Financialization, crisis and commodity correlation dynamics.*

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SUMMARY

We study conditional volatility and correlation dynamics for returns to commodity futures, stocks and bonds, from May 1990-July 2009 using DSTCC- GARCH. The models allow correlation to vary smoothly between extreme states via transition functions. Expected stock volatility (VIX) and money manager open interest in futures markets are relevant transition variables. Results show increasing integration between commodity futures and stocks: commodity returns volatility is predicted by common factors but also by financial traders' open positions. We observe higher and more variable correlations between commodity futures and stock returns from mid-sample, with many series showing a structural break in the conditional correlation processes from the late 1990s.

Keywords: commodity futures; double smooth transition; conditional correlation; financialization

JEL Classification: G01 G11 C22

1 Introduction

Over the past decade, commodity prices have undergone a dramatic boom and bust, propelled by demand from industrializing economies and financial investor interest. Two investor groups have increased their activity in commodities markets: 'buy and hold' investors such as pension funds, endowments and mutual funds, who have accrued collateralized long positions in futures, and hedge funds, who have actively traded derivatives. After the stock market crash in 2001, institutional investors began viewing commodities as prime sources of portfolio diversification rather than as assets that were imprudent and difficult to hedge (Tang and Xiong, 2009). Jack Meyer, CEO of Harvard Management Company, stated that 'commodities are a diversifying asset class with no correlation - and in some cases negative correlation - with other asset classes' (quoted in Sesit, 2004). His opinion was representative of many institutional managers who embraced commodities as a profitable alternative asset, relying on low correlations with conventional assets, positive co-movement of commodity prices with inflation and a tendency to backwardation in the futures curve. (Gorton and Rouwenhorst, 2006, Kat and Oomen, 2007, Chong and Miffre, 2010, Büyükşahin *et al.*, 2010).

As financial investor interest in commodities has escalated, it is natural to ask whether shocks from financial markets have begun to overshadow commodity fundamentals, weakening the diversification value of commodities and changing price dynamics. If commodity securities and conventional financial assets are both held by more investors, the set of common state variables driving stochastic discount factors grows, so that bad news in one market can cause liquidation across several markets (Kyle and Xiong, 2001). And if heterogenous commodity futures are treated as a single asset class by index investors, relatively unrelated commodities may move in synch (Pindyck and Rotemberg, 1990, Tang and Xiong, 2009). If commodity and conventional asset markets have become more integrated, systematic shocks may increasingly dominate commodity returns, raising correlation with other asset classes and generating more time-variation in correlation and volatility.

Here we use recent improvements in conditional correlation modelling to test stock, bond and commodity futures returns correlations for evidence of increased integration. We model bi-variate conditional volatility and correlation for 24 individual commodity futures returns with benchmark equity indices for the US, UK, Germany, and France, and with US fixed interest, using weekly data from May 1990 to July 2009. Because our sample includes the global financial crisis we can test investor beliefs about the diversification value of commodities during a widespread and deep downturn.

Long run trends such as industrialization and financialization are likely to move correlation gradually, so we use Double Smooth Transition Conditional Correlation models (DSTCC–GARCH) (Silvennoinen and Teräsvirta, 2005, 2009) in contrast to earlier studies which have relied on rolling correlation estimation and/or Dynamic Conditional Correlation (DCC) models. DSTCC models allow conditional correlations to change smoothly between (up to) four extreme states, in a convex combination which depends on two logistic transition functions. These transition functions can be governed by observable economic variables, giving an interpretation to correlation dynamics. Thus one advantage of our chosen modelling framework is that it allows us to test the presence of links between time-varying correlations and indicators of financial market conditions, and to identify their sign and strength. We test the expected stock market volatility index, VIX, as a gauge to investor sentiment, and the percentage of non-commercial traders' open interest in futures markets from the Commodity Futures Trading Commission (CFTC) reports, which is a measure of the intensity of interest of money managers or hedge funds. We examine commodities individually in order to pick up heterogeneous features and we include common and idiosyncratic factors in the conditional mean and variance of each commodity to reduce biases in correlation dynamics.

Conditional variance estimation confirms significant spillovers from financial factors into commodity futures volatility. This effect is marked for commodities that are components of the investable Goldman Sachs Commodities Index (GSCI).[1] Significant factors include expected stock market volatility (VIX), the US dollar exchange rate, short interest rates and corporate bond spreads. Financial traders' positions also influence commodity volatility. An increase in the percentage of open interest held short by money managers increases futures returns volatility, but the impact of increasing long interest varies between markets, sometimes raising and sometimes lowering volatility. Variation in commodity futures returns volatility is therefore likely to have been amplified by the intensification of hedge fund trading activity over the past decade.

Dynamic correlation patterns show that the diversification benefits of commodities to equity market investors have weakened, contrary to findings of earlier studies (Chong and Miffre, 2010, Büyükşahin, *et al.*, 2010). Correlations between S&P500 returns and returns

[1] Tang and Xiong (2009) find similar results. See also Mayer (2009).

to the majority of commodity futures have increased, sometimes sharply and only during the recent crisis, but in many cases, gradually, and from a much earlier date. For 12 of the 24 commodities we study, correlations with S&P500 returns rise in high VIX states, implying that both stock and commodities returns are falling as VIX increases. We find this effect is concentrated later in the sample (from around 2000 onwards) consistent with increased commodity and stock market integration over recent years. We also identify time breaks in the correlation structure around the beginning of the past decade, between stocks and most metals, some grains and some foods. This break occurs during a period when both underlying demand and financial investor interest were intensifying, but the relevance of VIX points to strong financial influences. Further evidence for financialization is that futures market positions of non-commercial traders drive some correlation transition functions. In these cases, correlation dynamics indicate that money managers can time their commodity futures positions to offset stock market losses.

Correlation between commodities and European stock market returns show similar patterns, whereas fixed interest correlations have shown less variation, if anything tending more negative. Expected stock market volatility and financial trading intensity measures are again relevant to correlation dynamics in many instances.

Section 2 gives background on commodity futures price trends, financialization and current empirical studies. Section 3 outlines the sources and construction of the series used here and Section 4 describes the model and estimation process. Results and conclusions follow.

2 Background

Following on more than four decades of real average declines, rises in commodity prices over the past decade are historically unprecedented in scope and strength (Helbling *et al.*, 2008, Vansteenkiste, 2009, IMF, 2006). Figure 1 graphs group averages of nominal commodity prices from May 1990 to July 2009, showing positive trends from 2002 as well as the 2008-9 boom and bust. Energy prices peaked at around eight times 1990 levels, metals were two to three times higher, and crop prices almost doubled.

Demand and supply conditions have contributed to this cycle. A sustained depreciation in the US dollar and low interest rates created a stimulatory environment, while industrialization in China, India and emerging Asia accelerated consumption of fuels, metals and food

(Helbling *et al.,* 2008). Further, changes to biofuel policies in developed countries placed pressure on food prices and production, as feedstocks were diverted to biofuel, and energy prices pressured food prices. General demand pressure was aggravated by a slow supply response in many markets. The supply lag was partly caused by low inventories and production capacity after several decades of weak prices but also by structural and technological constraints on production, crucially for oil, a key input to the production of other commodities. Macroeconomic fundamentals such as these may increase commodity futures correlations with other assets via common drivers such as interest rates and spreads, and via expectations of economic growth.

2.1 Financialization

Financialization also may have increased commodity price exposure to financial shocks compared with past cycles. Financial activity in commodity securities markets relative to world commodity production has grown substantially since 2000. The number of open contracts in commodity exchanges grew by 170% between 2002-2008:2, putting volumes of exchange traded derivatives at 20 to 30 times physical production for many commodities. Similar trends have shown up in over-the-counter trade (Redrado *et al.,* 2008, Domanski and Heath, 2007).

Increases in capital flows from institutional investors have been marked, with some commentators estimating passive investment at $150-200 billion by 2008. Trends in the GSCI also point to increasing integration with conventional securities: Figure 2 graphs the GSCI total returns index value against returns indices for US and major European stock markets. The GSCI looks independent of stock index trends in the first decade of the sample, declining during the bull market of the '90s and relatively unaffected by the downturn in 2000, however from 2002 the GSCI trends up with stock indices, before plunging in 2008, slightly ahead of the S&P500.

Hedge funds and exchange traded commodity funds have been active in commodities derivatives markets.[2] The Commodity Futures Exchange Commission (CFTC) reported that as early as 2003, the majority of the largest US hedge funds were operating as Commodity Pool Operators (CPOs), which invest pooled funds into futures or options on behalf of customers, or Commodity Trading Advisors (CTAs), which provide advice or analysis on commodity

[2] Financial interest in commodity futures markets is volatile, tends to a long position on average and is positively correlated with the spot price (Redrado *et al.,* 2008).

securities value (Brown-Hruska, 2004). Indeed, hedge fund activity in commodity futures markets tripled between 2004 and 2007 (Domanski and Heath, 2007).

The Commodity Futures Modernization Act of 2000 may have made commodity investments more attractive to some groups. The Act aimed to 'rationalize regulation for sophisticated or otherwise regulated entities' by exempting certain groups of investors from registration with the National Futures Association and consequently freeing then from some aspects of compliance. These exempt groups included 'funds engaging in *de minimus* futures investments...; otherwise regulated entities such as mutual funds, insurance companies, and banks; and funds that cater to highly sophisticated investors...'(quoting from Brown-Hruska, 2004). CFTC policy also aimed to protect hedge funds from extensive disclosure of their holdings and asset selection strategies.[3]

Financialization could affect commodity price volatility and correlation with conventional assets in several ways. First, if commodity securities, stocks and bonds are all held by a growing number of investors with similar portfolios, the set of common state variables driving stochastic discount factors, and therefore securities prices in each market, increases. A larger set of common shocks raises correlation between asset classes since bad news becomes more likely to force liquidation of asset holdings in several markets at the same time, as the marginal investor adjusts his or her portfolio (Kyle and Xiong, 2001). Second, if commodity futures tend to be viewed more as a unified group than as individual securities by index investors, we could also see increasing co-movement between relatively unrelated commodities (Pindyck and Rotemberg, 1990, Tang and Xiong, 2009). Third, theoretical models of financial markets (Pavlova and Rigobon, 2008, Schornick, 2009) show that if traders such as CPOs and CTAs hold diffuse beliefs, changes to regulation like the Modernization Act may raise time-variation in capital flows to commodities derivatives markets, creating swings in correlation. Fourth, we could see post-liberalization volatility rise if greater capital flow volatility raises risk premia (Schornick 2009). On the other hand, if easier access to futures markets increases liquidity available to hedgers of non-marketable risk, such as commodity producers, then the premium paid for bearing non-marketable risk will decline and futures price volatility may fall.

[3] In her Keynote Address to the Securities Industry Association Hedge Funds Conference in 2004, Acting Chairman of the CFTC Sharon Brown-Hruska argued that the SEC and CFTC 'must not stifle the innovative and entrepreneurial spirit that has characterized the hedge fund industry. And ... must also strive not to burden funds with duplicative requirement and regulations. ... An even greater risk to enacting a prescriptive regulatory program that includes a securities style disclosure regime is that it will chill innovation by forcing fund managers to reveal too much information about their holdings and their asset selection.'

Other things being equal, the systematic component of commodity prices may increasingly dominate returns, raising correlation with other asset classes, creating more time-variation in correlation and causing volatility to track systematic shocks more closely.

2.2 Correlation and integration

Empirical studies of the period leading up to the 2008 crash conclude that conditional correlations between stock returns and commodities are insignificantly different from zero in the majority of cases, have tended to decline over time, and are noticeably lower during periods of high stock market risk (Chong and Miffre, 2010, Büyükşahin *et al.*, 2010). These authors encourage investors to choose commodities as a refuge during periods of stress in traditional asset markets, arguing that macroeconomic shocks tend to work on commodity and stock prices in opposite directions. They find no evidence that the increased financialization of commodity futures markets has changed co-movement patterns with traditional asset classes, confirming the diversification benefits of commodity exposures.

The coincidence of an increase in derivatives trading with strongly increasing commodity prices has prompted several other investigations of whether price effects have been amplified by financial trading. Most have concluded that higher prices may be driving speculation rather than the reverse, though a direction for causality is difficult to establish (IMF, 2006, Redrado, *et al.* 2008, Frankel and Rose, 2009). Price movements may be sufficiently well explained by macroeconomic fundamentals and idiosyncratic commodity shocks (Vansteenkiste, 2009). Hedge funds appear to provide liquidity to futures market rather than destabilizing them (Haigh *et al.,* 2005).

Tang and Xiong (2009) reach different conclusions. They find an increase in the impact of world equity shocks and US dollar exchange rates shocks on the GSCI investable commodities index in the past few years, coinciding with increased financialization. Further evidence that this higher exposure to common shocks is driven by financialization rather than macroeconomic fundamentals is that individual commodities in the investable indices (GSCI and DJ-AIG) exhibit stronger responses than similar commodities that are not in the indices. They identify volatility spillovers from the financial crisis as a key driver of recent commodity price volatility.[4]

[4] Mayer (2009) studies the positions of index traders and other non-commercial traders and concludes that they cause commodity price changes.

In what follows, we focus on time-varying volatility and conditional correlation, reviewing the hypothesis that the connection between commodity futures and other assets is unaffected by financialization, and that the attractive features of commodities as an alternative asset class have been robust to the crisis. Our contribution is to estimate models that allow for possibly slow-moving trends in correlation dynamics and that can identify both the timing of changes in correlation regimes and relevant drivers. We include data from the GFC, capturing correlation dynamics during a severe downturn in major markets. Further, for the first time we control for an array of common factors in conditional mean and variance equations and better isolate the dynamic correlation process. In the next section we describe the commodity futures pricing model and data.

3 Futures pricing model and data

Heterogeneity is a key feature of commodity markets so we take a disaggregated approach, collecting daily spot and futures prices on 24 commodities from May 1990 to July 2009. (The Appendix lists all series and sources.) We include grains and oilseeds, meat and livestock, food and fibre and metals and petroleum. Where no spot price series is reported, we treat the nearest futures contract as spot, and use all (complete) actively-traded futures contracts prices to compute average futures returns. We extract weekly from daily series using Wednesday closing prices or the preceding Tuesday where Wednesdays are missing. The return at time t, to commodity future contract i, with maturity date τ, is

$$\tilde{r}_{i,t,\tau} = 100 \ln\left(\frac{F_{i,t,\tau}}{F_{i,t-1,\tau}}\right) \tag{1}$$

where $F_{i,t,\tau}$ is the time t price of the futures contract. For all commodities except base metals, the daily futures price data are continuous series that track a particular contract until its last trading day, whereupon the series switches into the next nearby contract. Consequently, we use the continuous series to compute the return to an investor who closes out their position on the last Wednesday prior to the contract's final trading day and then immediately purchases the next nearest futures contract. For London Metal Exchange (LME) base metals, however, daily settlement prices are quoted for spot and for the futures contracts closest to a fixed maturity period (3-months and 15-months) rather than continuous futures, and weekly returns do not need to account for the contract switch.

To capture as full a measure of the futures curve as possible, we collect prices on all actively traded contracts with maturity dates up to one year ahead. We then average across all returns in each period and collateralize by adding the 3-month US Treasury Bill rate (adjusted to weekly). The averaged weekly futures return is

$$y_{it,F} = \frac{1}{K}\sum_{k=1}^{K} \tilde{r}_{i,t,\tau_k} + r_{f,t}, \tag{2}$$

where $y_{it,F}$ is the average of the K collateralized futures returns and $r_{f,t}$ is the weekly short rate. By collateralizing, we treat the investor as holding a risk-free investment equivalent to a long position in the commodity futures contract.

3.1 Pricing Factors

The conventional cost of carry relationship for commodity i that links the forward price at time t for delivery at time τ, $f_{i,t,\tau}$, and the current spot price $S_{i,t}$, depends on interest rates, storage costs and the 'convenience yield', that is, the benefit to inventory holders of supplying the market at some future time if spot prices are unexpectedly high.[5] The convenience yield is stochastic, positively correlated with the spot price, and will be high when the basis (the difference between the forward price and current spot) is strongly negative. The forward pricing condition is

$$f_{i,t,\tau} = S_{i,t}\left(1 + r_{f,t}\right) + w_{i,t,\tau} - \varphi_{i,t,\tau}, \tag{3}$$

where $r_{f,t}$ is the relevant risk free interest rate, $w_{i,t,\tau}$ is the cost of storing commodity i until period τ, and $\varphi_{i,t,\tau}$ is the convenience yield for the period between t and τ. Hence inventory conditions are one idiosyncratic factor for commodity futures returns, and interest rates and the term structure are systematic factors. Equation (3) is not a perfect arbitrage condition because of the likelihood of stockouts, limitations on shorting the spot commodity and the fact that not all commodities can be stored indefinitely.[6]

[5] The theory of storage predicts that convenience yields are non-linearly declining in inventories (Pindyck, 1993, Routlege *et al.,* 2000), whereas the theory of stockouts suggests that commodity prices will exhibit regimes of sharp spikes followed by long periods of doldrums (Deaton and Laroque, 1992, Routlege *et al.*, 2000, Carlson *et al.*, 2007). For empirical analysis of storage and stockouts see Deaton and Laroque (1996), Heaney (2005) and Gorton, Hayashi and Rouwenhorst (2007).

[6] While stores of the physical commodity are part of the market portfolio, futures contracts are in zero net supply and are not necessarily of any influence on spot markets, so any risk premium to holders of futures

For common pricing factors, we use the nominal 3 month US Treasury Bill rate (weekly), and the corporate bond spread, measured as the difference between the yield on Moody's AAA Corporate Bonds and the T-bill (Hong and Yogo 2009). For idiosyncratic commodity factors we use the interest-adjusted commodity basis and relevant exchange rate changes. The basis is the ratio of futures and spot prices: an important indicator of market conditions and a proxy for inventory levels. We compare the spot price (or nearest futures price) with the average futures prices collected for each commodity and adjust for interest rates, writing the basis as

$$b_{i,t} = 100 \ln \left(\frac{\frac{1}{K} \sum_{k=1}^{K} F_{i,t,\tau_k}}{S_{i,t}} \right) - r_{f,t}, \tag{4}$$

where $S_{i,t}$ is the spot price at time t.[7]

We also collect data on the investable continuous commodities index the GSCI, and CRB commodity price index (Reuters-Commodity Research Bureau spot and futures indexes), the DXY US dollar futures index (measuring the value of the USD against six major world currencies) and an array of USD exchange rates for commodity-producing countries.

To compute correlations with equity and bond returns we use total returns stock price indices for the US (S&P500), UK (FTSE100), Germany (DAX) and France (CAC) in local currencies, a total returns fixed interest index for US Treasuries (JP Morgan US Government Bonds). Returns to stock, bond and commodity indices, and exchange rates, are the logarithm of Wednesday on Wednesday prices scaled by 100. All data sources and samples are listed in the Appendix.

3.2 Transition variables

DSTCC-GARCH models use observed transition variables to move correlation between extreme states, and we look at four indicators: time, scaled as t/T where t is the current observation number and T is the sample size; the weekly lagged level of the CBOE volatility

contracts accrues only when futures positions carry non-diversifiable market risk (Black, 1975). Under some pricing kernels, however, the systematic risk premium could be zero. On the other hand, commodity futures may receive a residual risk premium when underlying claims (such as shares in the commodity production process) are not traded, and/or where transactions costs or capital constraints apply (Stoll, 1979, Hirshleifer, 1988a, Hirshleifer,1988b, de Roon *et al.*, 2000, Acharya *et al.*, 2009). Hedgers, such as producers who stock the physical commodity, will pay a premium to insure the non-marketable component of their exposure to spot price variability, creating a positive return to (long) futures. Such 'hedging pressure' can be positive or negative, producing either backwardation which pays positive returns to buyers of futures (where the future price is lower than expected future spot) or contango, which profits sellers (where the future price is higher).

[7] The number of contracts and their maturity dates vary between commodities. See the Appendix for details.

index, VIX, which represents the stock market expectation of 30 day volatility; the lagged percentage of long open interest held by non-commercial traders (OI) in each commodity, where available; and the lagged difference between (percentage) long and short open interest by non-commercial traders divided by total percentage non-commercial interest (DOI). The VIX is negatively correlated with the US stock index and is widely regarded as a indicator of future uncertainty or 'fear'. The percentage of all open interest attributable to non-commercial traders' long positions (OI) proxies overall money manager interest in futures markets. Non-commercial positions tend to be long on average and increase after a period of rising prices, consistent with momentum strategies (Gorton *et al.,* 2007, Redrado *et al.,* 2008).The difference series DOI, we compute as $DOI_t = (long\%_t - short\%_t)/(long\%_t + short\%_t + spread\%_t)$ which gauges the intensity of interest of non-commercial traders on either side of the contract. For all open interest data, we rely on the CFTC, which reports weekly (Tuesdays) on the percentage of all open interest (number of specified futures contracts) held by commercial and non-commercial traders.

Academic studies generally view 'non-commercial' traders as financial investors (Gorton *et al.*, 2007), since this category includes primarily money managers or speculators. The CFTC defines 'commercial' traders as those engaged in business activities hedged by the use of futures, including most financial organizations such as banks, endowments and pension funds as well as producers. Haigh *et al.* (2005) identify the non-commercial sub-category CPOs as predominantly hedge funds - managers who pool funds from smaller investors and can take long or short positions in the futures markets.

Harmonizing the open interest series with other components of our weekly data requires managing gaps and breaks. First, we can match up the OI and Bloomberg futures for 15 of the 24 commodities but in some cases the contracts underlying Bloomberg price data and the CFTC commodity codes underlying the OI data are not the same; in those cases we match by generic commodity name. Second, prior to October 1992, the open interest is reported mid- month and end-month, rather than weekly, so to enlarge our sample, albeit with limited information, we fill in the missing weeks by repeating the prior observation for the weeks of 2 May 1990 to 7 October 1992. Third, the specific CFTC commodity codes sometimes switch within sample, creating structural breaks. We model the breaks by regressing each long open interest series on a constant and as many indicator variables as needed to control for the switches. Each OI series thus enters the GARCH and transition equations as deviations from the mean. The DOI series is a proportion so we do not need to adjust it for structural breaks.

3.3 Summary statistics

Empirical distributions of individual commodity futures returns vary substantially, though the majority show lower return/risk ratios than stocks. Table 1 sets out summary statistics for all series used in estimation apart from individual exchange rates. The long open interest of non-commercial traders has trended up over the sample period for all of the contracts we study, confirming the increasing influence of financial traders in the futures markets. Mean long open interest exceeds mean short open interest for all contracts except cotton but percentages of interest both long and short were substantial, and show that non-commercial traders are active on both sides of the market. Non-commercial trading pressures are a significant driver of futures returns volatility and correlation, as we report below.

4 Modelling Strategy

Following Silvennoinen and Teräsvirta (2009), we define the vector of fully collateralized commodity futures, fixed interest and equity returns as a stochastic N-dimensional vector process

$$\mathbf{y}_t = E\left[\mathbf{y}_t|\mathcal{F}_{t-1}\right] + \boldsymbol{\varepsilon}_t, \qquad t = 1, ..., T \tag{5}$$

where $\mathcal{F}_{t-1}$ is the sigma-field generated by information up until time $t-1$, and the conditional mean is a function of common and idiosyncratic factors and ARMA terms, so that

$$y_{it}|\mathcal{F}_{t-1} = \delta_{i0} + \sum_{p=1}^{P} \phi_{ip} x_{ip,t-1} + \sum_{j=1}^{J} \delta_{ij} y_{i,t-j} + \sum_{m=1}^{M} \delta_{im} \varepsilon_{i,t-m} + \varepsilon_{it}. \tag{6}$$

The vector $\mathbf{x}_i$ includes common factors and commodity-specific factors, and the remaining terms capture seasonality and time dependence via autoregressive and/or moving average structure. In estimating conditional means, we aim to generate uncorrelated residuals and avoid biases in the estimation of DSTCC-GARCH. Following Hong and Yogo (2009), in every conditional mean equation we include known predictors of stock market and bond returns: the T-bill rate and the corporate bond spread. Commodity-specific factors in $\mathbf{x}_i$ are the interest-adjusted commodity basis (a proxy for the influences of inventories and convenience yield), and log changes in the DXY and/or exchange rates of major producers of commodity i, where statistically significant. Clement and Fry (2008) and Chen, Rogoff and Rossi (2008) draw attention to the potential predictive power of the exchange rates of major producers for some commodity prices, possibly due to market power or because of stronger forward-looking elements in exchange rate determination, while Tang and Xiong (2009) attribute it to integration with world financial markets. All elements of $\mathbf{x}_i$ are lagged one period.

Common, idiosyncratic and transition factors may also influence the conditional volatility process so excluding them can bias conditional correlation estimation. For GARCH estimation, we add the transition variables VIX, OI and DOI to the $\mathbf{x}_i$ vector and augment the conditional variance process by any elements of the $\mathbf{x}_i$ that are relevant. We write the univariate error processes as

$$\varepsilon_{it} = h_{it}^{1/2} z_{it}, \tag{7}$$

where h_{it} is a GJR-GARCH process expanded by lags of $\mathbf{x}_i$,

$$h_{it} = \alpha_{i0} + \sum_{j=1}^{J} \alpha_{ij}\varepsilon_{it-j}^2 + \alpha_{iJ+1}\varepsilon_{it-1}^2 I_{t-1} + \sum_{p=1}^{P} \zeta_{ip} x_{ip,t-1} + \sum_{k=1}^{K} \beta_{ik} h_{it-k}, \tag{8}$$

I_{t-1} is the indicator function equal to one when $\varepsilon_{it-1} < 0$ and zero otherwise (Glosten *et al.*, 1993) and z_{it} are *i.i.d.* random variables with mean zero and unit variance.

The conditional covariance matrix of the vector $\mathbf{z}_t$ is

$$E\left[\mathbf{z}_t\mathbf{z}_t' | \mathcal{F}_{t-1}\right] = \mathbf{P}_t, \tag{9}$$

which by virtue of the unit variance of z_{it} for all i, is also the correlation matrix for $\boldsymbol{\varepsilon}_t$ and has elements $\rho_{ij,t}$ which are time-varying for $i \neq j$. The conditional covariance matrix $\mathbf{H}_t = \mathbf{S}_t\mathbf{P}_t\mathbf{S}_t$, where $\mathbf{S}_t = diag\left(h_{1t}^{1/2}, ..., h_{Nt}^{1/2}\right)$, is positive definite when $\mathbf{P}_t$ is positive definite.

We model the bivariate conditional correlation structure in commodity futures, equity and bond returns using the Smooth Transition Conditional Correlation modelling framework set out in Silvennoinen and Teräsvirta (2005, 2009). The STCC–GARCH model incorporates time-variation in correlations that is attributable to a single transition variable, whereas the Double Smooth Transitions Conditional Correlation (DSTCC) GARCH model allows for two indicator variables. The STCC (DSTCC) framework can be used to describe correlation dynamics much like the DCC–GARCH (Engle, 2002) and VC–GARCH (Tse and Tsui, 2002) models do, by choosing a transition variable that utilizes information from the past correlations. It can also be seen as combining aspects of regime switching correlation models (e.g., Pelletier, 2006). The main advantage of the STCC framework is that, unlike in the models above, the transition variables can be chosen to be observable and interpretable economic quantities or general proxies for latent factors. It also provides a basis for testing the relevance of such indicators. In the STCC framework the conditional correlations move smoothly between two (STCC–GARCH model) or four (DSTCC–GARCH model) extreme states of constant correlations. This allows the model to track the correlation paths defined by the transition variables. In the estimations below, the transition variables are time, VIX, OI or DOI in the case of a single transition model, and one of the last three combined with time when using the double transition model.

The DSTCC–GARCH model proposes that correlation varies between four extreme correlation states where the paths between the states is smoothly governed by logistic functions of transition variables (here indexed as $i = 1, 2$). The conditional covariance matrix $\mathbf{P}_t$ is a convex combination of four positive definite matrices $\mathbf{P}_{(11)}, \mathbf{P}_{(12)}, \mathbf{P}_{(21)}$ and $\mathbf{P}_{(22)}$ each corresponding to an extreme state of constant correlation. The model is

$$\begin{aligned} \mathbf{P}_t &= (1 - G_{1t})\,\mathbf{P}_{(1)t} + G_{1t}\mathbf{P}_{(2)t} \\ \mathbf{P}_{(i)t} &= (1 - G_{2t})\,\mathbf{P}_{(i1)} + G_{2t}\mathbf{P}_{(i2)}, \quad i = 1, 2, \end{aligned} \tag{10}$$

with a logistic function for each transition variable,

$$G_{it} = \left(1 + e^{-\frac{\gamma_i}{\sigma_i}(s_{it} - c_i)}\right)^{-1}, \gamma_i > 0. \tag{11}$$

where s_{it} is the value of transition variable i at time t, γ_i defines the speed of transition, c_i is the location of the transition, and σ_i is the standard deviation of the transition variable i. By substitution, equation (10) can be rewritten as

$$\mathbf{P}_t = (1 - G_{2t})\left((1 - G_{1t})\,\mathbf{P}_{(11)} + G_{1t}\mathbf{P}_{(21)}\right) + G_{2t}\left((1 - G_{1t})\,\mathbf{P}_{(12)} + G_{1t}\mathbf{P}_{(22)}\right). \tag{12}$$

If the second transition variable is time ($s_{2t} = t/T$), early in the sample when $t/T < c_2$ and

G_{2t} is close to zero, more weight goes to the first term in equation (12) and $\mathbf{P}_t$ moves between the two correlation matrices $\mathbf{P}_{(11)}$ and $\mathbf{P}_{(21)}$. Later in time the matrices in the second term dominate. This formulation can match an array of conditional correlation paths. If using only one transition is sufficient, an STCC–GARCH model is employed instead. In this case, the model is simply

$$\mathbf{P}_t = (1 - G_t)\,\mathbf{P}_{(1)} + G_t \mathbf{P}_{(2)} \tag{13}$$

where G_t is the logistic function defined above.

We assume joint conditional normality of the errors:

$$\mathbf{z}_t | \mathcal{F}_{t-1} \sim N\left(\mathbf{0}, \mathbf{P}_t\right). \tag{14}$$

For inference, the asymptotic distribution of the ML-estimator of the DSTCC parameter vector denoted $\boldsymbol{\theta}$ is assumed to be normal

$$\sqrt{T}\left(\hat{\boldsymbol{\theta}}_T - \boldsymbol{\theta}_0\right) \xrightarrow{d} N\left(\mathbf{0}, \mathcal{J}^{-1}\left(\boldsymbol{\theta}_0\right)\right) \tag{15}$$

where $\boldsymbol{\theta}_0$ is the true parameter and $\mathcal{J}^{-1}\left(\boldsymbol{\theta}_0\right)$ is the population information matrix evaluated at $\boldsymbol{\theta} = \boldsymbol{\theta}_0$. For estimation, we divide the parameter vector into two sets: parameters for the correlations and for the transition functions. The log-likelihood is iteratively maximized and concentrated over each of the parameter subsets until convergence. We bound the speed of transition parameters γ_i between $0 < \gamma_i < 500$ to prevent them asymptoting towards infinity in series where switches between correlation states are especially rapid. In several cases the best estimated models use the upper bound on γ_i, consequently other estimated parameters in those models are conditioned on $\gamma_i = 500$. That is, these models follow a regime switching structure with respect to the transition variable i.

For model selection, we follows the steps outlined in Silvennoinen and Teräsvirta (2005, 2009). For each bivariate combination, we estimate a model with a constant level of correlation then carry out tests of constancy of correlations against single and double transition models. Where the constancy of correlations hypothesis is rejected, we estimate the alternative model. We follow a similar procedure after estimating a single transition model: first we perform the tests for a double transition, and if the single transition model is found insufficient, we estimate the double transition models. For each estimated STCC–GARCH or

DSTCC–GARCH model, this procedure ensures the parameters are identifiable and their estimates are consistent. We acknowledge the loss of efficiency due to the two-step estimation (i.e. the GARCH and the correlation parameters are estimated in two separate, consecutive stages), and hence allow for a higher than conventional level of the test (10%). The resulting final model candidates are evaluated for abnormalities such as large standard errors of the parameter estimates, insignificance of the level changes in correlations, inconsistent likelihood values (when compared across models with different combinations of transition variables), and inconsistencies in the test results. Based on these criteria, the best models are chosen for each bivariate system.

5 Estimation results and discussion

We estimate univariate mean and variance equations separately, and use conditionally demeaned and standardized residuals in 2-step maximum likelihood estimation of the parameters of the conditional correlation model. We then select conditional correlation models by indicators of fit and diagnostics.

5.1 Conditional means

Common and idiosyncratic factors are relevant for conditional means and variances of most commodities. For mean estimation, we include the T-bill rate, corporate bond spread and the commodity-specific interest-adjusted basis in each model even when estimated coefficients are not significant, and we retain any significant ARMA terms and exchange rate if the p-value of the estimated coefficient is less than 0.2. Commodity futures, stocks and bond index returns almost all show some significant serial correlation, and many commodity series have seasonal patterns. Table 2 reports estimation results for equation (6).

Interest rates affect futures returns directly via collateralization and the cost of carry relationship, since falling interest rates reduce current futures prices. Further, commodity price momentum (and potentially increased speculation) can be driven by accommodating macroeconomic policy, especially low short rates, creating both higher demand and stronger incentives for producers to restrict supply.[8] We confirm that lower interest rates and spreads predict higher commodity futures returns, especially among metals. Earlier studies argue

[8] See discussion in Frankel and Rose (2009) and references therein.

that a positive spread will forecast higher equity returns, and that the negative relationship between the corporate bond spread and commodities makes commodities a hedge for long-horizon equity investors (Hong and Yogo, 2009), but in our sample the coefficient on the lagged spread is significantly negative for the S&P500 and the CAC returns.

As for idiosyncratic factors, the interest-adjusted basis is significant for seven commodities, although the sign varies. Studies of longer runs of aggregated monthly data generally find a negative relationship between basis and futures returns (e.g., Hong and Yogo, 2009, Gorton *et al.*, 2007). We estimate a positive relationship between lagged basis and futures returns for live cattle, heating oil and natural gas, which suggests that the prevailing effect is mean reversion in spot prices: a high basis here implies that current futures exceed current spot and that the spot price must rise to create a positive return to the (long) futures investor. On the other hand, for wheat, coffee, platinum and Brent oil, the negative link between basis and futures may imply high future spot price volatility during periods of low inventory (low basis), and therefore higher returns to futures via a risk premium.

All of the significant exchange rate effects (excepting three base metals) apply to commodities included in the GSCI index, possibly showing their higher susceptibility to financial shocks. A USD depreciation makes futures contracts cheaper to foreign buyers, and we find that a fall in the USD predicts higher futures returns in 12 of 24 commodities. Significant effects in the reverse directions apply in a few cases.

5.2 Conditional variances

Omitting exogenous factors and nonlinearities can bias estimated GARCH coefficients, causing an overestimation of persistence in conditional volatility and making fitted conditional variance too high. It follows that estimated conditional correlations will be too low. We include these common factors and transition variables in estimation and show that they are predictors of conditional volatility of futures returns (Table 3).

Volatility rises as the T-bill rate falls for 10 of the 24 commodities and the link is especially strong for metals. A decline in the corporate bond spread also predicts higher volatility in wheat, hogs, gold, copper, nickel, tin, crude oil and natural gas, but lower volatility for pork bellies, coffee and platinum. Commodity returns volatility also tends to rise on a depreciation in the USD as measured by the lagged change in the DXY index (wheat, hogs, orange juice, gold, and platinum). Higher expected US stock volatility (VIX) predicts higher volatility in gold, nickel, all energy futures, the GSCI, and all stock indexes, but has the reverse sign for coffee and orange juice.

Our results have a similar flavour to Tang and Xiong (2009) who also noted the importance of spillovers from stock markets and the US exchange rate into commodity volatility. Like them we find significant positive spillovers from stock market volatility and the DXY for many commodities that are key components of the investable GSCI, such as energy commodities, and we find reverse signs on some spillover coefficients for orange juice, pork bellies and platinum, commodities that are not included in the GSCI index. These results also reflect the close connection between the energy-producing sector and general macroeconomic conditions (see, for example, Hamilton, 2009 and Barsky and Kilian, 2004).

Measures of market activity by non-commercial traders, OI and DOI, also predict changes in conditional variances. Rises in the percentage of long open interest held by non-commercials dampen volatility of soybean oil, live cattle and wheat returns. For coffee, sugar, gold and silver, volatility declines when the percentage of open interest held long exceeds the percentage held short, but increases when short interest exceeds long, whereas for corn, soybeans, and cotton, the interaction of the coefficients on OI and DOI means that rises in both long interest and short open interest increase volatility. So overall, an increase in the percentage of open interest held short by non-commercial traders always increases futures returns volatility, but the impact of rises in long interest varies between markets. This asymmetry between short and long non-commercial positions in some markets may reflect the calming role of money managers who provide liquidity to the market when acting as the long counterparty to (net short) commodity producers. In other markets, a higher proportion of non-commercial trade, both long and short, unambiguously raises expected volatility.

Nonlinearities (leverage effects) in stock index volatility are well-known, and although less well documented, non-linear volatility regimes in commodity returns are also supported theoretically and empirically (Deaton and Laroque, 1992, Carlson, Khoker and Titman, 2007, Fong and See, 2001). While higher volatility is linked to bear markets in stocks, commodities price volatility may increase when prices are abnormally high because of stresses on inventories. Consequently we expect the GJR parameter, which adjusts predicted variance for negative returns shocks, to lower commodity returns volatility. Here we find significant negative GJR parameters for most metals, GSCI, and bonds, and significant positive GJR parameters for all stock indices, three agricultural series and the CRB spot index.

In addition, mean fitted conditional volatility was considerably higher for most commodity futures returns from 2001 onwards, the period of greater investor interest in commodities. The last rows of Table 3 show that predicted volatility rose for all but three commodities. We can get an idea of how commodity volatility increases post-2000 by comparing with stocks: the S&P500 volatility was around 17% higher from 2001 whereas commodities experienced a rise of around 30% on average (across those series showing volatility increases).

5.3 Conditional correlation

We estimate conditional correlation using $\hat{\mathbf{z}}_t$, the standardized residuals. Table 4 reports sample unconditional correlation coefficients between commodities and stock and bond indices. For stocks, correlations with agricultural commodities and metals are low and significant but insignificant for gold and energy commodities. Bond correlations tend to be low and negative, and the sample correlations for GSCI and CRB indices are all low and significant, negative for bonds and positive for equities. Conditional correlations give us more insight into the dynamics of stock, bond and commodity markets linkages. We begin by reviewing results for US and European stocks and then US bonds.

5.3.1 US Stocks

Figure 3 graphs estimated conditional correlations between individual commodity futures and GSCI returns, and returns to the S&P500. Table 5a reports estimated parameters of preferred DSTCC models. Beginning with the meat and livestock group, conditional correlation between live cattle and stocks switches between four states where transitions depend on VIX and time. High expected stock market volatility (high VIX) raises correlation significantly, from 0 to 0.3 early in the sample (up to mid 1993) and from -0.13 to 0.16, later. Correlations for live hogs and pork bellies are constant and insignificant. Live cattle and hogs futures are components of the investable commodities indices, whereas pork belly futures are not, but we find that only cattle futures correlations are predicted by stock market uncertainty.

Of the four commodities in the food and fibre group, only orange juice is excluded from the investable indices (DJ-AIG and GSCI) and its correlation with stock returns are constant. By contrast, coffee transitions between a low (0.06) and high (0.6) correlation state when expected stock volatility is high, with peaks in 2001-02 and 2008-09. Cotton and sugar correlations have four regimes, transitioning on DOI and time. For both of these futures series, highest correlation with stocks occurs during the most recent decade at times when short open interest by money managers is strong relative to long interest. These results indicate that money managers may be successfully timing a hedge between stocks and commodities in these markets since short commodities positions can payoff against losses in long stock market positions.

The best correlation models for grains and oilseeds all show marked peaks during the 2008-09 crisis, generally in high VIX states. (Wheat responds to increasing long open interest.) Both wheat and corn show time breaks in the correlation structure, in 2004 and 2007 respectively.

Similar breaks in correlation regime show up in precious and base metals. Platinum and silver switch to significantly higher correlation states (around 0.3 from 0) from '03-'04 onwards, and all the base metals correlations increase from '99-'01 onwards. Platinum, silver, lead and tin correlations rise during high VIX states later in the sample, but are not significantly responsive to VIX earlier. These results indicate a stronger integration between stock and metals markets over the past decade that has produced higher and more time-varying correlation. Finally, all the oil futures returns series switch to high correlation with stocks (around 0.4 from low negative levels) largely in step, during high VIX states, with a sustained increase during the '08-'09 period.

In summary, most conditional correlations between commodity futures returns and US stock index returns have increased, generally peaking in the recent crisis at levels dramatically higher than earlier. Low commodity correlation with stocks do not appear to have held up in the recent crisis. Further, financial shocks appear to be important predictors of correlation dynamics. For 12 of the 24 commodities, high expected stock market volatility shifts correlations upwards. Since VIX is negatively correlated with stock returns, we conclude that both stock and futures returns are falling as VIX increases and the concentration of this effect later in the sample points to increased commodity and stock market integration over time. Further, breaks in the correlation structure emerge for most metals, some grains and some foods, around the beginning of the current decade when both fundamentals and financial investor interest were intensifying. VIX also introduces more time-variation in conditional correlation, as is consistent with theoretical predictions for liberalized markets where traders hold diffuse beliefs (Pavlova and Rigobon, 2008, Schornick, 2009). Futures market positions of non-commercial traders drive correlations with stocks for 3 contracts in a direction suggesting that money managers may be able to time their positions to offset stock market losses. No regular pattern has emerged for commodities in the GSCI index compared with excluded commodities but the new relevance of VIX and DOI or OI from the early 2000's points to increasing importance of financial trading and common shocks to correlation dynamics.

European stocks We consider European stock returns indices to see if correlation patterns between commodity futures returns and other developed economies are consistent with the US. Estimated parameters of the models are reported in Table 5(b-d) but to save space, we do not graph the correlations.

We find that many of the features of US stock commodity futures correlations are repeated in the German, French and UK stock markets. For meat and livestock, live cattle correlations transition on VIX and time and show the highest correlation in high VIX states, and for hogs, VIX becomes a relevant transition variable for correlation with the CAC and DAX around the middle of the sample.

For the food and fibre commodities and coffee, correlation patterns follow the US, with all three European stocks correlations close to 0.6 during high VIX states later in the sample (FTSE and DAX correlations have a significant time break). Findings for cotton are also similar to the US, confirming a high correlation state when money manager open interest is concentrated short in the second half of the sample. Sugar correlations with CAC and DAX rise dramatically as long open interest (OI) falls, but the time break is later than for the US. Unlike the US, orange juice correlation with FTSE, DAX and CAC also depends on money manager interest. Grain and oilseed correlations with European indices rise to around the same levels as for the S&P500, although time breaks between '04 and '06 are more marked.

Time breaks to regimes of higher correlation in base metals are consistent with the US results also. For the precious metals, we find a more significant role for the OI and DOI transition variables and significant time breaks in the correlation structure between mid-sample and 2006. Brent, crude and heating oil correlations rise but reach lower peaks for Europe than for the US, and transition effects vary considerably.

5.3.2 US bonds

Conditional correlations between bond and commodity futures returns are generally low and negative (Figure 4 and Table 5f), and crisis effects are less marked than for stocks. Meat and livestock, food and fibre and precious metals correlation regimes are close to zero. However, all base metals, energy and GSCI correlations transition on VIX, indicating integration with wider financial market conditions. With a couple of exceptions, high VIX levels generally switch bond and commodity correlations to significantly stronger negative correlation rather than positive correlation, as for stocks.

Time breaks again show up in the base metals series around the locations of the related breaks in stock correlations, whereas oil correlations have sharp regime switches during the early to mid 1990s which calm over the remaining sample. Preferred models for sugar, silver and grains and oilseeds include OI or DOI as transition variables. For sugar, soybean oil and silver, increasing long open interest predicts less negative correlations, mirroring the position with stocks.

6 Conclusion

Unlike other recent examinations of commodity futures returns such as Büyükşahin *et al.* (2010) and Chong and Miffre (2010), our results do not show weakening correlation between commodities and conventional stock and bond returns. On the contrary, we present evidence favoring closer commodity and financial market integration, consistent with Tang and Xiong (2009). We use several different methods in estimating temporal variation in correlation that may partly explain differences in our result from those of earlier studies. First we extend the sample to cover the latter part of 2008 and early 2009 and thus introduce a large amount of new variation to the data. Second, we include a careful modelling of common and idiosyncratic factors in means and variances, capturing relevant currency predictions and seasonal effects in means, and exogenous factors and nonlinearities in conditional variances. Third, we introduce the DSTCC structure with an explicit treatment of expected stock volatility and financial traders' open interest.

Commodity futures correlation dynamics with US stocks in the 1990-2009 period exhibit increases, typically rising towards 0.5 from levels close to zero in the 1990s. For most metals, and some agriculturals these increases begin mid-sample. Such patterns are also evident in correlations with stocks traded in European markets.

Also consistent across developed- country stock markets is the role of indicators of financial market conditions in predicting the correlation state. Increases in the VIX index are linked to higher commodity-stock correlation, at least from the middle of our sample. For the majority of DSTCC models that use time and VIX as transition variables, this link is significant from some point since the late 1990s. Since VIX typically co-varies negatively with stocks, our results suggest that returns to some commodity futures and stocks are now both decreasing in volatile markets, whereas in the 1990s they were largely unrelated. In models where changes in the percentage of non-commercial traders open interest is relevant, we observe similar switches, but in the reverse direction to VIX, so that higher-than-normal long OI foreshadows a decrease in the correlation between commodity futures returns and stocks. One possible explanation is that hedge fund managers are timing changes to their futures exposure to exploit hedging opportunities.

Appendix: Data sources

Commodities Futures, Wednesday closing prices or previous Tuesday when Wednesday is unavailable, from Bloomberg:

Agriculture:

- Corn: Bloomberg tickers C 1-C 5 Comdty; exchange CBT; sample 1 January 1986-1 July 2009; active months Mar May Jul Dec; major trading countries China, Brazil.
- Soybeans: Bloomberg tickers S 1-S 6 Comdty; exchange CBT; sample 1 January 1986-1 July 2009; active months Jan Mar May Jul Aug Nov; major trading countries Brazil, Argentina, China, India.
- Soybean oil: Bloomberg tickers BO1-BO8 Comdty; exchange CBT; sample 1 January 1986-1 July 2009; active months Jan Mar May Jul Aug Sep Oct Dec.
- Wheat: Bloomberg tickers W 1-W 5 Comdty; exchange CBT; sample 1 January 1986-1 July 2009; active months Mar May Jul Sep Dec; major trading countries Canada, EU, China, India, Russia, Australia.
- Lean hogs: Bloomberg tickers LH1-LH6 Comdty; exchange CME; sample 7 May 1986-1 July 2009; active months Feb Apr Jun Jul Aug Oct Dec.
- Live cattle: Bloomberg tickers LC1-LC6 Comdty; exchange CME; sample 1 January 1986-1 July 2009; active months Feb Apr Jun Aug Oct Dec.
- Pork bellies: Bloomberg tickers PB1-PB5 Comdty; exchange CME; sample 1 January 1986-1 July 2009; active months Feb Mar May Jul Aug.
- Coffee: Bloomberg tickers KC1-KC5 Comdty; exchange CSCE; sample 1 January 1986-1 July 2009; active months Mar May Jul Sep Dec
- Cotton: Bloomberg tickers CT1-CT4 Comdty; exchange NYCE; sample 1 January 1986-1 July 2009; active months Mar May Jul Dec; major trading countries China, India, Pakistan
- Orange Juice: Bloomberg tickers JO1-JO6 Comdty, exchange NYCE; 15 January 1986-1 July 2009; active months Jan Mar May Jul Sep Nov; major trading countries Brazil, US.
- Sugar: Bloomberg tickers SE1-SE4 Comdty; exchange CSCE; sample 1 January 1986-1 July 2009; active months Mar May Jul Oct; major trading countries Brazil, EU, Thailand, Australia.

Metals:

- Gold: Bloomberg tickers, GOLDS Comdty, GC1-GC5 Comdty; sample 1 January 1986-1 July 2009; exchange COMEX; Active months Mar May Jul Sep Dec; major trading countries South Africa, Russia , Canada, Australia.

- Platinum: Bloomberg tickers, PLAT Comdty, PL1-PL3 Comdty; sample 28 May 1986-1 July 2009; exchange COMEX; Active months Jan Apr Jul Oct; major trading countries South Africa, Russia
- Silver: Bloomberg tickers, SILV Comdty, SI1-SI5 Comdty; sample 1 January 1986-1 July 2009; exchange COMEX; Active months Mar May Jul Sep Dec; major trading countries Peru, Mexico, China, Chile.
- Aluminium: Bloomberg tickers LMAHDY Comdty, LMAHDS03 Comdty, LMAHDS15 Comdty ; exchange LME; sample 2 September 1987-1 July 2009; Active all 12 calendar months; major trading countries China, Russia, Canada , Australia.
- Copper: Bloomberg tickers LMCADY Comdty, LMCADS03 Comdty, LMCADS15 Comdty ; exchange LME; sample 2 April 1986-1 July 2009; Active all 12 calendar months; major trading countries Chile, Peru
- Nickel: Bloomberg tickers LMNIDY Comdty, LMNIDS03 Comdty, LMNIDS15 Comdty ; exchange LME; sample 7 January 1987-1 July 2009; Active all 12 calendar months; major trading countries Russia, Japan, Canada, Australia
- Lead: Bloomberg tickers LMPBDY Comdty, LMPBDS03 Comdty, LMPBDS15 Comdty ; exchange LME; sample 7 January 1987-1 July 2009; Active all 12 calendar months; major trading countries China
- Tin: Bloomberg tickers LMSNDY Comdty, LMSNDS03 Comdty, LMSNDS15 Comdty; exchange LME; sample 7 June 1989-1 July 2009; Active all 12 calendar months; major trading countries China, Indonesia, Peru
- Zinc: Bloomberg tickers LMZSDY Comdty, LMZSDS03 Comdty, LMZSDS15 Comdty ; exchange LME; sample 4 January 1989-1 July 2009; Active all 12 calendar months; major trading countries China, Australia, Canada

Energy:

- Brent oil; Bloomberg tickers, CO1-CO6 Comdty; sample 6 July 1988-1 July 2009; exchange NYMEX; Active all 12 calendar months.
- Crude oil WTI; Bloomberg tickers, CL1-CL9 Comdty; sample 2 July 1986-1 July 2009; exchange NYMEX; Active all 12 calendar months; major trading countries, Saudi Arabia, USA, Russia, Iran, Mexico.
- Heating oil; Bloomberg tickers, HO1-HO9 Comdty; sample 2 July 1986-1 July 2009; exchange NYMEX; Active all 12 calendar months.
- Natural gas; Bloomberg tickers, NG1- NG10 Comdty; sample 4 April 1990-1 July 2009; exchange NYMEX; Active all 12 calendar months; major trading countries, USA, Russia, Canada.

Commodity Indices:

- CRB spot: Commodity Research Bureau Continuous commodity index; Bloomberg ticker CRY Index; sample 1 January 1986-1 July 2009.

- CRB futures: Commodity Research Bureau Continuous commodity index; Bloomberg ticker CRB CMDT Index; sample 1 January 1986-1 July 2009.

- GSCI: Standard and Poors GSCI spot total returns index; 2 April 1990-1 July 2009.

Financials:

- Short rate: US Treasury Bill 3 month secondary market rate, Federal Reserve Board of Governors: H15/H15/RIFLGFCM03_N.B, sample 1 January 1986-1 July 2009.

- Yield spread: Moody's AAA Corporate Bond yield less short rate; Bloomberg ticker MOODCAAA; sample 1 January 1986-1 July 2009.

- USA Stocks: S&P500 Composite returns index; Datastream mnemonic S&PCOMP(RI); sample 1 January 1986-1 July 2009.

- German Stocks: DAX 30 returns index (Euros); Bloomberg ticker DAX TR IDX; sample 1 January 1986-1 July 2009.

- UK Stocks: FTSE100 (BPD); Bloomberg ticker UKX TR IDX; sample 6 January 1988-1 July 2009.

- France Stocks: CAC 40 (Euro); Bloomberg ticker CAC TR IDX; sample 1 January 1986-1 July 2009.

- USA Bonds: JP Morgan US Govt Bond total returns; Datastream mnemonic JP-MUSU$(RI); sample 1 January 1986-1 July 2009.

- Volatility: CBOE VIX volatility index; Bloomberg ticker VIX Comdty; sample 1 January 1986-1 July 2009.

- USA exchange rate Index future DXY: US Dollar Index (average of US dollar exhange rate with six major currencies); Bloomberg ticker DXY Curncy; sample 1 January 1986-1 July 2009.

- Exchange rates: Bloomberg tickers Argentina USDARS Curncy, Australia USDAUD Curncy, Brazil USDBRL Curncy, Canada USDCAD Curncy, Chile USDCLP Curncy ChinaUSD CNY Curncy, Colombia USDCOP Curncy, EU EURUSD Curncy, Ghana USDGHS Curncy, Guatemala USDGTQ Curncy, India USDINR Curncy, Indonesia USDIDR Curncy, Iran USDIRR Curncy, Ivory Coast USDXOF Curncy, Mexico USD-MXN Curncy; Peru USDPEN Curncy, Russia USDRUB Curncy, Saudi Arabia USDSAR Curncy, South Africa USDZAR.

Open interest

- Commodity Futures Exchange Commission, per cent of open interest non-commercial long, non-commercial short and non-commercial spread, all, mid and end month 15 May 1990 - 30 September 1992, then weekly 6 October 1992 - 30 June 2009, Contracts: *Coffee C* - Coffee, Cocoa and Sugar Exchange, *Copper* - Commodity Exchange Inc.; *Corn* - Chicago Board Of Trade; *Cotton No. 2* - New York Cotton Exchange; *Crude Oil, Light 'Sweet'* - New York Mercantile Exchange; *Gold* - Commodity Exchange Inc.; *Heating*

Oil No. 2, N.Y. HARBOR - New York Mercantile Exchange; *Lean hogs* - Chicago Mercantile Exchange; *Live Cattle* - Chicago Mercantile Exchange; *Natural Gas* - New York Mercantile Exchange; *Frozn concentrated Orange Juice* - Citrus Association of NY Cotton Exchange; *Platinum* - New York Mercantile Exchange; *Silver* - Commodity Exchange Inc.; *Soybean Oil* - Chicago Board Of Trade; *Soybeans* - Chicago Board Of Trade; *Wheat* - Chicago Board Of Trade.

References

Acharya VV, Lochstoer L, Ramadorai T. 2009. Limits to arbitrage and hedging: evidence from commodity markets. Unpublished manuscript, Columbia University. http://ssrn.com/abstract=1105546, accessed December 2009.

Barsky RB, Kilian L. 2004. Oil and the macroeconomy since the 1970s. *Journal of Economic Perspectives* **18** : 115-134. DOI: 10.1257/0895330042632708

Black F. 1975. The pricing of commodity contracts. *Journal of Financial Economics* **3** : 167-179. DOI:10.1016/0304-405X(76)90024-6

Brown-Hruska S. 2004. Securities Industry Association Hedge Funds Conference Keynote address. http://www.cftc.gov./opa/speeches04/opabrown-hruska-22.htm, accessed December 2009.

Büyükşahin B, Haigh MS, Robe MA. 2010. Commodities and equities: Ever a "market of one"? *Journal of Alternative Investments* 12 : 76-81. DOI: 10.3905/JAI.2010.12.3.076

Carlson M, Khoker Z, Titman S. 2007. Equilibrium exhaustible resource price dynamics. *Journal of Finance* **62** : 1663-1703. DOI: 10.1111/j.1540-6261.2007.01254.x

Chen Y, Rogoff K, Rossi B. 2008. Can exchange rates forecast commodity prices? NBER Working Paper 13901, National Bureau of Economic Research, Cambridge. http://www.nber.org/papers/w13901.

Chong J, Miffre J. 2010. Conditional return correlations between commodity futures and traditional assets. *Journal of Alternative Investments* **12** : 61-75. DOI: 10.3905/JAI.2010.12.3.061

Clement KW, Fry R. 2008. Commodity currencies and currency commodities. *Resources Policy* **33** : 55-73. DOI:10.1016/j.resourpol.2007.10.004

de Roon FA, Nijman TE, Veld C. 2000. Hedging pressure effects in futures markets. *Journal of Finance* **55** : 1437-1456. DOI: 10.1111/0022-1082.00253

Deaton A, Laroque G. 1992. On the behavior of commodity prices. *Review of Economic Studies* **59** : 1-23.

Deaton A, Laroque G. 1996.Competitive storage and commodity price dynamics. *Journal of Political Economy* **104** : 896-923. DOI: 10.1086/262046

Domanski D, Heath A. 2007. Financial investors and commodity markets. *BIS Quarterly Review* March.

Engle R. 2002. Dynamic conditional correlation: a simple case of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics* **20** : 339-350. DOI:10.1198/073500102288618487

Fong WM, See KH. 2001. Modelling the conditional volatility of commodity index futures as a regime switching process. *Journal of Applied Econometrics* **16** : 133-163. DOI: 10.1002/jae.590

Frankel JA, Rose AK. 2009. Determinants of agricultural and mineral commodity prices. Unpublished manuscript, Harvard University.

Glosten L, Jagannathan R, Runkle D. 1993. On the relationship between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* **48** : 1779-1801.

Gorton G, Rouwenhorst KG. 2006. Facts and fantasies about commodity futures. *Financial Analysts Journal* **62** : 47-68. DOI: 10.2469/faj.v62.n2.4083

Gorton G, Hayashi F, Rouwenhorst K.G. 2007. The fundamentals of commodity futures returns. NBER Working Paper w13249, National Bureau of Economic Research, Cambridge MA.

Haigh MS, Hranaiova J, Overdahl JA. 2005. Price dynamics, price discovery and large futures trader interactions in the energy complex. Working Paper, U.S. Commodity Futures Trading Commission, Washington DC.

Hamilton J. 2009. Causes and consequences of the oil shock of 2007-1008, Working Paper, UC San Diego.

Heaney R. 2005. An empirical analysis of commodity pricing. *Journal of Futures Markets* **26** : 391-415. DOI: 10.1002/fut.20202

Helbling T, Mercer-Blackman V, Cheng K. 2008. Riding a wave. *Finance and Development* March. http://www.imf.org/external/pubs/ft/fandd/2008/03/pdf/helbling.pdf

Hirshleifer D. 1988a. Residual risk, trading costs, and commodity futures risk premia. *Review of Financial Studies* **1** : 173-193. DOI:10.1093/rfs/1.2.173

Hirshleifer D. 1988b. Risk, futures pricing and the organization of production in commodity markets. *Journal of Political Economy* **96** : 1206-1220. DOI: 10.1086/261584

Hong H, Yogo,M. 2009. Digging into commodities. Working Paper, Department of Economics, Princeton University, Princeton NJ.

IMF 2006. The boom in nonfuel commodity prices: can it last? IMF World Economic Outlook, chapter 5, http://www.imf.org/external/pubs/ft/weo/2006/02/pdf/c5.pdf

Kat HM, Oomen RCA. 2007. What every investor should know about commodities, part II. *Journal of Investment Management* **5** : 1-25.

Kyle A, Xiong W. 2001. Contagion as a wealth effect. *Journal of Finance.* **56** : 1401-1440. DOI: 10.1111/0022-1082.00373

Mayer J. 2009. The growing interdependence between financial and commodity markets. UNCTAD Discussion paper no.165., Geneva.

Pavlova A, Rigobon R. 2008. The role of portfolio constraints in the international propagation of shocks. *Review of Economic Studies* **75** : 1215-1256. DOI: 10.1111/j.1467-937X.2008.00509.x

Pelletier D. 2006. Regime switching for dynamic correlations. *Journal of Econometrics* **131** : 445-473. DOI:10.1016/j.jeconom.2005.01.013

Pindyck RS. 1993. The present value model of rational commodity pricing. *Economic Journal* **103** : 511-530.

Pindyck RS, Rotemberg JJ. 1990. The excess co-movement of commodity prices. *Economic Journal* **100** : 1173-1189.

Redrado M, Carrera J, Bastourre D, and Ibarluccia J. 2008. Financialization of commodity markets: non-linear consequences from heterogenous agents' behavior. Working Paper, Central Bank of Argentina.

Routledge BR, Seppi DJ, Spatt CS. 2000. Equilibrium forward curves for commodities. *Journal of Finance* **55** : 1297-1338. DOI: 10.1111/0022-1082.00248

Schornick A. 2009. Competing capital constraints. Working Paper, INSEAD, Fontainebleau, France.

Sesit M.R. 2004. Commodities enter the investment mainstream. The Global Player 9 September. http://www.fullermoney.com/content/2004-09-09/MichaelSesitCommoditiesTHEGLOBALPLAYER.pdf

Silvennoinen A, Teräsvirta T. 2005. Multivariate autoregressive conditional heteroskedasticity with smooth transitions in conditional correlation. SSE/EFI Working Paper Series in Economics and Finance N0.577, Stockholm School of Economics, Stockholm.

Silvennoinen A, Teräsvirta T. 2009. Modelling multivariate autoregressive conditional heteroskedasticity with the double smooth transition conditional correlation GARCH model. *Journal of Financial Econometrics* **7** : 373-411. DOI: 10.1093/jjfinec/nbp013

Stoll H. 1979. Commodity futures and spot price determination and herding in capital market equilibrium. *Journal of Financial and Quantitative Analysis* **14** : 873-894.

Tang K, Xiong W. 2009. Index investing and the financialization of commodities. Working Paper, Princeton University, Princeton NJ.

Tse YK, Tsui KC. 2002. A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business and Economic Statistics* **20** : 351-362. DOI:10.1198/073500102288618496

Vansteenkiste I. 2009. How important are common factors in driving non-fuel commodity prices? A dynamic factor analysis. ECB working paper no 1072, European Central Bank, Frankfurt.

Table 1: Summary statistics, 2 May 1990- 1 July 2009.

Table reports summary statistics for weekly collateralized commodity futures returns, interest rates, spreads, stock and bond returns, VIX, commodity index returns and percentage of open interest in commodity futures contracts held long or short by non-commercial traders. Appendix lists all data sources and complete samples. Weekly returns are the log difference of Wednesday closing prices (or preceding Tuesday where Wednesday is missing) scaled by 100. Commodity futures returns are the average of weekly returns on a range of contracts from nearest to expiry to one year to maturity where complete data are available, collateralized by adding the 3-month Treasury Bill rate (adjusted to a weekly equivalent from annualized). For LME metals futures, we average returns to the 3 and 15 months to maturity contracts and collateralize.
For open interest of non-commercial traders we repeat mid-month and end-month values to proxy for weekly observations from 2 May 1990 to 7 October 1992. After that date the CFTC reports every week on Tuesday positions.

Collateralized commodity futures, annualized weekly returns, %

	Grains and Oilseeds				Livestock and Meat			Food and Fibre			
	corn	soybeans	soybean oil	wheat	lean hogs	live cattle	pork bellies	coffee	cotton	orange juice	sugar
mean	-3.40	6.02	3.44	0.95	4.03	5.78	4.29	-1.99	-3.43	-6.62	3.80
median	-0.67	4.74	7.58	-5.89	7.13	8.80	-7.60	-4.95	0.62	0.33	10.99
maximum	683.98	776.62	752.83	996.19	379.24	316.88	732.39	1620.30	688.49	917.94	715.93
minimum	-836.85	-795.25	-606.76	-893.19	-814.74	-641.65	-736.40	-1164.81	-732.61	-803.92	-1142.50
std. dev.	23.03	22.00	21.78	24.45	17.81	10.54	29.60	34.90	22.58	26.87	27.78
skewness	-0.10	-0.20	0.02	0.33	-0.58	-0.85	0.18	0.42	-0.09	0.11	-0.46
kurtosis	5.76	5.15	4.61	5.56	5.81	9.59	3.82	7.13	4.16	5.11	5.42
Obs.	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

	Metals									Energy			
	gold	platinum	silver	aluminium	copper	lead	nickel	tin	zinc	brent oil	crude oil	heating oil	natural gas
mean	8.41	-0.66	5.60	4.36	7.78	8.16	7.25	7.69	4.17	14.57	14.49	12.53	4.74
median	4.82	13.58	4.81	4.87	11.81	4.39	3.62	9.31	5.10	20.38	22.18	17.05	6.87
maximum	663.44	975.80	736.79	545.83	617.33	1136.27	1566.46	1389.91	644.08	1128.94	1149.23	1038.31	928.10
minimum	-688.66	-1190.74	-1025.40	-580.19	-841.17	-1059.23	-963.11	-1027.47	-965.83	-1575.44	-1215.34	-1216.40	-1061.89
std. dev.	15.72	25.89	26.91	16.36	20.87	25.84	31.36	21.43	22.22	31.13	28.39	28.12	33.22
skewness	0.01	-1.19	-0.38	-0.12	-0.50	-0.22	0.10	-0.15	-0.51	-0.51	-0.48	-0.35	-0.15
kurtosis	7.98	10.12	6.09	6.20	7.40	9.24	7.80	15.72	7.64	8.01	6.85	6.77	4.03
Obs.	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

Table 1 Continued

Interest rates and total returns to indices, (annualized weekly data)												
	Interest rates		Stock return indices				Bonds	Volatility	Commodity indices			USD
	USA 3-mth T bill	USA yield spread	USA S&P500	Germany DAX	UK FTSE100	France CAC	USA JPMorgan	VIX (level)	CRB spot	CRB futures	GSCI	DXY
mean	3.81	2.96	7.43	5.08	6.76	4.48	6.92	20.12	1.46	0.18	4.3	-0.8
median	4.34	2.58	15.04	22.86	14.28	15.48	8.47	18.46	1.76	3.62	6.2	-1.2
maximum	7.85	6.30	530.49	892.04	723.92	864.51	117.02	74.26	163.32	446.57	640.6	317.3
minimum	0.00	0.13	-851.48	-791.65	-659.41	-769.41	-131.61	9.31	-352.95	-501.89	-815.8	-416.2
std. dev.	0.25	1.42	16.59	22.92	17.03	21.74	4.61	8.45	7.09	13.00	21.5	8.5
skewness	0.42	0.10	-0.09	0.11	-0.20	0.02	-0.46	2.06	-0.46	-0.46	-0.52	0.02
kurtosis	7.13	1.84	4.16	5.11	5.15	4.61	5.42	10.19	5.42	5.42	5.86	6.48
Obs.	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

Percentage of open interest held by non-commercial traders (long and short)																
	Agriculture															
	corn		soybeans		soybean oil		wheat		live cattle		coffee		cotton		orange juice	
	long	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*
mean	18.3	10.7	20.3	11.7	23.8	10.8	26.4	14.2	22.3	13.8	21.8	15.5	18.0	19.8	26.1	17.6
median	17.6	9.3	19.9	9.4	13.7	8.9	23.5	10.7	22.3	13.0	20.9	13.9	18.0	18.1	24.6	15.3
maximum	37.5	30.9	36.5	41.1	72.4	52.4	61.40	46.50	51.3	32.2	50.2	48.7	50.3	52.7	54.5	49.5
minimum	1.9	0.6	4.1	1.5	0.7	0.9	5.4	1.5	4.6	1.8	6.0	1.1	1.1	1.1	1.4	1.3
std. dev.	7.4	6.8	7.8	7.5	22.2	7.8	11.9	9.8	7.9	5.9	8.4	9.6	10.5	12.9	12.1	10.2

			Metals								Energy					
	sugar		gold		platinum		silver		copper		crude oil		heating oil		natural gas	
	long	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*	*long*	*short*
mean	18.8	10.5	21.7	18.9	42.2	13.2	24.5	12.5	21.4	17.3	9.9	8.5	9.3	6.6	8.1	9.0
median	19.1	8.2	21.2	17.6	44.9	11.3	23.2	12.0	19.2	15.4	8.9	8.3	8.8	5.9	8.0	6.8
maximum	44.3	36.3	55.7	49.8	77.0	54.1	56.9	44.9	61.6	45.6	24.3	21.2	26.3	20.8	24.8	44.9
minimum	2.4	0.0	1.6	1.5	7.2	0.0	3.9	1.5	1.2	0.8	0.7	0.4	0.2	0.1	0.0	0.0
std. dev.	9.4	8.0	13.7	9.7	17.2	9.9	11.8	7.1	10.8	10.5	5.4	4.5	5.5	4.2	4.8	8.4

Table 2: Estimated coefficients of conditional mean equations.

Table reports estimated coefficients and fit for preferred conditional mean equations for weekly commodity futures, stock, bond and commodity index returns. Appendix lists data sources and samples. For calculation of dependent variables see notes to Table 1. Returns are regressed on a constant, and the lagged interest-adjusted basis (the log difference between the average futures prices and current spot (or nearest futures) multiplied by 100, less the weekly T-bill rate), the lagged 3-month Treasury Bill secondary market rate, the lagged corporate bond spread (difference between Moodys AAA Corporate bond yield and the T-bill rate), the lagged log change (x100) in the DXY US dollar future contract price and lagged log changes (x100) of currencies of major trading countries of the commodity, as listed in Appendix. Seasonality and serial correlation are modelled by AR and MA terms selected using Ljung-Box Q statistics to 100 lags. All significant coefficients with p-values at 20% or less are marked in boldface.

Collateralized commodity futures, conditional mean equations, estimated coefficients

	Grains and oilseeds				Meat and livestock			Food and fibre			
	corn	soybeans	soybean oil	wheat	lean hogs	live cattle	pork bellies	coffee	cotton	orange juice	sugar
constant	**0.704**	1.072	1.002	**1.013**	-0.047	-0.115	0.005	0.409	-0.662	0.212	-0.016
adj.basis(t-1)	-0.012	0.021	-0.011	**-0.217**	-0.004	**0.024**	-0.006	**-0.048**	-0.005	0.021	-0.003
bond spread(t-1)	**-0.181**	-0.132	-0.164	**-0.223**	-0.011	0.031	0.039	0.027	0.063	-0.141	0.071
t-bill(t-1)	-0.044	**-0.147**	-0.111	-0.073	0.044	0.036	0.022	-0.076	0.108	-0.002	-0.030
ar | lag	***-0.08*** *6*		**0.10** *17*	**0.06** *2*	**0.07** *2*	**-0.08** *2*	**0.06** *2*	**-0.05** *1*	**-0.10** *21*	**0.08** *8*	**0.06** *1*
ar | lag	***-0.08*** *24*			**0.06** *5*	**-0.08** *19*	**0.05** *3*	**0.08** *9*	**-0.05** *4*		**-0.11** *14*	**0.10** *17*
ar | lag				**0.09** *13*		**0.10** *4*		**-0.05** *6*			
ar | lag				**-0.09** *17*		**0.70** *7*		**0.05** *8*			
ar | lag						**0.12** *29*		**0.08** *10*			
ar | lag								**-0.08** *22*			
DXY(t-1)											**0.249**
Mexico (t-1)								**-0.167**			
Canada (t-1)				**0.189**							
Australia (t-1)				**-0.123**		**-0.07**					
Adjusted R^2	0.011	0.000	0.010	0.022	0.007	0.038	0.006	0.019	0.009	0.015	0.014
Obs.	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

Table 2 continued

Collateralized commodity futures, conditional mean equations, estimated coefficients

	Metals								
	gold	platinum	silver	aluminium	copper	lead	nickel	tin	zinc
constant	**0.845**	**2.031**	**1.544**	0.633	**1.399**	**1.871**	0.831	**1.375**	**1.139**
adj. basis(t-1)	-0.040	**-0.130**	-0.001	0.016	0.014	-0.019	-0.011	0.0083	0.003
bond spread(t-1)	**-0.112**	**-0.311**	**-0.223**	**-0.143**	**-0.241**	**-0.332**	-0.132	**-0.216**	**-0.209**
t-bill(t-1)	**-0.077**	**-0.220**	**-0.195**	-0.042	**-0.131**	**-0.182**	-0.081	**-0.152**	**-0.114**
ar | lag	**-0.06** *2*	**-0.04** *1*	-0.08* *5*	**0.06** *4*	**0.08** *2*	**-0.12** *2*	-0.06 *2*	**-0.07** *1*	-0.06 *1*
ar | lag	**-0.10** *4*	**-0.06** *5*		**0.09** *8*	**0.08** *3*	**0.07** *3*	0.09 *6*	**-0.04** *3*	0.05 *4*
ar | lag	**-0.10** *5*	**0.12** *13*		**0.09** *13*	**0.06** *6*	**0.05** *4*		**0.05** *4*	-0.08 *7*
ar | lag	**0.10** *12*	**0.10** *26*		**-0.13** *21*	**-0.05** *7*	**0.15** *9*		**0.05** *5*	0.10 *9*
ar | lag	**-0.09** *24*				**0.09** *9*			**-0.07** *7*	-0.**08** *12*
ar | lag					**-0.06** *16*			**0.07** *8*	
								0.10 *9*	
								0.16 *10*	
								-0.11 *26*	
DXY(t-1)	**-0.339**				**-0.121**				
South Africa (t-1)	**0.094**								
Canada(t-1)	**-0.238**						**0.210**		
Mexico (t-1)			**-0.094**						
Australia (t-1)	**-0.252**			**-0.150**			**-0.269**		**-0.244**
Adjusted R^2	0.206	0.059	0.008	0.041	0.028	0.047	0.012	0.066	0.035
Obs	1001	1001	1001	1001	1001	1001	1001	1001	1001

Table 2 continued

Collateralized commodity futures and commodity, stock and bond indices, conditional mean equations, estimated coefficients												
	Energy				**GSCI**	**CRB**		**Stocks**				**Bonds**
	Brent oil	Crude oil	Heating oil	Natural gas	GSCI spot	CRB spot	CRB futures	US S&P500	Germany DAX	UK FTSE100	France CAC	US JPMorgan
constant	1.127	0.756	0.488	-0.685	0.146	**0.686**	0.495	**0.686**	0.495	0.197	0.619	-0.207
adj. basis(t-1)	**-0.075**	-0.009	**0.045**	**0.020**								
bond spread(t-1)	**-0.194**	-0.123	-0.086	0.064	-0.063	**-0.114**	-0.085	**-0.114**	-0.085	-0.042	**-0.125**	**0.051**
t-bill(t-1)	**-0.085**	-0.031	0.008	0.131	0.031	**-0.083**	-0.061	**-0.083**	-0.061	0.014	-0.041	**0.048**
ar | lag	**-0.06** *1*	**0.14** *3*	**0.12** *3*	**0.11** *3*	**0.15** *3*	**0.81** *1*	**0.1** *3*	**-0.12** *7*	**-0.09** *1*	**-0.09** *7*	**-0.13** *1*	**-0.09** *25*
ar | lag	**0.13** *3*	**0.12** *14*	**0.09** *10*	**0.10** *4*		**0.03** *9*	**0.09** *8*					
ar | lag	**0.11** *14*	**0.07** *26*	**0.15** *14*			**-0.08** *16*	**0.15** *14*					
ar | lag						**0.08** *17*	**-0.1** *25*					
ma						**-0.58** *1*						
Canada (t-1)			**-0.234**	**-0.191**								
Adjusted R^2	0.032	0.036	0.028	0.018	0.022	0.079	0.047	0.079	0.047	0.005	0.015	0.016
Obs	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

Table 3: Estimated coefficients of GARCH equations.

Table reports estimated coefficients of preferred conditional variance equations estimated using residuals from mean equations described in Table 2. GARCH models include a constant, ARCH, GARCH and GJR terms, and where relevant, lagged interest-adjusted commodity basis, the lagged yield spread, the lagged 3-month Treasury Bill secondary market rate, the lagged log change (x100) in the DXY US dollar future contract price, lagged levels of the VIX volatility index, lagged OI (% of long open interest in the futures contract held by non-commercial traders) and DOI (proportional difference between net long and net short open interest held by non-commercial futures traders). All fitted values of the conditional variance are strictly positive. All coefficients **except** those marked with an asterisk are significant at 10%.

Collateralized commodity futures, GARCH equations, estimated coefficients

	Grains and oilseeds				**Meat and livestock**			**Food and fibre**			
	corn	soybeans	soybean oil	wheat	lean hogs	live cattle	pork bellies	coffee	cotton	orange juice	sugar
constant	2.528	1.060	2.540	0.356	0.164	0.139	-2.385	4.470	0.298	0.158	0.481
adj.basis(t-1)	-0.057	-0.063			-0.001	-0.006	0.068	-0.168	-0.027		
bond spread(t-1)				-0.065	-0.009		0.69	0.688			
t-bill(t-1)			-0.195	-0.022	-0.011		0.556				
DXY(t-1)				-0.273	-0.054		0.668			-0.304	
VIX(t-1)								-0.085		-0.006	
OI(t-1)	0.151	0.049	-0.195	-0.008		0.009			0.045		
DOI(t-1)	-2.273	-1.108				-0.173		-3.868	-0.755		-0.466
ARCH (1)	0.047*	0.065	0.114	-0.017*	-0.052	-0.003*	0.051	0.180	0.093	-0.011	0.072
ARCH (2)	0.115	0.108		0.165		0.149					
ARCH (3)		-0.096		-0.131							
GJR					0.067	0.149				0.035	
GARCH(1)	0.056*	0.832	0.681	1.006	1.001	0.871	0.839	0.772	0.856	0.991	-0.466
GARCH(2)	0.060										
Mean h(t)											
1990-2000	18.9	19.0	19.6	18.4	17.8	8.3	33.2	36.6	19.0	27.4	26.0
2001-2009	26.2	24.6	23.4	19.0	31.0	12.6	24.8	31.5	26.1	25.3	29.9

Table 3 continued

Collateralized commodity futures and commodity, stock and bond indices, GARCH equations, estimated coefficients

	Metals								
	gold	platinum	silver	aluminium	copper	lead	nickel	tin	zinc
constant	0.150	-1.634	0.599	0.147	1.031	0.169	3.188	3.129	0.119
adj.basis(t-1)						-0.010			
bond spread(t-1)	-0.023	0.405			-0.105		-0.464	-0.203	
t-bill(t-1)	-0.028				-0.094		-0.347	-0.325	-0.019
DXY(t-1)	-0.073	-0.343							
VIX(t-1)	0.009						0.057		
OI(t-1)									
DOI(t-1)	-0.089		-0.833						
ARCH (1)	0.173	0.195	0.148	0.078	0.103	0.068	0.084	0.325	0.059
ARCH (2)	-0.080	0.086							
ARCH (3)	0.080								
ARCH (13)		0.223							
GJR	-0.150	-0.165	-0.111	-0.030				-0.122	-0.029
GARCH(1)	0.866	0.504	-0.882	0.907	0.852	0.918	0.828	0.579	0.953
Mean h(t)									
1990-2000	10.6		22.0	14.7	16.1	17.8	25.9	14.7	15.8
2001-2009	13.9		31.2	17.1	24.5	31.0	36.2	25.8	26.5

	Energy				**GSCI**	**CRB**		**Stocks**				**Bonds**
	Brent oil	Crude oil	Heating oil	Natural gas	GSCI spot	CRB spot	CRB futures	US S&P500	Germany DAX	UK FTSE100	France CAC	US JPMorgan
constant	1.540	1.103	-0.243*	0.196*	0.911	0.001	0.035	-0.893	-2.254	0.015*	-3.63	0.004*
adj.basis(t-1)												
bond spread(t-1)		-0.241		-0.090	-0.188				0.182		0.404	
t-bill(t-1)	-0.288	-0.210			-0.134						0.419	
DXY(t-1)						-0.010					-0.407	
VIX(t-1)	0.127	0.085	0.051	0.029	0.040			0.125	0.264	0.033	0.196	
OI(t-1)			0.040									
DOI(t-1)												
ARCH (1)	0.138	0.098	0.098	0.100	0.138	-0.002*	0.074	-0.130	-0.008*	-0.026	0.012*	0.081
ARCH (2)				-0.066		0.092						
ARCH (3)						-0.093						
ARCH (4)						0.136						
ARCH (5)						-0.151						
GJR					-0.066	0.020		0.275	0.228	0.311	0.223	-0.073
GARCH(1)	0.755	0.815	0.848	0.943	0.822	1.007	0.914	0.707	0.511	0.739	0.505	0.947
Mean h(t)												
1990-2000	28.1	24.7	24.7	28.6	17.8	5.7	9.6	16.3	20.7	15.0	20.8	3.9
2001-2009	33.1	30.9	30.4	37.1	24.5	6.2	15.5	19.0	25.1	19.3	22.1	5.2

Table 4: Commodity futures and financial indices, unconditional correlations, 2 May 1990 – 1 July 2009.

Table shows sample unconditional correlation between weekly commodity futures returns and bond and stock returns. Correlations significant at the 10% level are bold. Appendix lists all data sources and samples. See notes to Table 1 for computation of returns series.

	US Bonds	S&P500	DAX	FTSE100	CAC
Corn	-0.04	**0.09**	**0.05**	**0.05**	0.02
Soybeans	-0.03	**0.12**	**0.09**	**0.09**	**0.06**
Soybean oil	-0.04	**0.15**	**0.11**	**0.12**	**0.09**
Wheat	-0.04	**0.08**	0.05	0.05	0.03
Live hogs	-0.01	0.05	0.04	0.04	0.03
Feeder cattle	-0.04	**0.12**	**0.10**	**0.12**	**0.10**
Pork bellies	-0.01	0.01	0.00	0.00	-0.00
Coffee	**-0.08**	**0.09**	**0.13**	**0.10**	**0.09**
Cotton	**-0.06**	**0.12**	**0.10**	**0.10**	**0.08**
Orange Juice	0.02	**0.07**	0.03	**0.06**	**0.06**
Sugar	**-0.07**	0.02	0.03	0.00	0.15
Gold	-0.00	-0.03	-0.04	-0.05	-0.03
Platinum	**-0.10**	**0.05**	**0.06**	**0.06**	0.03
Silver	**-0.06**	**0.10**	**0.10**	**0.12**	**0.08**
Aluminium	**-0.15**	**0.15**	**0.14**	**0.13**	**0.13**
Copper	**-0.15**	**0.21**	**0.19**	**0.19**	**0.19**
Lead	**-0.12**	**0.14**	**0.13**	**0.13**	**0.11**
Nickel	**-0.14**	**0.22**	**0.17**	**0.18**	**0.17**
Tin	**-0.10**	**0.21**	**0.17**	**0.19**	**0.18**
Zinc	**-0.14**	**0.17**	**0.20**	**0.19**	**0.18**
Brent oil	**-0.11**	0.04	-0.01	0.04	-0.00
WT crude oil	**-0.11**	**0.06**	-0.00	**0.07**	0.01
Heating oil	**-0.10**	0.04	-0.02	0.04	-0.01
Natural gas	-0.02	0.04	0.01	**0.06**	0.05
CRB futures	**-0.13**	**0.18**	**0.13**	**0.16**	**0.12**
CRB spot	**-0.13**	**0.14**	**0.10**	**0.09**	**0.09**
GSCI total returns	**-0.11**	**0.07**	0.01	**0.01**	0.02

Table 5: Preferred conditional correlation models, weekly commodity futures returns.

Table reports estimated parameter values for preferred conditional correlation models of commodity futures returns with USA stock market returns (5a), USA bond index returns (5b), German stock market returns (5c), UK stock market returns (5d), French stock market returns (5e) and crude oil futures returns (5f). Correlation models are estimated using standardized residuals from GARCH equations as described in Table 3. We estimate the DSTCC models by maximum likelihood by iteratively concentrating the likelihood function over correlation and transition function parameters. The DSTCC process treats conditional correlation as a convex combination of (up to) four extreme values, P(11)-P(22), where the weights of the convex combination are given by up to two logistic transition functions dependent on transition variable s_i with location c_i and transition speed γ_i. When both transition variables are in their low state ($s_i < c_i$) conditional correlation tends to P(11), to P(22) when both are above the location threshold, and to P(12) or P(21) in intermediate locations. Values of P(ij) significant at 10% are in bold typeface.

US Stocks

		Meat and Livestock			Food and Fibre				Grains and Oilseeds				GSCI
		live hogs	live cattle	pork bellies	coffee	cotton	o.juice	sugar	corn	soybeans	soybean oil	wheat	
transition 1	s_1		VIX		VIX	DOI		DOI	VIX	VIX	VIX	OI	time
transition 2	s_2		time			time		time	time			time	
low s_1 - low s_2	P(11)	0.051	0.077	0.031	**0.061**	-0.071	**0.068**	0.029	0.063	0.058	**0.067**	0.039	-0.031
low s_1 - high s_2	P(12)	0.051	**-0.13**	0.031	**0.061**	**0.296**	**0.068**	**0.51**	-0.093	0.058	**0.067**	**-0.284**	-0.031
high s_1 - low s_2	P(21)	0.051	**0.321**	0.031	**0.602**	0.038	**0.068**	**-0.279**	-0.091	**0.379**	**0.574**	-0.059	**0.521**
high s_1 - high s_2	P(22)	0.051	**0.162**	0.031	**0.602**	-0.099	**0.068**	**-0.18**	**0.493**	**0.379**	**0.574**	**0.226**	**0.521**
location 1	c_1		17.32		36.04	-0.054		0.138	30.17	33.01	37.16	2.234	0.954
location 2	c_2		0.155			0.454		0.561	0.804			0.727	
transition speed 1	γ_1		∞		∞	∞		3.786	2.787	∞	4.688	∞	∞
transition speed 2	γ_2		∞			∞		∞	∞			∞	

		Precious Metals				Base Metals					Energy			
		gold	plati-num	sliver	alumin-ium	copper	lead	nickel	tin	zinc	brent oil	WT crude	heating oil	natural gas
transition 1	s_1		VIX	VIX	time	time	VIX	time	VIX	time	VIX	VIX	VIX	
transition 2	s_2		time	time			time		time					
low s_1 - low s_2	P(11)	-0.047	-0.01	0.038	-0.015	0.046	0.087	-0.076	0.089	-0.02	-0.054	-0.057	**-0.063**	0.035
low s_1 - high s_2	P(12)	-0.047	-0.08	**0.182**	-0.015	0.046	-0.014	-0.076	0.036	-0.02	-0.054	-0.057	**-0.063**	0.035
high s_1 - low s_2	P(21)	-0.047	0.00	**-0.147**	**0.257**	**0.24**	-0.116	**0.294**	-0.009	**0.243**	**0.426**	**0.358**	**0.431**	0.035
high s_1 - high s_2	P(22)	-0.047	**0.262**	**0.301**	**0.257**	**0.24**	**0.313**	**0.294**	**0.286**	**0.243**	**0.426**	**0.358**	**0.431**	0.035
location 1	c_1		17.74	23.86	0.465	0.503	15.59	0.454	18.71	0.515	36.04	34.21	33.62	
location 2	c_2		0.684	0.726			0.672		0.572					
transition speed 1	γ_1		∞	∞	∞	12.55	∞	3.132	∞	17.32	∞	∞	∞	
transition speed 2	γ_2		80.17	∞			4.56		70.84					

Table 5 Continued
(b)

		DAX- German stocks											
		Meat and Livestock			**Food and Fibre**				**Grains and Oilseeds**				**GSCI**
		live hogs	live cattle	pork bellies	coffee	cotton	sugar	o.juice	corn	soybeans	soybean oil	wheat	
transition 1	s_1	VIX	VIX	VIX	VIX	DOI	OI	OI	VIX	VIX	VIX		time
transition 2	s_2	time	time		time	time	time	time	time	time	time		
low s_1 - low s_2	P(11)	**0.16**	-0.01	**0.46**	**0.08**	0.12	0.02	0.02	**0.09**	**0.09**	0.05	0.03	**-0.44**
low s_1 - high s_2	P(12)	-0.06	-0.10	**0.46**	0.10	**0.21**	**0.58**	**0.29**	**-0.98**	0.03	0.04	0.03	**-0.44**
high s_1 - low s_2	P(21)	-0.06	**0.11**	-0.03	0.12	**0.15**	-0.11	**-0.10**	-0.07	-0.15	**-0.52**	0.03	0.05
high s_1 - high s_2	P(22)	**0.14**	**0.35**	-0.03	**0.63**	-0.08	**-0.55**	0.05	**0.32**	**0.46**	**0.57**	0.03	0.05
location 1	c_1	13.70	17.48	11.34	27.49	-0.04	5.25	2.66	21.58	26.71	32.26		0.08
location 2	c_2	0.62	0.70		0.67	0.31	0.93	0.82	0.91	0.64	0.64		
transition speed 1	γ_1	∞	∞	∞	34.53	∞	∞	∞	5.24	∞	6.04		∞
transition speed 2	γ_2	∞	∞		25.71	∞	∞	∞	∞	∞	∞		

		Precious Metals				**Base Metals**					**Energy**			
		gold	plati-num	sliver	alumin-ium	copper	lead	nickel	tin	zinc	brent oil	WT crude	heating oil	natural gas
transition 1	s_1	DOI	VIX	DOI	VIX	VIX	time	VIX	VIX	time	VIX	OI	VIX	
transition 2	s_2	time	time	time	time	time		time	time		time	time	time	
low s_1 - low s_2	P(11)	**-0.25**	**0.12**	-0.01	-0.07	-0.01	**-0.08**	0.03	**0.06**	0.03	-0.13	**-0.75**	0.09	0.01
low s_1 - high s_2	P(12)	0.24	0.05	-0.20	**0.17**	-0.03	**-0.08**	0.03	**0.06**	0.03	-0.02	**0.15**	-0.06	0.01
high s_1 - low s_2	P(21)	0.10	-0.08	0.04	**0.18**	0.04	**0.15**	**0.48**	**0.28**	**0.24**	**-0.77**	0.12	**-0.70**	0.01
high s_1 - high s_2	P(22)	**-0.14**	**0.26**	**0.28**	**0.47**	**0.35**	**0.15**	**0.48**	**0.28**	**0.24**	**0.11**	**-0.11**	0.07	0.01
location 1	c_1	0.35	23.21	-0.17	34.80	15.11	0.56	29.65	28.18	0.47	20.34	0.88	17.75	
location 2	c_2	0.53	0.76	0.78	0.47	0.58					0.04	0.04	0.04	
transition speed 1	γ_1	148.53	∞	∞	22.62	13.89	24.36	3.51	∞	∞	500.00	173.90	∞	
transition speed 2	γ_2	4.45	∞	∞	∞	10.77					162.04	78.22	∞	

Table 5 Continued
(c)

FTSE100-UK stocks														
		Meat and Livestock			Food and Fibre				Grains and Oilseeds				GSCI
		live hogs	live cattle	pork bellies	coffee	cotton	o.juice	sugar	corn	soybeans	soybean oil	wheat	
transition 1	s_1		VIX		VIX	DOI	OI	VIX	VIX	time	time	VIX	
transition 2	s_2		time		time	time		time	time			time	
low s_1 - low s_2	P(11)	0.03	-0.059	0.003	0.02	-0.07	0.09	**-0.12**	0.03	0.00	0.03	0.05	0.03
low s_1 - high s_2	P(12)	0.03	-0.109	0.003	**0.22**	**0.30**	0.09	0.02	-0.07	0.00	0.03	-0.07	**0.22**
high s_1 - low s_2	P(21)	0.03	**0.126**	0.003	0.14	-0.05	-0.11	-0.05	-0.13	**0.22**	**0.26**	**-0.14**	**-0.17**
high s_1 - high s_2	P(22)	0.03	**0.237**	0.003	**0.63**	0.06	-0.11	**0.65**	**0.40**	**0.22**	**0.26**	**0.27**	**0.45**
location 1	c_1		17.32		27.21	-0.06	8.64	26.28	25.49	0.84	0.84	22.29	26.30
location 2	c_2		0.667		0.79	0.53		0.76	0.83			0.64	0.79
transition speed 1	γ_1		∞		30.53	∞	∞	∞	14.54	∞	∞	∞	∞
transition speed 2	γ_2		∞		∞	∞		∞	∞			∞	∞

		Precious Metals				Base Metals					Energy			
		gold	plati-num	sliver	alumin-ium	copper	lead	nickel	tin	zinc	brent oil	WT crude	heating oil	natural gas
transition 1	s_1	time	time	OI	VIX	OI	time	VIX	time	time	time	time	time	
transition 2	s_2			time	time	time		time						
low s_1 - low s_2	P(11)	**-0.12**	0.02	**0.08**	-0.03	0.03	-0.03	-0.03	0.01	-0.03	-0.01	0.00	-0.02	**0.07**
low s_1 - high s_2	P(12)	**-0.12**	0.02	**0.35**	**0.25**	**0.30**	-0.03	0.06	0.01	-0.03	-0.01	0.00	-0.02	**0.07**
high s_1 - low s_2	P(21)	-0.01	**0.23**	-0.12	**-0.37**	**-0.53**	**0.25**	-0.05	**0.20**	**0.27**	**0.28**	**0.27**	**0.25**	**0.07**
high s_1 - high s_2	P(22)	-0.01	**0.23**	**0.14**	**0.24**	**0.21**	**0.25**	**0.34**	**0.20**	**0.27**	**0.28**	**0.27**	**0.25**	**0.07**
location 1	c_1	0.38	0.84	5.04	27.95	12.60	0.83	15.74	0.55	0.53	0.79	0.79	0.79	
location 2	c_2			0.75	0.49	0.55		0.57						
transition speed 1	γ_1	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	
transition speed 2	γ_2			∞	∞	∞		17.18						

Table 5 Continued
(d)

CAC - France stocks

		Meat and Livestock			Food and Fibre				Grains and Oilseeds				GSCI
		live hogs	live cattle	pork bellies	coffee	cotton	o.juice	sugar	corn	soybeans	soybean oil	wheat	
transition 1	s_1	VIX	VIX		time	DOI	DOI	OI	VIX	VIX	VIX	OI	time
transition 2	s_2	time				time	time	time	time	time	time	time	
low s_1 - low s_2	P(11)	-0.07	-0.05	-0.01	**0.07**	0.04	**0.25**	0.00	0.01	0.04	0.06	-0.01	**-0.41**
low s_1 - high s_2	P(12)	-0.01	-0.05	-0.01	**0.07**	**0.26**	**0.08**	**0.61**	**-0.88**	0.03	0.02	**-0.24**	**-0.41**
high s_1 - low s_2	P(21)	**0.32**	**0.14**	-0.01	**0.64**	-0.02	-0.11	**-0.13**	-0.11	**-0.21**	-0.34	-0.10	**0.07**
high s_1 - high s_2	P(22)	-0.01	**0.14**	-0.01	**0.64**	-0.08	-0.06	**-0.56**	**0.32**	**0.42**	**0.47**	**0.21**	**0.07**
location 1	c_1	17.84	18.43		0.96	-0.05	0.18	5.31	22.37	26.71	29.39	2.07	0.08
location 2	c_2	0.36				0.47	0.35	0.94	0.91	0.64	0.57	0.73	
transition speed 1	γ_1	∞	∞		∞	0.04	∞	75.93	5.75	∞	1.65	∞	∞
transition speed 2	γ_2	25.08				0.26	∞	∞	∞	∞	∞	∞	

		Precious Metals			Base Metals						Energy		
		gold	plati-num	sliver	alumin-ium	copper	lead	nickel	tin	zinc	brent oil	WT crude	heating oil	natural gas
transition 1	s_1	DOI		OI	VIX	VIX	time	VIX	VIX	time	time	OI	VIX	
transition 2	s_2	time		time	time	time		time	time			time	time	
low s_1 - low s_2	P(11)	**-0.30**	0.04	-0.02	-0.01	0.06	**-0.10**	0.04	**0.11**	-0.02	**-0.46**	**-0.66**	0.24	**0.07**
low s_1 - high s_2	P(12)	0.20	0.04	**0.31**	**0.18**	-0.03	**-0.10**	-0.01	0.01	-0.02	**-0.46**	**0.18**	0.01	**0.07**
high s_1 - low s_2	P(21)	**0.12**	0.04	0.04	**-0.13**	-0.03	**0.15**	-0.07	0.02	**0.25**	**0.07**	0.18	**-0.67**	**0.07**
high s_1 - high s_2	P(22)	**-0.12**	0.04	**0.17**	**0.28**	**0.34**	**0.15**	**0.34**	**0.26**	**0.25**	**0.07**	**-0.10**	**0.08**	**0.07**
location 1	c_1	0.36		0.30	15.72	14.49	0.59	15.60	18.73	0.49	0.04	0.84	20.13	
location 2	c_2	0.50		0.71	0.47	0.53		0.53	0.55			0.04	0.04	
transition speed 1	γ_1	∞		∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	
transition speed 2	γ_2	3.80		∞	∞	∞		6.82	∞			72.64	172.17	

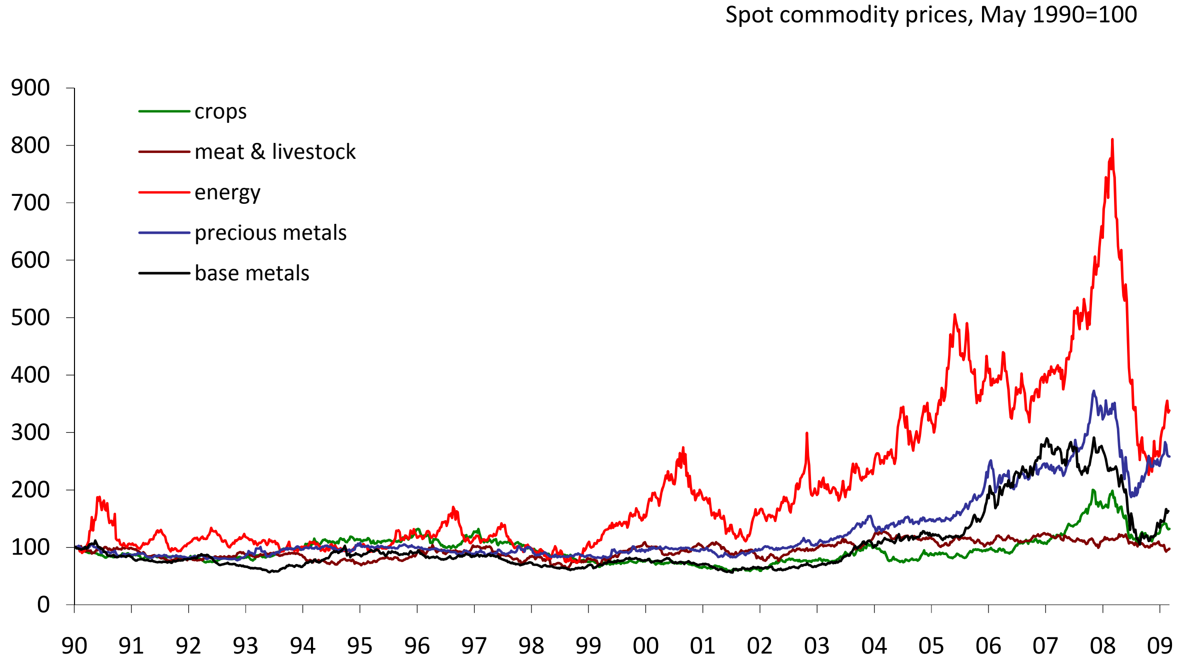
Table 5 Continued
(e)

US Bonds

		Meat and Livestock			**Food and Fibre**				**Grains and Oilseeds**				**GSCI**
		live hogs	live cattle	pork bellies	coffee	cotton	o.juice	sugar	corn	soybeans	soybean oil	wheat	
transition 1	s_1	VIX		VIX			VIX	DOI	DOI	OI	OI		VIX
transition 2	s_2	time						time	time	time	time		time
low s_1 - low s_2	P(11)	0.078	-0.041	-0.03	**-0.084**	**-0.07**	**0.123**	-0.042	**-0.135**	0.079	0.004	**-0.053**	-0.015
low s_1 - high s_2	P(12)	**-0.153**	-0.041	-0.03	**-0.084**	**-0.07**	**0.123**	**-0.095**	-0.04	0.028	**-0.842**	**-0.053**	0.027
high s_1 - low s_2	P(21)	-0.089	-0.041	**0.186**	**-0.084**	**-0.07**	-0.012	**-0.24**	**0.283**	0.055	**0.112**	**-0.053**	**-0.457**
high s_1 - high s_2	P(22)	**0.129**	-0.041	**0.186**	**-0.084**	**-0.07**	-0.012	0.052	-0.092	**-0.172**	**-0.139**	**-0.053**	-0.111
location 1	c_1	23.65		29.17			17.44	0.167	0.18	2.533	-1.331		18.54
location 2	c_2	0.459						0.349	0.297	0.303	0.75		0.315
transition speed 1	γ_1	∞		∞			∞	∞	∞	∞	∞		∞
transition speed 2	γ_2	∞						∞	∞	∞	∞		∞

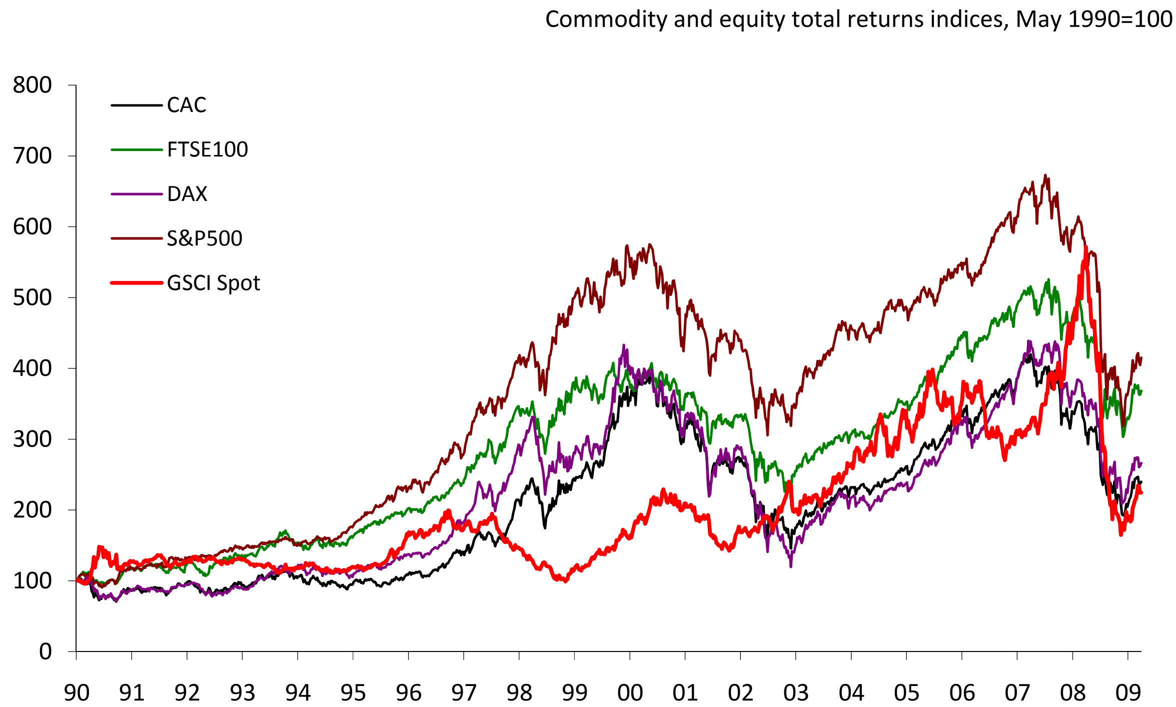
		Precious Metals				**Base Metals**					**Energy**			
		gold	plati-num	sliver	alumin-ium	copper	lead	nickel	tin	zinc	brent oil	WT crude	heating oil	natural gas
transition 1	s_1			DOI	VIX	VIX	VIX	VIX	VIX	VIX	VIX	VIX	VIX	VIX
transition 2	s_2			time	time		time	time			time	time	time	time
low s_1 - low s_2	P(11)	0.012	**-0.073**	**-0.225**	-0.051	-0.041	0.079	-0.059	0.042	-0.056	-0.045	-0.059	-0.076	**0.171**
low s_1 - high s_2	P(12)	0.012	**-0.073**	**-0.198**	-0.073	-0.041	-0.069	**0.213**	0.042	-0.056	2E-04	0.021	-0.003	-0.02
high s_1 - low s_2	P(21)	0.012	**-0.073**	**-0.129**	-0.04	**-0.279**	**-0.145**	**-0.24**	**-0.191**	**-0.226**	**-0.412**	**-0.432**	**-0.507**	**-0.488**
high s_1 - high s_2	P(22)	0.012	**-0.073**	0.042	**-0.332**	**-0.279**	**-0.378**	**-0.276**	**-0.191**	**-0.226**	**-0.092**	**-0.107**	-0.068	-0.041
location 1	c_1			-0.129	23.75	24.28	20.91	23.78	24.93	20.94	18.56	18.55	18.49	19.11
location 2	c_2			0.398	0.499		0.742	0.844			0.313	0.315	0.221	0.273
transition speed 1	γ_1			∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	6.343
transition speed 2	γ_2			∞	∞		∞	∞			∞	∞	∞	∞

Figure 1: Spot commodity price movements, 2 May 1990 – 1 July 2009



Note: Figure graphs arithmetic averages of Wednesday closing prices for spot or nearest futures for crops (corn, wheat, sugar, soybeans, cotton, coffee & soy oil), meat & livestock (lean hogs, pork bellies, feeder cattle & live cattle), energy (WT crude oil, Brent oil, natural gas & heating oil), precious metals (gold, silver & platinum), base metals (aluminium, copper nickel, lead, zinc & tin). 2 May 1990 =100. Data sources in Appendix.

Figure 2: Commodity and stock total returns index movements, 2 May 1990 – 1 July 2009



Note: Figure graphs Wednesday closing values for commodity and stock total returns indices, 2 May 1990 =100. Data sources in Appendix.

Figure 3: Conditional correlations between commodity futures and US stock index returns

Note: Figure graphs estimated conditional correlations between weekly US stock returns and commodity futures returns, 2 May 1990 - 1 July 2009. For returns computations see notes to Table 1 and for conditional mean estimation see notes to Table 2. Fitted DSTCC-GARCH model parameters are listed in Table 5a. Data sources in Appendix.

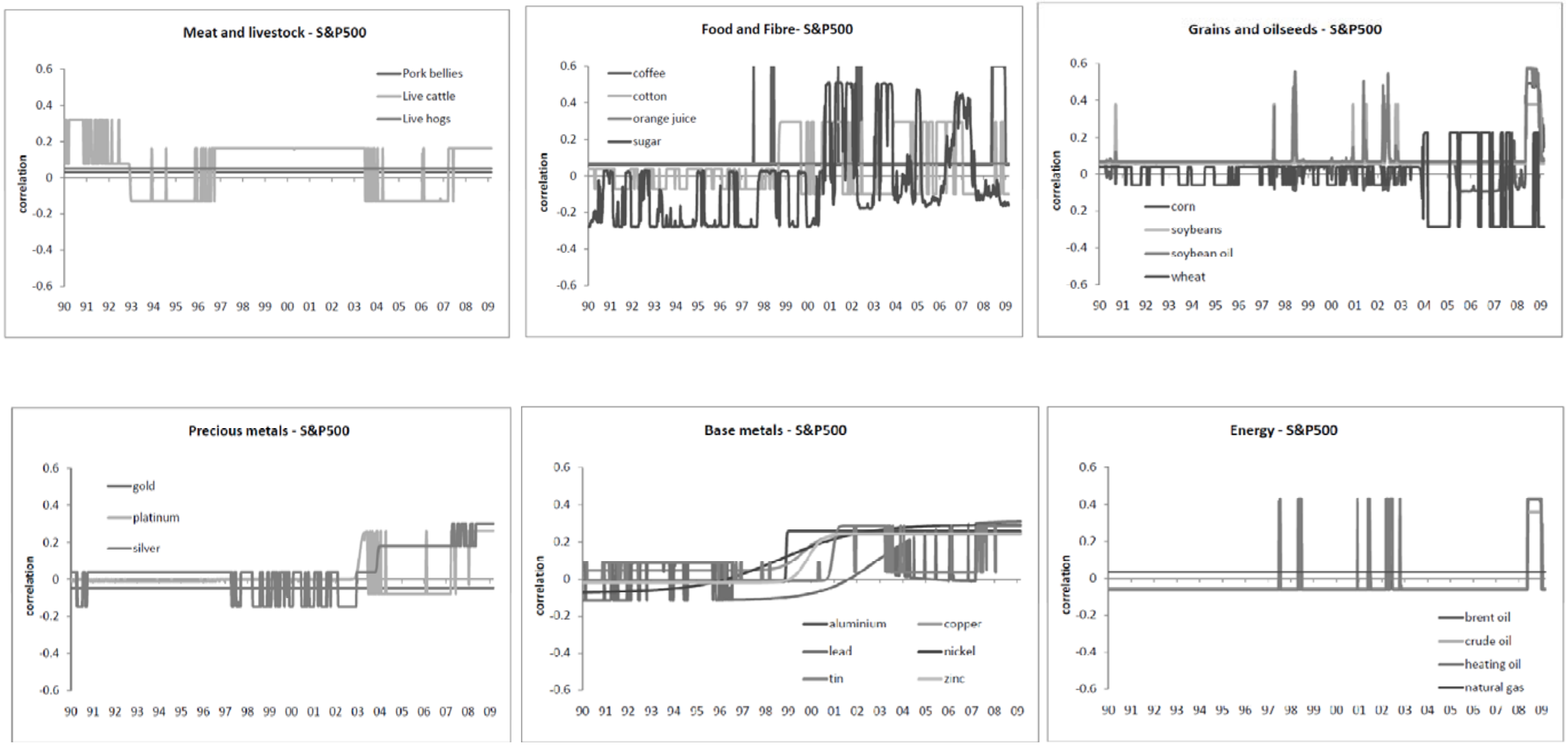


Figure 4: Conditional correlations between commodity futures and US bond index returns

Note: Figure graphs estimated conditional correlations between weekly US bond index total returns and commodity futures returns, 2 May 1990 - 1 July 2009. For returns computations see notes to Table 1 and for conditional mean estimation see notes to Table 2. Fitted DSTCC-GARCH model parameters are listed in Table 5e. Data sources in Appendix.