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Financialization, Crisis and Commodity Correlation Dynamics

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Financialization, crisis and commodity correlation dynamics

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Abstract

Stronger investor interest in commodities may create closer integration with conventional asset markets. We estimate sudden and gradual changes in correlation between stocks, bonds and commodity futures returns driven by observable financial variables and time, using double smooth transition conditional correlation (DSTCC–GARCH) models. Most correlations begin the 1990s near zero but closer integration emerges around the early 2000s and reaches peaks during the recent crisis. Diversification benefits to investors across equity, bond and stock markets were significantly reduced. Increases in VIX and financial traders' short open interest raise futures returns volatility for many commodities. Higher VIX also increases commodity returns correlation with equity returns for about half the pairs, indicating closer integration.

Keywords: smooth transition, financial integration, global financial crisis

JEL: G01, G11, C22

1. Introduction

Many institutional managers 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 (Gorton and Rouwenhorst, 2006, Kat and Oomen, 2007, Chong and Miffre, 2010, Büyükşahin et al., 2010). Jack Meyer, then CEO of Harvard Management Company, stated that 'commodities are a diversifying asset class with no correlation – and in some cases negative correlation – with other asset classes' (quoted in Sesit, 2004). These characteristics could encourage investors to choose commodities as a refuge during periods of stress in traditional asset markets, especially if macroeconomic shocks tend to work on commodity and stock prices in opposite directions.

Recent events in commodities markets have cast doubt on these views. Following on more than four decades of real average declines, the past decade saw historically unprecedented and widespread rises in nominal commodity prices. Demand from emerging Asia, a depreciating US dollar, low interest rates, biofuel policy changes and a slow supply response contributed to the trend (Helbling et al., 2008, Vansteenkiste, 2009, IMF, 2006). However, financial activity by institutional investors, hedge funds and exchange traded funds (EFTs) in commodity securities markets has also grown substantially since 2000.

The number of open contracts in commodity exchanges almost doubled over the past decade, putting volumes of exchange-traded derivatives at 20 to 30 times physical production for many commodities, with similar trends in over-the-counter trade (Redrado et al., 2008, Domanski and Heath, 2007). Capital flows from institutional investors escalated from $15 to $200 billion between 2003 and 2008 (Tang and Xiong 2010) while hedge fund activity tripled between 2004 and 2007 (Brown-Hruska, 2004, Domanski and Heath, 2007).[1]

[1]The Commodity Futures Modernization Act of 2000 may have contributed to this ac-

With more investors including commodities in their portfolios, it is natural to ask whether shocks from financial markets are overshadowing commodity fundamentals in price dynamics. If commodity securities and conventional financial assets are concurrently held by more investors, the set of common state variables driving stochastic discount factors grows. Bad news in one market may cause liquidation across several markets (Kyle and Xiong, 2001). If heterogenous commodity futures are treated as a single asset class by index investors, otherwise unrelated commodities may move in synch (Pindyck and Rotemberg, 1990, Tang and Xiong, 2010). Furthermore, if commodity and conventional asset markets have become more integrated, systematic shocks may increasingly dominate commodity returns, raising correlation with other asset classes and generating more time-variation in correlation and volatility.

Tang and Xiong (2010) find evidence of higher exposure to common shocks among commodities included in investable commodities indices (S&P-GSCI and DJ-AIG), driven by investor interest rather than macroeconomic fundamentals. Mayer (2009) studies the positions of index traders and other non-commercial traders and concludes that they cause commodity price changes.[2] Büyükşahin and Robe (2010) go further, breaking down the com-

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tivity. It aimed to 'rationalize regulation for sophisticated or otherwise regulated entities' by exempting certain groups of investors such as mutual funds, banks, etc. from registration with the National Futures Association and consequently freeing them from some aspects of compliance. CFTC policy also aimed to protect hedge funds from extensive disclosure of their holdings and asset selection strategies.

[2]Other studies conclude 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, 2010).

position of financial trade in commodity futures markets using a detailed, non-public CFTC dataset. They show that the speculative activity of hedge funds who trade actively in both equity and commodity future markets has explanatory power for the correlation between stocks and commodities, but that hedge fund activity is lower during periods of market stress. Hedge funds may have provided stabilizing liquidity to futures markets (Haigh et al., 2005).

In this paper, we search for evidence of closer integration between conventional asset and commodity futures returns, testing the hypothesis that the connection is unaffected by financialization. We focus on the commodity-equity market connection and identify indicators of financial market conditions that drive correlation dynamics. In addition, we estimate the points in time at which integration began to accelerate by using recent improvements in conditional correlation modeling.

In Section 2 below, we set out the advantages of Double Smooth Transition Conditional Correlation models (DSTCC–GARCH) (Silvennoinen and Teräsvirta, 2009) over conventional rolling correlation or Dynamic Conditional Correlation (DCC) estimations. First, unlike DCC–GARCH models, where conditional correlation tends to be dominated by local and past dynamics and persistence can be over-stated in the presence of structural breaks, DSTCC–GARCH models are able to detect breaks or gradual changes in dynamics that might result from financialization. Second, we can test for links between time-varying correlations and observable or latent state variables, giving an interpretation of dynamics: DSTCC–GARCH allows correlation to transition smoothly or sharply between a set of extreme states where the transition path can be governed by time and/or key indicators of financial market conditions such as VIX or open interest measures. Third, we can estimate the size and sign of these links.[3]

In Section 3, we examine pairwise links between commodity futures returns and equity returns in order to pick up heterogeneous features. By including common and idiosyncratic factors in the conditional mean and variance of each commodity, we reduce biases in estimated correlation dynamics. Conditional variance estimation confirms significant spillovers from financial factors, including VIX and open interest measures, into commodity futures volatility. This effect is marked for commodities that are components of the S&P-GSCI.

Estimated dynamic correlation patterns show that the diversification benefits of commodities to equity market investors have weakened. Our results are largely consistent with the portfolio analysis of Daskalaki and Skiadopoulos (2011) and Cheung and Miu (2010) but contrary to findings of some earlier studies based on samples from more tranquil periods (Chong and Miffre, 2010, Büyükşahin, et al., 2010). Correlations between S&P500 returns and returns to the majority of commodity futures have increased, sometimes sharply and only during the recent crisis, but in many cases, gradually, and from a much earlier date. For many commodities, correlations with S&P500 returns rise in high VIX states, pointing to strong financial influences. Sensitivity analysis to European and Japanese markets show similar patterns, whereas fixed interest correlations are less variable.

2. Model and method

In this section, we outline the DSTCC–GARCH correlation models, data and pricing factors.

[3] See Silvennoinen and Teräsvirta (2009) for a brief comparison study.

2.1. Modelling strategy

We model the bivariate conditional correlation structure in commodity futures, equity and bond returns using the Double Smooth Transition Conditional Correlation modelling framework set out in Silvennoinen and Teräsvirta (2009). The DSTCC–GARCH model incorporates time-variation in correlations that is attributable to up to two transition variables and 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 transition variables that utilize 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 DSTCC–GARCH framework is that, unlike 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, see Silvennoinen and Teräsvirta (in press and 2009). 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. We estimate commodity futures dynamics in three steps to ensure unbiased correlation estimation: conditional means, conditional variances and conditional correlation.

2.1.1. Conditional means

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

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

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

$$y_{it}|\mathcal{F}_{t-1} = \delta_{i0} + \sum_{p=1}^{P} \phi_{ip} x_{ip,t-1} + \sum_{j=1}^{J} \delta_{ij} y_{i,t-j} + \sum_{m=1}^{M} \delta_{im} \varepsilon_{i,t-m} + \varepsilon_{it}. \tag{2}$$

The $x_{ip}, p = 1, ..., P$ are the common factors and commodity-specific factors and the remaining terms capture seasonality and time dependence via autoregressive structure.

2.1.2. Conditional variance

Common, idiosyncratic and transition factors may also influence the conditional volatility process so excluding them can bias conditional correlation estimation. We add stock and commodity market state variables (transition variables defined below), and any x_{ip} variables that are relevant, to the standard GARCH set up. The univariate error processes is

$$\varepsilon_{it} = h_{it}^{1/2} z_{it}, \tag{3}$$

where h_{it} is a GJR–GARCH process expanded by lags of x_{ip},

$$h_{it} = \alpha_{i0} + \sum_{j=1}^{J} \alpha_{ij} \varepsilon_{it-j}^2 + \alpha_{iJ+1} \varepsilon_{it-1}^2 I_{t-1} + \sum_{p=1}^{P} \zeta_{ip} x_{ip,t-1} + \sum_{k=1}^{K} \beta_{ik} h_{it-k}, \tag{4}$$

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

2.1.3. Transition functions and conditional correlations

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

$$E\left[\mathbf{z}_t\mathbf{z}_t'|\mathcal{F}_{t-1}\right] = \mathbf{P}_t, \tag{5}$$

which, by virtue of the unit variance of z_{it} for all i, is also the correlation matrix for the error vector $\boldsymbol{\varepsilon}_t$ 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.

The DSTCC–GARCH model proposes that correlation varies between four extreme correlation states where the path between the states is governed by logistic functions of transition variables (here indexed as $k = 1, 2$). The conditional correlation matrix $\mathbf{P}_t$ is a convex combination of four positive definite matrices $\mathbf{P}_{(11)}, \mathbf{P}_{(12)}, \mathbf{P}_{(21)}$ and $\mathbf{P}_{(22)}$ each corresponding to an extreme state of constant correlation. The off-diagonal elements of these four matrices are estimated freely by the numerical optimization, along with the parameters governing the transition between the states. The model is

$$\begin{aligned}
\mathbf{P}_t &= \left(1 - G_{1t}\right)\mathbf{P}_{(1)t} + G_{1t}\mathbf{P}_{(2)t} \qquad (6)\\
\mathbf{P}_{(k)t} &= \left(1 - G_{2t}\right)\mathbf{P}_{(k1)} + G_{2t}\mathbf{P}_{(k2)}, \quad k = 1, 2,
\end{aligned}$$

with a logistic function for each transition variable,

$$G_{kt} = \left(1 + e^{-\frac{\gamma_k}{\sigma_k}(s_{kt} - c_k)}\right)^{-1}, \gamma_k > 0, \tag{7}$$

where s_{kt} is the value of transition variable k at time t, σ_k is the standard deviation of the transition variable k, and the parameters γ_k and c_k define the speed and the location of the transition k. By substitution, equation (6) can be rewritten as

$$\mathbf{P}_t = \left(1 - G_{2t}\right)\left(\left(1 - G_{1t}\right)\mathbf{P}_{(11)} + G_{1t}\mathbf{P}_{(21)}\right) + G_{2t}\left(\left(1 - G_{1t}\right)\mathbf{P}_{(12)} + G_{1t}\mathbf{P}_{(22)}\right). \tag{8}$$

If the second transition variable s_{2t} is time, early in the sample when $s_{2t} < c_2$ and G_{2t} is close to zero, more weight goes to the first term in equation (8) 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 and can be simplified to one transition or constant correlation.

In the estimations reported below, we evaluate four indicators. First, time to proxy underlying macroeconomic conditions or other latent factors, scaled as t/T where t is the current observation number and T is the sample size. Second, risk appetite in equity markets, as given by the weekly lagged level of the CBOE volatility index, VIX. VIX is regarded as a proxy for risk aversion or world investor sentiment (Bekaert et al 2011) and is useful for predicting equity market crises (Coudert and Gex 2008) and changes in trading patterns in commodity futures markets (Cheng et al 2012).[4] Third, overall money manager interest in commodity futures, the lagged percentage of long open interest in a key contract for a commodity held by non-commercial traders such as financial investors, hedge funds, money managers or speculators (Gorton et al., 2007; Haigh et al. 2005) (OI), where available; and fourth, a gauge of the intensity of interest of non-commercial traders on either side of the contract, the lagged difference between (percentage) long and short open interest by non-commercial traders divided by total percentage non-commercial interest (DOI), $DOI_t = (long\%_t - short\%_t)/(long\%_t + short\%_t + spread\%_t)$.

[4] The importance of VIX to conditional correlation dynamics in major equity markets was demonstrated in Silvennoinen and Teräsvirta (2009).

2.1.4. Estimation and model selection

Estimation is carried out in three stages. Each time series is first subjected to modelling, estimation, and evaluation of the conditional mean, followed by the same procedure for the conditional variance. As a last stage, the dynamic conditional correlations are examined for each bivariate combination. For that purpose, we divide the parameter vector into two sets: parameters for the extreme state correlations and for the transition functions. The log-likelihood (assuming joint conditional normality of the errors $\mathbf{z}_t$) is iteratively maximized and concentrated over each of the parameter subsets until convergence. We bound the speed of transition parameters γ_k between $0 < \gamma_k < 500$ 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_k, consequently other estimated parameters in those models are conditioned on $\gamma_k = 500$. That is, these models follow a regime switching structure with respect to the transition variable i, (see also Cheung and Miu 2010). The restriction $\gamma_k > 0$ ensures the identification of the extreme states in that G_{kt} in (7) is an increasing function of s_{kt}. In this way, we estimate the extreme states of correlations freely from the data, without imposing restrictions on the relative strengths of the correlations represented by the two (four) matrices.

For model selection, we follow the steps outlined in Silvennoinen and Teräsvirta (2009). For each bivariate combination, we estimate a model with a constant level of correlation then carry out tests of constancy of correlations against single and double transition models. Where the constancy of correlations hypothesis is rejected, we estimate the alternative model. We follow a similar procedure to decide between a single and double transition model. This procedure ensures the parameters of each model are identifiable and their estimates are consistent.[5] The resulting final model candidates are evaluated for abnormalities such as large standard errors of the parameter estimates, insignificance of the level changes in correlations,[6] inconsistent likelihood values (when compared across models with different combinations of transition variables), and inconsistencies in the test results.

2.2. Data

We compute Wednesday–Wednesday log returns to futures contracts on 24 commodities from May 1990 to July 2009, including grains and oilseeds, meat and livestock, food and fibre, metals and petroleum. (The Appendix lists all data sources and computation details.) Following Hong and Yogo (2012), we take an equally-weighted average across returns to actively traded contracts with maturity dates up to one year ahead in each period and collateralize with the 3-month US Treasury Bill (T-bill) rate.[7] The weekly futures return to commodity i at time t, $y_{it,F}$, an average over $k = 1, ..., K$ active contracts, is

$$y_{it,F} = \frac{1}{K} \sum_{k=1}^{K} \tilde{r}_{i,t,\tau_k} + r_{f,t}, \tag{9}$$

[5] We acknowledge the loss of efficiency due to the two-step estimation (i.e., the GARCH and the correlation parameters are estimated in two separate, consecutive stages), and hence allow for a higher than conventional level of the test (10%).

[6] We use the test of partially constant correlations (see Silvennoinen and Teräsvirta (2009) for details) to determine the significance of the level changes between the extreme states. An example of such situation would be that of correlations being constant at the beginning of the sample, but exhibiting variation with s_{1t} towards the end of the sample.

[7] The correlations between the averaged returns measure used here and the returns to the nearest contract (or next nearest when no spot series is available) are all greater than 0.8.

where $\tilde{r}_{i,t,\tau_k}$ is the log return to future contract with maturity τ_k and $r_{f,t}$ is the weekly T-bill rate. By collateralizing, we treat the investor as holding a risk-free investment equivalent to a long position in the commodity futures contract. Averaging across returns to all actively traded contracts captures the range of returns available to financial investors, who may hold portfolios of futures that include long-dated maturities rather than only contracts approaching expiry.

Equity and bond returns are weekly log changes in total returns stock price indices for the US (S&P500), UK (FTSE100), Germany (DAX), France (CAC) and Japan (TOPX) in local currencies, and a total returns fixed interest index for US Treasuries (JP Morgan US Government Bonds). Currency changes are measured by the DXY US dollar futures index (giving the value of the USD against six major world currencies) and an array of USD exchange rates for commodity-producing countries.

2.3. Pricing factors

The conventional cost of carry relationship[8] 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 $S_{i,t}$, is

$$f_{i,t,\tau} = S_{i,t}\left(1 + r_{f,t}\right) + w_{i,t,\tau} - \varphi_{i,t,\tau}, \tag{10}$$

where $w_{i,t,\tau}$ 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.[9] Hence inventory

[8]Equation (10) is not a perfect arbitrage condition because of the likelihood of stock-outs, limitations on shorting the spot commodity and the fact that not all commodities can be stored indefinitely.

[9]The convenience yield is the benefit to inventory holders of supplying the market at some future time if spot prices are unexpectedly high. It is stochastic, positively

conditions are one idiosyncratic factor for commodity futures returns, and interest rates and the term structure are systematic factors.

For estimation, systematic pricing factors are the nominal 3 month US Treasury Bill rate (weekly), and the corporate bond spread, i.e., the difference between the yield on Moody's AAA Corporate Bonds and the T-bill (Hong and Yogo 2009). Idiosyncratic commodity factors are relevant exchange rate changes and the basis, where the basis for commodity i at time t, $b_{i,t}$, is

$$b_{i,t} = 100 \ln \left(\frac{\frac{1}{K} \sum_{k=1}^{K} F_{i,t,\tau_k}}{S_{i,t}} \right), \tag{11}$$

where F_{i,t,τ_k} is the future contract price at time t maturing at τ_k and $S_{i,t}$ is the spot price (or nearest future price where spot is not available) at time t. The basis reflects market conditions and proxies for pressure on inventories.[10]

3. Results and discussion

We estimate univariate mean and variance equations separately, and use conditionally de-meaned and standardized residuals in 2-step maximum likelihood estimation of the parameters of the conditional correlation model. Final selection of conditional correlation models is based on indicators of fit and diagnostics.

correlated with the spot price, and will be high when the basis, i.e., the difference between the forward price and current spot, is strongly negative. The theory of storage predicts that convenience yields are non-linearly declining in inventories (Pindyck, 1993, Routledge 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, Routledge et al., 2000, Carlson et al., 2007).

[10]For estimation, we deduct the weekly T-bill rate from the basis as calculated in (11).

3.1. Summary statistics

The majority of commodity futures returns series show lower return/risk ratios than stocks; in some cases mean returns are negative. (Table 1 sets out summary statistics for all series used in estimation apart from individual exchange rates.) Based on fitted time trends reported in the final row of Table 1, 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.

Academic studies generally view 'non-commercial' traders as financial investors (Gorton et al., 2007), since this category includes primarily money managers, hedge funds 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. As a percentage of total open interest held by non-commercial traders, mean long open interest exceeds mean short open interest for all contracts except cotton and natural gas, however percentages of open interest, both long and short, were substantial, and show that non-commercial traders are active on both sides of the market. The dominance of long open interest is consistent both with growth in speculators who accept risk from commodity suppliers and with institutional investors taking long positions in commodity futures directly as an alternative asset class, or via a commodity index. The fact that short interest has also been substantial is consistent with hedge fund activity and or speculators active on the other side of contracts. We discuss the impact of open interest on volatility below.

3.2. Conditional means

Common and idiosyncratic factors are relevant for conditional means and variances of most commodities, and almost all conditional means include significant serial correlation and seasonality.[11] We also confirm that lower interest rates and yield spreads (systematic factors) predict higher commodity futures returns, especially among metals (Hong and Yogo, 2009). As for idiosyncratic factors, the interest-adjusted basis is significant for four commodities, although the sign varies. Studies of longer runs of aggregated monthly data generally find a negative relationship between basis and futures returns (e.g., Hong and Yogo, 2009, Gorton et al., 2007). We estimate a significant positive relationship between lagged basis and futures returns for live cattle, while for wheat, coffee and platinum, the significant negative link implies a risk premium to compensate for high future spot price volatility during periods of low inventory.

3.3. Conditional variances

Adding exogenous factors to conditional variance equations allows us to test the relevance of financial factors and volatility spillovers while also ensuring more robust conditional correlation estimation. Omitting exogenous factors and nonlinearities can bias estimated GARCH coefficients, causing an overestimation of persistence in conditional volatility. Accordingly, fitted conditional variances will be too high and estimated conditional correlations will be too low. Table 2 shows that common factors and financial market state variables are significant drivers of conditional volatility of futures re-

[11] For reasons of space we do not report estimated parameters for conditional mean equations. Results are available from the authors on request.

turns in many cases. However, relevant factors vary from commodity to commodity.[12]

Higher expected US stock volatility (VIX) predicts higher volatility in all energy futures (except natural gas) and stock indices apart from the FTSE, pointing to greater equity and energy market integration. Significant effects for non-commercial futures traders' open interest emerge for commodities that are included in the investable indices. Rises in the percentage of long open interest held by non-commercials (increases in OI) raise volatility of live cattle returns. For coffee, sugar and silver, volatility declines when the percentage of open interest held long exceeds the percentage held short (increases in DOI), but increases when short interest exceeds long. This is also generally true for corn, soybeans, cotton and crude oil: the interaction of the coefficients on OI and DOI means that rises in the proportion of short open interest always increases volatility, but increases in long open interest generally dampen volatility. Increases in long open interest may raise volatility only when the current proportion of short open interest is very low, say less than 3% or 4%.

So overall, an increase in the percentage of open interest held short by non-commercial traders always increases futures returns volatility, and rises in long interest almost always dampens volatility. This asymmetry between short and long non-commercial positions in some markets may reflect the calming role of money managers who provide liquidity to the market when acting as the long counterparty to (net short) commodity producers (Haigh, et al. 2005, Brunetti and Büyükşahin 2009).

[12] Along similar lines, Vivian and Wohar (2012) show that structural breaks in commodity volatility are generally idiosyncratic rather than common.

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 et al., 2007, Fong and See, 2001). While higher volatility is linked to bear markets in stocks, commodity price volatility may increase when prices are abnormally high because of stress on inventories. Consequently we may expect the GJR parameter, which adjusts predicted variance for negative returns shocks, to lower commodity returns volatility. Consistent with this prediction, we find significant negative GJR parameters for wheat, coffee, gold, platinum, silver and bonds, and significant positive GJR parameters for all stock indices and three agricultural series.

In summary, while commodities show considerable heterogeneity in conditional variance factors, we find a consistent impact of stock market uncertainty and risk aversion (proxied by VIX) into energy markets, and of non-commercial traders positions in commodities listed on investable indices, as evidence for commodity and financial market integration.

3.4. Conditional correlation

Prior to the late 2000s, the dominant view among institutional investors was that commodities showed low, and sometimes negative, correlation with stocks. The sample unconditional correlations reported in Table 3 support this statement: for stocks, correlations with commodities are low and mostly significant, with the exceptions of gold, gas, and some meats. Bond correlations are low and negative.

In this section, we use smooth transition models of correlation dynamics to re-evaluate this view. We map the time-path of correlations identifying the sign, size and timing of regime changes, and test the relative power of time and VIX in explaining correlation dynamics. Accurate correlation estimation is key to risk management and efficient portfolio choice.

3.4.1. US stocks and bonds

Estimated correlations between commodity futures returns and returns to the S&P500 are almost all significantly higher in the 2000s than in the 1990s, rising from close to zero in the first decade of the sample towards 0.5. (Table 4 reports estimated parameters of preferred models.) Moreover, for agriculturals and metals, shifts to higher correlation regimes almost all began well before the onset of the global financial crisis (GFC) in 2008. Oil and equity correlations were consistently higher during the GFC. Along with time, regime switches are often driven by the VIX transition variable so that high predicted stock market volatility predicts higher correlation between stocks and futures returns. The estimation detects a significant number of gradual time transitions but many are sharp. High transition speeds are the outcome of steep changes in the transition state variables. For VIX, this is related to the high variability in the measure itself, and for the time transitions, typically related to the onset of the financial crisis.

Figure 1 graphs estimated conditional correlations between individual commodity futures and returns to the S&P500. Meat and livestock futures are not very closely correlated with stock returns. Live cattle and hog futures are components of the investable commodities indices, whereas pork belly futures are not, but we find that only cattle futures correlations are predicted by stock market uncertainty. In high VIX states, correlation between cattle and stocks increase but this increase is in fact weaker later in the sample period. Correlations for live hogs and pork bellies are very close to zero through the sample.

Of the four commodities in the food and fibre group, only orange juice is excluded from the investable indices (DJ-AIG and S&P-GSCI) and its correlations with stock returns are low, with a negative state during the late 1990s to mid 2000s. By contrast, coffee transitions between a low (0.06) and high (0.64) correlation state but only during the crisis period in 2008–09. Cotton and sugar correlations have four regimes, transitioning on VIX and time. For both of these futures series, highest correlation with stocks (0.3 and 0.7) occurs during the most recent decade at times when VIX exceeded its average. The time transitions for these regime changes were located well before the GFC in 2001 and 2003 respectively, around the time that index investor interest in commodities increased.

All the grains and oilseeds are included in the investable indices. The best correlation models for soybeans and soybean oil show structural change in mid-2002, with correlation increasing markedly in high VIX states towards 0.5. For corn, the correlation strengthen in early 2003 after a weaker period from 1996-2002, whereas wheat futures correlation with stocks shot up dramatically towards 0.5 during the financial crisis.

Similar breaks in correlation regimes show up in silver and base metals. Silver switches to significantly higher correlation states (around 0.3 from 0.03) from 2001 onwards, and all the base metals correlations increase from the early part of the past decade onwards. Aluminium, copper, lead and zinc correlations rise during high VIX states later in the sample, but the latter three are not significantly responsive to VIX earlier. These results indicate a stronger integration between stock and metals markets over the past decade that has produced higher and more time-varying correlation. In energy futures markets, results vary. Natural gas correlation is low and constant but oil products show sharp increases in correlation with stocks during the crisis.

Table 5 reports preferred DSTCC–GARCH models for commodity correlations with returns to the JP Morgan US Government bonds total returns index. While agricultural commodity correlations have largely remained constant, all industrial metals correlations with bond returns switch to more negative regimes during high VIX states, moving from close to zero towards -0.3. As with the stock correlations, these regime changes begin in the later 1990s or early 2000s.

In summary, most conditional correlations between commodity futures returns and US stock index returns have increased, some at levels dramatically higher than earlier. (Effects on bond correlations are less widespread, but show up in industrial metals futures with similar intensity and timing as for stocks and with the expected opposite sign.) Further, financial shocks appear to be important predictors of correlation dynamics. For 11 of the 24 commodities, high expected stock market volatility raises correlations with equities. Somewhat surprisingly, the correlation regime switch for oil futures and stocks occurred during the GFC, rather than earlier in the decade, and preferred models do not include the VIX transition variable. Since VIX is negatively correlated with stock returns, we conclude that for those pairs where VIX is relevant, both stock and commodity futures returns are falling as VIX increases. 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. It seems that the evidence of gradual and early increases in conditional correlations are most apparent for base metals and pre-date the most intense period of financialization from 2003-4. However, the new relevance of VIX from the early 2000s points to increasing importance of financial trading and common shocks to correlation dynamics.

3.4.2. Sensitivity analysis

Sensitivity analysis for German, French, UK and Japanese stock returns indices show correlation patterns between commodity futures returns and other developed economies stock indices are largely consistent with the US. For commodities with significant regimes shifts, correlations shift upwards towards 0.5 during the second half of the sample with time breaks and choice of transition variable also consistent with the US results in many cases. Some differences with the US worth noting are the correlation patterns between the DAX, FTSE and TOPX and oil commodities: correlation transitions are driven by high VIX and the time breaks typically occur well before the GFC. Estimated parameters of the preferred models are reported in Tables 6–9 but to save space, we do not graph the correlations.

These results confirm that the evidence for increased commodity futures and stock market integration is not unique to the US. The timing, size and sign of correlation patterns are common across major equity markets.

4. Conclusion

Unlike other recent examinations of commodity futures returns such as Büyükşahin et al. (2010) and Chong and Miffre (2010), our results do not show weakening correlation between commodities and conventional stock and bond returns. On the contrary, we present evidence favoring closer commodity and financial market integration, more consistent with Daskalaki and Skiadopoulos (2011), Büyükşahin and Robe (2010), Cheung and Miu

(2010) and Tang and Xiong (2010). We introduce several innovations to modelling correlation dynamics that may partly explain differences in our results from those of earlier studies. First we extend the sample to cover the latter part of 2008 and early 2009 and thus introduce a large amount of new variation to the data. Second, we include a careful modelling of common and idiosyncratic factors in means and variances, capturing relevant currency predictions and seasonal effects in means, and exogenous factors and nonlinearities in conditional variances. Omitting these exogenous and non-linear factors from variance equations leads to upwardly biased conditional volatility estimates, and consequently, under-estimated conditional correlation. Third, we introduce the DSTCC–GARCH structure with an explicit treatment of expected stock volatility. This model allows for possible gradual changes in the correlation regime, driven by observable transition variables. We demonstrate the presence of structural breaks in the correlation process that are not picked up by DCC–GARCH models, and we also present evidence for the relevance of a financial transition variable that is omitted from most existing correlation studies.

Commodity futures correlation dynamics with US stocks in the 1990–2009 period frequently exhibit increases, typically rising towards 0.5 from levels close to zero in the 1990s. For most metals and agriculturals, these increases begin mid-sample. Such patterns are also evident in correlations with stocks traded in European and Japanese markets. Increasing correlation across equity and commodity returns, particularly during the crisis, would discourage investors from choosing commodities as a refuge during periods of stress in traditional asset markets.

Also consistent across developed country stock markets is the role of indicators of financial market conditions in predicting the correlation state.[13] 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–GARCH 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 high volatility states, whereas in the 1990s they were largely unrelated.

[13] Linkages between negative price shocks and strengthened asset correlations have been discussed and given theoretical justification in Kroner and Ng (1998) and Cappiello, Engle, and Sheppard (2003). Silvennoinen and Teräsvirta (in press) provide empirical evidence that links both general market turbulence and asymmetric news to strong positive asset correlation.

Data Appendix

We sample continuously compounded weekly log returns to futures contracts on 24 commodities from May 1990 to July 2009. Where no spot price series is reported, we treat the nearest futures contract as spot, and average across returns to all (complete) actively-traded futures contracts. Returns are Wednesday–Wednesday closing prices or the preceding Tuesday where Wednesdays are missing. For all commodities except base metals, the daily futures price data are continuous and we compute the return by closing out on the last Wednesday before the final trading day and then purchasing the next nearest futures contract. For London Metal Exchange (LME) base metals, daily settlement prices are quoted for spot and for the futures contracts closest to a fixed maturity period (3-months and 15-months).

Bloomberg tickers and contracts

Agriculture:

Corn: C1–C5 Comdty; Mar May Jul Dec; Soybeans: S1–S6 Comdty; Jan Mar May Jul Aug Nov; Soybean oil: BO1–BO8 Comdty; Jan Mar May Jul Aug Sep Oct Dec; Wheat: W1–W5 Comdty; Mar May Jul Sep Dec; LH1–LH6 Comdty; Feb Apr Jun Jul Aug Oct Dec; Live cattle: LC1–LC6 Comdty; Feb Apr Jun Aug Oct Dec; Pork bellies: PB1–PB5 Comdty; Feb Mar May Jul Aug; Coffee: KC1–KC5 Comdty; Mar May Jul Sep Dec; Cotton: CT1–CT4 Comdty; Mar May Jul Dec; Orange Juice: JO1–JO6 Comdty; Jan Mar May Jul Sep Nov; Sugar: SE1–SE4 Comdty; Mar May Jul Oct.

Metals:

Gold: GOLDS Comdty, GC1–GC5 Comdty; Mar May Jul Sep Dec; Platinum: PLAT Comdty, PL1–PL3 Comdty; Jan Apr Jul Oct; Silver: SILV Comdty, SI1–SI5 Comdty; Mar May Jul Sep Dec; Aluminium: LMAHDY

Comdty, LMAHDS03 Comdty, LMAHDS15 Comdty; 12 calendar months; Copper: LMCADY Comdty, LMCADS03 Comdty, LMCADS15 Comdty; 12 calendar months; Nickel: LMNIDY Comdty, LMNIDS03 Comdty, LMNIDS15 Comdty; 12 calendar month; Lead: LMPBDY Comdty, LMPBDS03 Comdty, LMPBDS15 Comdty; 12 calendar months; Tin: LMSNDY Comdty, LMSNDS03 Comdty, LMSNDS15 Comdty; 12 calendar months; Zinc: LMZSDY Comdty, LMZSDS03 Comdty, LMZSDS15 Comdty; 12 calendar months.

Energy:

Brent oil: CO1–CO6 Comdty; 12 calendar months; Crude oil WTI: CL1–CL9 Comdty; 12 calendar months; Heating oil: HO1–HO9 Comdty; 12 calendar months; Natural gas: NG1–NG10 Comdty; 12 calendar months

Financials:

Short rate: US Treasury Bill 3 month secondary market rate; Federal Reserve Board of Governors: H15/H15/RIFLGFCM03_N.B; Yield spread: Moody's AAA Corporate Bond yield less short rate; Bloomberg ticker MOODCAAA; USA Stocks: S&P500 Composite returns index; Datastream mnemonic S&PCOMP(RI); German Stocks: DAX 30 returns index (EUR); Bloomberg ticker DAX TR IDX; UK Stocks: FTSE100 (BPD); Bloomberg ticker UKX TR IDX; France Stocks: CAC 40 (EUR); Bloomberg ticker CAC TR IDX; USA Bonds: JP Morgan US Govt Bond total returns; Datastream mnemonic JPMUSU$(RI); Volatility: CBOE VIX volatility index; Bloomberg ticker VIX Comdty; USA exchange rate Index future DXY: US Dollar Index (average of US dollar exhange rate with six major currencies); Bloomberg ticker DXY Curncy

Open interest

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

- 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* – 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; *Frozen concentrated Orange Juice* – Citrus Association of NY Cotton Exchange; *Platinum* – New York Mercantile Exchange; *Silver* – Commodity Exchange Inc.; *Soybean Oil* – Chicago Board Of Trade; *Soybeans* – Chicago Board Of Trade; *Wheat* – Chicago Board Of Trade.

References

Bekaert, G., Harvey, C.R., Lundblad, C.T., Siegel, S., 2011. What segments equity markets? Review of Financial Studies 24, 3841-3890.

Brown-Hruska, S., 2004. Securities Industry Association Hedge Funds Conference Keynote address. `http://www.cftc.gov./opa/speeches04/opabrown-hruska-22.htm` Accessed April 2012.

Brunetti, C., Büyükşahin, B., 2009. Is speculation destabilizing? Working Paper, U.S. Commodity Futures Trading Commission, Washington DC.

Büyükşahin, B., Haigh, M., Robe, M., 2010. Commodities and equities: Ever a "market of one"? Journal of Alternative Investments 12, 76–81.

Büyükşahin, B., Robe, M., 2010. Speculators, commodities and cross-market linkages. Working Paper, American University Washington D.C.

Cappiello, L., Engle, R. F., Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial Econometrics 4, 537–572.

Carlson, M., Khoker, Z., Titman, S., 2007. Equilibrium exhaustible resource price dynamics. Journal of Finance 62, 1663–1703.

Cheng, I-H., Kirilenko, A., Xiong, W., 2012. Convective risk flows in commodity futures markets. NBER Working Paper 17921, National Bureau of Economic Research, Cambridge MA.

Cheung, C.S., Miu, P., 2010 Diversification benefits of commodity futures. Journal of International Financial Markets, Institutions and Money 20, 541–474.

Chong, J., Miffre, J., 2010. Conditional return correlations between commodity futures and traditional assets. Journal of Alternative Investments 12, 61–75.

Coudert, V., Gex, M., 2008. Does risk aversion drive financial crises? Testing the predictive power of empirical indicators. Journal of Empirial Finance 15, 167–184.

Daskalaki, C., Skiadopoulos, G., 2011. Should investors include commodities in their porfolios after all? New evidence. Journal of Banking and Finance 25, 2606–2626.

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

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

Engle, R., 2002. Dynamic conditional correlation: a simple case of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business and Economic Statistics 20, 339–350.

Fong, W., See, K., 2001. Modelling the conditional volatility of commodity index futures as a regime switching process. Journal of Applied Econometrics 16, 133–163.

Frankel, J., Rose, A., 2010. Determinants of agricultural and mineral commodity prices. Faculty Research Working Paper RWP10-138, Harvard University, Cambridge, MA.

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

Gorton, G., Rouwenhorst, K., 2006. Facts and fantasies about commodity futures. Financial Analysts Journal 62, 47–68.

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

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

Helbling, T., Mercer-Blackman, V., Cheng, K., 2008. Riding a wave. Finance and Development 45, 10–15.

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

Hong, H., Yogo, M., 2012. What does futures market interest tell us about the macroeconomy and asset prices? Journal of Financial Economics 105, 473–490.

IMF 2006. The boom in nonfuel commodity prices: can it last? IMF World Economic Outlook, chapter 5, `http://www.imf.org/external/pubs/ft/weo/2006/02/pdf/c5.pdf` Accessed April 2012.

Kat, H., Oomen, R., 2007. What every investor should know about commodities, part II. Journal of Investment Management 5, 1–25.

Kroner, K. F., Ng, V. K., 1998. Modeling asymmetric comovements of asset returns. The Review of Financial Studies 11, 817–844.

Kyle, A., Xiong, W., 2001. Contagion as a wealth effect. Journal of Finance 56, 1401–1440.

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

Pelletier, D., 2006. Regime switching for dynamic correlations. Journal of Econometrics 131, 445–473.

Pindyck, R., 1993. The present value model of rational commodity pricing. Economic Journal 103, 511–530.

Pindyck, R., Rotemberg, J., 1990. The excess co-movement of commodity prices. Economic Journal 100, 1173–1189.

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

Routledge, B., Seppi, D., Spatt, C., 2000. Equilibrium forward curves for commodities. Journal of Finance 55, 1297–1338.

Sesit, M., 2004. Commodities enter the investment mainstream. The Global Player 9 September. `http://www.fullermoney.com/content/2004-09-09/MichaelSesitCommoditiesTHEGLOBALPLAYER.pdf` Accessed April 2012.

Silvennoinen, A., Teräsvirta, T., 2009. Modelling conditional correlations of asset returns: A smooth transition approach. Econometric Reviews, forthcoming.

Silvennoinen, A., Teräsvirta, T., (in press). Modelling multivariate autoregressive conditional heteroskedasticity with the double smooth transition conditional correlation GARCH model. Journal of Financial Econometrics 7, 373–411.

Tang, K., Xiong, W., 2010. Index investment and the financialization of commodities. NBER Working Paper w16385, National Bureau of Economic Research, Cambridge MA. Princeton NJ.

Tse, Y., Tsui, K., 2002. A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business and Economic Statistics 20, 351–362.

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

Vivian, A., Wohar, M.E., 2012. Commodity volatility breaks. Journal of International Financial Markets, Institutions & Money 22, 395–422.

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

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 reports summary statistics for weekly collateralized commodity futures (log) 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. Commodity futures returns are the average of weekly returns on a range of contracts from nearest to expiry (or next nearest when no spot series is available) 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. Trend per cent long open interest is the estimated coefficient on a time trend fitted to de-meaned OI series where means are adjusted for changes in the specific contracts used in the CFTC report via indicator variables where necessary. All time trends are significant at the 1% level or less.

Table 1 continued

Interest rates and total returns to indices, (annualized weekly data)										
	Interest rates		Stock return indices					Volatility	Bonds	USD
	USA 3-mth T bill	USA yield spread	USA S&P500	Germany DAX	UK FTSE100	France CAC	Japan TOPX	VIX (level)	USA JPMorgan	DXY
mean	3.81	2.96	7.43	5.08	6.76	4.48	-0.91	20.12	6.92	-0.8
median	4.34	2.58	15.04	22.86	14.28	15.48	0.00	18.46	8.47	-1.2
maximum	7.85	6.30	530.49	892.04	723.92	864.51	757.90	74.26	117.02	317.3
minimum	0.00	0.13	-851.48	-791.65	-659.41	-769.41	-774.10	9.31	-131.61	-416.2
std. dev.	0.25	1.42	16.59	22.92	17.03	21.74	2.75	8.45	4.61	8.5
skewness	0.42	0.10	-0.09	0.11	-0.20	0.02	0.12	2.06	-0.46	0.02
kurtosis	7.13	1.84	4.16	5.11	5.15	4.61	4.57	10.19	5.42	6.48
Obs.	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
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
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
Time trend (long)	0.013		0.009		0.007		0.004		0.014		0.014		0.016		0.028	

			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
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
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
Time trend (long)	0.008		0.02		0.035		0.011		0.009		0.014		0.011		0.006	

Table 2
Estimated coefficients of GARCH equations.

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	1.142***	0.991***	0.689**	0.264**	0.245*	0.099***	-2.385**	4.356***	0.232*	0.303**	0.493**
adj.basis(t-1)							0.068***	-0.154***			
bond spread(t-1)				-0.038**			0.699**	0.642***	0.108**		
T-bill(t-1)							0.556**				
DXY(t-1)							0.668**				
VIX(t-1)								-0.084***		-0.008**	
OI(t-1)	0.084***	0.066***				0.005***			0.034**		
DOI(t-1)	-1.044**	-1.190**						-3.636***	-0.416**		-0.482**
ARCH	0.092***	0.085**	0.089***	0.057***	-0.019	0.028	0.051**	0.189***	0.105***	-0.009	0.071***
GJR				-0.058**	0.066**	0.151***		-0.232***		0.047***	
GARCH	0.815***	0.832***	0.833***	0.956***	0.943***	0.850***	0.839***	0.779***	0.840***	0.976***	0.905***

Table reports estimated coefficients of preferred conditional variance equations estimated using residuals from mean equations. GARCH models include a constant, ARCH, GARCH and GJR terms, and where relevant at the 10% level or less, 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.

Table 2 continued

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

	Precious Metals			Base Metals					
	gold	platinum	silver	aluminium	copper	lead	nickel	tin	zinc
constant	0.140**	0.601	0.594**	0.170*	1.080**	0.11	0.506**	0.040	0.094
adj.basis(t-1)									
bond spread(t-1)					-0.113**				
T-bill(t-1)					-0.096*				
DXY(t-1)									
VIX(t-1)									
OI(t-1)									
DOI(t-1)			-0.825**						
ARCH	0.196***	0.147***	0.145***	0.072***	0.108***	0.081***	0.073***	0.066***	0.072***
GJR	-0.148**	-0.113**	-0.105**						
GARCH	0.846***	0.922***	0.882***	0.894***	0.845***	0.912***	0.902***	0.935***	0.919***

	Energy				Stocks					Bonds
	Brent oil	Crude oil	Heating oil	Natural gas	US S&P500	Germany DAX	UK FTSE100	France CAC	Japan TOPX	US JPMorgan
constant	-0.577	-0.305	-0.213	0.339*	-0.977***	-0.983*	0.314***	-9.721***	-0.475*	0.005
adj.basis(t-1)										
bond spread(t-1)								1.070***	0.112**	
T-bill(t-1)								1.073***		
DXY(t-1)					-0.172**			-0.602***	-0.397**	
VIX(t-1)	0.102**	0.626***	0.046**		0.125***	0.161***		0.494***	0.082***	
OI(t-1)		0.403***								
DOI(t-1)		-9.708***								
ARCH	0.139***	0.151***	0.107***	0.057***	-0.098***	-0.008	-0.019*	0.016	0.032	0.085***
GJR					0.223***	0.232***	0.277***	0.182**	0.144***	-0.071***
GARCH	0.779***		0.846***	0.929***	0.652***	0.646***	0.817***		0.748***	0.942***

Table 3
Commodity futures and financial indices, unconditional correlations, 2 May 1990 – 1 July 2009.

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

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

Table 4

Preferred conditional correlation models, weekly commodity futures returns and US stocks

S&P 500 - US stocks

		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	time	VIX			VIX	time	VIX	time	VIX	VIX	VIX
transition 2	s_2	time	time		time	time	time	time	time	time	time	time
low s_1 - low s_2	$P_{(11)}$	0.103	-0.028	0.026	0.057	-0.031	0.207	-0.069	0.118	0.032	0.074	0.029
high s_1 - low s_2	$P_{(21)}$	-0.103	0.315			-0.031	-0.076	-0.069	-0.063	0.032	-0.235	0.029
low s_1 - high s_2	$P_{(12)}$		-0.139		0.635	-0.058		-0.176		0.074	0.064	-0.119
high s_1 - high s_2	$P_{(22)}$	0.096	0.133			0.269	0.127	0.701	0.127	0.461	0.513	0.466
location 1	c_1	Dec96	17.32			20.13	Jan96	29.75	Feb96	28.12	28.80	32.80
location 2	c_2	Mar02	Jul97		Jul08	Jan01	Mar05	Apr03	Mar03	Sep02	Jul02	Sep04
transition speed 1	γ_1	∞	∞			∞	83.37	3.01	∞	∞	∞	∞
transition speed 2	γ_2	∞	∞		∞	∞	∞	22.20	∞	∞	∞	∞

		Precious Metals			**Base Metals**					**Energy**			
		gold	plati-num	silver	alumin-ium	copper	lead	nickel	tin	zinc	Brent oil	WTI crude	heating oil	natural gas
transition 1	s_1	time		VIX	VIX	VIX	VIX			VIX	time	time	time	
transition 2	s_2	time		Time	time	time	time	time	time	time	time	time	time	
low s_1 - low s_2	$P_{(11)}$	-0.109	-0.050	0.030	0.117	0.039	-0.026	-0.080	0.040	-0.009	-0.492	-0.446	-0.466	0.023
high s_1 - low s_2	$P_{(21)}$	0.076		-0.148	-0.134	0.039	-0.026			-0.009	-0.017	-0.009	-0.021	
low s_1 - high s_2	$P_{(12)}$			0.146	0.144	-0.046	-0.052	0.274	0.193	0.110				
high s_1 - high s_2	$P_{(22)}$	-0.082		0.338	0.284	0.362	0.299			0.284	0.519	0.494	0.527	
location 1	c_1	Jul97		25.15	15.73	15.45	14.79			17.33	Jan91	Jan91	Jan91	
location 2	c_2	Jan03		May01	Mar99	Jan01	Apr03	May01	May01	Mar00	Aug08	Aug08	Aug08	
transition speed 1	γ_1	∞		∞	∞	∞	∞			∞	159.07	∞	∞	
transition speed 2	γ_2	∞		∞	∞	5.74	∞	2.99	∞	15.20	∞	∞	∞	

Table reports estimated parameter values for preferred conditional correlation models of commodity futures returns with S&P500 index returns. Correlation models are estimated using standardized residuals from GARCH equations as described in Table 2. The DSTCC process treats conditional correlation as a convex combination of (up to) four extreme values, where the weights of the convex combination are given by up to two logistic transition functions (k=1,2) dependent on transition variable s_{kt} with location c_k and transition speed γ_k. When both transition variables are in their low state ($s_k < c_k$) 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. The differences $P_{(11)}$-$P_{(21)}$ and $P_{(12)}$-$P_{(22)}$ are significant at 5% level, as is at least one of the differences in the extreme states across time.

Table 5
Preferred conditional correlation models, weekly commodity futures returns and US Bonds

US Bonds

		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							time				
transition 2	s_2							time		time	time	
low s_1 - low s_2	$P_{(11)}$	0.002	-0.039	-0.001	-0.075	-0.067	0.046	-0.138	-0.037	0.030	0.051	-0.050
high s_1 - low s_2	$P_{(21)}$							0.027				
low s_1 - high s_2	$P_{(12)}$									-0.198	-0.154	
high s_1 - high s_2	$P_{(22)}$							-0.144				
location 1	c_1							Jan97				
location 2	c_2							Jan06		Nov06	Sep06	
transition speed 1	γ_1							∞				
transition speed 2	γ_2							∞		∞	∞	

		Precious Metals			**Base Metals**						**Energy**		
		gold	plati-num	silver	alumin-ium	copper	lead	nickel	tin	zinc	Brent oil	WTI crude	heating oil	natural gas
transition 1	s_1	time		time	VIX	VIX	VIX	VIX	VIX	VIX	time			time
transition 2	s_2	time		time	time	time	time	time	time		time		time	time
low s_1 - low s_2	$P_{(11)}$	-0.059	-0.011	-0.146	-0.057	-0.025	0.082	-0.058	0.105	-0.057	-0.336	-0.104	-0.389	-0.209
high s_1 - low s_2	$P_{(21)}$	0.047		0.085	-0.057	-0.025	-0.144	-0.233	0.105	-0.237	-0.043			0.024
low s_1 - high s_2	$P_{(12)}$				-0.046	-0.026	-0.067	0.156	0.066				-0.045	
high s_1 - high s_2	$P_{(22)}$	-0.237		-0.151	-0.324	-0.314	-0.381	-0.278	-0.274		-0.185			-0.103
location 1	c_1	Sep92		Sep98	18.980	18.11	20.91	23.78	18.99	20.95	Jul92			Apr92
location 2	c_2	Mar08		Sep04	Sep01	Sep01	Jul04	Jun05	Oct01		Nov07		Jul92	Aug06
transition speed 1	γ_1	∞		∞	∞	∞	∞	∞	∞	∞	∞			∞
transition speed 2	γ_2	∞		∞	∞	∞	∞	∞	∞		∞		∞	∞

Table reports estimated parameter values for preferred conditional correlation models of commodity futures returns with US Bond index returns. Correlation models are estimated using standardized residuals from GARCH equations as described in Table 2. The DSTCC process treats conditional correlation as a convex combination of (up to) four extreme values, where the weights of the convex combination are given by up to two logistic transition functions (k=1,2) dependent on transition variable s_{kt} with location c_k and transition speed γ_k. When both transition variables are in their low state ($s_k < c_k$) 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. The differences $P_{(11)}$-$P_{(21)}$ and $P_{(12)}$-$P_{(22)}$ are significant at 5% level, as is at least one of the differences in the extreme states across time.

Table 6

Preferred conditional correlation models, weekly commodity futures returns and German stocks

DAX- German stocks

		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	time	VIX		VIX	time		VIX	time	time	VIX	time
transition 2	s_2	time	time			time		time	time	time	time	time
low s_1 - low s_2	$P_{(11)}$	0.116	0.070	-0.002	0.092	0.109	0.004	-0.010	0.121	0.125	0.009	0.118
high s_1 - low s_2	$P_{(21)}$	-0.115	0.070		0.317	0.010		-0.010	-0.068	-0.008	0.009	-0.041
low s_1 - high s_2	$P_{(12)}$		-0.111					-0.089			-0.019	
high s_1 - high s_2	$P_{(22)}$	0.086	0.346			0.297		0.586	0.091	0.218	0.333	0.339
location 1	c_1	Dec95	17.64		26.72	Jun95		26.28	Sep96	Mar97	21.28	Sep96
location 2	c_2	Apr02	Oct03			May07		Apr03	Jul03	Jan06	Apr01	Sep08
transition speed 1	γ_1	∞	∞		∞	∞		∞	∞	∞	∞	∞
transition speed 2	γ_2	∞	∞			∞		∞	∞	19.23	∞	∞

		Precious Metals			Base Metals					Energy			
		gold	plati-num	silver	alumin-ium	copper	lead	nickel	tin	zinc	Brent oil	WTI crude	heating oil	natural gas
transition 1	s_1			VIX	VIX	VIX		VIX	VIX	VIX	VIX	VIX	time	VIX
transition 2	s_2			time	time	time	time	time		time	time	time	time	time
low s_1 - low s_2	$P_{(11)}$	-0.043	-0.048	0.024	-0.073	0.006	-0.100	-0.070	0.050	0.065	0.005	-0.009	-0.437	-0.006
high s_1 - low s_2	$P_{(21)}$			0.024	-0.073	0.006		-0.070	0.351	0.215	-0.576	-0.506	-0.009	-0.310
low s_1 - high s_2	$P_{(12)}$			0.163	0.162	0.130	0.144	-0.009		0.294	-0.043	-0.035		-0.006
high s_1 - high s_2	$P_{(22)}$			0.445	0.282	0.440		0.324		0.543	0.126	0.127	0.463	0.507
location 1	c_1			27.01	21.70	23.94		15.72	31.07	26.12	20.17	19.96	Nov91	34.73
location 2	c_2			Oct04	Mar99	May01	Dec00	Oct99		Feb06	Apr97	May97	Sep08	Feb08
transition speed 1	γ_1			∞	∞	∞		429.95	3.12	∞	51.65	∞	∞	∞
transition speed 2	γ_2			18.32	∞	8.93	24.10	3.30		∞	∞	∞	∞	∞

Table reports estimated parameter values for preferred conditional correlation models of commodity futures returns with DAX stock market index returns. Correlation models are estimated using standardized residuals from GARCH equations as described in Table 2. The DSTCC process treats conditional correlation as a convex combination of (up to) four extreme values, where the weights of the convex combination are given by up to two logistic transition functions (k=1,2) dependent on transition variable s_{kt} with location c_k and transition speed γ_k. When both transition variables are in their low state ($s_k < c_k$) 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. The differences $P_{(11)}$-$P_{(21)}$ and $P_{(12)}$-$P_{(22)}$ are significant at 5% level, as is at least one of the differences in the extreme states across time.

Table 7

Preferred conditional correlation models, weekly commodity futures returns and UK stocks

FTSE100-UK stocks

		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	time	VIX		VIX			time			VIX	time
transition 2	s_2	time	time		time	time		time		time	time	time
low s_1 - low s_2	$P_{(11)}$	0.259	-0.060	0.002	0.038	-0.053	0.042	-0.138	0.018	-0.009	0.009	0.234
high s_1 - low s_2	$P_{(21)}$	-0.045	0.124		0.038			-0.031			0.009	-0.050
low s_1 – high s_2	$P_{(12)}$		-0.107		0.247	0.181				0.239	-0.016	
high s_1 - high s_2	$P_{(22)}$	0.092	0.223		0.630			0.646			0.328	0.416
location 1	c_1	Jul91	17.32		27.40			Apr98			21.29	Jun92
location 2	c_2	Apr02	Oct02		Oct05	Jun00		Sep08		May06	Apr01	Sep08
transition speed 1	γ_1	∞	∞		42.38			∞			∞	2.60
transition speed 2	γ_2	∞	∞		∞	∞		∞		∞	∞	∞

		Precious Metals			Base Metals					Energy			
		gold	platinum	silver	alumin-ium	copper	lead	nickel	tin	zinc	Brent oil	WTI crude	heating oil	natural gas
transition 1	s_1			VIX	time	VIX		VIX	VIX	VIX	VIX	VIX	time	time
transition 2	s_2			time	time	time	time	time	time	time	time	time	time	time
low s_1 - low s_2	$P_{(11)}$	-0.048	0.006	0.076	0.003	0.010	-0.036	-0.031	0.003	-0.111	0.045	0.051	-0.179	0.107
high s_1 - low s_2	$P_{(21)}$			-0.105	-0.279	0.010		-0.031	0.003	0.050	-0.174	-0.176	0.008	-0.066
low s_1 - high s_2	$P_{(12)}$			0.199		-0.012	0.255	0.071	0.043	0.265	0.259	0.260		
high s_1 - high s_2	$P_{(22)}$			0.461	0.258	0.347		0.313	0.295	0.265	0.259	0.260	0.241	0.161
location 1	c_1			26.26	Oct97	14.49		15.74	18.97	17.59	24.86	26.32	Apr92	Jun99
location 2	c_2			Sep04	Oct99	Nov00	Apr06	Dec00	Nov00	Jul00	May05	May05	May05	Apr05
transition speed 1	γ_1			∞	∞	∞		∞	∞	∞	∞	∞	∞	∞
transition speed 2	γ_2			∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞

Table reports estimated parameter values for preferred conditional correlation models of commodity futures returns with FTSE100 stock market index returns. Correlation models are estimated using standardized residuals from GARCH equations as described in Table 2. The DSTCC process treats conditional correlation as a convex combination of (up to) four extreme values, where the weights of the convex combination are given by up to two logistic transition functions (k=1,2) dependent on transition variable s_{kt} with location c_k and transition speed γ_k. When both transition variables are in their low state ($s_k < c_k$) 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. The differences $P_{(11)}$-$P_{(21)}$ and $P_{(12)}$-$P_{(22)}$ are significant at 5% level, as is at least one of the differences in the extreme states across time.

Table 8

Preferred conditional correlation models, weekly commodity futures returns and French stocks

CAC - France stocks

		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	time	VIX		VIX	time		VIX	time		VIX	
transition 2	s_2	time	time		time	time		time	time		time	
low s_1 - low s_2	$P_{(11)}$	0.361	0.067	-0.014	0.054	0.157	0.054	-0.025	0.246	0.045	0.003	-0.006
high s_1 - low s_2	$P_{(21)}$	-0.087	0.398		0.054	-0.013		-0.025	-0.093		0.003	
low s_1 - high s_2	$P_{(12)}$		-0.127		0.068			-0.098			0.000	
high s_1 - high s_2	$P_{(22)}$	0.061	0.110		0.629	0.522		0.615	0.085		0.306	
location 1	c_1	Apr91	17.79		27.52	May93		26.28	Jul92		21.29	
location 2	c_2	Mar02	Nov94		Jul03	Aug08		Apr03	Apr03		Apr01	
transition speed 1	γ_1	∞	∞		29.72	∞		∞	∞		∞	
transition speed 2	γ_2	∞	∞		12.79	∞		∞	∞		∞	

		Precious Metals			**Base Metals**					**Energy**			
		gold	platinum	silver	aluminium	copper	lead	nickel	tin	zinc	Brent oil	WTI crude	heating oil	natural gas
transition 1	s_1	time			time	VIX		VIX	VIX	VIX	time	time	time	VIX
transition 2	s_2	time		time	time	time	time	time		time	time	time	time	time
low s_1 - low s_2	$P_{(11)}$	-0.260	-0.026	0.002	-0.014	0.005	-0.123	-0.002	0.087	-0.074	-0.532	-0.464	-0.452	0.056
high s_1 - low s_2	$P_{(21)}$	0.060			-0.264	0.005		-0.002	0.293	0.071	0.032	0.032	0.008	0.056
low s_1 - high s_2	$P_{(12)}$			0.223		-0.028	0.131	-0.009		0.255				-0.577
high s_1 - high s_2	$P_{(22)}$	-0.076			0.259	0.352		0.343		0.255	0.485	0.457	0.489	0.499
location 1	c_1	Jul92			Jan97	14.49		15.61	31.13	16.98	Jan91	Jan91	Jan91	34.50
location 2	c_2	Apr01		Nov03	Apr99	Nov00	Sep00	Mar01		Jun00	Sep08	Sep08	Sep08	Jul08
transition speed 1	γ_1	∞			4.78	∞		313.39	3.17	∞	∞	104.31	∞	186.42
transition speed 2	γ_2	∞		∞	∞	∞	∞	12.75		∞	∞	∞	∞	∞

Table reports estimated parameter values for preferred conditional correlation models of commodity futures returns with CAC stock market index returns. Correlation models are estimated using standardized residuals from GARCH equations as described in Table 2. The DSTCC process treats conditional correlation as a convex combination of (up to) four extreme values, where the weights of the convex combination are given by up to two logistic transition functions (k=1,2) dependent on transition variable s_{kt} with location c_k and transition speed γ_k. When both transition variables are in their low state ($s_k < c_k$) 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. The differences $P_{(11)}$-$P_{(21)}$ and $P_{(12)}$-$P_{(22)}$ are significant at 5% level, as is at least one of the differences in the extreme states across time.

Table 9

Preferred conditional correlation models, weekly commodity futures returns and Japanese stocks

TOPX - Japanstocks

		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		VIX		VIX	VIX	time	time	VIX	
transition 2	s_2		time		time		time	time	time	time	time	
low s_1 - low s_2	$P_{(11)}$	-0.006	0.010	0.020	0.084	0.056	0.208	-0.100	0.015	0.139	-0.029	0.024
high s_1 - low s_2	$P_{(21)}$		0.010		-0.099		-0.055	-0.100	-0.127	-0.052	-0.029	
low s_1 - high s_2	$P_{(12)}$		-0.054		0.241		0.164	-0.051			0.103	
high s_1 - high s_2	$P_{(22)}$		0.422		0.241		0.164	0.273	0.124	0.181	0.337	
location 1	c_1		21.06		17.59		17.35	23.60	Jun98	Jan93	21.18	
location 2	c_2		Aug02		May01		Dec98	Feb01	Apr03	Nov01	Jul01	
transition speed 1	γ_1		∞		∞		∞	11.01	∞	∞	∞	
transition speed 2	γ_2		∞		∞		∞	∞	∞	∞	3.67	

		Precious Metals			Base Metals					Energy			
		gold	plati-num	silver	alumin-ium	copper	lead	nickel	tin	zinc	Brent oil	WTI crude	heating oil	natural gas
transition 1	s_1			VIX	VIX	time	VIX		time	VIX	VIX	VIX	VIX	VIX
transition 2	s_2			Time	time	time	time	time	time	time	time	time	time	time
low s_1 - low s_2	$P_{(11)}$	-0.016	-0.024	0.099	0.030	0.007	0.010	-0.013	0.050	-0.080	0.066	0.064	0.040	0.184
high s_1 - low s_2	$P_{(21)}$			-0.230	0.177	0.107	0.010		-0.173	0.135	-0.167	-0.175	-0.149	-0.078
low s_1 - high s_2	$P_{(12)}$			0.311	0.260		0.010	0.214		0.326	0.238	0.210	0.166	0.046
high s_1 - high s_2	$P_{(22)}$			0.311	0.260	0.323	0.227		0.192	0.326	0.458	0.419	0.508	0.279
location 1	c_1			23.78	20.30	Oct96	11.64		Jan97	20.79	26.30	26.33	26.33	20.10
location 2	c_2			Jan01	Apr03	Mar06	Mar02	Jul02	Jun00	Sep04	Jan05	Dec04	Jan05	Jul03
transition speed 1	γ_1			∞	∞	∞	∞	∞	21.50	∞	∞	∞	∞	∞
transition speed 2	γ_2			16.52	∞	∞	∞		∞	8.73	∞	∞	∞	∞

Table reports estimated parameter values for preferred conditional correlation models of commodity futures returns with TOPX index returns. Correlation models are estimated using standardized residuals from GARCH equations as described in Table 2. The DSTCC process treats conditional correlation as a convex combination of (up to) four extreme values, where the weights of the convex combination are given by up to two logistic transition functions (k=1,2) dependent on transition variable s_{kt} with location c_k and transition speed γ_k. When both transition variables are in their low state ($s_k < c_k$) 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. The differences $P_{(11)}$-$P_{(21)}$ and $P_{(12)}$-$P_{(22)}$ are significant at 5% level, as is at least one of the differences in the extreme states across time.

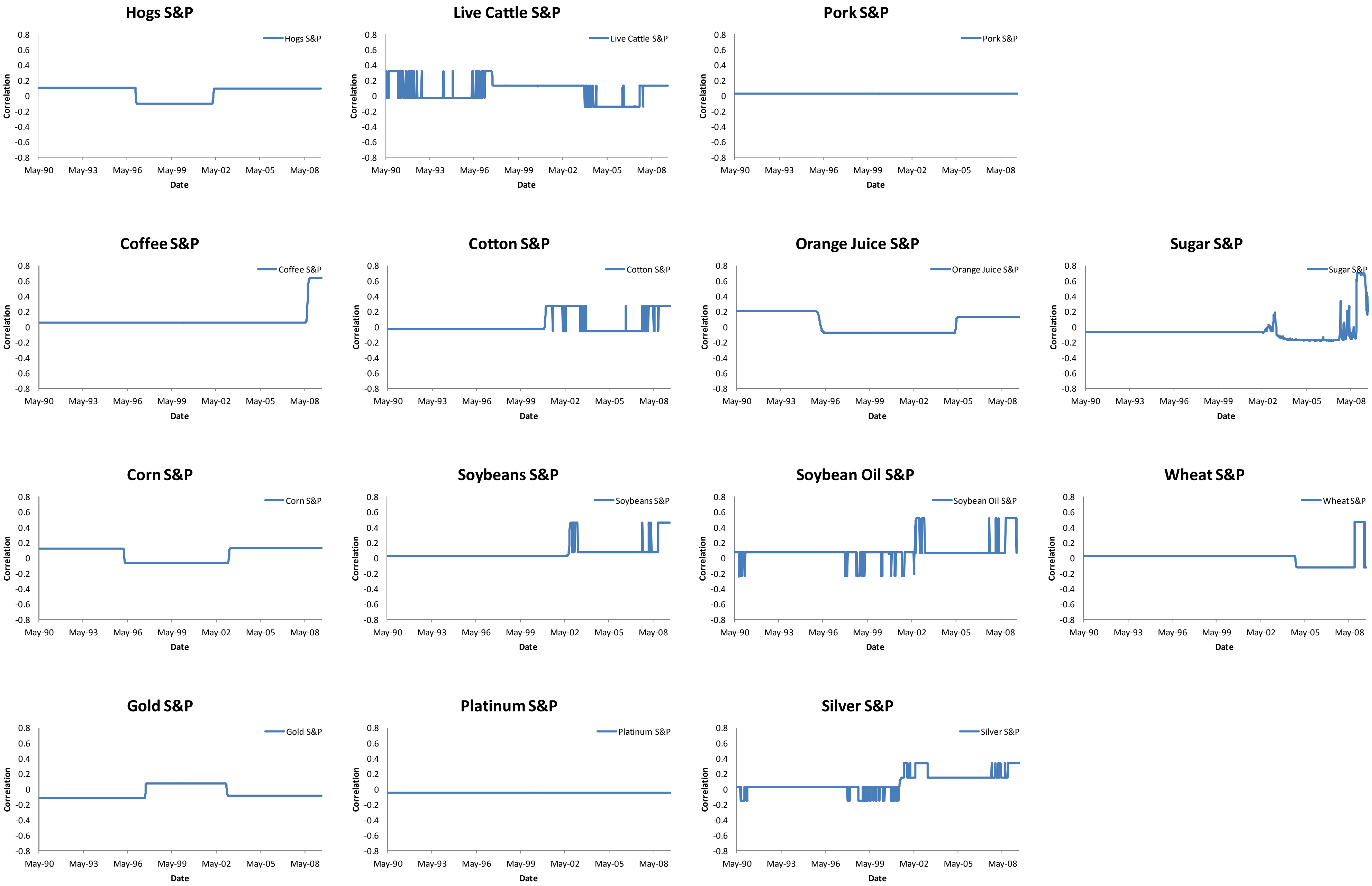

Fig 1: Commodity futures and S&P500 returns, correlation dynamics.

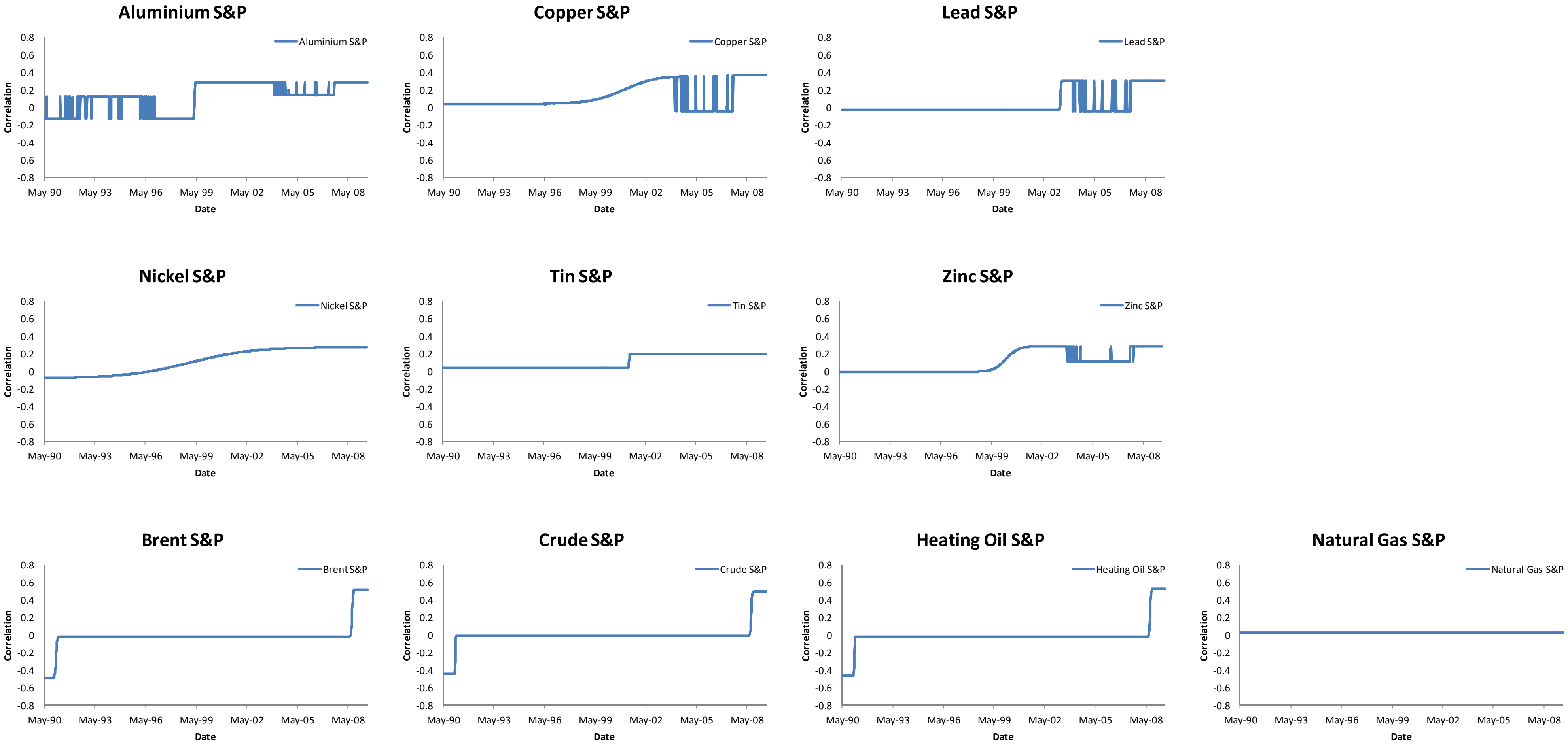

Fig 1: continued