Speculators, Commodities and Cross-Market Linkages

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Abstract

We utilize non-public data to construct a comprehensive dataset of individual trader positions in seventeen U.S. commodity futures markets and document the financialization of those markets between 2000 and 2010. We then show that the correlations between the returns on investable commodity and equity indices increase amid greater participation by speculators generally and hedge funds especially. We find no such effect for other kinds of commodity futures traders. The impact of hedge fund activity is complex. In particular, it is lower during periods of financial market stress. Our results indicate that *who* trades helps explain the joint distribution of equity and commodity returns.

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

Introduction

In the past ten years, financial institutions have assumed an ever greater role in commodity futures markets. We provide novel evidence of this "financialization" and empirically show that it helps explain an important aspect of the joint distribution of commodity and equity returns.

A large literature investigates whether the composition of trading activity (i.e., *who* trades) matters for asset pricing. First, 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). Insofar as hedge funds are less constrained than other investors (e.g., Teo, 2009) and commodity markets are partly segmented from other financial markets (Bessembinder, 1992), this theoretical argument suggests that increased hedge fund activity could strengthen cross-market linkages. Second, suppose that the same traders who help link markets in normal times face, during periods of financial market stress, borrowing constraints or sundry pressures to liquidate risky positions. Then, their exit from "satellite" markets (such as emerging markets or commodity markets) after a major shock in a "central" asset market (such as the U.S. equity market) could in theory bring about cross-market contagion (Kyle and Xiong (2001), Kodres and Pritsker (2002), Broner, Gelos and Reinhart (2006), and Pavlova and Rigobon (2008)).[2] In the aftermath of the initial shock, conversely, reduced activity by value arbitrageurs or convergence traders could lead to a decoupling of the markets that they had helped link in the first place.

In this paper, we show that hedge funds activity matters for market linkages, and that this impact differs in good *vs*. bad times. Controlling for macro-economic and commodity-market fundamentals, we find that commodity-equity co-movements are positively related to greater commodity market participation by financial speculators as a whole and by hedge funds especially – notably by hedge funds that trade in *both* equity and commodity futures markets. We find no such effect for other kinds of traders. The impact of hedge fund activity is complex. For instance, we find that it is weaker during periods of turmoil in financial markets. Our results contribute to the debate on the consequences of "financialization" in commodity markets.

A major innovation of our paper is its dataset. In general, investigating whether specific types of traders contribute to cross-market linkages is empirically difficult because doing so

[2] See Gromb and Vayanos (2010) for a thorough review of the theoretical work on limits to arbitrage and contagion.

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 raw data, which are non-public, originate from the U.S. Commodity Futures Trading Commission's (CFTC) large trader reporting system (LTRS). The LTRS contains information on the end-of-day positions of every large trader in each of these seventeen markets, as well as information on each trader's main line of business. The individual position information in the LTRS covers more than 85% of the total open interest in the largest U.S. commodity futures markets from July 2000 to March 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 (macroeconomic fundamentals, trading, or both) drives those fluctuations.[3] Third, we seek to add significantly not just to the literature on asset pricing but also to a fast-growing literature on the "financialization" of commodities – see, e.g., Acharya, Lochstoer and Ramadorai (2009), Büyükşahin and Robe (2009), Korniotis (2009), Tang and Xiong (2010), Etula (2010), Hong and Yogo (2010), and Stoll and Whaley (2010).

In this last respect, we make three contributions. One, we provide a decade's worth of novel data on the growing importance of different types of financial traders in a large number of U.S. commodity-futures markets. Two, we provide evidence about the extent to which different kinds of traders in those markets (in particular, hedge funds) also trade equity futures and show that such cross-market trading has grown substantially. Three, we use this heretofore unavailable information to shed light on the impact of financialization on cross-market linkages.

[3] Theoretically, arguments have long existed that equities and commodities should be negatively correlated (Bodie, 1976; Fama, 1981). Although there is to our knowledge no formal model of a common factor driving an equilibrium relationship between equity and commodity returns, empirical work shows that returns on commodity futures are driven not only by commodity-specific hedging pressures but also by some of the same macroeconomic factors that are priced for stocks – see, e.g., Bessembinder (1992), de Roon, Nijman and Veld (2000) and Khan, Khokher and Simin (2008). Consistent with these findings, Büyükşahin, Haigh and Robe (2010) and Chong and Miffre (2010) document that the dynamic conditional correlations between the rates of returns on equities and on commodites vary considerably over time around unconditional means close to zero (see also Gorton and Rouwenhorst (2006)).

We show that variations in the make-up of the commodity futures open interest do help explain long-term fluctuations in commodity-equity return co-movements. We employ ARDL regressions, using lagged values of the variables in the regression to tackle serial autocorrelation and possible endogeneity issues (arising from the possibility that speculative activity could result from high volatility and correlations, rather than the other way around). We find that a 1% increase 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%.

We show 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 identify two patterns. First, we show that equity-commodity co-movements are positively related to the TED spread (our proxy for financial-market stress). 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 ("high TED") episodes is statistically significant and negative. In other words, the impact of hedge fund activity is reduced during periods of global market stress.

Second, we document that commodity-equity correlations soared after the demise of Lehman Brothers and remained exceptionally high through the Winter of 2010. Over and above the explanatory power of the TED spread, a time dummy capturing the post-Lehman period (September 2008 to March 2010) is highly statistically significant in all of our specifications. This finding suggests that the recent crisis is different from previous episodes of financial market stress and that this difference is reflected, in part, by an increase in cross-market correlations.

The paper proceeds as follows. Section I discusses our contribution to the literature. Section II gives evidence on equity-commodity linkages. Section III presents our position data and describes the financialization of commodity futures markets. Section IV presents our regressions and traces changes in equity-commodity return linkages to fundamentals as well as to hedge fund activity, stress, and the interaction of the last two factors. 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 the present paper squarely within a fast-growing literature that analyzes whether the financialization of commodity markets in the past decade affects the levels or distributions of commodity prices.

Three recent papers investigate the impact of financial speculation on commodity prices and returns. Using different techniques, Hamilton (2009), Korniotis (2009) and Kilian and Murphy (2010) conclude that macroeconomic fundamentals, rather than speculation, were most likely behind the 2004-2008 boom-bust commodity price cycle. Three other studies look at the impact of financialization through the lens of risk premia in commodity markets. Hong and Yogo (2010) argue that the growth (rather than the composition) of open interest in commodity futures markets drives commodity returns. Two related studies conclude that the risk-bearing capacities of broker-dealers (Etula, 2010) and the risk appetites of commodity producers (Acharya *et al*, 2009) play significant roles in determining commodity risk premia.

Those six papers focus on price levels, returns or risk premia. We focus instead on commodities' co-movements with equities. Through this lens and thanks to uniquely disaggregated data, we show that the composition of the open interest in commodity markets is an important explanatory factor of this aspect of commodities' return distributions. Consistent with the predictions of theoretical models, we identify the activities of hedge funds and cross-market traders as relevant to cross-market linkages. We also show that the extent to which speculative positions help explain linkages is weaker in periods of high financial-market stress.

Related to our query, therefore, are two contemporaneous studies that utilize publicly-available data to investigate the possible impact of commodity index trading (CIT) on cross-commodity correlations in the past decade. One of those studies finds a CIT impact (Tang and Xiong, 2010); the other concludes that there is no causal relationship (Stoll and Whaley, 2010).

Unlike those papers, our main interest is in the co-movements between commodity and equity markets rather than the linkages between different commodity futures markets. Our paper further differs with respect to the types of financial traders whose behaviors and market impacts we analyze (not only index traders but also hedge funds and other types of commodity traders). Finally, our paper differs in how we measure financial activity in commodity markets.

Absent other publicly available information, extant studies approximate total CIT activity in commodity futures markets by extrapolating from public CFTC information on CIT positions in 12 agricultural markets. Such data are only available starting in 2006. In contrast, we utilize the CFTC's non-public trader-level position data for all U.S. markets dating from 2000. These data allow us to identify the daily and weekly shares of commodity futures open interest held not only by CITs but also by hedge funds and several other categories of commodity futures traders.[4]

Using the disaggregated data, we find little direct evidence that commodity-index trading drove long-term changes in equity-commodity co-movements. Our econometric analyses instead suggest that (besides macroeconomic fundamentals) it is mostly *hedge fund* positions that help explain changes in the strength of equity-commodity linkages. We furthermore show 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 another literature – that 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) 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, in periods when the TED spread shows elevated levels of financial-market stress, higher hedge fund participation *ceteris paribus* weakens (rather than increases) cross-market correlations.

Our analysis is thus also related to empirical papers that ask if speculators (in particular, hedge funds) can at times exert a destabilizing effect on financial markets. In equity markets, Brunnermeier and Nagel (2004) and Griffin, Harris, Shu and Topaloğlu (2011) argue that hedge

[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 1990s, and Büyükşahin, Haigh, Harris, Overdahl and Robe (2009) on the crude oil market in 2000-2009.

funds moved stock prices during the technology bubble. In futures markets, however, Brunetti and Büyükşahin (2009) conclude that hedge funds do not affect price levels yet are key to the functioning of these markets through the liquidity that their trading provides to other market participants.[5] Those studies focus on price levels for a given type of asset (in other words, on the first moments of an asset's 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.

II. Commodity-Equity Co-movements, 1991-2010

This paper seeks to ascertain whether, in addition to economic fundamentals, commodity-market participation by certain types of traders (speculators in general and hedge funds or index traders in particular) helps explain the extent to which a smaller "satellite" asset market (in our case, commodity futures) moves together with a "core" asset market (in our case, U.S. equities).

This Section provides summary statistics for the returns on equity and commodity index investments, and plots our estimates of the dynamic conditional correlation (DCC, Engle 2002) between equity and commodity returns. This analysis extends, complements, or updates through the post-Lehman period a number of earlier 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), Büyükşahin *et al* (2010), Chong and Miffre (2010), Silvennoinen and Thorp (2010), Stoll and Whaley (2010), Tang and Xiong (2010)).

A. Commodity and Equity Return Data

We use daily and weekly returns on benchmark commodity and stock market indices.[6] We obtain price data from Bloomberg. Our sample runs from January 1991 (when the Goldman Sachs Commodity Index or GSCI was introduced as an investable benchmark) to March 2010.

For commodities, we use 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. Because it uses weights that reflect each commodity's

[5] The evidence from foreign exchange and emerging markets on whether hedge funds are destabilizing is mixed. Chan, Getmansky, Haas and Lo (2006) provide a review the prior literature on hedge funds.

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

worldwide production figures, it is heavily tilted toward energy (see Table I). In robustness checks, we therefore use total (unlevered) returns on the second most widely used investable benchmark, Dow Jones' DJ-UBS (until May 2009, DJ-AIG) total-return commodity index. This rolling index covers nineteen physical commodities and was designed to provide a more "diversified benchmark for the commodity futures market." We find similar results for the GSCI and DJ-UBS indices, and therefore we focus our discussion on the GSCI.

For equities, we focus on Standard and Poor's S&P 500 index. This stock index is broad-based, making it a natural choice. Furthermore, the trading activity in the Chicago Mercantile Exchange's S&P 500 e-Mini futures far exceeds that of other equity-index futures in the United States, making the S&P 500 e-Mini the ideal market in which to test the hypothesis that cross-market traders may contribute to commodity-equity linkages. We find similar DCC patterns using Dow-Jones' Industrial Average (DJIA) index, and therefore we focus our discussion on the S&P500.[7] For comparison purposes, we also provide figures for the (generally slightly higher) correlations between the GSCI and the MSCI World Equity index (MSCI).

B. Descriptive statistics

Table II 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.

[7] On both equity indices, we use returns that omit dividends. This approach underestimates expected equity returns (Shoven and Sialm, 2000). Insofar as large U.S. corporations smooth dividend payments over time (Allen and Michaely, 2002), however, the correlation estimates that are the focus of our paper should be essentially unaffected.

Turning to volatility, Table II shows that the rate of return on a well-diversified basket of equities (S&P 500) is generally less volatile than that on commodities (GSCI). The standard deviation of the rate of return on commodities was particularly high after 2003.

C. Dynamic Conditional Correlations

Our main interest is in the relationship between commodity and equity returns at various points in time. With unconditional techniques such as rolling correlations or exponential smoothing, the sensitivity of the estimated correlations to volatility changes restricts inferences about the true nature of the relationship between variables, and periods of high volatility only magnify concerns of heteroskedasticity biases – see Forbes and Rigobon (2002). Consequently, we use the dynamic conditional correlation (DCC) methodology of Engle (2002) in order to obtain dynamically correct estimates of the intensity of commodity-equity co-movements.

In essence, the DCC model is based on a two-step approach to estimating the time-varying correlation between two series. First, we estimate time-varying variances using a GARCH(p,q) model. For our sample, p=q=1. Second, we estimate a time-varying correlation matrix using the standardized residuals from the first-stage estimation.

Figure 1A (*1B*) plots, from January 1991 to March 2010, our estimates of the dynamic conditional 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. As a benchmark, 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 U.S. equity index, the Dow Jones DJIA.

Several facts are clear from Figures 1A-1B. First, in the eighteen months following the demise of Lehman Brothers in September 2008, equity-commodity correlations rose to levels never seen in the prior two decades. Second, prior to the Lehman collapse, equity-commodity correlations used to fluctuate substantially over time. At both weekly and daily frequencies, the equity-commodity DCC range was -0.38 to 0.4, approaching 0.4 in 1998, 2001-2002, mid-2006, and again in Fall 2008. Third, despite those ample fluctuations, there is no apparent up-trend in equity-commodity correlations prior to August 2008.

D. Discussion

Our finding that there was no obvious secular increase in commodity-equity correlations until Fall 2008 is in line with the conclusions of Büyükşahin *et al* (2010, p. 78) and Tang and

Xiong (2010, p.21) using weekly or daily data. It is also consistent with findings in Chong and Miffre (2010) and Silvennoinen and Thorp (2010) regarding dynamic correlations between the returns on the S&P 500 and on a number of individual commodity futures. Nevertheless, given that the DCC measure is the dependent variable in the econometric analyses of Section IV, we carry out several robustness checks.

Figures 1A and 1B jointly show that the measurement frequency (daily *vs*. weekly) and the choice of commodity index (GSCI *vs*. DJ-UBS) are qualitatively immaterial. Figures 1C and 1D likewise show that the choice of equity index (world *vs*. U.S.) does not alter this conclusion.

In the present paper, we use the U.S. S&P 500 stock index (rather than a global stock market index) to compute equity-commodity correlations. There are two reasons why we do so. One, it minimizes the confounding effects of exchange rate fluctuations on the measurement of commodity-equity co-movements. Two, it allows us to match the correlation we seek to explain with the available equity-futures position data. Suppose, though, that the variable of interest *were* the MSCI-GSCI return co-movements: a comparison of Figure 1C (*1D*) with Figure 1A (*1B*) shows that we would still find no visible up-trend in equity-commodity correlations prior to September 2008.

Figures 1E and 1F, which are based on unconditional rolling correlations, caution that not controlling for time-variations in return volatilities *could* lead to incorrect inferences. First, one might conclude from Figure 1F (based on unconditional one-year rolling correlations) that GSCI-MSCI rolling correlations strengthened as early as 2006, i.e., well before the Lehman crisis – even though we know from Figure 1D (based on DCC) that such was not the case. Second, one might conclude from a comparison of Figures 1E and 1F (both based on one-year rolling correlations) that the choice of equity index (world *vs*. U.S.) matters – even though we know from a comparison of Figure 1C (*1D*) with Figure 1A (*1B*) that such is not the case.

Having established that correlations fluctuated substantially, but not dramatically, prior to the Great Recession and having identified a structural break in mid-September 2008, we now ask what drives the fluctuations depicted in Figures 1A and 1B. Do market fundamentals explain the observed patterns or is the latter due partly to the financialization of commodity futures markets?

III. The Financialization of U.S. Commodity Futures Markets, 2000-2010

In most U.S. commodity futures markets, the open interest is much greater in 2010 than it was a decade earlier. In this Section, we construct a comprehensive dataset of trader positions in seventeen futures markets and provide novel evidence that this growth entailed major changes in the composition of the overall open interest. In particular, we document considerable increases in the presence of hedge funds and in the extent to which equity futures traders are also active in commodity futures markets.

We assemble our dataset by utilizing confidential data on individual trader positions from the U.S. government's futures and options market regulator (i.e., the CFTC). This uniquely detailed information provides the foundation for the regression analyses of Section IV, in which we examine whether participatory changes have explanatory power for equity-commodity returns linkages.

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 prior literature.[8] Section III.C establishes that, compared to commercial activity, overall speculative activity has increased significantly since 2000. We then disaggregate this information and provide evidence on growth in these markets of hedge fund activity (Section III.C), cross-market trading (Section III.D) and commodity index trading (Section III.E).

A. Trader Position Data

We construct a database of daily trader positions in 17 U.S. commodity futures markets (see list in Table I) and the S&P 500 e-Mini futures market from July 1, 2000 to March 1, 2010.

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

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

[8] Only a handful of earlier 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 prices of crude oil futures across the maturity structure.

detecting and deterring market manipulation, the CFTC's Division of Market Oversight collects position-level information on the composition of open interest across all futures and options-on-futures contracts for each commodity. It gathers this information for each trader whose position exceeds a certain threshold (which varies by market). The CFTC also collects information from each large trader about his respective underlying business (hedge fund, swap trader, commodity producer, etc.) and about the purpose of his positions in different U.S. futures markets.

Many smaller traders' positions are also voluntarily reported to the CFTC and are thus included in the raw data made available for the present study. Depending on the specific market, our dataset therefore covers from 75% to more than 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 underlying raw information is the one which the CFTC summarizes in weekly "Commitment of Traders (COT) Report" that it publishes every Friday at 3:30 p.m. Consequently, the information we provide in this Section can be contrasted with numerous extant studies of commodity markets that rely on COT data.[9]

2. Publicly Available Information

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

Prior to September 2009, COT reports separated traders between two broad categories: "commercial" *vs*. "non-commercial." The CFTC classifies all of a trader's futures and options positions in a given commodity as "commercial" if the trader used futures contracts in that particular commodity for hedging as defined in CFTC regulations. A trading entity generally is classified as "commercial" by filing a statement with the CFTC that it is commercially "engaged in business activities hedged by the use of the futures or option markets".[10] The "non-commercial" group aggregates various types of mostly financial traders, such as hedge funds, mutual funds, floor brokers, etc.

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[9] 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, pre-2000, was lower than weekly.

[10] 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.

Since September 4, 2009, COT reports differentiate between four (rather than two) kinds of traders. The reports now split commercial traders between "traditional" commercials (producers, processors, commodity wholesalers or merchants, etc.) and commodity swap dealers (in most markets this category includes commodity index traders). They also now differentiate between managed money traders (i.e., hedge funds) and "other non-commercial traders" with reportable positions.[11] As of Fall 2010, however, the CFTC has not indicated plans to make this more detailed information available retroactively prior to 2006 or to break down the aggregate position information by contract maturity.

3. Non-Public Information

The LTRS data allow for much more differentiation than the simple COT classifications. Specifically, each reporting trader is classified into one of 28 (rather than a few) sub-categories – e.g., commercial dealers, swap dealers, producers, refiners, hedge funds, floor traders, brokers,...

Because the LTRS data are contract-specific, they also make it possible to disentangle the activities of various kinds of traders at the near and far ends of the commodity-futures term structure. In contrast, public COT reports do not separate between traders' positions at different contract maturities. Our results in Section IV show that this additional information is critical, in that it is the positions held by hedge funds in shorter-dated contracts (rather than further along the maturity curve) that contain explanatory power for equity-commodity index-return linkages.

An independent contribution of the present paper is thus to provide, in Sections III.B to III.E, 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 summarize the individual position data for this paper.

B. Increased Excess Speculation

To gauge the growth of speculative activity in U.S. commodity futures markets, we use Working's (1960) "*T*". This index compares the activities of all "non-commercial" commodity futures traders (commonly referred to as "speculators") to the demand for hedging that originates from "commercial" traders (commonly referred to as "hedgers").

[11] COT reports also provide data on the positions of non-reporting traders (speculators, prop and other small traders).

1. *Measuring "Excess Speculation"*

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

For each of the seventeen commodities in our sample (i = 1, 2, …, 17), we calculate Working's T every Tuesday from 2000 to 2010. In each market, we compute two "T" indices – one for short-term contracts ($SIS_{i,t}$) only, and one for all maturities ($SIA_{i,t}$). The latter measure can be computed using the publicly-available COT reports, which allows reader without access to the LTRS data to replicate this part of our results.

For $SIS_{i,t}$, we use the three shortest-maturity contracts with non-trivial open interest. We do so based on the notion that it is those near-dated contracts whose prices are used to compute the commodity return benchmarks. Formally, in the i^{th} commodity market in week t:

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

where $SS_i \geq 0$ is the (absolute) magnitude of the short positions held in the aggregate by all non-commercial traders ("<u>S</u>peculators <u>S</u>hort"); $SL_i \geq 0$ is the (absolute) value of all non-commercial long positions; $HS_i \geq 0$ stands for all commercial ("<u>H</u>edge <u>S</u>hort") short positions and $HL_i \geq 0$ stands for all long commercial positions.

We then average these individual index values to provide a general picture of speculative activity across all seventeen commodity markets in our sample:

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

where the weight $w_{i,t}$ for commodity *i* in a given *week t* is based on the weight of the commodity in the GSCI 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 the LTRS position data are available. Table I lists the annual commodity weights per commodity, per year.

To obtain a picture of excess speculation across *all* contract maturities, we also compute:

$$WSIA_t = \sum_{i=1}^{17} w_{i,t}\, SIA_{i,t}$$

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

Table III.A provides summary statistics of the weighted average speculative indices (*WSIS* and *WSIA*) from July 2000 to March 2010. During that period, the minimum value was 1.11 for both short-term and all contracts; the maximum was 1.5 in near-term contracts (1.42 across all maturities). In other words, speculative positions were on average 11% to 50% greater than what was minimally necessary to meet net hedging needs at the market-clearing prices.

Figure 2A documents the growing importance of speculation in commodity markets in the past decade. Excess speculation increased substantially, from about 11% in 2000 to about 40-50% in 2008.[12] Interestingly, a comparison of the *WSIS* and *WSIA* curves in Figure 2A shows that, at almost all times in the sample period, excess speculation was several percentage points greater in near-term contracts than further out on the maturity curve. Notably, excess speculation fell after 2008, especially in near-term contracts (*WSIS* fell from 1.5 to 1.35).

In sum, Figure 2A identifies a long-term increase, but also substantial variations, in excess commodity speculation. Those patterns will be of particular interest in the analysis of Section IV. Before proceeding to regression analyses, however, we investigate whether the changes in overall speculative activity hide differential patterns for distinct types of financial traders – hedge funds (III.C), index traders (III.D) and cross-market traders (III.E).

C. Increased Hedge Fund Activity

Working's *T* lumps together all non-commercial traders: floor brokers and traders, hedge funds, other non-commercial traders not registered as managed money traders. Yet, there is little

[12] The values in Figure 2 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).

reason to believe that floor brokers in a specific commodity market should affect commodity-equity linkages. Hedge funds, in contrast, are plausible candidates for such a role.

1. *Measuring Hedge Fund Activity*

We utilize the granularity of the LTRS data to compute summary statistics and plot time series of hedge funds' share of the overall commodity futures open interest (see the Appendix for a formal definition of "hedge fund" in U.S. futures markets). We also compute similar market share figures for commodity swap dealers (a category that includes commodity index traders in most U.S. futures markets – see Section III.D) and for traditional commercial traders. For each sub-category of traders, we compute market shares across the three nearest-maturity futures with non-trivial open interest as well as across all contract maturities.

Formally, we compute the open-interest or "market share" of a given category of traders, in each commodity futures market each Tuesday, by expressing the average of the long and short positions of all traders from this group in that market as a fraction of the total open interest in that market that same Tuesday. We then average these commodity-specific market shares across our seventeen commodity futures markets, using the commodity weights from Table I.

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

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

The green line in Figure 2A depicts changes in the *WMSS_MMT* measure over time. This chart, together with Tables III.B and III.C, highlights several important market changes.

First and foremost, hedge funds' contribution to the commodity futures open interest more than tripled between 2000 and 2008. Their share grew from less than a tenth (*a twentieth*) of the near-term (*overall*) open interest in early 2002 to over a third (*almost 30%*) in early 2008.

Second, Tables III.B and III.C, which provide summary statistics for various kinds of traders in near-term (III.B) and all (III.C) futures contracts, show that *WMSS_TCOM* and *WMSA_TCOM* both fell from 53% to less than 20% during that period. During the same period, the market share of floor brokers and traders did not change drastically. Thus, hedge funds' greater market share echoes a sharp drop in traditional commercial traders' relative contribution to the overall open interest. This finding generalizes, to a cross-section of commodity futures markets, some of the observations of Büyükşahin *et al* (2009) in the specific case of WTI crude oil futures.

Third, Figure 2A shows that the market share of hedge funds *as a whole* started trending downward in the second half of 2008. Interestingly, this trend has persisted in 2009 and 2010, i.e., in the period when cross-market correlations were unusually elevated.

A natural question is whether *all* hedge funds pulled back from commodities in the post-Lehman turmoil. We debunk this notion in Section III.D, by showing that one type of hedge funds – those that trade in both commodity and equity markets – in fact increased its collective percentage contribution to the commodity open interest during that period.

D. Increased Cross-Market Trading

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

1. Measuring Cross-Trading Activity

Every reporting trader is uniquely identified in the CFTC's LTRS. For each trading day, we use the unique ID of each commodity futures trader holding open positions at the market close that day to ascertain whether that trader also held overnight positions in the CME's e-Mini S&P 500 equity futures at any point in our sample period. In the affirmative, we consider such a commodity-futures trader to be a "cross-market trader".

This exercise, which we summarize in Table III.D and discuss in Section III.D.2 below, tells us how many cross-traders there are on a given trading day. Intuition suggests, however, that traders that are active in both commodity and equity markets likely hold larger positions than do other commodity futures traders. We therefore also compute cross-market traders' share of the overall open interest in a given commodity market on each trading day. To do so, we use the approach of Section III.C: for each group or subgroup of traders, we compute the open interest attributable to that group or sub-group as the average of the long and short positions of the traders in that group in that market on that day as a fraction of the total open interest in that market on that same day.

We denote by $CMSA\_MMT_{i,t}$, $CMSA\ \_AS_{i,t}$ and $CMSA\ \_ALL_{i,t}$ the shares of the open interest in the i^{th} commodity held respectively by cross-trading hedge funds (*MMT*), swap dealers (*AS*) and all commodity futures traders (*ALL*) (i = 1, 2, …, 17). We then use the commodity weights from Table I to calculate the weighted-average market share of different types of traders (xxx = *MMT*, *AS* or *ALL*), across the seventeen commodity futures markets in our sample:

$$WCMSA\_\mathrm{xxx}_t = \sum_{i=1}^{17} w_{i,t}\, CMSA\_\mathrm{xxx}_{i,t}$$

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

Table III.D provides information the number of cross-market traders, and on the make-up of cross-trading activity, in the seventeen commodity futures markets in our sample period. 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 (Column 1). In all but three of the smallest markets (feeder cattle, Kansas wheat and heating oil), at least 10% of all large commodity futures traders also traded equity futures in that period (Column 2).

Using median figures (means are similar), we see that cross-market traders account for 15% of all large commodity futures traders active at some point between July 2000 and March 2010 (Column 2). Hedge funds make up almost 50% (Column 6) whereas commodity swap dealers account for less than 6% (Column 4) of the cross-trading contingent. Approximately 38.9% of all cross-traders are classified as hedge funds in equity futures markets (Column 8).

These median figures obscure two patterns. One, more than a quarter of all crude oil and gold traders also hold equity futures positions. Two, in contrast, only a seventh or less of all large traders in smaller futures markets ("softs", "livestock" and heating oil) are cross-market traders. In smaller markets, more than half of the cross-traders are hedge funds while hedge funds make up about a third of all cross-traders in larger commodity markets.

A comparison of Table III.D with the last four columns of Table III.C shows that the median weighted average share of the commodity futures open interest held by equity-commodity cross-traders was 40.9% during the sample period *vs*. 15% of the trader count. This difference implies that cross-market traders typically hold (much) larger overnight positions than other types of commodity futures traders.

The purple line in Figure 2A shows that the market share of cross-traders increased substantially between 2000 and 2010, from less than 20% of the total commodity futures open interest in 2000 and 2001 to around 40-47% since mid-2005. The light blue line in Figure 2A shows that cross-market-trading hedge funds' share of the commodity open interest also grew substantially during that time period, but that the magnitude of their positions did not move in sync with the positions of other cross-market traders.

Most striking is the difference between the activities of hedge funds that trade across markets *vs*. hedge funds that only hold positions in commodity futures markets. As a whole, the market share of hedge funds started a downward trend several months before the Lehman crisis. Notwithstanding some fluctuations, this trend accelerated the week following Lehman's demise. In contrast, cross-trading hedge funds' market share was fairly stable during that period and then *increased* steadily after mid-November 2008.

E. Commodity Index Trading (CIT)

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 CFTC's non-public LTRS, CIT-related positions cannot be identified within the overall positions held by commodity swap dealers.[13]

One solution to this issue (see, e.g., Stoll and Whaley (2010) and Tang and Xiong (2010)) 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, weekly, 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). Furthermore, after 2006, the quality of that approximation depends on whether the magnitudes of investment flows into commodity markets were similar for ags and other types of commodities. In fact, the precision of the approximation gets worse over time insofar as specialized ag funds

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

have grown in importance since 2006 and insofar as the open interest in ag futures markets has a different maturity structure than in energy and futures insofar markets.

We draw instead on the granularity of the non-public CFTC data and on the notion that CIT activity has tended to concentrate in near-dated contracts. Specifically, we proxy the near-term CIT market shares in each of our seventeen commodity futures markets each week by the shares of the near-dated open interest held by swap dealer in the same market.[14]

Figure 2B plots *WMSS_AS* and *WMSA_AS*, i.e., the weighted-average market shares of swap dealers in respectively the three nearest-dated and all commodity futures. For shorter-term contracts in which CIT activity has tended to concentrate (Büyükşahin *et al*, 2009), Figure 2B shows that swap dealers' contribution to the commodity open interest increased about two-thirds between mid-2002 and early-2007. Both *WMSS_AS* and *WMSA_AS* peaked in late October 2008 before sharply falling in the following two months. In 2009, both series moved sideways with *WMSS_AS* approaching 25% of the near-dated open interest (a pattern seen from 2007 onward).

IV. Economic Fundamentals, Speculation 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 utilized a unique dataset of daily trader positions to quantify various aspects of financialization in U.S. commodity futures markets in the last decade.

A comparison of Figures 1A and 2B suggests that the patterns exhibited by swap dealers' positions do not much resemble the equity-commodity returns correlation patterns. Figure 2A, in contrast, suggests that the same is not true for hedge funds positions – especially for the positions of hedge funds that are active in both equity and commodity futures markets.

In this Section, we ask formally whether long-term fluctuations in the intensity of speculative activity or in the relative importance of some kinds of trader (in particular, hedge funds) can help explain the extent to which commodity returns move in sync with equity returns. Besides speculative activity, of course, prior literature suggests that economic fundamentals and financial market stress should influence commodity-equity return correlations. Section IV.A

[14] An alternative methodology might be to proxy CIT activity by swap dealer positions changes that are common to all near-dated commodity futures.

therefore introduces our real-sector and financial-sector controls. Section IV.B discusses our ARDL regression methodology, which tackles possible endogeneity issues as well as the fact that some of our variables are stationary in levels while others are only stationary in first differences. Section IV.C presents our regression results.

Tables III.A-B provide summary statistics for all the variables. Tables IV.A-B provide simple cross-correlations between the variables. Tables V-VIII summarize our regression results.

A. Real Sector and Financial-Market Conditions

1. Macroeconomic Fundamentals

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 crude oil price increases depends on whether the increase is the result of a demand shock or of a supply shock in the crude oil space (Kilian and Park, 2009). These empirical facts point to the need to control for real-sector factors when explaining 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 accounts for the existence of "different fixed effects for different routes, commodities and ship sizes." It is deflated with the U.S. consumer price index (CPI), and linearly detrended to remove the impact of the "secular decrease in the cost of shipping dry cargo over the last forty years." This indicator is available monthly from 1968.[15] We derive weekly estimates (which we denote *SHIP*) by cubic spline.

Table III.A contains summary statistics for *SHIP*. Figure 3, which charts its value from 2000 to 2010, shows an inverse long-term relationship between *SHIP* and our DCC estimates – suggesting that correlations increase when world demand for commodities is low.

While SHIP provides a measure of *worldwide* economic activity, U.S. macroeconomic conditions are central to U.S. equity prices and could affect commodity prices. Consequently, we also consider two macroeconomic variables that may be relevant when studying commodity-

[15] We are grateful to Lutz Kilian for providing an update of his monthly series (Kilian, 2009) through March 2010.

equity relationships. One, which we denote *ADS*, is the Aruoba-Diebold-Scotti (2008) gauge of U.S. economic activity. This measure is available at weekly frequency for the entire sample period (1991-2010). The other variable captures U.S. inflationary expectations and the intuition that commodities may provide a better hedge against inflation than equities do. We use the figures released each month by the Federal Reserve Bank of Cleveland and carry out a linear interpolation to derive weekly figures, which we denote *INF*. Table III.A provides summary statistics for these two other macroeconomic indicators.

2. *Financial Stress and Lehman Crisis*

Cross-market co-movements increase during episodes of financial stress. Hartmann, Straetmans and de Vries (2004) identify cross-asset extreme linkages in the case of 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. For commodities, Büyükşahin, Haigh and Robe (2010) show that equity and commodity markets can behave like a "market of one" during extreme events. We account for this reality in two ways.

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

Second, Figure 4 shows that the TED spread, though particularly high after the onset of the Lehman crisis, had already started rising in the previous 13 months (starting in August 2007 when a French financial group froze two funds exposed to the sub-prime market). In contrast, equity-commodity correlations did not *visibly* increase until *after* the demise of Lehman Brothers in September 2008, and remained exceptionally high through the Winter of 2010. This difference suggests that the post-Lehman sub-period is exceptional. We use a time dummy (*DUM*) to account for specificities of that sub-period which the TED spread might not capture.

B. 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 Dickey Fuller (ADF) tests. Unit root tests for the variables in our estimation equation are summarized at the bottoms of Tables III.A and III.B. They show that some of the variables are I(1) whereas the others are I(0).

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

In order to find the long run effects of different variables on commodity-equity return correlations, we use an autoregressive distributed lag (ARDL) model estimated by ordinary least squares. In this model, the dynamic conditional correlation is explained by lags of itself and current and lagged values of a number of regressors (fundamentals as well as traders' positions). The lagged values of the dependent variable are included to account for slow adjustment of the correlation between commodities and equities. This approach also allows us to calculate the long-run effect of the regressors on the correlation. If our correlation measure is, in fact, stationary, then the ARDL model, estimated by OLS, should give us consistent parameter estimates. If our DCC variable is non-stationary, as suggested by the ADF test statistics, then both short-run and long run parameters in the ARDL model can be consistently estimated by OLS if there is a cointegrating relationship (Pesaran and Shin (1999)).

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

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

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

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

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

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

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

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

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

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

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

C. Regression Results

Tables V to VIII sumarize our regression results. Table V establishes the explanatory power of economic fundamentals (*SHIP* and, to a lesser extent, *ADS*) and financial stress (*TED*).

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

Table VI establishes the additional explanatory power of speculation and hedge fund activities. Tables VII and VIII present some of our robustness checks.

1. Real sector and financial stress variables

Panels A and B in Table V show that, for our sample period (2000-2010) as well as for an extended period (1991-2000, starting when the GSCI first became investable but before the start of our detailed position dataset), the commodity-equity DCC measure is statistically significantly negatively related to *SHIP*. Insofar as *SHIP* captures world demand for commodities, this finding confirms the intuition that cross-market correlations increase in globally bad economic times.

Our two U.S. macroeconomic indicators (*ADS* and *INF*) have less explanatory power. The coefficient for *ADS* is consistently positive but is not always statistically significant. Intuitively, if equities and commodities respond differently to high inflation, then *DCC* and *INF* should be negatively related. Column 7 of Panel A (using data from 1991-2010) supports this prediction. In most of our other regressions, however, *INF* is not statistically significant. As Gorton and Rouwenhorst (2006) note, asset returns are volatile relative to inflation; consequently, longer-term correlations better capture the inflation properties of commodity and equity investments. The lack of significance of *INF*, especially in regressions using data from 2000-2010 only, may therefore be a mere artifact of sample length.

All of our models include a variable capturing momentum in equity markets (denoted *UMD*). This variable always has a positive coefficient (consistent with the notion that equity momentum could spill over into other risky assets such as commodities) but we never find *UMD* to be a statistically significant explainer of commodity-equity correlations.

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

Our ARDL estimations show that commodity-equity return correlations also have a positive long-term relationship to the *TED* variable (our proxy for stress in financial markets). In 2000-2010, a 1% increase in the TED spread brought about a 0.20 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; see Table VII).

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

2. Speculative activity and hedge fund market share

Table VI.A is key to our contribution. It shows that trading activity in commodity futures markets helps explain long-term changes in commodity-equity linkages.

Intuitively, there is no reason to expect that traditional commercial traders (oil refiners, grain elevators, etc.) should drive correlations between commodity and stock index returns. Table VI.A confirms this intuition, showing little or no explanatory power for *WMSS_TCOM*.

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

The main finding in Table VI.A is that, after controlling for economic fundamentals, it is speculative activity in commodity futures markets that helps explain 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 (*WMSS_MMT*) is associated with dynamic conditional equity-commodity correlations that are approximately 4% to 7% higher (given a mean hedge fund market share of about 25%).

Crucially, Working's "T" index of excess speculation in commodity futures markets, which aggregates the activities of *all* non-hedgers across *all* maturities, has less explanatory power than hedge fund activity in short-dated contracts. Precisely, the *WSIA* variable is often but not always significant and, when it is statistically significant, its level of statistical significance is typically lower than that of *WMSS_MMT*. A comparison of likelihood ratios supports this reading – suggesting that it is the positions of hedge funds specifically, rather than the activities of non-commercial traders in general, that help explain the correlation patterns.

3. *Cross-market trading*

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

4. *Interaction between hedge funds and financial stress*

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

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

5. *Implications for portfolio management*

Our results suggest that non-public information on the composition of commodity futures open interest (or, more generally, the make-up of trading activity in financial markets) could be 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 types (commodity producer; manufacturer or refiner; wholesaler, dealer or merchant; other), etc.[18]

D. 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 this investment has, in turn, found its way into futures markets through commodity swap dealers. In our regressions, however, we never find the *WMSS_AS* variable (which measures commodity swap dealers' market share in short-dated contracts) to be statistically significant and positive.

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

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

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

[18] It is worth noting that *WMSA_MMT* and *WSIA* (but not *WMSS_MMT*) can, after 2006, be constructed on the basis of the CFTC's COT reports. In other words, some of the information that we show matters is publicly available.

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

Table VII repeats the analysis of Table VI except that we measure speculative activity and different traders' market shares using position information across all maturities (rather than just the three nearest-maturity contracts with non-trivial open interest). The statistical significance of all the position variables drops dramatically, except for the variable capturing hedge fund activity (*WMSA_MMT* is sometimes significant at the 5% level). Again, Table VII shows little statistical evidence that swap dealers or traditional commercial traders affect the dynamic cross-market correlations.

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

3. *The Lehman crash*

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

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

Table VIII provides additional evidence of robustness. It repeats the analysis of Table VI, 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 VIII are qualitatively similar to those in Table VI. 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 VI, 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.

V. Conclusion and Further Work

Over the course of the past two decades, the strength of commodity-equity linkages has fluctuated substantially. The last decade also witnessed growing commodity-market activity by hedge funds, commodity index traders, and other financial traders. These facts provide fertile grounds to analyze whether the make-up of trading activity helps explain the joint distribution of commodity and equity returns.

To ascertain whether *who* trades matters for asset pricing, we use non-public trader-level information from the CFTC. We create a daily dataset of all large trader positions in seventeen U.S. commodity and equity futures markets from 2000 to 2010. Using this uniquely detailed dataset, we present novel evidence on the financialization of commodity-futures markets. We then document that, besides macro-economic fundamentals, variations in the composition of the open interest in commodity futures markets do help explain fluctuations in the extent of commodity-equity co-movements.

We trace this explanatory power to the activities of speculators in general and hedge funds in particular – especially hedge funds that are active in *both* equity and commodity futures markets. We find that the positions of other kinds of participants commodity-futures market (swap dealers and index traders, traditional commercial traders, floor brokers and traders, etc.) do not have much explanatory power for cross-market correlation patterns – whether or not they take positions in both equity and commodity markets.

We identify two clear patterns when considering the impact of financial market stress on equity-commodity co-movements. First, both before and after Lehman Brothers' demise, we find commodity-equity correlations to be positively related to the TED spread (our proxy for financial 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* in periods of stress. Second, commodity-equity correlations soared after the demise of Lehman Brothers in Fall 2008 and remained unusually high through Spring 2010.

This last finding suggests a natural venue for further research. Our analyses in this paper establish that, in the long run, macroeconomic fundamentals, hedge fund activity, and the TED spread (a proxy for financial-market stress) help explain observed fluctuations in commodity-equity correlations. An interaction term between hedge fund activity and TED spread is also significant. Yet, in addition to those other variables, we find that a time dummy for the crisis period (September 2008 to March 2010) is always highly significant. Further research is thus needed to explain the dummy.

One possible explanation might be that, amid a crisis of historical proportion and massive uncertainty, a radical shortening of market participants' horizons could have made both equities and commodities much more (*less*) sensitive to short-term (*long-term*) economic developments. Another possibility might be that the increased financialization of commodity markets we have documented in this paper could have made commodity markets more susceptible to "financial market sentiment" – either directly (for example, if collective decisions by passive investors to exit risky markets when uncertainty rises lead to greater correlations between different risky assets) or indirectly (for example, if the prevalence of gloom among too many traders overwhelmed value arbitrageurs' willingness to take on risky positions). A companion project investigates those possibilities – in particular, whether sentiment (interacted or not with our proxies for value arbitraging and for index trading activity) helps explain the increases of equity-commodity correlations, of cross-commodity correlations and of the common component of stock returns during the Great Recession.

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Figure 1: Return Correlations between U.S. Equity *vs.* GSCI Commodity Indices

Figure 1A: Weekly Returns Correlations (DCC), January 1991 to March 2010

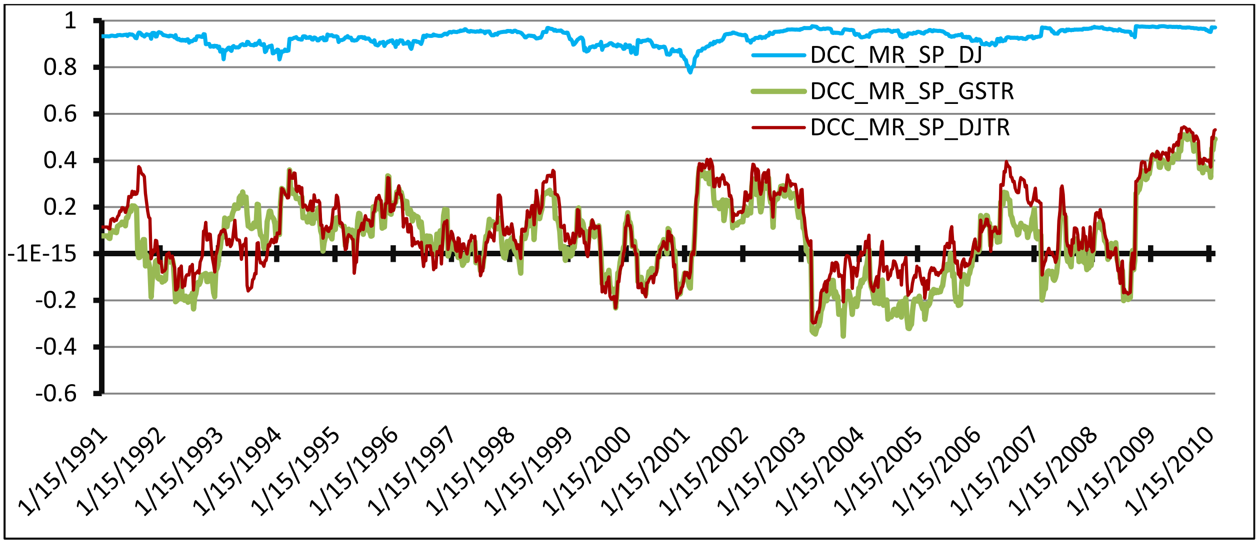
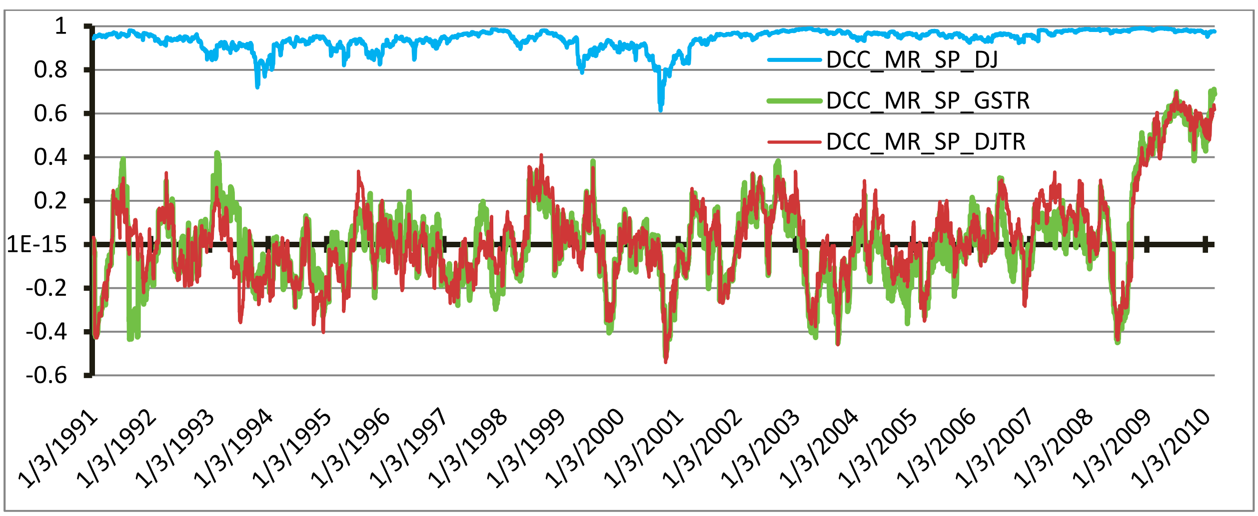


Figure B: Daily Returns Correlations (DCC), January 1991 to March 2010



***Notes*:** Figure 1A (*1B*) depicts the time-varying correlation between the **weekly (*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 Tuesday-to-Tuesday returns from January 3, 1991 to March 1, 2010.

Figure 1C: Weekly Return DCC -- World Equity *vs.* Commodity Indices, 1991 to 2010

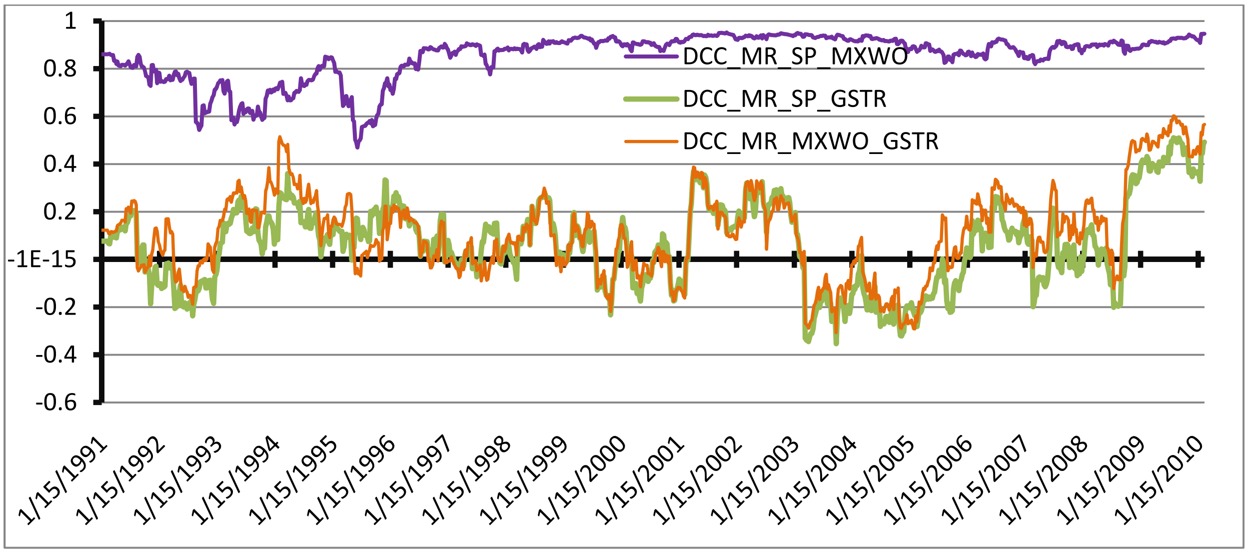
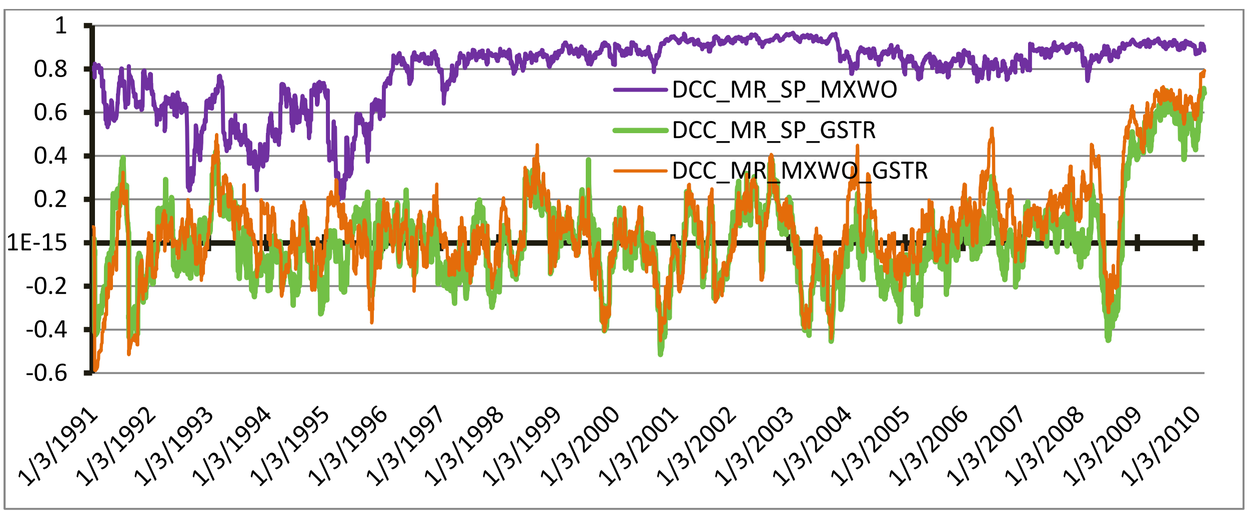


Figure 1D: Daily Return DCC -- World Equity *vs.* Commodity Indices, 1991 to 2010



***Notes*:** Figure 1C (*1D*) depicts the dynamic conditional correlations between the **weekly (*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**). 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). 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. Patterns are suimilar, though equity-commodity correlations are slightly greater when estimated with the world equity index rather than with the US equity index. After 2003, the difference between US and world correlations is typically 0.05 to 0.1.

Figure 1E: Daily Return Correlations (Rolling) -- US Equity *vs.* Commodity Indices, 1991 to 2010

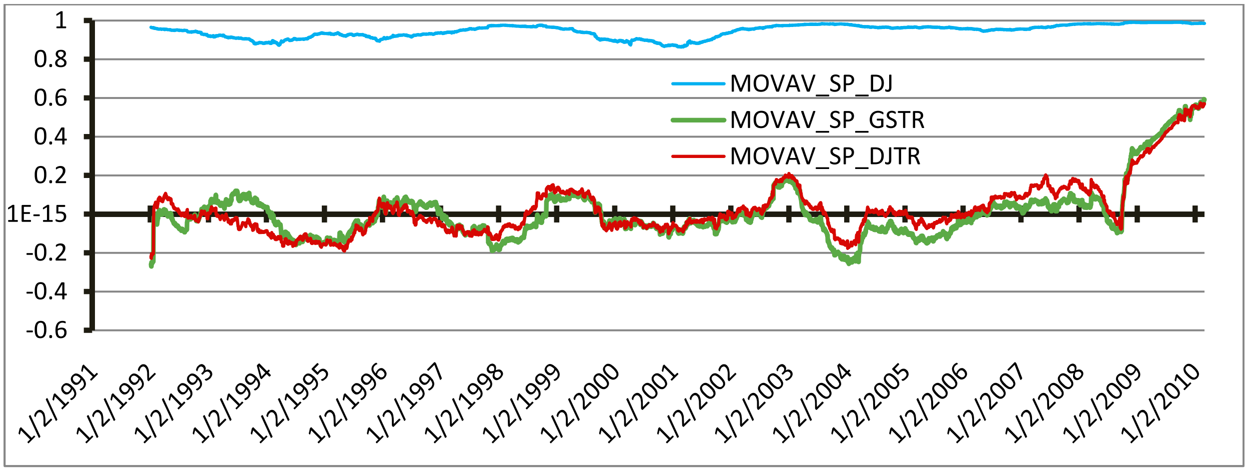
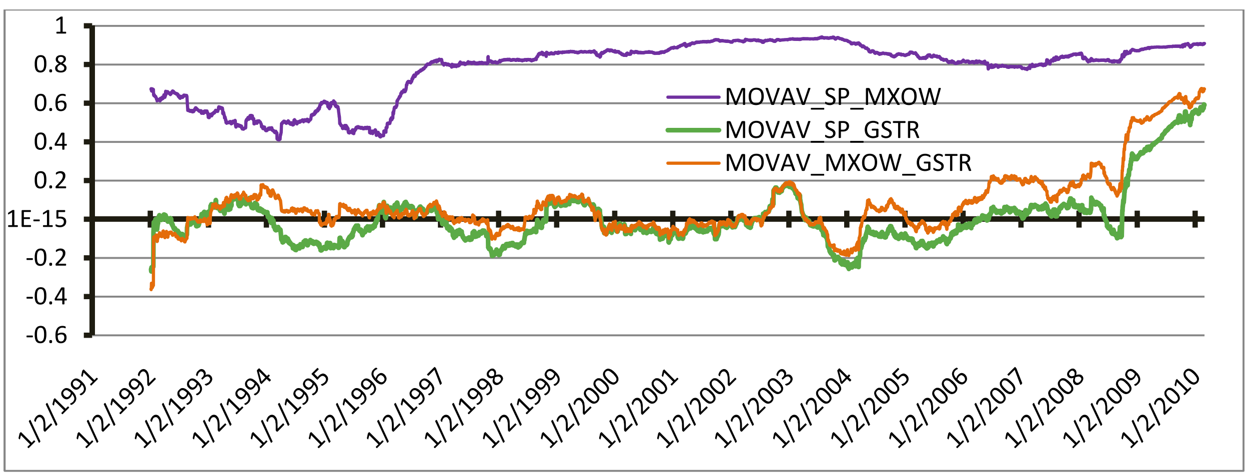


Figure 1F: Daily Return Correlations (Rolling) -- World Equities *vs.* Commodities, 1991 to 2010



Notes**:** Figures 1E and 1F depict **unconditional rolling correlations** between the **daily** rates of return on commodity indices and on U.S. (S&P 500, Fig. 1E) or world (MSCI, Fig. 1F) equity indices. Precisely, Figure 1E depicts one-year rolling correlations 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 rolling correlation between the S&P 500 equity index and the Dow Jones Industrial Average equity index (DJIA, **blue line** on top). Figure 1F depicts one-year rolling correlations 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**). As a benchmark, Figure 1F also plots the correlation between the S&P 500 US equity index and the MSCI World equity index (**purple line** on top). A comparison of, respectively, Figure 1E with Figure 1C and of Figure 1F with Figure 11D shows the importance of controlling for timve-varying variances .

Figure 2: Financialization of Commodity Markets

Figure 2A: Excess Speculation, Hedge-fund activity and Cross-Market Trading

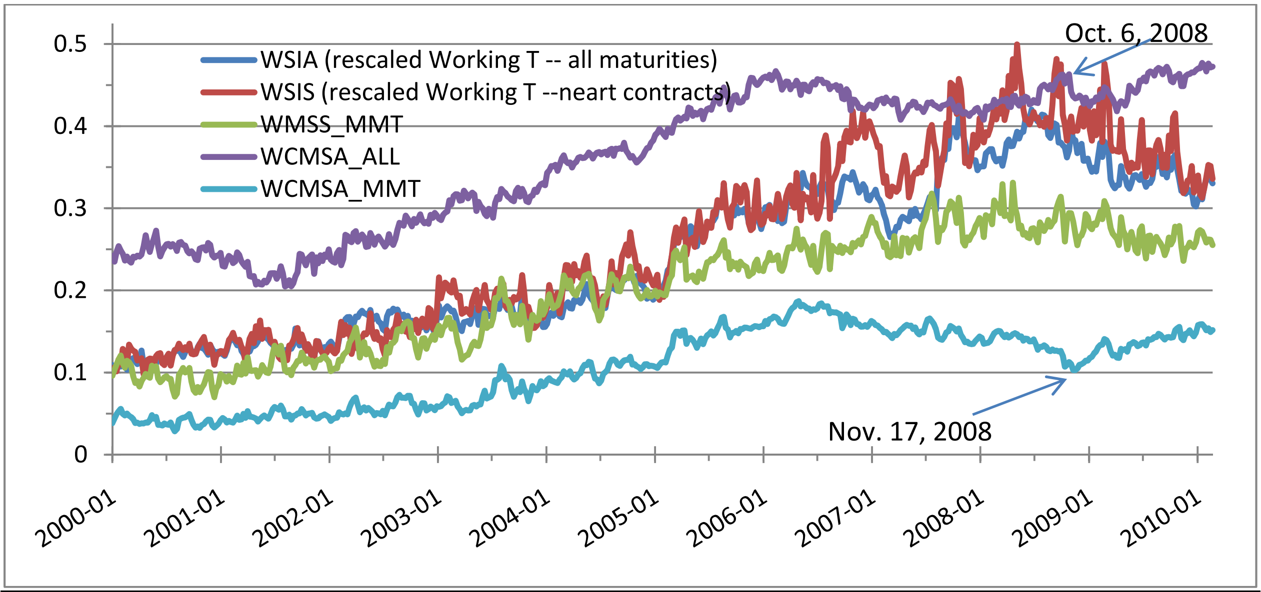
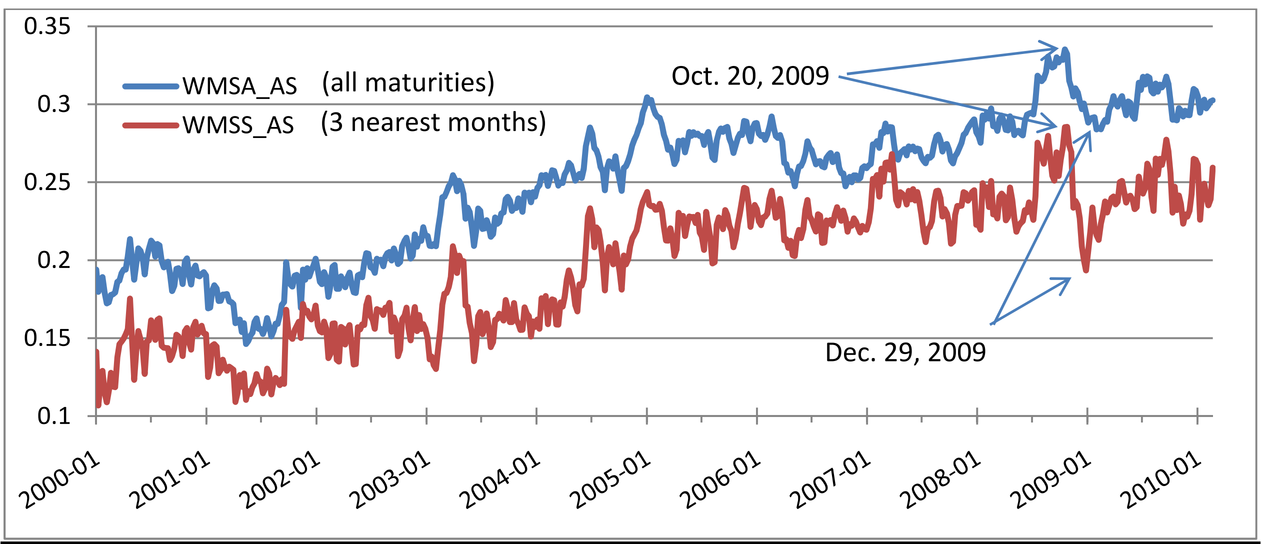
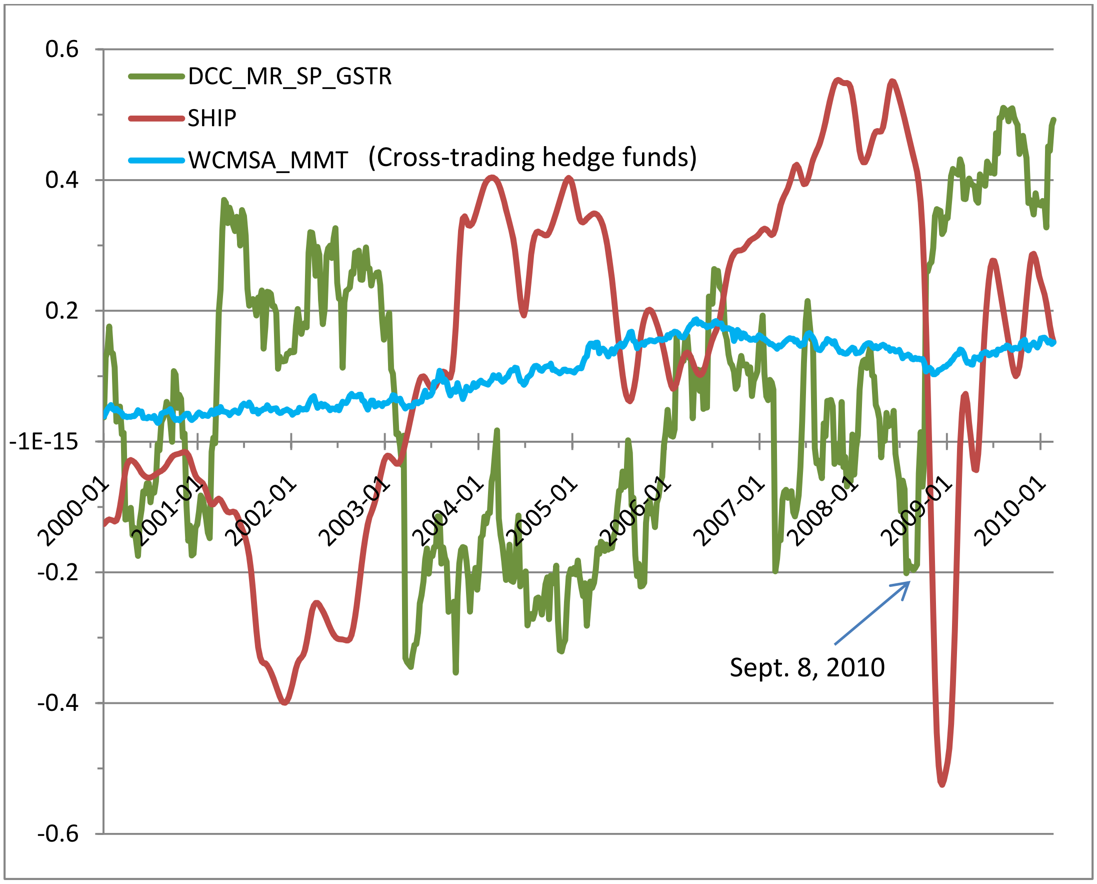


Figure 2B: Swap Dealing (including Commodity Index Trading)



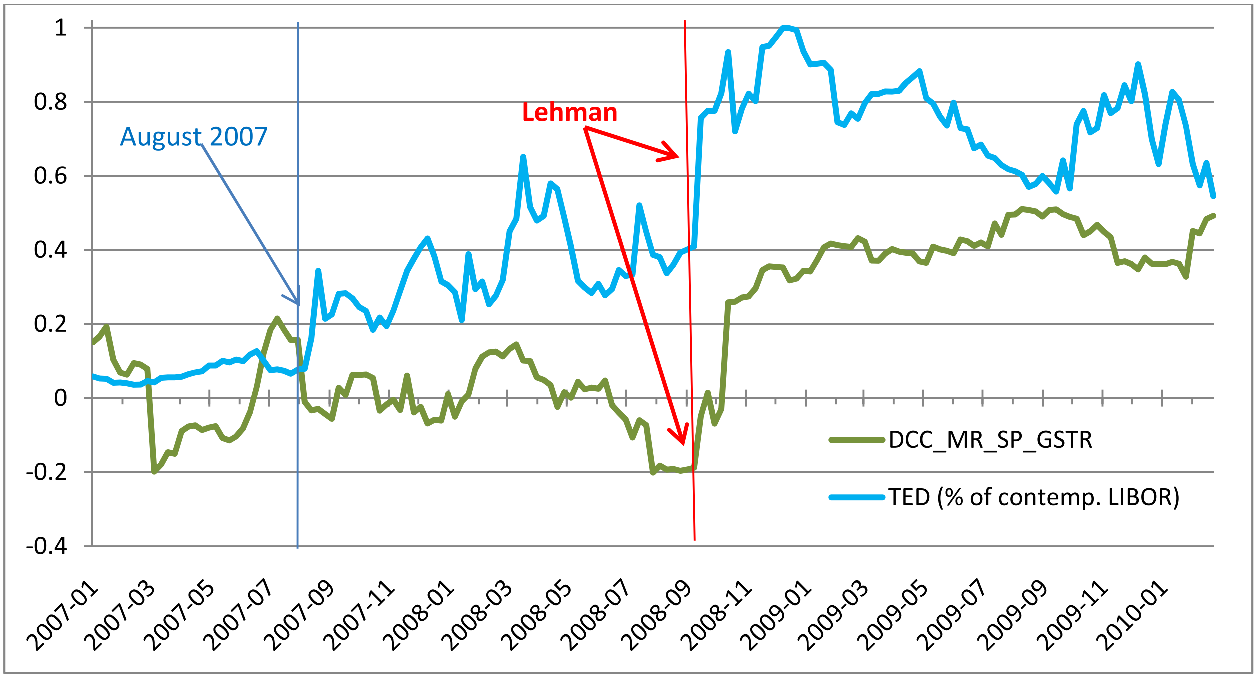
Notes**:** Figure 2A plots the weighted-average speculative pressure index ("Working's T") in the 17 U.S. commodity futures markets linked to the GSCI index in near term contracts (**dark red**, *WSIS*) or across all maturities (**dark blue**, *WSIA*).between the first week of January 2000 and the first week of March 2010. The **green line** shows the aggregate share of the short-term open interest held by hedge funds in the same commodity markets (*WMSS_MMT*). The **purple line** shows the share of the commodity futures positions held by large commodity futures traders that also trade US equity futures (*WCMSA_ALL*), and the **bright blue** line shows the market share of hedge funds that also trade US equity futures (*WCMSA_MMT*). During the same time period, Figure 2B shows the market shares of commodity swap dealers in the same 17 commodity futures markets during the last decade across all contract maturities (**dark blue**, *WMSA_AS*).or in the nearest three months (**dark red**, *WMSS_AS*).

Figure 3: Equity-Commodity Correlations, Economic Activity, and Hedge-fund Cross-Trading



***Notes*:** The **green line** in Figure 3 shows, between the first Tuesday of January, 2000 and the last Tuesday 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 use Tuesday-to-Tuesday return to estimate dynamic conditional correlations by log-likehood for mean-reverting model (*DCC_MR*; Engle, 2002). The dark **red line** (*SHIP*) shows the Kilian (2009) index of worldwide economic activity. The **blue line** shows the weighted-average proportion of hedge funds trading in U.S. commodity futures markets that also trade U.S. equity futures (*WCMSA_MMT*). A negative relationship between *SHIP* and *DCC* is clearly apparent as is, after 2003, a positive long-term relationship between *DCC* and *WCMSA_MMT*.

Figure 4: TED Spread and Equity-Commodity Correlations, August 2007 to March 2010



Notes**:** The **green line** in Figure 4 shows, between the first Tuesday of July, 2007 and the last Tuesday 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 use Tuesday-to-Tuesday return to estimate dynamic conditional correlations by log-likehood for mean-reverting model (*DCC_MR*; Engle, 2002). The **blue line** shows the the 90-day TED spread, expressed as a percentage of the contemporaneous 90-day LIBOR (Source: Bloomberg). Figure 4 shows that this TED-based measure of financial market went up an order of magnitude in the year leading up to Lehman's demise, but that equity-commodity correlations did not increase sharply until right after Lehman's demise.

Table I: 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: Table I shows the average weights of the 17 GSCI commodities (out of 24 commodities in the index) for which we have trader position data. We use these 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.

Table II: 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 II 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 III.A: Summary Statistics on Macroeconomic and Market Fundamentals, July 2000 to March 2010

	Dynamic Conditional Correlations (DCC_MR)		Macroeconomic Fundamentals			Financial Market Conditions				Excess Commodity Speculation *(Working's "T")*	
	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: Dynamic conditional correlation (DCC) are between the Tuesday-to-Tuesday unlevered rates of return (precisely, changes in log prices) on the S&P GSCI total return index (GSTR) and either the S&P 500 equity index (SP) or the MSCI World equity index (MXWO). DCC estimated by log-likehood for mean-reverting model (Engle, 2002). **SHIP** is a measure of worldwide economic activity (Kilian, 2009). **ADS** is a measure of U.S. economic activity (Aruoba, Diebold and Scotti, 2008). INF measures expected inflation (source: Federal Reserve). **LIBOR** and **TED** are the 90-day annualized LIBOR rate and Ted spread (source: Bloomberg). **UMD** is the Fama-French momentum factor for U.S. equities. Excess commodity speculation for the three nearest-term futures (**WSIS**) and all contract maturities (**WSIA**) is the weigthed-average 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). 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: June 26, 2000 to February 26, 2010.

Table III.B: Summary Statistics on Positions by Trader Types (Short-dated Commodity Futures), July 2000 to 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: June 26, 2000 to February 26, 2010.

Table III.C: Summary Statistics of Positions by Trader Type (All Maturities), July 2000 to March 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***
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: **WMSA_MMT**, **WMSA_NON**, **WMSA_AS**, **WMSA_ANC** and **WMSA_TCOM** stand, respectively, for the weighted-average shares of the overall futures open interest across ***all*** futures contract maturities 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 III.A, 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: June 26, 2000 through February 26, 2010.

Table III.D: Equity-Commodity Cross-Trading Activity, 2000-2010

Commodity	Classifications in Commodity Markets						Equity Futures Classification	
	All Cross-Market Traders		Commodity Swap Dealers		Hedge Funds		Hedge Funds	
	Count	% of all traders	Count	% of all cross-traders	Count	% of all cross-traders	Count	% of all cross-traders
Cocoa	417	10.5%	29	7.0%	218	52.3%	168	40.3%
Coffee	619	15.6%	37	6.0%	298	48.1%	236	38.1%
Copper	679	17.2%	29	4.3%	290	42.7%	227	33.4%
Corn	786	19.9%	27	3.4%	322	41.0%	256	32.6%
Cotton	587	14.8%	38	6.5%	314	53.5%	245	41.7%
Crude Oil	1108	28.0%	63	5.7%	363	32.8%	274	24.7%
Feeder Cattle	129	3.3%	15	11.6%	66	51.2%	57	44.2%
Gold	1058	26.7%	43	4.1%	366	34.6%	275	26.0%
Heating Oil	335	8.5%	26	7.8%	170	50.8%	138	41.2%
Kansas Wheat	251	6.3%	21	8.4%	142	56.6%	114	45.4%
Lean Hogs	426	10.8%	23	5.4%	229	53.8%	183	43.0%
Live Cattle	469	11.9%	24	5.1%	242	51.6%	196	41.8%
Natural Gas	743	18.8%	49	6.6%	300	40.4%	235	31.6%
Silver	604	15.3%	35	5.8%	249	41.2%	201	33.3%
Soybeans	742	18.7%	31	4.2%	305	41.1%	247	33.3%
Sugar	453	11.4%	38	8.4%	230	50.8%	178	39.3%
CBOT Wheat	704	17.8%	27	3.8%	311	44.2%	246	34.9%
Median		15.0%		5.9%		49.4%		38.7%

Notes: For seventeen commodity futures markets, Table III.D provides information on the number and relative importance of the subset of large commodity futures traders who also held, at some point in the sample period (July 1, 2000 through February 26, 2010), positions in the S&P500 e-Mini equity futures contract.

Table IV.A: Simple Correlations, 2000-2010 (*Dependent and Explanatory Variables*)

	DCC_MR SP_GSTR	DCC_MR MXWO_GSTR	SHIP	ADS	VIX	LIBOR	TED	INF	WSIS	UMD	WMSS_AS	WMSS_ MMT	WMSS_ TCOM	WCMSA_ ALL
DCC_MR_ SP_GSTR	1.0000													
DCC_MR_ MXWO_GSTR	0.9576***	1.0000												
SHIP	-0.4463***	-0.2839***	1.0000											
ADS	-0.3070***	-0.3284***	0.3058***	1.0000										
VIX	0.4916***	0.4464***	-0.5028***	-0.6855***	1.0000									
LIBOR	-0.1824***	-0.1455***	0.1422***	0.0464	-0.2890***	1.0000								
TED	0.0823*	0.2085***	0.1876***	-0.5504***	0.5031***	0.2026***	1.0000							
INF	-0.1912***	-0.2836***	-0.1728***	0.3263***	-0.3869***	0.6692***	-0.2580***	1.0000						
WSIS	0.1930***	0.4073***	0.5488***	-0.2747***	0.0653	0.0605	0.5525***	-0.5043***	1.0000					
UMD	0.0030	-0.0101	-0.0405	0.0869**	-0.0168	0.0167	-0.1045**	0.0949**	-0.0852*	1.0000				
WMSS_AS	0.0331	0.2245***	0.5787***	-0.0579	-0.0668	0.0134	0.4090***	-0.4233***	0.8394***	-0.0779*	1.0000			
WMSS_MMT	0.1045**	0.3240***	0.6183***	-0.1452***	-0.0354	-0.0235	0.4613***	-0.5307***	0.9511***	-0.0694	0.8599***	1.0000		
WMSS_TCOM	-0.0713	-0.2883***	-0.6143***	0.1325***	0.0205	0.0608	-0.4581***	0.5489***	-0.9472***	0.0800*	-0.9274***	-0.9726***	1.0000	
WCMSA_ALL	0.0572	0.2756***	0.6151***	-0.0097	-0.1429***	-0.0085	0.3410***	-0.4750***	0.8860***	-0.0745*	0.9263***	0.9346***	-0.9577***	1.0000

Note: Table IV.A shows the simple correlations of the variables in our regression analyses. Stars (*,**,***) highlight correlations that are statistically significantly different from 0 at, respectively, the 10%, 5% and 1% levels of statistical significance. The dependent variables (DCC_MR) are described in the footnote to Figures 1A (SP_GSTR) and 1B (SP_MXWO). The DCC measures are described the footnotes to Table III. Sample period: June 26, 2000 through February 26, 2010.

Table IV.B: Simple Correlations, 2000-2010 *(Speculation)*

	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						
WSIA	0.2166***	0.9738***	1.0000					
WMSS_AS	0.0331	0.8394***	0.8583***	1.0000				
WMSS_MMT	0.1045**	0.9511***	0.9379***	0.8599***	1.0000			
WCMSA_ALL	0.0572	0.8860***	0.9025***	0.9263***	0.9346***	1.0000		
WCMSA_MMT	0.0370	0.8404***	0.8570***	0.8305***	0.9102***	0.9446***	1.0000	
WCMSA_AS	0.0204	0.7749***	0.7922***	0.9095***	0.8134***	0.9119***	0.7405***	1.0000

Note: Table IV.B shows the sample correlations of the left-hand side variable (DCC_MR) and some of the explanatory variables in our regression analyses. Stars (*,**,***) highlight correlations that are statistically significantly different from 0 at, respectively, the 10%, 5% and 1% levels of statistical significance. The dependent variable (DCC_MR) is described in the footnote to Figure 1A. The DCC measure is described the footnotes to Table III.A. Sample period: June 26, 2000 through February 26, 2010.

Table V: 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)
Log likelihood	811.133	855.65	1656.98	811.218	857.236	1658.69	813.068	856.317	1657.7

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 III.A. 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 V: Market Fundamentals as Long-run Determinants of the GSCI-S&P500 Dynamic Conditional Correlation

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

	Model 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	-0.00925942	-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)
Log likelihood	859.856	1663.9	862.685	1664.68	861.654	1664.06

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 III.A, except for *DUM* – a time dummy that takes the value *DUM*=0 prior to September 1, 2008 and *DUM*=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.

<u>Table VI – Panel A: Speculative Activity as a Long-run Contributor to the GSCI-S&P500 Dynamic Conditional Correlation</u>

	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 ***		2.99394		1.64474 **		3.24842 ***
		(1.048)		(1.842)		(0.8008)		(1.057)
INT_TED_MMT	-8.19136 **		-7.71792 **		-5.22160 **	N.A.	-4.16390 **	
	(3.651)		(3.543)		(2.409)	N.A.	(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)
Log likelihood	867.929	861.365	868.866	862.06	871.537	865.766	874.812	868.424

<u>Notes:</u> The dependent (equity-commodity weekly return DCC) and most of the explanatory variables are described in Tables III.A to III.C. *DUM* is a time dummy for the post-Lehman period (Septemer 2008 to March 2010). Long-run estimates are from a 2-step ARDL(*p*,*q*) estimation (Pesaran and Shin, 1999). The Schwarz information criterion suggests optimal lag lengths *p*=1 and *q*=1. Sample period: July 1, 2000 to February 26, 2010.

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

	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			
	(8.375)		(8.591)		N.A.		(5.354)		(3.072)			
INT_TED_WSIA					-4.19862	*					-1.85232	*
					(2.280)						(1.026)	
DUM							0.356019	**	0.612165	***	0.523899	***
							(0.1430)		(0.1104)		(0.09996)	
Log lik.	869.216		869.797		862.067		871.446		877.968		870.883	

Notes: The dependent variable, most of the dependent variables and the methodology are described in Table VI.A. *INT_TED_CMMTA* and *INT_TED_WSIA* are interaction terms of the TED spread with, respectively, the weekly shares of open interest held by cross-market trading hedge funds (MMT) and swap dealers (AS). Sample period: July 1, 2000 to February 26, 2010.

Table VII: 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 Tables VI.A and VI.B. 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.

Table VIII: 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 Tabls 6A-6B. 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: Defining Hedge Funds.

"Hedge fund" activity in commodity derivatives markets has been the subject of intense scrutiny. Yet, there is no accepted definition of a "hedge fund" in futures markets, and there is nothing in the U.S. statutes governing futures trading that defines a hedge fund.

Still, many hedge fund complexes are either advised or operated by CFTC-registered Commodity Pool Operators (CPOs) or Commodity Trading Advisors (CTAs) and Associated Persons (APs) who may also control customer accounts. Through its LTRS, the CFTC therefore obtains positions of the operators and advisors to hedge funds, even though it is not a requirement that these entities provide the CFTC with the name of the hedge fund (or another trader) that they are representing.[19]

Clearly, many 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.

[19] 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.