energy markets. The connection to hedge fund activity *weakens* at time of financial market stress. We find, in contrast, no statistically significant evidence of a relationship between the strength of energy-equity market linkages and the positions of commodity index traders. Our empirical results have ramifications in the debate on the financialization of energy markets.

JEL Classification: G10, G12, G13, G23
Keywords: Energy paper markets, Hedge funds, Commodity index Traders (CIT), Financialization, Commodity-equity linkages, Dynamic conditional correlations (DCC).

Introduction

Over the course of the past twelve years, a growing share of the activity in energy futures (or "paper") markets has stemmed from trading by index funds and hedge funds whose investors or principals also trade financial assets. We use a comprehensive dataset of trader positions in U.S. energy futures markets to document this revolution and to show that it helps predict an important characteristic of the distribution of energy returns.

Several recent papers examine the respective impacts of commodity supply and demand factors and of financial speculation on energy prices or volatility. In particular, Hamilton (2009), Büyükşahin and Harris (2011), Alquist and Kilian (2011), Kilian and Lee (2014) and Kilian and Murphy (2014) investigate the 2004-2008 oil and earlier boom-bust price cycles. Some other articles analyze whether trading by index funds or hedge funds increases (Cheng, Kirilenko and Xiong, 2012) or dampens (Brunetti, Büyükşahin and Harris, 2011) price volatility in individual commodity markets. We focus on a different element of the distribution of energy futures returns: the extent to which they move in sync with returns on equity investments.

Predicting these comovements is critical for hedgers as well as investors. Starting with Pindyck and Rotemberg (1990), numerous studies have used various techniques to disentangle the relevance of fundamental factors *versus* market frictions and investor sentiment. That literature focuses on the excess comovements between commodities – see, e.g., Ai, Chatrath and Song (2006), Tang and Xiong (2012) and references cited therein. Amid widespread concern that commodities and equities may have recently become a "Market of One",[2] the present paper investigates empirically whether energy-equity correlation patterns have changed and, in the affirmative, whether the financialization of commodities is associated with this transformation.

Intuitively, there are several reasons why such a development could have taken place. First, commodity markets have historically been partly segmented from one another and from equity and bond markets (Bessembinder, 1992). As noted above, a key difference between traditional commodity traders and financial institutions is that the latter – but not the former – typically trade in multiple asset markets. As a result, the expansion of financial institutions in commodity markets (i.e., "financialization") could improve risk sharing, lessening the relevance of commodity-specific shocks to commodity risk premia (Bruneti and Reiffen, 2011; Hamilton and Wu, 2014) and increasing the importance of common shocks. The literature on the limits to

[2] See Büyükşahin, Haigh and Robe (2010) and references cited therein.

arbitrage (Gromb and Vayanos, 2010) identifies various additional channels through which financial institutions could in theory transmit shocks across different markets or asset classes. Finally, insofar as financial institutions pit their own commodity managers' performances against the returns on a commodity index, Başak and Pavlova (2013) predict an increase in commodity return comovements with equity returns.

Taken as a whole, those theoretical arguments suggest that not only economic fundamentals but also the make-up of trading activity may help predict the distribution of energy returns. They further suggest that financialization could matter differentially in periods of generalized financial stress. We provide empirical support consistent with these hypotheses.

We show that energy-equity return correlations fluctuate substantially in our sample period. Controlling for physical-market and macroeconomic fundamentals, we document that energy-equity return comovements are positively related to greater energy market participation by speculators in general and hedge funds in particular – especially by hedge funds that take positions in both equity and energy futures markets. We also show empirically that the predictive power of hedge fund activity is weaker during periods of turmoil in financial markets. Importantly for the debate on the impact of commodity index traders in commodity markets, we find no statistical evidence of a link between CIT positions and energy-equity return correlations.

Key to our contribution is our use of a comprehensive dataset of individual positions in the most liquid U.S. futures markets for energy (crude oil, heating oil, natural gas) and equities (S&P 500 e-Mini) that is maintained by the U.S. Commodity Futures Trading Commission (CFTC). We focus on futures traders because, in our sample period, energy price discovery generally took place on futures exchanges rather than over-the-counter – see, e.g., Kofman, Michayluk and Moser (2009).

The CFTC dataset contains detailed information about every large trader's end-of-day futures positions, main line(s) of business and purpose for trading. We use this non-public information to construct weekly measures of index fund, hedge fund, and traditional commercial activities in near-dated (three nearest maturities) and far-dated (all other maturities) contracts.[3] Using these measures, we are able to show that the paper market activities of some types of traders – but not others – are informative.

[3] In our sample, large traders account for over 83% of the total energy futures open interest. We aggregate the individual data so that no single or multiple set of information that we provide in any part of the paper could allow anyone to uniquely identify any trader's underlying position(s) or trade secrets and strategies.

We estimate an autoregressive distributed lag (ARDL) model to establish the existence of a long run relationship between the variables (return correlations, macroeconomic and physical market fundamentals, trader position variables) and to provide consistent, unbiased estimator of the long run parameters. The model includes lagged values to tackle serial autocorrelation and endogeneity concerns (due to the possibility that speculation change with correlations rather than the other way around). Our estimations show that, whereas CIT positions have little predictive power, a 1% increase in the overall energy-futures market share of hedge funds is associated in equilibrium with an increase in dynamic conditional energy-equity return correlations of 5%.

The existence of a long-run relationship has implications for the short run behavior of the variables: there has to be some mechanism that drives them to their long-run equilibrium relationship. After establishing cointegration between the variables, we model this mechanism by an error-correction mechanism (ECM) in which the equilibrium error also drives the short run dynamics of the series. Buttressing the long run results, our ECM analysis singles out hedge fund activity and financial stress as the drivers of short-run dynamics.

We show that it is not simply changes in overall energy speculation that help forecast the observed correlations. Rather, predictive power relates more narrowly to the activities of one type of financial speculators – hedge funds, especially those active in *both* equity and energy futures markets (which generally hold much larger futures positions than other hedge funds). To our knowledge, these findings provide the first empirical evidence of the need to account, in energy futures markets, for heterogeneity among different sorts of hedge funds (i.e., market participants that all share the same public CFTC classification of “managed money traders”).

We also investigate the importance of financial market stress for energy-equity linkages. In regular times (meaning, in our sample, prior to the collapse of U.S. investment bank Lehman Brothers in 2008), we find that energy-equity return comovements are positively related to a proxy for broad-based financial-market stress, the TED spread. Precisely, a 1% increase in the TED spread predicts a 0.19% to 0.30% increase in the energy-equity dynamic conditional correlation estimate. Interestingly, the sign of the interaction term we use to capture the behavior of hedge funds during financial stress (“high TED”) episodes is statistically significant but *negative*. In other words, the informativeness of hedge fund activity appears reduced during periods of elevated financial market stress.

The period after Lehman Brothers' demise is exceptional. Energy-equity correlations soared in the Fall of 2008 and remained exceptionally high through the end of our sample period. A time dummy that captures the post-Lehman period (September 2008 to March 2010) is highly statistically significant in all of our model specifications. Because this statistical significance obtains despite the inclusion of the TED spread in our regressions, this finding suggests that the recent crisis is qualitatively different from previous episodes of financial market stress and that this difference is reflected, in part, by an increase in cross-market correlations.

The remainder of the paper proceeds as follows. Section I places this paper within the exisiting literature. Section II provides evidence on energy-equity linkages. Section III presents our data on trader positions and documents the financialization of energy futures markets. Section IV contains the econometric analyses that tie changes in the strength of energy-equity co-movements to market fundamentals, stress, and hedge fund activity. Section V concludes.

I. Related Work

Within the fast-growing literature on the financialization of commodities, our focus on linkages between commodity and stock markets connects us to several papers that study the impact of financialization on cross-maturity, cross-commodity or cross-asset linkages.

Stoll and Whaley (2010), Tang and Xiong (2012) and Bruno, Büyükşahin and Robe, (2013) use public data to ask whether the arrival of commodity index funds (Stoll and Whaley, Tang and Xiong) or increased financial speculation (Bruno *et al*) has brought about an increase in the extent to which different kinds of commodities move in sync. Büyükşahin, Haigh, Harris, Overdahl and Robe (2011) use non-public CFTC data (2000-2010) to show that, amid growth in commodity index trading and improved contract liquidity, greater hedge fund activity in long-dated crude oil futures has helped link oil prices across the futures maturity curve. Rather than the linkages between diverse commodities or between different-maturity contracts on a single commodity, we are interested in the co-movements between energy and equity paper markets. Our paper also differs from the first three studies through the ability to make economically and statistically relevant distinctions between the activities of CITs, hedge funds and other traders before 2006 (i.e., before markets became financialized) and between traders' short- and long-dated positions (which, even today, remains impossible using public data).

Closest to our endeavor is an article by Büyükşahin and Robe (2014) on return linkages between broad, well-diversified commodity and equity portfolios. That paper constructs measures of trader activity that are aggregated across seventeen different commodities. In the present paper, our interest is trader positions and cross-trading patterns in energy paper markets. This focus and the heretofore unavailable information we use[4] enable us to show that not only macroeconomic variables, but also fundamental factors specific to *physical* energy markets as well as the intensity of hedge fund activity in energy *paper* markets, help predict the extent to which energy and equity returns move together. Furthermore, whereas Büyükşahin and Robe (2014) only report long run analyses, we also provide an ECM analysis. Importantly, the ECM singles out hedge fund activity and financial stress (but not other variables) as the drivers of short-run dynamics.

Part of the literature on the financialization of commodities investigates connections between market stress, financial risk taking and commodity return distributions. For example, Raman, Robe and Yadav (2012) use intraday oil-futures data to establish that high-frequency traders (a type of financial trader not present in energy markets until 2006) pull back from liquidity provision during episodes of market stress. Acharya, Lochstoer and Ramadorai (2013) and Etula (2013) provide evidence, respectively, that the risk-bearing capacities of broker-dealers and the risk aversion of energy producers play significant roles in determining energy risk premia. Cheng, Kirilenko and Xiong (2012) provide empirical evidence of a convective flow of risk from distressed financial traders to commercial hedgers in agricultural markets and discuss the flow's relevance to risk premia. By documenting that the positions of hedge funds help predict another key moment of energy returns' distribution (cross-correlations) and that this relationship is weakened by financial market stress, our findings complement those empirical studies as well as theoretical work on limits to arbitrage.[5]

More broadly, our analysis of hedge fund activity and its relevance to energy returns connects our paper to a vast finance literature on hedge funds. Closest here is a body of empirical work on whether hedge funds destabilize markets. In equity markets, Brunnermeier and Nagel (2004) and Griffin, Harris, Shu and Topaloğlu (2011) argue that hedge funds drove

[4] We obtained clearance from the CFTC to summarize its non-public energy-market information in a manner that respects the confidentiality laws under which the agency operates. Articles similarly based on non-public CFTC futures position data going back to Harzmark's (1987) investigation of the trading performance of individual traders in nine commodity futures markets from July 1977 to December 1981.
[5] See Büyükşahin *et al* (2014) for references and Gromb and Vayanos (2010) for a detailed review of that literature.

stock prices during the technology bubble. For crude oil, Büyükşahin and Harris (2011) and Brunetti, Büyükşahin and Harris (2011) conclude that hedge funds' end-of-day futures positions do not drive up oil price levels or volatility but, instead, are key to the smooth functioning of the oil market through the liquidity that they provide to other types of traders.[6] Those papers focus on price levels for a given asset (i.e., on the first moments of that asset's returns) or on volatility. Our paper, which measures linkages between two types of asset markets, instead deals with another moment of the joint distributions of asset returns.

II. Two decades of Commodity-Equity Co-movements

The present paper investigates whether, in addition to macroeconomic and commodity-specific fundamentals, the market activities of certain types of traders (speculators generally and hedge funds or index traders especially) explain how energy and equity futures markets comove. This Section summarizes our return data and plots our estimates of the dynamic conditional correlation between the weekly returns on passive equity and energy investments.

Our sample covers a full two decades after 1991, when commodity index vehicles first became readily available to investors. This part of our analysis extends a number of prior studies documenting changes over time in the extents to which commodity returns move together with the returns on other kinds of investments.[7] It also complements studies on the susceptibility of stock prices to oil shocks (Kilian and Park, 2009) and on excess comovements between commodities (e.g., Stoll and Whaley, 2010; Tang and Xiong; 2012).

A. Return Data

We analyze weekly returns on benchmark energy and stock market indices.[8] We obtain price data from Bloomberg from January 1991 (when Goldman Sachs' commodity indices were first introduced as investable benchmarks) to May 2011.

[6] In other types of financial markets, the evidence on whether hedge funds are destabilizing is mixed. See Chan, Getmansky, Haas and Lo (2006) for a review of the earlier literature on hedge funds.

[7] See, e.g., Gorton and Rouwenhorst (2006, using data from 1959-2004), Erb and Harvey (2006, using data from 1982 to mid-2004), Chong and Miffre (2010, using data from 1991-2006) and Büyükşahin, Haigh and Robe (2010, using data from 1991 through Fall 2008).

[8] Precisely, we measure the percentage rate of return on the I^{th} investable index in period t as $r^I_t = 100 \text{ Log}(P^I_t / P^I_{t-1})$, where P^I_t is the value of index I at time t.

For energy, we use the unlevered total return on Standard and Poor's S&P GSCI-Energy index ("GSENTR"), i.e., the return on a "fully collateralized energy futures investment that is rolled forward from the fifth to the ninth business day of each month." The GSCI-Energy index averages the prices of six nearby energy futures contracts, using weights that reflect worldwide production figures.[9]

For equities, we use Standard and Poor's S&P 500 index.[10] The most active equity-index futures in the United States is the Chicago Mercantile Exchange's (CME) S&P 500 e-Mini futures, making the S&P 500 index and futures market the ideal choices to investigate whether cross-market traders contribute to commodity-equity linkages.[11]

B. Dynamic Conditional Correlations

In order to obtain dynamically correct estimates of the intensity of commodity-equity co-movements, we follow Engle (2002) and compute dynamic conditional correlations (DCC). In essence, the DCC model uses a two-step approach. In the first step, we estimate time-varying variances using a GARCH(*1*,*1*) model. In the second step, we estimate a time-varying correlation matrix using the standardized residuals from the first-stage estimation.

Figure 1 plots, from January 3, 1991 to May 10, 2011, the dynamic conditional correlations between the weekly unlevered rates of return on the GSCI-Energy investable index and on the S&P 500 ("SP") equity index. For comparison, it also plots the DCC between the weekly rates of return on the GSCI Energy and MSCI World Equity ("MXWO") indices.

Several facts emerge from Figure 1. First, energy-equity correlation patterns appear broadly similar for U.S. and world equity indices even though, after 2003, energy-equity DCC estimates are often slightly higher for the MSCI than for US-only equity indices.[12] Second,

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[9] The GSCI-Energy index gives a very large weight to crude oil. In robustness checks, we therefore use the total (unlevered) returns on the second most widely used investable benchmark, Dow-Jones's DJAIG (since May 2009, DJ-UBSCI Total-Return Energy Index). This second index was designed to provide a more "diversified benchmark for the commodity futures market." We find similar results for both indices, so we focus on results with the GSCI.

[10] We use equity returns that omit dividend yields. This approach leads to an underestimation of the expected returns on equity investments (Shoven and Sialm, 2000). Insofar as large U.S. corporations smooth dividend payments over time (Allen and Michaely, 2002), however, the correlation estimates that are the focus of our paper should be essentially unaffected.

[11] We find quite similar energy-equity correlation patterns using the Dow-Jones Industrial Average equity index, so there is no loss of generality in discussing only the S&P 500.

[12] Tang and Xiong (2011) and Büyükşahin and Robe (2010) find a similar difference using broad-based commodity indices. They show that the difference is due to the emerging market component of the MSCI World equity index. Tang and Xiong interpret the latter component as a "proxy for the economic growth of emerging economies" that

energy-equity correlations (DCC) fluctuate substantially: prior to the demise of Lehman Brothers, the range was (-0.37, 0.38). Third, there was no visible DCC up-trend before September 2008. Finally, and most strikingly, from late November 2008 through May 2011, energy-equity weekly return correlations hovered around levels unseen in the prior two decades (almost always well above 0.34, up to 0.62).

III. The Financialization of Energy Futures Markets, 2000-2010

Trading activity and open interest levels in most commodity futures markets are greater now than a decade ago. In this Section, we draw on a comprehensive dataset of trader positions in U.S. energy futures markets to show that the latter's growth entailed major changes in the composition of the overall open interest. We find substantial increases in the activities of hedge funds and commodity index traders, extending over time and generalizing across energy commodities the findings of Büyükşahin *et al* (2011) in the specific case of crude oil. Further, we provide the first evidence of the extent to which equity futures traders are also active in energy paper markets.

We construct our dataset from confidential CFTC data on individual trader positions in key U.S. energy (crude oil, natural gas and heating oil) and equity (S&P 500 e-Mini) futures markets. These data provide the foundation for the regression analyses that examine, in Section IV, whether these structural changes have explanatory power for energy-equity returns linkages.

Section III.A contrasts our information with the less-detailed, publicly available data on energy futures open interest mostly used in prior literature. Section III.B establishes that, compared to commercial activity, speculative activity has grown substantially since 2000. We then provide more specific evidence on the growth of commodity index trading (Section III.C), hedge fund activity (Section III.D), and cross-market trading (Section III.E).

A. Trader Position Data

We use a database of daily trader positions in three U.S. energy futures and S&P 500 e-Mini futures markets from July 1, 2000 to March 1, 2010. The trader-level position data we

pushed up commodity prices after 2003. In our regression analysis of correlation drivers in Section IV, we control for "macro" fundamentals by means of a non-equity based measure of world economic activity (Kilian, 2009).

utilize, and the individual trader classifications on which we rely to create aggregate measures of activity by trader type, originate in the CFTC's Large Trader Reporting System.

1. Raw Data on the Purpose and Magnitude of Individual Positions

The CFTC collects confidential position-level information on the composition of open interest across every futures and options-on-futures contract for every exchange traded commodity. It gathers this information for each trader with position above a certain threshold (which varies by market). The CFTC also collects information from each large trader about its respective underlying business (hedge fund, swap trader, crude oil producer, refiner, etc.) and about the purpose of its positions in different U.S. futures markets.

Many smaller traders' positions are also voluntarily reported to the CFTC and are thus included in the raw data made available for the present study. On average, our dataset covers 83% of the total open interest for our three markets and for our sample period.

The CFTC receives information on individual positions for every trading day. In our weekly analysis, we focus on the Tuesday reports because the underlying raw information is what the CFTC summarizes in weekly "Commitment of Traders (COT) Report" published every Friday at 3:30 p.m (U.S. Eastern Time). Thus, the information we provide in this Section can be contrasted with numerous extant studies of commodity markets that rely on COT data.

2. Publicly Available Information

For every futures market with a certain level of market activity, the CFTC's weekly COT reports provide information on the overall open interest. They also break down this figure between two (until 2009) or four (since 2009) categories of traders.

Prior to September 2009, the COT reports separated traders between two broad categories – "commercial" *vs*. "non-commercial." The CFTC classified all of a trader's futures and options positions in a given commodity as "commercial" if the trader used futures contracts in that particular commodity for hedging as defined in CFTC regulations. A trading entity generally is classified as "commercial" by filing a statement with the CFTC that it is commercially "engaged in business activities hedged by the use of the futures or option markets".[13] The "non-

[13] In order to ensure that traders are classified accurately and consistently, the CFTC staff may exercise judgment in re-classifying a trader in light of additional information about the trader's use of the markets.

commercial" group aggregated various types of mostly financial traders, such as hedge funds, mutual funds, floor brokers, etc.

Since September 4, 2009, the CFTC's COT reports differentiate between four (rather than just two) kinds of traders. It now splits commercial traders between "traditional" commercials (e.g., energy producers, refiners, oil dealers and merchants, etc.) and commodity swap dealers (a category that includes commodity index traders in most markets). It also now differentiates the reportable positions of non-commercial traders between those of managed money traders (i.e., hedge funds) and those of "others". As of Spring 2014, however, the CFTC has not indicated plans to make this more detailed information available retroactively prior to 2006 or to break down the publicly-available position data by contract maturity.

3. Non-Public Information

The LTRS data allow for finer classifications of traders than the two or four broad COT categories (see Appendix 1 for a discussion of the main trader categories). Importantly, it allows for such classifications throughout our sample period, not just after 2006. Furthermore, because the LTRS data are not only commodity-, but also maturity-, specific, they allow us to disentangle the activities of various kinds of traders at the near and far ends of the commodity-futures term structure. In contrast, the COT reports do not separate between traders' positions at different contract maturities. Section IV shows that this additional disaggregation is critical, in that it is the positions held by hedge funds in shorter-dated energy contracts (rather than further along the futures maturity curves) that help explain energy-equity return comovements.

Finally, but crucially, the LTRS dataset follows each large trader's activities in different markets. We use this information to provide the first evidence of the extent to which traders are active in both equity and energy paper markets. In Section IV, furthermore, we show that the positions of hedge funds active in both equity and energy markets hold explanatory power for cross-market linkages.

B. Increased Excess Speculation

To measure the extent and growth of speculative activity in energy futures markets, we use Working's (1960) "*T*". This commonly used index compares the activities of all "non-commercial" commodity futures traders (often known as "speculators") to the net demand for hedging originating from "commercial" traders (also known as "hedgers").

1. Measuring "Excess Speculation"

Working's "*T*" is predicated on the idea that, if long and short hedgers' respective positions in a given futures market were exactly balanced, then their positions would always offset one another and speculators would not be needed in that market. In practice, of course, long and short hedgers do not always wish to trade simultaneously or in the same quantity. Hence, speculators must step in to fill the unmet hedging demand. Working's "*T*" measures the extent to which speculation exceeds the level required to offset any unbalanced hedging at the market-clearing price (i.e., to satisfy hedgers' net demand for hedging at that price).

For each energy markets in our sample (i = 1, 2, 3), we compute Working's T every Tuesday from July 1, 2000 to March 1, 2010. In each market, we compute two "*T*" indices – one for short-term futures only ($SIS_{i,t}$), and one for all contract maturities ($SIA_{i,t}$). This second measure can be computed using the publicly-available COT reports, which allows readers without access to the LTRS data to replicate our results.

For $SIS_{i,t}$ we use position data from the three shortest-maturity contracts with non-trivial open interest. The idea is that it is near-dated futures prices that form the basis of the GSCI-Energy return benchmark. Formally, in the i^{th} energy market in week *t*:

$$SIS_{i,t} \equiv T_{i,t} = \begin{cases} 1 + \dfrac{SS_{i,t}}{HL_{i,t} + HS_{i,t}} & if\ HS_{i,t} \geq HL_{i,t} \\ 1 + \dfrac{SL_{i,t}}{HL_{i,t} + HS_{i,t}} & if\ HL_{i,t} \geq HS_{i,t} \end{cases} \qquad (i = 1,2,3)$$

where $SS_{i,t} \geq 0$ is the (absolute) magnitude of the short positions held in the aggregate by all non-commercial traders ("Speculators Short"); $SL_{i,t} \geq 0$ is the (absolute) value of all non-commercial long positions; $HS_{i,t} \geq 0$ stands for all commercial short positions ("Hedge Short") and $HL_{i,t} \geq 0$ stands for all long commercial positions.

We then average these individual index values to provide a general picture of speculative activity across energy paper markets:

$$WSIS_t = \sum_{i=1}^{3} w_{i,t}\, SIS_{i,t}$$

where the weight $w_{i,t}$ for commodity *i* in a given *week t* is based on the weight of the commodity in the GSCI-Energy index that *year* (Source: Standard and Poor), rescaled to account for the fact that we focus on the three U.S. markets (out of six GSCI-Energy markets) for which position data are available.

To get a picture of excess energy speculation across *all* contract maturities, we compute:

$$WSIA_t = \sum_{i=1}^{3} w_{i,t}\, SIA_{i,t}$$

2. Excess Speculation in U.S. Energy Futures Markets, 2000-2010

Table 2 provides summary statistics of the weighted average speculative indices (*WSIS* and *WSIA*) between July 2000 and March 2010. During that period, the minimum *v*alue was approximately 1.05 for short-dated as well as for all energy contracts; the maximum was 1.57 in near-term contracts but lower (1.46) across all maturities. Put differently, speculative positions averaged 5% to 57% more than what was minimally necessary to meet net hedging needs at the market-clearing prices.

Figure 2A shows the relative growth of speculation in energy paper markets in the past decade. Excess speculation increased substantially, from about 5-10% early in the decade to 37-57% in 2008.[14] A comparison of the *WSIS* and *WSIA* plots shows similar excess speculation patterns in near-dated and other contracts prior to the Summer of 2006. Between the Summer of 2006 and the Summer of 2009, however, short-term excess speculation was often 10% greater than further out on the futures maturity curve. Excess speculation fell notably in 2009, especially in near-term contracts (*WSIS* peaked at 1.57 in April 2008 but fell to 1.34 in late 2009).

In sum, Figure 2A identifies a long-term increase, but also substantial variations, in excess commodity speculation. Those patterns will be of particular interest in the analysis of Section IV. Before proceeding to regression analyses, however, we investigate whether the

[14] The values for energy markets in Figure 2 are generally lower than for agricultural commodities. Peck (1981) gets values of 1.57-2.17; Leuthold (1983), of 1.05-2.34. See also Irwin, Merrin and Sanders (2008).

changes in overall speculative activity hide differential patterns for distinct types of financially-motivated traders: index traders (III.C), hedge funds (III.D) and cross-market traders (III.E).

C. Increased Commodity Index Trading (CIT)

CIT's arrival in energy markets has received a lot of attention from policy makers (ITF, 2008) and academic researchers (e.g., Irwin and Sanders, 2011; Singleton, 2014). We utilize the LTRS data to provide novel evidence of CIT's growing importance in energy futures markets.

1. Measuring Index Trading Activity

While the non-public data to which we were granted access yields precise information to compute market shares for most trader categories (including, importantly, hedge funds – see Section III.D), the LTRS does not identify CIT activity in energy markets at the daily or weekly frequency. This is because CIT activity percolates into energy futures partly through CIT interactions with commodity swap dealers but, even in the CFTC's non-public data, CIT-related positions in energy markets cannot be identified within the overall positions held by commodity swap dealers in those markets.

Various approaches have been suggested to circumvent this pitfall using publicly available data (see Appendix 2 for a discussion). The present paper draws instead on the granularity of the non-public CFTC data and on the fact that CIT activity has tended to concentrate in near-dated contracts. Specifically, we approximate the near-term (*overall*) CIT market shares in our three energy futures markets each week by the shares of the near-dated (*overall*) open interest held by swap dealer in each of these three markets. We compute similar market share figures for hedge funds (see Section III.D) and for traditional commercial traders.

Formally, for each sub-category of traders, we compute the open-interest or "market" share of a given category of traders, in each energy futures market each Tuesday, by expressing the average of the long and short positions of all traders from this group in that market as a fraction of the total open interest in that market that same Tuesday. We then average these commodity-specific market shares across our three energy futures markets, using the annual commodity weights. We compute these market shares across the three nearest-maturity futures with non-trivial open interest as well as across all contract maturities.

We denote by *WMSS_MMT*, *WMSS_AS*, and *WMSS_TCOM* the respective weighted-average market shares of hedge funds (or MMT, "managed money traders"), commodity swap dealers (AS, including CIT – commodity index traders), and traditional commercial traders (TCOM) in short-dated contracts. We denote each type of traders' contribution to the total open interest (i.e., across all contract maturities) as *WMSA_MMT, WMSA_AS,* and *WMSA_TCOM*.

2. Index Trading in U.S. Energy Futures Markets, 2000-2010

Figure 2A plots *WMSS_AS* (WMSA_AS), i.e., the weighted-average market shares of commodity swap dealers in *near-dated* (all) energy futures. Both *WMSS_AS* and *WMSA_AS* peaked in the second half of October 2008 before sharply falling in the following two months and then recovering slowly in 2009 and 2010.

Throughout our sample period (2000-2010), commodity swap dealers' positions account for approximately 10% more of the overall open interest than they contribute to the near-dated open interest. For the near-dated energy futures (where CIT activity has tended to concentrate), Figure 2A shows that swap dealers' market share grew approximately by two thirds between early 2003 and the beginning of 2007. Interestingly, following the dismal last quarter of 2008 and amid a strong rebound of the energy futures open interest in 2009 and 2010, swap dealers' positions accounted for a greater proportion of the long-dated open interest than at any time earlier – suggesting a further lengthening of the maturity structure of their energy exposure, a pattern that was first identified in the crude oil market by Büyükşahin *et al* (2011).

D. Increased Hedge Fund Activity

Working's *T* lumps together all non-commercial traders: floor brokers and traders, hedge funds, and other non-commercial traders that are not registered as "managed money traders". Yet, there is little reason to believe that floor brokers in a specific market should affect energy - equity linkages. Hedge funds, in contrast, are much more plausible candidates for such a role.

1. Measuring Hedge Fund Activity

We utilize the LTRS data on the individual positions of "managed money traders" to compute hedge funds' contribution to the total energy futures open interest (see Appendix 3 for a formal definition of a "hedge fund" in the context of U.S. energy futures markets). We calculate hedge fund market shares across the three nearest-maturity futures with non-trivial open interest (*WMSS_MMT*) as well as across all contract maturities (*WMSA_MMT*).

2. Hedge Funds in U.S. Energy Futures Markets, 2000-2010

The *red* (blue) line in Figure 2B depicts changes in *WMSS_MMT* (WMSA_MMT) over time. This chart, together with Tables 3B and 3C, highlights several important market changes.

First and foremost, hedge funds' contribution to the energy futures open interest more than tripled between 2000 and 2008. Their market share grew from less than a tenth of the open interest prior to 2002 to between a quarter and a third of the total after 2006.

Second, Tables 3B and 3C, which provide summary statistics for various kinds of traders in near-term (3B) and all (3C) futures contracts, show that *WMSS_TCOM* and *WMSA_TCOM* both fell from over 60% to less than 20%. That is, hedge funds' greater market share echoes a sharp drop in traditional commercial traders' relative contribution to the overall open interest. This finding generalizes, to a cross-section of energy futures markets, some of the observations of Büyükşahin *et al* (2011) in the specific case of WTI crude oil futures.

Third, Figure 2A shows that the market share of hedge funds *as a whole* started trending downward in the Spring of 2008. Interestingly, this trend persisted in 2009 and 2010, i.e., in the period when cross-market correlations were unusually elevated. A natural question is whether, as a group, hedge funds pulled back from energy paper markets in the post-Lehman turmoil. We debunk this notion in Section III.E, by showing that one particular kind of hedge funds did not pull back (in fact, increased their collective share of the open interest) during that period.

E. Increased Cross-Market Trading

Of particular interest for this study are commodity futures traders that are also active in equity markets. Table 4 provides information on the number of such traders in each of the commodity futures market in our sample. Figure 2B and Table 3A document their growing contribution to the overall commodity-futures open interest in the past decade.

1. Measuring Cross-Trading Activity

For each trading day, we use the unique ID of each energy futures trader active that day to ascertain whether that trader also held overnight positions in the CME's e-Mini S&P 500 equity futures at any point in our sample period. In the affirmative, we consider such an energy futures trader to be a "cross-market trader". This exercise tells us how many cross-traders there are on a given trading day.

While the number of cross-market traders is of some interest, their market share is of independent interest. This is because intuition suggests that traders active in *both* equity and commodity markets are likely better capitalized, and hence can hold larger positions, than other futures traders. We therefore compute these cross-market traders' share of the overall open interest in a given commodity market on each trading day. To do so, we use the approach of Section III.C-D: for each group or subgroup of traders, we compute the open interest attributable to that group or sub-group as the average of the long and short positions of traders in that group in that market on that day as a fraction of the total open interest in that market on that same day.

We denote by $CMSA\_MMT_{i,t}$, $CMSA\ \_AS_{i,t}$ and $CMSA\ \_ALL_{i,t}$ the shares of the open interest in the i^{th} commodity held respectively by cross-trading hedge funds (*MMT*), energy swap dealers (*AS*) and all energy-futures traders (*ALL*) (i = 1, 2, 3). We then use annual commodity weights to calculate the weighted-average market share of several trader types (xxx = *MMT*, *AS* or *ALL*) across the three energy futures markets in our sample:

$$WCMSA\_\mathrm{xxx}_t = \sum_{i=1}^{3} w_{i,t}\, CMSA\_\mathrm{xxx}_{i,t}$$

2. Equity-Energy Cross-Market Activity in U.S. Futures Markets, 2000-2010

Table 4 provides information on the number of cross-market traders, and on the make-up of cross-trading activity, in the three energy futures markets in our sample. In each of these energy markets, hundreds of traders also held positions in the Chicago Mercantile Exchange's e-Mini S&P 500 equity futures market (column 1). Except for heating oil, well over a sixth (natural gas) or over a fourth (crude oil) of all large commodity futures traders also traded equity futures in that period (column 2).

Hedge funds make up a plurality of cross-market traders, whereas commodity index traders make up a low-single-digit proportion of the total number of cross-traders. Depending on the market, between 25% and 41% of those cross-market traders are classified as hedge funds in equity futures markets (column 8).

The last four columns of Table 3B show that the median weighted average share of the commodity futures open interest held by equity-commodity cross-traders was 43% during the sample period (*vs*. 28% or less of the trader count in Table 4). This difference confirms our intuition that cross-market energy futures traders hold much larger overnight positions than other types of market participants. Furthermore, the green line in Figure 2B shows that the market share of cross-trading hedge funds increased substantially between 2000 and 2010, from less than 5% of the total energy futures open interest in 2000 and 2001 to around 20% by mid-2006.

Most striking is the difference in Figure 2B between the behaviors of hedge funds as a whole (blue line) *vs*. hedge funds that also trade equity futures (green line). In particular, the market share of hedge funds that only hold positions in commodity futures markets started a downward trend several months before the Lehman crisis. Notwithstanding some fluctuations, this trend accelerated the week following Lehman's demise. In contrast, cross-trading hedge funds' market share was fairly stable during that period and then *increased* steadily after mid-November 2008. In other words, our investigation establishes, to our knowledge for the first time, a clear heterogeneity among two kinds of hedge funds that are active in commodity futures markets. In the next section, we show that this heterogeneity helps explain the joint distribution of commodity and equity returns.

IV. Economic Fundamentals, Speculation and Commodity-Equity Comovements

In Section II, we showed that the conditional correlation between the weekly returns on investible equity and energy indices fluctuates substantially over time. In Section III, we utilized a unique dataset of daily trader positions to quantify various aspects of U.S. energy futures markets' financialization during the same time period. In this Section, we ask empirically whether long-term fluctuations in the intensity of speculative activity or the relative importance of some types of trader (in particular, hedge funds and index traders) help explain the extent to which energy returns move in sync with equity returns.

Of course, as discussed in the introduction, a substantial theoretical literature predicts that macro-economic conditions, physical energy market fundamentals, and financial market stress should also affect commodity returns. Section IV.A proposes a list of variables to control for real- and financial-sector factors. Section IV.B discusses our ARDL regression methodology, which tackles possible endogeneity issues and the fact that some of our variables are stationary in levels while others are only stationary in first differences. Section IV.C presents our results.

A. Macroeconomic, Physical-Market and Financial-Market Conditions

A number of theoretical models show the importance of macroeconomic and commodity-specific fundamentals for energy price levels and volatility (Pirrong, 2011) and commodity risk premia (e.g., Breeden, 1980; Hirshleifer, 1989). Although there is no unifying theory predicting time-variations in the correlations between the returns on commodity *vs*. other investments (Erb and Harvey, 2006), that prior literature suggests several variables for our empirical analysis.

1. Macroeconomic Fundamentals

Equity and commodity inverstments are known to perform differentially at successive stages of business cycles (e.g., Gorton and Rouwenhorst, 2006; Dhume, 2010). Furthermore, the response of U.S. stock returns to crude oil price increases depends on whether the increase is the result of a demand shock or of a supply shock in the crude oil space (Kilian and Park, 2009). These empirical regularities point to the need to control for world and U.S. business cycles when seeking to explain time variations in the strength of equity-commodity linkages.

For global real economic activity, we draw on Kilian (2009), who shows that "increases in freight (shipping) rates may be used as indicators of (…) demand shifts in global industrial commodity markets." The Kilian (2009) measure is a global index of single-voyage freight rates for bulk dry cargoes including grain, oilseeds, coal, iron ore, fertilizer and scrap metal. This index accounts for the existence of "different fixed effects for different routes, commodities and ship sizes." It is deflated with the U.S. consumer price index (CPI), and linearly detrended to remove the impact of the "secular decrease in the cost of shipping dry cargo over the last forty years." This indicator is available monthly from 1968 to 2011; in our regression analyses, we derive weekly estimates (which we denote *SHIP*) by cubic spline.

U.S. macroeconomic conditions also affect energy prices and U.S. equity prices. Since the strength of energy-equity linkages could therefore fluctuate over U.S. business cycles, we use an U.S. economic activity index developed by Aruoba, Diebold and Scotti (2009). This index, denoted *ADS*, is unique in that it is designed to "track real business conditions at high frequency" and is available weekly in 1991-2011. Table 3.A gives summary statistics for *SHIP* and *ADS*.

2. *Physical-Market Fundamentals*

Conditions in physical energy markets may affect equity-energy correlations in two ways. On the one hand, when changes in nearby energy futures prices mostly reflect physical inventory conditions, they are unlikely to be met by contemporaneous changes in equity valuations. Hence, we refrain from including inventory measures in the econometric analysis. On the other hand, when energy demand increases amid strong economic growth, it can eventually exhaust the crude oil “spare” production capacity that OPEC has historically tried to maintain – leading to a sharp increase in oil prices; conversely, lower energy prices amid greater “surplus” production capacity likely reflect a poor macroeconomic environment. These facts suggest a positive relationship between spare oil output capacity and energy-equity return correlations.

We use data from the U.S. Department of Energy’s Energy Information Administration (EIA, 2010) to calculate the total spare crude oil production capacity outside of Saudi Arabia. Figure 3 plot the spot price of WTI crude oil *vs*. the non-Saudi spare crude production capacity from 1995 to 2010. We focus on non-Saudi figures because the clearest evidence of a major change in energy market fundamentals is evident in this variable (as opposed to world oil consumption, Saudi surplus oil production capacity, OECD stocks of crude oil, etc.). Figure 3 highlights a major change in the physical crude oil market. From January 1995 to February 2004, when spare capacity was relatively plentiful, prices fluctuated around \$29. Likewise, from January 2009 through September 2010, spare capacity was non-trivial and again prices fluctuated around \$75. From March 2004 to August 2008, in contrast, non-Saudi spare capacity was close to zero and spot oil prices ranged between \$27 and \$142.

3. *Financial Stress and Lehman Crisis*

Following a slump in a major asset market, levered and similarly-constrained position holders may face pressures to liquidate other asset holdings. A number of theoretical papers show that those selling pressures may bring about cross-asset contagion even if the fundamental factors driving the returns on different assets are independent (see Gromb and Vayanos (2010) for an excellent literature review). Danielsson *et al* (2011a, 2011b) show that, depending on the make-up of market activity (i.e., *who* trades) and investor risk appetite, the resulting cross-asset correlations can remain elevated long after the initial shock.[15]

Those results suggest that, *ceteris paribus*, energy-equity correlations should be higher during periods of elevated levels of market stress and in the period after a major market crash. We use two variables to test this hypothesis.

First, we include the TED spread in our regressions as a proxy of financial-market stress. Table 3.A provides statistical information on the *TED* variable. It fluctuates greatly during our sample period, with a minimum of 0.027% and a maximum of 4.33%.

Second, the TED spread, while especially high right after the onset of the Lehman crisis in September 2008, had already started rising in the previous 13 months (starting in August 2007 when a French banking group froze two funds exposed to the sub-prime market). In contrast, Figure 1 shows that equity-energy correlations did not visibly increase until *after* the demise of Lehman Brothers, and remain exceptionally high as of mid-2011. These facts together suggest that the post-Lehman sub-period is exceptional. We use a time dummy (*DUM*) to account for the specificities of that sub-period that the TED spread might not capture.

B. Methodology

Before testing the explanatory power of different variables on the equity-energy returns DCC, we check the order of integration of all variables using Augmented Dickey Fuller (ADF) tests. Unit root tests for the variables in our estimation equation are summarized at the bottoms of Tables 3.A and 3.B. They show that many of the variables are I(1) while some are I(0).

By construction, correlations are bounded above (+1) and below (-1) so the DCC variable should intuitively be stationary. Yet, the ADF tests do not reject the non-stationarity of the DCC estimates in our sample period. This result holds at the 1% level of significance for the entire sample period (2000-2010, see Table 3.A) and at the 10% level of significance for a sub-sample ending prior to the demise of Lehman Brothers (2000 to September 2008).[16]

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[15] Hartmann, Straetmans and de Vries (2004) identify cross-asset extreme linkages in the case of bond and equity returns from the G-5 countries. Longin and Solnik (2001) document that international equity market correlations increase in bear markets. Büyükşahin, Haigh and Robe (2010) show that equity and commodity markets behave like a "market of one" on days of extreme market downward movements.

[16] Because it is well known that ADF tests have low power with short time spans of data, we also employ another test developed by Kwiatkowski *et al* (KPSS, 1992) to further analyze the DCC variable. Unlike the ADF test, the KPSS test has stationarity as the null hypothesis. With the KPSS test, we find that the null of stationarity cannot be rejected at the 1% level of significance but is rejected at the 5% significance level.

In order to find the long run effects of different variables on commodity-equity return correlations, we use an autoregressive distributed lag (ARDL) model estimated by ordinary least squares. In this model, the dynamic conditional correlation is explained by lags of itself and current and lagged values of a number of regressors (fundamentals as well as traders' positions). The lagged values of the dependent variable are included to account for slow adjustments of the correlation between commodities and equities. This approach also allows us to calculate the long-run effect of the regressors on the correlation.

Regardless of the time series properties of our DCC variable, the ARDL model, estimated by OLS, should yield consistent parameter estimates. More precisely, Pesaran and Shin (1999) show that the ARDL model can be used to test the existence of a long-run relationship between underlying variables and to provide consistent, unbiased estimators of long-run parameters in the presence of I(0) and I(1) regressors. The ARDL estimation procedure reduces the bias in the long run parameter in finite samples, and ensures that it has a normal distribution irrespective of whether the underlying regressors are I(0) or I(1). By choosing appropriate orders of the ARDL(*p*,*q*) model, Pesaran and Shin (1999) show that the ARDL model simultaneously corrects for residual correlation and for the problem of endogenous regressors.

We start with the problem of estimation and hypothesis testing in the context of the following ARDL(*p*,*q*) model:

$$y_t = \delta w_t + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{i=0}^{q} \alpha_i x_{t-i} + \varepsilon_t \tag{1}$$

where y is a t x 1 vector of the dependent variable, x is a t x k vector of regressors, and ω stands for a t x s vector of deterministic variables such as an intercept, seasonal dummies, time trends, or exogenous variables with fixed lags.[17] In vector notation, Equation (1) is:

$$\gamma(L)y_t = \delta w_t + \alpha(L)x_t + \varepsilon_t$$

where $\gamma(L)$ is the polynomial lag operator $1 - \gamma_1 L - \gamma_2 L^2 - \dots \gamma_p L^p$; $\alpha(L)$ is the polynomial lag operator $\alpha_0 + \alpha_1 L + \alpha_2 L^2 + \dots + \alpha_q L^q$; and L represents the usual lag operator ($L^r x_t = x_{t-r}$). The estimate of the long run parameters can then be obtained by first estimating the parameters

[17] The error term is assumed to be serially uncorrelated.

of the ARDL model by OLS and then solving the estimated version of (1) for the cointegrating relationship $y_t = \psi w_t + \theta x_t + \nu_t$ by:

$$\hat{\theta} = \frac{\hat{\alpha}_0 + \hat{\alpha}_1 + \ldots + \hat{\alpha}_q}{1 - \hat{\gamma}_1 - \hat{\gamma}_2 - \cdots - \hat{\gamma}_p}$$

$$\hat{\psi} = \frac{\hat{\delta}}{1 - \hat{\gamma}_1 - \hat{\gamma}_2 - \cdots - \hat{\gamma}_p}$$

where $\hat{\theta}$ gives us the long-run response of *y* to a unit change in *x* and, similarly, $\hat{\psi}$ represents the long run response of *y* to a unit change in the deterministic exogenous variable.

When estimating the long-run relationship, one of the most important issues is the choice of the order of the distributed lag function on y_t and the explanatory variables x_t. We carry out a two-step ARDL estimation approach proposed by Pesaran and Shin (1999). First, the lag orders of p and q must be selected using some information criterion. Based on Monte Carlo experiments, Pesaran and Shin (1999) argue that the Schwarz criterion performs better than other criteria. This criterion suggests optimal lag lengths *p*=1 and *q*=1 in our case. Second, we estimate the long run coefficients and their standard errors using the ARDL(1,1) specification.

C. Regression Results

Tables 3.A to C provide summary statistics for all the variables. Tables 5 to 8 summarize our regression results. Table 5 establishes the explanatory power of economic fundamentals (*SHIP, SPARE* and, to a lesser extent, *ADS*) and financial market stress (*TED*).[18] Table 6 establishes the additional explanatory power of speculation and hedge fund activities. Tables 7 and 8 present some of our robustness checks.

1. Real sector and financial stress variables (Table 5)

Estimates for Model 1 in Panels A and B of Table 5 show that, for our sample period (2000-2010) as well as for an extended period (1991-2000, starting when the GSCI first became investable but before the start of our detailed position dataset), the energy-equity DCC measure

[18] For completeness, all of our models also include a variable capturing momentum in equity markets (denoted *UMD*). This variable always has a positive coefficient (consistent with the notion that equity momentum could spill over into other risky assets such as commodities) but we seldom find *UMD* to be a statistically significant explainer of commodity-equity correlations and, when it is at all statistically significant, the significance level is only 10%.

is statistically significantly negatively related to *SHIP*. Insofar as we use the *SHIP* variable to capture the world demand for commodities, this finding confirms the intuition that cross-market correlations increase in globally bad economic times.

Model 3 shows that, in contrast, the U.S. macroeconomic indicator (*ADS*) has less explanatory power. The coefficient for *ADS* is consistently positive but is not always significant.

We argued intuitively that, insofar as *SPARE* measures tightness in the physical crude oil market and as this tightness extends to other energy markets, then *DCC* and *SPARE* should be positively related. Model 2 (using spare production capacity) supports this prediction – see Column 5 of Panel A and, especially, Columns 3 and 4 of Panel B.

The difference between Panels A and B is that the specifications in Panel B include a dummy for the post-Lehman period (*DUM*). That time dummy is always strongly statistically significant and positive. Its inclusion clearly improves the likelihood ratio – supporting the graphical evidence in Section II that this sub-period is exceptional.

Our ARDL estimations show that energy-equity return correlations also have a positive long-term relationship to the *TED* variable (our proxy for stress in financial markets). In 2000-2010, a 1% increase in the TED spread brought about a 0.19% to 0.30% increase in the dynamic equity-energy correlation (after controlling for the specifics of the post-Lehman period); this increase is statistically significant at the 5% confidence level (at the 1% level in 2000-2008; see Table 7).

Interestingly, Panel A suggests that *TED* was not a significant factor in 1991-2000. The differential importance of the TED spread in those two successive decades raises the question of whether changes in trading activity might help explain this evolution. We now turn to this issue.

2. Speculative activity and hedge fund market share (Table 6)

Table 6 is key to our contribution. It shows that financial activity in energy futures helps explain long-term variations in energy-equity linkages.

Intuitively, there is no reason to expect that traditional commercial traders (oil refiners, producers, etc.) should drive correlations between commodity and stock index returns. All three panels of Table 6 support this intuition, in that they seldom show any explanatory power for the *WMSS_TCOM* variable.

Likewise, insofar as commodity swap dealing overwhelmingly reflects swap dealers' over-the-counter relationships with traditional commercials or with *unlevered*, *long-only*, *passive* commodity-index traders (CITs), we would not expect swap dealers' positions to affect cross-market correlations. This is because CITs do not engage in value-arbitraging and may not alter their positions under financial-market stress. Table 6 buttresses this intuition: swap dealers' share of commodity open interest (*WMSS_AS*) is never statistically significantly positive. These findings present an interesting counterpoint to the conclusions of Stoll and Whaley (2010) and Tang and Xiong (2012), regarding the impact of commodity index trading on intra-commodity market linkages.

The main finding in Tables 6.A and 6.B is that, after controlling for macroeconomic and physical fundamentals, several variables measuring speculative activity in energy markets help explain fluctuations in the energy-equity DCC estimates over time. Those variables are statistically significantly, and their inclusion measurably improves likelihood ratios.

Ceteris paribus, an increase of 1% in the overall commodity-futures market share of hedge funds (*WMSS_MMT*) is associated with dynamic conditional equity-commodity correlations that are approximately 4% to 7% higher (given a mean hedge fund market share of about 20%). Crucially, Working's "T" index of excess speculation in commodity futures markets, which aggregates the activities of *all* non-hedgers across *all* maturities, has less explanatory power than hedge fund activity in short-dated contracts. Precisely, the *WSIA* variable is often significant but a comparison of likelihood suggests that it is the positions of hedge funds specifically, rather than the activities of non-commercial traders in general, that help explain the correlation patterns.

3. Cross-market trading

Table 6.C uses specifications similar to Tables 6.A and 6.B but focuses on cross-market traders. Two interesting results emerge. First, as intuition would suggest, the market share of hedge funds that trade in both equity and energy paper markets helps explain long-term linkages between equity and energy returns. Second, the market share of commodity swap dealers that are also active in equity markets is sometimes statistically significant – but always with a *negative* sign. These results suggests that it is value arbitrageurs' willingness to take positions in

both equity and commodity markets, rather than the trading activities of commodity index traders and of more traditional commodity market participants, that help tie satellite and central markets.

4. Interaction between hedge funds and financial stress

Table 6 shows that greater hedge fund participation enhances cross-market linkages. Yet if the same arbitrageurs or convergence traders, who bring markets together during normal times, face borrowing constraints or other pressures to liquidate risky positions during periods of financial market stress, then their exit from "satellite markets" after a major shock in a "central" market could lead to a decoupling of the markets that they had helped link in the first place.

To test this hypothesis, some specifications in Table 6 include an interaction term that captures the behavior of hedge funds in financial stress episodes. This interaction term is always significant and, as expected, negative. That is, *ceteris paribus*, the ability of hedge fund activity to explain energy-equity comovements is *lower* during periods of elevated market stress.

D. Robustness

Our results are qualitatively robust to using additional proxies for energy investment; introducing dummies to control for unusual circumstances in financial markets; and employing alternative measures of financial activity in commodity paper markets.

1. Commodity indexing activity

In the past decade, investors have sought an ever greater exposure to commodity prices. Part of this exposure has been acquired through passive commodity index investing. Some of this investment has, in turn, found its way into futures markets through commodity swap dealers. In our regressions, however, we never find the *WMSS_AS* variable (which measures commodity swap dealers' market share in short-dated contracts) to be statistically significant and positive.

One possible reason is that, although a part of commodity swap dealers' positions in short-dated energy futures reflects their over-the-counter interactions with index traders, the rest of their futures positions reflect over-the-counter deals with more traditional commercial commodity traders. In other words, the *WMSS_AS* variable is only an imperfect proxy of commodity index trading activity in commodity futures markets.

We therefore also used another proxy for investor interest in commodities: the post-2004 daily trading volume in the SPDR Gold Shares exchange-traded fund (ETF). Although this volume grew massively between 2004 and 2010, the *GOLD_VOLUME* variable does not help explain changes in commodity-equity correlations.

Taken together with the lack of significance of the *WMSS_AS* variable, our interpretation is that the activities of *passive* commodity investors do not affect equity-commodity linkages. This result presents an interesting counterpoint to the findings of Büyükşahin *et al* (2009), who show that increased commodity index trading activity in the WTI crude oil futures market provided additional liquidity that helped integrate crude oil prices across contract maturities.

2. The Lehman crash

In the last 30 months of the sample period, the TED spread was very or extremely high compared to spreads in most of the previous decade. The TED spread first jumped in August 2007, following the suspension of investor withdrawals from some funds managed by a French bank. It reached stratospheric levels in September 2008, following the Lehman debacle.

A natural question is whether our results are affected by unusual TED spread patterns during the latter part of our sample period. The answer is negative: our results are qualitatively robust to the introduction of either one of two dummies (one for the August 2007 - August 2009 period or one for the September 2008-March 2010 period), and to the concomitant introduction of interaction terms between the relevant dummy and the TED variable.

Table 7 provides additional evidence of robustness. It repeats the analysis of Table 6.A, with a sample that ends prior to November 2008 – the month when DCC estimates soared upward of 0.4 for the first time since the inception of the investable GSCI commodity index. The results in Table 7 are qualitatively similar to those in Table 6.A. The main difference is that the statistical significance of the hedge fund variables is stronger pre-crisis. Combined with the strong statistical significance of the post-Lehman dummy (*DUM*) in every single specification in Table 6, as well as with the negative sign of the *INT_TED_MMT* interaction term, this finding suggests that hedge fund activity *per se* is not responsible for the exceptionally high correlation levels observed since the end of 2008.

3. Hedge fund activities in near-dated commodity futures vs. across the maturity curve

Table 8 repeats the analysis of Table 6.A except that we measure speculative activity and different traders' market shares using position information across *all* maturities (rather than just the three nearest-maturity contracts with non-trivial open interest). The statistical significance of all the position variables drops dramatically, except for the variable capturing hedge fund activity (*WMSA_MMT* is sometimes significant at the 10% level). Again, Table 8 shows little statistical evidence that swap dealers or traditional commercial traders affect the dynamic cross-market correlations.

Taken together, Tables 6 and 8 imply that it is the positions of hedge funds in shorter-dated commodity futures (rather than their activities in commodity markets further along the futures maturity curve) that help explain equity-commodity linkages. This result is intuitive, in that the GSCI index is constructed using short-dated futures contracts and, hence, one expects that it is short-dated positions that may matter for commodity-equity correlations.

V. Conclusion and Further Work

The sign and the strength of the correlation between the returns on passive investments in equity and energy markets have fluctuated substantially in the past two decades. The same time period witnessed growing activity in energy paper markets by hedge funds, commodity index funds, and other financial institutions.

In this paper, we analyze empirically whether changes in the make-up of trading activity help explain the joint movements of energy and equity returns. To do so, we construct a daily dataset of all large trader positions in U.S. equity and three U.S. energy futures markets from 2000 to 2010. Our dataset draws on non-public, trader-level information from the U.S. Commodity Futures Trading Commission (CFTC). We utilize these data to provide novel information on the financialization of energy futures markets and the first evidence on cross-trading activity in those markets.

We find that, over and above the fundamental factors that drive asset returns, the overall amount of speculative activity in energy futures markets has explanatory power for the time variations in the correlation between the returns on investable energy-futures and equity indices. We trace this power to the activities of hedge funds, especially those active in both equity and commodity futures markets. In contrast, we find that the positions of other kinds of participants in commodity-futures market (swap dealers and index traders, floor brokers and traders, traditional commercial traders, etc.), whether or not they take positions in both types of markets, do not help explain cross-market correlation patterns.

Our findings suggest two natural venues for further research. First, we find that, over the long run, macroeconomic fundamentals, hedge fund activity, and financial-market stress all help explain the changes in energy-equity correlations over time. An interaction term between hedge fund activity and a proxy for financial-market stress is also significant. Yet, in addition to those variables, we find that a time dummy for the post-Lehman period (September 2008 to March 2010) is always highly significant. Further research is therefore needed to explain that dummy. One possibility is market sentiment, perhaps interacted with our proxies for overall speculative activity and index trading – the idea to be investigated being that collective decisions by passive investors to exit risky markets when uncertainty rises might lead to greater correlations between individual equities and broad stock market indices, and similarly might increase equity-commodity correlations. We tackle those questions in a companion paper.

Second, even though a number of theoretical models show the importance of macroeconomic and commodity-specific fundamentals for equilibrium price levels and volatility (Pirrong, 2011) and commodity risk premia (e.g., Hirshleifer, 1988), and though other theoretical models analyze the impact of different types of traders on cross-market linkages in good or in bad times (e.g., Danielsson et al (2011a, 2011b)), there is no unifying theory regarding the ideal level of comovements between commodities or between commodities and other assets. Additional theoretical work is thus needed, if one is to ascertain whether the impact of financialization on cross-correlations represents a welcome improvement in market efficiency or, instead, is a worrisome development.

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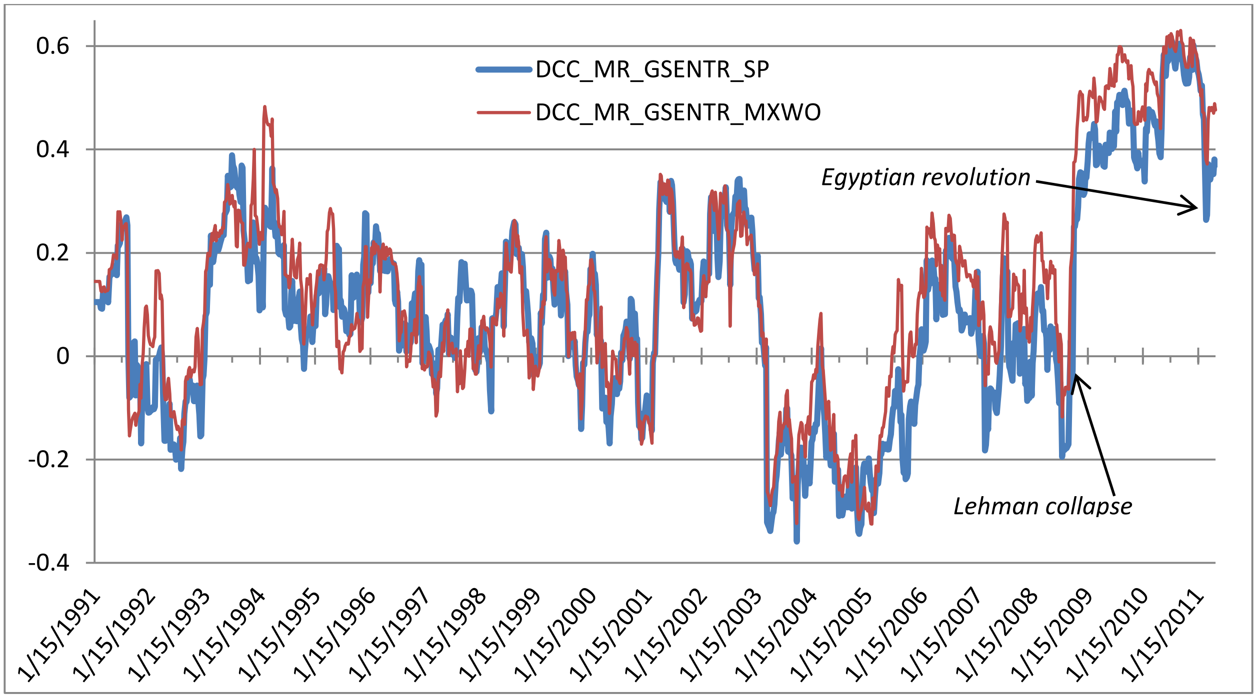
Figure 1:

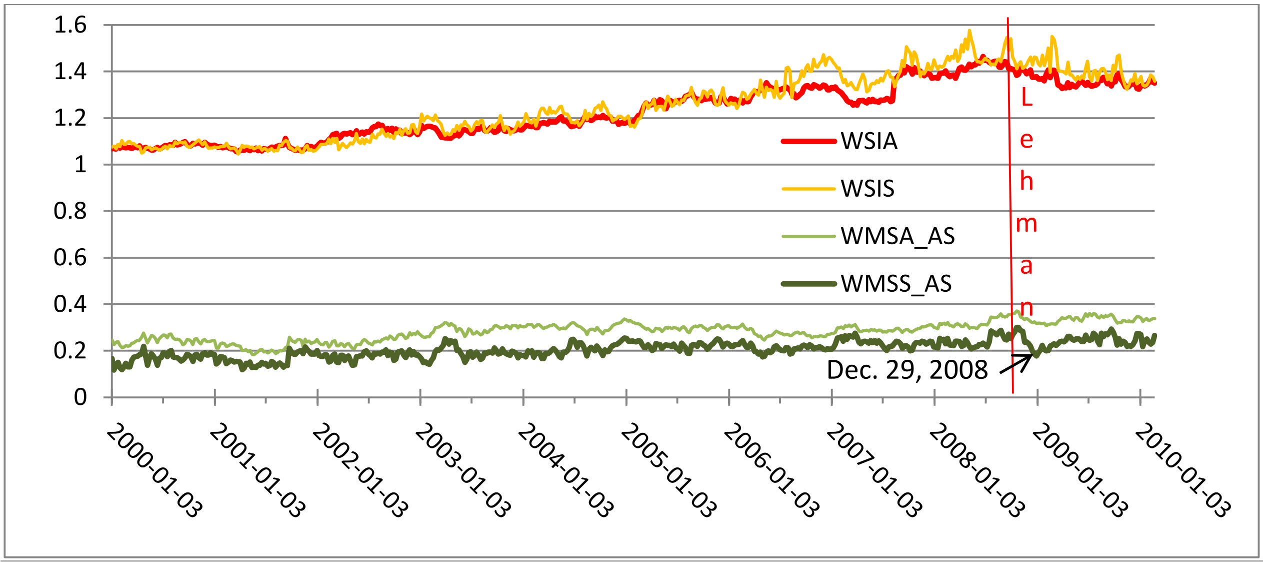
Weekly Return Correlations (DCC) between Passive Energy and Equity Investments, 1991-2010



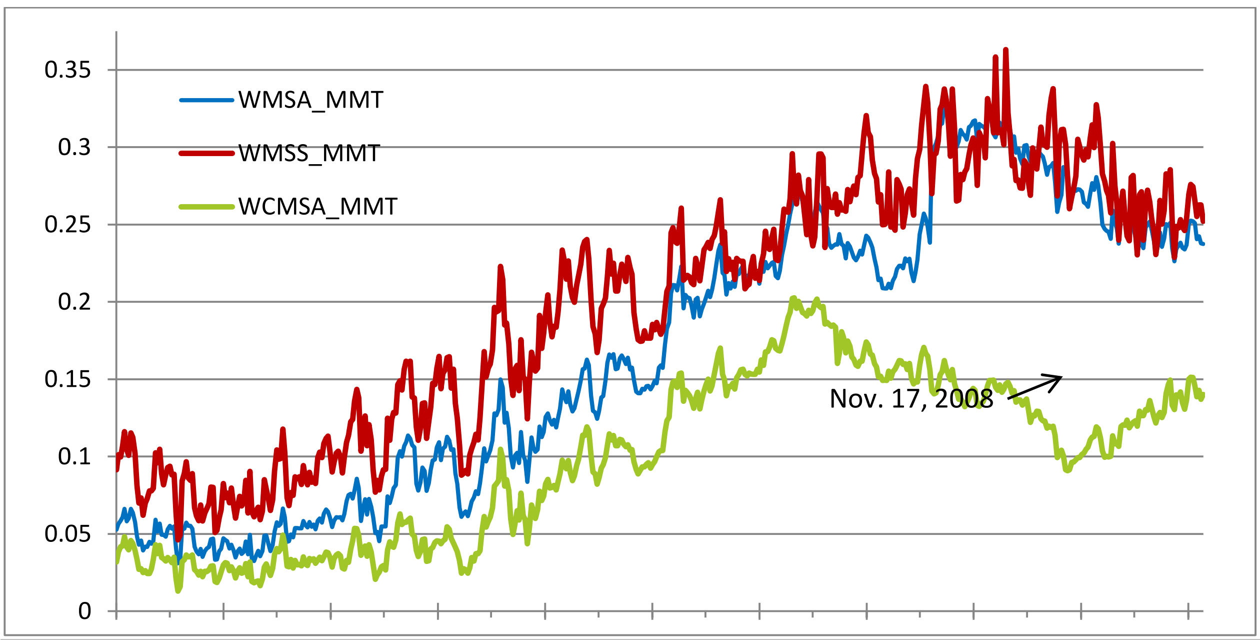
Notes**:** Figure 1 plots the time-varying correlation (DCC) between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P GSCI-Energy total return index ("GSENTR") and: (i) the S&P 500 equity index ("SP", **blue line**) or (ii) the MSCI World equity index ("MXWO", **red line**). We estimate dynamic conditional correlations by log-likehood for mean-reverting model (DCC_MR, Engle, 2002) from January 3, 1991 to May 10, 2011.

Figure 2: Financialization of Energy Futures Markets, 2000-2010

Panel A: Excess Speculation and Commodity Swap Activity (incl. Index Trading)

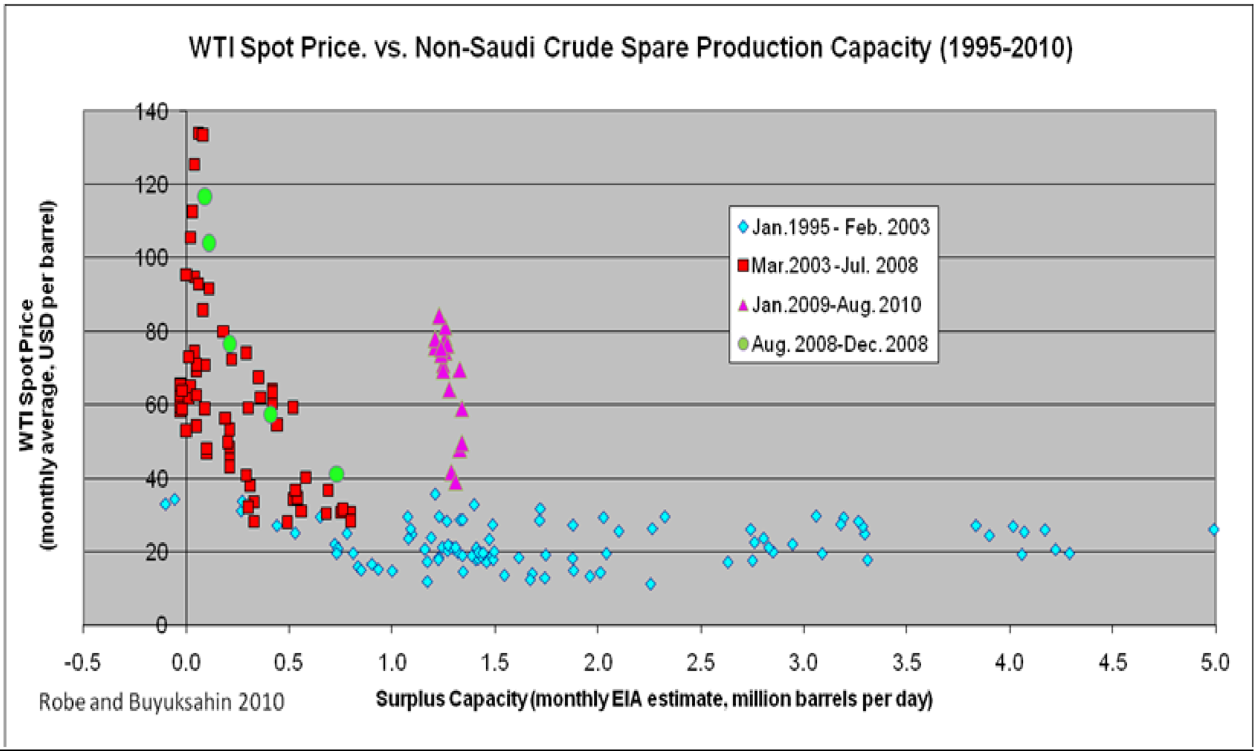


Panel B: Hedge Fund Share of the Energy Futures Open Interest (incl. Cross-Market Traders)



***Notes*:** **Figure 2A** plots the weighted-average speculative pressure index ("Working's T") in three U.S. energy paper markets linked to the GSCI-Energy index across all maturities (**red**, *WSIA*) or in near-dated futures (**orange**, *WSIS*) from January 2000 till March 2010. Indices are rescaled so that a value of 0 means speculative positions exactly offset the net hedging demand from market participants holding underlying exposures to energy price risk. A value greater than 0 is the fraction of speculative activity in excess of this net hedging demand. The **dark green line** shows the aggregate share of the short-term open interest held by commodity (including index traders) in the same energy markets (*WMSS_AS*). The **lighter green line** shows the share of the overall energy futures open interest held by commodity swap dealers (*WMSA_AS*). **Figure 2B** plots the proportion of the short-term (SS) or overall (SA) open interest made up by hedge funds (MMT), including those active in *both* energy and equity markets (WCMSA).

<u>Figure 3:Physical Energy Market Fundamentals</u>



***Notes*: Figure 3** plots the spot price for West Texas Intermediate crude oil (U.S. dollars per barrel) *vs*. the crude oil spare production capacity outside of Saudi Arabia (million barrels per day). Monthly data from January 1995 to August 2010 are from the Energy Information Administration (U.S. Department of Energy).

Table 2: Macroeconomic and Market Fundamentals, July 2000 to March 2010

	Dynamic Conditional Correlations (DCC_MR)		Macroeconomic Fundamentals			Financial Market Conditions				Excess Commodity Speculation *(Working's "T")*	
	S&P500 - GSENTR	MSCI World-GSENTR	SHIP Index	ADS Index	SPARE (mb/day)	LIBOR (%)	TED (%)	VIX	UMD	All contract Maturities (WSIA)	Short-term contracts (WSIS)
Mean	0.048628	0.102904	0.128101	-0.475016	0.911582	3.058959	0.487749	21.99812	0.003010	1.237615	1.261085
Median	0.042930	0.101840	0.156134	-0.246892	0.435730	2.715900	0.296456	20.41000	0.090000	1.258071	1.254774
Maximum	0.502230	0.589450	0.553002	0.992458	4.990000	6.802500	4.330619	67.64000	4.550000	1.463901	1.576830
Minimum	-0.362670	-0.330420	-0.524973	-3.747359	-0.260839	0.248800	0.027512	9.900000	-6.560000	1.054720	1.045349
Std. Dev.	0.219156	0.226524	0.263191	0.787462	1.153071	1.874571	0.517985	9.744099	1.127080	0.115355	0.138361
Skewness	0.191897	0.213649	-0.463355	-1.789994	1.697494	0.328567	2.951072	1.653419	-0.700811	0.065602	0.127205
Kurtosis	2.038428	2.397085	2.329421	6.952640	5.136673	1.842329	14.63722	6.761389	8.153885	1.686974	1.749409
Jarque-Bera	22.55495***	11.49062***	27.53235***	598.4182***	338.5880***	37.28642***	3582.557***	527.7928***	600.2571***	36.63883***	34.27062***
Sum	24.55707	51.96660	64.69118	-239.8829	460.3491	1544.774	246.3134	11109.05	1.520000	624.9958	636.8481
Sum Sq. Dev.	24.20690	25.86184	34.91194	312.5287	670.1042	1771.064	135.2274	47853.53	640.2358	6.706668	9.648420
Observations	505	505	505	505	505	505	505	505	505	505	505
ADF (Level)	-1.922987	-1.708451	-1.928436	-3.137666**	-1.959157	-1.414196	-2.880949**	-2.995549**	-24.261***	-1.410025	-1.580680
ADF (1st Diff)	-23.02921***	-23.09147***	-6.6142***	-12.2230***	-5.7425***	-10.9312***	-12.8887***	-12.3767***	-12.6374***	-24.69425***	-16.82226***

Note: Dynamic conditional correlation (DCC) are between the Tuesday-to-Tuesday unlevered rates of return (precisely, changes in log prices) on the S&P GSCI total return Energy index (GSENTR) and either the S&P 500 equity index (SP) or the MSCI World equity index (MXWO). DCC estimated by log-likehood for mean-reverting model (Engle, 2002). **SHIP** is a measure of worldwide economic activity (Kilian, 2009). **ADS** is a measure of U.S. economic activity (Aruoba, Diebold and Scotti, 2009). **SPARE** measures the daily crude oil spare production capacity outside of Saudi Arabia (source: International Energy Agency). **LIBOR** and **TED** are the 90-day annualized LIBOR rate and Ted spread (source: Bloomberg). **UMD** is the Fama-French momentum factor for U.S. equities. Excess commodity speculation for the three nearest-term futures (**WSIS**) and all contract maturities (**WSIA**) is the weigthed-average excess speculation index (Working's "T") for the three U.S. energy futures markets in the GSCI-Energy index (source: CFTC, S&P and authors' calculations); annual weights equal the average of the daily GSCI weights that year (source: Standard & Poor). For the augmented Dickey-Fuller (ADF) tests, stars (*, **, ***) indicate the rejection of non-stationarity at standard levels of statistical significance (10%, 5% and 1%, respectively); critical values are from McKinnon (1991). Most series are I(1); the optimal lag length *K* is based on the Akaike Information Criterion (AIC). Sample period for all statistics: June 26, 2000 to February 26, 2010.

Table 3A: Shares of the Near-Term Energy Futures Open Interest by Trader Type, July 2000 to March 2010

	Weighted-average Market Shares in Short-term Energy Futures (WMSS)				
	Hedge Funds (WMSS_MMT)	All Non-Commercials (WMSS_NON)	Swap Dealers (WMSS_AS)	Non-Commercials + Swap Dealers (WMSS_ANC)	Traditional Commercials (WMSS_TCOM)
Mean	0.204235	0.316131	0.208559	0.524690	0.366909
Median	0.224358	0.331227	0.210753	0.541441	0.343538
Maximum	0.363110	0.496264	0.300792	0.762634	0.627804
Minimum	0.046028	0.122514	0.118168	0.248365	0.168771
Std. Dev.	0.081043	0.103196	0.034956	0.130087	0.114400
Skewness	-0.324538	-0.230910	-0.085032	-0.269752	0.479703
Kurtosis	1.846900	1.735042	2.689814	1.882217	2.150438
Jarque-Bera	36.84269	38.15685	2.633101	32.41476	34.55491
Sum	103.1388	159.6460	105.3225	264.9684	185.2889
Sum Sq. Dev.	3.310232	5.367349	0.615845	8.529033	6.596028
Observations	505	505	505	505	505
ADF (Level)	-1.721169	-1.589767	-2.713347*	-1.319877	-1.417037
ADF (1st Diff)	-16.57380***	-16.69709***	-11.51933***	-20.81283***	-18.64831***

Note: **WMSS_MMT**, **WMSS_NON, WMSS_AS**, **WMSS_ANC** and **WMSS_TCOM** stand, respectively, for the weighted-average shares of the short-term open interest in the three nearest-dated futures with non-trivial open interest (for the three U.S. energy futures markets in the GSCI-Energy index) of: hedge funds (**MMT**, "managed money traders"), non-commercial traders (**NON**, including MMT), commodity swap dealers (**AS**, including **CIT** – commodity index traders), non-commercial plus swap dealers (ANC), and traditional commercial traders (**TCOM**) (source: CFTC and authors' computations). The averaging weights are set each year equal to average of the GSCI weights for those three commodities that year and rescaled to account for GSCI-Energy markets for which no large trader position data are available (Source: S&P). For the augmented Dickey-Fuller (ADF) tests, stars (*, **, ***) indicate the rejection of non-stationarity at standard levels of statistical significance (10%, 5% and 1%, respectively); critical values are from McKinnon (1991). The optimal lag length is based on the Akaike Information Criterion (AIC). Sample period for all statistics: June 26, 2000 to February 26, 2010.

Table 3B: Shares of the Total Energy Futures Open Interest and Cross-Market Activity by Trader Type, July 2000 to March 2010

	Weighted-average Market Shares in All Energy Futures Contracts (WMSA)					Weighted-average Market Share of Cross-Market Traders across All Maturities (WCMSA)			
	Hedge Funds (WMSA_MMT)	All Non-Commercials (WMSA_NON)	Swap Dealers (WMSA_AS)	Non-Commercials + Swap Dealers (WMSA_ANC)	Traditional Commercials (WMSA_TCOM)	All traders (WCMSA_ALL)	Hedge Funds (WCMSA_MMT)	All Non Commercials (WCMSA_NON)	Swap Dealers (WCMSA_AS)
Mean	0.173578	0.293981	0.285505	0.579486	0.341241	0.400092	0.101453	0.139761	0.222761
Median	0.202450	0.316496	0.292806	0.610701	0.316082	0.434336	0.107234	0.162134	0.223914
Maximum	0.327426	0.444671	0.371463	0.788862	0.613303	0.505472	0.202706	0.250336	0.293365
Minimum	0.030903	0.097950	0.182555	0.298708	0.157066	0.230213	0.012921	0.030224	0.154758
Std. Dev.	0.089989	0.098899	0.039300	0.130139	0.117216	0.074367	0.053045	0.067002	0.023727
Skewness	-0.088256	-0.197356	-0.428193	-0.339882	0.474538	-0.664140	-0.095215	-0.247110	-0.334840
Kurtosis	1.614198	1.759610	2.693191	2.068953	2.267934	2.153634	1.697554	1.538885	3.332162
Jarque-Bera	41.06497	35.65226	17.41257	27.96283	30.22985	52.19728	36.45738	50.06047	11.75815
Sum	87.65707	148.4602	144.1800	292.6402	172.3266	202.0466	51.23389	70.57925	112.4941
Sum Sq. Dev.	4.081399	4.929670	0.778439	8.535780	6.924773	2.787348	1.418142	2.262561	0.283726
Observations	505	505	505	505	505	505	505	505	505
ADF (Level)	-1.324479	-1.383007	-1.495602	-0.855454	-0.974017	-0.895255	-1.465850	-1.025759	-1.495602
ADF (1st Diff)	-22.24594***	-24.01600***	-10.57921***	-17.08184***	-21.97107***	-12.52812***	-20.92032***	-17.52282***	-10.57921***

Note: **WMSA_MMT**, **WMSA_NON**, **WMSA_AS**, **WMSA_ANC** and **WMSA_TCOM** stand, respectively, for the weighted-average shares of the overall futures open interest across ***all*** futures contract maturities (for the three U.S. energy futures markets in the GSCI-Energy index) of: hedge funds (**MMT**), non-commercial traders (**NON**, including MMT), commodity swap dealers (**AS**, including **CIT**), non-commercial + swap dealers (**ANC**), and traditional commercial traders (**TCOM**) (source: CFTC and authors' computations). Weights are set each year equal to the average of the GSCI weights for those three commodities that year and rescaled to account for GSCI-Energy markets for which no large trader position data are available (Source: S&P). For three trader groupings (MMT, AS, and NON) as well as all large traders (ALL), the **WCMSA** variables measure the proportion of commodity traders who also hold positions in the S&P 500 e-Mini equity futures ("cross-market traders). In the Augmented Dickey-Fuller (ADF) tests, stars (*, **, ***) indicate the rejection of non-stationarity at standard levels of statistical significance (10%, 5% and 1%, respectively). Critical values are from McKinnon (1991). The optimal lag length is based on the Akaike Information Criterion (AIC). Sample period for all statistics: June 26, 2000 through February 26, 2010.

Table 4: Cross-Market Trading Activity, 2000-2010

Commodity	**Classifications in Commodity Markets**						**Equity Futures Classification**	
	All Cross-Market Traders		Commodity Swap Dealers		Hedge Funds		Hedge Funds	
	Count	% of all traders	Count	% of all cross-traders	Count	% of all cross-traders	Count	% of all cross-traders
Crude Oil	1108	28.0%	63	5.7%	363	32.8%	274	24.7%
Heating Oil	335	8.5%	26	7.8%	170	50.8%	138	41.2%
Natural Gas	743	18.8%	49	6.6%	300	40.4%	235	31.6%

Notes: For the three main energy futures markets for which trader-level position data are available for the entire 2000-2010 period, Table 4 provides information on the number and relative importance of the subset of large commodity futures traders who also held, at some point in the sample period (July 1, 2000 through February 26, 2010), positions in the S&P500 e-Mini equity futures contract. The smallest number of cross-market-trading swap dealers in any one of the three energy futures markets is 26 (heating oil). Because we aggregate those 26 traders with 49 traders in natural gas and 63 in crude oil, the sample size for cross-trading swap dealers could range from 63 (the maximum of {15, 23, 24} if all 26 heating oil dealers also traded crude oil) to 138=26+49+63 (in the unlikely case there is no overlap across the 3 markets). Similarly, the number of cross-trading hedge funds in our sample is between 170 and 363.

Table 5: Market Fundamentals as Long-run Determinants of the GSCI-Energy *vs.* S&P500 Dynamic Conditional Return Correlations

Panel A: Treating the Post-Lehman Period as any other Period

	Model 1			Model 2			Model 3		
	1991-2000	2000-2010	1991-2010	1995-2000	2000-2010	1995-2010	1991-2000	2000-2010	1991-2010
Constant	0.199022 **	-0.0727729	-0.0640187	0.181332 ***	-0.291257 **	-0.180740	0.201441 **	-0.0495553	-0.0290865
	(0.07939)	(0.1121)	(0.07809)	(0.06578)	(0.1398)	(0.1106)	(0.08028)	(0.1111)	(0.07028)
ADS							-0.0891680	0.120929	-0.0940820
							(0.08694)	(0.1477)	(0.06288)
SHIP	-0.0934936	-0.597573 **	-0.274154				-0.113461	-0.754496 **	-0.277686 *
	(0.2653)	(0.2822)	(0.1855)				(0.2694)	(0.3682)	(0.1680)
SPARE				-0.0111549	0.134130 **	0.0581962			
				(0.02713)	(0.06252)	(0.04732)			
UMD	0.0469638	0.154878	0.102411	0.00106191	0.141386	0.0876287	0.0468735	0.141192	0.102172
	(0.06844)	(0.1092)	(0.07740)	(0.03897)	(0.1044)	(0.07926)	(0.06957)	(0.1082)	(0.06996)
TED	-0.309478 *	0.480288 **	0.297959 **	-0.164767	0.516236 **	0.362652 **	-0.269397	0.592622 **	0.193733
	(0.1735)	(0.2066)	(0.1382)	(0.1122)	(0.2046)	(0.1530)	(0.1754)	(0.2955)	(0.1274)
LogLklhd	**808.803**	**862.764**	**1662.03**	**504.142**	**862.37**	**1356.24**			

Notes: The dependent variable is the time-varying conditional correlation (DCC) between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and the S&P GSCI-Energy total return (GSENTR) index. Dynamic conditional correlations estimated by log-likehood for mean reverting model (Engle, 2002). The explanatory variables are described in Table 2. Long-run estimates are from the two step ARDL(p,q) estimation approach of Pesaran and Shin (1999). When estimating the long-run relationship, one of the most important issues is the choice of the order of the distributed lag function on y_t and the explanatory variables x_t. The Schwarz information criterion suggests that the optimal lag lengths are p=1 and q=1 in our case. The sample periods for the first and seventh columns are January 2, 1991 to June 30, 2000; for the second, fifth and eight columns: July 1, 2000 to February 26, 2010; for the other columns: June 30, 2005 to Febuary 26, 2010.

Table 5: Market Fundamentals as Long-run Determinants of the GSCI-S&P500 Dynamic Conditional Correlation

Panel B: Treating the Post-Lehman Period unlike previous Years

	Model 2 + DUM			
	2000-2010		**1995-2010**	
Constant	-0.189684 (0.06799)	***	-0.118617 (0.05827)	**
ADS				
SHIP				
SPARE	0.0973745 (0.03288)	***	0.0613461 (0.02581)	**
UMD	0.0858745 (0.05115)	*	0.0623155 (0.04212)	
TED	0.208681 (0.09205)	**	0.130900 (0.07568)	*
DUM	0.422350 (0.1075)	***	0.452321 (0.1003)	***
Log likelihood	**867.342**		**1363.33**	

Notes: The dependent variable is the time-varying conditional correlation (DCC) between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and the S&P GSCI-Energy total return (GSENTR) index. Dynamic conditional correlations estimated by log-likehood for mean reverting model (Engle, 2002). The explanatory variables are described in Table 2, except for DUM – a time dummy variable that takes the value 0 prior to September 1, 2008 and 1 afterwards ("Lehman dummy"). Long-run estimates are from the two step ARDL(p,q) estimation approach of Pesaran and Shin (1999). When estimating the long-run relationship, one of the most important issues is the choice of the order of the distributed lag function on y_t and the explanatory variables x_t. The Schwarz information criterion suggests that the optimal lag lengths are p=1 and q=1 in our case. The sample periods in the first, third and fifth columns are July 1, 2000 to February 26, 2010; the sample period for the second and sixth columns is January 2, 1991 to June 30, 2000; for the fourth column: June 30, 2005 to Febuary 26, 2010.

Table 6 – Panel A: Speculative Activity as a Long-run Contributor to Energy-Equity Dynamic Conditional Correlation

	2000-2010		2000-2010		2000-2010		2000-2010		2000-2010		2000-2010		2000-2010		2000-2010	
Constant	-1.33255	***	-3.35782	***	-2.43970		-3.69302		-0.883597	**	-2.99169	***	-2.80875		-3.87777	
	(0.3603)		(1.001)		(1.943)		(2.274)		(0.3499)		(1.002)		(2.313)		(2.403)	
ADS									0.0831803		0.0948211		0.0783511		0.0916956	
									(0.1059)		(0.08943)		(0.1062)		(0.08828)	
SHIP									-0.991052	***	-0.942787	***	-0.969616	***	-0.879629	***
									(0.3290)		(0.2555)		(0.3324)		(0.2763)	
SPARE	0.225132	***	0.192512	***	0.222424	***	0.188613	***								
	(0.05261)		(0.04506)		(0.05387)		(0.05087)									
UMD	0.0945118		0.0943261		0.0984478		0.0955083		0.108127		0.0964163		0.109796		0.0949859	
	(0.06361)		(0.06159)		(0.06539)		(0.06205)		(0.07765)		(0.06442)		(0.07869)		(0.06418)	
TED	2.79563	***	6.70761	***	2.76489	***	6.52361	***	2.24744	**	4.58889	**	2.17786	**	4.24447	*
	(0.8371)		(2.290)		(0.8476)		(2.489)		(0.9595)		(2.249)		(0.9529)		(2.308)	
WMSS_MMT	4.15750	***			5.48540	*			4.00675	***			6.35606	*		
	(1.290)				(2.839)				(1.522)				(3.424)			
WMSS_AS					1.63931		0.156530						2.73698		0.212229	
					(3.037)		(2.274)						(3.637)		(2.391)	
WMSS_TCOM					1.36403		0.259968						2.39518		0.689258	
					(2.370)		(1.631)						(2.808)		(1.674)	
WSIA			2.36713	***			2.54662	**			2.41098	***			2.89488	**
			(0.7563)				(1.280)				(0.7987)				(1.360)	
INT_TED_MMT	-8.49444	***			-8.39324	***			-6.59982	**			-6.38725	**		
	(2.719)				(2.755)				(3.054)				(3.037)			
INT_TED_WSIA			-4.63228	***			-4.50740	**			-3.13160	*			-2.89702	*
			(1.630)				(1.762)				(1.603)				(1.637)	
Log likelihood	**876.051**		**866.668**		**876.977**		**868.167**		**875.138**		**868.212**		**876.075**		**869.478**	

Notes: Explanatory variables are described in Tables 3 and 5. The dependent variable is the the time-varying conditional correlation (DCC) between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and the S&P GSCI-Energy total return (GSENTR) index. DCC estimated by log-likehood for mean reverting model (Engle, 2002). Long-run estimates are from the two step ARDL(p,q) estimation approach of Pesaran and Shin (1999). The Schwarz information criterion suggests optimal lag lengths p=1 and q=1. Sample period: July 1, 2000 to March 1, 2010.

Table 6 – Panel B: Speculation as a Long-run Contributor to the Energy-Equity Dynamic Conditional Correlation (Lehman control)

	2000-2010		2000-2010		2000-2010		2000-2010	
Constant	-0.826467	***	-1.96763	***	-2.56901	**	-3.17242	**
	(0.2323)		(0.7290)		(1.057)		(1.273)	
ADS								
SHIP								
SPARE	0.154870	***	0.135986	***	0.121034	***	0.107117	***
	(0.03576)		(0.03237)		(0.03185)		(0.03093)	
UMD	0.0710231	*	0.0727269	*	0.0579558	*	0.0586289	*
	(0.04025)		(0.03981)		(0.03378)		(0.03274)	
TED	1.77734	***	4.60514	***	1.38053	***	3.39324	**
	(0.5081)		(1.485)		(0.4230)		(1.346)	
WMSS_MMT	2.37960	***			5.22120	***		
	(0.8664)				(1.523)			
WMSS_AS					0.896538		-0.949729	
					(1.624)		(1.275)	
WMSS_TCOM					2.82919	**	1.07074	
					(1.358)		(0.9123)	
WSIA			1.32955	**			2.21413	***
			(0.5596)				(0.7198)	
INT_TED_MMT	-5.51366	***			-4.30584	***		
	(1.676)				(1.402)			
INT_TED_WSIA			-3.20403	***			-2.37744	**
			(1.064)				(0.9594)	
DUM	0.347098	***	0.350655	***	0.445824	***	0.380342	***
	(0.09457)		(0.09879)		(0.09043)		(0.08412)	
Log likelihood	**881.086**		**871.939**		**884.97**		**875.182**	

Notes: Explanatory variables are described in Tables 3 and 5, except for *DUM* (a "Lehman" time dummy that takes the value 0 prior to September 1, 2008 and 1 afterwards) and *INT_TED_xxx* (interaction terms of the TED spread with position variables). . The dependent variable is the the time-varying conditional correlation (DCC) between the weekly unlevered rates of return on the S&P 500 (SP) equity index and the S&P GSCI-Energy total return (GSENTR) index – see Table 6A. Long-run estimates are from the two step ARDL(p,q) estimation approach of Pesaran and Shin (1999). The Schwarz information criterion suggests optimal lag lengths *p*=1 and *q*=1. Sample period: July 1, 2000 to March 1, 2010.

Table 6, Panel C: Cross-Market Trading as a Long-run Contributor to the GSCI-S&P500 Dynamic Conditional Correlation

	2000-2010		2000-2010		2000-2010	
Constant	-0.778333	***	0.210448		-0.971063	
	(0.2196)		(0.4022)		(0.8296)	
ADS						
SPARE	0.178190	***	0.129834	***	0.104834	***
	(0.04215)		(0.03684)		(0.03318)	
UMD	0.0722604		0.0565843		0.0645123	*
	(0.04570)		(0.03696)		(0.03534)	
TED	1.37460	***	1.01301	***	3.29099	**
	(0.4684)		(0.3643)		(1.400)	
WCMSA_MMT	5.10806	***	3.92980	***		
	(1.717)		(1.358)			
WCMSA_AS			-3.73983	**	-2.86410	*
			(1.543)		(1.567)	
WSIA					1.08753	**
					(0.5081)	
INT_TED_CMMTA	-9.82038	***	-6.96981	**		
	(3.644)		(2.862)			
INT_TED_WSIA					-2.26677	**
					(1.005)	
DUM	0.214922	*	0.370933	***	0.431396	***
	(0.1120)		(0.1067)		(0.1017)	
Log likelihood	**881.802**		**885.162**		**875.116**	

Notes: Most variables are described in Tables 3C and 6B. *INT_TED_CMMTA* is an interaction terms of the TED spread with the shares of open interest held weekly by cross-market trading hedge funds (MMT). We report long-run estimates from the two step ARDL(p,q) estimation approach of Pesaran and Shin (1999). The Schwarz information criterion suggests optimal lag lengths p=1 and q=1 in our case. The sample period is July 1, 2000 to February 26, 2010.

Table 7: Pre-Lehman Determinants of Equity-Energy Dynamic Conditional Correlations

Variable	Model 2 2000-2008	Model 3 2000-2008	Model 4 2000-2008	Model 5 2000-2008
Constant	-1.6746	-2.4958**	-3.9349**	-4.4461***
	(1.252)	(1.205)	(1.570)	(1.491)
SHIP	-0.6143***	-0.7603***	-0.5533***	-0.6764***
	(0.1669)	(0.1639)	(0.1427)	(0.1446)
UMD	0.0322	0.0242	0.0257	0.0184
	(0.0395)	(0.0363)	(0.0333)	(0.0313)
TED	0.2903***	1.3782***	0.2002***	1.0994***
	(0.0755)	(0.3954)	(0.0714)	(0.3476)
WMSS_AS	0.2601	0.7225	0.9328	1.2839
	(1.949)	(1.817)	(1.681)	(1.597)
WMSS_MMT	4.0546**	6.7724***	4.0345**	6.3014***
	(1.885)	(2.000)	(1.582)	(1.710)
WMSS_TCOM	2.1266	2.5937*	3.4385**	3.7444***
	(1.501)	(1.408)	(1.445)	(1.375)
INT_TED_MMT		-4.3087***		-3.5321***
		(1.481)		(1.279)
WSIA			1.3509**	1.2395*
			(0.6650)	(0.6362)
Observations	436	436	436	436

Notes: Explanatory variables are described in Tables 3 and 6. The dependent variable is the the time-varying conditional correlation between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and the S&P GSCI-Energy total return (GSENTR) index. Dynamic conditional correlations estimated by log-likehood for mean reverting model (Engle, 2002). When estimating the long-run relationship, one of the most important issues is the choice of the order of the distributed lag function on y_t and the explanatory variables x_t. Long-run estimates are from the two step ARDL(p,q) estimation approach of Pesaran and Shin (1999). The Schwarz information criterion suggests that the optimal lag lengths are p=1 and q=1 in our case. The sample period is July 4, 2000 to November 11, 2008.

Table 8: Pre-Lehman Determinants of Energy-Equity Dynamic Conditional Correlations

Variable	Model 6 2000-2008	Model 7 2000-2008	Model 8 2000-2008	Model 9 2000-2008
Constant	0.4696	0.7722	0.6525	2.7811
	(1.211)	(1.249)	(0.6525)	(2.716)
SHIP	-0.5079***	-0.5934***	-0.4983***	-0.5889***
	(0.1675)	(0.1746)	(0.1669)	(0.1763)
UMD	0.0283	0.0325	0.0205	0.0213
	(0.0368)	(0.0380)	(0.0372)	(0.0386)
TED	0.2307***	1.1399***	0.2296***	1.2577***
	(0.0766)	(0.3968)	(0.0826)	(0.4404)
WMSA_AS	-2.6751	-3.3830*	-2.9115	-4.6060*
	(2.110)	(2.178)	(2.358)	(2.571)
WMSA_MMT	1.1362	1.8172	1.1569	2.6090
	(1.491)	(1.519)	(1.718)	(1.836)
WMSA_TCOM	0.0324	-0.7522	-0.0664	-1.7066
	(1.323)	(1.412)	(1.589)	(1.832)
INT_TED_MMTA		-3.4831**		-3.8345**
		(1.419)		(1.533)
WSIA			-0.0713	-1.2107
			(1.349)	(1.492)
Observations	436	436	436	436

Notes: Explanatory variables are described in Tables 3 and 6. The dependent variable is the the time-varying conditional correlation between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and the S&P GSCI-Energy total return (GSENTR) index. Dynamic conditional correlations estimated by log-likehood for mean reverting model (Engle, 2002). When estimating the long-run relationship, one of the most important issues is the choice of the order of the distributed lag function on y_t and the explanatory variables x_t. Long-run estimates are from the two step ARDL(p,q) estimation approach of Pesaran and Shin (1999). The Schwarz information criterion suggests that the optimal lag lengths are p=1 and q=1 in our case. The sample period is January 2, 2000 to November 11, 2008.

Appendix 1: Large trader categories

The four main commercial trader subcategories in the New York Mercantile Exchange's (NYMEX) West Texas Intermediate (WTI) sweet crude oil futures market are oil dealers and merchants (wholesalers, exporters and importers, marketers, etc); manufacturers (oil refiners, fabricators, etc.); crude oil producers; and (iv) commodity swap dealers.[19] These categories typically make up more than 95% of the WTI commercial open interest in 2000-2010, and close to 99% in the last five years of that period.

Traders in the dealer/merchant, manufacturer and producer sub-categories are often referred to as "traditional" hedgers. By contrast, the swap dealer sub-category (whose activity grew significantly after 2002) also includes the positions of non-traditional hedgers, including "entities whose trading predominantly reflects hedging of over-the-counter transactions involving commodity indices—for example, swap dealers holding long futures positions to hedge short over-the-counter (OTC) commodity index exposure opposite institutional traders such as pension funds."

The three main non-commercial sub-categories are (i) "Floor Brokers and Traders"; (ii) "Hedge Funds", which comprise all reporting commodity pool operators, commodity trading advisors, "associated persons" controlling customer accounts as well as other "managed money" traders;[20] (iii) "Non-registered participants." The latter category, whose importance we shall see has increased substantially since 2000, mostly comprises financial traders whose positions are large enough to warrant reporting to the CFTC but who are not registered as managed money traders or floor brokers and traders under the Commodity Exchange Act. NRPs also include some smaller non-commercial traders who do not have a reporting obligation but whose positions are nevertheless reported to the CFTC. In 2000-2008, these three categories made up about 90% of the total non-commercial WTI open interest (including non-reporting traders).

[19] This category also includes financial swap dealers and arbitrageurs/broker-dealers. There are only a few such traders in the sample – a mere two.in the whole 2000-2004 period, for example.

[20] See Appendix 2 for a discussion of the term "hedge funds" in the context of commodity futures markets.

Appendix 2: Measuring Commodity Index Trading (CIT) Activity.

The CFTC's non-public (LTRS) dataset does not identify CIT activity in energy markets at the daily or weekly frequency. This is because CIT activity percolates into energy futures partly through CIT interactions with commodity swap dealers – yet, even in the non-public CFTC data to which we had access, CIT-related positions are not identified within the overall energy futures positions held by commodity swap dealers.[21]

Certainly, information on CIT positions is publicly available for 12 agricultural ("ag") markets at the weekly frequency after January 2006. One could thus attempt to extrapolate, to other commodities, the overall market share of CITs in those ag markets – see, e.g., Gilbert (2009), Stoll and Whaley (2010) and Singleton (2014). After 2006, though, the quality of an approximation based on the "ag CIT" data depends on whether weekly index investment flows are similar in magnitudes across all commodity futures markets and, within each market, across all contract maturities. In fact, the precision of the approximation gets worse over time insofar as specialized "ag" funds have grown in importance since 2006 and insofar as the futures open interest has a very different maturity structure in "ag" *vs*. energy futures markets (Irwin and Sanders, 2011).[22] Besides, the "ag" position information is not available before 2006 – restricting the scope of a possible study.

One possible solution to those issues might be to reconstruct CIT position data in energy markets on the basis of the CFTC's (non-public) list of CIT accounts.[23] Unfortunately, discussions with market experts indicate that the use of this list should not be extended to prior years because of structural differences in CIT activity before and after 2005.

The present paper therefore draws instead on the granularity of the non-public CFTC data and on the fact that CIT activity has tended to concentrate in near-dated contracts. Specifically, in the spirit of Büyükşahin *et al* (2009), we approximate the near-term (*overall*) CIT market shares in our three energy futures markets each week by the shares of the near-dated (*overall*)

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[21] Starting in September 2008, the CFTC started providing reports about off- and on-exchange commodity index activity in a number of U.S. commodity markets. The frequency of those reports, however, is far too low for our purpose – quarterly till June 2010, then monthly after July 2010.
[22] Even in ag markets, "…some traders assigned to the Index Traders category are engaged in other futures activity that could not be disaggregated (...) Likewise, the Index Traders category will not include some traders who are engaged in index trading, but for whom it does not represent a substantial part of their overall trading activity" (CFTC 2008, quoted in Aulerich, Irwin and Sanders (2011)).
[23] See Brunetti and Reiffen (2011) and Aulerich, Irwin and Sanders (2011) for information on the methodology behind the CFTC's CIT classification.

open interest held by commodity swap dealer in each of these three markets. While this approximation may not be perfect, it offers the key advantage of yielding a consistent measure for the entire sample period (2000-2010).

Appendix 3: Defining Hedge Funds.

"Hedge fund" activity in commodity derivatives markets has been the subject of intense scrutiny in recent years by academic researchers, market participants, policy makers, and the media. Yet, there is no accepted definition of a "hedge fund" in futures markets, and there is nothing in the statutes governing futures trading that defines a hedge fund.

Still, many hedge fund complexes are either advised or operated by CFTC-registered commodity pool operators (CPOs) or Commodity Trading Advisors (CTAs) and associated persons (APs) who may also control customer accounts. Through its LTRS, the CFTC therefore obtains positions of the operators and advisors to hedge funds, even though it is not a requirement that these entities provide the CFTC with the name of the hedge fund (or another trader) that they are representing.[24]

It is clear that many of the large CTAs, CPOs, and APs are considered to be hedge funds and hedge fund operators. Consequently, we conform to the academic literature and common financial parlance by referring to these three types of institutions collectively as "hedge funds." As well, we include in the hedge fund category participants not registered in any of these three categories but tagged in the LTRS with a "managed money" indicator.

[24] A commodity pool is defined as an investment trust, syndicate or a similar form of enterprise engaged in trading pooled funds in futures and options on futures contracts. A commodity pool is similar to a mutual fund company, except that it invests pooled money in the futures and options markets. Like its securities counterparts, a commodity pool operator (CPO) might invest in financial markets or commodity markets. Unlike mutual funds, however, commodity pools may be either long or short derivative contracts. A CPO's principal objective is to provide smaller investors the opportunity to invest in futures and options markets with greater diversification with professional trade management. The CPO solicits funds from others for investing in futures and options on futures. The commodity-trading advisor (CTA) manages the accounts and is the equivalent of an advisor in the securities world.