It Matters Who Trades:

Hedge Funds, Swap Dealers, and Cross-Market Linkages

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

First Draft: September 12, 2009
Current Draft: October 6, 2010

Abstract

We provide direct empirical evidence that *who* trades helps explain the joint distribution of commodity and equity returns. Using a unique dataset of all large trader positions in 17 US commodity and equity futures markets from 2000 to 2010, we show that the correlations between the returns on commodity and equity indices increase significantly amid greater activity by speculators in general and one type of traders in particular – hedge funds. We also find that the impact of hedge fund activity is lower during periods of financial market stress. Our results support the notion that the composition of trading activity matters for asset pricing. They also have important implications for the debate on the "financialization" of commodity markets.

JEL Classification: G10, G12, G13, G23
Keywords: Cross-Market Linkages, Trader identity, Hedge funds, Index funds, Commodities, Equities, Financialization, Dynamic conditional correlations (DCC).

---

[1] **Büyükşahin**: Senior Econometrician, U.S. Commodity Futures Trading Commission (CFTC), 1155 21st St. NW, Washington, DC 20581. Tel: (+1) 202-418-5123. Email: bbuyuksahin@cftc.gov. **Robe (Corresponding author)**: Associate Professor 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 thank Hank Bessembinder, Robert Hauswald, Jim Overdahl and Christophe Pérignon for many useful suggestions. We also thank Bob Jarrow, Pete Kyle, Delphine Lautier, Stewart Mayhew, Matt Pritsker, Wei Xiong, Pradeep Yadav, and seminar participants at the U.S. Securities and Exchange Commission (SEC), the European Central Bank (ECB), the International Energy Agency (IEA), the 2nd CEPR Conference on Hedge Funds (Paris), the 20th Cornell-FDIC Conference on Derivatives, and the 2010 CFTC Mini-Conference on the Financialization of Commodity Markets for helpful comments. A companion paper focusing on energy-equity market linkages was presented at the 2010 Meeting of the American Economic Association in Atlanta under the title "Commodity Traders' Positions and Energy Prices: Evidence from the Recent Boom-Bust Cycle". We are grateful to Arek Nowak and Mehrdad Samadi for research assistance. The present paper builds on results derived while Michel 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 CFTC, the SEC, the Commissioners, or other staff at either Commission. Errors or omissions, if any, are the authors' sole responsibility.

It Matters Who Trades:

Hedge Funds, Swap Dealers, and Cross-Market Linkages

Executive Summary

We provide direct empirical evidence that *who* trades helps explain the joint distribution of commodity and equity returns. Our results support the notion that the composition of trading activity matters for asset pricing. They also have important implications for the debate on the financialization of commodity markets.

In the past two decades, the strength of commodity-equity linkages has fluctuated substantially, offering fertile ground for an analysis of what (macroeconomic fundamentals, trading activity, or both) drives such fluctuations. We utilize non-public information from the U.S. Commodity Futures Trading Commission (CFTC) to construct a unique daily dataset of all large trader positions in 17 US commodity and equity futures markets from 2000 to 2010. We document major changes in the composition of the open interest in commodity-futures markets, and find that they help explain the correlation patterns between the returns on passive commodity and equity indices. After controlling for fundamentals, we show that the dynamic conditional return correlations increase significantly amid greater activity by hedge funds.

We find that, in contrast, the positions of other kinds of commodity-futures market participants (swap dealers, index traders, traditional commercial traders, floor brokers and traders, etc.) do not help explain cross-market correlation patterns. In a similar vein, changes in the *overall* amount of speculative activity in commodity futures markets have somewhat less explanatory power. Instead, we trace the explanation to hedge funds in general and, especially (and quite intuitively), to the subset of funds that are active in *both* equity and commodity futures markets.

We document that commodity-equity correlations soared after the demise of Lehman Brothers in Fall 2008 and remained unusually high through Winter 2010. We show that, even before the 2008-2010 crisis, equity-commodity co-movements were 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 impact of hedge fund activity is lower during periods of stress.

JEL Classification: G10, G12, G13, G23

Keywords: Cross-Market Linkages, Trader identity, Hedge funds, Index funds, Commodities, Equities, Financialization, Dynamic conditional correlations (DCC).

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 in theory help alleviate price discrepancies (Rahi and Zigrand, 2009) and improve risk transfers across markets (Başak and Croitoru, 2006).

On the one hand, insofar as hedge funds are less constrained than other investors (see, e.g., Teo, 2009), this theoretical argument suggests that increased hedge fund participation could enhance cross-market linkages. On the other hand, suppose that 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" (such as emerging stock markets or commodity markets) after a major shock in a "central" market (such as the U.S. equity market) could in theory bring about cross-market contagion – see, e.g., Kyle and Xiong (2001), Xiong (2001), Kodres and Pristker (2002), 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. Controlling for macro-economic fundamentals, we show that commodity-equity co-movements increased between 2000 and 2010 amid greater participation in commodity markets by financial speculators in general one type of traders in particular – hedge funds. We also show, however, that the impact of hedge fund activity is lower during periods of turmoil in financial markets. These results have implications for asset pricing in general as well as for the debate on the consequences of "financialization" in commodity markets.

From an empirical perspective, investigating whether specific types of traders contribute to cross-market linkages is generally 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 critical data pitfall by constructing a daily dataset of individual trader positions in seventeen U.S. commodity and equity futures markets. The underlying data, which are non-public, originate from the U.S. Commodity Futures Trading

Commission's (CFTC) large trader reporting system. The latter collects information on the end-of-day positions of every large trader in each of these markets, as well as 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 the largest U.S. commodity futures markets from December 2000 through February 2010.

We focus on the linkages between commodity and equity markets for several reasons. First, we need comprehensive data on trading 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 Kofman, Michayluk and Moser, 2009) and it is precisely about the futures open interest that we have comprehensive information. Second, commodity-equity linkages fluctuate much more than the linkages between some other asset classes – offering fertile ground for an analysis of what (macro-economic fundamentals, trading, or both) drives those fluctuations.[2] Third, we seek to make a significant contribution to the literature on asset pricing and to the recent but fast-growing literature on commodity markets' "financialization"– see, e.g., Acharya, Lochstoer and Ramadorai (2009), Büyükşahin and Robe (2009), Hong and Yogo (2009), Ettula (2010), Stoll and Whaley (2010), Tang and Xiong (2010).

At the descriptive level, we provide novel information on the growing importance of financial traders across a large number of U.S. commodity-futures market. We also provide the first evidence of the extent to which different kinds of commodity futures traders (in particular, hedge funds) also trade equity futures. At the analytical level, we use this heretofore unavailable information to shed light on the possible impact of financial traders on the strength of cross-market linkages.

Our co-integration analyses establish that variations in the make-up of the commodity-futures open interest do help explain long-term fluctuations in commodity-equity return co-movements. An increase of 1% in the overall commodity-futures market share of hedge funds is associated *ceteris paribus* with an increase in equity-commodity return correlations of about 4%.

[2] In theory, it is not clear whether the returns on commodities and equities should be correlated. Arguments have long existed that equities and commodities should be negatively correlated (Bodie, 1976; Fama, 1981), but there is no theoretical model of a common factor driving the equilibrium relation between equity and commodity prices Still, recent empirical work shows that the dynamic conditional correlations between the rates of returns on equities and commodites (Büyükşahin, Haigh and Robe, 2010; Chong and Miffre, 2010) fluctuate considerably over time around unconditional means close to zero (see also Gorton and Rouwenhorst, 2006). There is, furthermore, some evidence that returns on commodity futures vary with macroeconomic factors after controlling for hedging pressures (Bessembinder, 1992; de Roon, Nijman, and Veld, 2000; Khan, Khokher and Simin, 2008).

We find that, in contrast, the positions of other kinds of commodity-futures market participants (traditional commercial traders, swap dealers and index traders, floor brokers and traders, etc.) hold little explanatory power for cross-market dynamic conditional correlations. Indeed, it is not just changes in the *overall* amount of speculative activity in commodity futures markets that helps explain the observed correlation patterns. Instead, we trace the explanatory power to hedge funds and, especially (and quite intuitively), to the subset of hedge funds that are active in *both* equity and commodity futures markets.

Turning to the impact of financial turmoil on cross-market linkages, we document that commodity-equity correlations soared in Fall 2008 and remained exceptionally high through Winter 2010. A time dummy that captures the post-Lehman period (September 2008 to March 2010) is highly statistically significant all of our analyses. Over and above the effect of that dummy, we find that equity-commodity co-movements are positively related to the TED spread (our proxy for financial-market stress). This result is not an artefact of the near-meltdown of financial markets after the demise of Lehman Brothers: pre-Lehman (from July 2000 through August 2008), we find that a 1% increase in the TED spread brought about a 0.20% increase in the dynamic equity-commodity correlation estimate.

Intuitively, hedge funds could be an important transmission channel of negative equity market shocks into the commodity space. In fact, the sign of an interaction term we use to capture the behavior of hedge funds during financial stress episodes is statistically significant and negative. In other words, the impact of hedge fund activity is reduced during periods of global market stress.

The next Section discusses our contribution to the literature. Section II provides evidence on equity-commodity linkages. Section III presents our data on trader positions, and describes hedge fund behavior in commodity and equity 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.

I. Related Work

We contribute to several strands of the financial economics literature. As discussed in the introduction, we provide empirical evidence relevant to theoretical arguments that *who* trades helps explain some aspects of asset return patterns, and that the explanatory power of trader identity is different during periods of financial market stress. Our findings also place our paper squarely in a fast-growing literature that analyzes whether (and, if so, why) the financialization of commodity markets in the past decade has increased commodity prices' exposure to financial market shocks.

A number of recent studies assess the respective roles of fundamentals and financial speculation on commodity price levels, especially crude oil prices (e.g., Hamilton, 2009; Kilian and Murphy, 2010). Closer to our query are studies documenting fluctuations over time in the extents to which commodities co-move with one another or with other financial assets (e.g., Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006; Chong and Miffre, 2010; Büyükşahin, Haigh and Robe, 2010). Closest are two contemporaneous studies, based on publicly-available data, that investigate the possible impact of commodity index trading (CIT) on commodity-equity market linkages and on cross-commodity correlations in the past decade. One study traces finds evidence of an impact (Tang and Xiong, 2010); the other study finds no such causal relationship (Stoll and Whaley, 2010). Our paper, which looks not only at commodity index traders but also at hedge funds, differs in how we measure financial activity in commodity futures markets, in some of the questions we ask, and in our results.[3]

Absent other publicly available information, extant studies approximate total CIT activity in commodity futures markets by extrapolation from publicly available CFTC information on CIT positions in a subset of US agricultural markets after 2006. We utilize instead non-public CFTC trader-level position data for all US markets. This information allows us to identify the daily and weekly shares of commodity-futures open interests held not only by CITs but, as well, by hedge funds and by several other categories of commodity futures traders since 2000.[4]

---

[3] An additional difference with Tang and Xiong (2010) is that, in order to minimize the possible confounding effects of exchange rate fluctuations on the measurement of commodity-equity co-movements, we focus on U.S. stock-market indices (rather than global indices). After controlling for time-variations in return volatilities, we find a dramatic increase in equity-commodity correlations only *after* Lehman Brothers' demise. From 1991 through the Summer of 2008 , in contrast, we find no secular increase of the dynamic conditional correlation between the returns on passive investments in commodities and in equities. Instead, we document that these correlations had fluctuated (substantially, but not dramatically) around an unconditional mean close to zero.

[4] In this respect, our paper extends a small literature on the trading activities of specific types of market participants in U.S. futures markets – including Harzmark (1987) on speculative activity in agricultural commodity markets in 1977-1981, Ederington and Lee (2002) on the heating oil market in the early 1990's, and Büyükşahin, Haigh, Harris, Overdahl and Robe (2009) on the crude oil market in 2000-2009.

Using the disaggregated data, we find little direct evidence that commodity-index trading activity drove changes in equity-commodity co-movements. Instead, in our longer sample period, cointegration analyses suggest that – besides macroeconomic fundamentals – it is mostly *hedge fund* positions that help explain changes in the strength of equity-commodity linkages.

We show, furthermore, that the impact of hedge fund activity varies depending on the overall state of financial markets. Our interest in whether *who* trades matters differentially in periods of financial market stress links our paper to a literature on the financial *vs*. fundamental drivers of cross-market linkages. Part of that literature asks whether financial shocks propagate internationally through financial channels such as bank lending (e.g., van Rijckeghem and Weder, 2001, 2003) and international mutual funds (e.g., Broner *et al*, 2006) or whether, instead, shocks spill over through real-economy linkages such as trade relationships (e.g., Forbes and Chinn, 2004). Our findings suggest that, when indicators such as the TED spread show elevated levels of financial-market stress, higher hedge fund participation *ceteris paribus* reduces rather than decreases cross-market correlations.

Our analysis is thus also related to another part of this literature that asks if speculators – in particular, hedge funds – exert a destabilizing effect on financial markets. In equity markets, Brunnermeier and Nagel (2004) and Griffin, Harris, Shu and Topaloglu (2009) provide evidence that hedge funds moved stock prices during the technology bubble. In the next decade, in contrast, Brunetti and Büyükşahin (2009) conclude that hedge funds did not affect price levels in several large derivative markets even though hedge funds' trading activities are key to the functioning of these markets through the liquidity they provide to other participants[5]. Those extant studies focus on price levels in given markets (in other words, on the first moments of asset returns). Our paper, which measures the linkages between two types of asset markets, instead deals with the second moments of the joint distributions of asset returns.

[5] The evidence from other markets on whether hedge funds are destabilizing is mixed. For example, Fung and Hsieh (2000) argue that they had a significant market impact during the European Exchange Rate Mechanism crisis in the early 1990s. In 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. See Chan, Getmansky, Haas and Lo (2006) for a review the prior academic literature on hedge funds.

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

One of our main objectives is to ascertain whether participation by certain types of traders (hedge funds, in particular) help explain the extent to which smaller asset markets (in our case, U.S. commodity futures) moves together with a "core" asset market (U.S. equities). This section discusses our measurement of the returns on equity and commodity investments, gives summary statistics for these return series, and plots our estimates of the dynamic conditional correlation (DCC, Engle 2002) between equity and commodity returns.

A. Data

To compute estimates of the DCC between equity and commodity returns, we use daily and weekly returns on benchmark commodity and stock market indices.[6] We obtain price data on each index from Bloomberg. Our sample runs from January 1991 (when the Goldman Sachs Commodity Index was first introduced as an investable benchmark) through February 2010.

For equities, we use Standard and Poor's S&P 500 index (we obtain similar results with Dow-Jones's DJIA index).[7] For comparison purposes, we also provide correlation analyses using the MSCI World Equity Index.

For commodities, we focus on the unlevered total return on Standard and Poor's S&P GSCI ("GSCI"), i.e., the return on a "fully collateralized commodity futures investment that is rolled forward from the fifth to the ninth business day of each month."

The GSCI includes twenty-four nearby commodity futures contracts, using weights that reflect world-production figures. As a result, the GSCI is tilted toward energy commodities. In robustness checks, we use total (unlevered) returns on the second most widely used investable benchmark, the Dow-Jones's DJ-UBS (until May 2009, the DJ-AIG) total-return commodity index. This rolling index is composed of futures contracts on nineteen physical commodities, and was designed to provide a more "diversified benchmark for the commodity futures market."[8]

---

[6] 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.

[7] We use returns on both of these 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.

[8] As a result, in 2008 the DJ-UBS index assigned a weight of under 33% to energy commodities, including 13.2% to crude oil. By comparison, as of mid-August, 2008, the GSCI was assigning a weight of more than 75% to energy commodities, including 40.75% to crude oil (the nearby West Texas Intermediate or WTI futures contract).

We find similar results for the GSCI and DJ-UBS indices, and therefore we focus most of our discussion on the results obtained using the GSCI.

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 commodity index (Panel B).

From January 1991 through February 2010, the mean weekly total rate of return on the GSCI was 0.0606% (or 3.16% in annualized terms), with a minimum of -14.59% and a maximum of 14.90%. The typical rate of return varied sharply across the sample period: it averaged 0.14% in 1992-1997 (7.45 % annualized); 0.045% in 1997-2003 (or a mere 2.36% annualized); and, 0.0290% in 2003-2010 (1.51% annualized).

From January 1991 through February 2010, the mean weekly rate of return on the S&P 500 was on average higher that on a commodity investment: 0.125% (or 6.71% in annualized terms), with a minimum of –15.77% and a maximum of 12.37%. However, the rank-ordering of the returns on the two asset classes fluctuates dramatically over time: in particular, equity returns crushed commodity returns in 1992-1997, but the reverse happened in 2003-2008. These differences suggest that equities and commodities do not move in lockstep.

Turning to volatility, the rate of return on a well-diversified basket of equities (S&P 500) is generally less volatile than that on commodities (GSCI), and Table 1 shows that the standard deviation of the rate of return on commodities was particularly high in the last seven years.[9]

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 and DJ-UBS. Panel A lists figures for the entire sample period, while Panels B to E present the corresponding statistics for the three sub-periods introduced in Büyükşahin *et al* (2010).

Naturally, the simple correlation between the returns on the DJIA and S&P 500 equity indices is very high, especially in the last seven years (0.97). Likewise, the rates of return on the GSCI and DJ-UBS commodity indices are strongly positively correlated (0.91 for the sample).

---

[9] Consistent with the fact that the DJ-UBS commodity index is better diversified than is the GSCI, return volatility is much lower for the DJ-UBS (1.80% in 1991-2008) than for the GSCI (2.68% in 1991-2008).

In contrast, equity-commodity cross-correlations are *usually* 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 commodity and equity *returns* (as well as volatilities) seem to have been almost zero until May 2008.

This conclusion is tempered, however, by the indication that cross-correlations increased precisely when equity investors needed the benefits of diversification into commodities the most. Specifically, the same cross-correlations that are negative between June 2003 and *May* 2008 (Panel 2D) are instead economically and statistically significantly positive when we extend the third sub-period to include the Lehman demise and the following fifteen months (Panel 2E).

Table 2 suggests that the unconditional correlations between the rates of returns on equity and commodity investments usually vary mildly over time (and are often close to zero), but also that equity-commodity co-movements increased sharply amid and after the economic crisis and financial-market dislocations that befell the world economy in 2008-2010.

D. Dynamic Conditional Correlations

Table 1 identifies large differences, across sub-periods, in the means and variances of the rates of return on commodity and equity indices. In contrast, Table 2 leaves the impression that (until Fall 2008) the correlation between these rates of returns fluctuated quite mildly over time.

The unconditional estimates of Table 2, however, do not take into account the time variations in the other moments of the return distributions that Table 1 brought to light. 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). In essence (see Appendix 1A for 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 1A (*1B*) plots our DCC estimates of the time-varying correlations between the weekly (*daily*) rates of return on two investable commodity indices (GSCI and DJ-UBS) *vs*. the unlevered rate of return on the S&P 500 equity index. The sample period is January 1991 through February 2010. As a counterpoint, Figure 1A (*1B*) also provides a plot for the DCC between the weekly (*daily*) rates of return on the S&P 500 and a second benchmark equity index, the Dow Jones DJIA.[10]

On the one hand, Figure 1A supports Table 2, in that neither shows evidence of a secular increase in correlations from January 1991 through August 2008.[11] This conclusion is similar to that of Büyükşahin, Haigh and Robe (2010), and is in line also with the findings of Chong and Miffre (2010) regarding the correlations between 11 commodity futures and the S&P 500.

On the other hand, Figures 1A and 1B show that, even prior to the collapse of Lehman Brothers in September 2008, dynamically-estimated equity-commodity correlations used to fluctuate *substantially* over time (unlike the correlation between the returns on the main equity indices, which varied little). At both weekly and daily frequencies, the equity-commodity DCC estimate range from -0.38 to 0.4, approaching 0.4 in 1998, 2001-2002, mid-2006, and again in Fall 2008. More importantly, Figures 1A and 1B show that, in the eighteen months following the demise of Lehman Brothers, equity-commodity correlations reached levels never seen in the prior two decades.[12]

A natural question is what drives the fluctuations depicted in Figures 1A and 1B. Do market fundamentals help explain the observed patterns, or can the latter partly be traced to changes in futures market participation? We turn to this issue in the next two sections.

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

In most US futures markets, the overall open interest is much greater in 2010 than it was just a decade earlier. In this Section, we gather novel information on individual trader positions in seventeen U.S. commodity futures markets to show that this growth entailed major changes in the trader composition of the overall open interest. In particular, there have been significant increases in the importance of financial traders and in the extent to which equity-futures traders also trade in commodity futures markets. The information summarized in this Section provides

[10] Figures 1C to 1F in Appendix 1B provide similar plots at daily (*vs*. weekly) frequency,, as ell as plots using the Morgan Stanley MSCI World Equity Index instead of the S&P 500 or DJIAUS-only equity indices.

[11] 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.

[12] Figures 1C to 1F in Appendix 1B, show even more striking increases when using the MSCI World Equity Index (Figures 1C and 1D) or when not conditioning on time-varying volatility (Figures 1E and 1F).

the foundation of Section IV, in which we examine whether these changes have explanatory power for equity-commodity returns linkages.

We construct our dataset by utilizing a non-public dataset on individual trader positions in US futures markets. Sections 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.[13] Section III.C uses this publicly available data to establish that speculative activity has increased significantly in these seventeen 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. Section III.E discusses index trading activity. Finally, Section III.F provides information on the activities of equity-futures traders in commodity futures markets.

A. Data Source

We construct a database of daily trader positions in the S&P 500 equity futures market and in seventeen U.S. commodity futures markets from the last week of December 2000 through the last week of January 2010. The seventeen commodities are listed in Appendix 2.

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 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 specific market, our dataset covers between 75% and 95% of the total open interest.

The CFTC receives information on individual positions for every trading day. In our weekly analysis, we focus on the Tuesday reports because the Tuesday data are those which the CFTC summarizes in the weekly "Commitment of Traders (COT) Report" that it makes

[13] Only a handful of published studies have had access to disaggregated, non-public CFTC data. They are Harzmark (1987, 1991), studying the trading performance of individual traders in nine commodity futures markets from July 1977 to December 1981; Leuthold, Garcia and Lu (1994), extending Harzmark's work; Ederington & Lee (2002), analyzing *heating*-oil NYMEX futures position from June 1993 to March 1997; Chang, Pinegar & Schachter (1997), whose dataset includes six futures markets from 1983 to 1990; Haigh *et al* (2007), analyzing 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.

available to the public every Friday at 3:30 p.m. Consequently, our weekly findings are directly comparable with those of numerous extant studies that rely on COT data.[14]

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 information on the overall open-interest and breaks down the overall figure between several categories of traders. The breakdown is based on information that the CFTC collects from all large traders about their respective underlying businesses (hedge fund, swap trader, commodity producer, etc.) and about 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 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".[15] The "non-commercial" group comprised various types of mostly financial traders, such as hedge funds, mutual funds, floor brokers, etc.

The LTRS data made available for the present study allow for much more differentiation than the simple COT dichotomy. Specifically, each reporting trader is classified into one of twenty-eight (rather than a mere couple of) trader types. Appendix 3 uses the crude oil futures market to illustrate the increased level of disaggregation that is possible using the LTRS data.

Since September 4, 2009, the public COT reports have started to differentiate between four (rather than two) kinds of traders: "traditional" commercial traders (including producers, processors, commodity wholesalers and merchants, etc.); managed money traders (hedge funds); commodity swap dealers (a category that includes commodity index traders in most markets);

---

[14] 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 studies pre-2000.

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

and "other traders" with reportable positions.[16] As of Summer 2010, however, the CFTC has not hinted at plans to make this more detailed information available retroactively prior to 2006.

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 since 2000 and on the extent to which equity futures traders have started to trade commodity contracts. We obtained clearance from the CFTC to present these data in aggregate form.

Furthermore, 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 let us disentangle the activities of various kinds of traders at different ends of the commodity-futures term structure. Our results in Section IV show that this additional information is valuable, in that it is hedge funds' activities in shorter-dated contracts (rather than further along the maturity curve) that helps explain fluctuations in 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 helps explain the extent to which commodity 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 "speculators") to the demand for hedging that originates from "commercial" traders (often referred to as "hedgers"). The second type of indices, which we propose in sub-section III.D to F, measures the market shares of *a given* type of non-commercial traders (hedge funds in III.D; index traders in III.E; cross-market traders in III.F) 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

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

must step in to fill the unmet hedging demand. Working's speculative activity index "*T*" measures the extent to which, at the market-clearing price, speculation exceeds the level required to satisfy hedgers' net demand for hedging at that price (i.e., offset any unbalanced hedging).

For each of the seventeen commodities in our sample, we calculate Working's *T* weekly from 2000 to 2010. 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*:

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

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

To provide an overall picture of speculative activity across all seventeen commodity markets, we average these individual index values across all seventeen markets:

$$WSIS_t = \sum_{i=1}^{17} w_{i,t}\, WSIS_{i,t}$$

where, the weight for commodity *i* in a given *week* is based on the weight of the commodity in the GSCI index that *year* (Source: Standard and Poor), rescaled to account for the fact that we focus on the seventeen U.S. markets (out of twenty-four GSCI markets) for which position data are available. Appendix 2 lists the individual commodity weights w_i, per commodity, per year.

Table 3A provides summary statistics of this weighted average speculative index (*WSIS*) from December 2000 through January 2010. During that period, the minimum *WSIS* value was 1.11, and the maximum was close to 1.50. That is, at the market-clearing price, speculative positions were approximately 11% to 50% greater than what was minimally necessary to meet net hedging needs. The figures are very similar in Table 3B, which computes the speculative index across all maturities (*WSIA*) rather than the three nearest-maturity contracts (*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.[17] Second, Figure 2 shows that there have been over time substantial variations around this long-term trend. Those are the variations that might 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: floor brokers and traders, hedge funds, other non-commercial traders not registered as managed money 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 much more plausible candidates for such a role.

We can make use of the granularity of the LTRS data to compute time series of hedge funds' contribution to the overall open interest in commodity futures markets. For reference, we also compute correspponding figures ("market shares") for commodity swap dealers (a category that includes commodity index traders in most U.S. futures markets – see Section III.E below) and for 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) although we 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 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" -- see Appendix 4 for the market participants covered by this term), commodity swap dealers (AS, including CIT – commodity index traders), and traditional commercial traders (TCOM).

[17] The values in Figure 2, however, are generally lower than historical *T* values 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.

Figure 2 plots our *WMSA_MMT* measure over time. It identifies a striking 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 futures market, Figure 2 and Table 3 show that this long-term trend holds in a cross-section of commodity futures markets.

Figure 3 shows that hedge funds accounted for less than 10% of the open interest in 2000 but 20% or more after 2005. Tables 3A and 3B provide summary statistics of market shares for various kinds of traders. Table 3A shows that, over the course of the past decade, traditional commercial traders' market share felldecreased from over 52% to under 20% of the open interest in near-dated commodity futures contracts. During that same period, the market share of hedge funds grew from less than 10% to almost 30% of the near-dated open interest. Table 3B, which computes market shares across all maturities rather than the three nearest-maturity contracts, shows qualitatively similar patterns at different futures maturities.

E. Commodity Index Trading (CIT) Activity

While the non-public data to which we were granted access yields precise information on market shares for most trader categories (including, importantly, for hedge funds), it does not identify CIT activity in energy and metal markets at the daily or weekly frequency. This is because CIT activity percolates into commodity futures markets partly through CIT interactions with commodity swap dealers but, even in the non-public database, the CFTC does not disaggregate CIT-related positions from the overall positions held by commodity swap dealers.[18]

One solution to this issue (see Tang and Xiong (2010) and references therein) is to extrapolate, to all commodities, the overall market share of CITs in twelve agricultural ("ag") markets – information that has been published by the CFTC for those twelve markets since 2006. This approximation, unfortunately, cannot be extended to prior years because of structural differences in CIT activity before and after 2005 (Büyükşahin *et al*, 2009). Even after 2006, the quality of that approximation depends on whether the magnitudes of commodity investment flows were similar in all commodity futures markets – the precision of the approximation drops insofar as specialized "ag" funds have grown in importance since 2006 and as futures open interest in "ag" markets has a different maturity structure than in energy and metal markets.

[18] Since September 2008, the CFTC has provided quarterly reports about off- and on-exchange commodity index activity in a number of US commodity markets.

Our solution 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 daily (*weekly*) CIT market shares in each of our seventeen commodity futures markets by the daily (*weekly*) shares of near-dated swap dealer positions in the same market.[19]

F. Cross-Market Traders

Of particular interest for this study are commodity futures traders who also trade in equity markets. In this subsection, we provide information on the number (Table 4) and relative importance (Tables 3A and 3B, Figure 2) of those traders in the seventeen commodity futures markets that make up our sample.

Table 4 shows that, in each of these commodity futures markets, hundreds of traders also held positions in the Chicago Mercantile Exchange's e-Mini S&P 500 equity futures market. Except in two relatively small markets (feeder cattle and heating oil), at least 10% of all large commodity futures traders who were active at some point in 2001-2010 also traded equity futures during that time period. In some markets (gold and crude oil), the proportion of such "cross-traders" exceeds 25%.

Figure 2 summarizes the evolution of the importance of cross-market traders in the past decade, in terms of their share of the open interest (rather than as a fraction of the total number of large traders). The figure plots the weighted-average percentage of traders active each week who, at some point in the sample period, also held positions in e-Mini futures.[20] Cross-traders' share of the overall open interest has grown substantially over time, from less than 25% in 2000 to more than 40% since mid-2005. Comparing Figure 2 with Table 4 shows that cross-traders, on average, hold larger positions than reporting traders who only trade commodity futures.

[19] In future drafts, we shall test the robustness of our methodology by using swap dealer positions changes that are common to all near-dated commodity futures.

[20] For each of the 17 commodity futures markets in our sample, we computed the CMSA measure (cross market SA, whatever SA stands for? was it "share of activity"?) as follows::

(i) for each trader who reported position in any of the 17 commodity futures markets in our sample, take his trader ID and check whether this trader also traded e-Mini futures at any point in the sample period;

(ii) if the answer is yes, then assign to that trader ID a "cross-market trader" flag;

(iii) for each trading day in our sample, in each of the 17 commodity futures markets, compute the five CMSA measures (CMSA_ALL, _NON, _TCOM, _AS, _MMT) as the proportion of traders in each category (all, non-commercials, traditional commercials, swap dealers, hedge funds) who have the "cross-market trader" flag;

(iv) finally, compute the 5 WCMSA (_ALL, _NON, _TCOM, _AS, _MMT) measures as the weighted averages of the corresponding CMSA measures, with either equal weights or weights equal to the GSCI weights for that particular trading day (or year, as I remember we fix the weights for each year).

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 July 2000 to March 2010, 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 commodity-equity cross-correlations between January 2001 and August 2009 (we do not use the entirety of the sample, ecause some of the variables of interest were not availables for the whole sample). 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. Tables 3A and 3B provide summary statistics for all the variables, while Tables 3C and 3D provide simple cross-correlations.

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 shock or of 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-commodity linkages.

To do so, we use a measure of global real economic activity recently proposed by 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 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, which accounts for the existence of "different fixed effects for different routes, commodities and ship sizes", can be computed as far back as January 1968. 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."[21] This indicator is available monthly from 1968. We obtain weekly estimates by cubic spline.

Panel 1 in Table 3A contains summary statistics for this *SHIP* variable. Figure 3 charts its value from 1991 to 2010. Although a relationship between *SHIP* 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.

While commodity prices reflect worldwide market conditions and economic activity, U.S.-centric market conditions may also affect commodity prices and are central to U.S. equity prices. Consequently, we also consider two macroeconomic variables that may be relevant when studying commodity-equity relationships. One, which we denote *ADS*, is the Aruoba-Diebold Scotti (2008) measure of U.S. economic activity. It is available at weekly frequency for the entire sample period (1991-2010). The other variable, which we denote *INF*, captures U.S. inflationary expectations. We carry out a linear interpolation to derive weekly figures from the figures released each month by the Federal Reserve Bank of Cleveland. Panel 1 in Table 3A provides summary statistics for these two other macroeconomic indicators.

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, Haigh and Robe (2010) show that financial and commodity markets also become more of a "market of one" during extreme events. We account for this reality in two ways.

First, we include the TED spread in our formal analyses as a proxy for financial-market stress. Figure 3 and Table 3A provide graphical and statistical information on this variable. The TED spread varies widely during the sample period, between a minimum of 0.027% 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.

[21] We are grateful to Lutz Kilian for providing an update of his monthly series through March 2010.

Second, Section II showed equity-commodity correlations soaring after the demise of Lehman Brothers in September 2008 and remaining exceptionally high since. We use a time dummy to account for specificities of that period that the TED spread might not capture.

C. 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 are I(1).

Ordinary regression methods are not appropriate in such a situation. Pesaran and Shin (1999), however, propose a cointegration approach to solve 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 the dependent variable, x is a $t \times k$ vector of regressors, and ω stands for a $t \times s$ vector of deterministic variables such as an intercept, seasonal dummies, time trends, or exogenous variables with fixed lags.[22] In vector notation, Equation (1) is:

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

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

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.

1. *Real sector and financial stress variables*

Table 5 shows that, for the whole sample (1991-2009) as well as for the sub-sample for which we have detailed position data (2001-2009), the DCC measure of the extent to which commodities and equities move together is negatively related to the *SHIP* variable (a proxy for measure world economic activity and demand for industrial commodities). In contrast, our two U.S. macroeconomic indicators (*INF* and *ADS*) and momentum in equity markets (*UMD*) are almost never a statistically significant explainer of these correlations.

Panels A and B in Table 5 differ only in that Panel B specifications include a time dummy for the post-Lehman period. That dummy is always strongly statistically significant and positive. However, our cointegration analyses show that commodity-equity DCC measures have a long-term relationship to the *TED* variable (a proxy for stress in financial markets). In 2000-2010, a 1% increase in the TED spread brought about a 0.20 to 0.30% increase in the dynamic equity-commodity correlation; this increase is statistically significant at the 5% level of confidence (at the 1% level in 2000-2008).

In contrast, Panel A shows that the 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 the types of traders after mid-2000 might help explain this evolution.. We next turn to this issue.

2. *Speculative activity and hedge fund market share*

Table 6 is key to our contribution, in that it shows how speculative activity in commodity futures markets helps explain (over and above the *SHIP* and *TED* variables) the fluctuations in the commodity-equity DCC estimates over time. *Ceteris paribus*, an increase of 1% in the overall commodity-futures market share of hedge funds is associated with dynamic conditional equity-commodity correlations that are approximately 4% to 7% higher (given a mean hedge fund market share of about 25%). In contrast, we find little statistical evidence that commodity swap dealers' market share helps explain cross-market linkages.

Notably, in the various specifications used in Table 6, we see that the Working "T" speculative index, which aggregates the activities of *all* non-hedgers *across all maturities*, has somewhat less explanatory power than hedge fund activity (precisely, the *WSIA* variable is often but not always statistically significant and, when significant, the level of statistical significance is typically lower than for *WMSS_MMT*). This finding suggests that it is the activity of hedge fund specifically, raher than the activity of non-commercial commodity futures traders in general, that helps explain the correlation patters.[23]

3. *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, Table 6 includes an interaction term that captures the behavior of hedge funds amid financial stress episodes. This term is always statistically significant and, as expected, negative. That is, *ceteris paribus*, the power of hedge fund activity in explaining equity-commodity co-movements is *lower* during periods of elevated market 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.

[23] Interestingly, the WMSA_MMT and WSIA variables (but not the WMSS_MMT variable) can be constructed on the basis of information that the CFTC recently made available for a number of commodity futures markets. In other words, going forward, some of the information shown by this paper to matter will be publicly available.

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 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 that investment flow has in turn found its way into futures markets through commodity swap dealers. In our regressions, however, we never found the *WMSS_AS* variable (which measures commodity swap dealers' market share in short-dated contracts) to be 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 2009, 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 commodity investors do not affect equity-commodity linkages. This result presents an interesting counterpoint to the finding of Büyükşahin *et al* (2009) that increased commodity index trading activity in the WTI crude oil futures market has helped integrate crude oil prices across the futures maturity curve.

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

Tables 7 (Appendix 5) repeats the analysis of Table 6, with all the speculative-activity and trader-share variables recalculated using position information across all maturities, rather than across 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 5% level). In contrast, Table 7 shows little statistical evidence that other kinds of traders (swap dealers, traditional commercial traders) affect the dynamic cross-market correlations.

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. This result is intuitive, in that the GSCI index is constructed using short-dated futures contracts (so one would expect the short-dated positions to matter for commodity-equity correlations).

3. The Lehman crash

In the last 30 months 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-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 8 in Appendix 5 provides additional evidence of robustness. It repeats the analysis of Table 6, 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 8 are similar to those in Table 6. The main difference is that the statistical significance of the hedge fund variables is stronger pre-crisis. Combined with the 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. A fruitful approach to investigate the surprisingly high post-Lehman correlations must look elsewhere.

V. Conclusion and Further Work

Over the course of the past two decades, the strength of commodity-equity linkages fluctuated substantially. The same two decades witnessed growing commodity-market activity by hedge funds, commodity index traders, and other financial traders. These facts suggest fertile grounds to ascertain if the makeup of trading activity helps explain the joint distribution of commodity and equity returns.

To analyze whether *who* trades matters for asset pricing, we use non-public trader-level information from the U.S. Commodity Futures Trading Commission (CFTC). We construct a unique daily dataset of all large trader positions in 17 US commodity and equity futures markets from 2000 to 2010. After controlling for macroeconomic fundamentals, we document that variations in the composition of commodity-futures open interest *do* explain fluctuations in the extent of commodity-equity co-movements.

Although changes in the *overall* amount of speculative activity in commodity futures markets do not have much explanatory power, we show that the correlation between the returns on equity and commodity futures investment indices increases significantly amid greater activity by one group of speculators – hedge funds. We trace the explanatory power of hedge fund activity to the subset of funds that are active in *both* equity and commodity futures markets. In contrast, we find that the positions of other kinds of financial participants commodity-futures market (swap dealers and index traders, traditional commercial traders, floor brokers and traders, etc.), whether or not they take positions in both types of markets, do not help explain cross-market correlation patterns.

We document that commodity-equity correlations soared after the demise of Lehman Brothers in Fall 2008 and remained unusually high through Winter 2010. We show that, even before the 2008-2010 crisis, equity-commodity co-movements were 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 impact of hedge fund activity is lower during periods of stress.

Bibliography

Acharya, Viral V., Lars A. Lochstoer and Tarun Ramadorai (2009). "Limits to Arbitrage and Hedging: Evidence from Commodity Markets", CEPR Working Paper No. 7327, July. Presented at the *European Finance Association* 2009 (Bergen) and *American Finance Association* 2010 (Atlanta) Meetings. Revised, Columbia University, January 2010.

Allen, Franklin and Roni Michaely (2002). "Payout Policy." In Constantinides, G., Harris, M., and Stulz, R. [Eds.], *Handbook of Financial Economics*. North-Holland.

Aruoba, S. Borağan, Francis X. Diebold, Chiara Scotti (2009). "Real-time Measurement of Business Conditions". *Journal of Business and Economic Statistics*. 27 (4), pp. 417-27.

Başak, Süleyman and Benjamin Croitoru (2006). "On the Role of Arbitrageurs in Rational Markets". *Journal of Financial Economics*, 81(1), pp. 143-73.

Bessembinder, Hendrik (1992). "Systematic Risk, Hedging Pressure, and Risk Premiums in Futures Markets". *Review of Financial Studies*, 5 (4), pp. 637-67.

Broner, Fernando A., R. Gaston Gelos and Carmen M. Reinhart (2008). "When in Peril, Retrench: Testing the Portfolio Channel of Contagion", *Journal of International Economics*, 69 (1), pp. 203-30.

Brunetti, Celso and Bahattin Büyükşahin (2009). "Is Speculation Destabilizing?" Working Paper, John Hopkins University, July. http://ssrn.com/abstract=1393524

Brunnermeier, Markus K., and Stefan Nagel (2004). "Hedge Funds and the Technology Bubble", *Journal of Finance* 59, pp. 2013-2040.

Büyükşahin, Bahattin, Michael S. Haigh, Jeffrey H. Harris, James A. Overdahl, J.A., and Michel A. Robe (2009). "Fundamentals, Trading Activity and Derivative Pricing". Paper presented at the 36th Meeting of the *European Finance Association*. http://ssrn.com/abstract=966692

Büyükşahin, Bahattin, Michael S. Haigh and Michel A. Robe (2010). "Commodities and Equities: Ever a 'Market of One'?" *Journal of Alternative Investments*, 12 (3), pp. 75-95.

Büyükşahin, Bahattin and Michel A. Robe (2010). "Commodity Traders' Positions and Crude Oil Prices: Evidence from the Recent Boom-Bust Cycle." Paper presented at the 2010 *American Economic Association* Meeting, Atlanta, January. Revised, October 2010.

Chan, Nicholas, Mila Getmansky, Shane M. Haas, and Andrew W. Lo (2006). "Systemic Risk and Hedge Funds." In M. Carey and R. Stulz (eds.), *Risks of Financial Institutions*, Chicago, IL: University of Chicago Press, pp. 35-330.

Chong, James and Joëlle Miffre (2010). "Conditional Return Correlations between Commodity Futures and Traditional Assets". *Journal of Alternative Investments,* 12 (3), pp. 61-75.

de Roon, Frans A., Theo E. Nijman, and Chris Veld (2000). "Hedging Pressure Effects in Futures Markets". *Journal of Finance* 55 (3), pp. 1437-56

Ederington, Louis H. and Jae Ha Lee, 2002. "Who Trades Futures and How: Evidence from the Heating Oil Futures Market". *Journal of Business*, 75 (2), pp. 353-73.

Engle, Robert (2002). "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models". *Journal of Business and Economic Statistics*, 20 (3), pp. 339–50.

Erb, Claude B. and Campbell R. Harvey (2006). "The Strategic and Tactical Value of Commodity Futures". *Financial Analysts Journal*, 62 (2), pp. 69–97.

Forbes, Kristin and J. Roberto Rigobon (2002). "No Contagion, Only Interdependence: Measuring Stock Market Comovements". *Journal of Finance*, 57 (5), pp. 2223-61.

Fung, William and David A. Hsieh. (2000). "Measuring the Market Impact of Hedge Funds". *Journal of Empirical Finance,* 7 (1), pp. 1-36.

Gorton, Gary and K. Geert Rouwenhorst (2006). "Facts and Fantasies about Commodity Futures". *Financial Analysts Journal*, 62(2), pp. 47–68.

Griffin, John M., Jeffrey H. Harris, Tao Shu and Selim Topaloğlu (2009). "Who Drove and Burst the Tech Bubble?" Working Paper, University of Texas at Austin, July.

Gromb, Denis and Dimitri Vayanos (2002). "Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs". *Journal of Financial Economics*, 66 (2-3), pp. 361-407.

Haigh, Michael S., Jana Hranaiova, and James A. Overdahl (2007). "Price Volatility, Liquidity Provision, and the Role of Hedge Funds in Energy Futures Markets". *Journal of Alternative Investments,* 8 (4), pp. 10-38.

Hamilton, James D. (2009). "Causes and Consequences of the Oil Shock of 2007-08". NBER Working Paper No. 15002, May.

Hartmann, P., S. Straetmans and C. G. de Vries (2004). Asset Market Linkages in Crisis Periods. *Review of Economics and Statistics*, 86 (1), pp. 313-326.

Hartzmark, Michael L., 1987. "Returns to Individual Traders of Futures: Aggregate Results,"". *Journal of Political Economy*, 95 (6), pp. 1292-306.

Hartzmark, Michael L., 1991. "Luck versus*vs*. Forecast Ability: Determinants of Trader Performance in Futures Markets," *Journal of Business*, 64 (1), pp. 49-74.

Hong, Harrison and Motohiro Yogo, 2009. Commodity market interest and asset return predictability. Paper presented at the 2010 *American Finance Association* Meeting, Atlanta, January. Revised, Princeton University, March 2010.

Irwin Scott H., Merrin, Robert P. and Dwight R. Sanders (2008). The Adequacy of Speculation in Agricultural Futures Markets: Too Much of a Good Thing? Marketing and Outlook Research Reports #2, University of Illinois at Urbana-Champaign.

Kilian, Lutz and Dan Murphy (2010). The Role of Inventories and Speculative Trading in the Global Market for Crude Oil. CEPR Discussion Papers 7753, May.

Kofman, Paul, David Michayluk, and James T. Moser (2009). Reversing the Lead, or a Series of Unfortunate Events? NYMEX, ICE and Amaranth. *Journal of Futures Markets*.

Kyle, Albert S. and Wei Xiong, 2001. Contagion as a Wealth Effect. *Journal of Finance*, 56 (4), pp. 1401-1440

Khan, Saqib, Zeigham Khokher and Timothy Simin (2008). Expected Commodity Futures Returns. Working Paper, Penn State University, July.

Kilian, Lutz (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99 (3), pp. 1053-69.

Kilian, Lutz and Cheolbeom Park (2009). The Impact of Oil Price Shocks on the U.S. Stock Market. *International Economic Review*, 50 (4), pp. 1267-87.

Kyle, Albert S. and Wei Xiong (2001). Contagion as a Wealth Effect. *Journal of Finance*, 56 (4), pp. 1401-40.

Leuthold, Raymond M. (1983) "Commercial Use and Speculative Measures of the Livestock Commodity Futures Markets". *Journal of Futures Markets* 3 (2), pp. 113-35.

Leuthold, Raymond M., Philip Garcia, and Richard Lu (1994). "The Returns and Forecasting Ability of Large Traders in the Frozen Pork Bellies Futures Market," *Journal of Business*, 67 (3), pp. 459-73.

Longin, Francois and Bruno Solnik (2001). Extreme Correlation of International Equity Markets. *Journal of Finance*, 56 (2), pp. 649–76.

Pavlova, Anna and Roberto Rigobon (2008). The Role of Portfolio Constraints in the International Propagation of Shocks. *Review of Economic Studies*, 75 (4), pp. 1215-56.

Peck, Anne E (1981). "The Adequacy of Speculation on the Wheat, Corn, and Soybean Futures Markets." In Research in Domestic and International Agribusiness Management, R. A. Goldberg, ed.,Greenwich, CN: JAI Press, Inc., Vol. 2, pp. 17-29.

Rahi, Rohit and Jean-Pierre Zigrand (2009). Strategic Financial Innovation in Segmented Markets. *Review of Financial Studies*, 22 (6), pp. 2941-71.

Shoven, John. B. and C. Sialm. (2000). "The Dow Jones industrial average: The impact of fixing its flaws." *Journal of Wealth Management,* 3 (3), pp. 9–18.

Stoll, Hans R. and Robert E. Whaley (2010). Commodity Index Investing and Commodity Futures Prices. *Journal of Applied Finance*, 2010 (1), forthcoming.

Tang, Ke and Wei Xiong. (2010)· Index Investing and the Financialization of Commodities. Working Paper, Princeton University, March 2010.

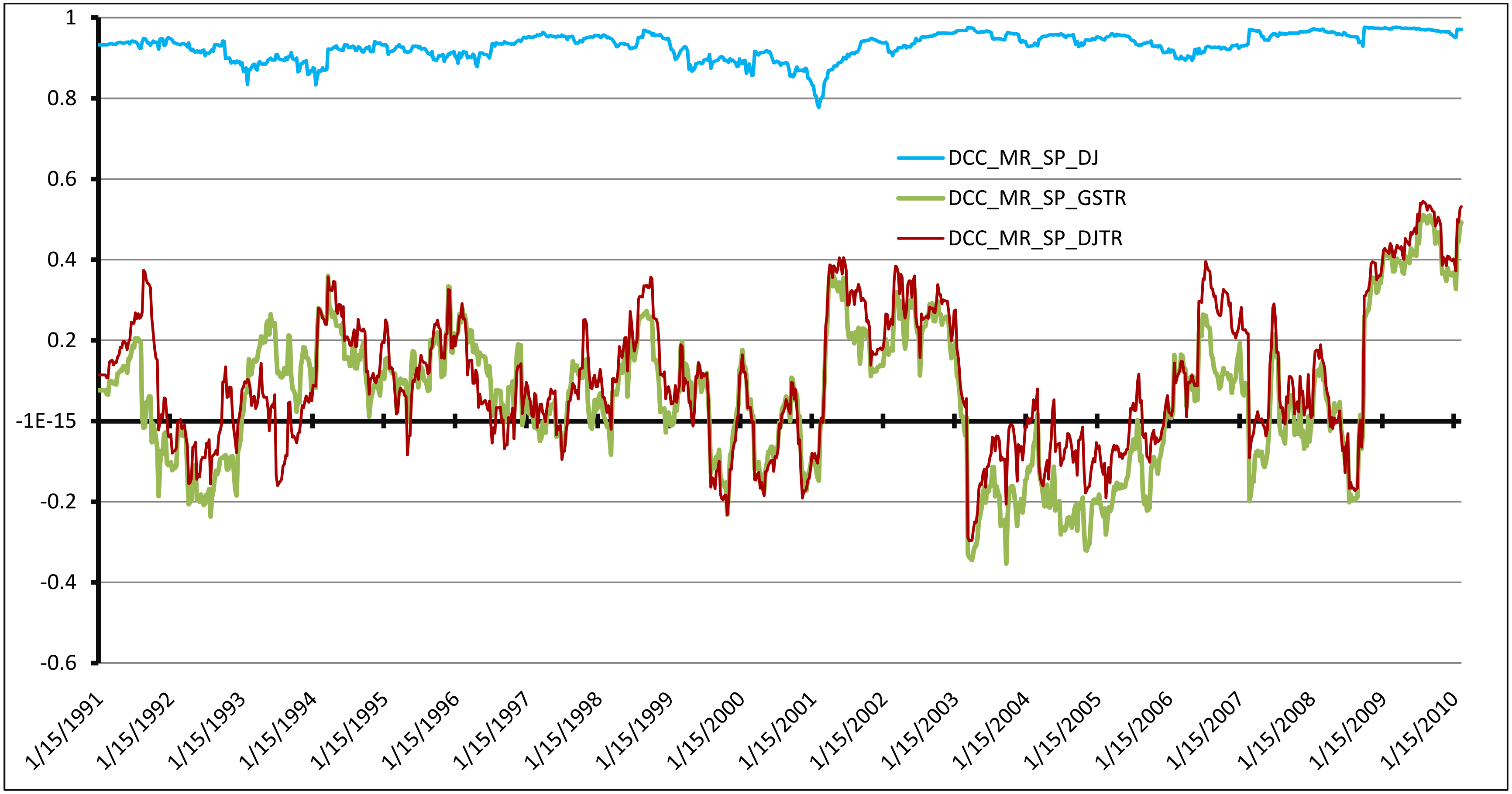
Teo, Melvyn (2009). The Geography of Hedge Funds. *Review of Financial Studies*, 22 (9), pp. 3531-61.

Van Rijckeghem, Caroline and Beatrice Weder (2003). Spillovers through banking centers: a panel data analysis of bank flows. *Journal of International Money and Finance*, 22 (4), pp. 483-509.

Xiong, Wei (2001). Convergence Trading with Wealth Effects: An Amplification Mechanism in Financial Markets. *Journal of Financial Economics*, 62 (2), pp. 247-92.

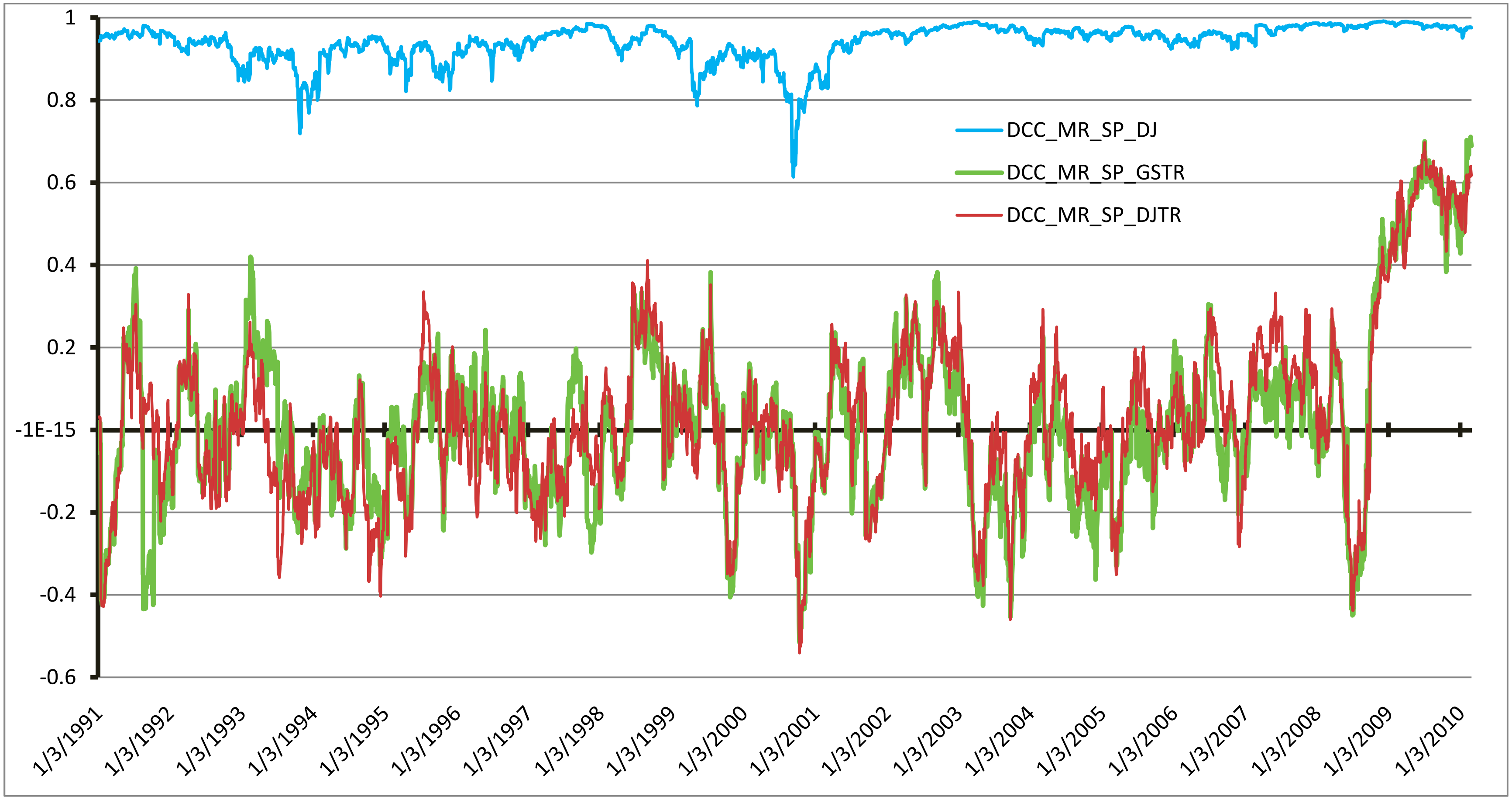
Working, Holbrook (1960). Speculation on hedging markets, *Stanford University Food Research Institute Studies* 1, pp. 185-220.

Figure 1A: Weekly Return Correlations (DCC) -- US Equity *vs.* Commodity Indices, January 1991 to March 2010



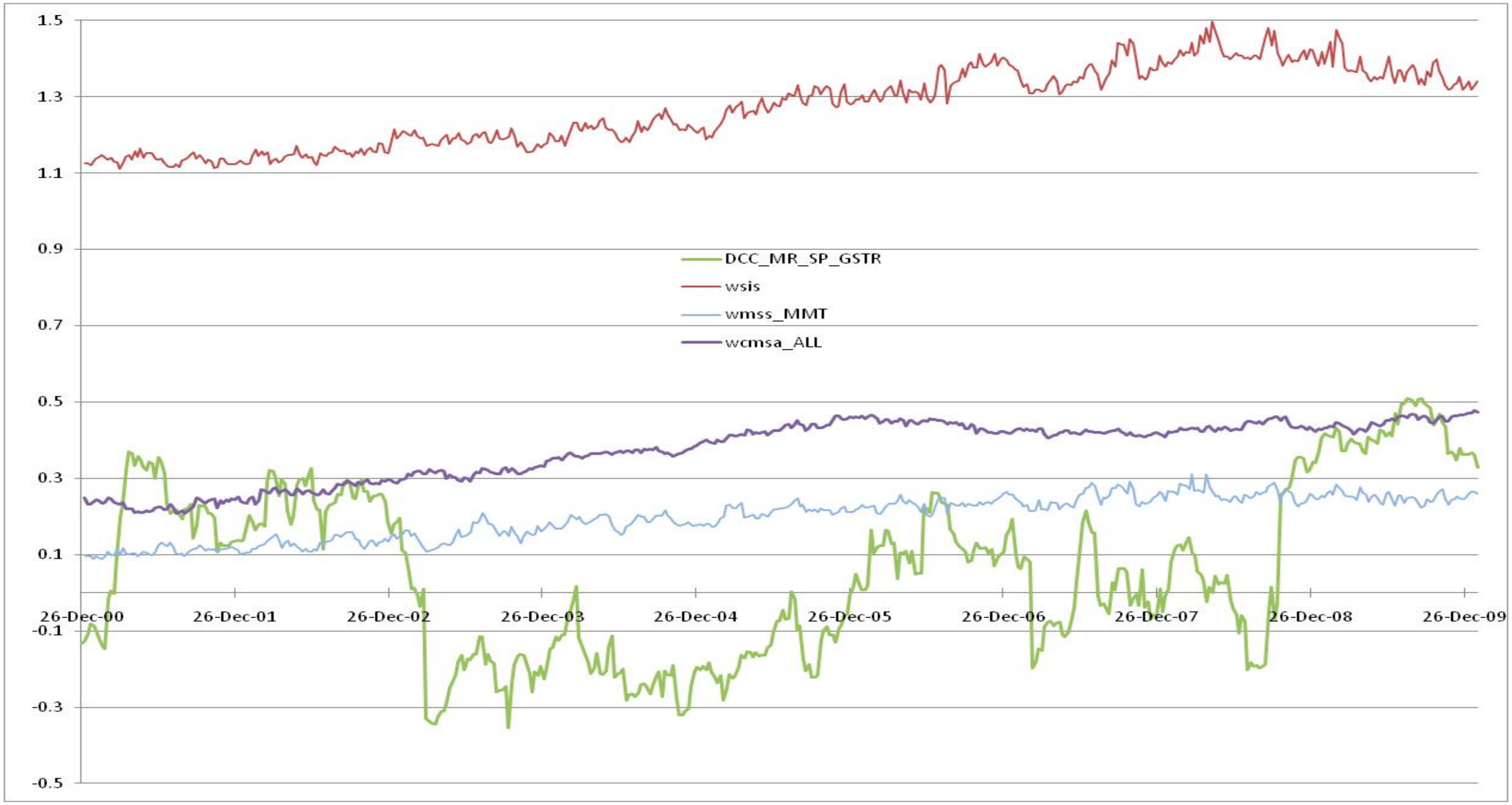
***Notes*:** Figure 1A depicts the time-varying correlation between the **weekly** unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and: (i) the S&P GSCI total return commodity index (GSTR, **green line**) or (ii) the DJ-UBS total return commodity index (DJTR, **red line**). As a benchmark, the Figure also plots the correlation between the S&P 500 equity index and the other traditional equity index, the Dow Jones Industrial Average equity index (DJIA, **blue line** on top). In each case, we estimate dynamic conditional correlation by log-likehood for mean-reverting model (DCC_MR, Engle, 2002) using Tuesday-to-Tuesday returns from January 3, 1991 to March 1, 2010.

<u>Figure 1B: Daily Return Correlations (DCC) -- US Equity *vs.* Commodity Indices, January 1991 to March 2010</u>



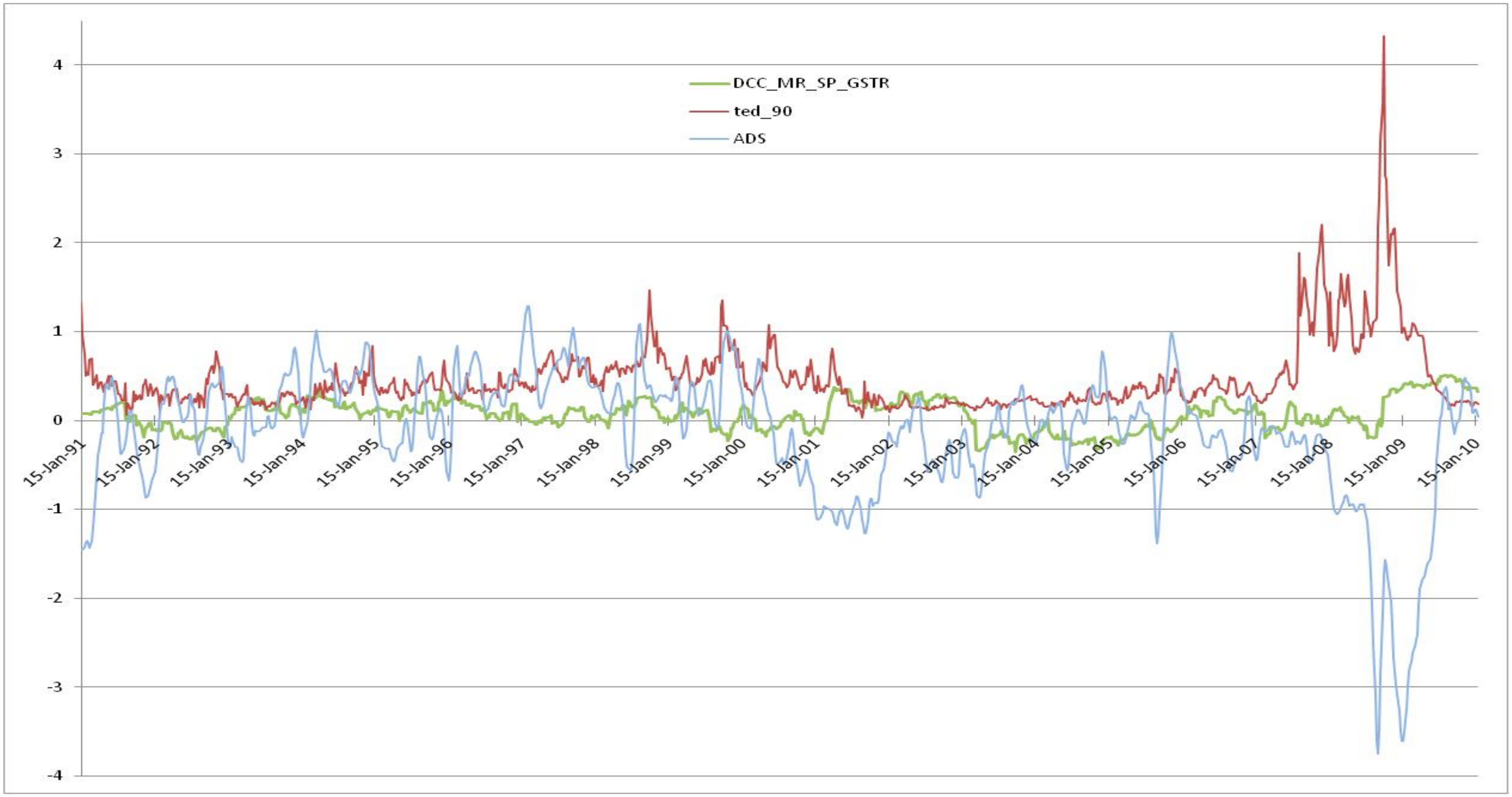
Notes**:** Figure 1B depicts the time-varying correlation between the **daily** unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and: (i) the S&P GSCI total return commodity index (GSTR, **green line**) or (ii) the DJ-UBS total return commodity index (DJTR, **red line**). As a benchmark, the Figure also plots the correlation between the S&P 500 equity index and the other traditional equity index, the Dow Jones Industrial Average equity index (DJIA, **blue line** on top). In each case, we estimate dynamic conditional correlation by log-likehood for mean-reverting model (DCC_MR, Engle, 2002) using daily data from January 3, 1991 to March 1, 2010. .

Figure 2: Equity-commodity Correlations, Overall speculation, and Hedge-fund activity



***Notes*:** The **green line** in Figure 2 shows, between the last week of December 2000 and the first week of February 2010, the dynamic conditional correlation 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 total return (GSTR) index. We estimate dynamic conditional correlations by log-likehood for mean reverting model (DCC_MR; Engle, 2002). The dark **red line** (WSIS) plots the weighted-average speculative pressure index ("Working's T") in the 17 U.S. commodity futures markets linked to the GSCI index. The **blue line** shows the aggregate share of the short-term open interest in those 17 markets held by hedge funds (wmss_MMT for "Managed Money Traders"). The **purple** line shows the weighted-average proportion of large traders in those same 17 markets that also trade US equity futures (wcmsa_ALL).

Figure 3: Equity-commodity Correlations, Ted spread, and Economic activity



Notes**:** Figure 3 depicts the dynamic 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 (**green line**); the 90-day TED spread (**blue line**), and the Kilian (2009) index of worldwide economic activity (**red line**) from January 15, 1991 to February 28, 2010. We use Tuesday-to-Tuesday rates of return to estimate dynamic conditional correlations by log-likehood for mean-reverting model (DCC_MR; Engle, 2002).

Table 1: Weekly Rates of Return – Summary Statistics
(%, January 1991 to March 2010)

Panel A: S&P 500 Equity Index

	1991-2010	1992-1997	1997-2003	2003-2010
Mean	0.124839	0.272260	0.039058	0.049310
Median	0.292318	0.345607	0.366951	0.247137
Maximum	12.37463	4.194317	12.37463	7.818525
Minimum	-15.76649	-4.112432	-12.18282	-15.76649
Std. Dev.	2.348732	1.440671	2.943599	2.371901
Skewness	-0.596507	-0.258227	-0.026150	-1.440103
Kurtosis	7.920789	3.371816	4.791780	10.70166
Jarque-Bera	1066.091***	4.42	42.04***	994.47***
Observations	998	262	314	353

Panel B: S&P GSCI Commodity Index

	1991-2010	1992-1997	1997-2003	2003-2010
Mean	0.060691	0.138182	0.044902	0.028993
Median	0.188237	0.148651	0.023027	0.416007
Maximum	14.90087	5.340624	7.479387	14.90087
Minimum	-14.59139	-9.208887	-14.59139	-13.12567
Std. Dev.	3.023849	1.811528	2.876870	3.870732
Skewness	-0.527095	-0.395102	-0.445674	-0.406732
Kurtosis	5.668868	5.426632	4.888678	4.058999
Jarque-Bera	342.40***	71.10***	57.06***	26.23***
Observations	998	262	314	353

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 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 8, 1991 to March 1, 2010. The second, third and fourth columns use, respectively, weekly rates of returns for three successive sub-periods: May 26, 1992 to May 27, 1997; May 27, 1997 to May 27, 2003; and, May 27, 2003 to February 27, 2010. 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 March 2010)

	DJIA	S & P 500	DJAIG	GSCI
DJIA	1.0000			
S & P 500	0.9471***	1.0000		
DJAIG	0.1840***	0.2123***	1.0000	
GSCI	0.1390***	0.1736***	0.91463***	1.0000

Panel B: May 1992 through May 1997

	DJIA	S & P 500	DJAIG	GSCI
DJIA	1.0000			
S & P 500	0.9200***	1.0000		
DJAIG	0.0960	0.0578	1.0000	
GSCI	0.1265**	0.0950	0.8221***	1.0000

Panel C: May 1997 through May 2003

	DJIA	S & P 500	DJAIG	GSCI
DJIA	1.0000			
S & P 500	0.9376**	1.0000		
DJAIG	0.0915	0.1132**	1.0000	
GSCI	0.0490	0.0816	0.9346***	1.0000

Panel D: June 2003 through May 2008

	DJIA	S & P 500	DJAIG	GSCI
DJIA	1.0000			
S & P 500	0.9587***	1.0000		
DJAIG	-0.0050	0.0399	1.0000	
GSCI	-0.1179*	-0.0553	0.8897***	1.0000

Panel E: June 2003 through February 2010

	DJIA	S & P 500	DJAIG	GSCI
DJIA	1.0000			
S & P 500	0.9720***	1.0000		
DJAIG	0.3063***	0.3516***	1.0000	
GSCI	0.2556***	0.3031***	0.9239***	1.0000

Notes: Table 2 gives simple cross-correlations for the weekly unlevered **rates of return** (precisely, 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 commodity indices. Table 2A provides cross-correlations for the whole sample (January 8, 1991 to March 1, 2010). Tables 2B, 2C, 2D and 2E provide cross-correlations for four sub-periods: May 26, 1992 to May 27, 1997 (2B); May 27, 1997 to May 27, 2003 (2C); June 1, 2003 to May 26, 2008 (2D); and May 27, 2003 to February 23, 2010. 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 lost-Lehman data are included

Table 3A, Panel 1: Summary Statistics on Macroeconomic and Market Fundamentals, January 2001 to March 2010

	Dynamic Conditional Correlations (DCC_MR)		Macroeconomic Fundamentals			Financial Market Conditions				Excess Commodity Speculation *(Working's "T")*	
	SP500 - GSCI	**MSCI - GSCI**	**SHIP Index**	**ADS Index**	**INF (expected inflation)**	**LIBOR (%)**	**TED (%)**	**VIX**	**UMD**	**All contract Maturities (WSIA)**	**Short-term contracts (WSIS)**
Mean	0.058803	0.124428	0.128101	-0.475016	0.023591	3.058959	0.487749	21.99812	0.003010	1.248605	1.266054
Median	0.051580	0.135190	0.156134	-0.246892	0.023665	2.715900	0.296456	20.41000	0.090000	1.266179	1.264821
Maximum	0.510420	0.602070	0.553002	0.992458	0.033083	6.802500	4.330619	67.64000	4.550000	1.420035	1.499443
Minimum	-0.353440	-0.306940	-0.524973	-3.747359	0.015084	0.248800	0.027512	9.900000	-6.560000	1.112184	1.108470
Std. Dev.	0.219529	0.224322	0.263191	0.787462	0.003213	1.874571	0.517985	9.744099	1.127080	0.091597	0.106134
Skewness	0.186990	0.151839	-0.463355	-1.789994	-0.091070	0.328567	2.951072	1.653419	-0.700811	0.097695	0.149171
Kurtosis	1.974010	2.284501	2.329421	6.952640	3.066411	1.842329	14.63722	6.761389	8.153885	1.521860	1.646277
Jarque-Bera	25.09252***	12.71253***	27.53235***	598.4182***	0.790863	37.28642***	3582.557***	527.7928***	600.2571***	46.77718***	40.43314***
Sum	29.69551	62.83637	64.69118	-239.8829	11.91341	1544.774	246.3134	11109.05	1.520000	630.5457	639.3573
Sum Sq. Dev.	24.28930	25.36143	34.91194	312.5287	0.005201	1771.064	135.2274	47853.53	640.2358	4.228546	5.677296
Observations	505	505	505	505	505	505	505	505	505	505	505
ADF (Level)	-1.943171	-1.785006	-1.928436	-3.137666**	-1.959157	-1.414196	-2.880949**	-2.995549**	-24.261****	-1.379492	-1.566416
ADF (1st Diff)	-22.8378***	-22.9515***	-6.6142***	-12.2230***	-5.7425***	-10.9312***	-12.8887***	-12.3767***	-12.6374***	-22.9845***	-16.8664***

Note: Time-varying 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 (GSTR) index and either the S&P 500 (SP) equity index 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, 2008). INF measures expected inflation (source: Federal Reserve). SPARE is the excess 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). Excess commodity speculation for the three nearest-term futures (WSIS) and all contract maturities (WSIA) is the weigthed-average Working "T" for the 17 U.S. commodity futurees in the GSCI index (source: CFTC, S&P and authors' calculations); annual weights equal the average of the daily GSCI weights that year (source: Standard & Poor). UMD is the Fama-French momentum factor for U.S. equities. 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 momentum series is I(0); the others are I(1); the optimal lag length *K* is based on the Akaike Information Criterion (AIC). Sample period for all statistics: January 2, 2001 to February 26, 2010.

Table 3A, Panel 2: Summary Statistics on Positions by Trader Types (Short-dated Commodity Futures), January 2001-March 2010

	Weighted-average Market Shares in Short-term Commodity Futures (WMSS)					Weighted-average Market Share of Cross-Market Traders across All Maturities (WCMSA)			
	Hedge Funds (WMSS_MMT)	All Non-Commercials (WMSS_NON)	Swap Dealers (WMSS_AS)	Non-Commercials + Swap Dealers (WMSS_ANC)	Traditional Commercials (WMSS_TCOM)	All traders (WCMSA_ALL)	Hedge Funds (WCMSA_MMT)	All Non Commercials (WCMSA_NON)	Swap Dealers (WCMSA_AS)
Mean	0.205009	0.323114	0.200292	0.523406	0.350287	0.366633	0.108932	0.145403	0.189023
Median	0.219606	0.330037	0.214260	0.547531	0.323999	0.409356	0.115865	0.169236	0.193769
Maximum	0.331050	0.462969	0.285468	0.726409	0.535883	0.476945	0.186921	0.233494	0.262532
Minimum	0.069817	0.176206	0.109090	0.309224	0.191607	0.204867	0.028521	0.049580	0.115570
Std. Dev.	0.067763	0.081353	0.042617	0.119861	0.094142	0.083519	0.045061	0.058244	0.030872
Skewness	-0.334458	-0.192197	-0.294154	-0.257259	0.398954	-0.495232	-0.230657	-0.275388	-0.308004
Kurtosis	1.784851	1.671668	1.867022	1.646867	1.866572	1.720597	1.608840	1.492605	2.455440
Jarque-Bera	40.48491***	40.23639***	34.29254***	44.09696***	40.42775***	55.08477***	45.20034***	54.19478***	14.22439***
Sum	103.5296	163.1725	101.1477	264.3202	176.8947	185.1498	55.01070	73.42855	95.45680
Sum Sq. Dev.	2.314283	3.335603	0.915365	7.240772	4.466850	3.515615	1.023347	1.709729	0.480348
Observations	505	505	505	505	505	505	505	505	505
ADF Level	-1.730639	-1.624713	-1.543089	-1.268780	-1.430115	-0.778171	-1.521733	-1.099423	-1.193593
ADF First Diff	-16.2192***	-16.5962***	-11.5294***	-20.40521***	-18.5002***	-11.9348***	-17.1272***	-17.5837***	-8.5710***

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 17 commodity futures markets 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 17 commodities that year and rescaled to account for GSCI commodity markets for which no large trader position data are available (Source: S&P). For three trader types (MMT, AS,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). 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: January 2, 2001 to February 26, 2010.

Table 3B: Summary Statistics of Positions by Trader Type (All Maturities), January 2001-January 2010

	Weighted-average Market Shares in All 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	0.179422	0.305027	0.251360	0.556387	0.338149	0.366633	0.108932	0.145403	0.189023
Median	0.203755	0.318948	0.263481	0.594333	0.305290	0.409356	0.115865	0.169236	0.193769
Maximum	0.299671	0.426953	0.335178	0.743590	0.537561	0.476945	0.186921	0.233494	0.262532
Minimum	0.056014	0.171564	0.146260	0.327628	0.185196	0.204867	0.028521	0.049580	0.115570
Std. Dev.	0.074465	0.079310	0.045016	0.120579	0.096908	0.083519	0.045061	0.058244	0.030872
Skewness	-0.132589	-0.145310	-0.522460	-0.315453	0.408567	-0.495232	-0.230657	-0.275388	-0.308004
Kurtosis	1.543973	1.614327	2.205411	1.764964	1.966243	1.720597	1.608840	1.492605	2.455440
Jarque-Bera	46.08829***	42.17908***	36.25959***	40.47064***	36.53593***	55.08477***	45.20034***	54.19478***	14.22439***
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000815
Sum	90.60832	154.0387	126.9370	280.9757	170.7651	185.1498	55.01070	73.42855	95.45680
Sum Sq. Dev.	2.794682	3.170228	1.021327	7.327757	4.733181	3.515615	1.023347	1.709729	0.480348
Observations	505	505	505	505	505	505	505	505	505
ADF Level	-1.379692	-1.440425	-1.193593	-1.043211	-1.135093	-0.778171	-1.521733	-1.099423	-1.517613
ADF First Diff	-21.94130***	-23.08369***	-8.5710***	-20.19457***	-21.98602***	-11.9348***	-17.1272***	-17.5837***	-10.59537***

Note: WMSS_MMT, WMSS_NON, WMSS_AS, WMSS_ANC and WMSS_TCOM stand, respectively, for the weighted-average shares of the overall futures open interest across ***all*** futures contract maturities in 17 commodity markets 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 17 commodities that year, and rescaled to account for GSCI commodity markets for which no large trader position data are available (Source: S&P). WCMSA variables are as in Table 3A, Panel 2. 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: January 2, 2001 through February 26, 2010.

Table 3C: Simple Correlations, 2001-2010

	DCC_MR SP_GSTR	DCC_MR MXWO_GSTR	SHIP	ADS	VIX	LIBOR_90	TED_90	TBILL_90	WSIS	UMD	WMSS_AS	WMSS_MMT	WMSS_TCOM	WCMSA_ALL
DCC_MR_SP_GSTR	1													
DCC_MR_MXWO_GSTR	0.954	1												
SHIP	-0.524	-0.362	1											
ADS	-0.410	-0.439	0.303	1										
VIX	0.536	0.494	-0.509	-0.701	1									
LIBOR_90	-0.032	0.069	0.276	0.121	-0.353	1								
TED_90	0.149	0.292	0.202	-0.544	0.513	0.190	1							
TBILL_90	-0.082	-0.028	0.211	0.303	-0.526	0.945	-0.141	1						
WSIS	0.121	0.344	0.537	-0.329	0.075	0.319	0.625	0.113	1					
UMD	0.017	0.001	-0.045	0.095	-0.024	0.020	-0.110	0.056	-0.097	1				
WMSS_AS	-0.155	0.042	0.604	-0.060	-0.117	0.307	0.469	0.153	0.802	-0.080	1			
WMSS_MMT	0.032	0.257	0.613	-0.191	-0.033	0.270	0.537	0.094	0.946	-0.081	0.824	1		
WMSS_TCOM	0.068	-0.158	-0.634	0.172	0.036	-0.258	-0.548	-0.078	-0.942	0.091	-0.913	-0.962	1	
WCMSA_ALL	-0.091	0.137	0.619	-0.049	-0.162	0.289	0.414	0.154	0.868	-0.082	0.906	0.919	-0.947	1

Note: Table 3C 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 January 1, 2001 to January 31, 2010.

Table 3D: Simple Correlations, 2001-2010 *(Explanatory Variables)*

	DCC_MR_SP_GSTR	WSIS	WSIA	WMSS_AS	WMSS_MMT	WCMSA_ALL	WCMSA_MMT	WCMSA_AS
DCC_MR_SP_GSTR	1.0000							

WSIS	**0.1930**	1.0000						
	0.0000	-----						
WSIA	**0.2166**	**0.9738**	1.0000					
	0.0000	0.0000	-----					
WMSS_AS	0.0331	**0.8394**	**0.8583**	1.0000				
	0.4584	0.0000	0.0000	-----				
WMSS_MMT	**0.1045**	**0.9511**	**0.9379**	**0.8599**	1.0000			
	0.0188	0.0000	0.0000	0.0000	-----			
WCMSA_ALL	0.0572	**0.8860**	**0.9025**	**0.9263**	**0.9346**	1.0000		
	0.1993	0.0000	0.0000	0.0000	0.0000	-----		
WCMSA_MMT	0.0370	**0.8404**	**0.8570**	**0.8305**	**0.9102**	**0.9446**	1.0000	
	0.4070	0.0000	0.0000	0.0000	0.0000	0.0000	-----	
WCMSA_AS	0.0204	**0.7749**	**0.7922**	**0.9095**	**0.8134**	**0.9119**	**0.7405**	1.0000
	0.6476	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----

Note: Table 3D shows the sample correlations of the variables in our regression analyses (p values in box below each correlation figure). Bolded correlation figures denote correlations that are statistically significantly different from 0 at the 5% or above level of statistical significance. The dependent variable (DCC) is described in the footnote to Figure 1. The independent variables are described in the footnotes to Tables 3A and 3B. Sample period for all statistics: January 2, 2001 to February 26, 2010.

Table 4: Equity-Commodity Cross-Trading Activity, 2001-2009

Market	Number of Cross Traders (2001-2009)	Percentage of cross-traders (% of all reporting traders, 2001-2009)
cocoa	405	10.23
coffee	615	15.53
Copper	657	16.60
Corn	777	19.63
Cotton	557	14.07
Crude oil (WTI)	1073	27.10
Feeder Cattle	129	3.26
Gold	1038	26.22
Heating Oil	335	8.46
Lean Hogs	420	10.61
Live Cattle	466	11.77
Natural Gas	720	18.19
Silver	592	14.95
Soybeans	732	18.49
Sugar	498	12.58
CBOT Wheat	698	17.63

Notes: For sixteen commodity futures markets, Table 4 provides information on the number and relative importance of large commodity futures traders who also held, at some point in the sample period (January 1, 2001 through January 31, 2010), large positions in the S&P500 e-Mini futures contract.

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

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

	Model 1			Model 2			Model 3		
	1991-2000	2000-2010	1991-2010	1991-2000	2000-2010	1991-2010	1991-2000	2000-2010	1991-2010
Constant	0.182915 **	-0.0676649	-0.0769808	0.183340 **	-0.0425855	-0.0456055	0.983731 **	0.198942	0.266539
	(0.08855)	(0.1154)	(0.08335)	(0.08916)	(0.1139)	(0.07643)	(0.3937)	(0.5670)	(0.2853)
ADS				-0.0192282	0.136424	-0.0784245			
				(0.09266)	(0.1530)	(0.06634)			
INF							-0.240932 **	-0.104337	-0.118612
							(0.1138)	(0.2242)	(0.09807)
SHIP	-0.03187	-0.607037 **	-0.247640	-0.0328020	-0.785661 **	-0.249104	0.268479	-0.649011 **	-0.342061 *
	(0.2955)	(0.2892)	(0.1946)	(0.2987)	(0.3811)	(0.1790)	(0.2753)	(0.2745)	(0.1947)
UMD	0.0375003	0.141408	0.0915841	0.0399188	0.126140	0.0924424	0.0274178	0.130264	0.0872112
	(0.07593)	(0.1081)	(0.07970)	(0.07709)	(0.1070)	(0.07331)	(0.06095)	(0.09883)	(0.07288)
TED	-0.273596	0.500917 **	0.332428 **	-0.264308	0.630212 **	0.240228 *	-0.268425 *	0.476131 **	0.288970 **
	(0.1932)	(0.2171)	(0.1497)	(0.1967)	(0.3125)	(0.1410)	(0.1550)	(0.2112)	(0.1370)

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 total return (GSTR) index. Dynamic conditional correlations estimated by log-likehood for mean reverting model (Engle, 2002). The explanatory variables are described in Table 3A, 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 for the first, fourth 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: January 2, 1991 to February 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 as any other Period

	Model 1 + DUM				Model 2 + DUM				Model 3 + DUM			
	2000-2010		1991-2010		2000-2010		1991-2010		2000-2010		1991-2010	
Constant	-0.0314680		-0.0201306		-.00925942		-0.0193913		-0.661521		-0.122517	
	(0.06202)		(0.04778)		(0.05749)		(0.04863)		(0.4067)		(0.2137)	
ADS					0.153715	*	0.00826134					
					(0.08115)		(0.04729)					
INF									0.255100		0.0363735	
									(0.1599)		(0.07387)	
SHIP	-0.407224	**	-0.256007	**	-0.596757	***	-0.251052	**	-0.361970	**	-0.229830	*
	(0.1609)		(0.1165)		(0.1880)		(0.1165)		(0.1539)		(0.1294)	
UMD	0.0929004		0.0695521		0.0760120		0.0692592		0.0762112		0.0686126	
	(0.05706)		(0.04675)		(0.05278)		(0.04678)		(0.05147)		(0.04673)	
TED	0.201796	*	0.110997		0.334082	**	0.111721		0.211402	**	0.113062	
	(0.1061)		(0.08428)		(0.1368)		(0.08770)		(0.09905)		(0.08472)	
DUM	0.426993	***	0.487423	***	0.485022	***	0.486330	***	0.551450	***	0.518016	***
	(0.1220)		(0.1136)		(0.1232)		(0.1243)		(0.1442)		(0.1311)	

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 total return (GSTR) index. Dynamic conditional correlations estimated by log-likehood for mean reverting model (Engle, 2002). The explanatory variables are described in Table 3A, 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 other columns is January 2, 1991 to June 30, 2000.

Table 6A: Speculative Activity as a Long-run Contributor to the GSCI-S&P500 Dynamic Conditional Correlation

	Model 1 int with ADS	Model 2 int with ADS	Model 3 int with ADS	Model 4 int with ADS	Model 1 int with ADS + DUM	Model 2 int with ADS + DUM	Model 3 int with ADS + DUM	Model 4 int with ADS + DUM
	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010	2000-2010
Constant	-1.08653 ***	-3.85024 ***	-3.42068	-3.10830	-0.582685 **	-2.08797 **	-3.47333 **	-4.18156 **
	(0.4039)	(1.328)	(2.801)	(3.180)	(0.2820)	(0.9959)	(1.718)	(1.827)
ADS	0.0900166	0.103863	0.0819206	0.110121	0.121550	0.132858 *	0.120917 *	0.130751 **
	(0.1031)	(0.09492)	(0.1009)	(0.09684)	(0.07598)	(0.07009)	(0.06433)	(0.05701)
SHIP	-1.04023 ***	-0.933864 ***	-1.00618 ***	-0.939143 ***	-0.716249 ***	-0.693805 ***	-0.600611 ***	-0.496998 ***
	(0.3210)	(0.2664)	(0.3116)	(0.3016)	(0.2348)	(0.1905)	(0.1989)	(0.1783)
UMD	0.0879904	0.0893486	0.0826899	0.0896561	0.0703609	0.0712289	0.0543494	0.0562307
	(0.07248)	(0.06653)	(0.07076)	(0.06753)	(0.05058)	(0.04622)	(0.04210)	(0.03717)
TED	2.58964 **	6.24366 **	2.44687 **	6.60861 *	1.70441 **	4.27775 **	1.37623 **	3.04952 *
	(1.076)	(3.120)	(1.041)	(3.448)	(0.6964)	(2.102)	(0.5685)	(1.832)
WMSS_MMT	5.07041 ***		8.63094 **		2.56186 *		7.59681 ***	
	(1.789)		(4.267)		(1.338)		(2.564)	
WMSS_AS			1.84774	-1.68847			1.08052	-1.84586
			(4.015)	(3.330)			(2.453)	(1.914)
WMSS_TCOM			3.54272	-0.879623			4.70689 *	1.39127
			(3.967)	(2.595)			(2.487)	(1.502)
WSIA		3.07302 ***	N.A.	2.99394		1.64474 **		3.24842 ***
		(1.048)	N.A.	(1.842)		(0.8008)		(1.057)
INT_TED_MMT	-8.19136 **		-7.71792 **		-5.22160 **		-4.16390 **	
	(3.651)		(3.543)		(2.409)		(1.986)	
INT_TED_WSIA		-4.37543 *		-4.64281 *		-2.96711 *		-2.12497
		(2.261)		(2.490)		(1.533)		(1.335)
DUM					0.398321 ***	0.391434 ***	0.480248 ***	0.448907 ***
					(0.1393)	(0.1273)	(0.1258)	(0.1092)

Notes: Explanatory variables are described in Table 3A. The dependent variable is the 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 total return (GSTR) 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 that the optimal lag lengths are *p*=1 and *q*=1 in our case. The sample period is July 1, 2000 to March 1, 2010.

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

	Model 1 int with ADS		Model 2 int with ADS		Model 3 int with ADS		Model 1 int with ADS + DUM		Model 2 int with ADS + DUM		Model 3 int with ADS + DUM	
	2000-2010		**2000-2010**		**2000-2010**		**2000-2010**		**2000-2010**		**2000-2010**	
Constant	-0.865047	**	-0.506191		-3.77118	***	-0.414669		0.755510	***	-1.86592	***
	(0.3862)		(0.5007)		(1.354)		(0.2550)		(0.2726)		(0.6797)	
ADS	0.121594		0.105277		0.103118		0.138361		0.112309	**	0.128177	***
	(0.1249)		(0.1232)		(0.09608)		(0.08670)		(0.05263)		(0.04763)	
SHIP	-0.948281	***	-0.898426	***	-0.913188	***	-0.738715	***	-0.484892	***	-0.495065	***
	(0.3531)		(0.3492)		(0.2732)		(0.2386)		(0.1500)		(0.1365)	
UMD	0.0948335		0.0914709		0.0954178		0.0689901		0.0335555		0.0450556	
	(0.08516)		(0.08515)		(0.06932)		(0.05648)		(0.03449)		(0.03143)	
TED	2.42418	**	2.55259	**	6.00666	*	1.23989	*	0.719877	*	2.67971	*
	(1.173)		(1.209)		(3.148)		(0.7334)		(0.4138)		(1.401)	
WCMSA_MMT	7.85698	**	9.43273	**			3.82713	*	4.83782	***		
	(3.248)		(4.018)				(2.231)		(1.491)			
WCMSA_AS			-2.94989		-0.256259				-7.06668	***	-5.18637	***
			(3.406)		(2.633)				(1.756)		(1.459)	
WSIA					3.05038	**					2.26676	***
					(1.210)						(0.5859)	
INT_TED_CMMTA	-15.5298	*	-16.3698	*	N.A.		-7.24763		-3.52202		N.A.	
	(8.375)		(8.591)		N.A.		(5.354)		(3.072)		N.A.	
INT_TED_WSIA					-4.19862	*					-1.85232	*
					(2.280)						(1.026)	
DUM							0.356019	**	0.612165	***	0.523899	***
							(0.1430)		(0.1104)		(0.09996)	

Notes: The dependent variable is the 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 total return (GSTR) index. Dynamic conditional correlations estimated by log-likehood for mean reverting model (Engle, 2002). Most explanatory variables are described in Table 3A. INT_TED_CMMTA and INT_TED_WSIA interact cross-trader's market shares with the TED spread. 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.

Appendix 1A: 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

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

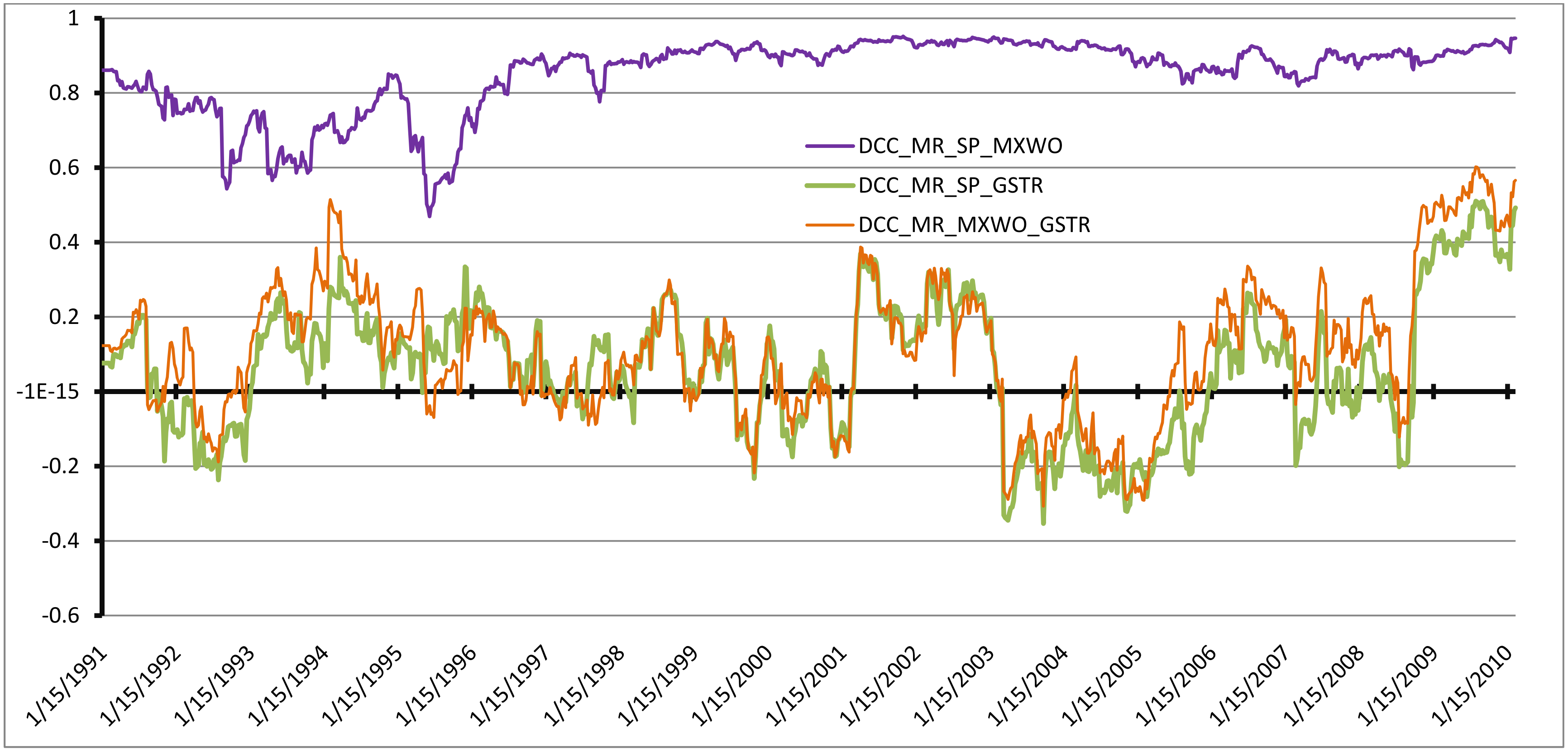
This specification ensures the mean reversion as long as $\phi_1 + \phi_2 < 1$. The resulting estimator is called DCC by log-likelihood with mean reverting model. The log-likelihood of the DCC model outlined above is given by:

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

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.

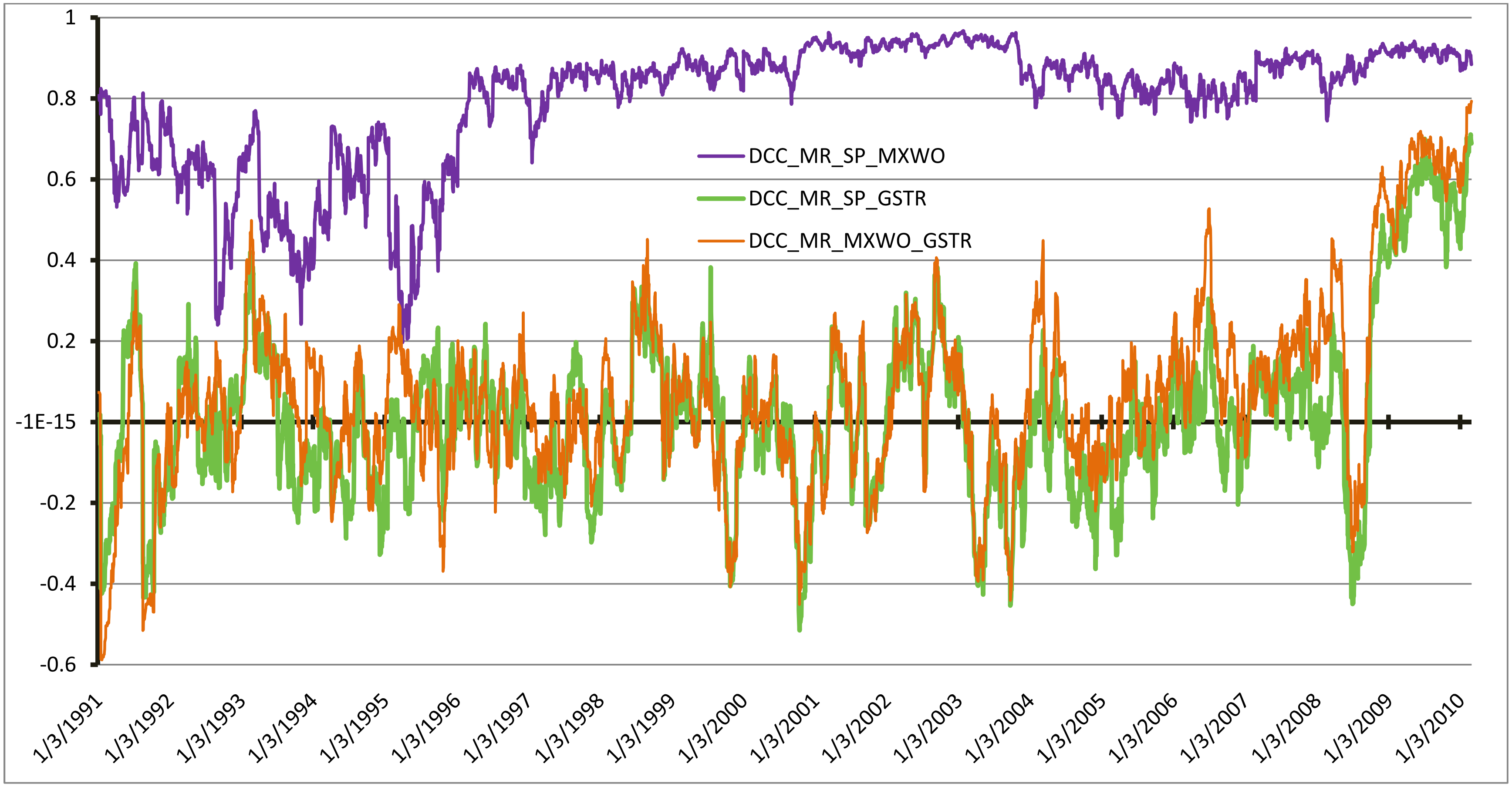
Appendix 1B: Alternative Correlation Estimates

Figure 1C: Weekly Return Correlations (DCC) -- World Equity *vs.* Commodity Indices, January 1991 to March 2010



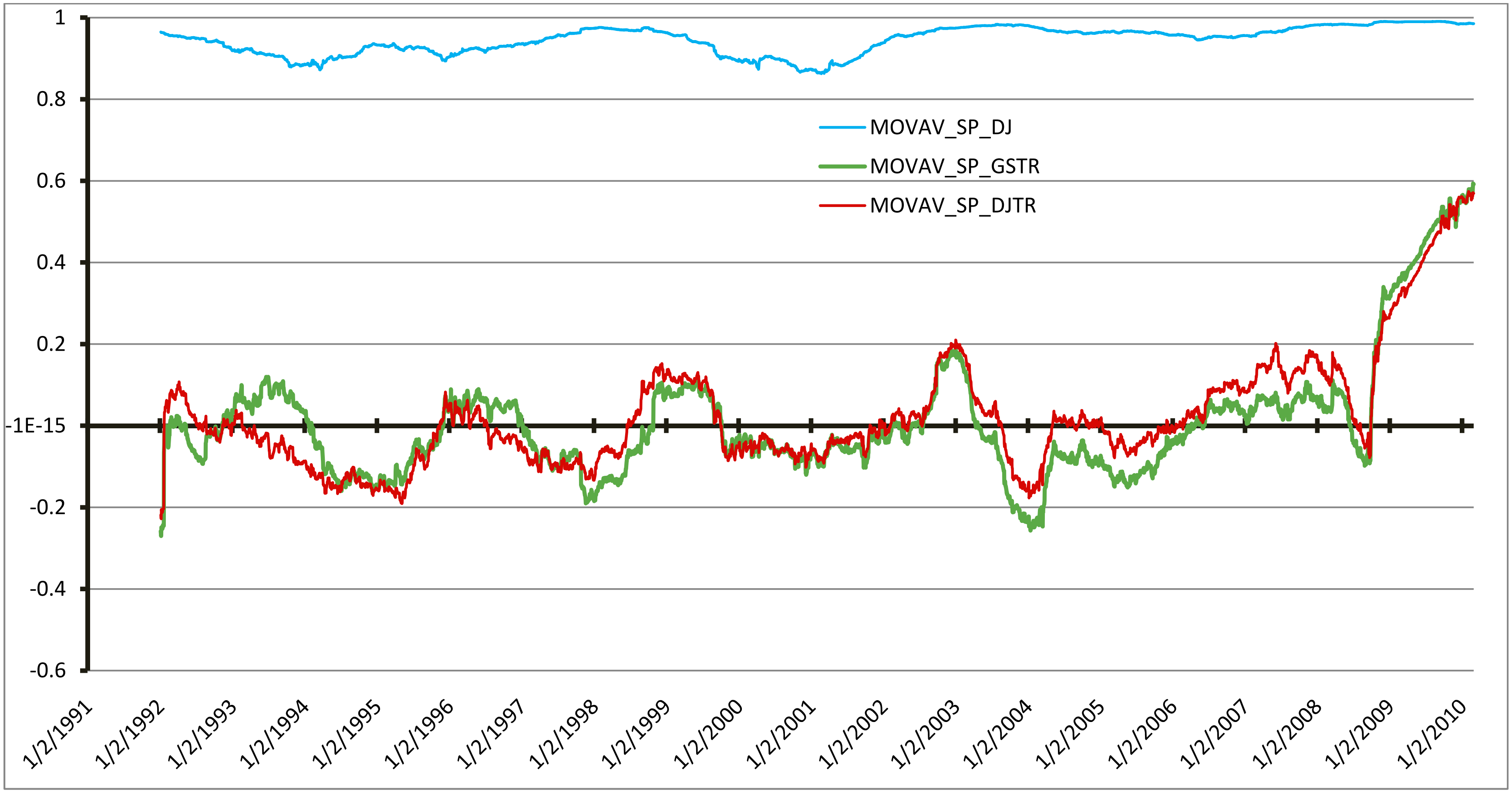
***Notes*:** Figure 1C depicts the time-varying correlation between the **weekly** unlevered rates of return (precisely, changes in log prices) on S&P's GSCI total return commodity index and: (i) the S&P 500 (SP) equity index (**green line**) or (ii) the MSCI World Equity Index (MXWO, **orange line**). In each case, dynamic conditional correlation are estimated by log-likehood for mean-reverting model (DCC_MR, Engle, 2002) from January 3, 1991 to March 1, 2010. Figure 1C shows that weekly equity-commodity correlations are slightly greater when estimated with the world equity index rather than with the US equity index, especially since 2005 (the difference is about 0.1). As a benchmark, Figure 1C also plots the correlation between the S&P 500 US equity index and the MSCI World Equity Index (**purple line** on top). Plots are similar when the S&P 500 is replaced by the the Dow Jones Industrial Average (DJIA) equity index.

Figure 1D: Daily Return Correlations (DCC) -- World Equity *vs.* Commodity Indices, January 1991 to March 2010



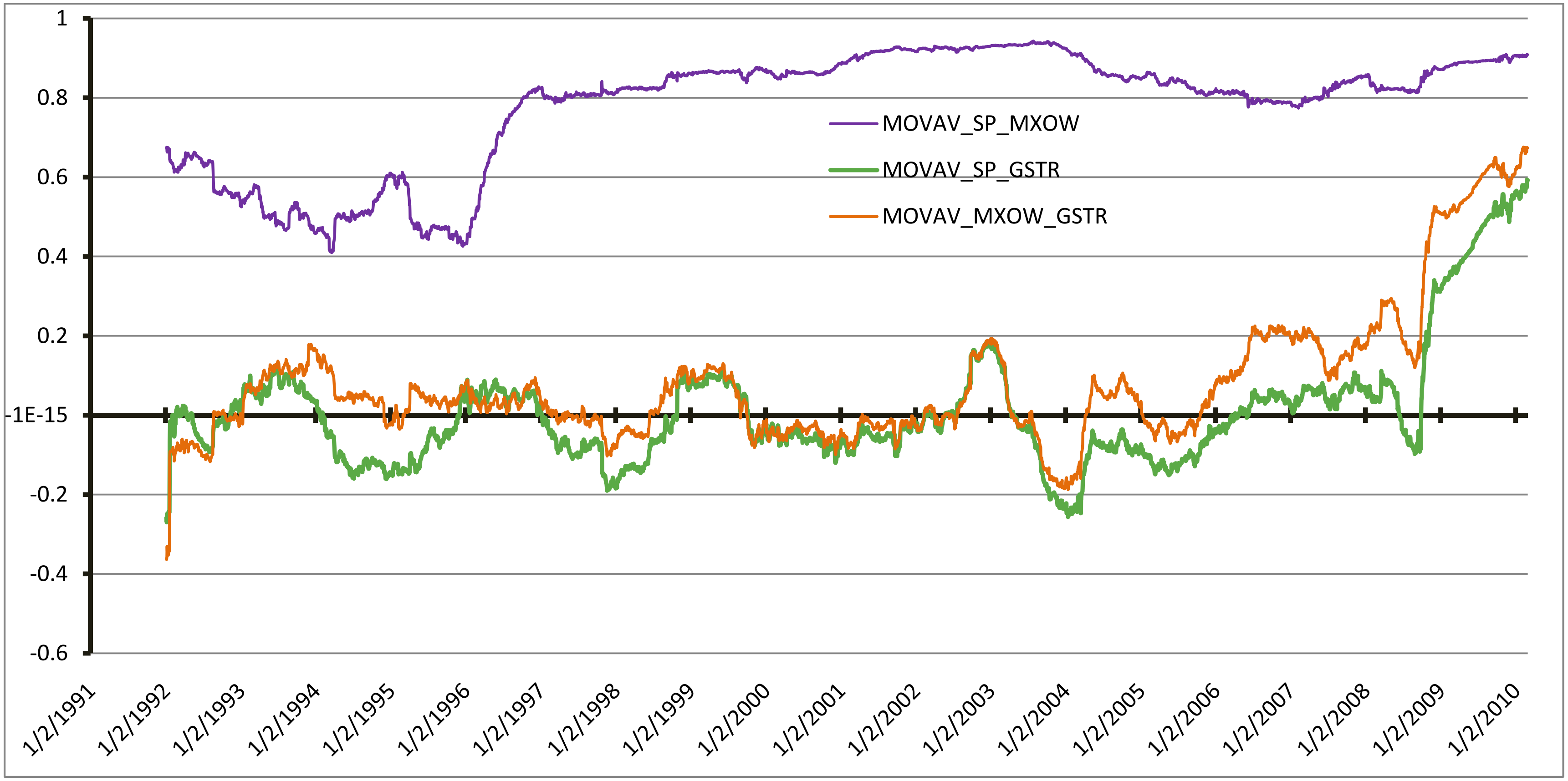
***Notes*:** Figure 1D depicts the time-varying correlation between the **daily** unlevered rates of return (precisely, changes in log prices) on S&P's GSCI total return commodity index and: (i) the S&P 500 (SP) equity index (**green line**) or (ii) the MSCI World Equity Index (MXWO, **orange line**). In each case, dynamic conditional correlation are estimated by log-likehood for mean-reverting model (DCC_MR, Engle, 2002) from January 3, 1991 to March 1, 2010. Figure 1D shows that daily equity-commodity correlations are often slightly greater when estimated with the world equity index rather than the US equity index -- especially since Fall 2003. As a benchmark, Figure 1D also plots the correlation between the S&P 500 US equity index and the MSCI World Equity Index (**purple line** on top). Plots are similar when the S&P 500 is replaced by the the Dow Jones Industrial Average (DJIA) equity index.

<u>Figure 1E: Daily Return Correlations (Moving-Average) -- US Equity *vs.* Commodity Indices, January 1991 to March 2010</u>



Notes**:** Figure 1E depicts the time-varying correlation between the **daily** unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and: (i) the S&P GSCI total return commodity index (GSTR, **green line**) or (ii) the DJ-UBS total return commodity index (DJTR, **red line**). As a benchmark, the Figure also plots the correlation between the S&P 500 equity index and the other traditional U.S. equity index, the Dow Jones Industrial Average equity index (DJIA, **blue line** on top). In each case, rolling correlation are estimated on a one-year period starting January 3, 1991 to March 1, 2010.

Figure 1F: Daily Return Correlations (Moving-Average) -- World Equity *vs.* Commodity Indices, January 1991 to March 2010



***Notes*:** Figure 1F depicts the time-varying correlation between the **daily** unlevered rates of return (precisely, changes in log prices) on S&P's GSCI total return commodity index and: (i) the S&P 500 (SP) equity index (GSTR, **green line**) or (ii) the MSCI World Equity Index (MXWO, **orange line**). In each case, rolling correlation are estimated on a one-year period, starting January 3, 1991 to March 1, 2010. Figure 1F shows that equity-commodity correlations are slightly greater when estimated with the world equity index rather than the US equity index, especially since Fall 2003. As a benchmark, the Figure also plots the correlation between the S&P 500 US equity index and the MSCI World Equity Index (**purple line** on top). Plots are similar when the S&P 500 is replaced by the the Dow Jones Industrial Average (DJIA) equity index.

Appendix 2: Commodity weights

Year	CBOT wheat	Kansas wheat	Corn	Soybeans	Coffee	Sugar	Cocoa	Cotton	Lean hogs	Live cattle	Feeder cattle	Heating oil	Crude	Natural gas	Copper	Gold	Silver
2000	3.5%	1.3%	4.0%	2.0%	1.3%	2.0%	0.4%	2.2%	3.0%	6.1%	0.0%	7.6%	47.4%	9.6%	7.2%	2.0%	0.2%
2001	4.1%	1.4%	4.4%	2.1%	0.9%	2.2%	0.5%	1.7%	3.1%	6.6%	0.0%	6.8%	47.1%	10.0%	6.9%	2.1%	0.2%
2002	4.5%	1.8%	4.7%	2.4%	0.9%	1.8%	0.7%	1.6%	2.4%	4.9%	0.9%	7.2%	48.4%	8.6%	6.6%	2.4%	0.2%
2003	4.0%	1.5%	4.1%	2.5%	0.8%	1.6%	0.5%	1.9%	2.2%	4.2%	1.0%	6.9%	48.4%	11.7%	6.4%	2.1%	0.2%
2004	3.3%	1.4%	3.6%	2.4%	0.7%	1.3%	0.3%	1.4%	2.1%	3.5%	0.8%	7.7%	51.6%	10.7%	7.1%	2.0%	0.2%
2005	2.4%	0.9%	2.3%	1.6%	0.7%	1.3%	0.2%	1.0%	1.8%	2.7%	0.7%	8.6%	55.8%	11.4%	6.6%	1.7%	0.2%
2006	2.6%	1.0%	2.5%	1.4%	0.7%	1.7%	0.2%	0.9%	1.5%	2.3%	0.6%	8.2%	56.5%	8.1%	9.6%	2.0%	0.3%
2007	3.5%	1.2%	3.2%	1.9%	0.7%	1.1%	0.2%	0.9%	1.4%	2.6%	0.6%	5.9%	57.1%	7.4%	10.1%	2.0%	0.3%
2008	3.8%	0.9%	3.6%	2.2%	0.6%	1.1%	0.2%	0.8%	1.1%	2.2%	0.4%	5.2%	61.8%	6.9%	6.8%	2.0%	0.2%
2009	4.6%	1.0%	4.6%	3.2%	0.9%	2.0%	0.4%	1.0%	1.9%	3.3%	0.6%	4.3%	55.9%	5.5%	6.8%	3.4%	0.4%
2010	4.6%	1.0%	4.6%	3.2%	0.9%	2.0%	0.4%	1.0%	1.9%	3.3%	0.6%	4.3%	55.9%	5.5%	6.8%	3.4%	0.4%

Note: Appendix 2 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 index (SIS and SIA). Excluded are four GSCI commodities (aluminum, lead, nickel and zinc) that accounted for less than 5% of the GSCI in 2008 and 2009. The GSCI weight of London Metal Exchange (LME) copper is applied to Nymex copper positions. Finally, the weight assigned to WTI crude oil is the GSCVI weight of WTI crude, plus the weights of Brent crude, gasoil and RBOB gasoline.

Appendix 3: Large trader categories

Appendix 3 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.[24] 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;[25] (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).

[24] 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.

[25] 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 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.[26]

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).

[26] 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.

Appendix 5.

Table 7: Long-run Determinants of GSCI-S&P500 Correlations, pre-Lehman

Variable	Model 6 2000-2008	Model 7 2000-2008	Model 8 2000-2008	Model 9 2000-2008
Constant	-0.3374	0.3935	-0.6700	2.6124
	(1.4730)	(1.5120)	(2.3950)	(2.8380)
SHIP	-0.529***	-0.5681***	-0.521***	-0.6084***
	(0.1688)	(0.1699)	(0.1709)	(0.1794)
UMD	0.0254	0.0253	0.0219	0.0150
	(0.0363)	(0.0366)	(0.0369)	(0.0376)
TED	0.2094***	1.198***	0.203***	1.4042***
	(0.0711)	(0.4270)	(0.0752)	(0.5043)
WMSA_AS	-2.7322	-4.4055*	-2.6185	-5.5734*
	(2.5210)	(2.6040)	(2.6170)	(2.9240)
WMSA_MMT	3.2591*	3.9145**	3.0660	5.5919**
	(1.8280)	(1.8320)	(2.3060)	(2.5420)
WMSA_TCOM	0.9390	-0.4773	1.0720	-1.4469
	(1.9110)	(2.0190)	(2.0040)	(2.3250)
INT_TED_MMTA		-4.111**		-4.8562**
		(1.6870)		(1.9450)
WSIA			0.2370	-1.5383
			(1.4070)	(1.6330)
Observations	437	437	437	437

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 5.

Table 8: Long-run Determinants of GSCI-S&P500 Correlations, pre-Lehman

Variable	Model 2 2000-2008	Model 3 2000-2008	Model 4 2000-2008	Model 5 2000-2008
Constant	-2.3482	-3.2999*	-5.1089**	-5.3486**
	(1.7890)	(1.7390)	(2.1470)	(2.1140)
SHIP	-0.7083***	-0.8846***	-0.6126***	-0.775***
	(0.1818)	(0.1846)	(0.1593)	(0.1738)
UMD	0.0369	0.0240	0.0324	0.0204
	(0.0441)	(0.0410)	(0.0373)	(0.0364)
TED	0.3232***	1.7639***	0.2329***	1.4261***
	(0.0891)	(0.5417)	(0.0811)	(0.4992)
WMSS_AS	0.8208	0.7740	0.9516	0.9502
	(2.6290)	(2.4640)	(2.2190)	(2.1810)
WMSS_MMT	5.3721**	9.143***	5.0791**	8.2813***
	(2.6490)	(2.9180)	(2.2280)	(2.5880)
WMSS_TCOM	2.9873	3.4884	4.5071**	4.663**
	(2.3960)	(2.2690)	(2.2210)	(2.1890)
INT_TED_MMT		-5.924***		-4.8259**
		(2.1200)		(1.9220)
WSIA			1.803*	1.4199
			(0.9239)	(0.9360)
Observations	437	437	437	437

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.