Commodity Traders' Positions and Energy Prices:

Evidence from the Recent Boom-Bust Cycle

Bahattin Büyükşahin **Michel A. Robe**[1]

December 29, 2009

[1] **Büyükşahin**: U.S. Commodity Futures Trading Commission (CFTC), 1155 21st St. NW, Washington, DC 20581. Tel: (+1) 202-418-5123. Email: bbuyuksahin@cftc.gov. **Robe**: CFTC and Department of Finance, Kogod School of Business at American University, 4400 Massachusetts Ave. NW, Washington, DC 20016. Tel: (+1) 202-885-1880. Email: mrobe@american.edu. We are grateful to Robert Hauswald, Stewart Mayhew, Josh White, and seminar participants at the U.S. Securities and Exchange Commission (SEC), the CFTC, and the European Central Bank (ECB) for useful comments on a companion paper, and to Lutz Kilian for providing an update of his shipping cost series. We thank Arek Nowak for research assistance with the position data. This paper builds on results derived while Robe was a consultant to the SEC. The CFTC and the SEC, as a matter of policy, disclaim responsibility for any private publication or statement by any of their employees or consultants. The views expressed herein are those of the authors only and do not necessarily reflect the views of the SEC, the CFTC, the Commissioners, or any other staff upon either Commission. All errors and omissions, if any, are the authors' sole responsibility.

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Abstract

In the last two decades, there has been no secular increase in the correlation between the returns on passive investments in US equities and in energy futures. Those correlations, however, do fluctuate substantially over time. Using a unique dataset of daily trader positions in U.S. energy futures markets between 2000 and 2008, we show that the composition of open interest in energy markets helps explain those fluctuations. *Ceteris paribus*, energy-equity comovements increase amid greater hedge fund activity. In contrast, we find little evidence that the market shares of other kinds of energy futures traders (commodity swap dealers and index traders, traditional commercial traders, etc.) help explain energy-equity correlations. We show that cross-market comovements are also positively related to financial market stress. Intuitively, hedge funds could be an important transmission channel of negative equity market shocks into the commodity space. In fact, we find that the explanatory power of hedge fund activity is reduced during periods of stress. Overall, our results indicate that *who* trades helps explain the joint distribution of energy and equity returns.

JEL Classification: G10, G13, L89

Keywords: Energy prices, Equities, Hedge funds, Cross-market linkages, DCC, Dynamic conditional correlations.

I. Introduction

An important question in finance is whether the composition of trading activity (i.e., *who* trades) matters for asset pricing. In frictionless markets, the identity of traders should not matter. In practice, however, many traders face constraints on their choices of trading strategies. Hence, the arrival of traders facing fewer restrictions should help alleviate price discrepancies (Rahi and Zigrand, 2009) and improve the transfer of risks across markets (Başak and Croitoru, 2006).

On the one hand, insofar as hedge funds are less constrained than other investors (e.g., Teo 2009), this theoretical argument suggests that more hedge fund participation could enhance cross-market linkages. On the other hand 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 bring about cross-market contagion (Xiong, 2001; Kyle and Xiong, 2001; Broner, Gelos and Reinhart, 2006; Pavlova and Rigobon, 2008). In turn, reduced activity by those traders in the aftermath of the initial shock could lead to a decoupling of the markets that they had helped link in the first place.

In this paper, we provide empirical support for both arguments. We show that, in general, energy-equity comovements increase amid greater participation in energy markets by one type of trader (hedge funds). We also show, however, that the impact of hedge fund activity is reduced during periods of turmoil in financial markets.

From an empirical perspective, ascertaining whether specific types of traders contribute to cross-market linkages is often difficult, because doing so requires detailed information about the trading activities of all market participants as well as knowledge of each participant's main motivation for trading. We overcome this typical pitfall, by constructing a dataset of daily trader positions in the three largest U.S. energy futures markets from 2000 through 2008: WTI crude oil, heating oil, and natural gas. The underlying data originate from the U.S. Commodity Futures Trading Commission's (CFTC) large trader reporting system. This system collects information on all of the end-of-day positions of every large trader in each of these markets, and information on each trader's line of business. Our unique dataset covers the individual positions of all large traders (and more than 85% of the total open interest) in those three futures markets during our sample period.

We focus on the linkages between energy and equity markets for two reasons. First, we need comprehensive data on trading activity in the "satellite market". Commodity markets are ideal in this respect, because commodity price discovery generally takes place on futures exchanges (rather than spot or over-the-counter; see, e.g., Kofman, Michayluk and Moser, 2009) and it is precisely about the futures open interest that we have detailed composition information. Second, commodity-equity linkages fluctuate much more than the linkages between some other asset classes – offering fertile ground for an analysis of what drives those fluctuations.[2]

Our regression analyses establish that these fluctuations are partly explained by variations in the make-up of open interest in commodity-futures markets. Ceteris paribus, an increase of 1% in the overall commodity-futures market share of hedge funds is associated with an approximately 3.2% increase in dynamic equity-energy correlations. In contrast, we find little statistical evidence that the market share of other kinds of traders (swap dealers, traditional commercial traders, etc.) helps explain the dynamic cross-market correlations.

Turning to the impact of financial turmoil on cross-market linkages, we find that equity-energy comovements are positively related to the TED spread. In the 2000-2008 period, a 1% increase in the TED spread brought about a 0.2% increase in the dynamic equity-commodity correlation estimate.

Intuitively, via leverage or wealth effects, hedge funds could be an important channel to transmit negative equity market shocks into the commodity space. An interaction term we use to capture the behavior of hedge funds during financial stress episodes is indeed statistically significant – but its sign is negative. In other words, we find that power of hedge fund activity to explain energy-equity return correlations is reduced during periods of global market stress.

Overall, we find that, after accounting for business cycle and other economic factors, the trading activity of one goup of traders (hedge funds) helps explain equity-energy co-movements. We also find that the importance of these financial traders varies, depending on the overall state

[2] In theory, it is not clear whether the returns on commodities and equities should be correlated. Of course, arguments have long existed that they should be negatively correlated (Bodie, 1976; Fama, 1981). However, there is no formal theoretical model of a common factor driving the equilibrium relation between equity and commodity prices, and the traditional risk factors behind equity returns have historically had no forecasting power in commodity markets (Erb and Harvey, 2006). Empirically, Büyükşahin, Haigh and Robe (2010) and Chong and Miffre (2010) show that the dynamic conditional correlations (Engle, 2002) between the returns on equities and commodites fluctuate considerably over time around unconditional means close to zero. See also Gorton and Rouwenhorst (2006). There is, furthermore, evidence that returns on commodity futures vary with systematic (i.e., market) risk after controlling for hedging pressures (Bessembinder, 1992; de Roon, Nijman, and Veld, 2000; Khan, Khokher and Simin, 2008).

of financial markets. In this respect, we contribute to the literature on financial *vs*. fundamental drivers of cross-market linkages. Part of the extant literature studies whether financial shocks are propagated internationally through financial channels such as bank lending (e.g., van Rijckeghem and Weder, 2001, 2003) or international mutual funds (e.g., Broner *et al*, 2006) or whether these shocks instead spill over through stable real linkages such as trade relationships (e.g., Forbes and Chinn, 2004). Our analysis is more closely related to a second set of papers, which focus on the concern that speculators – and, in particular, hedge funds – may exert a destabilizing effect on commodity markets.[3]

In equity markets, Brunnermeier and Nagel (2004) and Griffin, Harris and Topaloglu (2006) provide evidence that hedge funds did not move stock prices during the technology bubble. In a cross-section of derivative markets, Brunetti and Büyükşahin (2009) find that hedge funds do not affect price levels (though their activities are key to the functioning of these markets through the liquidity they provide to other participants). Those studies focus on price levels (in other words, on the first moments of asset returns). Our paper, which focuses on cross-market linkages instead, deals with the second moments of the joint distributions of asset returns.

An independent contribution of our paper is to provide information on the composition of open interest across a set of commodity futures markets – specifically, on the relative importance of hedge funds in energy markets. (In future drafts, we shall document the extent to which energy futures traders -- in particular, hedge funds – also trade equity futures; this extension will allow us to further identify traders responsible for linking markets) In this sense, the present paper adds to extant work on the trading activities of specific types of market participants in individual U.S. commodity futures markets – especially, Ederington and Lee (2002) in the heating oil market during the early 1990's, and Büyükşahin, Haigh, Harris, Overdahl and Robe (2008) in the crude oil market in 2000-2008.

Section II provides evidence on equity-energy linkages. Section III presents our data on trader positions, and describes hedge fund behavior in energy futures markets. Section IV presents the regression analyses that link the fluctuations in equity-commodity return correlations to changes in hedge fund activity and market stress. Section V concludes.

[3] Chan, Getmansky, Haas and Lo (2006) provide a concise review of the large academic literature on hedge funds. The evidence on whether such funds are destabilizing is mixed. For example, Fung and Hsieh (2000) argue that hedge funds had a significant market impact during the European Exchange Rate Mechanism crisis in the early 1990s. By contrast, Choe, Kho and Stulz. (1999), Fung, Hsieh and Tsatsaronis (2000), and Goetzmann, Brown and Park (2000) conclude that hedge funds were not responsible for the Asian crisis in the late 1990s.

II. Returns Data, Summary Statistics, and Commodity-Equity Comovements

This section discusses the measurement of returns on passive equity and energy investments, provides summary statistics for these return series, and plots our estimates of the dynamic conditional correlation (DCC, Engle 2002) between equity and energy returns.

A. Data

Our main objective is to ascertain whether participation by some types of trader (hedge funds, in particular) help explain the extent to which smaller asset markets (in our case, energy futures markets) moves together with a "core" asset market (US equities). To compute estimates of the DCC between stocks and energy futures contracts, we use weekly returns on benchmark energy- and stock-market indices.[4] We obtain return data on each index from Bloomberg. Our returns sample runs from January 1991, when the Goldman Sachs Commodity Index ("GSCI") was first introduced as an investable benchmark, through November 2008.

For equities, we use Standard and Poor's S&P 500 index (we obtain similar results with Dow-Jones's DJIA index).[5] For energy commodities, we focus on the unlevered total return on Standard and Poor's S&P GSCI-Energy, which is the return on a "fully collateralized futures investment that is rolled forward from the fifth to the ninth business day of each month."

The GSCI averages the prices of six nearby energy futures contracts, using weights that reflect world-production figures. As a result, the GSCI is tilted toward crude oil. In robustness checks, we use total (unlevered) returns on the second most widely used investable benchmark, Dow-Jones's DJAIG (since May 2009, DJUBS) total-return Energy index. This rolling index was designed to provide a more "diversified benchmark for the commodity futures market." We find similar results for the GSCI and DJ-AIG indices, and therefore we focus most of the discussion on the results obtained using the S&P 500.

B. Descriptive statistics

Table 1 presents descriptive statistics for the weekly rates of return on the S&P 500 equity index (Panel A) and on the S&P GSCI-Energy commodity index (Panel B).

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[4] 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.

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

From January 1991 through November 2008, the mean weekly total rate of return on the GSCI-Energy index was 0.19% (or 10.35% in annualized terms), with a minimum of -21.55% and a maximum of 14.68%. The typical rate of return fluctuated across the sample period: it averaged 0.14% in 1992-1997 (7.8 % annualized); 0.25% in 1997-2003 (or 14.14% annualized); and, 0.20% in 2003-2008 (10.84% annualized).

Over the course of our entire sample period (1991-2008), the mean weekly rate of return on the S&P 500 was on average lower that on an energy investment: 0.11% (or 6.03% in annualized terms), with a minimum of -15.77% and a maximum of 12.37%. Although the rank-ordering of the returns on the two asset classes does not change much over time, energy returns crushed equity returns in 1997-2003 and again in 2003-2008 – but not in 1991-1997. These differences suggest that equities and commodities do not move together.

Turning to volatility, the rate of return on a well-diversified basket of equities (S&P 500) is typically about half as volatile as that on energy commodities (GSCI), but Table 1 shows fluctuations here as well. In particular, returns on passive energy-futures investments were more than twice as volatile as the S&P 500 returns in 1991-1997 and 2003-2008, but only about 50% more volatile in 1997-2003.

C. Simple Cross-Asset Correlations: Returns and Return Volatilities

Table 2 computes simple unconditional correlations between our four benchmark weekly asset-return series: S&P 500, DJIA, S&P GSCI-Energy and DJAIG-Energy. Panel A lists figures for the entire sample period, while Panels B to E present the corresponding statistics for different sub-periods.

Of course, the simple correlation between the returns on the DJIA and S&P 500 equity indices is very high, especially in the last five years (0.967). Likewise, the rates of return on the GSCI and DJ-AIG energy indices are strongly positively correlated (0.95 or more).

In contrast, the unconditional equity-energy cross-correlations are very low or even negative. Indeed, despite a popular view that equity and commodity *prices* moved in tandem after 2003, the simple cross-correlations between *weekly returns* on (as well as volatilities of) passive energy and equity investments were in reality almost zero until May 2008.

It is also worth noting that, whereas co-movements between equity markets and a broader sample of seventeen commodity futures markets increased sharply amid the economic crisis and temporary financial-market dilocations that befell the world economy in late 2008 (Büyükşahin, Haigh and Robe, 2010), the same is less true of equity-energy co-movements. These cross-correlations, which were slightly negative and statistically insignificant between June 2003 and *May* 2008 (Panel 2D), only become just mildly positive (and still barely statistically significant) when we extend the third sub-period to include the *second half* of 2008 (Panel 2E).

D. Dynamic Conditional Correlations

Table 1 identifies sharp differences, across sub-periods, in the means and variances of the rates of return on energy and equity indices. In contrast, Table 2 leaves the impression that (except perhaps in the second half of 2008) the correlation between these rates of returns varies only mildly over time. The unconditional correlations in Table 2, however, do not account for the time variations in the other moments of the return distributions brought to light by Table 1.

To obtain dynamically correct estimates of the intensity of commodity-equity co-movements, we use the dynamic conditional correlation (DCC) methodology proposed by Engle (2002). Essentially (Appendix 1 provides more details), the DCC model is based on a two-step approach to estimating the time-varying correlation between two return series. In the first step, time-varying variances are estimated using a GARCH model. In the second step, a time-varying correlation matrix is estimated using the standardized residuals from the first-stage estimation.

Figure 1 plots our DCC estimates of the time-varying correlations between the weekly rates of return on two investable energy indices (GSCI and DJAIG) *vs*. the unlevered rate of return on the S&P 500 equity index. The sample period is January 1991 to November 2008. As a counterpoint, Figure 1 also provides a plot for the DCC between the weekly rates of return on the S&P 500 and a second benchmark equity index, the Dow Jones DJIA.

On the one hand, Figure 1 supports Table 2, in that neither shows evidence of a secular increase in correlations during the 1991-2008 sample period.[6] This conclusion is in line with the results for individual equity-commodity pairs in Chong and Miffre (2010), and with the results for a broad commodity protfolio in Büyükşahin *et al*. (2010).

On the other hand, Figure 1 shows that equity-energy correlations do fluctuate a lot over time (unlike the correlation between the returns on then S&P 500 and DJIA equity indices, which

[6] Figure 1 shows that the equity-commodity return DCC estimates are similar regardless of the commodity index. The results are similar with daily or monthly returns. Graphs are available from the authors upon request.

varies little). The DCC estimate of equity-energy co-movements ebbs and flows from -0.38 to 0.34 (Table 3A), being high in 1993, 1998, 2001-2002, mid-2006, and again in Fall 2008.

A natural question is what drives those fluctuations and, in particular, whether changes in the relative importance of financial traders in commodity futures markets may affect the extent to which commodities move in sync with equities. We turn to this issue in the next two sections.

III. Speculative Pressure and Hedge Fund Activity in Commodity Futures Markets

In this Section we provide novel information on individual trader positions in three U.S. energy futures markets between 2000 and the end of 2008. During this period, the overall open interest grew significantly in those markets. We find that this growth entailed major changes in the trader composition of this open interest.

We establish these facts by exploiting non-public data on trader positions in exchange-traded commodity futures. Section III.A and III.B describe the dataset and contrast it with the less-detailed (but publicly available) information on futures open interest used in the literature.[7] Section III.C uses this publicly available data to establish that speculative pressure has increased significantly in these four markets since 2000. Section III.D then uses the non-public data to provide the first evidence on changes in hedge funds' market activities in these same markets.

A. Data Source

We construct a database of daily trader positions in the S&P 500 equity futures market and in three of the largest U.S. energy futures markets from the first week of July 2000 to the second week of November 2008. The three energy commodities are WTI crude oil, Henry Hub natural gas, and No.2. heating oil. Detailed position data are not available prior for part or all of the sample period for the other three contracts in the GSCI-Energy index: RBOB gasoline, Gas oil, and Brent crude oil.

The raw position data we utilize, and the trader classifications on which we rely, originate in the CFTC's Large Trader Reporting System (LTRS). Specifically, to help fulfill its mission of

[7] Only a handful of other studies use disaggregated, non-public CFTC data. They are Ederington and Lee (2002), who analyze *heating*-oil NYMEX futures position from June 1993 to March 1997; Chang, Pinegar and Schachter (1997), whose dataset includes six futures markets from 1983 to 1990; Haigh et al (2007), who analyze possible linkages between hedge fund activity and energy futures market volatility between August 2003 and August 2004; and Büyükşahin *et al* (2009), who document that increased market participation by hedge funds and commodity index traders since 2002 has helped link the pricing of crude oil futures across the maturity structure.

detecting and deterring market manipulation, the CFTC's market surveillance staff collects position-level information on the composition of open interest across all futures and options-on-futures contracts for each commodity. Information is obtained about each trader whose positions exceed a certain reporting threshold (which varies by market). Many smaller positions are also voluntarily reported to the CFTC and are included in the database. Depending on the market, our dataset covers between 75% and 95% of the total open interest.

The CFTC receives information on individual positions for every trading day. We focus on the Tuesday reports, for two reasons. First, the weekly frequency matches the frequency at which we elect to sample the index returns in Sections II and IV. Second, the Tuesday data are those that the CFTC summarizes in the weekly "Commitment of Traders (COT) Report" that it makes available to the public every Friday at 3:30 p.m. Consequently, our findings are directly comparable with those of numerous extant studies that rely on COT data.[8]

B. Public *vs*. Non-Public Data on the Purpose and Magnitude of Individual Positions

For each futures market with a certain level of market activity, the CFTC publishes a weekly COT report that contains the overall open-interest figure and breaks down the reporting traders between several categories. The breakdown is based on information that the CFTC also collects from all large traders on their respective underlying businesses (hedge fund, swap trader, gas producer, oil refiner, etc.) and on the purpose of their positions in each U.S. futures market.

Prior to September 2009, the public COT reports separated reporting traders between just two broad categories – "commercial" or "non-commercial." The CFTC classified all of a trader's reported 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 was classified as "commercial" by filing a statement with the CFTC that it was commercially "engaged in business activities hedged by the use of the futures or option markets." In order to ensure that traders were classified accurately and consistently, the CFTC staff would exercise judgment in re-classifying a trader if it has additional information about the trader's use of the markets. The "non-commercial" group comprises various types of mostly financial traders, such as hedge funds, mutual funds, floor brokers, etc.

[8] A minor difference is that the large trader dataset we use includes *all* positions reported to the CFTC by reporting firms – even those positions of traders small enough that they have no regulatory obligation to do so. Thus, even our aggregate data are a bit more precise than the publicly available data. A second difference is COT frequency, which is less than weekly in pre-2000 studies.

The LTRS data that underpin the public COT reports, which was made available for our study, allows for more differentiation. Specifically, each reporting trader is classified into one of twenty-eight (not two) possible trader types. Appendix 2 uses the crude oil futures market to illustrate the level of aggregation implicit in the creation of the "commercial" and "non-commercial" super-categories.

Since September 4, 2009, the public COT reports have started to differentiate between four (rather than two) kinds of traders in a limited number of commodity futures markets: "traditional" commercial traders (i.e., producers, processors, commodity wholesalers, merchants, etc.); managed money traders (hedge funds); commodity swap dealers (a category that includes commodity index traders in most markets); and "other traders" with reportable positions.[9] As of December 2009, however, the CFTC has not indicated plans to retroactively provide this more detailed information beyond 2005.

An independent contribution of the present paper is therefore to provide otherwise unavailable information on the composition of open interest in a cross-section of commodity futures markets, in particular on the positions held by hedge funds, between 2000 and 2008.

More importantly, whereas neither the old nor the new COT reports separate between traders' positions at different contract maturities (but the non-public data made available for this study do), our trader-level position data to disentangle the activities of the various kinds of traders at different ends of the commodity futures term structure. Our results in Section IV show that this additional information is highly valuable, in that it is hedge funds' activities in shorter-dated contracts (rather than further along the maturity curve) that helps explain equity-commodity linkages.

C. Speculation and Hedging in Commodity Futures Markets

One of the hypotheses we investigate in Section IV is whether, aside from business cycle factors, changes in the importance of financial *vs*. other types of commodity traders help explain the extent to which energy-futures returns move in sync with equity returns. To carry out formal tests of this hypothesis, we compute two indices that gauge the importance of financial traders. The first index, discussed in this sub-section (III.C), is Working's (1960) "*T*". It relates the activities of *all* "non-commercial" commodity futures traders (commonly referred to as

[9] COT reports also provide data on the positions of non-reporting traders, which include speculators, proprietary traders and smaller traders.

"speculators") to the demand for hedging that originates from "commercial" traders (often referred to as "hedgers"). The second index, which we propose in sub-section III.D, measures the market shares of *one* type of non-commercial trader – hedge funds – in commodity markets.

Our first measure of speculative activity is Working's "*T*". This index is based on the notion that, if long and short hedgers' respective positions in a given commodity futures market were exactly balanced (i.e., of the same magnitude), 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 trade simultaneously or in the same quantity. Hence, speculators must step in to fill the unmet hedging demand. Working's speculative activity index "*T*" measures the extent to which speculation exceeds the level required to satisfy hedgers' net demand for hedging (i.e., offset any unbalanced hedging).

For each of the markets in our sample, we calculate Working's *T* weekly from 2000 to 2008. In each market, we use the three shortest-maturity contracts with non-trivial open interest, on the basis that these near-dated contracts are the ones whose prices may be used to compute commodity return benchmarks. Formally, in the i^{th} commodity market in week *t*:

$$WSIS_{i,t} \equiv T_{i,t} = \begin{cases} 1 + \dfrac{SS_i}{HL_{i,t} + HS_{i,t}} & if\ HS_{i,t} \geq HL_{i,t} \\ 1 + \dfrac{SL_i}{HL_{i,t} + HS_{i,t}} & if\ HL_{i,t} \geq HS_{i,t} \end{cases} \qquad (i = 1, \dots, 17)$$

where $SS_i \geq 0$ is the (absolute) magnitude of the short positions held in the aggregate by all non-commercial traders; $SL_i \geq 0$ is the (absolute) value of all non-commercial long positions; $HS_i \geq 0$ stands for all non-commercial long positions and $HL_i \geq 0$ stands for all long hedge positions.

To provide an overall picture of speculative activity in energy futures markets, we average these individual index values across our three energy markets as follows:

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

where, the weight for commodity i in a given *week* 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 drop three of the futures contracts in the GSCI index for which position data are not available prior to 2006. Appendix 3 lists the individual commodity weights w_i, per commodity, per year. Typical weights are about 72-85% (crude), 8-17% (nat. gas), and 7-11% (heating oil).

Table 3A provides summary statistics of this weighted average speculative index (*WSIS*) between July 2000 and November 2008. During that period, the minimum *WSIS* value was 1.045, and the maximum exceeded 1.56. That is, speculative positions were between 4.5% and 56% greater than what was minimally necessary to meet net commercial hedging needs. The figures are similar in Table 3B, in which we use the same methodology to compute a weighted-average speculative index across all maturities (denoted *WSIA*) rather than across the three nearest-maturity contracts (denoted *WSIS*).

Figure 2 plots the *WSIS* measure over time. It provides further insights into changes in the relative importance of speculative activity in commodity futures markets over the course of the last decade. First, and most strikingly, it identifies what appears to be a secular increase in the amount of commodity speculation in relation to the amount of hedging pressure (it is worth noting, however, that the T values in Figure 2 are lower than historical T values for agricultural commodities.[10]) Second, Figure 2 shows that there have been substantial time variations around this long-term trend. Those are the variations that should be of particular interest in the analysis of Section IV.

D. Hedge Fund Activity

The *WSIS* speculative index of Section III.C lumps together all non-commercial traders. There is no reason to believe, however, that floor brokers and traders in a specific commodity market should be instrumental in bringing about stronger commodity-equity linkages. Hedge funds, in contrast, are likely candidates for such a role.

In this Section, we make use of the granularity of the LTRS data, to compute a weekly time series of hedge funds' market share in commodity markets. For reference, we also compute the market shares of commodity swap dealers (a category that includes commodity index traders in most U.S. futures markets) and of traditional commercial traders. For these three trader categories, we again focus on the market shares in the three shortest-maturity contracts that have non-trivial open interest (Table 3A) but also look across all contract maturities (Table 3B).

Formally, we compute the market share of a given trader group, in each commodity futures market each week, by expressing the average of the long and short positions of all traders

[10] Peck (1981) gets values of 1.57-2.17; Leuthold (1983), of 1.05-2.34. See also Irwin, Merrin and Sanders, 2008.

of this group in that market, as a fraction of the total open interest in that market that same week. We then average these commodity-specific market shares across our seventeen commodity futures markets, using the same weights as we do for the *WSIS* index. We denote by *WMSS_MMT*, *WMSS_AS*, and *WMSS_TCOM*, respectively, the 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).

Figure 2 plots our *WMSA_MMT* measure over time. It identifies a dramatic increase in the amount of hedge fund activity. Generalizing the findings of Büyükşahin *et al* (2009) in the specific case of the WTI crude oil market, Figure 2 shows that this long-term trend holds across an assortment of commodity futures markets, with hedge funds accounting for a single- or low-double digit fraction of the open interest in 2000 and 20% or more after 2005.

Tables 3 and 4 provide summary statistics of market shares for various kinds of traders. Table 3A shows that, in the past decade, traditional commercial traders' (TCOM, which excludes swap dealers) market share has dropped from one half to one fifth of the open interest in near-dated commodity futures contracts. During that period, hedge funds' market share has grown from 7.5% to approximately 20-25% of the near-dated open interest. Table 3B, which computes market shares across all maturities rather than the three nearest-maturity contracts, shows comparable market shares regardless of futures maturity.

IV. Speculation, Hedge Fund Activity, and Commodity-Equity Co-movements

In Section II, we showed that the conditional correlation between the weekly returns on investible equity and commodity indices fluctuates substantially over time. In Section III, we used a unique dataset of daily trader positions from 2000 through 2008, to construct measures of "speculative" activity (relative to net hedging demand) and hedge fund importance (relative to other kinds of traders) in seventeen U.S. commodity futures markets.

In this section, we ask whether changes in the intensity of speculative activity or in the relative importance of some trader categories (in particular, hedge funds) can help explain energy-equity cross-correlations. Section IV.A introduces our real-sector and financial-sector controls. Section IV.B discusses our regression methodology, which accounts for possible endogeneity issues and for the fact that some variables are stationary in levels while others are only stationary in first differences. Section IV.C presents our regression results. Table 3 has summary statistics for all the variables, while Table 4 provides simple cross-correlation tables.

A. Real Sector

Business cycle factors affect commodity returns (e.g., Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). Furthermore, the response of U.S. stock returns to oil price increases depends on whether the increase is the result of a demand or a supply shock in the crude oil space (Kilian and Park, 2009). These facts point to the need to control for real-sector factors when trying to explain time-variations in the strength of equity-energy linkages.

To do so, we use three variables: a measure of global real economic activity (Kilian, 2009); the natural logarithm of the US industrial production index (IPI), and the US 90-day T-bill rate.[11] Kilian shows that "increases in freight (shipping) rates may be used as indicators of (…) demand shifts in global industrial commodity markets." He constructs 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" and can be computed as far back as January 1968. It is deflated with the U.S. consumer price index, and linearly detrended to remove the impact of the "secular decrease in the cost of shipping dry cargo over the last forty years."

Table 3A provides summary statistics for these three variables. Figure 3 charts the Kilian shipping index from 1991 to 2008. Although a relationship between this index and our DCC estimates is not readily apparent in the first half of the sample, a clearly negative relationship between the two variables emerges after 1999.

B. Financial Stress

Cross-market co-movements increase during episodes of financial stress. To wit, Hartmann, Straetmans and de Vries (2004) identify cross-asset extreme linkages in the case of the bond and equity returns from the G-5 countries. In a similar vein, Longin and Solnik (2001) document that international equity market correlations increase in bear markets. Closest to the present study, Büyükşahin *et al*. (2010) show that financial and commodity markets also become more of a "market of one" during extreme events. We account for this reality, by including the TED spread as an explanatory variable in our regressions.

[11] Because the Kilian index and the US IPI are monthly series, we use weekly interpolations of both measures.

Table 3A and Figure 3 provide graphical and statistical information on this measure of financial stress. The TED spread varies widely during the sample period, between a minimum of three basis points and a maximum of 4.33%. The variable is elevated in the last two years of the sample period (starting August 10 2007, with the suspension of investor withdrawals from three funds managed by a French bank) and is particularly elevated at the onset of the Lehman crisis.

C. Regression Methodology

Before testing the explanatory power of different variables on the DCC between equity and commodity returns, we check the order of integration of each variable using Augmented Fuller (ADF) tests. Unit root tests for the variables in our estimation equation are summarized at the bottoms of Tables 3A and 3B; they show that some of the variables, including the dependent variable, are I(0), whereas the others variables are I(1).

Ordinary regression methods are not appropriate in such a situation. Pesaran and Shin (1999), however, propose a cointegration approach to this problem. Their approach is related to an instrumental-variable methodology proposed by Bewley (1979). Specifically, Pesaran and Shin show that the autoregressive distributed lag (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) variables. 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 using lagged values of the dependent variables as instruments, this methodology also solves issues of endogeneity that might arise from using a single co-integration equation.

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 $t \times 1$ vector of dependent variable, x is a $t \times k$ vector of regressors, *and* w stands for a $t \times s$ vector of deterministic variables such as an intercept, seasonal dummies, time trends, or exogenous variables with fixed lags.[12] In vector notation, Equation (1) is:

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

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

where $\gamma(L)$ is the polynomial lag operator $1 - \gamma_1 L - \gamma_2 L^2 - ...\gamma_p L^p$; $\alpha(L)$ is the polynomial lag operator $\alpha_0 + \alpha_1 L + \alpha_2 L^2 + +... + \alpha_q L^q$; *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 of the ARDL model by OLS and then solving the estimated version of (1) for the cointegrating relationship $y_t = \psi w_t + \theta x_t + v_t$ by

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

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

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 .

In practice, we obtain the standard errors of the long run coefficients using "Bewley regressions." Bewley's (1979) approach involves the estimation of the following regression

$$y_t = \psi w_t + \theta x_t + \sum_{i=0}^{p-1} \eta_i \Delta y_{t-i} + \sum_{i=0}^{q-1} \kappa_i \Delta x_{t-i} + \xi_t$$

by the instrumental variable method, using $(w_t, x_t, \Delta x_t, \Delta x_{t-1}, \Delta x_{t-q+1}, y_{t-1}, ...y_{t-p})$ as instruments. Pesaran and Shin (1999) show that the instrumental variable estimators of ψ and θ obtained using the Bewley (1979) method are numerically identical to the OLS estimators of ψ and θ based on the ARDL model (the latter alone, of course, provides an ECM representation when the variables under study are cointegrated).

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 the 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.

D. Regression Results

Tables 5, 6 and 7 sumarize our regression results. Table 5 establishes the base case in the absence of information on trader positions, while Table 6 establishes the additional explanatory power of speculation and hedge fund activities. Table 7 presents some of our robustness checks. We provide two versions of each Table, one with (Tables 5-6-7.A) and one without (Tables 5-6-7.B) the US IPI as a regressor.

1. Real sector and financial stress variables

Table 5 shows that, for the whole sample (1991-2008) as well as for the sub-sample for which we have detailed position data (2000-2008), the DCC measure of the extent to which energy commodities and equities move together is negatively related to the *SHIP* variable (a proxy for measure world economic activity and demand for industrial commodities) and positively related to the *TED* variable (a proxy for stress in financial markets). In the latter case, a 1% increase in the TED spread brings about a 0.2% increase in the dynamic equity-commodity correlation; this increase is statistically significant at the 1% level of confidence. In contrast, momentum in equity markets (*UMD*) is never a statistically significant of equity-commodity correlations.

2. Speculative activity and hedge fund market share

Table 6 is key to our contribution, in that it shows that speculative activity in energy futures markets helps explain (over and above the *SHIP* and *TED* variables) the fluctuations over time in the energy-equity DCC estimates. Specifically, Models 2 and 4 in Table 6 show that an increase of 1% in the overall commodity-futures market share of hedge funds is associated with an approximately 3.2% increase in dynamic conditional equity-commodity correlations (assuming a mean hedge fund market share of about 20%). In contrast, we find little statistical evidence that the relative importance of commodity swap dealers' positions help explain the dynamic cross-market correlations.

A comparison of Tables 6 and 7 shows the importance of distinguishing between hedge fund positions in short- *vs*. long -dated contracts. Specifically, *WMSA_MMT* in Table 7 is never statistically significant, whereas *WMSS_MMT* in Table 6 is always highly significant. This result is intuitive, in that the GSCI-Energy index is constructed using short-dated futures contracts (so one would expect the short-dated positions to matter for energy-equity correlations).

Notably, in Models 4 and 5 of Table 6 and 7, the Working speculative index, which aggregates the activities of *all* non-hedgers *across all maturities*, has little explanatory power beyond the information content of hedge fund activity. Precisely, the *WSIA* variable is at best marginally significant whereas the *WMSS_MMT* (Table 6) and *WMSA_MMT* (Table 7) variables are highly significant.

3. Interaction between hedge fund positions and financial stress

Table 6 suggests 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, Models 3 and 5 in Table 6 include an interaction term that captures the behavior of hedge funds amid financial stress episodes. The sign of this term is statistically significant but negative. That is, *ceteris paribus*, the impact of hedge fund activity seems reduced during periods of stress.

4. Implications for portfolio management

Our results suggest that detailed information on the composition of commodity-futures open interest (or, more generally, the make-up of trading activity in financial markets) is relevant to asset allocation decisions. A corollary is that portfolio managers could benefit from a recent CFTC decision to disaggregate the position information that it makes available to the public, and to separate between aggregate trader positions according to the traders' underlying businesses (hedge fund; commodity-swap dealer; one of several "traditional commercial" categories (commodity producer; manufacturer or refiner; wholesaler, dealer or merchant; other), etc.

E. Robustness

Our results are qualitatively robust to using additional proxies for commodity investment; to introducing dummies to control for unusual circumstances in financial markets; and to use of alternative measures of hedge fund activity in commodity futures markets.

1. Commodity investor activity

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

One possible reason is that, although a part of commodity swap dealers' positions in short-dated commodity futures reflects their over-the-counter interactions with index traders, the rest of their futures positions reflects 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 2008, 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, a possible interpretation of this finding is that the activities of passive energy-futures investors do not affect equity-commodity linkages. This result presents an interesting counterpoint to the finding of Büyükşahin *et al* (2008) that increased trading due to commodity index activity in the WTI oil futures futures market, has helped link oil futures prices across the futures maturity curve.

2. The Lehman crash

In the last two years of the sample period, the TED spread was very or extremely high, compared to values taken during most of the previous decade. The TED spread first jumped in August 2007, following the suspension of investor withdrawals from three 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 robust to the introduction of either one of two dummies (one for the August 2007-November 2008 period or one for the September 2008-November 2008 periods, and to the concomitant introduction of interaction terms between the relevant dummy and the TED variable.

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

Tables 7A and 7B repeat the analysis of Tables 6A and 6B, with all the speculation and position variables recalculated using position information across all maturities, rather than across the three nearest-maturity contracts with non-trivial open interest.[13] The statistical significance of all the position variable drops, including for the variable capturing hedge fund activity. Taken together, Tables 6 and 7 imply that it is hedge funds' activities in shorter-dated commodity futures (rather than their activities in commodity markets further along the futures maturity curve) that helps explain equity-commodity linkages.

V. Conclusions

The dynamic conditional correlations between the weekly returns on investible US equity and energy indices are stationary but fluctuate substantially over time, around a mean close to 0. We utilize a unique dataset of daily trader positions in the three largest U.S. commodity and equity futures markets from 2000 through 2008, to show that hedge funds activity in energy futures markets (specifically, their share of the open interest) is statistically and economically significant in explaining fluctuations of equity-energy correlations. In contrast, we find little evidence that other kinds of traders (swap dealers and index traders, traditional commercial traders, etc.) help explain these correlations. Our findings support the claim that detailed information on the composition of commodity-futures open interest (and thus more generally, the make-up of trading activity in financial markets) is relevant to portfolio decision-making.

Using the TED spread as a proxy for financial-market stress, we also show that greater equity-energy co-movements are associated with mayhem in financial markets. Intuitively, hedge funds could be an important transmission channel of equity market shocks into the commodity space. In fact, we find that ability of hedge fund activity to explain energy-equity return correlations is statistically and economically significantly lower during periods of global market stress.

Our results in this paper are consistent with the notion that hedge fund activity enhances linkages between equity and energy-futures markets. The hedge fund category, however, is heterogenous. Of particular relevance to the present study, some funds take positions in different

[13] We ran a series of aditional robustness checks, all of which yielded qualitatively similar results.

asset classes but others specialize in commodity investments and do not trade equities. There is little reason to believe, *a priori*, that the behavior of the latter group should matter for equity-commodity correlations. At the same time, some commodity futures traders other than hedge funds also trade equities – and the activities of those traders might also contribute to linking commodity and equity markets.

It would therefore be interesting to examine whether changes in the proportion of cross-market traders, in the overall commodity open interest, have explanatory power for the equity-energy dynamic correlations over and above the explanatory power of hedge fund activity as a whole. Of independent interest, doing so would generate information that has never before been presented – including the proportion of different energy futures trader types that hold positions in both equity and commodity markets; the mean and median magnitudes of their respective absolute net positions and of their open interest, relative to other traders who do not trade across markets; the correlation between their "de-trended" positions (as a group) and the TED spread, relative to other similar-category traders; etc.

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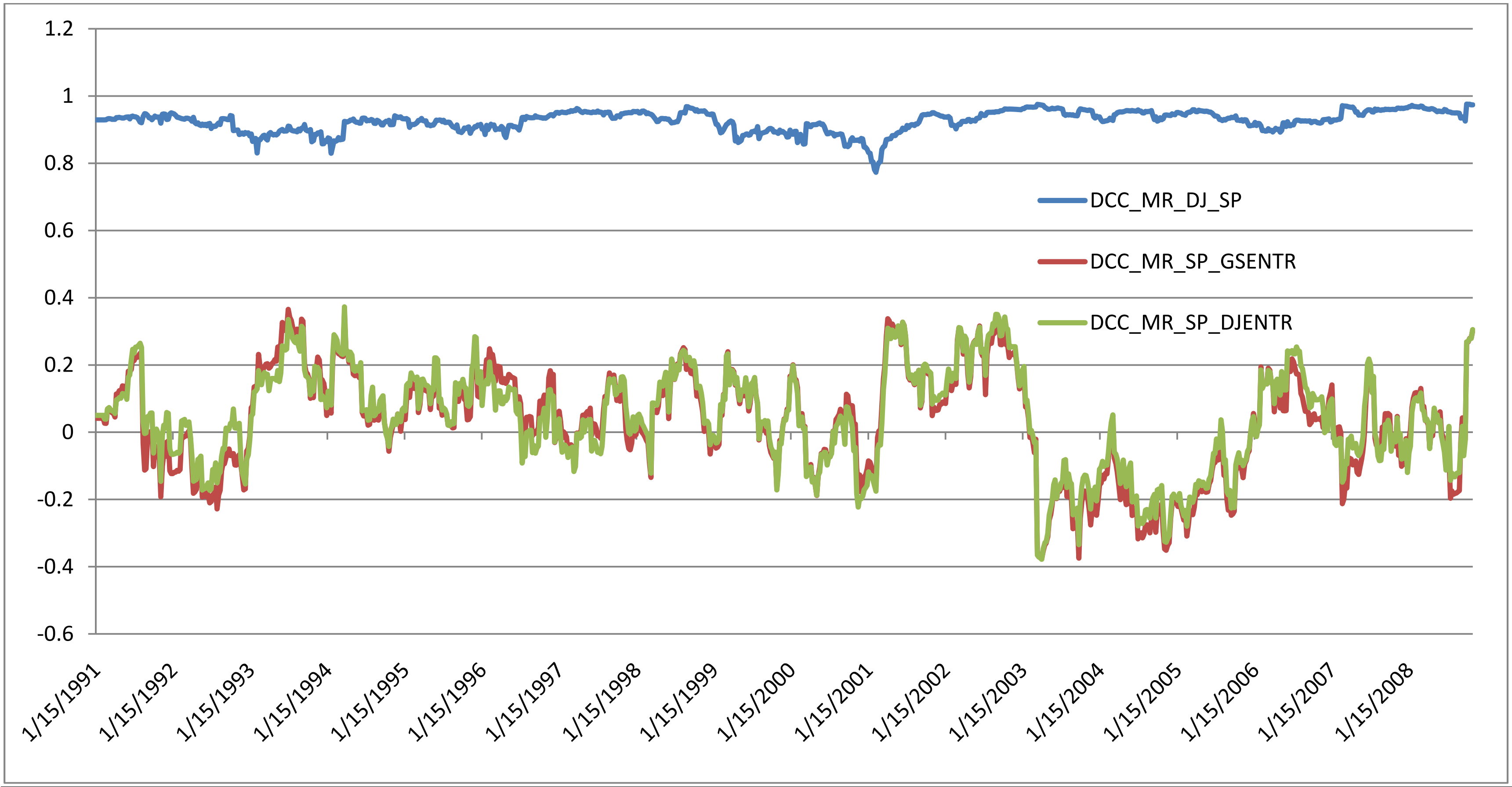
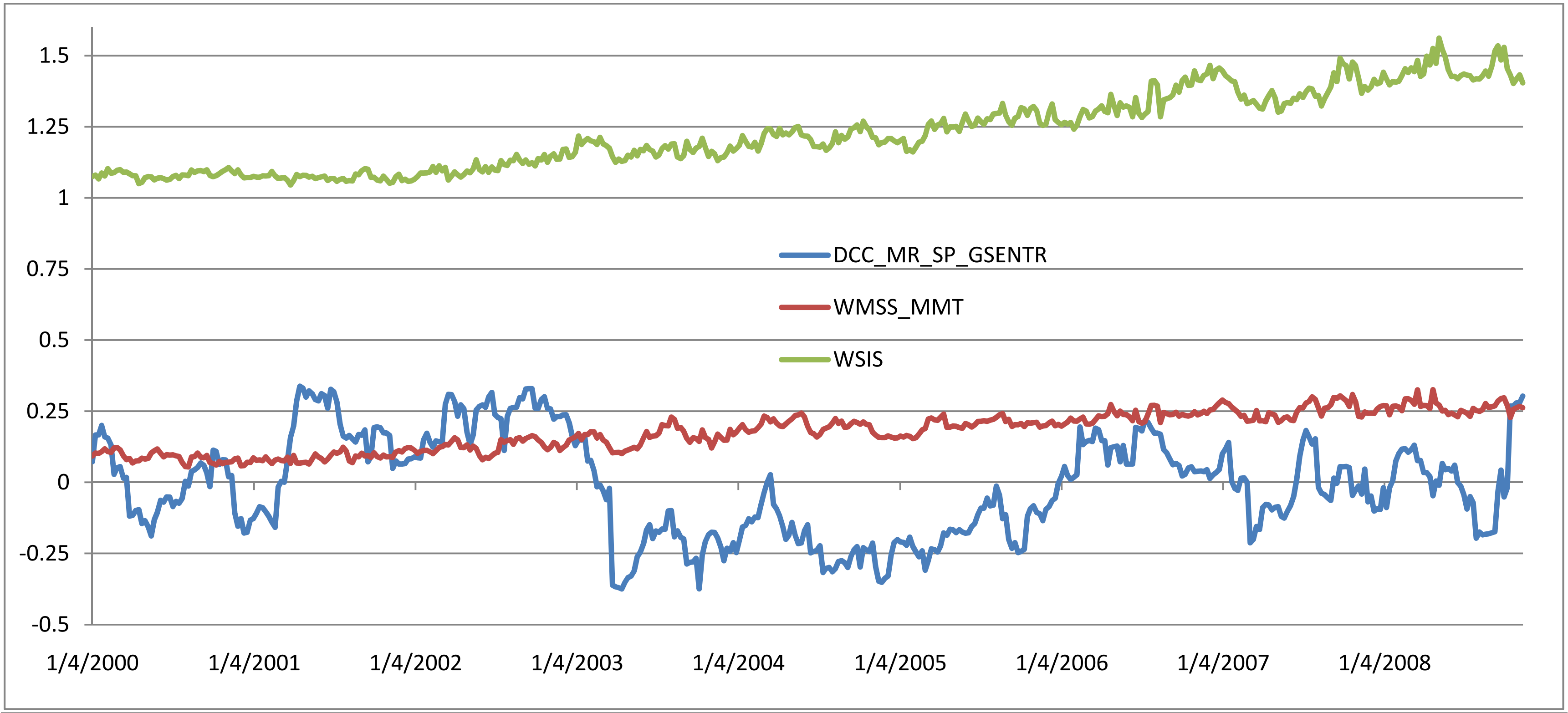
Figure 1: Equity-Energy Correlations vs. DJIA-S&P500 Correlations



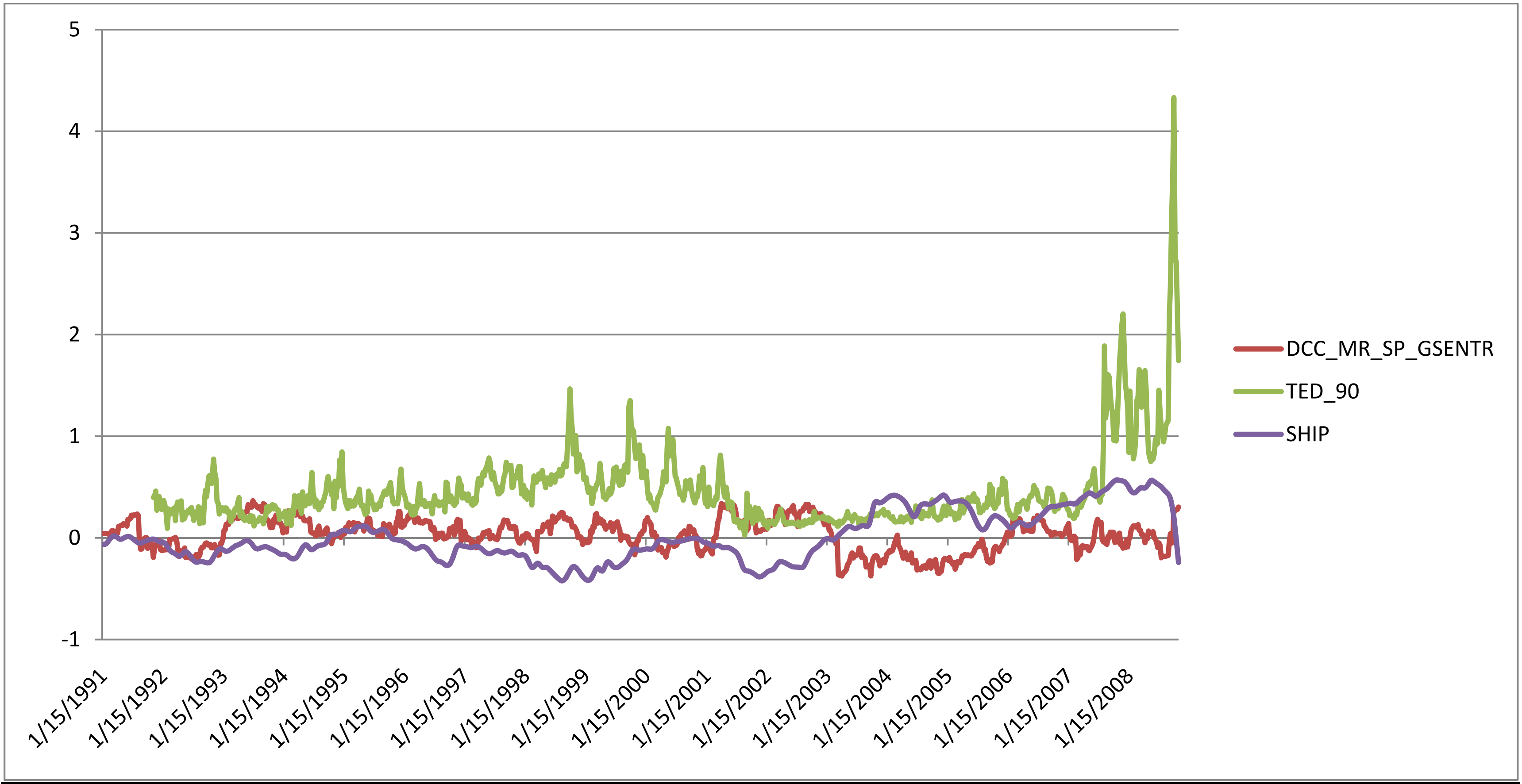
***Notes*:** Figure 1 depicts the time-varying correlation between the **weekly** unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and: (i) the Dow Jones Industrial Average equity index (DJIA, blue line); S&P's GSCI-Energy total return commodity index (GSENTR, red line), and DJ-AIG total return energy index (DJENTR, green line). In each case, dynamic conditional correlation are estimated by log-likehood for mean-reverting model (Engle, 2002) from January 2, 1991 to November 13, 2008. Plots using two alternative methods to estimate time-varying correlations (exponential smoother with 0.94 smoothing parameter, and rolling historical correlation) are similar, as are plots when the S&P 500 is replaced by the the Dow Jones Industrial Average (DJIA) equity index.

Figure 2: Equity-Energy Correlations, Overall Speculation, and Hedge-fund Activity in Commodity Futures Markets



Notes**:** The blue line in Figure 2 shows, between January 4, 2000 and November 13, 2008, the time-varying correlation (DCC) between the **weekly** unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and on the S&P GSCI-Energy total return (GSENTR) index. The green line plots the weighted-average speculative pressure index in three US energy futures markets that are linked to the GSCI index. The red line shows the aggregate share of the short-term open interest held in these three markets by hedge funds (MMT or "Managed Money Traders"). Dynamic conditional correlations are estimated by log-likehood for mean reverting model (DCC_MR; Engle, 2002).

Figure 3: Equity-Energy Correlations, TED Spread, and Economic Activity



***Notes*:** Figure 3 depicts the time-varying 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, the 90-day TED spread, and the Kilian (AER, 2009) measure of worldwide economic activity from January 4, 2000 to November 13, 2008. Dynamic conditional correlation estimated by log-likehood for mean reverting model (Engle, 2002).

Table 1: Weekly Rates of Return – Summary Statistics
(%, January 1991 to November 2008)

Panel A: S&P 500 Equity Index

	1991-2008	1991-1997	1997-2003	2003-2008
Mean	0.1127	0.2723	0.0391	-0.0080
Median	0.2765	0.3456	0.3670	0.1752
Maximum	12.3746	4.1943	12.3746	6.7067
Minimum	-15.7665	-4.1124	-12.1706	-15.7665
Std. Dev.	2.2598	1.4406	2.9435	2.0750
Skewness	-0.5743	-0.2580	-0.0255	-2.1055
Kurtosis	8.6149	3.3717	4.7886	16.5372
Jarque-Bera	1274.17***	4.41	41.89***	2395.09***
Observations	931	262	314	286

Panel B: GSCI-Energy (Commodity) Index

	1991-2008	1991-1997	1997-2003	2003-2008
Mean	0.1895	0.1436	0.2546	0.1982
Median	0.2694	0.0548	0.2626	0.6225
Maximum	14.6776	9.0001	14.6776	14.6048
Minimum	-21.5522	-14.5584	-19.3599	-14.8979
Std. Dev.	4.1581	3.1647	4.4476	4.5736
Skewness	-0.3629	-0.1770	-0.2047	-0.3383
Kurtosis	4.5609	4.4443	3.8423	3.3113
Jarque-Bera	114.95***	24.14***	11.48***	6.61**
Observations	931	262	314	286

Notes: Table 1 provides summary statistics for the unlevered rates of return on the S&P 500 equity index (excluding dividends; Panel A), as well as on the S&P GSCI-Energy commodity index (total return; Panel B). In each Panel, the first column uses sample moments computed using weekly rates of return (precisely, changes in log prices multiplied by 100) from January 2, 1991 to November 11, 2008. The second, third and fourth columns use, respectively, weekly rates of returns for three successive sub-periods: June 1, 1992 to May 31, 1997; June 1, 1997 to May 31, 2003; and, June 1, 2003 to November 11, 2008. One, two or three stars indicate that normality of the return distribution is rejected at, respectively, the 10%, 5% or 1% level of statistical significance.

Table 2: Weekly Correlations – Rates of Return on Equity and Commodity Indices

Panel A: Entire Sample Period (January 1991 to November 2008)

	DJIA	S & P 500	DJAIG-Energy	GSCI-Energy
DJIA	1			
S & P 500	0.943***	1		
DJAIG-Energy	0.045	0.084**	1	
GSCI-Energy	0.041	0.079**	0.967***	1

Panel B: June 1992 to May 1997

	DJIA	S & P 500	DJAIG-Energy	GSCI-Energy
DJIA	1			
S & P 500	0.920***	1		
DJAIG-Energy	0.088	0.080	1	
GSCI-Energy	0.126**	0.113*	0.947***	1

Panel C: June 1997 to May 2003

	DJIA	S & P 500	DJAIG-Energy	GSCI-Energy
DJIA	1			
S & P 500	0.939***	1		
DJAIG-Energy	0.058	0.096*	1	
GSCI-Energy	0.045	0.084	0.983***	1

Panel D: June 2003 to May 2008

	DJIA	S & P 500	DJAIG-Energy	GSCI-Energy
DJIA	1			
S & P 500	0.959***	1		
DJAIG-Energy	-0.114*	-0.048	1	
GSCI-Energy	-0.145**	-0.078	0.957***	1

Panel E: June 2003 to November 2008

	DJIA	S & P 500	DJAIG-Energy	GSCI-Energy
DJIA	1			
S & P 500	0.966***	1		
DJAIG-Energy	0.035	0.105*	1	
GSCI-Energy	0.036	0.105*	0.960***	1

Notes: Table 2 provides simple cross-correlations for the weekly unlevered **rates of return** (precisely, for the changes in log prices) on four investable indices: the Dow Jones Industrial Average (DJIA) and S&P 500 equity indices, as well as Dow Jones' DJAIG and S&P's GSCI energy indices. Table 2A provides cross-correlations for the whole sample (January 1991 to November 2008). Tables 2B, 2C, 2D and 2E provide cross-correlations for four sub-periods: June 2, 1992 to May 31, 1997 (2B); June 1, 1997 to May 31, 2003 (2C); and, June 1, 2003 to either May 26, 2008 (2D) or November 11, 2008 (2E). One, two or three stars indicate that an estimate is statistically significantly different from zero at the 10%, 5% or 1% level, respectively. Note the increase in correlations once the Summer-Fall of 2008 are included.

Table 3A: Summary Statistics (Position Data on Near-dated Contracts)

	DCC	SHIP	LY	LIBOR_90	TED_90	TBILL_90	WSIS	UMD	WMSS_ANC	WMSS_AS	WMSS_MMT	WMSS_NON	WMSS_TCOM
Mean	-0.011	0.157	4.646	0.034	0.465	0.029	1.237	0.035	0.488	0.190	0.183	0.298	0.396
Median	-0.009	0.186	4.639	0.031	0.291	0.025	1.217	0.090	0.500	0.191	0.196	0.311	0.378
Maximum	0.338	0.569	4.719	0.068	4.331	0.064	1.561	3.860	0.727	0.283	0.326	0.480	0.641
Minimum	-0.375	-0.384	4.583	0.010	0.028	0.003	1.045	-4.300	0.236	0.109	0.054	0.123	0.177
Std. Dev.	0.180	0.263	0.039	0.017	0.510	0.017	0.131	0.973	0.126	0.035	0.066	0.098	0.117
Skewness	0.052	-0.384	0.372	0.254	3.312	0.386	0.363	-0.465	-0.074	-0.026	-0.195	-0.062	0.229
Kurtosis	2.045	2.062	1.880	1.739	17.448	1.801	1.971	6.060	1.866	2.538	1.944	1.746	2.010
Jarque-Bera	16.801	26.769	32.891	33.692	4599.887	37.041	28.896	186.214	23.825	3.942	23.080	28.925	21.647
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.139	0.000	0.000	0.000
Sum	-4.894	68.674	2030.293	14.868	203.162	12.836	540.556	15.230	213.470	83.136	79.888	130.333	173.230
Sum Sq. Dev.	14.048	30.076	0.647	0.133	113.231	0.124	7.446	413.112	6.922	0.545	1.914	4.190	5.918
Observations	437	437	437	437	437	437	437	437	437	437	437	437	437
ADF Level	-2.623*	-1.411	-0.539	-1.74	0.037	-1.083	-1.162	-22.369***	-0.28	-1.676	-2.181	-1.395	-0.522
ADF F-D	-21.439***	-2.288**	-3.960***	-8.819***	-11.404***	-21.454***	-15.836***	-14.731***	-19.405***	-11.132***	-24.220***	-24.527***	-17.189***

Note to Table 3A: DCC 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 correlatios estimated by log-likehood for mean reverting model (Engle, 2002). SHIP is the Kilian (AER 2008) index of worldwide economic activity. LY is the natural logarithm of the US industrial production index (IPI). LIBOR_90, TED_90 and TBILL_90 are the 90-day annualized LIBOR rate, TED spread, and T-bill rate (source: Bloomberg). LY is the natural logarithm of the US industrial production index (Source: Federal Reserve Bank of St Louis). WSIS is the weigthed average speculative index, with weights set each year equal to average of the GSCI weights that year for 3 energy commodities in the GSCI Energy index (Source: Standard and Poor); for each commodity, the speculative index measures the extent to which speculative positions exceed the hedging demand in the three shortest-maturity contracts (source: CFTC , S&P and authors' calculations). UMD is the Fama-French momentum factor for US equities. WMSS_AS, WMSS_MMT 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 3 energy futures markets of traditional commercial traders (TCOM), commodity swap dealers (AS, including CIT – commodityindex traders), and hedge funds (HF or MMT, "managed money traders") in the three shortest-maturity contracts (source: CFTC and authors' computations); weights are set each year equal to average of the GSCI weights for those 3 commodities that year and rescaled to account for GSCI energy markets for which no large trader position data are available (Source: Standard and Poor). For the augmented Dickey-Fuller (ADF) tests, the optimal lag length *K* is based on the Akaike Information Criterion (AIC); 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 DCC and momentum series are I(0); the other series are I(1);. All estimates are for July 4, 2000 to November 11, 2008.

Table 3B: Summary Statistics *(Position data on all maturities)*

	DCC	SHIP	LY	LIBOR_90	TED_90	TBILL_90	WSIS	UMD	WMSS_ANC	WMSS_AS	WMSS_MMT	WMSS_NON	WMSS_TCOM
Mean	-0.011	0.157	4.646	0.034	0.465	0.029	1.219	0.035	0.538	0.260	0.161	0.277	0.378
Median	-0.009	0.186	4.639	0.031	0.291	0.025	1.189	0.090	0.546	0.268	0.147	0.267	0.364
Maximum	0.338	0.569	4.719	0.068	4.331	0.064	1.472	3.860	0.758	0.340	0.311	0.446	0.626
Minimum	-0.375	-0.384	4.583	0.010	0.028	0.003	1.056	-4.300	0.283	0.169	0.036	0.099	0.173
Std. Dev.	0.180	0.263	0.039	0.017	0.510	0.017	0.112	0.973	0.120	0.034	0.079	0.094	0.111
Skewness	0.052	-0.384	0.372	0.254	3.312	0.386	0.393	-0.465	-0.172	-0.588	0.237	0.033	0.295
Kurtosis	2.045	2.062	1.880	1.739	17.448	1.801	2.025	6.060	2.160	2.796	1.800	1.895	2.298
Jarque-Bera	16.801	26.769	32.891	33.692	4,599.887	37.041	28.566	186.214	15.022	25.939	30.299	22.328	15.293
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Sum	-4.894	68.674	2,030.293	14.868	203.162	12.836	532.902	15.230	234.976	113.835	70.456	121.142	165.308
Sum Sq. Dev.	14.048	30.076	0.647	0.133	113.231	0.124	5.496	413.112	6.299	0.506	2.734	3.869	5.374
Observations	437	437	437	437	437	437	437	437	437	437	437	437	437
ADF Level	-2.623*	-1.411	-0.539	-1.74	0.037	-1.083	-1.162	-22.369***	-0.28	-1.676	-2.181	-1.395	-0.522
ADF F-D	-21.439***	-2.288**	-3.960***	-8.819***	-11.404***	-21.454***	-15.836***	-14.731***	-19.405***	-11.132***	-24.220***	-24.527***	-17.189***

<u>Note to Table 3B:</u> DCC_MR 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-Energy total return (GSENTR) index. Dynamic conditional correlation estimated by log-likehood for mean reverting model (Engle, 2002). SHIP is the Kilian (AER 2008) index of worldwide economic activity. LIBOR_90, TED_90 and TBILL_90 are the 90-day annualized LIBOR rate, Ted spread, and T-bill rate (source: Bloomberg). LY is the natural logarithm of the US industrial production index (Source: Federal Reserve Bank of St Louis). WSIA is the weigthed average speculative index, with weights set each year equal to average of the GSCI weights that year for 3 energy commodities in the GSCI Energy index (Source: Standard and Poor); for each commodity, the speculative index measures the extent to which speculative positions exceed the hedging demand across all contract maturities (source: CFTC , S&P and authors' own calculations). UMD is the Fama-French momentum factor for US equities. WMSA_AS, WMSA_MMT and WMSA_TCOM stand, respectively, for the weighted-average shares of the overall open interest across all futures contract maturities in 3 commodity markets of traditional commercial traders (TCOM), commodity swap dealers (AS, including CIT – commodityindex traders), and hedge funds (HF or MMT, "managed money traders") (source: CFTC and authors' own computations); weights are set each year equal to average of the GSCI weights for those 3 commodities that year and rescaled to account for GSCI commodity markets for which no large trader position data are available (Source: Standard and Poor). For the augmented Dickey-Fuller (ADF) tests, the optimal lag length *K* is based on the Akaike Information Criterion (AIC); 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 DCC and momentum series are I(0); the other series are I(1);. All estimates are for July 4, 2000 to November 11, 2008.

<u>Table 4: Simple Correlations *(Explanatory Variables)*</u>

	DCC	SHIP	LY	LIBOR_90	TED_90	TBILL_90	WSIS	UMD	WMSS_ANC	WMSS_AS	WMSS_MMT	WMSS_NON	WMSS_TCOM
DCC	1												
SHIP	-0.519*	1											
LY	0.124*	0.540*	1										
LIBOR_90	0.186*	0.143*	0.483*	1									
TED_90	0.076	0.380*	0.632*	0.263*	1								
TBILL_90	0.170*	0.034	0.310*	0.957*	-0.029	1							
WSIS	-0.104**	0.769*	0.810*	0.264*	0.572*	0.101**	1						
UMD	0.046	-0.088	-0.039	0.000	-0.068	0.021	-0.064	1					
WMSS_ANC	-0.225*	0.788*	0.764*	0.193*	0.528*	0.040	0.958*	-0.074	1				
WMSS_AS	-0.357*	0.635*	0.620*	0.197*	0.486*	0.057	0.721*	-0.080	0.843*	1			
WMSS_MMT	-0.153*	0.762*	0.698*	0.110**	0.444*	-0.021	0.930*	-0.052	0.950*	0.668*	1		
WMSS_NON	-0.161*	0.783*	0.758*	0.177*	0.503*	0.031	0.971*	-0.067	0.981*	0.723*	0.980*	1	
WMSS_TCOM	0.266*	-0.798*	-0.713*	-0.128*	-0.506*	0.020	-0.948*	0.072	-0.991*	-0.826*	-0.951*	-0.976*	1

<u>Note:</u> Table 4 shows the sample correlations of the variables in our regression analyses. Stars (*, **) highlight correlations that are statistically significantly different from 0 at, respectively, the 1% and 5% levels of statistical significance. The dependent variable (DCC) is described in the footnote to Figure 1. The independent variables are described the footnotes to Tables 3A and 3B. All data are from July 4, 2000 to November 11, 2008.

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

Variable	Model 1		
	1991-1999	2000-2008	1991-2008
Constant	-0.8672	-9.4521**	0.4307
	(1.473)	(4.717)	(0.9039)
SHIP	-0.040	-0.6642***	-0.2981**
	(0.265)	(0.1338)	(0.127)
UMD	0.0397	0.0401	0.0479
	(0.066)	(0.0429)	(0.0495)
TED	-0.3524*	0.2127**	0.1938**
	(0.2057)	(0.0903)	(0.0860)
LY	0.2521	2.0356**	-0.1034
	(0.3513)	(1.021)	(0.2015)
Observations	448	436	885

Notes: Explanatory variables are described in Table 1. 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). The explanatory variables are described in Table 3A. 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 variablesx_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 periods in the first, second and third columns are March 5, 1991 (when to June 29, 2000; July 5, 2000 to November 11, 2008; and, March 5, 1991 to November 11, 2008.

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

Variable	Model 1 1991-1999	 2000-2008	 1991-2008
Constant	0.1803**	-0.0602	-0.0472
	(0.0744)	(0.0512)	(0.0475)
SHIP	-0.0847	-0.5944***	-0.3181***
	(0.2495)	(0.1502)	(0.1161)
UMD	0.0431	0.0519	0.0472
	(0.0647)	(0.0532)	(0.0504)
TED	-0.2818*	0.3308***	0.1818**
	(0.1608)	(0.0994)	(0.0856)
Observations	448	436	885

Notes: Explanatory variables are described in Table 1. 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). The explanatory variables are described in Table 3A. 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 variablesx_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 periods in the first, second and third columns are March 5, 1991 (when to June 29, 2000; July 5, 2000 to November 11, 2008; and, March 5, 1991 to November 11, 2008.

Table 6A: Long-run Determinants of the GSCI-S&P500 Dynamic Conditional Correlation

Variable	**Model 2** 2000-2008	**Model 3** 2000-2008	**Model 4** 2000-2008	**Model 5** 2000-2008
Constant	-10.2735**	-9.4336**	-9.1175**	-8.2892**
	(4.106)	(3.976)	(4.023)	(3.867)
SHIP	-0.5938***	-0.7027***	-0.5576***	-0.6563***
	(0.1424)	(0.1434)	(0.1372)	(0.1376)
UMD	0.0236	0.0187	0.0216	0.0163
	(0.0327)	(0.0312)	(0.0309)	(0.0295)
TED	0.2031***	1.1232***	0.1726**	1.0319***
	(0.0685)	(0.3578)	(0.0676)	(0.3360)
LY	1.9965**	1.6501*	1.4046	1.0481
	(0.9075)	(0.8891)	(1.015)	(0.9785)
WMSS_AS	-0.7443	-0.1820	-0.0273	0.5514
	(1.651)	(1.604)	(1.694)	(1.633)
WMSS_MMT	2.8464*	5.2200***	3.1789**	5.4358***
	(1.645)	(1.823)	(1.583)	(1.728)
WMSS_TCOM	1.5502	2.0047	2.5307*	3.0292**
	(1.255)	(1.223)	(1.481)	(1.427)
INT_TED_MMT		-3.5918***		-3.3636***
		(1.322)		(1.237)
WSIA			0.8340	0.8858
			(0.7365)	(0.7024)
Observations	436	436	436	436

Notes: Explanatory variables are described in Table 1. 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. DCC 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 optimal lag lengths p=1 and q=1 in our case. The sample period is July 4, 2000 to November 11, 2008.

Table 6B: Long-run Determinants of the GSCI-S&P500 Dynamic Conditional Correlation

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 Table 1. 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 7A: Long-run Determinants of the GSCI-S&P500 Dynamic Conditional Correlation

Variable	Model 6 2000-2008	Model 7 2000-2008	Model 8 2000-2008	Model 9 2000-2008
Constant	-3.6606	-1.8449	-3.2236	-1.1944
	(5.676)	(5.744)	(-3.2236)	(5.810)
SHIP	-0.5005***	-0.5725***	-0.4899***	-0.5689***
	(0.1667)	(0.1708)	(-0.4899)	(0.1726)
UMD	0.0288	0.0336	0.0200	0.0221
	(0.0362)	(0.0371)	(0.0367)	(0.0376)
TED	0.2132***	1.1450***	0.2182***	1.2514***
	(0.0771)	(0.3947)	(0.0827)	(0.4280)
LY	0.9527	0.5728	0.9969	0.9332
	(1.297)	(1.309)	(1.406)	(1.428)
WMSA_AS	-2.8050	-3.2387	-3.2665	-4.6500*
	(2.125)	(2.155)	(2.539)	(2.683)
WMSA_MMT	0.3841	1.5118	0.5555	2.0465
	(1.853)	(1.878)	(1.900)	(1.976)
WMSA_TCOM	-0.3186	-0.8199	-0.6208	-2.0146
	(1.441)	(1.485)	(1.929)	(2.100)
INT_TED_MMTA		-3.5656**		-3.8829**
		(1.415)		(1.501)
WSIA			-0.3589	-1.3199
			(1.490)	(1.591)
Observations	436	436	436	436

Notes: Explanatory variables are described in Table 1. 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 7B: Long-run Determinants of the GSCI-S&P500 Dynamic Conditional Correlation

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 Table 1. 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 total return (GSTR) 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: DCC Methodology

We use the dynamic conditional correlation (DCC) methodology proposed by Engle (2002) to obtain dynamically correct estimates of the intensity of co-movements (or the lack thereof) between commodities and equities. This methodology can account adequately for changes in volatility of the relevant variables.

The DCC model is based on a two-step approach to estimating the time-varying correlation between two series. In the first step, time-varying variances are estimated using a GARCH model. In the second step, a time-varying correlation matrix is estimated using the standardized residuals from the first-stage estimation.

Formally, consider a $n \times 1$ vector of normally-distributed returns series r_t of n assets with mean 0 and covariance matrix H_t assumed to have the following structure:

$$r_t \sim N(0, H_t) \tag{1}$$

$$H_t = D_t R_t D_t \tag{2}$$

where, H_t is the conditional covariance matrix; R_t is the time varying correlation matrix; D_t is a diagonal matrix of time-varying standard deviations given by $D_t = \text{diag}\sqrt{E_{t-1}(r_{i,t}^2)} = \text{diag}\sqrt{h_{i,t}}$; and i=1,2,…n. The $h_{i,t}$ can be thought of as univariate GARCH models, so the standardized disturbance can be expressed as $\varepsilon_{i,t} = r_{i,t}/\sqrt{h_{i,t}} = D_t^{-1} r_{i,t}$, where $\varepsilon_{i,t} \sim N(0, R_t)$. Consider the conditional correlations:

$$\rho_{ij,t} = \frac{E_{t-1}[r_{i,t} r_{j,t}]}{\sqrt{E_{t-1}[r_{i,t}^2 r_{j,t}^2]}} \tag{3}$$

Re-writing these conditional correlation in terms of standardized residuals from GARCH estimates yields:

$$\rho_{ij,t} = E_{t-1}[\varepsilon_{i,t} \varepsilon_{j,t}] \tag{4}$$

Equation (4) implies the equivalence of conditional correlation of returns and conditional covariance between the standardized disturbances. Therefore, the matrix R represent the time-varying conditional correlation matrix of returns as well as the conditional covariance matrix of the standardized residuals (Engle, 2002).

The DCC model of Engle (2002) suggests the following dynamics of the correlation matrix:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5}$$

$$Q_t = (1 - \phi_1 - \phi_2)\overline{Q} + \phi_1(\varepsilon_{i,t-1} \varepsilon_{j,t-1}) + \beta Q_{t-1} \tag{6}$$

where $\overline{Q}$ is the unconditional correlation matrix of standardized residuals and Q^*_t is a diagonal matrix composed of square root of the diagonal elements of Q_t. The correlation estimator is given by the typical element of R_t in the form of

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$$

This specification ensures the mean reversion as long as $\phi_1 + \phi_2 < 1$. The resulting estimator is called DCC by log-likelihood with mean reverting model. The log-likelihood of the DCC model outlined above is given by:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + 2\log(|D_t|) + \log(|R_t|) + \varepsilon' R_T^{-1}\varepsilon)$$

In essence, the log-likelihood function has two components: the volatility part, which contains terms in D_t; and the correlation part, which contains terms in R_t. In the first stage of the estimation, n univariate GARCH(1,1) estimates are obtained, which produces consistent estimates of time-varying variances (D_t). In the second stage, the correlation part of the log-likelihood function is maximized, conditional on the estimated D_t from the first stage.

Appendix 2: Large trader categories

This Appendix uses the Nymex West Texas Intermediate (WTI) crude oil futures market to illustrate the level of disaggregation within the CFTC's "commercial" and "non-commercial" subcategories, highlighting (in bold) the trader types that are the most active.

The four main commercial subcategories are (i) "Dealer and Merchant", i.e., crude oil wholesalers, exporters and importers, marketers, etc.; (ii) "Manufacturers", i.e., oil refiners, fabricators, etc; (iii) "Producers", a self-explanatory grouping; (iv) "Commodity Swap Dealers", gathering all reporting swap dealers and arbitrageurs/broker-dealers.[14] These categories typically make up more than 95% of the WTI commercial open interest in our 2000-2008 sample, and close to 99% in the last five years.

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 has grown significantly since 2000) 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 OTC commodity index exposure opposite institutional traders such as pension funds".

The three most active 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;[15] (iii) "Non-registered participants" (NRP). 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. During the 2000-2008 sample period, these three categories made up about 90% of the total non-commercial WTI open interest (including non-reporting traders).

[14] The CFTC merged the previously separate financial swap dealers and arbitrageurs/broker-dealer sub-categories with commodity swap dealers partway through our sample period. In the period August 2003 – August 2004, there was only 1 arbitrageur/broker-dealer and 1 financial swap dealer.

[15] See Appendix 4 for a discussion of the term "hedge funds" in the context of commodity futures markets.

Panel A: Commercial Traders

CFTC Code	*CFTC Name*	
18	Co-Operative	In **Panel A**, "**Dealer/Merchant**" (AD) includes wholesalers, exporter/importers, crude oil marketers, shippers, etc. "**Manufacturer**" (AM) includes refiners, fabricators, etc. "Agricultural / Natural Resources – Other" (AO) may include, for example, end users. "**Commodity Swaps/Derivatives Dealer**" (AS) aggregates all reporting "Swaps/Derivatives Dealers" (FS) and "Arbitrageurs or Broker Dealers" (FA), two categories that were merged in the CFTC's internal reporting system part-way through our 2000-2008 sample period. "**Hedge funds**" involved in financial contracts that are shown to be hedging would be included in the "commercial" category FH.
AD	Dealer/Merchant	
AM	Manufacturer	
AO	Agricultural/Natural Resources – Other	
AP	Producer	
AS	Commodity Swaps/Derivatives Dealer	
FA	Arbitrageur or Broker/Dealer	
FB	Non U.S. Commercial Bank	
FC	U.S. Commercial Bank	
FD	Endowment or Trust	
FE	Mutual Fund	
FF	Pension Fund	
FG	Insurance Company	
FH	Hedge Fund	
FM	Mortgage Originator	
FO	Financial – Other	
FP	Managed Account or Pool	
FS	Financial Swaps/Derivatives Dealer	
FT	Corporate Treasurer	
LF	Livestock Feeder	
LO	Livestock – Other	
LS	Livestock Slaughterer	

Panel B: Non-commercial Traders

CFTC Code	*CFTC Name*	
HF	**Hedge Fund**	In **Panel B**, "**Hedge Funds**" (HF) aggregate all reporting Commodity Pool Operators (CPO), Commodity Trading Advisors (CTAs), "Associated Persons" (APs) controlling customer accounts, as well as other "Managed Money" (MM) traders. "**Floor Brokers / Traders**" (FBT) aggregate all reporting floor brokers and floor traders. "**Non-registered participants**" (NRP) are non-commercial traders who are not registered under the Commodity Exchange Act (CEA). This category, which has grown significantly since 2000, mostly comprises financial traders with positions large enough to warrant reporting to the CFTC; it also includes smaller traders who do not have a reporting obligation to the CFTC but whose positions are nevertheless reported.
FBT	Floor Broker /Trader	
FCM	Futures Commission Merchant	
IB	Introducing Broker	
NRP	Non-Registered Participant	

Notes: Appendix 1 lists the trader sub-categories in the CFTC's large-trader reporting system (LTRS). Bolded entries are those on which most of our analysis focuses. When the CFTC publishes its weekly Commitment of Traders Report, these various sub-categories are aggregated in two broad groups: "**Commercials**" (Panel A), who have declared an underlying hedging purpose, and "**Non-commercials**" (Panel B), who have not.

Appendix 3: Commodity Weights

Year	Heating Oil	WTI Crude Oil	Natural Gas
2000	0.11732	0.73476	0.14793
2001	0.10603	0.73756	0.15640
2002	0.11267	0.75347	0.13386
2003	0.10367	0.72193	0.17440
2004	0.10951	0.73689	0.15359
2005	0.11379	0.73622	0.14999
2006	0.11326	0.77585	0.11089
2007	0.08360	0.81109	0.10532
2008	0.07071	0.83521	0.09408
2009	0.06502	0.85037	0.08461

Note: Appendix 3 provides the weights used to compute the weighted average measures of trader importance ($WMSS_i$ and $WMSA_i$, where i = AS, AD, AM, AP, MMT, NRP, etc.) as well as the weighted average speculative indices (WSIS and WSIA).

Appendix 4: 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. Furthermore, there is nothing that requires hedge funds to be categorized in the CFTC's Large Traders Reporting System (LTRS).

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.[16]

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." In addition, for the purposes of this paper, market surveillance staff at the CFTC identified other participants who were not registered in any of these three categories but were known to be managing money –these are also included in the hedge fund category (see bottom of Appendix 1).

[16] 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.