Speculation, Commodities and Cross-Market Linkages

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March 18th, 2013

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Abstract

Using a public dataset of trader positions in 17 U.S. commodity futures markets, we compute an index of "excess" speculation (speculative activity beyond meeting net hedging demand) to provide evidence of those markets' financialization during the past decade. Controlling for commodity supply and demand fundamentals, we show that this index helps predict the dynamic conditional correlation between the rates of return on commodities and on equities. The predictive power of the speculative index is weaker in periods of generalized financial market stress. Our results support the notion that *who* trades helps predict the joint distribution of commodity and equity returns.

Introduction

In the past decade, financial institutions have assumed an ever greater role in commodity futures markets. We use aggregate position data published by the U.S. Commodity Futures Trading Commission (CFTC) to provide evidence of this "financialization" and to document its association with an important aspect of the joint distribution of commodity and equity returns.

Since Friedman (1953), a large body of work has investigated whether the composition of trading activity (i.e., *who* trades) matters for asset pricing. In particular, 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 financial traders like hedge funds are less constrained than other kinds of market participants (Teo, 2009) and as commodity markets have historically been partly segmented from other financial markets (Bessembinder, 1992), this theoretical argument suggests that increased speculative activity – especially if it reflects the arrival of traders not previously active in commodity markets – could strengthen cross-market linkages.

In a related vein, though, the same traders who help link markets in normal times often face, in periods of financial market stress, borrowing constraints and sundry other pressures to liquidate risky positions. In that case, 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 – see, e.g., Kyle and Xiong (2001), Kodres and Pritsker (2002), Broner, Gelos & Reinhart (2006), Pavlova and Rigobon (2008) and Danielsson, Shin & Zigrand (2011a-b). Finally, in the aftermath of a shock, reduced activity by value arbitrageurs or convergence traders could in turn lead to a decoupling of markets that they had helped link in the first place.

In this paper we present empirical evidence that, after controlling for macroeconomic and commodity-market fundamentals, an index of speculative activity in commodity futures markets helps predict commodity-equity cross-market linkages. This predictive power varies over time. Strikingly, it is weaker during periods of turmoil in financial markets. These findings contribute to the debate on the implications of the "financialization" of commodity markets.

In general, testing whether specific types of traders contribute to cross-market linkages is difficult because doing so requires detailed information about the trading activities of all market

participants, as well as knowledge of each participant's main motivation for trading. We overcome this empirical pitfall by utilizing a public dataset of futures trader positions in 17 U.S. commodity markets between July 2000 and March 2010. The underlying raw data, which are non-public, originate from the CFTC's large trader reporting system (LTRS). The LTRS contains information on the end-of-day positions of every large trader in each of these 17 markets, as well as information on each trader's main line of business and purpose for trading. The position information is comprehensive; the LTRS information on business lines covers well over 75% of the total open interest in the largest U.S. commodity futures markets (Fishe and Smith, 2012).

We focus on the linkages between commodity and equity markets for several reasons. First, we need comprehensive data on positions 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 (Kofman, Michayluk and Moser, 2009) – and it is precisely about the futures open interest that we have 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) predicts those fluctuations.[2] Third, we seek to add not only to the asset pricing literature but also to a fast-growing literature on the financialization of commodity markets – see, e.g., Acharya, Lochstoer & Ramadorai (2011), Brunetti, Büyükşahin & Harris (2011), Brunetti and Reiffen (2011), Büyükşahin, Haigh, Harris, Overdahl & Robe (2009), Büyükşahin and Robe (2010), Cheng, Kirilenko & Xiong (2012), Etula (2010), Hamilton and Wu (2012), Henderson, Pearson & Wang (2012), Hong and Yogo (2012), Irwin and Sanders (2012), Kilian and Murphy (2012), Korniotis (2009), Singleton (2013), Stoll and Whaley (2010), or Tang and Xiong (2012).

This paper contributes to the debate on the financialization of commodities by identifying a relationship between financialization and the intensity of cross-market linkages. Specifically, we show that variations in the make-up of the commodity futures open interest help predict long-term fluctuations in commodity-equity return co-movements. We employ ARDL regressions,

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[2] 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 suggests that returns on commodity futures are driven by commodity-specific hedging pressures as well as 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 correlations between the rates of returns on equities and on commodites have historically varied considerably over time around unconditional means close to zero – see also Gorton and Rouwenhorst (2006).

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 an increase in "excess speculation" – a measure of speculative activity over and above the gap between the positions of long and short hedgers – is associated, *ceteris paribus*, with a statistically and economically significant increase in equity-commodity return correlations.

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, financial traders 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 speculators during financial stress ("high TED") episodes is statistically significant and negative. In other words, the predictive power of speculative 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 2010. Over and above the predictive 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 discusses 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 speculative 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 can help predict some aspects of asset return patterns and that the predictive 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 on whether the financialization of commodity markets in the past decade affects the levels or distributions of commodity prices.

Several recent papers investigate the impact of financial speculation on commodity prices or returns. Using various techniques, Büyükşahin and Harris (2011), Hamilton (2009), Korniotis (2009), Irwin and Sanders (2012) and Kilian and Murphy (2012) conclude that fundamentals, not speculation, were most likely behind the 2004-2008 boom-bust commodity price cycle.

A number of other studies look at the impact of financialization through the lens of risk premia in commodity markets. Hong and Yogo (2012) argue that the growth – rather than the composition – of the commodity futures open interest helps predict commodity returns. Other studies suggest that who trades matters in that they find that the risk-bearing capacities of broker-dealers (Etula, 2010), the risk appetites of commodity producers (Acharya *et al*, 2011), or the influx of commodity index traders (Brunetti and Reiffen, 2011; Hamilton and Wu, 2012; Singleton, 2013) play significant roles in the determination of commodity risk premia.

All the above papers focus on price levels, returns or risk premia. We focus instead on commodity returns' correlation with equity returns. The extent to which this statistic is predicted by the activities of financial players, and the extent to which commodity returns and other asset returns might be increasingly responding to common factors, are clearly important to commodity market participants who use futures to hedge some underlying commercial exposures. Similarly, correlations matter to portfolio managers' risk-return optimizations and diversification decisions.

We show that the composition of the commodity open interest is an important predictor of cross-market co-movements. Consistent with the theoretical models mentioned in the introduction, we identify the relative importance of commercial and non-commercial traders as mattering for cross-market linkages. We also show that, during periods of stress in financial markets, the predictive power of speculative activity is weaker.

Related to our query are two studies that exploit publicly available data to investigate the possible impact of commodity index trading (CIT) on cross-commodity return correlations in the past decade. One of those studies finds a CIT impact (Tang and Xiong, 2012); the other concludes that there is no causal relationship (Stoll and Whaley, 2010).

Unlike those papers, our focus is on 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 we analyze and how we measure financial activity in commodity markets. Specifically, whereas those two papers focus on commodity index traders (CITs), we focus on the relative magnitude of spec activity *vs.* net hedging demand.

Our results complement those of Büyükşahin and Robe (2011). That study uses non-public CFTC position data to analyze energy-commodity market linkages. Rather than focus on energy futures markets, we construct measures of trader activity covering 17 commodities in six different commodity groups. We then use this broad-based information to show that not only fundamental macroeconomic variables, but also the intensity of speculation in commodity paper markets, predict the extent to which commodity and equity returns move together. We show, furthermore, that the predictive power of "excess" speculation depends on the level of stress in financial markets. Specifically, we show that *who* trades matters less in periods of financial market stress.

This last finding provides empirical support for theoretical papers on limits to arbitrage.[3] It also links our paper to earlier work on financial *vs.* fundamental drivers of cross-border market linkages. Part of that economics literature asks if financial shocks are propagated 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 if, instead, shocks spill over through real economy linkages such as trade relationships (e.g., Forbes and Chinn, 2004). Our paper presents an interesting counterpoint in commodity markets by showing that, when the TED spread signals elevated levels of financial stress, higher relative spec activity is associated *ceteris paribus* with weaker (rather than stronger) equity-commodity return correlations.

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

We seek to ascertain whether, in addition to economic fundamentals, commodity-market participation by certain types of traders helps predict the extent to which smaller "satellite" asset markets (here, commodity futures) moves together with a "core" asset market (U.S. equities).

Several papers document fluctuations in the extent to which commodities co-move with one another or with financial assets over time – see, e.g., Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Büyükşahin, Haigh and Robe (2010), Chong and Miffre (2010), Stoll and

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

Whaley (2010), Tang and Xiong (2012) and Silvennoinen and Thorp (2013). This Section complements and extends those studies beyond the immediate post-Lehman period. It provides summary statistics for equity and commodity index returns and plots estimates of the dynamic conditional correlation (DCC, Engle 2002) between equity and commodity index returns.

A. Commodity and Equity Return Data

We use daily and weekly returns on benchmark commodity and stock market indices.[4] 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 24 nearby commodity futures contracts. Because it uses weights that reflect each commodity's worldwide production figures, it is heavily tilted toward energy (see Table I). In robustness checks, we therefore use another widely used unlevered investable benchmark, the Dow-Jones-UBS Commodity Index Total Return (DJ-UBSCITR; DJ-AIGTR till May 2009). This rolling index covers 19 physical commodities in our sample period and offers a more "diversified benchmark for the commodity futures market." We find similar results for the GSCI and DJ-UBS indices, and therefore we mainly discuss the GSCI.

For equities, we use 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.[5] For comparison purposes, we also provide figures for the (generally slightly higher) correlations between the GSCI and the MSCI World Equity index (MSCI).

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

[5] Our equity index returns omit dividends and, hence, underestimate actual returns (Shoven and Sialm, 2000). However, insofar as large U.S. corporations either smooth dividend payments over time (Allen and Michaely, 2002) or do not pay dividends, the correlation estimates that are the focus of our paper should be essentially unaffected.

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 than the return 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, as also noted by Büyükşahin, Haigh and Robe (2010), the rank-ordering of the returns on the two asset classes fluctuates dramatically over time: whereas equities massively outperformed commodities in 1992-1997, the reverse happened in 2003-2008. At the very least, these differences show that equities and commodities do not move in lockstep.

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 and 1B. First, in the 18 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 – but the range was smaller. 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 *until* September 2008.

D. Discussion

Our finding that there was no obvious secular increase in commodity-equity correlations prior to the Fall of 2008 is in line with the conclusions of Büyükşahin, Haigh and Robe (2010) and Tang and Xiong (2012) using weekly or daily data from an earlier sample period. It is also consistent with contemporaneous findings (Chong and Miffre, 2010; Silvennoinen and Thorp, 2013) 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.

We use a U.S. stock index (the S&P 500) rather than a global stock market index to compute equity-commodity correlations. We do so for two reasons. 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 Fall 2008, we now turn to the task of predicting the fluctuations depicted in Figures 1A and 1B. Do market fundamentals alone predict the observed patterns – or are the latter related to the financialization of commodity futures markets? The next two sections seek to answer these questions.

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

In most U.S. commodity futures markets, the open interest was much greater as of 2010 than a decade earlier. We utilize a public dataset of trader positions in 17 futures markets to document that this growth entailed a structural changes in the composition of the overall open interest. Section III.A describes the position data.[6] Section III.B establishes that, compared to commercial activity, overall speculative activity increased very substantially after 2002. This information provides the foundation for the analyses of Section IV, in which we examine whether participatory changes have predictive power for equity-commodity returns linkages.

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. *Public Data on the Purpose and Magnitude of Trader Positions*

For every U.S. futures market with a certain level of market activity, the CFTC's weekly

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[6] Only a handful of other studies use the CFTC's disaggregated, non-public position data: see footnote 3 in Section I.

COT reports provide information on the composition of the open interest. In particular, those COT reports break down the total open interest 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." A trading entity generally gets all of its futures and options positions in a given commodity 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" as defined in CFTC regulations.[7] The "non-commercial" group aggregates various types of mostly financial traders, such as hedge funds, mutual funds, floor brokers, etc.

Since September 4, 2009, COT reports differentiate between four (not two) trader types. They split commercials between "traditional" commercials (producers, processors, commodity wholesalers or merchants, etc.) and commodity swap dealers (in most markets, this category includes CITs). They also now differentiate between managed money traders (i.e., hedge funds) and "other non-commercial traders" with reportable positions.[8] As of March 2013, however, the CFTC has not published plans to make this more detailed information available retroactively prior to 2006 or to break down the aggregate position information by contract maturity.

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").

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 always exactly balanced, then their positions would always offset one another and speculators might 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

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[7] 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.
[8] COT reports also provide data on the positions of non-reporting traders (speculators, prop and other small traders).

extent to which speculation is in "excess" of 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). Despite its possibly confusing name, it is worth noting that "excess" speculation thus defined may not be "excessive" in that some "excess" speculation may be economically necessary in the presence of friction such as the mismatch in timing and maturity of trading contracts.

For each of the 17 commodities in our sample ($i = 1, 2, \ldots, 17$), we calculate Working's T every Tuesday from 2000 to 2010 for all maturities ($SIA_{i,t}$). Formally, in the ith commodity market in week t:

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

where $SS_i \geq 0$ is the (absolute) magnitude of the short positions held in the aggregate by all non-commercial traders ("<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 17 commodity futures markets in our sample:

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

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 17 U.S. markets (out of 24 GSCI markets) for which the LTRS position data are available. Table I lists the annual commodity weights per commodity, per year.

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

Table III provides summary statistics of the weighted average speculative index (*WSIA*) from July 2000 to March 2010. During that period, the minimum *v*alue was 1.11 for both short-

term and all contracts; the maximum was 1.42 across all maturities. In other words, speculative positions were on average 11% to 42% greater than what was minimally necessary to meet net hedging needs at the market-clearing prices.

Figure 2 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.[9] Notably, excess speculation fell after 2008. An interesting question, the answer to which would require more disaggregated data than are publicly available, is whether excess speculation in near-dated contracts is greater than it is further out on the maturity curve.

In sum, Figure 2 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.

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 provided a speculative activity index to summarize various aspects of financialization in U.S. commodity futures markets in the last decade.

Figure 2 suggests that the patterns exhibited by the index of "excess" speculation bear at least some resemblance with the equity-commodity returns correlation patterns. In this Section, we ask formally whether long-term fluctuations in the intensity of speculative activity can help predict 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 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. Table IV provides simple cross-correlations between the macro variables. Tables V-VIII summarize our regression results.

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[9] 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), values of 1.05-2.34. See also Irwin, Merrin and Sanders (2008).

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 increases are 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 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. We derive weekly estimates (which we denote *SHIP*) by cubic spline.

Table III 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-equity relationships. One, denoted *ADS*, is the Aruoba-Diebold-Scotti (2009) gauge of U.S. economic activity. It is available weekly 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, denoted *INF*. Table III provides summary statistics for these two macroeconomic indicators.

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2. Financial Stress and Lehman Crisis

Cross-market co-movements increase amid 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. Similarly, Longin and Solnik (2001) find that international equity market correlations increase in bear markets. For commodities, Büyükşahin, Haigh and Robe (2010) show that commodity and equity markets 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 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. They remained exceptionally high through the end of our sample in 2010. This difference suggests that the post-Lehman period is exceptional. We use a time dummy (*DUM*) to account for specificities of this sub-period that the TED spread might not capture.

B. Methodology

Before testing the predictive 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 rest 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) and at the 10% level of significance for a sub-sample ending prior to the demise of Lehman Brothers (2000 to September 2008).[10]

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[10] 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

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 DCC 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 still be consistently estimated by OLS if there is a single 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:

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

where y is a $t \times 1$ vector of the dependent variable, x is a $t \times k$ vector of regressors, and ω stands for a $t \times s$ vector of deterministic variables such as an intercept, seasonal dummies, time trends, or exogenous variables with fixed lags.[11] In vector notation, Equation (1) is:

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 10% significance level.

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

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

where $\gamma(L)$ is the polynomial lag operator $1 - \gamma_1 L - \gamma_2 L^2 - ... \gamma_p L^p$; $\alpha(L)$ is the polynomial lag operator $\alpha_0 + \alpha_1 L + \alpha_2 L^2 + ... + \alpha_q L^q$; 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:

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

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

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 predictive power of economic fundamentals (*SHIP* and, to a lesser extent, *ADS*) and financial stress (*TED*). Table VI establishes the additional predictive power of speculative activities.

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 predictor 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 graphical evidence (see Section II) that this sub-period is exceptional.

Our ARDL estimates show that commodity-equity return correlations also have a positive long-term relationship to our proxy for stress in financial markets (*TED*). 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; table available upon request).

Interestingly, Panel A suggests that *TED* was not a significant factor in 1991-2000. The difference in the TED spread's importance in those two successive decades suggests a possible role for trading activity. We next turn to this issue.

2. *Speculative activity*

Table VI shows that trading activity in commodity futures markets helps predict long-term changes in commodity-equity linkages. Specifically, after controlling for economic

fundamentals, "excess" speculation in commodity futures markets helps predict the fluctuations in the commodity-equity DCC estimates over time. *Ceteris paribus*, an increase of 1% in the speculative index (*WSIA*) is associated with dynamic conditional equity-commodity correlations that are approximately 4% to 7% higher (given a mean excess spec index of about 25%).

Intuitively, Working's "T" index of excess speculation in commodity futures markets, which aggregates the activities of *all* non-hedgers across *all* maturities, should have less predictive power than a measure of hedge fund activity in short-dated contracts. Similarly, the activities hedge funds that trade in both equity and commodity markets might better predict long-term linkages between equity and commodity returns. If so, this would suggest 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 link satellite and central markets. Answering these questions, however, requires disaggregated data and is left for another draft.

3. *Interaction between speculation and financial stress*

Table VI shows that greater "excess" speculation is associated with enhanced 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.

Building on this hypothesis, some specifications in Table VI include an interaction term that captures the behavior of speculators during financial stress episodes. This interaction term is almost always statistically significant and is always (as expected) negative. That is, *ceteris paribus*, speculative activity is *less* helpful in predicting commodity-equity return co-movements during periods of elevated market stress.

4. *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 by separating aggregate trader positions according to traders' principal businesses – hedge fund, commodity-swap dealer, one of several "traditional" commercial types (commodity producer; manufacturer or refiner; wholesaler, dealer or merchant; other), etc.

D. Robustness

Our results are qualitatively robust to using additional proxies for commodity investment; and to introducing dummies to control for unusual circumstances in financial 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.

Again focusing on public data and absent data on CIT activity in futures markets prior to June 2006, we use a proxy for index-investor interest in commodities: the daily trading volume in the SPDR Gold Shares exchange-traded fund (ETF). This volume grew massively between 2004 and 2010. However, the *GOLD_VOLUME* variable does not help explain changes in commodity-equity correlations. One interpretation is that the activities of *passive* commodity investors do not affect equity-commodity linkages.

2. The Lehman crash

In the last 30 months of the sample period, the TED spread was very 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.

We also repeated 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 are qualitatively similar to Table VI.

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 predict the joint distribution of commodity and equity returns.

To ascertain whether *who* trades matters for asset pricing, this paper uses public data from the CFTC on trader positions in 17 U.S. commodity and equity futures markets from 2000 to 2010. This dataset contains evidence on the financialization of commodity-futures markets. We then use this information to document that, besides macroeconomic fundamentals, variations in the composition of the open interest in commodity futures markets help predict fluctuations in the extent of commodity-equity co-movements.

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, financial traders could be an important transmission channel of negative equity market shocks into the commodity space. In fact, we find that the predictive power of "excess" speculation in commodity futures markets is *lower* in periods of stress.[12]

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.

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[12] The predictive power we identify relates to the activities of speculators in general. A natural question is whether it could be traced to hedge funds, especially to hedge funds that are active in *both* equity and commodity futures markets – natural candidates based on theoreitcal models of cros-market linkages. Another question is whether the positions of other kinds of participants in commodity-futures market (e.g., commodity index traders) have predictive power for cross-market correlation patterns. A third question is whether it is traders' positions in shorter-dated contracts (rather than further along the maturity curve) that contain predictive power for equity-commodity return linkages. Answering those questions would require more disaggregated data: we leave them for a separate paper.

Our paper establishes that macroeconomic fundamentals, speculative positions, and the TED spread (a proxy for financial market stress) help predict observed long-run fluctuations in commodity-equity correlations. An interaction term between speculative positions and the 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 needed to explain this last finding. One possible explanation is that, amid a crisis of historical proportion and massive uncertainty, a radical shortening of traders' horizons could have made both equities and commodities much more (*less*) sensitive to short-term (*long-term*) economic developments. Another possibility is that the financialization of commodity markets may 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 natural question is whether sentiment (interacted or not with proxies for value arbitraging and for index trading activity) helps predict the increases of commodity-equity or cross-commodity correlations and of the common component of stock returns during the Great Recession.

Finally, our findings highlight the need for theoretical research to help assess whether the empirical relationship that we document, between commodity-market financialization and cross-correlations, represents a welcome improvement in market efficiency or, instead, is a worrisome development. A unifying theory regarding the ideal level of co-movement between commodities and other assets (and between different commodities) is needed that would build on prior work showing the importance of macroeconomic and commodity-specific fundamentals for equilibrium price levels and volatility (Pirrong, 2011) and commodity risk premia (Hirshleifer, 1988), and on models analyzing the impact of different types of traders on cross-market linkages in good or in bad times (e.g., Danielsson, Shin and Zigrand, 2011a, 2011b).

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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**
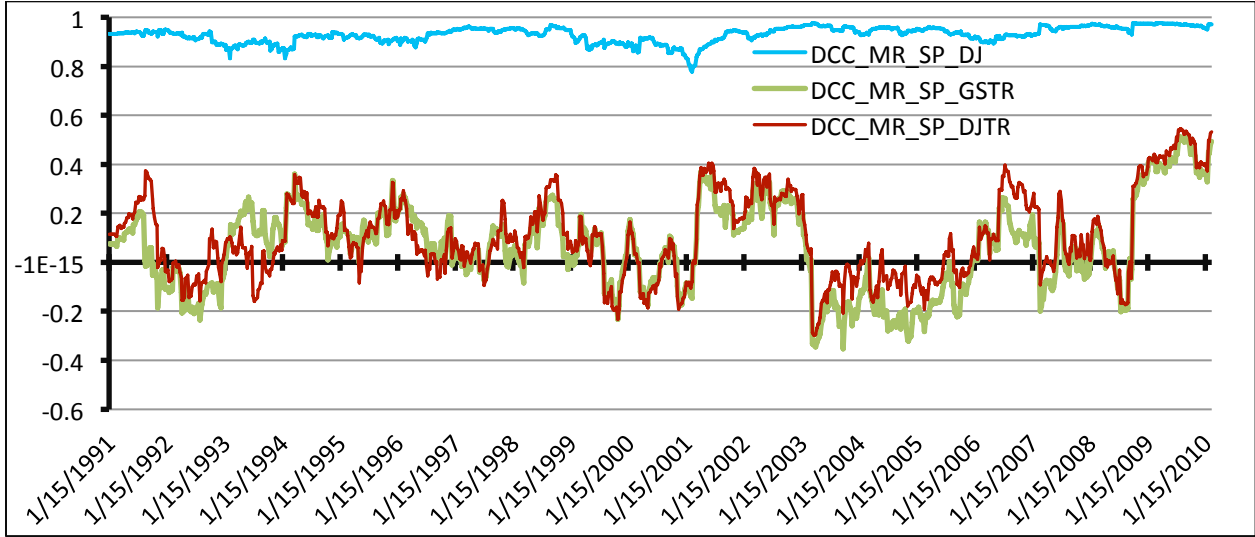
**Figure B: Daily Returns Correlations (DCC), January 1991 to March 2010**
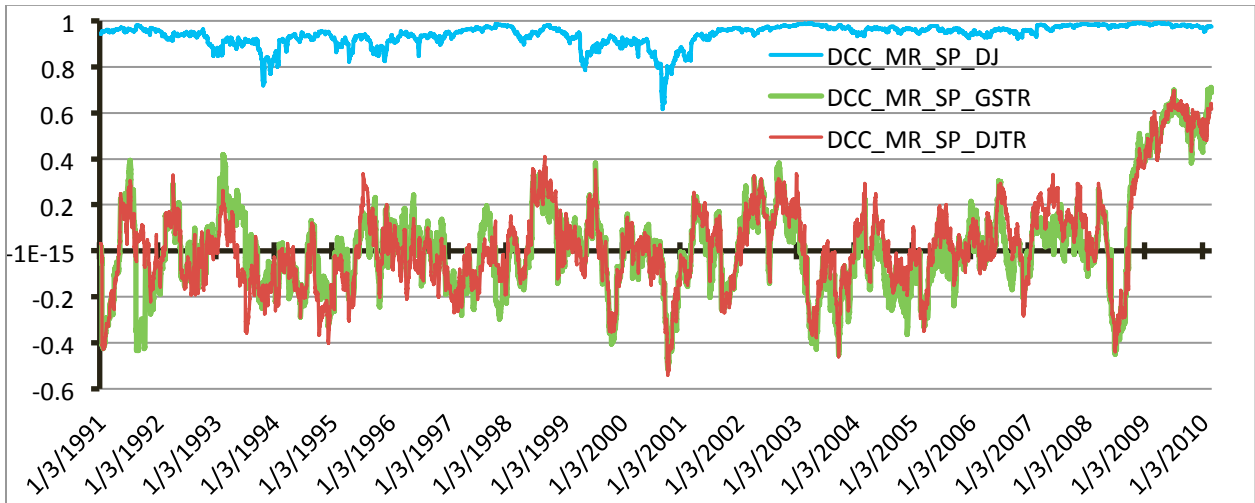
***Notes*:** Figure 1A (*1B*) depicts the time-varying correlation between the **weekly (*daily*)** unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and: (i) the S&P GSCI total return commodity index (GSTR, **green line**) or (ii) the DJ-UBS total return commodity 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
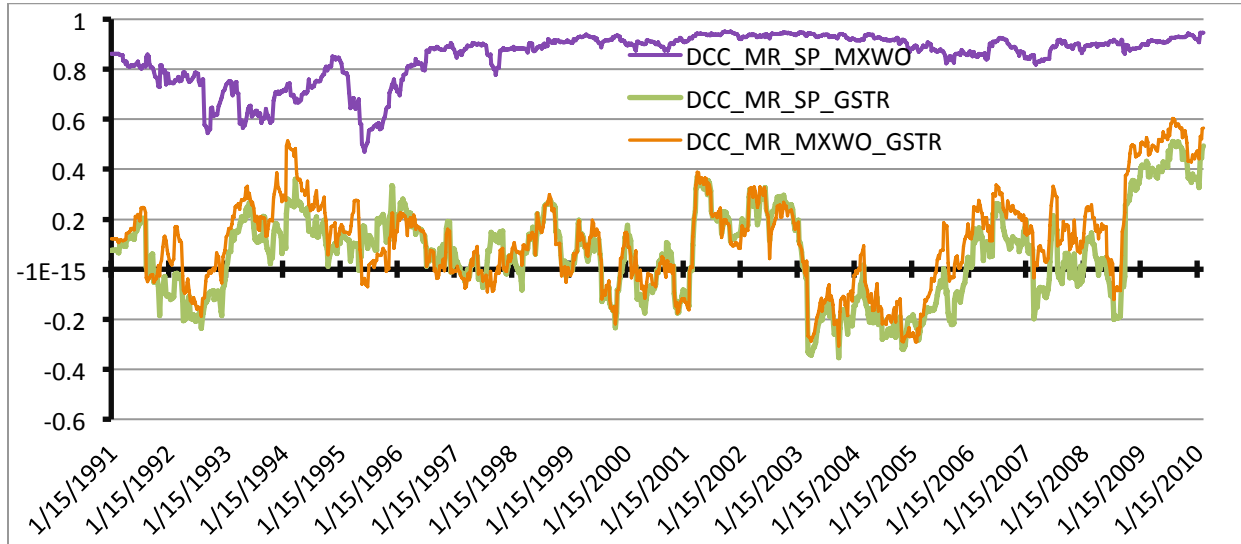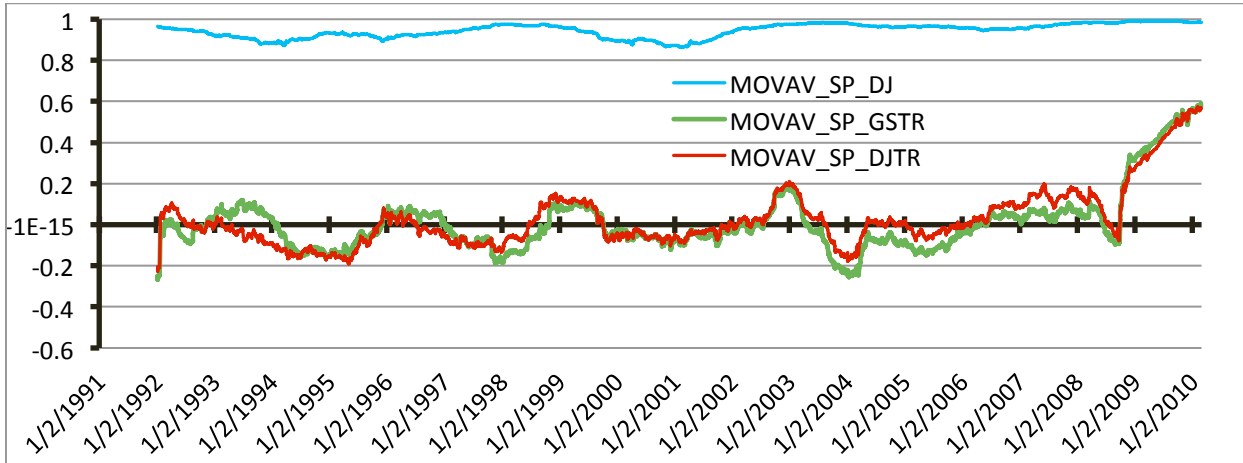

Figure 1D: Daily Return DCC -- World Equity *vs.* Commodity Indices, 1991 to 2010
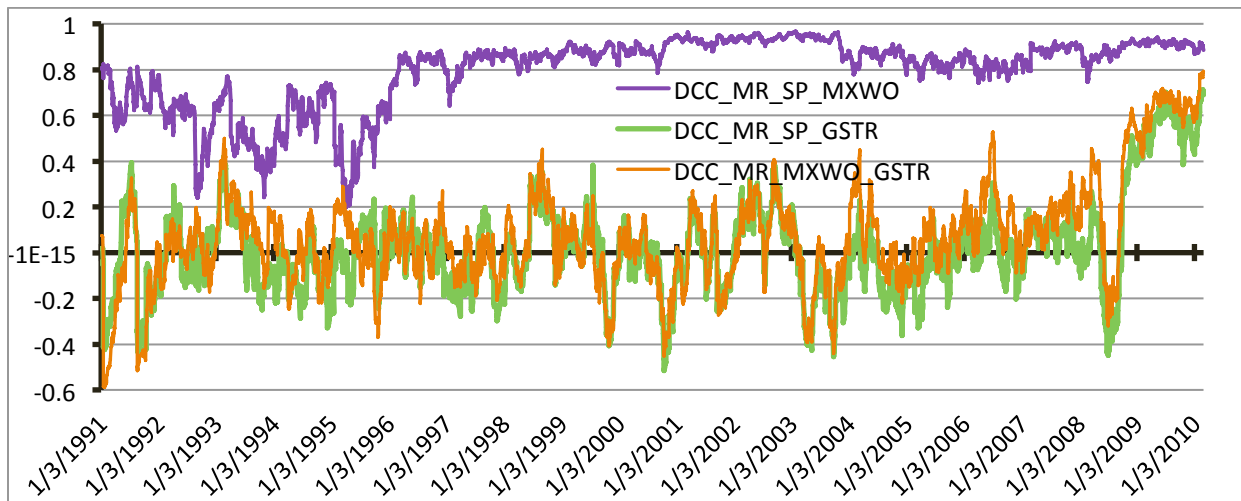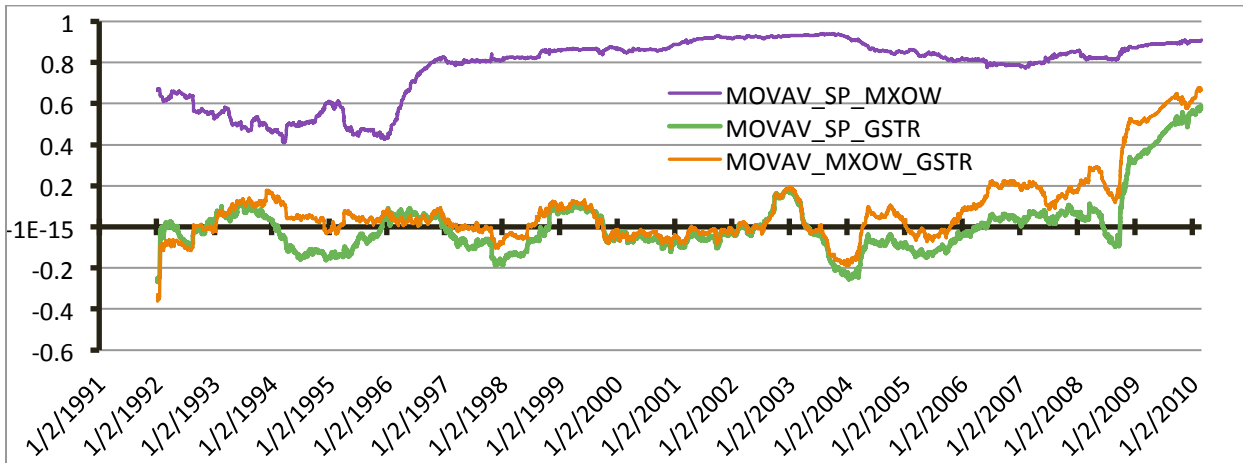

***Notes*:** Figure 1C (*1D*) depicts the dynamic conditional correlations between the **weekly (*daily*)** unlevered rates of return (precisely, changes in log prices) on S&P's GSCI total return commodity index and: (i) the S&P 500 (SP) equity index (**green line**) or (ii) the MSCI World Equity Index (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 U.S. 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 time-varying variances .

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Figure 2: Excess Speculation and Financialization of Commodity Markets
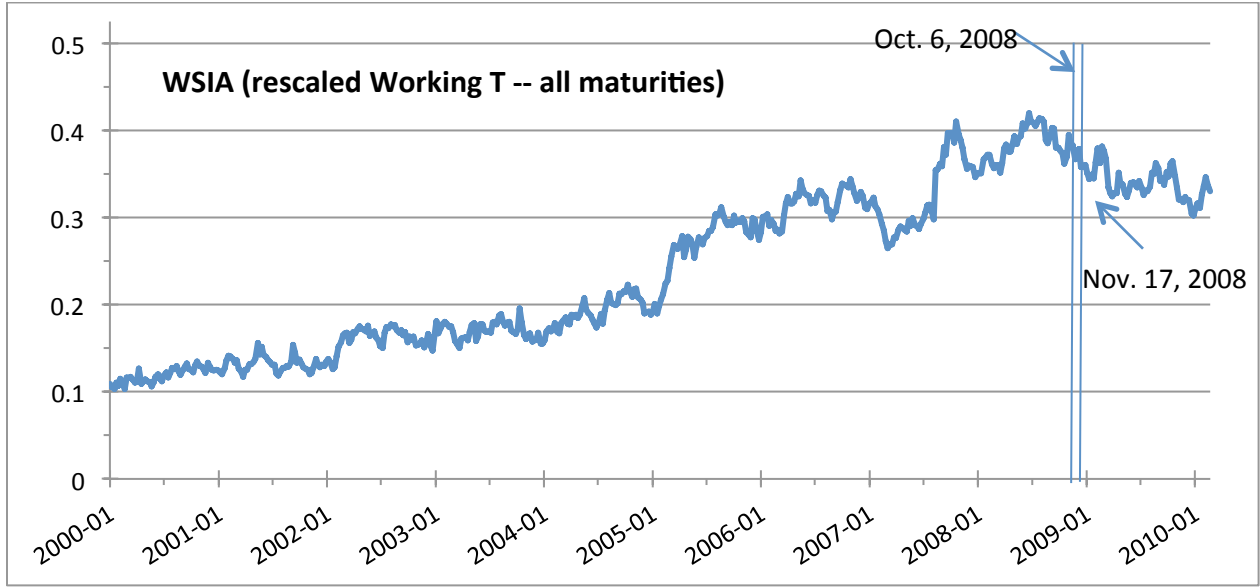
Notes: Figure 2 plots the weighted-average speculative pressure index ("Working's T") in the 17 U.S. commodity futures markets linked to the GSCI index in across all maturities (**dark blue**, *WSIA*) between the first week of January 2000 and the first week of March 2010. Source: U.S. CFTC, Public Commitment of Traders Reports.

Figure 3: Equity-Commodity Correlations, Economic Activity, and Hedge-Fund Cross-Trading
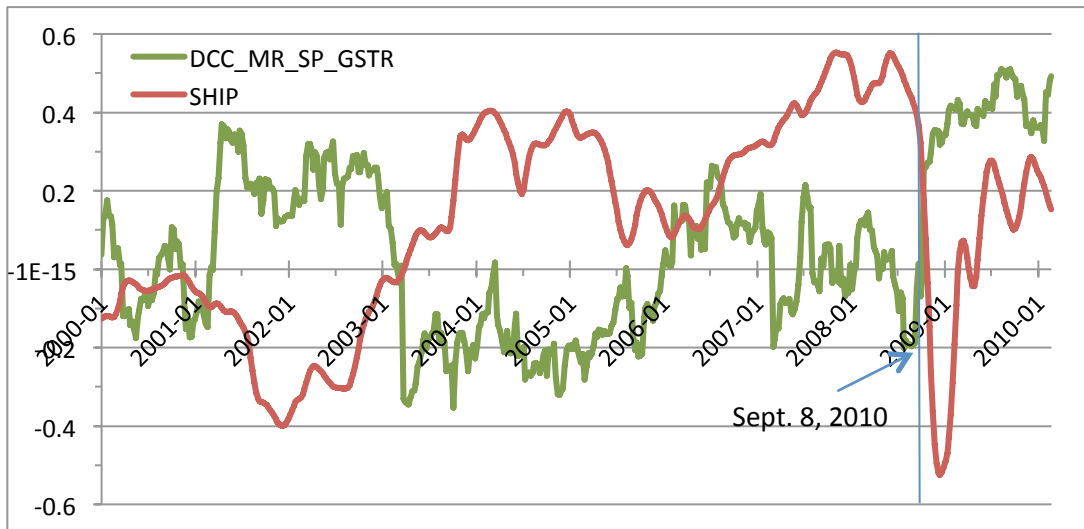
Notes: The **green line** in Figure 3 shows, between the first Tuesday of January, 2000 and the last Tuesday of February, 2010, the dynamic conditional correlation between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and on the S&P GSCI total return (GSTR) index. We use Tuesday-to-Tuesday return to estimate dynamic conditional correlations by log-likelihood for mean-reverting model (*DCC_MR*; Engle, 2002). The dark **red line** (*SHIP*) shows the Kilian (2009) index of worldwide economic activity. A negative relationship between *SHIP* and *DCC* is clearly apparent.

Figure 4: TED Spread and Equity-Commodity Correlations, August 2007 to March 2010
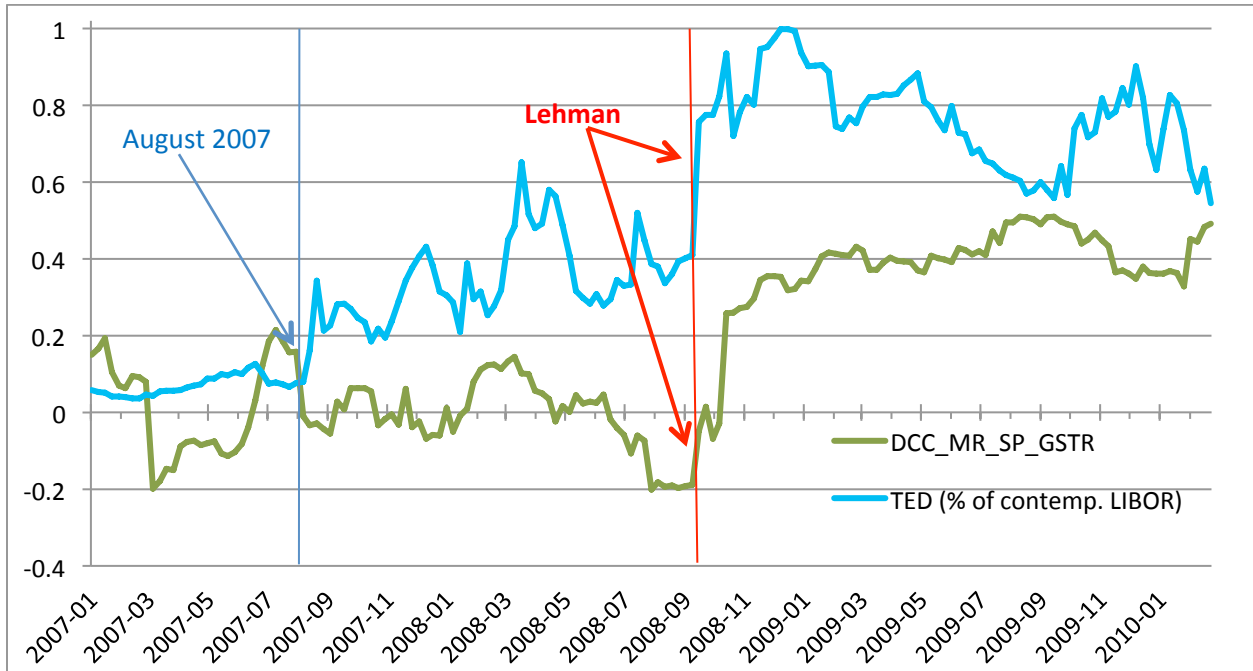
*Notes***:** The **green line** in Figure 4 shows, between the first Tuesday of July, 2007 and the last Tuesday of February, 2010, the dynamic conditional correlation between the weekly unlevered rates of return (precisely, changes in log prices) on the S&P 500 (SP) equity index and on the S&P GSCI total return (GSTR) index. We use Tuesday-to-Tuesday return to estimate dynamic conditional correlations by log-likelihood 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: 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)**
Mean	0.058803	0.124428	0.128101	-0.475016	0.023591	3.058959	0.487749	21.99812	0.003010	1.248605
Median	0.051580	0.135190	0.156134	-0.246892	0.023665	2.715900	0.296456	20.41000	0.090000	1.266179
Maximum	0.510420	0.602070	0.553002	0.992458	0.033083	6.802500	4.330619	67.64000	4.550000	1.420035
Minimum	-0.353440	-0.306940	-0.524973	-3.747359	0.015084	0.248800	0.027512	9.900000	-6.560000	1.112184
Std. Dev.	0.219529	0.224322	0.263191	0.787462	0.003213	1.874571	0.517985	9.744099	1.127080	0.091597
Skewness	0.186990	0.151839	-0.463355	-1.789994	-0.091070	0.328567	2.951072	1.653419	-0.700811	0.097695
Kurtosis	1.974010	2.284501	2.329421	6.952640	3.066411	1.842329	14.63722	6.761389	8.153885	1.521860
Jarque-Bera	25.09252***	12.71253***	27.53235***	598.4182***	0.790863	37.28642***	3582.557***	527.7928***	600.2571***	46.77718***
Sum	29.69551	62.83637	64.69118	-239.8829	11.91341	1544.774	246.3134	11109.05	1.520000	630.5457
Sum Sq. Dev.	24.28930	25.36143	34.91194	312.5287	0.005201	1771.064	135.2274	47853.53	640.2358	4.228546
Observations	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
ADF (1ˢᵗ Diff)	-22.8378***	-22.9515***	-6.6142***	-12.2230***	-5.7425***	-10.9312***	-12.8887***	-12.3767***	-12.6374***	-22.9845***

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-likelihood for mean-reverting model (Engle, 2002). **SHIP** is a measure of worldwide economic activity (Kilian, 2009). **ADS** is a measure of U.S. economic activity (Aruoba, Diebold and Scotti, 2009). 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 all contract maturities (**WSIA**) is the weighted-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 IV: Simple Correlations, 2000-2010 (*Dependent and Explanatory Variables*)

	DCC_MR SP_GSTR	DCC_MR MXWO_GSTR	SHIP	ADS	VIX	LIBOR	TED	INF	WSIS	UMD
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

Note: Table IV 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 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 ** (0.08855)	-0.0676649 (0.1154)	-0.0769808 (0.08335)	0.183340 ** (0.08916)	-0.0425855 (0.1139)	-0.0456055 (0.07643)	0.983731 ** (0.3937)	0.198942 (0.5670)	0.266539 (0.2853)
ADS				-0.0192282 (0.09266)	0.136424 (0.1530)	-0.0784245 (0.06634)			
INF							-0.240932 ** (0.1138)	-0.104337 (0.2242)	-0.118612 (0.09807)
SHIP	-0.03187 (0.2955)	-0.607037 ** (0.2892)	-0.247640 (0.1946)	-0.0328020 (0.2987)	-0.785661 ** (0.3811)	-0.249104 (0.1790)	0.268479 (0.2753)	-0.649011 ** (0.2745)	-0.342061 * (0.1947)
UMD	0.0375003 (0.07593)	0.141408 (0.1081)	0.0915841 (0.07970)	0.0399188 (0.07709)	0.126140 (0.1070)	0.0924424 (0.07331)	0.0274178 (0.06095)	0.130264 (0.09883)	0.0872112 (0.07288)
TED	-0.273596 (0.1932)	0.500917 ** (0.2171)	0.332428 ** (0.1497)	-0.264308 (0.1967)	0.630212 ** (0.3125)	0.240228 * (0.1410)	-0.268425 * (0.1550)	0.476131 ** (0.2112)	0.288970 ** (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 are estimated by log-likelihood for mean-reverting model (Engle, 2002). The explanatory variables are described in Table III. 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 (0.06202)	-0.0201306 (0.04778)	-0.00925942 (0.05749)	-0.0193913 (0.04863)	-0.661521 (0.4067)	-0.122517 (0.2137)
ADS			0.153715 * (0.08115)	0.00826134 (0.04729)		
INF					0.255100 (0.1599)	0.0363735 (0.07387)
SHIP	-0.407224 ** (0.1609)	-0.256007 ** (0.1165)	-0.596757 *** (0.1880)	-0.251052 ** (0.1165)	-0.361970 ** (0.1539)	-0.229830 * (0.1294)
UMD	0.0929004 (0.05706)	0.0695521 (0.04675)	0.0760120 (0.05278)	0.0692592 (0.04678)	0.0762112 (0.05147)	0.0686126 (0.04673)
TED	0.201796 * (0.1061)	0.110997 (0.08428)	0.334082 ** (0.1368)	0.111721 (0.08770)	0.211402 ** (0.09905)	0.113062 (0.08472)
DUM	0.426993 *** (0.1220)	0.487423 *** (0.1136)	0.485022 *** (0.1232)	0.486330 *** (0.1243)	0.551450 *** (0.1442)	0.518016 *** (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 are estimated by log-likehood for mean-reverting model (Engle, 2002). The explanatory variables are described in Table III, 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.

Table VI: Speculative Activity as a Long-Run Contributor to the GSCI-S&P500 Dynamic Conditional Correlation

	2000-2010		2000-2010	
Constant	-3.85024	***	-2.08797	**
	(1.328)		(0.9959)	
ADS	0.103863		0.132858	*
	(0.09492)		(0.07009)	
SHIP	-0.933864	***	-0.693805	***
	(0.2664)		(0.1905)	
UMD	0.0893486		0.0712289	
	(0.06653)		(0.04622)	
TED	6.24366	**	4.27775	**
	(3.120)		(2.102)	
WSIA	3.07302	***	1.64474	**
	(1.048)		(0.8008)	
INT_TED_WSIA	-4.37543	*	-2.96711	*
	(2.261)		(1.533)	
DUM			0.391434	***
			(0.1273)	
Log likelihood	861.365		865.766	

Notes: The dependent variable (equity-commodity weekly return DCC) and most of the explanatory variables are described in Tables III. *INT_TED_WSIA* is interaction terms of the TED spread with the Working T index of excess speculation (*WSIA*). *DUM* is a time dummy for the post-Lehman period (September 2008 to March 2010). Long-run estimates are from a two-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.