Understanding dynamic conditional correlations between commodities futures markets

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Abstract

We estimate a multivariate GARCH model to obtain the dynamic conditional correlations (DCCs) between 10 commodities in energy, metals and agriculture futures markets over the period 1998-2014. The DCCs increased sharply around year 2008 and subsequently decreased. To understand this trend, we look at the factors influencing those correlations. Adopting a pooled mean group (PMG) estimator, we observe that macroeconomic variables are significantly correlated with the agriculture-energy and metals-energy DCCs. Financial factors as well as speculative activity are statistically significant in explaining the agriculture-energy correlations but not the DCCs between metals and energy.

JEL classification: Q42; Q11; C32

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1. Introduction

Financial markets have been progressively liberalized in the last decades. As a consequence, volatilities in asset markets increased. Investors reacted shifting progressively towards alternative investment instruments, such as commodity futures, to hedge against higher risk in the stock markets. Indeed, commodity markets have been traditionally considered a desirable asset class eligible for portfolio diversification, as their volatilities were showing lower correlations with stocks in turbulent periods (Chong and Miffre, 2010) and high correlations with inflation (Gorton and Rouwenhorst, 2006; Delatte and Lopez, 2013). However, after the 2008 financial crisis, correlations between commodities have increased, limiting the benefits of this diversification strategy (Daskalaki and Skiadopoulos, 2011; Sadorsky, 2014).

Despite these recent findings, there is still a tendency to use commodities as a hedge strategy. Are these markets linked? If so, to what extent are they a good instrument for hedging against risk? Are the correlations between returns in different markets affected by external factors? As the interest in investing in commodities increased, inspecting time-varying covolatilities and the volatility transmission across commodities is essential to both investors and policy makers. If volatilities spillover from one market to another, the portfolio managers and policy makers have to adjust their decisions to prevent the risk of contagion in the advent of a crash in one of the markets. The relevance of this topic has risen in recent times, as the second half of the 2000s saw commodity prices, both energy and non-energy, following a similar path. These large and comparable fluctuations in commodity prices have renewed interest in the dynamic relationship between them.

Many studies have investigated the correlations between energy and non-energy commodities (Chang and Su, 2010; Du et al., 2011; Ji and Fan, 2012; Gardebroek and Hernandez, 2013; Ewing and Malik, 2013; Liu, 2014; Mensi et al., 2014; Charlot and Marimouto, 2014), as well as the correlations within the non-energy commodity markets (Sensoy, 2013; Lahiani et al. 2014; Todorova et al., 2014), mostly confirming the existence of significant correlations among commodity prices.

Some authors focus instead on time varying volatilities in commodity markets, examining the correlations between commodities and stocks markets (Büyükşahin and Robe, 2014) or between the commodity markets (Batten et al., 2010; Alquist and Coibion, 2013; Silvennoinen and Thorp, 2013; Karali and Ramirez, 2014).

In this study we investigate the factors that influence the dynamic conditional correlations between 10 commodities in the agriculture, energy and metals future markets. To the best of our knowledge, this is the first attempts to investigate these correlations within a unique framework: i.e., with a common methodology, looking at the same period of analysis and considering common explanatory variables, thus allowing a direct comparison of the results found across different markets.

First, we estimate a multivariate GARCH (Engle, 2002) which models jointly the second moments of futures returns in different commodity markets. We obtain a set of return variances and covariances that allow us to compute the dynamic conditional correlations for the period spanning from January 1998 to May 2014. During this interval these correlations started increasing in the years before the financial crisis and decreased in recent times.

As a second step, we are interested in understanding under which circumstances commodity returns tend to move in sync and display higher DCCs. We consider the long-term fluctuations of macroeconomic fundamentals, financial market characteristics and speculative activity. Since prior literature suggests that these factors might matter for commodity return correlations, we test whether they influence the DCCs in our setting. We estimate an Autoregressive Distributed Lag (ARDL) model by means of the pooled mean group estimator (PMG) proposed by Pesaran et al. (1999). Our analysis suggests that macroeconomic factors influence the agriculture-energy and metals-energy correlations, while financial correlations are significant in explaining the agriculture-energy correlations but not those between metals and energy commodities. Speculative activity in energy markets is significant in explaining correlations with agricultural commodities, but not with metals. Overall, few factors are significant in explaining the energy-metals correlations.

The paper is structured as follows. Section 2 provides a review of the literature, Section 3 describes the data, Section 4 illustrates the methodology. Section 5 discusses the empirical results while conclusions and policy implications are presented in Section 6.

2. Literature review

2.1. The linkages between commodity markets

It is generally acknowledged that an increase in the oil price affects prices of other commodities (Hooker, 2002; Hunt, 2006). This is not surprising, as energy and non-energy commodities are linked by several channels. First, energy prices affect the cost of a number of intermediate inputs both in agriculture (e.g. fertilizers and pesticides) and extractive industries as well as other production costs, such as processing and transportation (Hammoudeh and Yuan, 2008; Tyner, 2010; Barrera et al., 2011). Second, with respect to some crops raised to produce biofuels, the prices might be related to those of fossil fuels, for which they are substitutes (FAO, 2008). Third, commodity prices move in synch as they are often influenced by the same macroeconomic fundamentals, such as inflation, interest rates and industrial production (Hammoudeh and Yuan, 2008). An expansion of economic activity leads to a raise in demand for commodities such as copper, lumber or crude oil, since these are used as inputs in industrial production and raises the demand for non-industrial commodities, such as cocoa or wheat through the resulting increase in income (Pyndick and Rotenberg, 1990). Finally, the liberalization of capital flows, the development in market trading technologies and in new financial instruments and the improvement in information transmission have all contributed to an increased integration between commodity markets (Ji and Fan, 2012).

With respect to the linkages between prices and/or returns, the literature mostly adopts cointegration and error correction models, while variances are generally investigated by means of univariate, bivariate or multivariate GARCH-type methodologies.

In the first group of studies, several find a relationship between energy and agricultural prices (Baffes, 2007; Chen et al., 2010; Tyner, 2010; Natanelov et al., 2011; Ciaian and Kancs, 2011; Serra et al., 2011), while the evidence is mixed with respect to the correlation between energy and metal prices: Soytas et al. (2009) find that the oil price has no predictive power on precious metal prices while Sari et al. (2010) show that shocks in the precious metal and oil markets have a mutual but small positive impact on each other.

Focusing on volatilities, we find a wide array of empirical analyses. Several authors find statistically significant volatility spillovers from oil to agricultural markets, with a change in the dynamics of volatility transmission after the second half of 2000s. These results are obtained using different methodologies, such as bivariate EGARCH (Chang and Su, 2010; Ji and Fan, 2012), bivariate stochastic volatility models (Du et al., 2011), causality in variance test (Nazlioglu et al., 2013), VAR-BEKK-GARCH and VAR-DCC-GARCH models (Mensi et al., 2014) and the copula approach (Reboredo, 2012). Other researchers investigate the agriculture-ethanol-fossil fuels link, adopting multivariate GARCH models and finding strong volatility linkages, both in the U.S. and in emerging markets (Serra, 2011; Gardebroek and Hernandez, 2013; Wu and Li, 2013).

As for the spillovers between metal and energy markets, the previous literature mostly found a significant impact of oil price changes on the volatility of metals using univariate GARCH models (Melvin and Sultan, 1990; Hammoudeh and Yuan, 2008). Others find significant transmission of volatility between metals and oil prices (Ewing and Malik, 2013; Choi and Hammoudeh; 2010; Charlot and Marimoutou, 2014) as well as within metal commodities markets (Sensoy, 2013; Todorova et al., 2014).

2.2. The factors behind markets correlations

Scholars investigated the link between the volatilities of stock and commodity markets. Silvennoinen and Thorp (2013) find that the correlations between stocks, bonds and commodity futures returns have increased for most commodities. Often correlations have risen in high VIX states, pointing to strong financial influences. Their results are consistent with the analysis of Daskalaki and Skiadopoulos (2011) and Cheung and Miu (2010), but differ from the findings of some earlier studies, which are however referring to samples from quiter periods (Chong and Miffre, 2010; Büyüksahin et al., 2010). Büyükşahin and Robe (2014) concentrate on the role of financialization in commodity markets on stock-commodity co-movement, showing that the speculative activity of hedge funds that trade actively in both equity and commodity future markets has explanatory power on the correlation between stocks and commodities; however, they find that the predictive power of the speculative activity is weaker in periods of stress in financial market.

There is a considerable number of studies that investigate the effects of macroeconomic and financial factors on the volatility of commodity futures (Batten et al., 2010; Sanders and Irwin, 2011; Irwin and Sanders, 2012; Hayo et al., 2012; Aulerich et al., 2013; Manera et al., 2016), but only two works have recently started looking at correlations between these volatilities in different commodity markets. Karali and Ramirez (2014) analyze the time-varying volatility and spillover effects in energy futures markets, finding that macroeconomic variables, political and weather-related events have an effect on the volatilities and their correlations. Alquist and Coibion (2013) develop a general equilibrium macroeconomic model with commodities that yields a tractable factor structure for real commodity prices. They find that the factor that captures shocks that are not directly related to commodity demand and supply (such as aggregate productivity shocks and shocks to labor supply) accounts for approximately 60-70% of the variance in real commodity prices overall and much of the historical changes in commodity prices since the early 1970s. Direct commodity shocks have also played a role in accounting for some commodity price movements in specific periods of time, such as the run-up in commodity prices in the 2000s and their subsequent decline in 2008-2009.

The analysis of the factors influencing the dynamic conditional correlations between commodities is thus a field still not fully explored but relevant in the light of portfolio diversification.

3. Data description

3.1. Commodity futures returns

We focus on a sample of ten commodities belonging to three classes: agricultural products (corn, soybeans, wheat, oats and rice), metals (copper, gold and silver) and energy products (West Texas Intermediate crude oil and natural gas).[1] We consider the period ranging from 01/01/1998 to 05/30/2014.

Real daily futures prices are computed dividing the nominal one-month-ahead futures prices by the U.S. consumer price index (CPI), with 2010 as base year. The price series are sourced from the Custom Historical Data provided by the Commodity Research Bureau (CRB), while the U.S. CPI is obtained from the Federal Reserve Bank of St. Louis (FRED). The returns are computed as $r_{it} = \log\left(\frac{P_{it}}{P_{it-1}}\right)$, where r_{it} is the corresponding return, P_{it} is the corresponding real price, i=1…10 defines the future market and t is the date.[2]

3.2. Explanatory variables

To investigate the behavior of correlations between commodities, we consider a set of factors that could influence them.

[1] Agricultural commodities are traded on the Chicago Board of Trade (CBOT), metals on the Commodity Exchange Market (COMEX) and energy commodities on the New York Mercantile Exchange (NYMEX).

[2] Descriptive statistics and pairwise unconditional correlation matrix are provided in Table A.1 and Table A.2, respectively, in the online appendix.

a) Macroeconomic fundamentals

It is well documented that the business cycle positively affects commodity futures returns (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). We test whether the dynamic conditional correlations are influenced by the business cycle as well. To this aim, we use the Aruoba-Diebold-Scotti (ADS) business conditions index, which is designed to track real business conditions of the U.S. economy, following Büyükşahin and Robe (2014).[3] The ADS daily data is obtained from the Federal Reserve Bank of Philadelphia.

The literature on bond-stock correlations suggests that these can increase in periods of higher actual or expected inflation (Andersson et al., 2008; Dimic et al., 2016), while Büyükşahin and Robe (2014) and Chong and Miffre (2010) find that stock-commodity correlations decrease in periods of higher inflation, as commodities may provide a better hedge against inflation than equities do. Commodity markets are expected to react in the same way to higher inflation, thus inflation is likely to be positively associated with larger correlations between commodities. We test whether the expected inflation is related to commodities DCCs using weekly data from the Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis.

b) Financial markets

To investigate aspects pertaining to the financial markets, we include a number of controls suggested by the literature.

The short term interest rate and the yield spread are known to predict the common variation in commodity, bond, and stock returns (Fama and Schwert, 1977; Campbell, 1987; Fama and French,1989; Bessembinder and Chan, 1992; Silvennoinen and Thorp, 2013; Büyükşahin and Robe 2014). Akram (2009) finds that shocks to interest rates account for substantial shares of fluctuations

[3] The average value of the ADS index is zero, with positive values corresponding to better-than-average macroeconomic conditions and negative values to worse-than-average ones.

in the commodity prices. Other authors find that the monetary policy influences time varying correlations of international bond returns (Hunter and Simon, 2005) and stock-bond correlations (Dimic et al., 2016). We use the real three-month Treasury bill interest rate obtained from the Federal Reserve Bank of St. Louis (FRED) at weekly frequency.

We define the yield spread as the difference between Moody's seasoned AAA corporate bond yield and the three months Treasury yield (Hong and Yogo, 2012). This index captures what happens when the difference between a long-term un-secured yield, which mirrors the stability of industrial sector, and a short-term secured yield, which reflects the current government monetary policy, arises. We obtain this data from the Federal Reserve Bank of St. Louis (FRED) at weekly frequency.

Most international commodities are priced in U.S. dollars, as a consequence commodity prices are generally affected by the U.S. dollar exchange rate (Ji and Fan, 2012). A depreciation of the dollar would lead to a higher dollar price of the commodities (Akram, 2009), on the other side, a weaker U.S. dollar makes imports more expensive to U.S. consumers and causes a drop in imports, affecting thus domestic consumption and potentially prices (Karali and Ramirez, 2014). Given that most international commodity markets are priced in dollars, the effect of exchange rate on correlations of energy and non-energy commodities depends on the degree that domestic and foreign consumers react to the price changes induced by the exchange rates. We consider the trade weighted U.S Dollar Index, which is a weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group of major U.S. trading partners. For the two last variables, monthly data are obtained from the Federal Reserve Bank of St. Louis and are interpolated at weekly frequency.

To account for the volatility in financial markets, we include the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) obtained from CBOE. VIX has been adopted to predict changes in trading patterns in bond and stock markets (Dimic et al., 2016) and in commodity futures markets (Cheng et al., 2015) . Higher uncertainty in the stock market might drive investors to diversify into other markets such as commodities and bonds, with the effect of producing higher correlations between them (Andersson et al., 2008 and Connolly et al., 2005). Therefore, we expect stronger correlations between commodities volatilities as a result of higher VIX.

c) Speculative activity

The role of speculative activity on the volatility of futures prices has attracted much attention in recent times. On the one hand, speculators increase market liquidity thus reducing price volatility, on the other hand, an increasing trading volume, especially by speculators, could positively affect commodity volatilities (Manera et al., 2016), therefore the overall effect might be vague. Recent empirical analyses have tested the effect of financial speculation on prices, returns and volatility of commodities. For instance, Sanders and Irwin (2011), Irwin and Sanders (2012) and Aulerich et al. (2013) conclude that speculation generally does not influence the returns of commodities, Manera et al. (2016) suggest that speculation is associated with lower volatility in energy markets and Büyüksahin and Robe (2014) find that commodity-equity correlations rise amid greater participation by speculators. In this study, to account for commodity markets financialization, we use the Working's (1960) T index, which measures excess speculation, i.e. to what extent speculative positions exceed hedging ones. The index is computed as:

$$\begin{cases} 1+\dfrac{SS}{HS+HL} & if \quad HS \geq HL \\ 1+\dfrac{SL}{HS+HL} & if \quad HS < HL \end{cases} \tag{1}$$

where SS is speculation short, SL is speculation long, HS is hedging short and HL is hedging long. Therefore, the index presented in equation (1) is the ratio of speculative positions to total hedger's positions. Data for weekly "Commercial" and "Non-commercial" positions are obtained from the U.S Commodity Futures Trading Commission (CFTC). Commercials are considered as hedgers, and non-commercials as speculators. Besides, CFTC provides data for "Non-Reportable" agents, which are not classified into either of the two groups above: we attribute them 50% to the speculators and 50% to the hedgers group.

d) Time effects

We enrich the model including a set of annual dummies to investigate the impact of the 2001 and the 2008 financial crises, as well as to broadly account for business cycle dynamics. Additionally, we include a set of monthly dummies to control for seasonality in demand, which could be an issue in energy and agricultural markets.

4. Methodology

As a first check we test the stationarity of the commodity returns: the augmented Dickey Fuller (1979) unit root test confirms the stationarity of all returns at the 1% significance level. Then we inspect the residuals obtained from the OLS regression of each series of returns on a constant term: the Lagrange multiplier test suggests the existence of ARCH effects for all returns at the 1% and 5% levels of significance. There is also evidence of serial correlation for corn, oats, rice, copper and natural gas at the 1% and 10% levels of significance, while no serial correlation is detected for the other commodities.[4]

These preliminary tests suggest that we can jointly model the volatilities of the ten commodities considered in the analysis with a dynamic conditional correlation (DCC) GARCH model (Engle, 2002). This approach captures the effects on current volatility of own innovation and lagged volatility shock originated in a given market, as well as cross innovations and volatility spillovers from other futures markets. Thus, it allows us to investigate volatility in interconnected markets. The general multivariate GARCH model is defined as:

$$r_t = Cx_t + \varepsilon_t \qquad (2.a)$$

[4] The unit root and diagnostic tests results are reported in Table A.1 in the online Appendix.

$$\varepsilon_t = H_t^{1/2}\upsilon_t \tag{2.b}$$

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{2.c}$$

where r_t is a 10×1 vector of ten commodities returns, C is an $10\times k$ matrix of parameters, x_t is a $k\times 1$ vector of independent variables, which contains a constant and, if necessary to remove autocorrelation, an AR(1) term. The error term is defined by $H_t^{1/2}$, the Cholesky factor of the time varying conditional covariance matrix of the disturbances H_t times υ_t, a 10×1 vector of i.i.d. innovations with zero mean and unit variance. D_t is a diagonal matrix of conditional variances in which each σ_{it}^2 evolves according to a univariate GARCH process, which is defined as $\sigma_{it}^2 = s_i + \sum_{j=1}^{p_i} \alpha_j \varepsilon_{it-j}^2 + \sum_{j=1}^{q_i} \beta_j \sigma_{it-j}^2$. R_t is defined as:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{2.d}$$

$$Q_t = (1-\lambda_1-\lambda_2)R + \lambda_1 \tilde{\varepsilon}_{t-1}\tilde{\varepsilon}_{t-1}' + \lambda_2 Q_{t-1} \tag{2.e}$$

where R_t is a matrix of time-varying conditional quasi correlations, $\tilde{\varepsilon}_t$ is an 10×1 vector of standardized residuals ($D_t^{-1/2}\varepsilon_t$) and λ_1 and λ_2 are the two parameters that determine the dynamics of conditional quasi correlations. They are both non-negative, and they must satisfy the condition: $0 \le \lambda_1 + \lambda_2 < 1$. When Q_t is stationary, the R_t matrix is a weighted average of the unconditional covariance matrix of the standardized residuals $\tilde{\varepsilon}_t$ and the unconditional mean of Q_t.[5]

The multivariate GARCH model (2a)-(2e) is the first step of a two-step strategy aimed at modelling the DCCs associated with the agriculture, energy and metals returns. The first step of the analysis yields a panel of 45 dynamic conditional correlations over the period 1998-2014. The second step allows us more flexibility in dealing with the characteristics of the DCCs, i.e. the cross-sectional

[5] As the two matrices are different, the R_t matrix is neither the unconditional correlation matrix, nor the unconditional mean of Q_t. As a consequence, the parameters in R_t are known as quasi correlations (Engle, 2009).

dimension and the time series properties of the estimated correlations, as well as their long-run determinants.

More specifically, the second step is devoted to understand under which circumstances commodity returns move in sync. Thus, we look at the long-term fluctuations in a number of factors which prior literature suggests might matter for commodity return correlations. These are grouped, as discussed above, into economic fundamentals, financial market variables, speculative activity and a set of time dummies.

In order to proceed with this second step of our analysis, we need to match the frequency of our dependent variables, the DCCs, which are daily, with that of the independent variables, which are available mostly at weekly frequency. Thus, we compute the weekly averages of the dynamic conditional correlations and of those explanatory variables that are available at daily frequency, such as the ADS index.

A first concern to tackle, with a time span covering more than 16 years, is non-stationarity. We test the order of integration of the DCCs by means of the Im et al. (2003) and Hadri (2000) panel unit root tests. The Im et al. (2003) test assumes as null hypothesis that all panels contain unit roots and as alternative that some panels are stationary. The results suggest that we strongly reject the null hypothesis that all series contain a unit root in favour of the alternative that a nonzero fraction of the panels presents stationary processes.[6] The Hadri (2000) test instead assumes as null hypothesis that all panels are stationary. Again we do not accept the null hypothesis in favour of the alternative, i.e. that some panels contain unit roots. The ADF unit root test for the explanatory variables also shows that some of them are non stationary in levels.[7] Thus, we need a specification that deals with the fact that some variables are integrated of order 1, whereas the others are I(0).

[6] The panel unit root tests are reported in Table A.3 in the Appendix.
[7] The ADF unit root test results are presented in Table A.4 in the online Appendix.

In such a context, an autoregressive distributed lag (ARDL) model is the most appropriate. Pesaran and Shin (1999) show that it reduces the bias in the long-run parameter estimates in finite samples and ensures that it has a normal distribution irrespective of whether the underlying regressors are stationary or I(1). By choosing appropriate orders of lags in the ARDL model, it is possible to correct for residual correlation as well as for the problem of endogenous regressors (Pesaran and Shin, 1999). The DCCs are regressed on the lags of themselves, to account for slow adjustment of the correlations, and on current and lagged values of the independent variables. Such approach allows us to calculate the long-run effect of the independent variables on the DCCs.

A second issue to handle is the cross-sectional dimension of the estimated DCCs. While this two-step approach has been adopted to investigate the single commodity-equity return DCC (Buyuksahin and Robe, 2014), in this paper we are interested in modelling a panel of commodity returns correlations. To this aim, a number of alternatives are at hand. Recent developments in the dynamic panel data literature suggest that the assumption of homogeneity of slope parameters is often inappropriate. With this respect, two models have been proposed: the mean-group estimator by Pesaran and Smith (1995) and the pooled mean-group estimator proposed by Pesaran et al. (1999, 2001). While the first essentially estimates N time-series regressions and averages the coefficients, the second relies on a combination of pooling and averaging of coefficients. It allows intercepts, short-run coefficients and co-integrating terms to differ across cross-sections, while imposing restrictions only in the long run. These techniques are appealing in that they do not need any pretesting for the order of integration and co-integration as long as there exists a long run relationship among the variables of interest and the dynamic specification is sufficiently augmented that the regressors are strictly exogenous and the residuals are serially uncorrelated (Pesaran et al., 2001). In our case, the Hausman test on the hypothesis of slope homogeneity suggests that the PMG estimator is to be preferred.[8]

[8] The tests are not reported but are available upon request.

The PMG is based on an autoregressive distributive lag model ARDL(*p*,*q*,*q*,…*q*) model, where p is the number of lags of the dependent variable and q is the number of lags of the explanatory variables, X_{it-j} is a k x 1 vector of explanatory variables, d_i is the group-specific effect and the number of groups $i = 1,\ldots,N$ and the number of periods $t = 1, \ldots, T.$:

$$y_{it} = \sum_{j=1}^{p} \alpha_{ij} y_{it-j} + \sum_{j=1}^{q} \delta_{ij}' X_{it-j} + d_i + \varepsilon_{it} \tag{3a}$$

To enucleate the long-run parameters, we express the ARDL model in an error-correction form as follows:

$$\Delta y_{it} = \phi_i (y_{it-1} - \theta_{ij}' X_{it}) + \sum_{j=1}^{p} \alpha_{ij}^{*} y_{it-j} + \sum_{j=1}^{q} \delta_{ij}^{*'} X_{it-j} + d_i + \varepsilon_{it} \tag{3b}$$

where y_{it} is the pooled series of dynamic conditional correlations, the parameter that defines the error-correcting speed of adjustment is $\phi_i = -\left(1 - \sum_{j=1}^{p} \alpha_{ij}\right)$, and the vector that contains the long run relationships between the variables is $\theta_i = \sum_{j=0}^{q} \delta_{ij} / \left(1 - \sum_k \alpha_{ik}\right)$. Finally, $\alpha_{ij}^{*} = -\sum_{m=j+1}^{p} \alpha_{im}$ with $j=1,\ldots,p-1$ and $\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im}$ with $j=1,\ldots,q-1$. The vector X_{it-j} includes the different set of of explanatory variables discussed above.[9]

We report the results on the whole set of dynamic conditional correlations, $DCC_{agri\_metal\_en}$, (panel A), and then we focus on two subsamples of correlations which are of particular interest: those between agriculture and energy, DCC_{agri_en}, (panel B) and those between metals and energy, DCC_{metal_en} (panel C).

5. Results and discussion

5.1 DCC-GARCH estimation and co-volatilities

[9] The series of the Working's T indexes are multiplied by a dummy variable equal to one for the corresponding cross section and zero otherwise, so that for each DCC we include among the explanatory variables only the two Working's T indexes for the markets of interest.

Table 1 show the results of the DCC-GARCH model. As preliminary tests detected the presence of serial correlation in the returns series of corn, rice, copper and natural gas, we include a first order autoregressive term, AR(1), in their GARCH estimation. The variance equation shows that the ARCH (α) estimates are generally small (between 0.037 for copper and 0.081 for rice) and the GARCH (β) coefficients are between 0.914 for rice and 0.950 and above for gold, silver and copper, suggesting that a shock in the volatility series impacts on futures volatility over a long period, especially in metals markets. The α and β parameters are non-negative and their sum is less than one, confirming consistency and asymptotic normality for all commodities. Additionally, λ_1 and λ_2 are non-negative and the sum is less than one, confirming the stationarity of the DCC model.

[TABLE 1 ABOUT HERE]

To discuss the evolution of correlations over time, we propose a smoothed representation in Figure 1, which reports the median spline of DCCs between commodities. The plot shows that conditional correlations are positive and definitely varying over time. While the correlations have been rather stable in the first half of the time span considered, they display a stunning increase around the beginning of 2008. In November 2008 the pooled correlations reached an average value of 0.411. Correlations then decreased in the subsequent months and years to revert to comparable levels at the end of our period of investigation.[10] We thus split the analysis before and after 2008, in order to analyse separately these two periods, which display different dynamics.

If we focus on the correlations between energy and other class of commodities we observe that they share a similar trend over time. However, the DCCs between metals and energy commodities are

[10] The average value for DCCs in 1998 is the same as the average for the period comprising 2013 and the first months of 2014 and amounts to 0.194.

generally higher than those between agricultural commodities and energy ones, with average values equal to 0.163 and 0.106 respectively over the whole time span considered. This first set of results is consistent with those reported by Ji and Fan (2012), Silvennoinen and Throp (2013) and Mensi et al. (2014).[11]

[FIGURE 1 ABOUT HERE]

5.2 Pooled mean group estimations

As the dependent variables are correlations, which are bounded between -1 and +1, we apply the Fisher transformation to unrestrict them. According to the unit root tests previously discussed (see Tables A.3 and A.4) in the Appendix, we need to account for this mixture of stationarity orders. We estimate an ARDL model, and following the Hausman test, our choice falls on the PMG estimator proposed by Pesaran et al. (1999, 2001). Tables 2a-2c report the results for the long-run effects and Tables 3a-3c the results for the error correction component, presenting the short-run effects, the annual dummy variables and the error correction term. The lag length for dependent and explanatory variables in the ARDL model is one.[12] We now discuss the results for the different sets of explanatory variables considered.

[TABLES 2a-2c ABOUT HERE]

a) Macroeconomic fundamentals

The negative coefficient attached to the ADS variable in Table 2a suggests that dynamic conditional correlations in the full sample of commodities are larger in periods of worst economic conditions,

[11] The descriptive statistics reported in Table A.5 confirm that mean and standard deviations increased after 2008 for the whole set of DCCs as well as for the two subgroups of interest.
[12] The descriptive statistics for the explanatory variables in the PMG estimates are reported in Table A.6 in the online appendix.

which is consistent with the findings by Chow et al. (1999), Ji and Fan (2012) and Alquist and Coibion (2013). This seems to provide evidence in favour of a strengthening of linkages between different commodity markets during periods of economic slowdown, which could be induced by a generalized shift of investors towards those markets. Moreover, we find that the effect of business cycles becomes stronger after the 2008 crisis, as evident from the comparison between the pre and post 2008 estimates, reported in the second and the third column in Table 2a. If we specifically look at correlations between energy and agricultural commodities (Table 2b) and energy and metals (Table 2c), we find that this increase in correlations under weaker economic conditions only applies to the correlations between metals and energy. This seems to suggest that the effect of the 2008 crisis and the ensuing economic slowdown has indeed corresponded to a generalized shift of investors towards commodities markets, and metals and energy ones in particular. As for the correlations between agriculture and energy commodities, they do not appear to be significantly related to the ADS. The variable is not significant over the whole period nor in more recent times, while it has a positive coefficient in the 1998-2007 estimate.

Expected inflation displays a positive and significant coefficient, and this is confirmed across all time periods and subgroups of commodities: a higher inflation expectation leads investors to choose commodities as a safer heaven. This provides support for the intuition that commodities may provide an hedge against inflation. Interestingly, this result is robust for the different subgroups of DCCs considered and is not affected by the macroeconomic scenario ensuing the financial crisis.

b) Financial markets

Moving to the financial factors, we observe that the T-Bill return has a negative and significant coefficient. This suggests that lower interest rates are associated with a shift of investors towards other forms of investment, such as commodity futures and this is reflected in higher DCCs. This result is found on the whole set of correlations, as reported in Table 2a and is robust across different periods.

If we look at the subgroup of energy-agriculture DCCs, we get the same result, while the evidence for the metals-energy link is weaker as the estimated coefficient is not significant.

The positive coefficient for the Yield spread observed in the first column of Table 2a suggests that in periods of higher premium for corporate bonds the correlations between commodities are larger. As the yield spread is known to be countercyclical (Hong and Yogo, 2012) this positive coefficient is conveying a message coherent with that implied by the negative coefficient attached to the ADS variable. This effect is confirmed for the whole set of correlations, and is statistically significant mostly after the crisis. Again, this does not seem to have a role in explaining the metals-energy correlations.

VIX is consistently positive and significant when considering correlations between the whole set of commodities as well as between agriculture and energy ones, while the estimated coefficient is not significant when looking at energy-metals correlations only. As higher VIX means an expectation of higher instability in the stock market, the positive coefficient found supports the view that higher stock market uncertainty pushes investors to alternative assets (Andersson et al., 2008; Connolly et al., 2005). The negative coefficient in the metals-energy correlations after the 2008 crisis suggests that volatilities in these markets are less correlated in recent times as instability in the stock market increased. Again, the metal-energy DCCs display a different behavior from the agriculture-energy ones.

The exchange rate appears to be not significant when looking at correlations between all commodities. However, if we take a closer look we find a negative and significant coefficient in the panel of correlations between agriculture and energy markets (Table 2b) and in panel of correlations between metals and energy (Table 2c). Given the definition of the trade weighted U.S. dollar index provided by the Federal Reserve Bank of St. Louis, a strengthening of the dollar corresponds to an increase of the index. Thus, a stronger dollar is associated with lower correlations between energy and other commodities.

Overall, tendencies in financial factors appear to be relevant in understanding the dynamic conditional correlations between commodities returns. However, while they are helpful to investigate the agriculture-energy relationship, the energy-metals DCCs seem to be poorly influenced by the financial markets conditions.

c) Speculative activity

As for the measures of excess speculative activity in the different commodities markets, they appear to be generally not significant and mostly display a negative coefficient in the full sample (Table 2a). This suggests that a higher speculative activity in a specific commodity market corresponds to lower correlations with other markets. Two exceptions are rice and natural gas, in whose markets speculative activity seems to push towards higher correlations with other commodities. To draw some general conclusions from these variables, we test the joint significance of the Working's T indexes belonging to each of the three groups of commodities and we check whether the coefficients are statistically equal. The Wald tests for the joint significance of the Working's T indexes reveal that in the full sample the speculative activity in agricultural commodity markets and energy markets is statistically significant, while Working's T values in metals markets do not seem to significantly influence the correlations. The test for the equality of coefficients assumes as null hypothesis that the coefficients are statistically equal. This hypothesis is rejected in the case of agricultural and energy markets, which is not surprising given that in these two subgroups we find both positive and negative statistically significant coefficients, i.e. there is not an uniform role of speculative activity. Overall, the tests suggest that excess speculation, as measured by the Working's T index, might influence the correlations between commodities. Interestingly, higher levels of speculative activity in agricultural markets do not lead to higher correlations with other commodities, but rather correspond to lower levels of DCCs. Vice versa, in energy markets, and more precisely in the natural gas one, a higher level of excess speculation corresponds to stronger linkages with other commodities.

To understand better the impact of excessive speculative activity on the correlations between energy and other commodities we focus on the two subgroups of interest. Table 2b shows that speculative activity in agricultural markets does not significantly affect the correlations with energy markets, at least before the crisis, while again the Working’s T index for natural gas displays a positive and significant coefficient. Dynamic conditional correlations with agricultural commodities are larger as excess speculation in energy (notably natural gas) markets increases.

Moving to the correlations between metals and energy commodities (Table 2c) we find that the excess speculation measures are not significant. The Wald tests for the joint significance suggest that the Working's T indexes for metals and energy futures markets are jointly not significant. The DCCs between energy and metals appear thus to be poorly explained by speculative activity in those markets.

To sum up, when we look at specific sets of DCCs of particular interest, such as energy and agricultural markets in Table 2b, we find evidence that higher values of Working’s T index correspond to higher correlations between commodities, supporting the view that a larger speculative activity is reflected in an increased activity in different commodity markets, and higher correlations between them. Nonetheless, when we look at the correlations between metals and energy commodities the results are weaker. Overall, this latter set of DCCs seems to be poorly related to financial or speculative factors.

d) Time effects

Moving to the error correction terms and short run dynamics, reported in Tables 3a-3c, the error correction terms are negative and significant for all panels and time spans.

The annual dummy variables (Tables 3a-3c) show that correlations have been rising over time, displaying positive and significant coefficients for the years immediately before and after the crisis, and have recently decreased, as reported in the first column of Table 3a. Notice that in the third column we get negative coefficients as the reference year is 2008, a period which displays the highest correlations in the sample (see Figure 1). This behavior over time is confirmed also on the narrowers samples of agriculture-energy correlations (Table 3b) and metals-energy correlations (Table 3c).

[TABLES 3a-3c ABOUT HERE]

6. Conclusions and policy implications

In the second half of 2000s international commodity markets recorded an increase in commodity prices, followed by a sharp decline. These large fluctuations have increased the interest in the dynamic relationships between commodity prices and their volatilities. A better understanding of time-varying correlations between volatilities across commodity futures markets is essential to both international investors and policy makers. If volatilities spillover from one market to another, then portfolio managers and policymakers have to adjust their decisions to prevented the risk of contagion in the advent of a market crash.

In this study, we present a two step analysis. First, we estimate a DCC-GARCH model, to produce a set of dynamic conditional correlations between real daily futures returns for 10 commodities in the agricultural, energy and metals markets from January 1998 to May 2014. The estimated DCCs are derived from an unique GARCH model, which allows us to discuss and compare the correlations between energy and agricultural commodities and the one between energy and metals on a common ground.

We observe that the DCCs have increased in the months preceding the burst of the financial crisis and have fallen in the subsequent years. Overall, the DCCs between energy and metals are larger than the DCCs between energy and agricultural commodities. This suggests a stronger link between these two classes of commodities. This first set of results is relevant as it shows that dynamic conditional correlations increased sizably in a period of economic and financial turmoil.

Nonetheless, this descriptive evidence does not allow to understand the circumstances which might have influenced such behaviour. To this aim, we compute the weekly averages of the DCCs and regress them on a set of macroeconomic, financial and speculative factors, mostly available at weekly frequency.

As macroeconomic factors we consider the real business cycle, proxied by the ADS index, and the expected inflation. As for the financial variables we include the three months T-Bill rate, the yield spread, the VIX as a measure of uncertainty in stock market and the U.S. dollar trade-weighted exchange rate. We also include the Working's T index to proxy speculative activity in each commodity market and a set of yearly and monthly dummies.

The PMG analysis reveals a number of interesting results. First, macroeconomic variables are significantly related with commodities dynamic conditional correlations. This is confirmed when looking at specific subgroups of correlations of interest, such as the agriculture-energy DCCs and the metals-energy DCCs. Second, financial factors are relevant to understand agricultural-energy correlations but not metal-energy ones. Third, the financialization of commodity markets is significant when looking at the whole set of correlations, but is generally poorly significant when looking at metals-energy correlations. Finally, correlations between commodities started increasing in the years preceding the 2008 crisis, displayed a peak during that year and subsequently decreased. There is no evidence of the 2001 U.S. recession affecting commodity markets correlations, while the financial crisis and the ensuing global recession had a sizeable impact on them.

Overall, we find that the dynamic conditional correlations between commodities are influenced by the macroeconomic fundamentals. Investors tend to prefer commodities futures markets under weaker economic conditions and as a hedge against high inflation. Larger correlations, however, imply a stronger connection between markets, and relatedly a higher risk of contagion in case of a shock affecting one of these markets. Thus, according to the present evidence, financial markets regulators and investors shall be warned that, in the face of an economic slowdown or higher inflation, the likelihood of a contagion between these markets is larger.

We find that the dynamic conditional correlations between commodities, and those between energy and agriculture in particular, do respond to financial markets conditions. Notably, from a policy perspective, it is remarkable that higher volatility in markets (i.e. a larger VIX) is associated with larger DCCs, again signaling that the likelihood of a contagion increases under "shakier" markets.

Looking specifically at the speculative activity in future markets, we find that excess speculation in energy markets is associated with higher DCCs with agricultural commodities, while the excess speculation in agricultural markets does not seem to influence such DCCs. This suggests that any strengthened bond between these futures markets seems to be driven, if any, by speculators in energy markets. Thus, careful attention should be put on the activity of investors in these markets, as it corresponds to a stronger linkage with agricultural markets. Such result is not confirmed when considering the energy-metals DCCs.

The latter finding poses the question of the different behavior of the correlations between energy and agriculture and the DCCs between energy and metals. While the first respond to macroeconomic, financial and speculative factors, the latter seem to react only to macroeconomic conditions. Previous research generally focused on the energy-agriculture or the energy-metals link, thus preventing a direct comparison of the factors influencing the correlations. In our contribution we analyze these DCCs over the same period of analysis, starting from a common specification, and considering the same explanatory variables and observe this discrepancy. The metals-energy DCCs are on average higher that the DCCs between agriculture and energy, however their behaviour is more difficult to understand, as it does not seem to respond to financial contingencies, nor to speculative activity. This leaves room for further research on this relevant issue.

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Figure 1: Median spline of dynamic conditional correlations

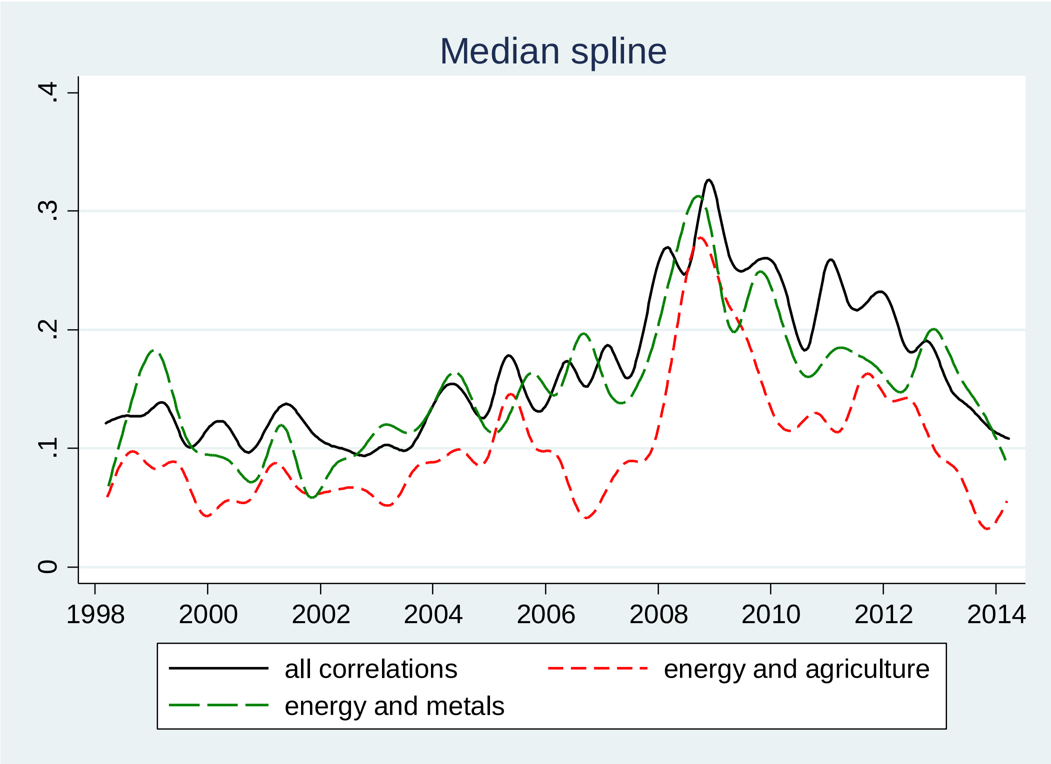

Table 1. Dynamic Conditional Correlation-GARCH estimation

		Corn	Soybeans	Wheat	Oats	Rice	Gold	Silver	Copper	WTI	NG
Mean equation											
c		0.0001	-0.00001	-0.0001	-0.0002	0.00004	-0.0002*	-0.0004**	-0.0001	0.0002	0.0003
		(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
AR(1)		0.051***			0.079***	0.079***			-0.061***		-0.026**
		(0.009)			(0.011)	(0.013)			(0.012)		(0.013)
Variance equation											
c		0.000004***	0.000002***	0.00001***	0.00001***	0.000004***	0.0000005***	0.000002***	0.000002***	0.000005***	0.00002***
		(0.0000005)	(0.0000003)	(0.000001)	(0.000001)	(0.0000007)	(0.00000008)	(0.0000004)	(0.0000003)	(0.000001)	(0.000003)
α		0.075***	0.059***	0.039***	0.059***	0.081***	0.044***	0.044***	0.037***	0.068***	0.069***
		(0.005)	(0.004)	(0.004)	(0.005)	(0.007)	(0.003)	(0.004)	(0.003)	(0.006)	(0.005)
β		0.918***	0.933***	0.947***	0.926***	0.914***	0.954***	0.950***	0.956***	0.924***	0.921***
		(0.005)	(0.004)	(0.005)	(0.007)	(0.008)	(0.003)	(0.004)	(0.004)	(0.007)	(0.005)
α+ β		0.993	0.992	0.986	0.985	0.995	0.998	0.994	0.993	0.992	0.990
DCC											
λ1	0.008										
λ2	0.984										
λ1+λ2	0.992										

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively; the values in parentheses are standard errors.

Table 2a. The long run dynamics from the PMG estimator for the full sample (panel A)

$DCC_{agri\_met\_en}$	1998-2014		1998-2007		2008-2014	
ADS	-0.009***	(0.002)	0.006	(0.004)	-0.019***	(0.003)
INF	0.013***	(0.003)	0.013***	(0.004)	0.015***	(0.004)
Tbill	-0.025***	(0.008)	-0.190***	(0.057)	-0.016**	(0.007)
Yield	0.048***	(0.015)	-0.001	(0.015)	0.294***	(0.051)
EX	0.180	(0.214)	-0.325	(0.305)	0.377	(0.262)
VIX	0.001***	(0.000)	0.002***	(0.000)	0.001***	(0.000)
Working's T_{copper}	-0.065	(0.044)	-0.062	(0.043)	-0.132	(0.102)
Working's T_{gold}	-0.041	(0.071)	-0.032	(0.078)	-0.067	(0.121)
Working's T_{silver}	-0.042	(0.038)	-0.065*	(0.037)	0.044	(0.094)
Working's T_{corn}	-0.291***	(0.066)	-0.208**	(0.090)	-0.338***	(0.078)
Working's T_{oats}	-0.044	(0.050)	-0.118*	(0.061)	0.183**	(0.073)
Working's T_{rice}	0.050*	(0.028)	0.092***	(0.030)	0.029	(0.053)
Working's $T_{soybeans}$	-0.118*	(0.066)	-0.126	(0.087)	-0.087	(0.086)
Working's T_{wheat}	-0.037	(0.062)	-0.209***	(0.060)	-0.068	(0.145)
Working's T_{wti}	0.153	(0.144)	0.268	(0.181)	-0.251	(0.198)
Working's T_{ng}	0.250***	(0.070)	0.109	(0.184)	0.170***	(0.061)
Joint significance test for Working's T						
Metals	3.77		5.30		2.19	
Agriculture	27.22***		32.17***		26.73***	
Energy	13.95***		2.27		9.30***	
Equality coefficient test for Working's T						
Metals	0.17		0.14		1.62	
Agriculture	25.83***		31.67***		26.00***	
Energy	0.37		0.38		4.11**	

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively; the values in parentheses are standard errors; the joint significance test and the equality test are asymptotically distributed as a Chi2.

Table 2b. The long run dynamics from the PMG estimator for agriculture and energy commodities (panel B)

DCC_{agri_en}	1998-2014		1998-2007		2008-2014	
ADS	-0.0008	(0.004)	0.031***	(0.008)	-0.006	(0.004)
INF	0.019***	(0.005)	0.017***	(0.007)	0.022***	(0.007)
Tbill	-0.051***	(0.014)	-0.199*	(0.103)	-0.031***	(0.011)
Yield	0.047*	(0.026)	-0.012	(0.028)	0.361***	(0.081)
EX	-0.968***	(0.374)	-1.966***	(0.553)	-0.336	(0.401)
VIX	0.003***	(0.000)	0.002***	(0.001)	0.003***	(0.000)
Working’s T_{corn}	-0.045	(0.117)	0.160	(0.149)	-0.307***	(0.110)
Working’s T_{oats}	0.045	(0.089)	-0.093	(0.124)	0.159	(0.116)
Working’s T_{rice}	0.087*	(0.045)	0.128**	(0.056)	-0.017	(0.085)
Working’s $T_{soybeans}$	0.144	(0.118)	0.057	(0.154)	0.087	(0.123)
Working’s T_{wheat}	0.102	(0.109)	-0.082	(0.102)	-0.014	(0.216)
Working’s T_{wti}	0.219	(0.161)	0.501**	(0.205)	-0.19	(0.218)
Working’s T_{ng}	0.364***	(0.093)	-0.027	(0.218)	0.374***	(0.079)
Joint significance test for Working's T						
Agriculture	6.53		7.80		10.33*	
Energy	16.99***		5.96**		23.08***	
Equality coefficient test for Working's T						
Agriculture	1.64		5.43		10.07**	
Energy	0.61		3.12*		6.01**	

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively; the values in parentheses are standard errors; the joint significance test and the equality test are asymptotically distributed as a Chi2.

Table 2c. The long run dynamics from the PMG estimator for metal and energy commodities (panel C)

DCC_{met_en}	1998-2014		1998-2007		2008-2014	
ADS	-0.016**	(0.007)	-0.036***	(0.012)	-0.030***	(0.008)
INF	0.037***	(0.008)	0.021**	(0.010)	0.033**	(0.014)
Tbill	-0.029	(0.022)	0.134	(0.161)	-0.026	(0.020)
Yield	0.047	(0.042)	-0.009	(0.044)	0.090	(0.147)
EX	-1.257**	(0.612)	0.019	(0.861)	-2.133***	(0.794)
VIX	0.001	(0.001)	0.004***	(0.001)	-0.002**	(0.001)
Working's T_{copper}	0.154	(0.112)	0.184*	(0.107)	-0.240	(0.323)
Working's T_{gold}	-0.108	(0.122)	-0.222	(0.151)	0.130	(0.176)
Working's T_{silver}	0.112	(0.073)	0.036	(0.079)	0.309	(0.195)
Working's T_{wti}	-0.432	(0.394)	-0.541	(0.360)	-0.675	(0.701)
Working's T_{ng}	0.094	(0.120)	0.181	(0.318)	-0.165	(0.136)
Joint significance test for Working's T						
Metals	5.01		5.10		5.27	
Energy	1.85		2.63		3.30	
Equality coefficient test for Working's T						
Metals	2.99		4.63*		2.07	
Energy	1.64		2.32		0.51	

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively; the values in parentheses are standard errors; the joint significance test and the equality test are asymptotically distributed as a Chi2.

Table 3a. The error correction term and short run dynamics for the full sample (panel A)

$DCC_{agri\_met\_en}$ (-1)	1998-2014		1998-2007		2008-2014	
ECT	-0.097***	(0.004)	-0.103***	(0.004)	-0.114***	(0.006)
C	0.017***	(0.004)	0.020***	(0.005)	0.037***	(0.006)
ADS(-1)	0.004***	(0.001)	-0.001	(0.002)	0.009***	(0.001)
INF(-1)	0.002**	(0.001)	0.003*	(0.002)	-0.000	(0.004)
Tbill(-1)	0.003***	(0.000)	0.011***	(0.003)	0.002***	(0.000)
Yield(-1)	0.001	(0.001)	0.005***	(0.001)	0.034***	(0.003)
EX(-1)	-0.027***	(0.010)	0.010	(0.020)	-0.075***	(0.015)
VIX(-1)	0.000	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Working's T_{copper}	-0.011***	(0.004)	-0.009***	(0.003)	-0.016***	(0.006)
Working's T_{gold}	-0.001	(0.002)	-0.005	(0.002)	-0.005	(0.004)
Working's T_{silver}	0.004***	(0.002)	0.005***	(0.001)	-0.018	(0.005)
Working's T_{corn}	-0.007	(0.006)	-0.007	(0.006)	-0.004	(0.005)
Working's T_{oats}	0.004*	(0.002)	0.002	(0.002)	0.004	(0.004)
Working's T_{rice}	-0.001	(0.002)	0.008	(0.001)	0.013	(0.005)
Working's $T_{soybeans}$	-0.003	(0.003)	-0.006	(0.004)	0.005	(0.006)
Working's T_{wheat}	-0.007**	(0.003)	-0.005*	(0.003)	-0.000	(0.006)
Working's T_{wti}	0.009	(0.007)	0.013*	(0.008)	0.007	(0.008)
Working's T_{ng}	-0.004*	(0.002)	-0.002**	(0.005)	-0.005	(0.002)
Annual dummies						
1999	-0.001**	(0.001)	-0.001	(0.001)		
2000	0.003**	(0.001)	-0.002**	(0.001)		
2001	0.003***	(0.001)	-0.001	(0.001)		
2002	-0.005***	(0.001)	-0.005***	(0.001)		
2003	-0.003***	(0.001)	-0.003***	(0.001)		
2004	-0.001	(0.001)	0.000	(0.001)		
2005	0.001	(0.001)	0.001	(0.001)		
2006	0.003***	(0.001)	0.004***	(0.001)		
2007	0.003***	(0.001)	0.005***	(0.001)		
2008	0.008***	(0.001)				
2009	0.006***	(0.001)			-0.002**	(0.001)
2010	0.006***	(0.001)			-0.002	(0.001)
2011	0.007***	(0.001)			-0.001	(0.001)
2012	0.002*	(0.001)			-0.006***	(0.001)
2013	-0.001	(0.001)			-0.011***	(0.002)
2014	-0.006***	(0.001)			-0.016***	(0.002)

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively; the values in parentheses are standard errors; monthly dummies are not reported.

Table 3b. The error correction term and short run dynamics for agriculture and energy commodities (panel B)

DCC_{agri_en} (-1)	1998-2014		1998-2007		2008-2014	
ECT	-0.116***	(0.008)	-0.118***	(0.007)	-0.154***	(0.011)
C	-0.050***	(0.006)	-0.037***	(0.014)	-0.027***	(0.023)
ADS(-1)	0.006***	(0.001)	-0.004	(0.003)	0.013***	(0.003)
INF(-1)	-0.004*	(0.002)	0.002	(0.003)	-0.020***	(0.004)
Tbill(-1)	0.003***	(0.001)	0.011**	(0.005)	0.002***	(0.001)
Yield(-1)	-0.006***	(0.001)	-0.001	(0.002)	-0.049***	(0.005)
EX(-1)	0.056***	(0.015)	0.151***	(0.040)	-0.009	(0.027)
VIX(-1)	0.000***	(0.000)	0.000**	(0.000)	0.000	(0.000)
Working's T_{corn}	-0.015	(0.013)	-0.019	(0.013)	-0.004	(0.019)
Working's T_{oats}	0.002	(0.005)	0.002	(0.004)	0.001	(0.008)
Working's T_{rice}	0.000	(0.001)	0.003	(0.004)	-0.013	(0.011)
Working's $T_{soybeans}$	0.001	(0.002)	-0.003	(0.005)	0.017	(0.016)
Working's T_{wheat}	-0.007	(0.005)	-0.007	(0.005)	0.016	(0.011)
Working's T_{wti}	-0.012	(0.014)	-0.009	(0.013)	-0.022	(0.026)
Working's T_{ng}	-0.004	(0.006)	0.020	(0.015)	-0.016**	(0.007)
Annual dummies						
1999	-0.001	(0.001)	0.000	(0.001)		
2000	-0.003	(0.002)	-0.002	(0.002)		
2001	-0.001	(0.003)	0.003*	(0.002)		
2002	-0.003**	(0.001)	-0.001	(0.001)		
2003	-0.001	(0.002)	0.000	(0.002)		
2004	0.000	(0.002)	0.001	(0.002)		
2005	0.003	(0.003)	0.004	(0.003)		
2006	0.000	(0.002)	0.001	(0.002)		
2007	0.002	(0.003)	0.004	(0.003)		
2008	0.012***	(0.003)				
2009	0.007**	(0.003)			-0.001	(0.002)
2010	0.004	(0.003)			-0.005***	(0.002)
2011	0.003	(0.003)			-0.009***	(0.002)
2012	-0.001	(0.003)			-0.011***	(0.002)
2013	-0.007***	(0.002)			-0.020***	(0.003)
2014	-0.009**	(0.004)			-0.024***	(0.003)

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively; the values in parentheses are standard errors; monthly dummies are not reported.

Table 3c. The error correction term and short run dynamics for metal and energy commodities (panel C)

DCC_{met_en} (-1)	1998-2014		1998-2007		2008-2014	
ECT	-0.093***	(0.010)	-0.102***	(0.006)	-0.102***	(0.019)
C	0.010	(0.015)	0.020	(0.024)	0.050***	(0.014)
ADS(-1)	0.011***	(0.001)	0.011***	(0.003)	0.017***	(0.002)
INF(-1)	0.005	(0.004)	0.017***	(0.002)	-0.020***	(0.007)
Tbill(-1)	0.004***	(0.001)	-0.006	(0.011)	0.003***	(0.001)
Yield(-1)	0.002	(0.001)	0.004**	(0.002)	-0.011*	(0.007)
EX(-1)	0.019**	(0.010)	-0.014	(0.025)	0.025***	(0.011)
VIX(-1)	0.000	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Working's T_{copper}	-0.007	(0.006)	-0.007	(0.006)	-0.002***	(0.002)
Working's T_{gold}	0.006	(0.008)	0.012	(0.009)	-0.012**	(0.013)
Working's T_{silver}	0.003	(0.003)	0.008	(0.006)	-0.051	(0.036)
Working's T_{wti}	0.095**	(0.044)	0.107**	(0.049)	0.114***	(0.056)
Working's T_{ng}	-0.033**	(0.015)	-0.029	(0.018)	-0.028**	(0.013)
Annual dummies						
1999	-0.006***	(0.001)	-0.005***	(0.001)		
2000	-0.007***	(0.002)	-0.007***	(0.002)		
2001	-0.007***	(0.002)	-0.009***	(0.002)		
2002	-0.006***	(0.003)	-0.007**	(0.003)		
2003	-0.001	(0.002)	-0.001	(0.002)		
2004	0.000	(0.001)	0.004***	(0.001)		
2005	-0.001	(0.002)	0.003**	(0.002)		
2006	0.004	(0.003)	0.011***	(0.004)		
2007	-0.001	(0.003)	0.004***	(0.003)		
2008	0.007***	(0.003)				
2009	0.002	(0.005)			-0.006**	(0.003)
2010	0.005	(0.004)			-0.003	(0.002)
2011	0.002	(0.004)			-0.005***	(0.001)
2012	-0.002	(0.006)			-0.010***	(0.004)
2013	-0.005	(0.003)			-0.014***	(0.002)
2014	-0.013	(0.003)			-0.020***	(0.005)

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively; the values in parentheses are standard errors; monthly dummies are not reported.