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Financialization, Crisis and Commodity Correlation Dynamics

Annastiina Silvennoinen and Susan Thorp

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Financialization, crisis and commodity correlation dynamics.

Annastiina Silvennoinen
Queensland University of Technology

Susan Thorp
University of Technology, Sydney

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Abstract

We study bi-variate conditional volatility and correlation dynamics for individual commodity futures and financial assets from May1990-July 2009 using DSTCC- GARCH (Silvennoinen and Teräsvirta 2009). These models allow correlation to vary smoothly between extreme states via transition functions driven by indicators of market conditions. Expected stock volatility and money manager open interest in futures markets are relevant transition variables. Results point to increasing integration between commodities and financial markets. Higher commodity returns volatility is predicted by lower interest rates and corporate bond spreads, US dollar depreciations, higher expected stock volatility and financial traders open positions. We observe higher and more variable correlations between commodity futures and financial asset returns, particularly from mid-sample, often predicted by higher expected stock volatility. For many pairings, we observe 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 shown rapid and widespread rises followed by sharp falls during the 2008-09 financial crisis. While macroeconomic forces, including demand from commodity-intensive industrializing economies, played a key role in this boom and bust, other factors, including the financialization of commodity derivatives markets, contributed. Institutional investors and hedge funds have intensified their interest in commodities as an alternative to traditional asset classes, allocating funds to indices such as the Goldman Sachs Commodities Index (GSCI), and trading in derivatives markets.

Much institutional investor interest is motivated by the belief that commodities offer reliable diversification against downturns in stock markets, exhibiting low correlation with traditional assets that is robust to extreme events (Gorton and Rouwenhorst 2006; Kat and Oomen 2006; Chong and Miffre 2008; Büyükşahn, Haigh and Robe 2008). But as financial investor interest in commodities expands, it is natural to ask whether shocks from conventional asset markets and the strategies of financial players, rather than underlying commodity market fundamentals, will begin to weaken the diversification value of commodities.

Here we re-examine the time path of correlation between conventional assets and returns to commodity futures over the past two decades for evidence of increased integration. We model bivariate correlation dynamics for 24 individual commodity futures returns with major equity indices for the US, UK, Germany, and France, and with US fixed interest, using weekly data from May 1990 to July 2009.

Financialization and macroeconomic are likely to change volatility and correlation gradually, so we model dynamics using Double Smooth Transition Conditional Correlation models (DSTCC–GARCH) (Silvennoinen and Teräsvirta 2005, 2009). Earlier studies use rolling correlation estimation and/or Dynamic Conditional Correlation (DCC) models. DSTCC models allow conditional correlation to change smoothly between (up to) four extreme states, combined in a convex combination which depends on two logistic transition functions. These transition functions can depend on observable economic variables, giving an interpretation to correlation dynamics. Hence one advantage of our chosen modelling framework is that it allows us to test the presence of links between time-varying correlations and important indicators of market conditions. Once the relevance of an indicator is established, the correlations are modelled, allowing us to draw conclusions regarding the quality of the time-variation in conditional correlations (e.g., whether the correlations are increasing or decreasing with the given indicator). Here 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. We examine commodities individually in order to pick up the heterogeneous features of the different markets.

If commodity and conventional asset markets become more integrated because of financialization, 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. We find evidence of these patterns in estimated volatility and correlation models.

Estimated conditional variance models confirm significant positive spillovers from common financial factors including equity market volatility (VIX), the exchange rate, short rates and spreads, for many commodities that are components of the investable GSCI[1]. Financial traders' positions also influence commodity volatility. An increase in the percentage of open interest held short by non-commercial commodity futures traders, such as hedge funds, increases futures returns volatility, but the impact of increasing long interest varies between markets, sometimes raising and sometimes lowering volatility. Since hedge fund activity has escalated over the past decade, swings in commodity returns volatility are thus likely to have been amplified.

Dynamic correlation patterns show that the diversification benefits of commodities to equity market investors are weaker, contrary to findings of other studies (Chong and Miffre 2008; Büyükşahn, Haigh and Robe 2008). Correlations between S&P500 returns and returns to the majority commodity futures have increased, sometimes sharply during the recent crisis, but in many cases also more gradually, and from much earlier in the sample. For 12 of the 24 commodities we study, high expected stock market volatility (VIX) shifts correlations with S&P500 returns upwards, suggesting that both stock and futures 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 current decade, between stocks and most metals, some grains and some foods, during a period when both underlying demand and financial investor interest were intensifying. Further we show that futures market positions of non-commercial traders drive some bi-variate correlations, with patterns suggesting that money managers can time their positions to offset stock market losses.

Correlation between commodities and stock markets returns for European stocks show similar

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

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.

Policy makers have also been concerned about sharp increases in energy prices and their potential impact on other commodities, both directly through price influences as more agricultural commodities interact with the biofuels industry, and also as an increase to input costs. We identify the strengthening links between agriculture and energy markets by tracking the correlation path between individual commodity futures and crude oil futures. Soy crops have shown strong increases with crude oil over the second half of the current decade. Other agricultural commodities also exhibit more co-movement with oil in the recent past, possibly reflecting competition among agricultural commodities and biofuels for production capacity.

Section 2 gives background on commodity futures price determination, 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

Advocates of commodity investment usually base their case on diversification benefits rather than expected returns since the theoretical and empirical evidence for excess returns to commodities is inconclusive. Conventional models treat commodity prices as driven by both systematic and idiosyncratic factors but exactly what these factors are, what is their quantitative impact on returns and volatility, and how they might be affected by increased financialization, are open questions. We briefly review pricing theory and outline the case for integration between conventional assets and commodity futures.

2.1 Commodity futures pricing

Common macroeconomic factors, such as the short interest rate, dividend yield and corporate bond spread, connect commodity futures to stock and bond markets but idiosyncratic factors create segmentation between commodities and financial assets, as well as between groups of commodities (Bessembinder and Chan 1992, Bailey and Chan 1993, Frankel and Rose 2009, Hong and Yogo 2009). It follows that the long run diversification benefits of commodity futures as alternative assets will erode if systematic risk factors rise or if a priced idiosyncratic component weakens.

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.[2] The convenience yield is stochastic, will be high when the basis (the difference between the forward price and current spot) is strongly negative, is economically significant, and positively correlated with the spot price.[3] The forward pricing condition is

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

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.[4]

Equation (1) 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. Without a strict arbitrage relationship, pricing a forward or futures contract requires another valuation method. 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 contracts accrues when futures positions carry non-diversifiable market risk (Black 1975). However, under some pricing kernels, this systematic risk premium could be zero.

Further, commodity futures may receive a residual risk premium when underlying claims (such as shares in the commodity production process) are not traded, and where transactions costs and/or capital constraints apply (Stoll 1979; Hirshleifer 1988a,b; de Roon, Nijman and Veld 2000; Acharya, Lochstoer and Ramadorai 2009). Hedgers, such as producers, who stock the physical

[2] 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, Khoker and Titman 2007). For early work on the theory of storage Kaldor (1939), Working (1949), Brennan (1958) and Telser (1958).

[3] We use the term 'basis' to mean the difference between forward or futures prices and current spot, and reserve the terms 'backwardation' and 'contango' for the relationship between current futures and expected future spot.

[4] The large amount of serial correlation in price data seems to refute simple versions of the stockout model (Deaton and Laroque 1996), although Heaney (2005) finds evidence for two regimes in metals prices consistent with periods of high pressure on inventories. On the relationship between storage, interest rates convenience yield and the basis, Gorton, Hayashi and Rouwenhorst (2007) argue that when market participants are risk averse, long futures receive a risk premium for bearing uncertainty about the future spot price when inventories are low and test this proposition using data on 31 commodities and physical inventories. Heaney also finds support for additional effects of storage on metals prices even after controlling for regime effects.

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 both backwardation which pays positive returns to buyers of futures (where the future price is lower than expected future spot) and contango, which profits sellers (where the future price is higher).

Empirical support for a positive systematic and/or residual risk premium on commodity futures is mixed.[5] In fact, studies conflict over whether commodity futures earn any long-term excess return: Gorton and Rouwenhorst (2006), for example, argue that a rebalanced portfolio of commodity futures consistently earns a return comparable to equities, whereas Erb and Harvey (2006) and Hochachka (2007) view this as an historical anomaly.

2.2 Price trends

Notwithstanding doubts about returns, recent rapid commodity price growth has drawn the attention of both investors and policy makers. After more than four decades of real declines on average, prices increased dramatically between 2002 and 2008 and although most real commodity prices failed to reach the peaks of the '60s and '70s, the recent cycle is historically unprecedented in scope and strength (Helbling, Mercer-Blackman and Cheng 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 rose to around eight times 1990 levels, metals were two to three times higher, and crop prices almost doubled.

2.2.1 Macroeconomic drivers

Demand and supply fundamentals 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). 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. On the other hand, supply was slow to respond, partly because of low inventories and production capacity after several decades of weak prices but also because of structural and technological constraints on production, crucially for oil, a key input to production of other commodities.

[5] Dusak (1973) finds that at least some commodities showed no systematic risk, whereas the futures premia due to hedging pressures are supported by Carter, Rausser and Schmitz (1983), Chang (1985) and Bessembinder (1992), even when the systematic risk premium is zero.

Macroeconomic fundamentals may increase commodity futures correlations with other assets via common drivers such as interest rates and spreads, and expectations of future world growth.

2.2.2 Financialization

In addition, recent financialization may have increased commodity price exposure to macroeconomic and 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).

Two groups have increased their activity in commodities markets: 'buy and hold' investors such as pension funds, endowments and mutual funds, accruing collateralized long positions in futures; and hedge funds, actively trading in derivatives. Jack Meyer, CEO of Harvard Management Company argued 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 is representative of many institutional investment managers who have 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. After the share 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).

Increases in capital flows from institutional investors have been marked: some commentators estimated 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, but from 2002, the GSCI trends up with stock indices, before plunging, slightly ahead of the S&P500, in 2008.

Hedge funds and exchange traded commodity funds also have been active in commodities derivatives markets.[6] 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

[6] 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).

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

Along with trending prices and low correlations, the Commodity Futures Modernization Act of 2000 may have made commodity investments even more attractive by reducing cost of futures trading 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.[7]

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).[8] On the other hand, if easier access to

[7] 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.'

[8] Empirical studies of emerging market integration show that volatility and correlation with previously separated markets may increase or decrease after liberalization (see, among others Bekeart and Harvey 1997; Miles 2002; Edison and Warnock). On time-variation in correlation see Calvo et al (1993) and Tylor and Sarno (1997).

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.

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.

2.3 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 2008; Büyükşahn, Haigh and Robe 2008). 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 futures market liquidity rather than destabilizing volatility (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.

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. We use double smooth transition conditional correlation models because they can capture both gradual and sudden changes in correlation regimes, picking up both slowly developing macroeconomic/financial trends and rapid changes in investor expectations. Our disaggregated approach compares individual commodity futures returns against stock and bond and crude oil futures returns, and allows us to compare commodities in and out of the major investable indices. The results catalogue underlying volatility dynamics including the exposure of conditional variances to financial trading positions in futures markets, stock and exchange rate spillovers, as well as size and time variation in correlation. We also identify structural changes in correlations between commodities and conventional asset classes using a range of potentially important indicators of market conditions.

3 Data

Heterogeneity is a key feature of commodity markets so we take a disaggregated approach, collecting daily spot and futures prices on 24 commodities, including grains and oilseeds, meat and livestock, food and fibre and metals and petroleum. (The Appendix lists all series and sources.) The complete data set covers the period from May 1990 to July 2009. Where no spot price series is reported, we treat the nearest futures contract as spot, and use all (complete) actively-traded futures price series 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[9] at time t, to commodity future contract i, with maturity date τ, is

$$\tilde{r}_{i,t,\tau} = 100 \ln(\frac{F_{i,t,\tau}}{F_{i,t-1,\tau}}) \tag{2}$$

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. (Futures contracts are usually closed before reaching expiration to avoid delivery of the underlying commodity along with associated freight and storage costs and for many financial futures, trading in a particular contract stops at the delivery period.) Consequently, the continuous series can give the return to an investor

[9] Our approach to computing returns and basis is similar to Hong and Yogo (2009).

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 futures 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. We then average across all returns in each period and collateralize by adding the 3-month Treasury Bill rate (adjusted to weekly). The averaged weekly futures return is

$$y_{it,F} = \frac{1}{K}\sum_{k=1}^{K} \tilde{r}_{i,t,\tau_k} + r_{f,t}, \tag{3}$$

where $y_{it,F}$ is the average of the K collateralized futures returns and $r_{f,t}$ is the weekly short rate.[10]

Common pricing factors are 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). Idiosyncratic commodity factors are 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, as discussed in section 2. 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.[11]

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 share price indices for the US (S&P500), UK (FTSE100), Germany (DAX) and France (CAC) in local currencies, a

[10] Collateralizing assumes that the investor has a risk-free investment equivalent to the long position in the commodity futures contract.

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

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.

3.1 Transition variables

DSTCC-GARCH models use observed transition variables to move correlation between extreme states, and we look at three indicators. The first is time, scaled as t/T where t is the current observation number and T is the sample size, second, the weekly lagged level of the CBOE volatility index, VIX, which represents the stock market expectation of 30 day volatility, third, the lagged percentage of long open interest held by non-commercial traders (OI) in each commodity, where available, and fourth 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.[12] 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. 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. (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, Hranaiova and Overdahl 2005)).

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 up generic

[12] Non-commercial positions tend to be long on average and increase following a period of rising prices, consistent with momentum strategies (Gorton et al. 2007; Redrado et al. 2008).

commodities. 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 model 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.) Finally, Haigh et al. (2005) point out that these series are highly aggregated and blur the positions of financial and non-financial investors but we have no disaggregated data.

3.2 Summary statistics

Empirical distributions of commodity futures returns vary substantially by commodity, though the majority show lower return/risk ratios than stocks. Table 1 sets out summary statistics for all series apart from individual exchange rates. Mean returns to agricultural commodity futures other than soybeans, meat and livestock were below the mean T-bill rate (3.8% in this sample), whereas most metals and energy futures returns exceeded it. Commodity volatility was higher than US equity returns for all but two series, sample skewness was negative for 17 of 24 commodities, and kurtosis was high. The GSCI return exceeded the mean T-bill rate and volatility exceeded the S&P500, reflecting its high weight in energy commodities.

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 on both sides were substantial, and show that non-commercial traders are active on both sides of the market. The maximum percentages of contracts held either long or short by non-commercials are never less than 21% (crude oil) and go as high as 77% (platinum). 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

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

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) we include in every conditional mean equation known predictors of stock market and bond returns: the T-bill rate and the corporate bond spread.[13] 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 commodity producers for some commodities, possibly due to market power on the part of some producers 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

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

[13] Hong and Yogo use the dividend yield as well but find that it is not relevant.

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, Jagannathan and Runkle 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 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 transition 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. In the bivariate models reported below each $\mathbf{P}_t$ is 2×2 but has only one interesting element on the off-diagonal. 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

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

where $\boldsymbol{\theta}_0$ is the true parameter and $\mathcal{J}^{-1}(\boldsymbol{\theta}_0)$ is the population information matrix evaluated at $\boldsymbol{\theta}=\boldsymbol{\theta}_0$. Estimation follows a similar process to that outlined in Silvennoinen and Teräsvirta (2009). 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.

The model selection follows the steps outlined in Silvennoinen and Teräsvirta (2005, 2009). For each bivariate combination, a model with a constant level of correlation is estimated. The tests of constancy of correlations against single and double transition models are then carried out. Where the constancy of correlations hypothesis is rejected, the alternative model is estimated. A similar procedure is followed after estimating a single transition model: the tests for needing a double transition are performed, and if the single transition model is found insufficient, the double transition models are estimated. For each estimated STCC–GARCH or DSTCC–GARCH model, this procedure ensures the parameters are identifiable and their estimates are consistent. Due to the two-step estimation (i.e. the GARCH and the correlation parameters are estimated in two separate, consecutive stages), we acknowledge the loss of efficiency and hence allow for a higher than conventional level of the test (10%). The resulting final model candidates are gauged 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 equations separately, use conditionally de-meaned residuals in 2-step maximum likelihood estimation of the parameters of the conditional correlation model, and select conditional correlation models using an array of indicators of fit and diagnostics.

5.1 Conditional means

Common and idiosyncratic factors are relevant in 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. In addition, we retain any exchange rate if the p-value of the estimated coefficient is less than 0.2, and any significant ARMA terms. (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) with estimated coefficients significant at 20% or lower marked with an asterisk.

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.[14] We confirm that lower interest rates and spreads predict higher commodity futures returns, and these effects are most clear among metals futures. Lower short rates predict higher returns to soybeans, most metals and Brent oil futures, the CRB spot index and the S&P500. The lagged corporate bond spread is also a significant negative predictor of corn and wheat futures returns, of all metal futures returns apart from nickel, of Brent oil futures, and of the CRB spot index. Earlier studies argue 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. Increases in the corporate bond spread and short rate forecast higher returns to the bond index.

As to idiosyncratic factors, the interest-adjusted basis is significant for seven commodities, although the sign varies. 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

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

imply high future spot price volatility during periods of low inventory (low basis), and therefore higher returns to futures via a risk premium. 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).

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 world shocks. A USD depreciation makes futures contracts cheaper to foreign buyers, and we find that a fall in the USD predicts higher futures returns to sugar (against major currencies DXY), coffee (against Mexican peso, MXN), live cattle (against Australian dollars, AUD), wheat (AUD and with the opposite sign against the Canadian dollar, CND), gold (DXY, CND, AUD and South Africa with the reverse sign), silver (MXN), aluminium, nickel and zinc (AUD), copper (DXY) and heating oil and natural gas (CND).

5.2 Conditional variances

Common factors and transition variables are also key 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 those of Tang and Xiong (2009) who also noted the importance of spillovers from equity markets and the US exchange rate into commodity volatility. Like them we find significant positive spillovers from equity 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 ineterest 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 counterparty to (net short) commodity producers. In other markets it appears that a higher proportion of non-commercial trade on either side 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 raise expected stock volatility, producing an increase in variance during bear markets, and possibly the opposite for commodities, so that variance is higher for large positive shocks. 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.

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.

Mean fitted conditional volatility was considerably higher for most commodity futures returns from 2001 onwards. 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 compare with stocks: the S&P500 volatility was around 17% higher but 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 from these univariate GARCH models. Commodities offer diversification benefits to investors in traditional asset classes when correlations are low and remain low during periods of market turbulence. Table 4 reports sample unconditional correlation coefficients between commodities and major 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, insignificant for grains and livestock, but significant for foods, metals (not gold) and energy. 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, US bonds and then consider the links between crude oil and other commodities.

5.3.1 US Stocks

Figure 3 graphs estimated conditional correlations between individual commodity futures returns and returns to the GSCI, and returns to the S&P500 over the sample from May 1990 to July 2009. 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 connected to 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, and in the low DOI states when short open interest by non-commercials is strong relative to long interest. In these states, correlation between cotton and stocks increases from 0 to 0.3, and from -0.18 to 0.5 for sugar. These results indicate that money managers and hedge funds may be successfully timing a hedge between stocks and commodities in these markets.

The best correlation models for grains and oilseeds all show marked peaks during the 2008-09 crisis. Corn correlation rises to around 0.5 from 0, from '05 onwards in high VIX states. Soybeans and soybean oil transition to high correlation states (0.4 and 0.6) during high expected stock volatility, whereas wheat responds to increasing long open interest. Both wheat and corn show time breaks in the correlation structure (2004 and 2007).

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 equity 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. 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. Futures market positions of non-commercial traders drive correlations with stocks for 3 contracts and switches suggest that money managers may be able to time their positions to offset stock market losses. No regular pattern has emerged between commodities in the GSCI index compared with excluded commodities.

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. 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, 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 all switch between regimes of correlations close to zero for most of the sample. However, all base metals, energy and GSCI correlations transition on VIX, indicating integration with wider financial market conditions, but high VIX levels generally switch bond and commodity correlations to significantly stronger negative correlation rather than positive correlation, as for stocks. The exceptions are live hogs and pork bellies where higher VIX raise correlation with bonds.

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.

5.3.3 Crude oil

Energy is an important input into production processes including the production of other commodities so that higher energy costs raise commodity prices generally. Environmental policy has more closely integrated markets for agricultural crops with energy. As well as affecting biofuel prices directly and raising input costs, there may be pass-through to food and fibre crops which compete with biofuels for land and production capacity. Here we consider whether the futures returns processes for crude oil and agricultural commodities are more closely integrated by looking at the path of conditional correlation.

Figure 5 plots conditional correlation paths for WT crude oil futures returns with agricultural and metal futures returns. Correlations (Table 5e) are clearly trending upwards for all agricultural commodities apart from orange juice and sugar. Not surprisingly, the strongest increases occur between crude oil and the grains and oilseeds group, which include biofuels. Soybean correlation rises from levels near zero earlier in the sample to a peak around 0.5, soybean oil rises to 0.6 between 2007-09, and correlations for corn and wheat increase to 0.5 and 0.3 from very low bases. Coffee and cotton crops also correlate more strongly with crude oil, stepping up during the crisis to levels around 0.3-0.5, whereas sugar and orange juice stay flat. The VIX plays a role as a transition variable in the cotton and two soybean models raising correlation. Likewise increases in short against long open interest (lower DOI) raise correlation between oil futures and coffee and corn. Time breaks appear again, indicating increasing conditional correlations from mid-sample for grains and oilseeds and from '04-'05 for coffee and cotton.

Structural changes in correlation between crude oil and metal futures begin from around the same time (lead and tin earlier). High correlation regimes are driven by high stock market volatility for platinum, aluminium, copper, lead and nickel, whereas aluminium and zinc correlations increase over time.

Common macroeconomics factors such as increasing (and then sharply decreasing) demand from industrializing economies are likely to have driven these changes along with energy costs and we cannot parcel out the effect of crude oil prices from underlying drivers, but the sharp rises in grain, oilseed and food and fibre correlations support an argument for increasing pressure on food production due to inelastic oil supply.

6 Conclusion

Unlike other recent examinations of commodity futures returns such as Büyükşahn et al. (2008) and Chong and Miffre (2008), 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, seasonal effects in means, and exogenous factors and common factors nonlinearities in both conditional means and variances. Third, we introduce the DSTCC structure with its explicit treatment of expected stock volatility and financial traders' open interest.

Commodity futures correlation dynamics with US stocks in the 1990-2009 period often 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.

The increasing integration of energy and agricultural markets also shows up in estimated conditional correlations. By the end of the sample, correlations between crude oil and biofuel futures returns rose strongly, and other grains, food and fibre commodities exhibited marked increases.

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 JPMUSU$(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 USDMXN 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.

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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	∞						∞	∞	∞	∞		∞

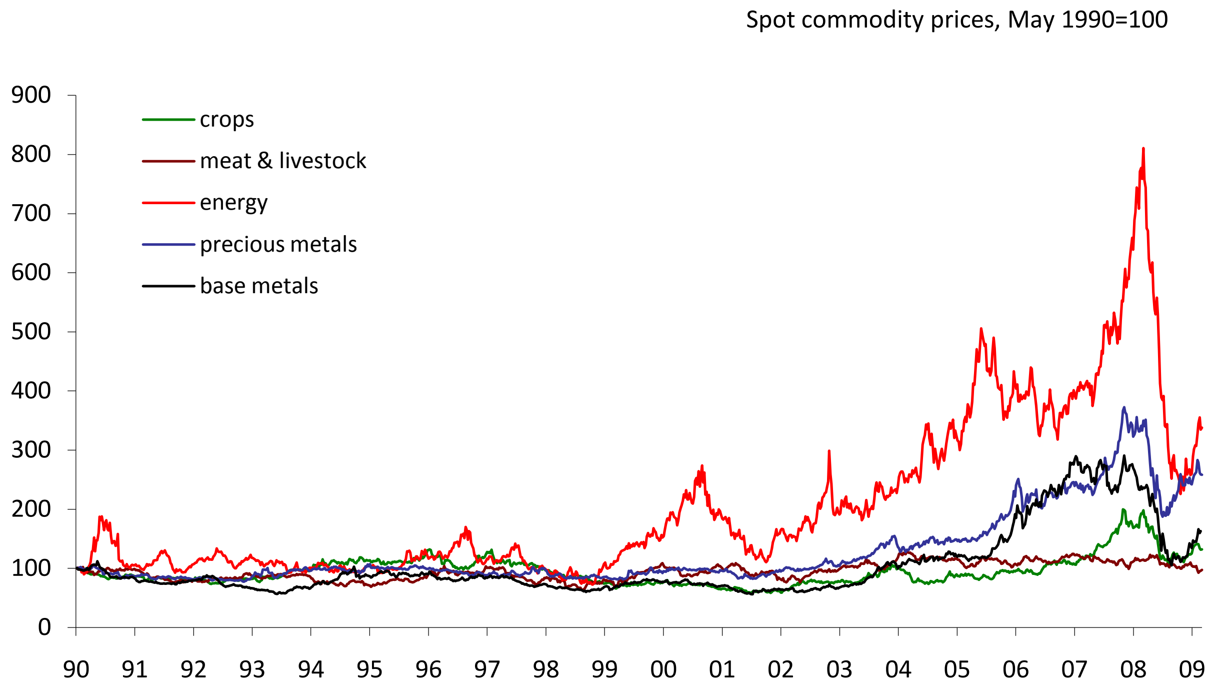
		Precious Metals				**Base Metals**					**Energy**			
		gold	plati-num	sliver	alumin-ium	copper	lead	nickel	tin	zinc	brent oil	WT crude	heating oil	natural gas
transition 1	s_1			DOI	VIX	VIX	VIX	VIX	VIX	VIX	VIX	VIX	VIX	VIX
transition 2	s_2			time	time		time	time			time	time	time	time
low s_1 - low s_2	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			∞	∞		∞	∞			∞	∞	∞	∞

Table 5 Continued
(f)

		WT crude oil										
		Meat and Livestock			Food and Fibre				Grains and Oilseeds			
		live hogs	live cattle	pork bellies	coffee	cotton	o.juice	sugar	corn	soybeans	soybean oil	wheat
transition 1	s_1		VIX		DOI	VIX		CRDOI	DOI	VIX	VIX	OI
transition 2	s_2		time		time	time		time	time	time	time	time
low s_1 - low s_2	P(11)	0.05	**0.09**	0.00	-0.01	**-0.13**	**0.06**	0.09	0.00	0.00	-0.05	0.06
low s_1 - high s_2	P(12)	0.05	0.03	0.00	**0.49**	**0.33**	**0.06**	0.07	**0.51**	**0.14**	**0.25**	-0.05
high s_1 - low s_2	P(21)	0.05	-0.07	0.00	-0.07	0.09	**0.06**	**-0.18**	**0.11**	-0.06	-0.02	**0.21**
high s_1 - high s_2	P(22)	0.05	**0.38**	0.00	**0.28**	**0.33**	**0.06**	**0.30**	0.13	**0.50**	**0.63**	**0.30**
location 1	c_1		22.31		0.27	19.64		0.36	0.07	17.75	18.51	2.70
location 2	c_2		0.77		0.76	0.75		0.31	0.91	0.69	0.76	0.51
transition speed 1	γ_1		∞		∞	∞		∞	∞	∞	3.09	∞
transition speed 2	γ_2		∞		∞	∞		∞	∞	6.47	∞	∞

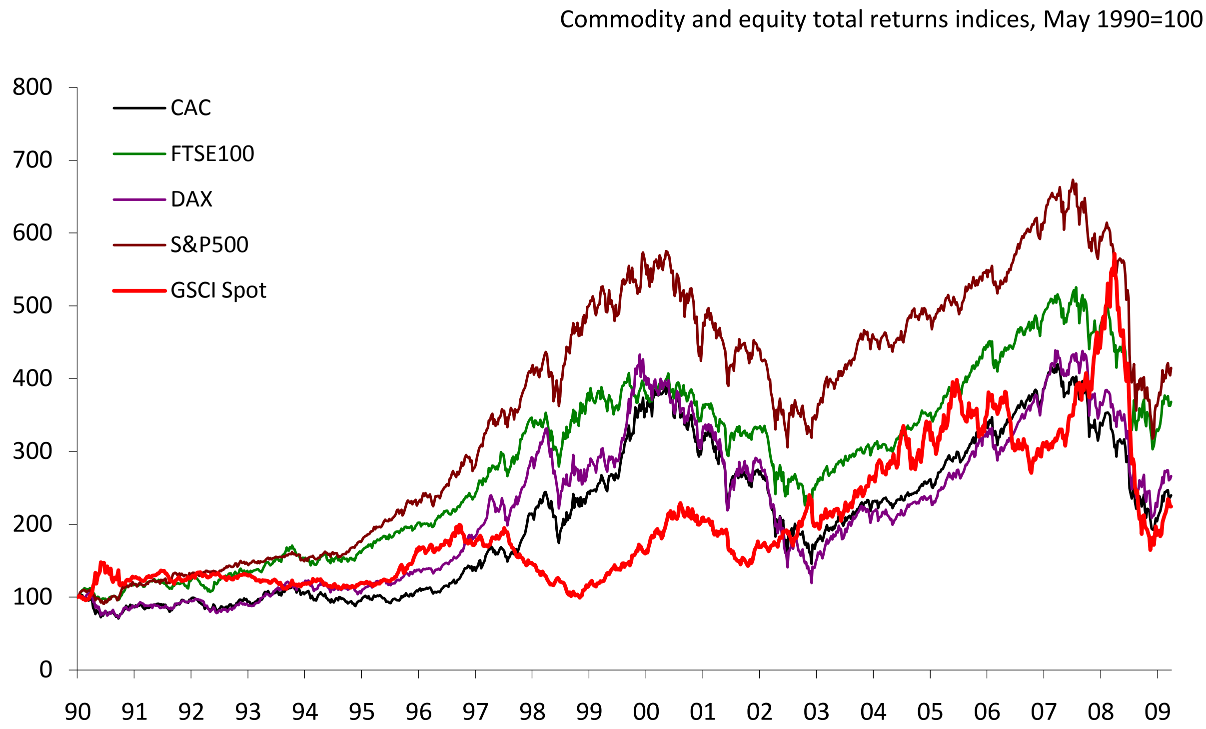
		Precious Metals			Base Metals					
		gold	plati-num	sliver	aluminium	copper	lead	nickel	tin	zinc
transition 1	s_1		VIX	DOI	time	VIX	VIX	VIX	VIX	time
transition 2	s_2		time	time		time	time	time	time	
low s_1 - low s_2	P(11)	-0.02	0.00	**0.29**	0.05	0.03	-0.10	-0.01	0.10	-0.02
low s_1 - high s_2	P(12)	-0.02	0.19	**0.48**	0.05	**0.26**	**0.08**	**0.22**	**0.26**	-0.02
high s_1 - low s_2	P(21)	-0.02	0.10	0.01	**0.52**	-0.06	-0.20	0.09	-0.16	**0.24**
high s_1 - high s_2	P(22)	-0.02	**0.51**	**0.42**	**0.52**	**0.56**	**0.47**	**0.35**	**0.15**	**0.24**
location 1	c_1		16.53	0.13	0.84	27.67	29.53	21.17	19.51	0.60
location 2	c_2		0.73	0.82		0.71	0.19	0.75	0.32	
transition speed 1	γ_1		∞	∞	4.02	∞	∞	∞	∞	∞
transition speed 2	γ_2		3.62	∞		∞	∞	∞	∞	

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.

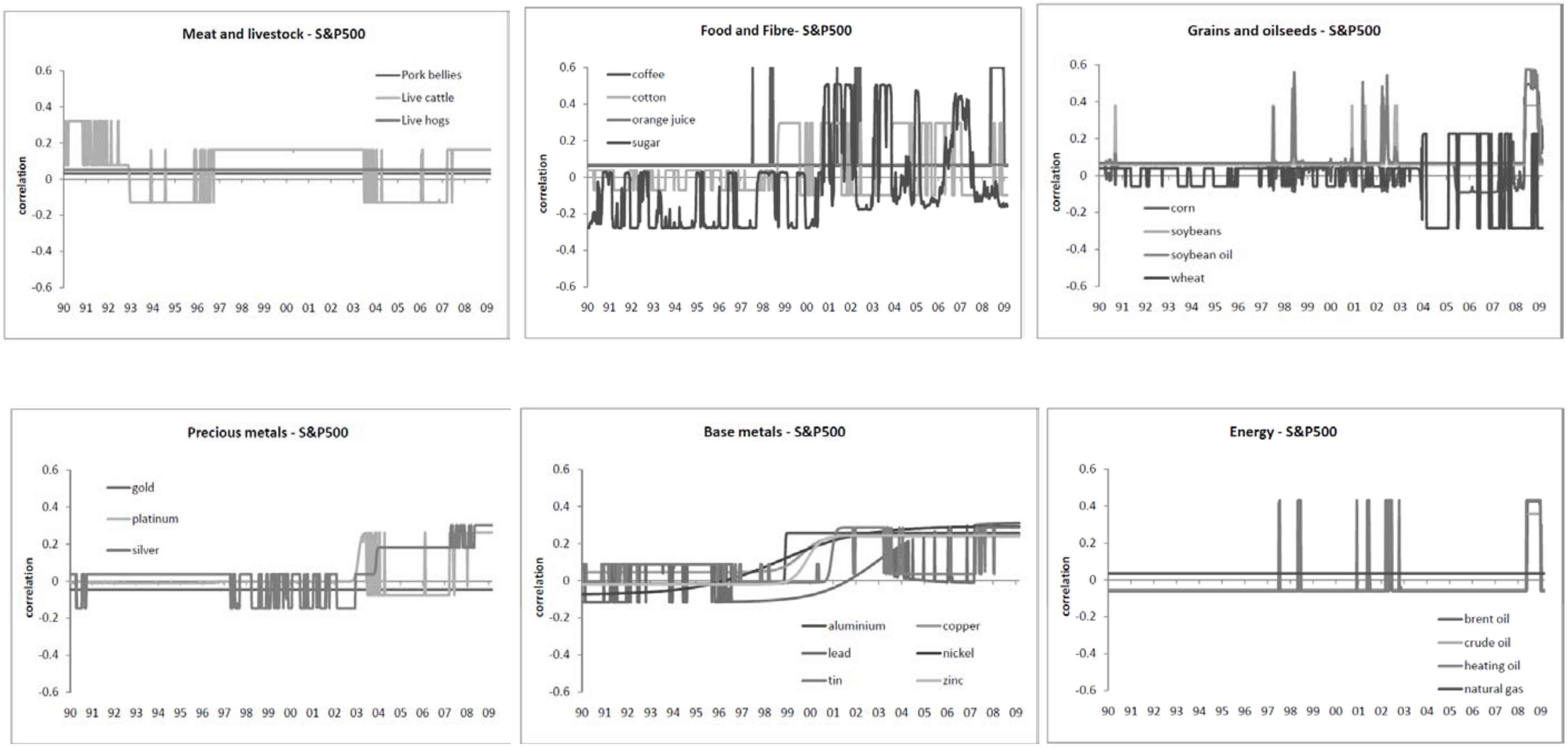


Figure 4: Conditional correlations between commodity futures and US bond index returns

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.

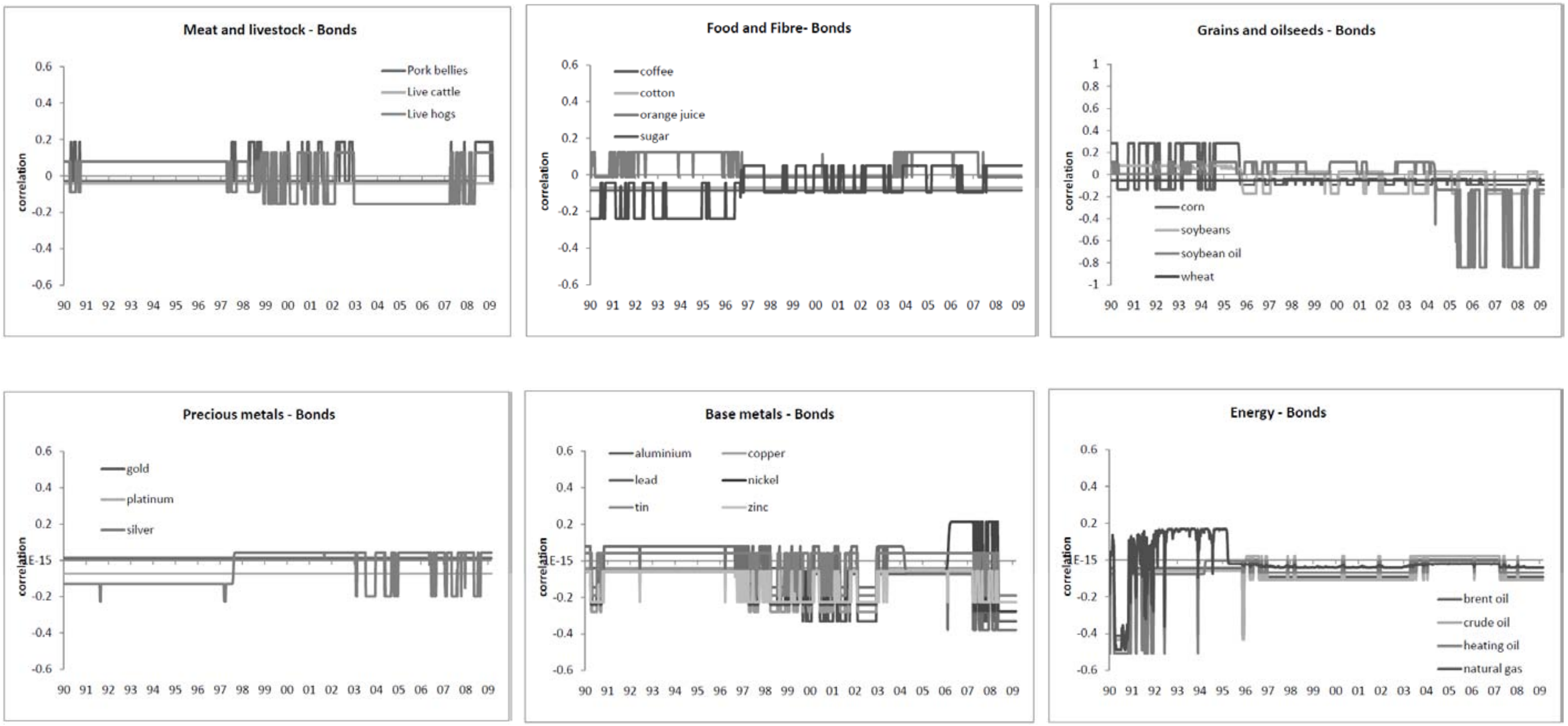


Figure 5: Conditional correlations between crude oil, agricultural and metal futures.

Note: Figure graphs estimated conditional correlations between weekly WT crude oil futures returns and other 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 4f. Data sources in Appendix.