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Summary

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Keywords: Multivariate GARCH, Dynamic Conditional Correlations, Future Markets, Commodities

JEL Classification: Q42, Q11, C32

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Understanding dynamic conditional correlations between commodities futures markets

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Abstract

We estimate dynamic conditional correlations between 10 commodities futures returns in energy, metals and agriculture markets over the period 1998-2014 with a DCC-GARCH model. We look at the factors influencing those correlations, adopting a pooled mean group (PMG) estimator. Macroeconomic variables are significantly correlated with agriculture-energy and metals-energy dynamic conditional correlations; while financial variables are relevant in the agriculture-energy correlations and poorly significant in the metals-energy ones. Speculative activity is generally not statistically significant. Correlations started increasing in the years before the financial crisis and decreased at the end of our period of analysis.

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1. Introduction

The last decades faced a rising liberalization in financial markets, which manifested itself in higher volatilities in asset markets. As a reaction, investors shifted progressively towards alternative investment instruments, such as commodity futures, to hedge against the risk in the stock markets. Indeed, commodity markets have been traditionally considered a desirable asset class eligible for portfolio diversification, as the 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, these correlations have increased, limiting the scope of 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 futures correlated? If so, to what extent are they a good instrument for hedging against risk? Are these correlations affected by external factors? As the interest in investing in commodities increased, understanding time-varying volatilities 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 market crash. The relevance of this topic has expanded in recent times, as the second half of the 2000s saw a generalized rise in commodity prices, both energy and non-energy, followed by a sharp decline. These large fluctuations in commodity prices have renewed interest in the dynamic relationship between them.

Many studies have investigated the correlations between the 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). Their results mostly confirm the existence of correlations among commodity prices.

Some authors examine the factors behind time varying volatilities in commodity markets, focusing on the correlations between commodities and stocks markets (Büyükşahin and Robe, 2014) or within 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, metals and energy future markets. To the best of our knowledge, this is one of the first attempts to investigate these correlations within a unique framework, with a common methodology, same period of analysis and common explanatory variables, thus allowing a direct comparison of the results found across different markets.

First, we obtain the dynamic conditional correlations for the period spanning from January 1998 to May 2014, by means of the multivariate GARCH methodology by Engle (2002). Then, we investigate how macroeconomic and financial variables, as well as speculative activity might affect those correlations. For this purpose, we adopt a pooled mean group estimator (PMG) by Pesaran et al. (1999). Our analysis suggests that macroeconomic factors influence the agriculture-energy and metals-energy correlations, while financial ones are significant in explaining the agriculture-energy correlations but not those between metals and energy commodities. Speculative activity is generally poorly significant. Additionally, we observe that correlations started increasing in the years before the financial crisis and decreased in recent times.

The paper is structured as follows: Section 2 provides a review of the literature, Section 3 describes the data and presents the methodology. Section 4 reports the empirical results and discussion. The conclusion is provided in Section 5.

2. Review of literature

2.1. Linkages among commodity markets

It is generally acknowledged that an increase in the oil price affects commodity prices (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 (e.g. processing and transportation) (Hammoudeh and Yuan, 2008; Tyner, 2010; Barrera et al., 2011). Second, some crops are raised to produce biofuels, whose prices are related to those of fossil fuels (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 increase in the rate of industrial production leads to a raise in demands for industrial commodities such as copper, lumber or crude oil, since these commodities are used as inputs of 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 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 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 dynamic correlations 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 co-volatilities

Scholars investigated the link between the volatilities of stock and commodity markets. Silvennoinen and Thorp (2013) find that the correlations between stock and commodity markets 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 based on 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 in commodity futures markets (Batten et al., 2010; Sanders and Irwin, 2011; Irwin and Sanders, 2012; Hayo et al., 2012; Aulerich et al., 2013; Manera et al., 2014), 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 and methodology

3.1. Commodity markets 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.

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

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 $R_t = \log\left(\frac{P_t}{P_{t-1}}\right)$, where R_t is the corresponding return and P_t is the corresponding real price.[2]

3.2. Explanatory variables

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

a) Macroeconomic variables

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

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

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

[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.

expected inflation in 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 variables

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

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 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 price (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) Speculation variables

The role of speculative activity on the volatility of futures prices has attracted much attention recently. 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., 2014), 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. (2014) 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:

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

where SS is speculation short, SL is speculation long, HS is hedging short and HL is hedging long. Therefore, this index is the ratio of speculative positions to total hedger's positions. Data for "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 dummies

We enrich the model including a set of annual dummies to enable us discussing the effect of the 2001 and the 2008 financial crises, as well as to broadly account for business cycle dynamics. We include a set of monthly dummies also to control for the presence of seasonality, which could be an issue mostly in energy and agricultural commodities.

3.3. Econometric modelling

We first test the stationary properties of returns: the augmented Dickey Fuller (1979) unit root test, confirms the stationarity of all returns at the 1% significance level. We model them by OLS and inspect the residuals: 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 tests suggest to jointly model the volatilities of the ten commodities considered 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

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

volatility spillovers from other futures markets. Thus, it allows us to investigate volatility in interconnected markets. The general multivariate GARCH model is defined as:

$$r_t = Cx_t + \varepsilon_t \tag{2.a}$$

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

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

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 matrix is a weighted average of the unconditional covariance matrix of the standardized residuals $\tilde{\varepsilon}_t$ and the unconditional mean of Q_t. As the two matrices are different, the R matrix is neither the unconditional correlation matrix, nor the unconditional mean of Q_t. As a consequence, the parameters in R are known as quasi correlations (Engle, 2009).

The first step of the analysis yields a panel of 45 dynamic conditional correlations over the period 1998-2014. With such time span, non-stationarity is a concern. Thus, we test the order of integration of the variables by means of the Im et al. (2003) panel unit root test for the panel of dynamic conditional correlations and the ADF unit root test for the explanatory variables.[5]

In order to estimate how macroeconomic and financial variables influence the DCCs, 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 (MG) estimator by Pesaran and Smith (1995) and the pooled mean-group (PMG) 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. What is appealing in these techniques is 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). The Hausman test on the hypothesis of slope homogeneity suggests that in our study the PMG estimator is to be preferred.[6]

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 $i = 1,\dots,N$ and the number of periods $t = 1, \dots, T$. :

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

We express it in an error-correction form as follows:

[5] The unit root test results are presented in Tables A.3 and A.4, respectively, in the online appendix.
[6] The tests are not reported but are available upon request.

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

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 $j=1,...,p-1$ and $\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im}$ with $j=1,...,q-1$. The vector X_{it-j} includes the different set of of explanatory variables discussed above.[7]

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 fossil fuels, DCC_{agri_en}, (panel B) and those between metals and fossil fuels, DCC_{metal_en} (panel C).

4. Results and Discussion

4.1. DCC-GARCH estimations and co-volatilities

Table 1 presents the results of the DCC-GARCH model. As we detect 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 0.00 for soybeans and 0.08 for rice) and the GARCH (β) coefficients are between 0.91 for corn and 0.95 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.

[7] The series of the Working's T indexes are multiplied by a dummy variable which takes the value of one for the corresponding cross section and zero otherwise.

[TABLE 1 ABOUT HERE]

Figure 1 reports the median spline of DCCs between commodities. The plot shows that conditional correlations are positive and definitely varying over time: we observe a peak in volatility interdependences around the beginning of 2008, which faded out in more recent years. Correlations between metals and fossil fuels are higher than those between agricultural commodities fossil fuels. These findings are consistent with Ji and Fan (2012), Silvennoinen and Throp (2013) and Mensi et al. (2014). Splitting the analysis before and after this year allows to better inspect the behavior of these correlations.[8]

[FIGURE 1 ABOUT HERE]

4.2. Pooled Mean Group estimations

As the dependent variables are correlations, which are bounded between -1 and +1, we apply the Fisher transformation to make them unrestricted. According to the unit root tests,[9] we need a model that allows for mixture of stationarity orders. Following the Hausman test, we opt for the pooled mean-group (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 model, 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.[10]

[TABLES 2a-2c ABOUT HERE]

[8] The descriptive statistics reported in Table A.5 confirm that mean and standard deviations increased after 2008 for the three series of DCCs.

[9] These are reported in reported in Table A.4 in the online appendix.

[10] The descriptive statistics for the explanatory variables in the PMG estimates are reported in Table A.6 in the online appendix.

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, 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 generalized shift of investors towards commodities markets during periods of economic slowdown. Moreover, we find that the effect of business cycles becomes stronger after the 2008 crisis, as evident from the comparison between 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 lower economic conditions only applies to the correlations between metals and energy. Vice versa, before the crisis agriculture and energy commodities displayed increasing correlations with larger ADS values.

Expected inflation displays a positive and significant coefficient across all time periods and subgroups of commodities. As commodities may provide a better hedge against inflation, a higher inflation expectation leads investors to choose commodities as a safer heaven.

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. This result is found in the whole set of correlations and when considering the correlations between energy and agricultural commodities. The evidence for the metals-energy link is weaker as the estimated coefficient is not significant.

The positive coefficient for the Yield spread might suggests that in periods of higher premium for corporate bonds correlations between commodities are larger. As the yield spread in known to be countercyclical (Hong and Yogo, 2012) the positive coefficient found is coherent with the negative one 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 and 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.

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 and to lower correlations between energy and other commodities.

As for the measures of excess speculative activity in the different commodities markets, in the full sample they appear to be generally not significant and mostly display a negative coefficient. 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.

If we focus on the two subgroups of interest, we find that speculative activity in agricultural markets does not significantly affect the correlations with energy markets, at least before the crisis (see Table 2b). Vice versa, excess speculation in energy markets always has a significant impact on the correlations, although the role of speculation in the two energy markets considered is different, as confirmed by the equality of coefficients test.

Moving to the correlations between metals and energy commodities (Table 2c) we find again poor results: the Wald tests for the joint significance suggest that the Working's T indexes of metals and energy are jointly not significant. The measures are generally not significant, and the equality test does not reject the null hypothesis that they are equal.

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 macroeconomic, financial or speculative factors.

Moving to the error correction terms and short run dynamics, reported in Tables 3a-3c, it is worth mentioning that 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]

5. Conclusion

In the second half of 2000s markets saw an increase in commodity prices, followed by a sharp decline. These large fluctuations in prices have increased the interest in the dynamic relationships between them. A better understanding of time-varying correlations between volatilities across commodity markets is essential to both international investors and policy makers. If volatilities spillover from one market to another, the 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 consider dynamic conditional correlations between real daily futures returns for 10 commodities in the agricultural, energy and metals markets from January 1998 to May 2014. These were obtained from the estimation of a DCC-GARCH model. We then investigate how macroeconomic, financial, speculation and time factors relate to these correlations. We consider the real business cycle proxied by the ADS index and the expected inflation as macroeconomic factors. 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 pooled mean group (PMG) analysis reveals a number of interesting results. First, macroeconomic variables are significantly related with commodities correlations. This is confirmed when looking at specific subgroups of correlations of interest, such as the agriculture-energy and metals-energy ones. 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, display 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.

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Figures and Tables

Figure 1: Median spline of dynamic conditional correlations

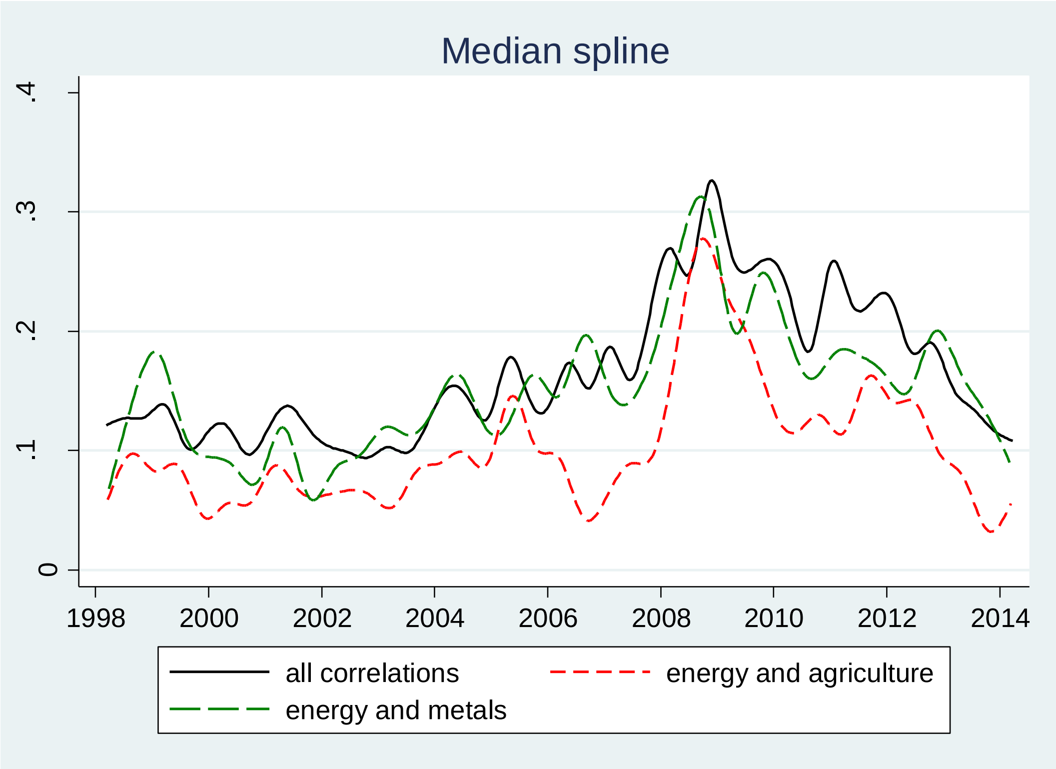

Table 1 Dynamic Conditional Correlation-GARCH estimation

GARCH(1,1)										
	Corn	Soybeans	wheat	Oats	Rice	Gold	Silver	Copper	WTI	NG
Mean equation										
c	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(0.69)	(-0.10)	(-0.35)	(-0.97)	-0.27	(-1.94)*	(-2.32)**	(-0.40)	(0.78)	(0.92)
AR(1)	0.051			0.079	0.079			-0.061		-0.026
	(5.40)***			(6.97)***	(5.90)***			(5.02)***		(-1.96)**
Variance equation										
c	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(7.80)***	(6.20)***	(6.41)***	(6.77) ***	(5.01)***	(5.78)***	(6.00)***	(5.05)***	(4.74)***	(6.26)***
α	0.07	0.00	0.03	0.05	0.08	0.04	0.04	0.03	0.06	0.06***
	(15.10)***	(14.71)***	(10.19)***	(10.78)***	(11.03)***	(14.50)***	(12.42)***	(11.01)***	(10.7)***	-14.73
β	0.91	0.93	0.94	0.92	0.91	0.95	0.95	0.95	0.92	0.92
	(184.11)***	(213.73)***	(187.28)***	(142.3)***	(115.6)***	(316.78)***	(233.19)***	(236.8)***	(130.89)***	(190.69)***
S-M	0.98	0.98	0.97	0.97	0.99	0.99	0.99	0.98	0.98	0.98

DCC	
λ1	0.008
λ2	0.984
λ1+λ2	0.992

Notes: *,**,*** indicate statistical significance at the 1%, 5% and 10% levels, respectively, S-M denotes the second moment condition, the values in parentheses are z-Statistics.

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)
Tbills	-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, joint significance test and equality test are 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)
Tbills	-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, joint significance test and equality test are 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)
Tbills	-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, joint significance test and equality test are 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)
Tbills(-1)	0.003***	(0.000)	0.011***	(0.003)	0.002***	(0.000)
Yeild(-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_{goldo}	-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)
Yeild(-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)
Yeild(-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.

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