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Co-Movement of Major Commodity Price Returns

A Time-Series Assessment

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ABSTRACT

This paper provides a comprehensive analysis of the degree of co-movement among the nominal price returns of 11 major energy, agricultural, and food commodities using monthly data between 1970 and 2013. The authors study the extent and the time evolution of unconditional and conditional correlations using a uniform-spacings testing approach, a multivariate dynamic conditional correlation model and a rolling regression procedure. The authors find that (1) the price returns of energy and agricultural commodities are highly correlated; (2) the overall level of co-movement among commodities increases in recent years, especially between energy and agricultural commodities and in particular in the cases of maize and soybean oil, which are important inputs in the production of biofuels and (3) stock market volatility is positively associated with the co-movement of price returns across markets, especially since 2007.

Keywords: commodity prices, co-movement, time-series models

JEL codes: Q02, E30, C32

1. INTRODUCTION

Commodity prices and their fluctuations have received substantial attention in the literature over the years.¹ A stylized fact of commodity prices that remains puzzling is their apparent co-movement.² In their seminal paper, Pindyck and Rotemberg (1990) showed that the prices of seven raw commodities move together even after controlling for macroeconomic and market conditions. They labeled this phenomenon as excess co-movement and attributed it to herd behavior in financial markets. Subsequent studies, however, have challenged the excess co-movement hypothesis. For example, Deb et al. (1996) argued that Pindyck and Rotemberg (1990) results were due to mis-specification in their modeling strategy, because they did not account for possible issues of heteroscedasticity or for the potential presence of structural breaks in the dynamics of commodity prices. Cashin et al. (1999) found strong evidence of price co-movement within agricultural and metal commodities, but not between them. Similarly, Ai et al. (2006) did not find excess co-movement in the price of agricultural commodities. From a more theoretical point of view Alquist and Olivier (2013) examined what drives the co-movement among commodity prices and built a model for thinking about the sources of commodity price co-movement and its implications in terms of macroeconomic dynamics. They suggested that commodity-related shocks have generally played a limited role in global business cycle fluctuations.

The general interest in the analysis of commodity prices is also motivated by the potentially large welfare implications of their properties. The presence of excess co-movement, for example, may cast doubts on the competitiveness and efficiency of commodity markets. Its existence might indicate that commodity traders react to herding behaviors instead of market fundamentals, missing arbitrage and hedging opportunities. Traders and exporting countries could also face substantial challenges in balancing their portfolios and could therefore be exposed to high income volatility. In the case of agricultural commodities, farmers growing multiple crops may experience strong income fluctuations due to synchronized changes in prices, with significant effects on food security. Furthermore, a simultaneous increase in several commodity prices may generate inflation pressures on highly dependent commodity-import countries.

The recent increases in both the level and volatility of commodity prices have reignited the interest of researchers and policymakers in the behavior of commodity prices and their co-movement. According to Ivanic et al. (2011), the upsurge in commodity prices of 2007/2008 and 2010/2011 had an overall negative effect on the population, especially among the poor, who spend a high fraction of their income on food consumption. Several studies have lately investigated the determinants of these price fluctuations. Frankel (2008) indicated that the real interest rate may be an important determinant of oil and other mineral and agricultural prices. Svensson (2008) underscored the importance of taking into account aggregate supply-and-demand shifts to explain commodity price dynamics. Gilbert (2010) asserted that the recent commonality of rises and falls in the price of energy, metals, and foods is unlikely to be coincidental and may be the result of a common set of macroeconomic and financial factors driving prices across a wide range of commodities. Byrne et al. (2013) documented a significant degree of price co-movement across 24 commodities and argued that such co-movement may be due to a common factor related to macroeconomic fundamentals, such as the real interest rate and stock market uncertainty.

This paper adopts a multivariate approach to comprehensively examine the degree of co-movement among major commodity markets. It first studies the extent of cross-section correlation and the time-varying pairwise unconditional and conditional correlations among 11 energy, agricultural, and food price returns using monthly data from January 1970 through May 2013. Specifically, the authors use the uniform-spacings method developed by Ng (2006) to test for the presence of and to evaluate the extent of unconditional co-movement in commodity price returns. The authors estimate a multivariate dynamic conditional correlation (DCC) model, based on Sheppard and Engle (2001) and Engle (2002), to analyze

¹ See, for example, Deaton (1999), Beck (2001), Cashin et al. (2002), Enders and Holt (2012) and Karali and J.Power (2013).

² Saadi (2011) provides a recent review of commodity price co-movement in international markets.

the time-varying conditional correlations between commodity price returns. Furthermore, they use a linear regression analysis to investigate whether bivariate rolling unconditional correlations between commodity price returns are statistically associated with specific macroeconomic and financial factors.

This paper contributes to the existing empirical literature on the topic along several dimensions. First, contrary to most previous studies, which mainly examined the co-movement of commodity price returns, this paper models the evolution of the interlinkages between markets by also allowing for time variation in price-specific conditional volatilities.³ Allowing for time variation in mixed and non-mixed conditional second moments permits a more accurate assessment of the dynamic relationships between markets (Gallagher and Twomey 1998). Second, this investigation is restricted to major energy, agricultural and food commodities with the goal of analyzing the extent of price correlations both within and across energy- and food-related markets. Agricultural commodities, for example, are expected to be correlated because they are generally close substitutes in demand, have similar input costs, and share common market information. Yet, growing financial market integration and the development of agricultural futures markets might have corroborated these interdependencies in recent years. Furthermore, the interlinkages between energy and agricultural markets, typically related through production and transportation costs, may have become stronger due to the recent development of the biofuel industry and the increasing demand for agricultural produce in the production of ethanol and biodiesel (Rajagopal and Silverman 2007). The period of analysis is sufficiently large to allow a characterization of the evolution of commodity prices in terms of trends and structural changes, which could be associated with particular events in the commodity markets (see Figure 1.1). The use of monthly data allows the authors to capture dynamics that would otherwise be hidden in lower-frequency data.⁴ Finally, motivated by the work of Frankel (2008), Gilbert (2010), Gruber and Vigfusson (2012) and Byrne et al. (2013) on the co-movement of commodity prices, the authors evaluate whether the correlations across markets are driven by real interest rates and by the volatility of stock market returns (a proxy for uncertainty in stock markets).

The empirical results that show that the price returns of related commodities are generally highly correlated. The uniform-spacings methodology indicates strong and positive correlations within cereal crops, between cereal crops and soybean oil (a reference agricultural commodity), and within energy commodities. The authors also find a recent increase in the degree of co-movement between energy and agricultural commodity price returns, particularly maize (another agricultural commodity used as a reference) and soybean oil, which are both important inputs in the production of biofuels. The evolution of the estimated dynamic conditional correlations confirms the presence of high levels of co-movement between the returns of energy commodities and maize and soybean oil in the past few years and a rising level of co-movement by the end of the sample. The results of this study provide evidence of the emergence of even stronger interlinkages between energy and agricultural markets in recent years, likely determined by the expansion of the biofuel industry. The concluding linear regression analysis suggests that several of the observed correlations within and across energy and agricultural markets are positively affected by the behavior of financial markets (measured by the volatility of stock market returns) particularly after 2007, but not by changes in macroeconomic conditions (measured by a real interest rate).

The remainder of the paper is organized as follows. Section 2 describes the data and the statistical properties of the price returns included in the analysis. It also presents the results of the breakpoint analysis for estimating breaks in the dynamics of nominal price returns. Section 3 discusses empirical results concerning the extent of cross-section correlation in the data, the dynamic conditional correlations of nominal price returns, and the statistical relevance of two potential driving factors (real interest rates and volatility of stock markets) of unconditional co-movement between commodity price returns. Section 4 concludes.

³Deb et al. (1996), Zhao and Goodwin (2011) and Gardebroek et al. (2013) are among the few studies that focus on market interactions in terms of conditional second moments. The authors of these studies estimate BEKK models following Engle and Kroner (1995). Deb et al. (1996) analyze excess co-movement across apparently unrelated commodities using a likelihood ratio test; the other two studies examine volatility spillovers between major agricultural commodities.

⁴At the same time, we avoid higher frequency data, which could instead be characterized by a high noise-to-signal ratio.

Figure 1.1 Timeline of major events in commodity markets

Source: Authors' calculations.

2. COMMODITY PRICES AND BREAKPOINTS IN PRICE RETURN DYNAMICS

Monthly prices of 11 commodities are the core of the dataset. This paper focuses on the main energy products (coal, crude oil, and natural gas), agricultural crops (barley, maize, rice, sorghum, soybean oil and wheat), and food products (coffee and sugar). Time series from January 1970 to May 2013 are obtained from the World Bank commodity price data.⁵

Figure 2.1 shows the evolution of nominal commodity price series over the period under investigation. Energy and agricultural prices, in particular (1) crude oil and coal, (2) soybean oil and rice, and (3) maize, wheat, barley, and sorghum follow similar patterns. Most of these prices reached peaks around the global food price crisis in 2007/2008 and, generally, in the last two years of the sample. Natural gas also showed a price spike in the early 2000s. The surge in soybean oil prices dates back to the mid-1970s and 1980s; when there were major supply shortages in the United States. Unlike energy and agricultural prices, the prices of sugar and coffee do not appear to co-move. Sugar prices are rather stable over the entire sample period, whereas coffee prices peaked in the late 1970s, mid-1990s, and 2011. Such peaks are all likely associated with bad weather conditions in Brazil and, more recently, Colombia.

The empirical analysis is based on month-to-month nominal commodity price returns, defined as $r_{m,t} = \ln P_{m,t} - \ln P_{m,t-1}$, where $P_{m,t}$ is the price of commodity m at time t .⁶ By means of a breakpoint analysis based on Qu and Perron (2007), whose technical details are described in Appendix A, the authors estimate breakpoints in the dynamics of the 11 commodity price returns in the sample. They consider an unrestricted vector autoregressive (VAR) model for the returns and estimate three breaks at unknown dates in the model coefficients and the variance-covariance matrix of the errors. The breaks are 1979M11, 1987M07, and 2007M05.⁷ The empirical investigation that follows is conducted on the full sample and on the four resulting subsamples: (S1) 1970M02/1979M10, (S2) 1979M11/1987M06, (S3) 1987M07/2007M04, and (S4) 2007M05/2013M05. As shown in Figure 1.1 the identified structural breaks generally coincide with significant events in energy and agricultural markets, which likely affect the dynamics of price returns. The first break can be associated with the Iranian revolution in 1979 and the subsequent war between Iran and Iraq, which led to a global oil crisis. The second break can be related to the severe droughts that occurred across most of the United States, which led to a major crop failure for soybeans and maize in 1988. The third break can be linked with the recent food price crisis, which started in 2007.

Table 2.1 reports summary statistics for the price returns computed over the full sample. Table B.2 in Appendix B reports the same statistics computed over the four previously determined subsamples. Crude oil exhibits the highest average monthly returns 0.8 percent over the full sample. The average returns of all commodities are higher in the 1970M02/1979M10 period than in the other subperiods. All average price returns fall in the subsequent 1979M11/1987M06 period and then generally and steadily rise until the end of the sample. However, in most cases, they do not reach the initial levels of the 1970s. Maize and sorghum are the only two commodities that show higher returns in the most recent subperiod relative to the first subperiod (approximately a 50 percent increase in the case of maize and a 14 percent increase in the case of sorghum). In addition to crude oil, the other two energy commodities and coffee show the most pronounced return decreases over time. The patterns of volatility are more mixed. Natural gas price returns are overall the most volatile. The price returns of sugar are similarly volatile. Crude oil and sugar are the most volatile commodities until almost the end of the 1980s. Barley, sugar, natural gas, and coffee exhibit the highest levels of volatility during the 1980s and the 1990s and up to 2007. The returns of the energy commodities are consistently the most volatile between the end of the 1980s and

⁵Data are publicly available from <http://go.worldbank.org/4ROCCIEQ50>. Table B.1 in Appendix B provides further details on the specific commodities included in the sample.

⁶The results that we present in this paper are robust to alternative measures of price returns (real price returns computed using a seasonally adjusted and a non-seasonally adjusted consumer price index). Details are available upon request.

⁷In order to assess the robustness of these results we perform several checks. Specifically, we apply the procedure to nominal and real returns and also consider VAR(0) and VAR(1) models to jointly describe and estimate the cross-correlation structure of price returns.

2013, with the exception of coal from 1987 to 2007. All return volatilities (with the exception of natural gas) rise between 2007 and 2013 when compared with the previous 20 year period.

Table 2.1 Summary statistics of commodity nominal price returns (1970M02–2013M05)

Commodity	Total	Mean	Median	SD	Min	Max	Skewness	Kurtosis	Shapiro-Wilk	Ljung-Box
Crude oil	520	0.008	0.000	0.099	-0.540	1.154	3.056	42.226	0.000	0.514
Coal	520	0.005	0.000	0.057	-0.329	0.463	1.650	21.181	0.000	0.000
Natural gas	520	0.006	0.000	0.107	-0.405	0.478	0.000	6.647	0.000	0.000
Soybean oil	520	0.003	0.000	0.065	-0.278	0.311	0.326	5.490	0.000	0.000
Barley	520	0.004	0.002	0.067	-0.279	0.287	0.125	6.206	0.000	0.000
Maize	520	0.003	0.000	0.058	-0.245	0.298	-0.028	5.907	0.000	0.509
Sorghum	520	0.003	0.000	0.061	-0.278	0.342	0.193	6.725	0.000	0.141
Rice	520	0.003	0.000	0.064	-0.242	0.582	2.326	20.935	0.000	0.000
Wheat	520	0.003	0.000	0.061	-0.219	0.519	1.406	13.545	0.000	0.014
Sugar	520	0.003	0.004	0.100	-0.308	0.376	0.244	4.265	0.000	0.000
Coffee	520	0.002	-0.001	0.075	-0.353	0.423	0.527	6.345	0.000	0.000

Source: Authors' calculations.

Notes: SD = Standard deviation; Min = Minimum; Max = Maximum. T stands for the number of monthly time observations. Price returns are computed as $\ln P_{m,t} - \ln P_{m,t-1}$, where $P_{m,t}$ is the nominal price of commodity m at time t . Prices are measured in nominal terms. The Shapiro-Wilk column reports the p-value of the Shapiro-Wilk test (the null hypothesis is that the series of returns has a normal distribution). The Ljung-Box column reports the p-value of the Ljung-Box test (the null hypothesis is that there is no autocorrelation in the series of squared returns up to 12 lags).

Turning to the other distributional properties of the data, maize price returns exhibit a distribution with a long left tail, whereas natural gas returns are the only ones with a symmetric distribution. All other returns have distributions with long right tails and median returns that are almost always smaller than average returns. A battery of Shapiro-Wilk tests run on the nominal price returns rejects the null hypothesis that the data are normally distributed in all cases. The kurtosis of all price returns is greater than three, as we observe leptokurtic data. Table 2.1 also reports the p-values from the Ljung-Box autocorrelation tests run on the squared returns. The null hypothesis of no autocorrelation up to 12 lags is mostly rejected at conventional statistical levels, except for the cases of crude oil, maize, and sorghum.

Figure 2.1 Monthly nominal prices

Source: Authors' calculations.

All of these findings are consistent with the presence of nonlinear time dependency in the series of price returns, perhaps due to the existence of time-varying conditional moments. Figure 2.2 plots the time evolution of each nominal price return, showing apparent fluctuations and volatility changes over. These descriptive results motivate the adoption of specific econometric techniques to characterize the time-varying properties of the second moments of the sample's commodity price returns. As already mentioned, particular attention is given to the second mixed moments, which are used in this study to measure the co-movement of price returns.

Figure 2.2 Monthly nominal price returns

Source: Authors' creation.

Note: The vertical lines represent the structural breaks identified with the Qu and Perron (2007) methodology: 1979M11, 1987M07, and 2007M05.

3. MEASURING THE CO-MOVEMENT OF COMMODITY PRICE RETURNS

This section describes and discusses the main empirical findings of the investigation. The authors study the co-movement of commodity price returns in three different ways. First they assess the extent of cross-section unconditional correlation over the full sample and four subperiods by means of Ng (2006)'s methodology. Then they study the time evolution of the dynamic conditional correlations by estimating a multivariate DCC model on the data, while allowing for time-varying conditional volatilities. Finally, they model the time evolution of the unconditional correlations using a rolling regression approach based on Tang and Xiong (2012). In this final context, the authors also run a regression analysis to statistically investigate the association between the unconditional co-movement of price returns and two of its possible determinants. Further details about the econometric techniques can be found in Appendix A.

Cross-Section Unconditional Correlations

This section formally examine's the cross-section co-movement of nominal price returns in energy, agricultural, and food markets by following the uniform-spacings methodology developed by Ng (2006). This methodology tests for the existence of and measures the extent of cross-section unconditional correlation in a panel of data in which the number of correlated series is unknown ex ante. This econometric approach improves upon standard tests for cross-section correlation, such as Breusch and Pagan (1980) because it requires less-restrictive assumptions to be satisfied in the data and allows precise identification of the series in the panel that determine's the rejection of the null hypothesis of no cross-section correlation. Ng (2006) methodology produces a split in the sample of all pairwise correlation coefficients (55 correlations in the sample of 11 commodity price returns) into two subsets of small and large absolute correlations. Building on the literature about spacings and adopting breakpoint analysis techniques, the procedure makes use of a spacings variance ratio test statistic to test the null hypothesis of no correlation within groups of correlation coefficients.⁸

The authors assess the cross-section unconditional correlation of the 11 commodity price returns over the full sample ($T = 520$ monthly observations) and over the four subsamples described in Section 2. ($T = 117$ monthly observations over S1, $T = 92$ monthly observations over S2, $T = 238$ monthly observations over S3 and $T = 73$ monthly observations over S4). As reported in Table 3.1, the authors reject the null hypothesis of no cross-section correlation at the 10 percent level in most time periods and for most values of q , a parameter that determines the length of the spacings needed to run the test. The only exception is the 1979M11/1987M06 period, for which the authors are unable to reject the null hypothesis of no cross-section correlation in the entire panel. It is worth noting that for the same 1979M11/1987M06 period, the extent of overall cross-section correlation is small: 12 pairs of price returns in the large correlation subset exhibit significant levels of (positive) correlation; the remaining 43 in the small correlation subset are, instead, not statistically different from zero. The results of the testing procedure also suggest a high level of generally positive co-movement (that is, positive correlation) of price returns concerning large groups of commodity pairs in all time periods. The extent of positive co-movement increases over time. The number of positive correlation coefficients is 41 in the first period and becomes 54 in the last period. More specifically, there are 37 positive correlation coefficients (out of 48 statistically significant correlations) in the 1970M02/1979M10 large correlation set, 12 positive correlation coefficients (out of 12 statistically significant correlations) in the 1979M11/1987M06 large correlation set and 23 positive correlation coefficients (out of 28 statistically significant correlations) in the 1987M07/2007M04 large correlation set. In the 2007M05/2013M05 period, the large correlation set includes 48 positive correlation coefficients (out of 48 statistically significant correlations).

⁸We provide further methodological details in Appendix A.

Table 3.1 Uniform-spacings analysis of commodity nominal price returns

<i>Full absolute correlation set</i>									
Sample period	Pairs	Positive correlations	Negative correlations	q=2		q=4		q=6	
				SVR	Prob.	SVR	Prob.	SVR	Prob.
Full sample	55	52	3	0.42	0.678	3.24	0.001	4.39	0.000
S1	55	41	14	-0.52	0.605	1.90	0.058	1.85	0.065
S2	55	40	15	1.55	0.121	1.37	0.169	1.07	0.283
S3	55	43	12	1.57	0.117	3.03	0.003	3.73	0.000
S4	55	54	1	3.25	0.001	2.20	0.028	2.50	0.012

<i>Large absolute correlation set (L) — First split</i>									
Sample period	Pairs	Positive correlations	Negative correlations	q=2		q=4		q=6	
				SVR	Prob.	SVR	Prob.	SVR	Prob.
Full sample	45	45	0	1.78	0.075	3.34	0.001	3.39	0.001
S1	48	37	11	4.31	0.000	5.59	0.000	7.37	0.000
S2	12	12	0	4.26	0.000	4.48	0.000	2.99	0.003
S3	28	23	5	2.69	0.007	4.18	0.000	5.01	0.000
S4	48	48	0	1.98	0.048	-0.05	0.962	0.87	0.382

<i>Small absolute correlation set (S) — First split</i>									
Sample period	Pairs	Positive correlations	Negative correlations	q=2		q=4		q=6	
				SVR	Prob.	SVR	Prob.	SVR	Prob.
Full sample	10	7	3	-1.19	0.234	-1.03	0.304	-0.51	0.607
S1	7	4	3	-1.38	0.169	-0.28	0.777	-1.07	0.285
S2	43	28	15	0.92	0.359	0.36	0.717	-0.04	0.969
S3	27	20	7	-0.88	0.378	-0.51	0.608	-0.59	0.558
S4	7	6	1	2.04	0.042	0.58	0.564	-1.07	0.285

Source: Authors' calculations.

Notes: Full sample corresponds to the period 1970M02-2013M05, S1 to 1970M02-1979M10, S2 to 1979M11-1987M06, S3 to 1987M07–2007M04, and S4 to 2007M05–2013M05. The null hypothesis of this testing procedure is that there is no cross-section correlation in the sample over the specified period of time. SVR is the standardized spacings variance ratio test statistic used to run the test. Parameter q indicates the order of the uniform spacings. The number of correlations in the L and S absolute correlation sets is estimated by maximum likelihood (see also Appendix A. The Pairs column reports the number of commodity pairs considered in the testing procedure.

Table B.3 in Appendix B provides additional information about the cross-section correlation of these commodities. The authors sort the pairs of commodities in the large absolute correlation sets over the full sample and subsamples in a descending order. Overall, the price returns of related commodities (that is, commodities in the same category) tend to be strongly positively correlated. There are strong and positive correlations within cereal crops (specifically maize, sorghum, barley, and wheat), between cereal crops and soybean oil, and within energy commodities (oil, coal, and gas). Related commodities are likely affected by similar supply-and-demand factors, because they are close substitutes in demand, have similar input costs, and share common market information. Such a positive correlation between related products is typically labeled as category-based co-movement, because investors (including hedgers and speculators) classify these crops as belonging to the same category, which means investors can shift resources to invest in other commodities or categories. For the full sample period, the returns of maize and sorghum exhibit the largest

correlation (0.81), followed by sorghum and wheat (0.53), and barley and maize (0.49). The returns of barley and wheat are the most highly correlated for the period 1970M1-1979M10 (correlation of 0.93), whereas the returns of maize and sorghum are the most highly correlated over the three subsequent subperiods (correlations of 0.68, 0.86, and 0.81, respectively).

The negative correlations between the returns of energy (coal and gas) and several agricultural commodities in the first subsample later become positive in most cases. For example, during the 1970M02/1979M10 period, the returns of coal and soybean oil, coal and barley, coal and maize, gas and maize, and gas and barley, among others, exhibit negative correlations, which change to positive in 2007M05/2013M05. Furthermore, crude oil and soybean oil show the second-largest positive return correlation during the 2007M05/2013M05 period (0.76), followed by maize and soybean oil (0.67), crude oil and barley (0.66), and coal and soybean oil (0.63). The large positive correlations between the returns of energy and agricultural commodities (particularly soybean oil and maize) can be explained by the recent rapid expansion of the production of biofuels, which have begun to use a significant portion of planted acres of starch and sugar-based crops, such as maize and sugarcane, and oilseed crops, such as soybean and rapeseed oil (see, for example, Rajagopal and Silverman 2007; Babcock 2011; Tangermann 2011). Increasing energy prices may not only directly affect agricultural prices through higher input and transportation costs, but may also create an incentive to use alternative energy sources like biofuels, which, in turn, may further stimulate agricultural prices. This possibility could also explain the recent large correlation between maize and soybean oil (0.67 in 2007M05/2013M05) / both commodities are important inputs for the production of ethanol and biodiesel in the United States.

Dynamic Conditional Correlations

This section focuses on the data's time dimension. The objective is to assess how the degree of correlation between commodity returns evolves over the years. The authors estimate a DCC model following Sheppard and Engle (2001) and Engle (2002).⁹ In particular, they first estimate a univariate generalized autoregressive conditional heteroscedasticity (GARCH) model for each return series and then derive a multivariate conditional correlation estimator from the transformed residuals of the first-stage models. The resulting conditional correlations between returns at each point are a function of the past correlations and of the history of each series' conditional volatility.

Figures 3.1 and 3.2 plot the estimated dynamic conditional correlations between the price returns of maize and soybean oil—which are this section are considered the two reference commodities because of their importance in the production of biofuels — and all of the other commodities in the sample.¹⁰ As shown in Figure 3.1, maize price returns are highly correlated with the returns of other cereal crops such as sorghum (average conditional correlation of about 0.8) and barley and wheat (average conditional correlation of about 0.50), as well as with the returns of soybean oil (average conditional correlation of about 0.45). An upward trend in the degree of conditional correlation between the returns of maize and wheat, coffee, and sugar starts around 2004. The dynamic correlations between the returns of maize and crude oil, natural gas, soybean oil, and rice increase between 2004 and around 2009; then they slowly decline until the end of the sample. The recent correlation increase between the returns of maize and crude oil to levels above 0.1 draws some attention, because, before 2006, such conditional correlation was steadily negative or close to zero.¹¹ The conditional correlations between the returns of maize and coal, rice, barley, and sorghum exhibit less steep or even nonexistent upward trends from 2004 and tend to decline toward the end of the sample. In Figure 3.2, the returns of soybean oil exhibit a relatively large average degree of correlation with the returns of maize (as previously argued), sorghum and barley

⁹The details of this method are presented in Appendix A.

¹⁰Estimates of the dynamic conditional correlations between all other commodities are available upon request as well as the full results related to the estimated DCC model.

¹¹The conditional correlation between maize and coal becomes greater than 0.1 in the late 1980s; the conditional correlation between maize and natural gas permanently exceeds 0.1 starting from the late 1990s.

(correlations of about 0.40) and, to a lower extent, wheat (average correlation of about 0.30). In all cases reported in the figure, the estimated dynamic conditional correlations moderately increase in the last few years of the sample, starting from about 2004; they then tend to fall after reaching a peak around 2009. Sharp increases to levels close to or above 0.2 occur in the conditional correlations between the returns of soybean oil and crude oil, coal, and coffee, starting from about 2003 to around 2009, after which such correlations mildly decline. It is not superfluous to point out that the majority of the unreported dynamic conditional correlations between the price returns of the other nine commodities follow similar (and more or less pronounced) hump-shaped evolutions in the last ten years of observations in the sample. The declines at the end of the sample observed in the reported and unreported dynamic correlations look relatively small in most cases, if compared with the correlation rises that occurred during the previous years.

Figure 3.1 Dynamic conditional correlations of maize nominal price returns

Figure 3.1 Continued

(e) Barley

(f) Sorghum

(g) Rice

(h) Wheat

Figure 3.1 Continued

Source: Authors' Aalculations.

Notes: The solid thin lines plot the estimated dynamic conditional correlations (DCC) and the solid thick lines represent their trends estimated by HP (Hodrick- Prescott) filter. The dashed lines are the estimated constant conditional correlations (CCC) based on Bollerslev (1990) and their corresponding 95 percent confidence intervals.

Figure 3.2 Dynamic conditional correlations of soybean oil nominal price returns

Figure 3.2 Continued

Figure 3.2 Continued

Source: Authors' calculations.

Note: The solid thin lines plot the estimated dynamic conditional correlations (DCC) and the solid thick lines represent their trends estimated by HP (Hodrick-Prescott) filter. The dashed lines are the estimated constant conditional correlations (CCC) based on Bollerslev (1990) and their corresponding 95 percent confidence intervals.

In another set of unreported results, the authors analyze the correlations between the estimated time-varying conditional standard deviations (volatilities) of the series of price returns. Large co-movements are detected in the conditional volatilities of agricultural products and crude oil price returns. In particular, the correlation between the estimated volatilities of soybean oil and crude oil returns more than quadruples from the 1970s to the last years in the sample and it more than triples in the case of maize and crude oil price returns over the same period. The conditional volatilities of sorghum and barley price returns also exhibit high correlations with the conditional volatility of crude oil price returns. The conditional volatility of soybean oil returns is also characterized by high levels of co-movement with the volatilities of coal and maize returns.¹²

Overall, these empirical outcomes represent additional evidence in support of the high levels of interrelation between agricultural and energy markets emerged in recent years. As briefly discussed above and in the related literature, such a pattern might be driven by the expansion of the biofuel industry.

Rolling Unconditional Correlations and Determinants

With the objective of understanding whether certain factors drive the co-movement under investigation, the authors adopt a flexible approach to compute rolling unconditional correlations between commodity nominal price returns, based on Tang and Xiong (2012).¹³ Only report and discuss results related to rolling correlations estimated using a 24-month rolling window are reported and discussed here. The empirical results are robust to alternative rolling windows. For example, a fixed rolling window of 60 monthly observations is also used for comparison purposes.¹⁴

Similar to the dynamic conditional correlations obtained from the estimation of the DCC model and discussed in the previous section, this section focuses on the unconditional correlations between maize and soybean oil price returns (used again as reference commodities) and the returns of all other commodities. The estimated unconditional correlations are plotted in Figures B.1. and B.2 in Appendix B. These rolling correlations exhibit fluctuations similar to those observed in the evolution of the dynamic conditional correlations.

Real interest rates and stock market uncertainty might, in principle, affect the co-movement of commodity price returns. Some of the reasons can be found, for example, in the work of Frankel (2008), Gruber and Vigfusson (2012) and Byrne et al. (2013). These studies argue that the correlations of commodity price returns should be inversely related to the real interest rate. The theoretical foundations of this claim, which can also be found in Deaton and Laroque (1992, 1996), are based on the idea that a fall in the interest rate lowers the volatility of prices (smoothing transitory shocks through lower inventory costs) and increases the correlations of price returns if covariant shocks are more persistent than idiosyncratic shocks. Byrne et al. (2013) argued that the standard deviation of stock market prices can be used as a proxy of market uncertainty, in line with the suggestions of Beck (1993) and Dixit and Pindyck (1994)'s that market risk and uncertainty might be associated with movements in commodity prices. According to Beck (1993), uncertainty may have a positive effect on commodity prices because volatile commodity prices are likely to reduce inventories and, consequently, their price. Dixit and Pindyck (1994) predicted a negative effect of uncertainty on commodity prices as uncertainty increases the option value of waiting (since investment in the production of primary commodities may be irreversible). Gilbert (2010) also suggested that co-movements across commodity prices can be better explained by macroeconomic and financial conditions than by market-specific factors.

This study we consider's two possible determinants of the co-movement of commodity price returns: (1) a real interest rate series, computed as the difference between an annualized three-month US Treasury bill interest rate series, obtained from the Board of Governors of the Federal Reserve System, and a series of annual inflation rates, calculated from a monthly nonseasonally adjusted consumer price index

¹²Additional details are available upon request.

¹³The technical details are presented in Appendix A.

¹⁴Further details are available upon request.

series taken from the Federal Reserve Bank of St Louis Economic Dataset (FRED); and (2) the standard deviation of Standard & Poor's 500 (S&P500) stock price returns (also taken from FRED), whose monthly series is derived as the standard deviation of the daily returns in each month in the sample. Motivated by the aforementioned studies about the possible effects of real interest rates and stock market uncertainty on the co-movement of commodity price returns, the authors regress the monthly series of estimated rolling absolute correlations between the price returns of commodities x and z — with $x \neq z$ and $x, z = 1, \dots, 11$ — on the annualized real interest rate and the standard deviation of S&P500 stock price returns. Specifically, they study the statistical properties of the model

$$\left| \widehat{\rho}_{xz,w,t} \right| = \alpha + \sum_{l=1}^L \beta_l \widehat{\rho}_{xz,w,t-l} + \delta \sigma_{SP500,t} + \gamma RR_t + \varepsilon_t,$$

where $\widehat{\rho}_{xz,w,t}$ is the estimated value of the rolling correlation between commodities x and z at time t and w is the length of the window used to compute the rolling correlations—that is $w = 24$ months, in this case. $L = 12$ is the maximum lag determined using the Schwarz criterion, RR_t is the real interest rate, and σ_{SP500} is the standard deviation of S&P500 returns. A Newey-West correction, based on a Bartlett kernel and a fixed bandwidth, is employed to produce reliable standard errors for the regression coefficients. The dependent variable in the regression is measured in absolute value to determine whether returns on safe assets (the real interest rates) or the volatility of stock markets (market uncertainty) are statistically associated with the degree of co-movement in commodity price returns, regardless of its sign.¹⁵ Table 3.2 reports the coefficients associated with the two regressors from the model estimated on the full sample. Table B.4 in Appendix B reports the coefficients estimated from the regressions run on the four different subsamples identified in Section 2.

¹⁵Qualitatively similar results are found when the dependent variable of the regression is the signed rolling correlation series (that is, without absolute values), given that most of the derived pairwise rolling correlations are positive.

Table 3.2 Determinants of absolute rolling correlations: Linear regression analysis

Sample period 1970M02–2013M05										
Regressor: Standard deviation of S&P500 returns ($\sigma_{SP500,t}$)										
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat	Sugar
Coal	0.011									
Natural gas	0.003	0.015***								
Soybean oil	0.009	0.013	0.003							
Barley	0.019*	0.020*	0.005	0.018**						
Maize	0.016	0.015	0.013***	0.015***	0.006					
Sorghum	0.009	0.009	0.011***	0.013**	0.004	-0.001				
Rice	0.007	0.000	0.007	0.011**	0.004	0.002	0.009			
Wheat	0.007	0.013	0.003	0.006	0.005	0.007	0.007	-0.006		
Sugar	0.005	0.008**	0.002	0.003	0.008	0.005	0.008	0.000	0.017***	
Coffee	0.017**	0.013*	0.006	0.015**	0.021***	0.005	0.005	-0.007	0.009	0.009
Regressor: Real interest rate (RR_t)										
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat	Sugar
Coal	-0.002									
Natural gas	-0.002	0.000								
Soybean oil	-0.001	-0.002***	0.001							
Barley	-0.001	-0.001	0.001	-0.001						
Maize	0.001	-0.001	0.000	-0.002**	0.000					
Sorghum	-0.001	-0.001	-0.001	-0.001	0.001	0.000				
Rice	0.002	0.000	0.000	0.000	0.001	0.002	0.001			
Wheat	0.000	0.001	0.001	-0.002	0.000	-0.002	0.000	0.000		
Sugar	0.001	0.000	-0.001	-0.001	-0.002	-0.001	0.000	-0.001	0.002	
Coffee	-0.001	-0.002	-0.001	-0.001	0.000	0.000	0.001	0.001	-0.001	-0.001

Source: Authors' calculations.

Notes: This table reports the ordinary least squares estimates of δ and γ in the equation

$$\left| \widehat{\rho}_{xz,w,t} \right| = \alpha + \sum_{l=1}^L \beta_l \widehat{\rho}_{xz,w,t-l} + \delta \sigma_{SP500,t} + \gamma RR_t + \varepsilon_t.$$

The model parameters are estimated over the full sample, 1970M02–2013M05. $\widehat{\rho}_{xz,w,t}$ is the estimated value of the rolling correlation between the nominal price returns of commodities x and z at time t , where w is the length of the window used to compute the rolling correlations ($w = 24$ months, in this case). $L = 12$ is the maximum lag allowed in the model; L is determined using the Schwarz criterion. A Newey-West correction is used to produce reliable standard errors. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels.

Unlike Byrne et al. (2013), the authors did not find a statistically significant association between the real interest rate and the co-movement of commodity price returns over the full sample of data. In particular, out of 55 real interest rate coefficients estimated in 55 linear models, only 2 are statistically significant and negative, as predicted by theoretical arguments. However, there seems to be some (limited) time variation in such association from a statistical point of view. From the regression analysis run on the four subsamples, statistically negative coefficients are observed in a few cases (10 and 8 cases) during the first two subperiods, especially when the dependent variable is the time-varying correlation between price returns of energy commodities and some agricultural commodities. Over the subsequent two subperiods, the number of statistically negative coefficients shrinks to 2 and 3 cases. A possible explanation for this finding is that Byrne et al. (2013) based their analysis on annual data spanning 1900—2008, this study works with monthly data over a shorter period. The impact of macroeconomic conditions on the co-movement of commodity price returns might be more easily detectable when considering long time spans. However, a statistically positive link between the standard deviation of S&P500 stock price returns and the co-movement of commodity price returns is much more evident. Over the full sample, 15 coefficients (out of 55) associated with the standard deviation of S&P500 stock price returns are statistically positive. Such a positive relationship considerably intensifies in recent years. Over the first subperiod, only one coefficient is statistically positive. In the subsequent three subperiods, this number increases to 6, 5, and 38. In other words, after 2007, increases in the stock market volatility are generally associated with increasing co-movement in most commodity price returns, both within and across energy and agricultural products. This specific finding is a possible indication of a high overall level of integration of energy and agricultural markets with financial markets in the past few years (that is, a higher *financialization* of commodity markets). In addition, it may be a direct effect of the recent global financial distress on commodity price dynamics.

4. CONCLUSIONS

The recent and recurrent increases in both the level and volatility of commodity prices has led researchers and policymakers to further analyze the behavior of commodity prices and the apparent co-movement of their returns. This paper, provides an extensive analysis of the degree and extent of co-movement among major energy, agricultural, and food commodity nominal price returns between 1970 and 2013. It measure's co-movement by means of unconditional and conditional correlations, paying particular attention to the characterization of the time-varying properties over the sample. The authors adopt a uniform-spacings testing procedure to assess the extent of unconditional co-movement in a panel of 11 commodity price returns. This procedure is run over the full sample under investigation and over four subsequent subsamples determined by a breakpoint analysis. A dynamic conditional correlation model allows the authors to estimate the time evolution of the conditional correlations of price returns, while also allowing them to model the conditional volatilities of the returns of each commodity and their time-varying properties. The authors then investigate whether time-varying unconditional correlations estimated by means of a rolling regression procedure are statistically associated with changes in macroeconomic and financial conditions, which are respectively measured by real interest rates and stock market volatility.

In general, positive correlations within energy and agricultural price returns were seen. This finding is in line with the fact that related commodities are generally close substitutes in demand, share common market information, and have similar input costs. Yet, there is an overall increase in the degree of co-movement between energy and agricultural price returns in recent years, especially in the cases of maize and soybean oil, which are important inputs in the production of biofuels. The empirical results provide supporting evidence of a higher association between energy and agricultural markets in recent years, likely driven by the expansion of the biofuel industry. Furthermore, there are clear signs of the existence of a statistically positive association between the co-movement of commodity price returns and stock market uncertainty, especially in the period starting from 2007. From a statistical point of view, however, real interest rates do not seem to have much effect on the co-movement of price returns.

Future research on this topic should further explore even the dynamic behavior of commodity prices, the degree and evolution of market interrelations, and their determinants. If increasing interdependencies across commodities occur, they may limit the effectiveness of diversification strategies aimed at reducing price risk. The steady expansion of the biofuel industry in the United States and the European Union may further strengthen the extent and size of correlations between agricultural and energy commodity prices in the near future. The growing financial integration of commodity markets may also continue stimulating cross-market dependencies, while the underlying factors driving these associations and their dynamics may keep changing over time.

APPENDIX A: ECONOMETRIC TECHNIQUES

In this appendix we briefly describe the econometric techniques that we adopt to produce the results presented in the main body of the paper, in the tables, and in the figures. The nominal commodity price returns are defined as $r_{m,t} = \ln P_{m,t} - \ln P_{m,t-1}$, where $P_{m,t}$ is the nominal price of commodity m at time t .

Qu and Perron (2007)'s Breakpoint Analysis

We estimate two unrestricted vector autoregressions (VAR) of orders 0 and 1 for the nominal price returns of the eleven commodities over the full sample of data (1970M02-2013M05). Both model specifications satisfy the conventional stability conditions ensuring stationarity. We evaluate the presence of structural breaks at unknown dates in the coefficients of the VAR equations and in the variance-covariance matrices of the error terms.

The errors are assumed to be normally distributed (quasi-maximum likelihood technique). The distribution of the relevant test statistic becomes degenerate as the estimated breaks approach the beginning or the end of the sample, or if any two breakpoints are too close to each other. In order to address this statistical issue, we set a trimming parameter of 15%; that is, 78 months (6.5 years) is the minimum distance between any two breakpoints, between the beginning of the sample and the first break, and between the last break and the end of the sample. The covariance matrices of the errors and the distributions of the regressors in the VAR models are allowed to change from each regime to the next, but no pre-whitening is applied for the construction of the breakpoint confidence intervals.

The multivariate approach that we adopt in this context is consistent with the rest of the analysis.¹⁶ The breaks detected may differ from the breaks in individual bivariate correlation coefficients. Our assumption is that only some parameters of the VAR equations present structural breaks at some point in time and that, when a break occurs, it occurs simultaneously in all model parameters and the variance-covariance matrix of the errors.

Our preferred specification is a VAR(1) model of the eleven nominal price returns. We generally allow for the presence of two breaks, which are estimated to occur in 1979M11 and 1987M07. When we allow for the presence of a third structural break, we generally come across a corner solution, due to the 15% trimming at the two ends of the sample. The implication is that the third structural break is likely to lie to the right of the identified value (corner solution), closer to the end of the sample period. We investigate this possibility by testing for the presence of a structural break only on a restricted sample of data ranging from 1990M01 to 2013M05. By restricting the sample in this way, we reduce the number of trimmed observations from 6.5 years down to 3.5 years, while keeping the trimming parameter constant at 15%. We find an additional structural break in 2007M05, at the onset of several agricultural price spikes.

Ng (2006)'s Uniform Spacings Test for Cross-Section Unconditional Correlation

Let $M = 11$ be the number of nominal commodity price returns in the sample and T the number of monthly observations. As long as the data sample is sufficiently large, the returns do not need to satisfy any specific distributional assumptions. The number of unique elements above (or below) the main diagonal of the sample unconditional correlation matrix is $N \equiv \frac{M(M-1)}{2} = 55$. $\bar{\rho} \equiv (|\hat{\rho}_1|, |\hat{\rho}_2|, \dots, |\hat{\rho}_N|)'$ is the vector of sample absolute correlation coefficients that collects the estimates of the absolute values of the population correlations in $\rho \equiv (\rho_1, \rho_2, \dots, \rho_N)'$. These N sample absolute correlation coefficients are then ordered from the smallest to the largest, $(\bar{\rho}_{[1:N]}, \bar{\rho}_{[2:N]}, \dots, \bar{\rho}_{[N:N]})'$. Finally, define the objects $\bar{\phi}_s \equiv \Phi(\sqrt{T}\bar{\rho}_{[s:N]})$, where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal random variable and $s = 1, 2, \dots, N$. Given that $\bar{\rho}_{[s:N]} \in [0, 1] \forall s = 1, 2, \dots, N$, then $\bar{\phi}_s \in [0.5, 1] \forall s = 1, 2, \dots, N$. The

¹⁶In fact, the unconditional correlations analyzed in Section 3. can be expressed as scalar functions of the VAR parameters.

q -order uniform spacings is defined as $\{(\bar{\phi}_s - \bar{\phi}_{s-q})\}_{s=q+1}^N$.

The N sample absolute correlations can be partitioned into two groups (first split), a group S containing the smallest absolute correlations and a group L containing the largest absolute correlations. The fraction of correlations in the sample contained in S is $\theta \in [0, 1]$. The statistical procedure, based on maximum likelihood techniques, determines the location of a slope change in the sequence of $\bar{\phi}_s$'s to estimate the parameter θ . The estimated number of correlations in S is then $\hat{K} \equiv \hat{\theta}N$, whereas the estimated number of correlations in L is $N - \hat{K} = (1 - \hat{\theta})N$.

As proved in Ng (2006), the null hypothesis $H_0 : \rho_s = 0$ is equivalent to the null $H_0 : \bar{\phi}_s \sim U[0.5, 1]$. We use a standardized spacings variance ratio test statistic, $SVR(n)$, to test the hypothesis of zero absolute correlation within each group. Such a statistic has a standard normal probability density function under the null of no correlation in a subsample of absolute correlations of size $n \rightarrow \infty$. Ng (2006) also shows that this testing strategy exhibits reliable small-sample properties. $SVR(n)$ depends on the choice of the lag-length parameter q and is based on a transformation of the return correlation spacings, which are exchangeable by construction – that is, the structure of dependence in $(\bar{\phi}_s - \bar{\phi}_{s-q})$ is the same for any s . With uncorrelated data, the $\bar{\phi}_s$'s all lie along a straight line with slope equal to $\frac{1}{2(n+1)}$ in a Cartesian space. The stronger the correlation intensity, the further away the $\bar{\phi}_s$'s are from that straight line. As proposed in the original theoretical framework, we test for each group (S or L) whether the variance of $\{(\bar{\phi}_s - \bar{\phi}_{s-q})\}_{s=q+1}^N$ is a linear function of q . The problem is then to test the uniformity and nonstationarity of a specific transformation of sample absolute correlations.¹⁷ If the uniformity hypothesis on the $\bar{\phi}_s$'s is rejected for S , testing whether the same hypothesis holds for L becomes uninformative. In fact, if the small correlations are statistically different from zero, then the absolute correlations in L must also be different from zero by construction.

Dynamic Conditional Correlations

The multivariate (MV) GARCH model assumes that the M demeaned nominal commodity price returns are conditionally multivariate normal with zero expected value and covariance matrix H_t . A dynamic conditional correlation DCC(J,K) MV-GARCH(P,Q) model is used on the transformed returns $\hat{r}_{m,t} = r_{m,t} - \bar{r}_m$, where $\bar{r}_m = \frac{\sum_{t=1}^T r_{m,t}}{T}$. Let $\bar{r} = (\bar{r}_1, \bar{r}_2, \dots, \bar{r}_M)'$, $\hat{r}_t = (\hat{r}_{1,t}, \hat{r}_{2,t}, \dots, \hat{r}_{M,t})'$, $\hat{r}_t \sim \mathcal{N}(0, H_t)$, and $H_t = D_t R_t D_t$. D_t is the $M \times M$ diagonal matrix of time-varying standard deviations from M univariate GARCH models. $\sqrt{h_{m,t}}$ is the m^{th} element of the main diagonal of D_t and R_t is a time-varying correlation matrix.¹⁸

Each element $h_{m,t}$ is described by a univariate GARCH model, $h_{m,t} = \omega_m + \sum_{p=1}^{P_m} \alpha_{m,p} \hat{r}_{m,t-p}^2 + \sum_{q=1}^{Q_m} \beta_{m,p} h_{m,t-q}$ for $m = 1, 2, \dots, M$.¹⁹ For each price return, P_m and Q_m are integers between 1 and 4, chosen according to the Schwarz criterion. They need not be the same. Also let $P = (P_1, P_2, \dots, P_M)'$ and $Q = (Q_1, Q_2, \dots, Q_M)'$.

The process $U_t = \left(1 - \sum_{j=1}^J \gamma_j - \sum_{k=1}^K \delta_k\right) \bar{U} + \sum_{j=1}^J \gamma_j (\hat{\varepsilon}_{t-j} \hat{\varepsilon}_{t-j}') + \sum_{k=1}^K \delta_k U_{t-k}$ is assumed to describe the conditional dynamic correlation structure used to model the data. $\hat{\varepsilon}_t \sim \mathcal{N}(0, R_t)$ is the vector of residuals obtained from the multiple OLS regressions $\hat{r}_t = \theta + \varepsilon_t$ and standardized by their conditional standard deviations. $\bar{U}$ is the unconditional covariance of the standardized residuals resulting from the

¹⁷The extent of cross-section correlation in the panel of data can be graphically assessed by means of a quantile-quantile (q-q) plot of the $\bar{\phi}_s$'s. If all correlations are nonzero, then the q-q plot will be shifted upward and its intercept will be larger than 0.5. If there is homogeneity in a subset of the correlations, then the q-q plot will be flat over a certain range. If S is characterized by zero correlations while L is not, then, in the q-q plot, the $\bar{\phi}_s$'s would be approximately linear in s until $s = \hat{K}$, then would rise steeply for $s > \hat{K}$, and eventually would flatten at the boundary of 1.

¹⁸The assumption of multivariate normality is not strictly required for consistency and asymptotic normality of the estimators. If returns have non-normal innovations, the DCC estimator corresponds to a quasi-maximum likelihood estimator.

¹⁹Conventional GARCH restrictions for non-negativity of variances and stationarity are imposed.

first-stage estimation. We assume that $R_t = (U_t^*)^{-1} U_t (U_t^*)^{-1}$, where

$$U_t^* = \begin{bmatrix} \sqrt{u_{11,t}} & 0 & 0 & \dots & 0 \\ 0 & \sqrt{u_{22,t}} & 0 & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & 0 \\ 0 & \dots & 0 & 0 & \sqrt{u_{MM,t}} \end{bmatrix},$$

such that U_t^* is a diagonal matrix composed of the square root of the diagonal elements of U_t . Under suitable conditions, the elements of R_t have the form $\rho_{xz,t}^* = \frac{u_{xz,t}}{\sqrt{u_{xx,t}u_{zz,t}}}$, with $x, z = 1, 2, \dots, M$.

Note that R_t can also be constant and equal to R . In such a case, the DCC(J,K) MV-GARCH(P,Q) model becomes a constant conditional correlation CCC MV-GARCH(P,Q) model (Bollerslev 1990). In this paper, J and K are always set equal to 1. While the main focus of our work is on the multivariate analysis of commodity price returns and their correlations, we also estimate bivariate (BV) models, DCC(J,K) BV-GARCH(P,Q), between all pairs of commodity returns and find qualitatively similar results.

Rolling Unconditional Correlations

Following Tang and Xiong (2012), we normalize the regular monthly commodity price returns by their respective averages and standard deviations, $r_{m,t}^* = \frac{r_{m,t} - \bar{r}_m}{\sqrt{\frac{\sum_{t=1}^T (r_{m,t} - \bar{r}_m)^2}{T-1}}}$. We then regress the normalized return

of commodity x , $r_{x,t}^*$, onto the normalized return of commodity z , $r_{z,t}^*$, with $x, z = 1, 2, \dots, M$ and $x \neq z$. $\hat{\rho}_{xz}$ obtained from the regression $r_{x,t}^* = \mu + \tilde{\rho}_{xz} r_{z,t}^* + \eta_t$ is the estimated unconditional correlation between the two commodity price returns. We assess the time-variation in the correlation coefficients between all pairs of commodity price returns by estimating rolling regressions with fixed windows of size equal to two and five years—meaning 24 and 60 months. Newey-West standard errors, based on a Bartlett kernel and a fixed bandwidth, correct for autocorrelation in the regression residuals and are used to derive reliable rolling 95 percent confidence intervals for $\tilde{\rho}_{xz}$.

APPENDIX B: SUPPLEMENTARY TABLES AND FIGURES

Table B.1 Commodities

Crude oil	Crude oil, Dubai Fateh 32° API for years 1985-present; 1960-84 refer to Saudi Arabian Light, 34° API
Coal	Coal (Australia), thermal GAR, f.o.b. piers, Newcastle/Port Kembla from 2002 onwards, 6,300 kcal/kg (11,340 btu/lb), less than 0.8% sulfur 13% ash; previously 6,667 kcal/kg (12,000 btu/lb), less than 1.0% sulfur, 14% ash
Natural gas	Natural Gas (US), spot price at Henry Hub, Louisiana
Soybean oil	Soybean oil (Any origin), crude, f.o.b. ex-mill Netherlands
Barley	Barley (US) feed, No. 2, spot, 20 days To-Arrive, delivered Minneapolis from May 2012 onwards; during 1980 - 2012 April Canadian, feed, Western No. 1, Winnipeg Commodity Exchange, spot, wholesale farmers' price
Maize	Maize (US), No. 2, yellow, f.o.b. US Gulf ports
Sorghum	Sorghum (US), No. 2 milo yellow, f.o.b. Gulf ports
Rice	Rice (Thailand), 5% broken, white rice (WR), milled, indicative price based on weekly surveys of export transactions, government standard, f.o.b. Bangkok
Wheat	Wheat (US), No. 1, hard red winter, ordinary protein, export price delivered at the US Gulf port for prompt or 30 days shipment
Sugar	Sugar (World), International Sugar Agreement (ISA) daily price, raw, f.o.b. and stowed at greater Caribbean ports
Coffee	Coffee (ICO), International Coffee Organization indicator price, other mild Arabicas, average New York and Bremen/Hamburg markets, ex-dock

Source: Authors' calculations.

Table B.2 Summary statistics of commodity nominal price returns: Subsample analysis

1970M02-1979M10	T	Mean	Median	SD	Min	Max	Skewness	Kurtosis	Shapiro-Wilk	Ljung-Box
Crude oil	117	0.029	0.000	0.128	-0.204	1.154	6.487	53.539	0.000	1.000
Coal	117	0.012	0.000	0.060	-0.029	0.463	6.118	42.426	0.000	0.384
Natural gas	117	0.017	0.000	0.053	-0.022	0.394	5.278	33.486	0.000	0.004
Soybean oil	117	0.008	0.007	0.083	-0.195	0.216	0.207	3.224	0.219	0.330
Barley	117	0.009	0.004	0.047	-0.108	0.278	1.588	10.973	0.000	0.984
Maize	117	0.006	0.000	0.057	-0.134	0.166	0.226	3.597	0.004	0.000
Sorghum	117	0.007	0.000	0.058	-0.164	0.214	0.817	5.134	0.000	0.004
Rice	117	0.008	0.004	0.082	-0.144	0.582	3.400	24.545	0.000	1.000
Wheat	117	0.010	0.000	0.075	-0.163	0.519	2.697	20.279	0.000	1.000
Sugar	117	0.010	0.010	0.118	-0.301	0.352	0.178	4.081	0.009	0.294
Coffee	117	0.012	0.009	0.078	-0.231	0.254	0.351	4.310	0.018	0.000
1979M11-1987M06	T	Mean	Median	SD	Min	Max	Skewness	Kurtosis	Shapiro-Wilk	Ljung-Box
Crude oil	92	-0.008	-0.003	0.093	-0.540	0.437	-1.173	19.038	0.000	0.871
Coal	92	-0.003	0.000	0.052	-0.213	0.228	-0.121	13.266	0.000	0.289
Natural gas	92	0.003	0.005	0.024	-0.069	0.045	-0.578	2.951	0.029	0.894
Soybean oil	92	-0.007	-0.009	0.072	-0.215	0.311	0.806	7.040	0.000	0.949
Barley	92	-0.002	0.000	0.092	-0.215	0.287	0.266	3.823	0.139	0.432
Maize	92	-0.004	-0.008	0.057	-0.221	0.126	-0.385	4.705	0.003	1.000
Sorghum	92	-0.005	-0.006	0.058	-0.211	0.118	-0.759	4.488	0.006	0.373
Rice	92	-0.006	0.000	0.043	-0.127	0.143	0.128	3.996	0.236	0.982
Wheat	92	-0.005	-0.005	0.035	-0.121	0.068	-0.585	3.714	0.069	0.745
Sugar	92	-0.007	-0.017	0.133	-0.275	0.376	0.425	2.972	0.155	0.973
Coffee	92	-0.008	-0.006	0.068	-0.177	0.235	0.290	4.741	0.003	0.005
1987M07-2007M04	T	Mean	Median	SD	Min	Max	Skewness	Kurtosis	Shapiro-Wilk	Ljung-Box
Crude oil	238	0.005	0.014	0.085	-0.309	0.491	0.237	7.899	0.000	0.864
Coal	238	0.003	0.000	0.040	-0.135	0.159	0.280	5.630	0.000	0.000
Natural gas	238	0.006	0.005	0.139	-0.405	0.478	-0.207	4.209	0.001	0.072
Soybean oil	238	0.003	0.002	0.053	-0.117	0.261	0.826	5.764	0.000	0.970
Barley	238	0.004	0.001	0.059	-0.203	0.283	0.115	6.365	0.000	0.001
Maize	238	0.003	0.004	0.054	-0.244	0.298	0.073	8.104	0.000	1.000
Sorghum	238	0.003	0.000	0.057	-0.180	0.342	0.720	8.689	0.000	1.000
Rice	238	0.002	0.003	0.055	-0.242	0.235	0.195	6.395	0.000	0.017
Wheat	238	0.003	0.000	0.051	-0.151	0.179	0.285	3.946	0.007	0.002
Sugar	238	0.002	0.007	0.078	-0.230	0.283	0.226	3.531	0.311	0.007
Coffee	238	0.000	-0.005	0.082	-0.353	0.423	0.684	7.151	0.000	0.060
2007M05-2013M05	T	Mean	Median	SD	Min	Max	Skewness	Kurtosis	Shapiro-Wilk	Ljung-Box
Crude oil	73	0.006	0.021	0.089	-0.335	0.187	-1.484	6.486	0.000	0.005
Coal	73	0.006	0.005	0.093	-0.329	0.364	-0.002	6.725	0.001	0.709
Natural gas	73	-0.009	-0.025	0.117	-0.301	0.375	0.598	3.987	0.092	0.680
Soybean oil	73	0.005	0.008	0.064	-0.278	0.117	-1.244	6.864	0.000	0.991
Barley	73	0.005	0.011	0.079	-0.279	0.233	-0.411	5.213	0.003	0.016
Maize	73	0.009	0.004	0.074	-0.245	0.220	-0.251	4.679	0.082	0.979
Sorghum	73	0.008	0.017	0.078	-0.278	0.254	-0.517	5.324	0.007	0.472
Rice	73	0.007	-0.004	0.079	-0.175	0.423	2.331	13.029	0.000	0.996
Wheat	73	0.007	0.006	0.088	-0.219	0.229	0.375	3.750	0.075	0.966
Sugar	73	0.008	-0.001	0.083	-0.308	0.197	-0.312	4.794	0.026	0.736
Coffee	73	0.003	0.002	0.054	-0.148	0.121	-0.170	3.092	0.927	0.977

Source: Authors' calculations.

Note: Price returns are computed as $\ln P_{m,t} - \ln P_{m,t-1}$, where $P_{m,t}$ is the nominal price of commodity m at time t . Prices are measured in nominal terms. T stands for the number of monthly time observations. SD stands for standard deviation. The Shapiro-Wilk column reports the p-value of the Shapiro-Wilk test (the null hypothesis is that the series of returns has a normal distribution). The Ljung-Box column reports the p-value of the Ljung-Box test (the null hypothesis is that there is no autocorrelation in the series of squared returns up to twelve lags).

Table B.3 Large absolute correlation sets based on Ng (2006)

1970M02-2013M05 (45 Pairs)
Positive Correlations: Maize-Sorghum (0.807), Sorghum-Wheat (0.527), Barley-Maize (0.491), Maize-Wheat (0.479), Barley-Sorghum (0.470), Soybean oil-Maize (0.465), Barley-Wheat (0.449), Soybean oil-Sorghum (0.419), Soybean oil-Barley (0.395), Crude oil-Coal (0.311), Soybean oil-Wheat (0.279), Coal-Natural gas (0.229), Wheat-Sugar (0.190), Soybean oil-Sugar (0.177), Sorghum-Sugar (0.176), Crude oil-Natural gas (0.172), Maize-Sugar (0.160), Wheat-Coffee (0.144), Coal-Maize (0.143), Sorghum-Coffee (0.138), Barley-Rice (0.136), Maize-Rice (0.134), Crude oil-Soybean oil (0.129), Coal-Sorghum (0.128), Sorghum-Rice (0.127), Soybean oil-Coffee (0.126), Soybean oil-Rice (0.125), Maize-Coffee (0.121), Coal-Sugar (0.112), Natural gas-Barley (0.112), Coal-Barley (0.109), Crude oil-Barley (0.108), Coal-Soybean oil (0.106), Coal-Wheat (0.093), Barley-Coffee (0.086), Crude oil-Sugar (0.086), Crude oil-Coffee (0.081), Natural gas-Maize (0.081), Crude oil-Wheat (0.080), Coal-Coffee (0.077), Rice-Wheat (0.075), Crude oil-Sorghum (0.069), Coal-Rice (0.069), Natural gas-Sugar (0.067), Barley-Sugar (0.063)
1970M02-1979M10 (48 Pairs)
Positive Correlations: Barley-Wheat (0.933), Coal-Natural gas (0.869), Maize-Sorghum (0.804), Barley-Maize (0.780), Barley-Sorghum (0.779), Sorghum-Wheat (0.614), Crude oil-Coal (0.527), Crude oil-Natural gas (0.514), Maize-Wheat (0.502), Soybean oil-Maize (0.489), Soybean oil-Sorghum (0.400), Soybean oil-Barley (0.352), Sorghum-Sugar (0.302), Maize-Coffee (0.276), Soybean oil-Sugar (0.265), Barley-Sugar (0.257), Wheat-Sugar (0.243), Soybean oil-Coffee (0.231), Soybean oil-Wheat (0.205), Crude oil-Sugar (0.199), Sorghum-Rice (0.195), Maize-Sugar (0.194), Barley-Rice (0.185), Soybean oil-Rice (0.171), Rice-Wheat (0.169), Barley-Coffee (0.163), Sorghum-Coffee (0.161), Maize-Rice (0.151), Crude oil-Sorghum (0.138), Sugar-Coffee (0.131), Crude oil-Soybean oil (0.117), Natural gas-Coffee (0.100), Coal-Sugar (0.084), Crude oil-Wheat (0.077), Crude oil-Coffee (0.077), Crude oil-Barley (0.067), Wheat-Coffee (0.067)
Negative Correlations: Natural gas-Sorghum (-0.162), Coal-Sorghum (-0.125), Natural gas-Rice (-0.120), Natural gas-Barley (-0.115), Natural gas-Maize (-0.109), Coal-Maize (-0.104), Natural gas-Wheat (-0.097), Coal-Barley (-0.096), Coal-Rice (-0.089), Coal-Soybean oil (-0.080), Coal-Wheat (-0.072)
1979M11-1987M06 (12 Pairs)
Positive Correlations: Maize-Sorghum (0.681), Soybean oil-Barley (0.566), Barley-Sorghum (0.538), Soybean oil-Sorghum (0.469), Sorghum-Wheat (0.468), Soybean oil-Maize (0.450), Barley-Maize (0.408), Barley-Wheat (0.376), Maize-Wheat (0.292), Coal-Natural gas (0.259), Natural gas-Wheat (0.242), Soybean oil-Wheat (0.236)
1987M07-2007M04 (28 Pairs)
Positive Correlations: Maize-Sorghum (0.859), Sorghum-Wheat (0.531), Maize-Wheat (0.455), Barley-Maize (0.424), Soybean oil-Maize (0.371), Barley-Sorghum (0.362), Soybean oil-Sorghum (0.330), Barley-Wheat (0.279), Soybean oil-Barley (0.223), Soybean oil-Wheat (0.218), Coal-Maize (0.191), Soybean oil-Sugar (0.166), Coal-Sorghum (0.149), Wheat-Sugar (0.148), Crude oil-Natural gas (0.135), Coal-Natural gas (0.115), Coal-Barley (0.106), Natural gas-Barley (0.104), Natural gas-Sugar (0.101), Maize-Sugar (0.097), Coal-Sugar (0.096), Sorghum-Sugar (0.095), Coal-Wheat (0.093)
Negative Correlations: Crude oil-Maize (-0.190), Crude oil-Sorghum (-0.158), Natural gas-Coffee (-0.103), Natural gas-Rice (-0.112), Crude oil-Rice (-0.098)
2007M05-2013M05 (48 Pairs)
Positive Correlations: Maize-Sorghum (0.806), Crude oil-Soybean oil (0.758), Soybean oil-Maize (0.668), Crude oil-Barley (0.655), Coal-Soybean oil (0.631), Soybean oil-Sorghum (0.609), Soybean oil-Barley (0.607), Maize-Wheat (0.595), Crude oil-Coal (0.575), Soybean oil-Wheat (0.563), Barley-Maize (0.539), Crude oil-Maize (0.538), Wheat-Coffee (0.535), Soybean oil-Coffee (0.526), Barley-Wheat (0.497), Sorghum-Wheat (0.497), Maize-Coffee (0.495), Crude oil-Sorghum (0.474), Coal-Barley (0.450), Coal-Coffee (0.430), Barley-Sorghum (0.412), Sorghum-Coffee (0.403), Soybean oil-Sugar (0.395), Coal-Maize (0.380), Crude oil-Coffee (0.372), Sugar-Coffee (0.347), Coal-Sorghum (0.338), Barley-Coffee (0.332), Crude oil-Wheat (0.313), Natural gas-Maize (0.312), Coal-Sugar (0.312), Natural gas-Barley (0.309), Barley-Rice (0.282), Coal-Natural gas (0.271), Coal-Wheat (0.263), Maize-Sugar (0.252), Natural gas-Coffee (0.246), Wheat-Sugar (0.246), Crude oil-Rice (0.231), Natural gas-Sorghum (0.221), Coal-Rice (0.220), Sorghum-Rice (0.219), Natural gas-Rice (0.208), Natural gas-Soybean oil (0.207), Sorghum-Sugar (0.206), Soybean oil-Rice (0.205), Crude oil-Sugar (0.188), Maize-Rice (0.172)

Source: Authors' calculations.

Note: Commodity pairs are ordered from largest to smallest absolute correlation (correlation reported in parenthesis). The number of correlations in the large absolute correlation set is estimated by maximum likelihood (see Appendix A).

Table B.4 Determinants of absolute rolling correlations: Subsample analysis

Panel A: Sample Period 1970M02-1979M10									
Regressor: Standard Deviation of S&P500 Returns ($\sigma_{SP500,t}$)									
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat
Coal	0.018								
Natural gas	0.021	0.030							
Soybean oil	0.006	0.013	-0.012						
Barley	-0.015	-0.021	-0.014	0.004					
Maize	0.000	-0.040**	-0.009	0.008	0.005				
Sorghum	0.001	-0.023	0.000	-0.008	-0.001	-0.005			
Rice	0.028	0.003	-0.014	-0.010	-0.035**	-0.033*	-0.024		
Wheat	-0.011	-0.006	-0.003	-0.004	0.000	-0.015	-0.003	-0.026**	
Sugar	0.006	0.007	0.012	-0.038	-0.011	-0.019	0.016	-0.035	-0.007
Coffee	0.017	0.034*	0.008	0.002	0.014	-0.002	-0.021	-0.003	-0.027
Regressor: Real Interest Rate (RR_t)									
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat
Coal	-0.002								
Natural gas	-0.002	0.002							
Soybean oil	0.000	0.000	-0.001						
Barley	-0.001	-0.008***	-0.006*	-0.008					
Maize	0.006	-0.011***	-0.007	-0.005	-0.002				
Sorghum	-0.003	-0.010***	-0.005*	-0.009	0.001	0.001			
Rice	0.015**	0.005	0.001	0.003	0.001	0.001	0.008		
Wheat	-0.005**	-0.003*	-0.001	-0.007	0.000	-0.005*	0.000	0.001	
Sugar	-0.005	0.004	0.004	-0.01*	-0.006	-0.009**	-0.003	-0.006	-0.001
Coffee	-0.002	0.001	0.003	-0.003	0.000	0.000	-0.003	0.003	-0.002

Table B.4 Continued

Panel B: Sample Period 1979M11-1987M06										
Regressor: Standard Deviation of S&P500 Returns ($\sigma_{SP500,t}$)										
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat	Sugar
Coal	-0.014									
Natural gas	0.004	0.041*								
Soybean oil	0.011	0.014	0.053*							
Barley	-0.039*	0.030	0.002	-0.071**						
Maize	-0.019	-0.016	0.005	0.007	-0.007					
Sorghum	-0.002	-0.032**	0.035	-0.052*	-0.015	-0.004				
Rice	0.062**	0.000	-0.008	-0.025	-0.008	0.001	0.000			
Wheat	-0.022	-0.036	0.011	-0.039	-0.035*	0.002	0.014	-0.010		
Sugar	-0.018	0.016	0.002	0.076**	0.006	-0.010	0.018	0.038*	0.012	
Coffee	-0.009	-0.004	-0.008	0.029	0.091**	-0.041	-0.006	0.029	-0.029	-0.025
Regressor: Real Interest Rate (RR_t)										
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat	Sugar
Coal	0.000									
Natural gas	-0.001	0.007								
Soybean oil	0.002	-0.008***	0.005***							
Barley	0.001	-0.002	0.001	-0.001						
Maize	0.002	0.001	0.004*	-0.003**	0.000					
Sorghum	0.001	-0.001	0.001	-0.004**	0.000	-0.002*				
Rice	0.001	0.002	-0.003	0.003	0.002	-0.001	-0.002			
Wheat	0.004	-0.004*	0.002	-0.005**	-0.003	-0.003*	-0.002	0.002		
Sugar	0.002	0.000	0.001	0.000	-0.007***	0.004*	0.005*	-0.002	0.007***	
Coffee	0.000	-0.001	-0.001	0.003	0.004	0.003	0.003	0.001	-0.002	0.000

Table B.4 Continued

Panel C: Sample Period 1987M07-2007M04									
Regressor: Standard Deviation of S&P500 Returns ($\sigma_{SP500,t}$)									
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat
Coal	0.003								
Natural gas	0.003	0.018*							
Soybean oil	-0.008	-0.002	-0.008						
Barley	0.004	0.014	-0.001	0.015**					
Maize	-0.003	0.006	0.013**	0.010*	0.006				
Sorghum	-0.007	-0.003	0.006	0.006	0.006	-0.007			
Rice	-0.009	-0.009	0.003	0.005	-0.001	-0.008	0.005		
Wheat	-0.001	0.010	0.008	-0.006	0.006	0.005	0.005	0.005	
Sugar	-0.008	-0.002	0.007	-0.012**	0.001	0.004	0.019**	-0.012**	0.019*
Coffee	0.001	-0.004	0.006	0.004	0.007	-0.009	-0.010	-0.005	0.002
Regressor: Real Interest Rate (RR_t)									
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat
Coal	0.001								
Natural gas	-0.001	-0.001							
Soybean oil	-0.002	0.000	0.003						
Barley	-0.001	0.001	0.003	0.000					
Maize	0.004*	0.002	0.001	-0.003	0.002				
Sorghum	0.000	0.003	0.001	-0.001	0.006	0.002			
Rice	0.001	-0.001	0.002	0.000	0.001	0.002	0.001		
Wheat	-0.002	0.005*	0.001	0.003	0.005	0.004	0.002	0.001	
Sugar	-0.002	0.002	-0.005**	0.004	0.000	0.000	0.000	0.001	0.000
Coffee	-0.004*	-0.003	-0.002	0.002	0.000	0.002	0.004*	-0.001	0.001

Table B.4 Continued

Panel D: Sample Period 2007M05-2013M05										
Regressor: Standard Deviation of S&P500 Returns ($\sigma_{SP500,t}$)										
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat	Sugar
Coal	0.017									
Natural gas	0.007	0.018***								
Soybean oil	0.011	0.022*	0.003							
Barley	0.043***	0.034*	0.012**	0.033***						
Maize	0.038***	0.039***	0.009	0.026***	0.016***					
Sorghum	0.024**	0.030***	0.009	0.029***	0.020***	0.004**				
Rice	0.015**	0.004	0.016***	0.021***	0.020	0.017**	0.026***			
Wheat	0.022*	0.028**	0.003	0.021***	0.017**	0.014*	0.018***	-0.021***		
Sugar	0.021***	0.015**	-0.001	0.009	0.023	0.011**	-0.010	0.011	0.026***	
Coffee	0.030**	0.031***	-0.008	0.024***	0.040***	0.019**	0.020**	-0.014**	0.021***	0.021**
Regressor: Real Interest Rate (RR_t)										
	Crude oil	Coal	Natural gas	Soybean oil	Barley	Maize	Sorghum	Rice	Wheat	Sugar
Coal	0.006									
Natural gas	-0.001	0.001								
Soybean oil	0.001	0.000	0.003							
Barley	-0.005	0.002	0.005	-0.007*						
Maize	0.002	0.002	0.001	-0.005	0.004					
Sorghum	0.001	-0.004	0.000	-0.001	0.000	0.001				
Rice	0.006*	0.019**	0.017***	-0.004	0.006	0.009*	0.000			
Wheat	0.003	0.002	0.000	0.000	0.004	-0.001	0.000	-0.009*		
Sugar	0.010***	0.001	-0.006	-0.005	0.004	-0.005	-0.004	0.003	0.005	
Coffee	0.003	-0.002	-0.004	0.000	0.003	0.001	0.003	-0.008*	-0.004	0.008*

Source: Authors' calculations.

Note: This table reports the OLS estimates of δ and γ in the equation

$$\left| \widehat{\rho}_{xz,w,t} \right| = \alpha + \sum_{l=1}^L \beta_l \widehat{\rho}_{xz,w,t-l} + \delta \sigma_{SP500,t} + \gamma RR_t + \varepsilon_t.$$

The model parameters are estimated over the indicated subsamples. $\widehat{\rho}_{xz,w,t}$ is the estimated value of the rolling correlation between the nominal price returns of x and z at time t , where w is the length of the window used to compute the rolling correlations ($w = 24$ months, in this case). $L = 12$ is the maximum lag allowed in the model; L is determined using the Schwarz criterion. A Newey-West correction is used to produce reliable standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.

Figure B.1 Rolling correlations of maize nominal price returns: Twenty-four month window

Source: Authors' creation.

Note: This figure reports a graphical representation of the evolution of $\hat{\rho}_{xz,w,t}$ —that is the rolling correlation between the nominal price returns of commodities x (maize) and z , where w is the length of the window used to compute the rolling correlations ($w = 24$ months, in this case). Ninety-five % confidence bands are also plotted.

Figure B.2 Rolling correlations of soybean oil nominal price returns: Twenty-four month window

Source: Authors' creation.

Note: This figure reports a graphical representation of the evolution of $\hat{\rho}_{xz,w,t}$ —that is the rolling correlation between the nominal price returns of commodities x (soybean oil) and z , where w is the length of the window used to compute the rolling correlations ($w = 24$ months, in this case). Ninety-five % confidence bands are also plotted.

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