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Co-movements in commodity prices: a note based on network analysis

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Abstract

This article analyses co-movements in a wide group of commodity prices during the time period 1992–2010. Our methodological approach is based on the correlation matrix and the networks inside. Through this approach we are able to summarize global interaction and interdependence, capturing the existing heterogeneity in the degrees of synchronization between commodity prices. Our results produce two main findings: (a) we do not observe a persistent increase in the degree of co-movement of the commodity prices in our time sample, however from mid-2008 to the end of 2009 co-movements almost doubled when compared with the average correlation; (b) we observe three groups of commodities which have exhibited similar price dynamics (metals, oil and grains, and oilseeds) and which have increased their degree of co-movement during the sampled period.

JEL classifications: C45, E37, Q33

Keywords: Commodity prices; Co-movement; Hierarchy and topology; Networks; Complex systems

1. Introduction and motivation

Commodities are frequently the most important source of export of foreign revenues for many developing and some developed countries. Additionally, commodities have become, in both derivative and cash markets, an important investment asset alternative to traditional stocks and bond portfolios.[1] In this way, changes in commodity prices can potentially affect both policymakers and trading investors. The former are affected in two key directions: firstly, because a long-term decline in commodity prices supports the hypothesis that the terms of trade for commodity-abundant countries deteriorates; secondly, because both the degree of volatility and persistence of commodity prices affect the external and internal balances, which jeopardizes the effectiveness of stabilization policies. In the latter case, trading investors are affected because commodities have become an alternative asset and their price variation raises the necessity of rebalancing and diversifying investors' portfolios.

Commodity price fluctuations have recently attracted the attention of policymakers, researchers, and the general public, as the world economy has (over the past decade) experienced the broader-based and longer-lasting nominal commodity price boom since the Second World War (see Helbling et al., 2008).[2] Literature on this issue is vast and diverse. Regarding the aims of this article, we can split the recent literature into two main strands.

The first strand has placed attention on commodity prices' time series properties to examine the duration, magnitude, and volatility in world commodity cycles (e.g., Cashin et al., 2002; Chen, 2010; Cuddington, 1992; Deaton, 1999; Roberts, 2009; Stigler, 2011). Some results arise from this literature: firstly, there is little evidence of a consistent shape to the cycles in commodity prices mainly because the probability of a slump in prices ending is independent of the period of time in which the slump is already occurring. Thus, there is no support for

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article.

[1] For instance, commodity contracts outstanding in December 2008 were in excess of US$4.4 trillion compared with equity related contracts of US$6.5 trillion (Batten et al., 2010).

[2] During the 1990s the global International Monetary Fund (IMF) commodity index rose by 17%, however from 2000 to 2010 (July) the increase reached almost 150%. The highest increase in commodity prices occurred after 2007 whereas most commodity prices were either stagnant or on a downward trend during the 1980s and 1990s (see Fig. 1).

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the existence of long-term trends in commodity prices (Cashin et al., 2002; Roberts, 2009) even though some studies have argued that the world economy is currently at the early stage of a "super-cycle" expansion, interpreted as an important long-term above-trend upward movement in a wide range of base material prices (e.g., Heap, 2005, 2007). Another interesting finding is that commodity price volatility has a tendency to revert back to the mean over time; however, during the last few decades the dynamics of commodity prices have shown that volatility has tended to be wider under floating than fixed exchange rates (Chen, 2010; Cuddington and Liang, 1998; Pindyck, 2004).

The second strand of interest is linked to the common observation that related and unrelated commodity prices have exhibited a tendency to move together (e.g., Baffes, 2007; Byrne et al., 2013; Cashin et al., 2002; Headey et al., 2010; Jerret and Cuddintong, 2008; Lombardi et al., 2010; Vansteenkiste, 2009).[3] The substantial proportion of significant cross-correlation found in the studies suggests that common factors may be at the heart of the commodity price co-movement. Some of the key factors that have caused commodity prices to rise in the last decade are: the decline in the real interest rate from the beginning of the new century (e.g., Byrne et al., 2013; Calvo, 2008; Frankel, 2008), the decline in the value of the US Dollar beginning in 2002 first against developed and later against many developing countries' currencies (e.g., Headey and Fun, 2010; Piesse and Thirtle, 2009), the importance of permanent or temporal shifts in global supply and demand patterns (e.g., Byrne et al., 2013; Headey and Fun, 2010; Helbling et al., 2008), the importance of uncertainty with respect to economic outcomes (particularly for investment, see e.g., Dixit and Pyndick, 1994), the role of speculation in both cash and derivatives markets (e.g., Ajanovic, 2011; Helbling et al., 2008; Piesse and Thirtle, 2009;), the recent and intense links between biofuels production and food commodity prices (e.g., Abott et al., 2008; Ajanovic, 2011; Headey and Fun, 2008; Headey et al., 2010; Kristoufek et al., 2012; Mitchell, 2008), and the most common observation that crude oil price changes present a positive pass-through to the overall nonenergy commodity prices (e.g., Baffes, 2007; Headey et al., 2010).

Other factors affecting prices have been found in different groups of commodities. For instance, the commodity stock decline as a result of deliberated policies since approximately 2000, the harvest failures due to unfavorable weather conditions (likely related to climate change) or the "trade shocks" such as exports restrictions, discretionary government-to-government purchases or panic purchases to ensure sufficient stocks to feed population, are among the factors that specifically have been found to affect food commodity prices (e.g., Headey, 2011; Headey and Fun, 2010; Headey et al., 2010; Lobell et al., 2011; Mitchell, 2008; Piesse and Thirtle, 2009, among others). In the case of oil prices, the political instability in the Middle East, Nigeria, and Venezuela, the supply decisions made by the Organization of Petroleum Exporting Countries (OPEC) and increasing Chinese demand are found to be main factors explaining oil prices rise (Headey and Fun, 2010; WRTG Economics, 2008).[4]

While specific supply and demand shocks in one commodity market may explain spill-over effects to related commodities, only macroeconomic shocks and speculation overreactions to new information or a more uncertain environment are able to explain the excess of co-movement for unrelated commodity prices (Labys et al., 1999; Pindyck and Rotemberg, 1990).

Some studies in this literature point to the existence of a striking degree of heterogeneity with respect to co-movement among different commodity prices (e.g., Byrne et al., 2013; Cashin et al., 2002; Lombardi et al., 2010). Such heterogeneity indicates that measurement and characterization of commodity price cycles may prove difficult. Similarly, it may be hard to identify the role of common factors driving movements in commodity prices. Some papers have exogenously selected related groups of commodities to tackle this shortcoming; especially important has been the analysis of metals (e.g., Chen, 2010; Jerret and Cuddington, 2008; Labys et al., 1999; Roberts, 2009) and agricultural commodities (e.g., Esposti and Listorti, 2013; Listorti and Esposti, 2012; Piesse and Thirtle, 2009, among many others).

In this study, however, we are interested in analyzing heterogeneity and co-movements in a wide group of commodity prices. We employ a general approximation based on the organization of the correlation matrix according to the closeness relation among its elements (commodity prices) and the construction of a hierarchical network derived from it. This network approach enables us to summarize the interaction and interdependence of all elements in the network, thereby presenting an accurate topology and hierarchy. Complex network analysis has been increasingly recognized as a powerful tool to model interactions between economic agents. It has been especially applied to economic topics such as: cross-border financial flows; international trade structure; stock and index market prices interaction; financial spillovers and contagion; and world economic interdependence, among others (e.g., Hidalgo and Haussman, 2009; Minoiu and Reyes, 2013; Miskiewicz and Ausloos, 2010; Reyes et al., 2010). Recently, this approach has been applied to biofuels and related commodity prices (Kristoufek et al., 2012).[5] To the best of our knowledge, this is the first work

[3] For instance, Byrne et al. (2011) apply panel of nonstationary and idiosincratic components to a 24 commodity prices for more than 100 years. They find evidence of a sizeable degree of correlation for 70% of the commodities included in their study.

[4] There are mixed empirical results regarding some factors. For instance, there are several studies which failed to find financial speculation in future markets being a major cause of commodity price rise (e.g., Buyuksahin and Harris, 2011; Irwin et al., 2009; Sanders and Irwin, 2010, among others) while other studies find positive evidence for some commodity prices (e.g., Ajanovic, 2011; Gilbert, 2010; Piesse and Thirtle, 2009). Food declining stocks are to some extent controversial in the literature; while some studies put the stress on this factor (Headey and Fun, 2010; Piesse and Thirtle, 2009) other works argue that stocks decline are driven by other factors rather than explicit policy decisions, the exception being China (Headey et al., 2010).

[5] In this article no dynamic analysis was implemented and, therefore, the authors do not study the dynamics of synchronism between commodity prices.

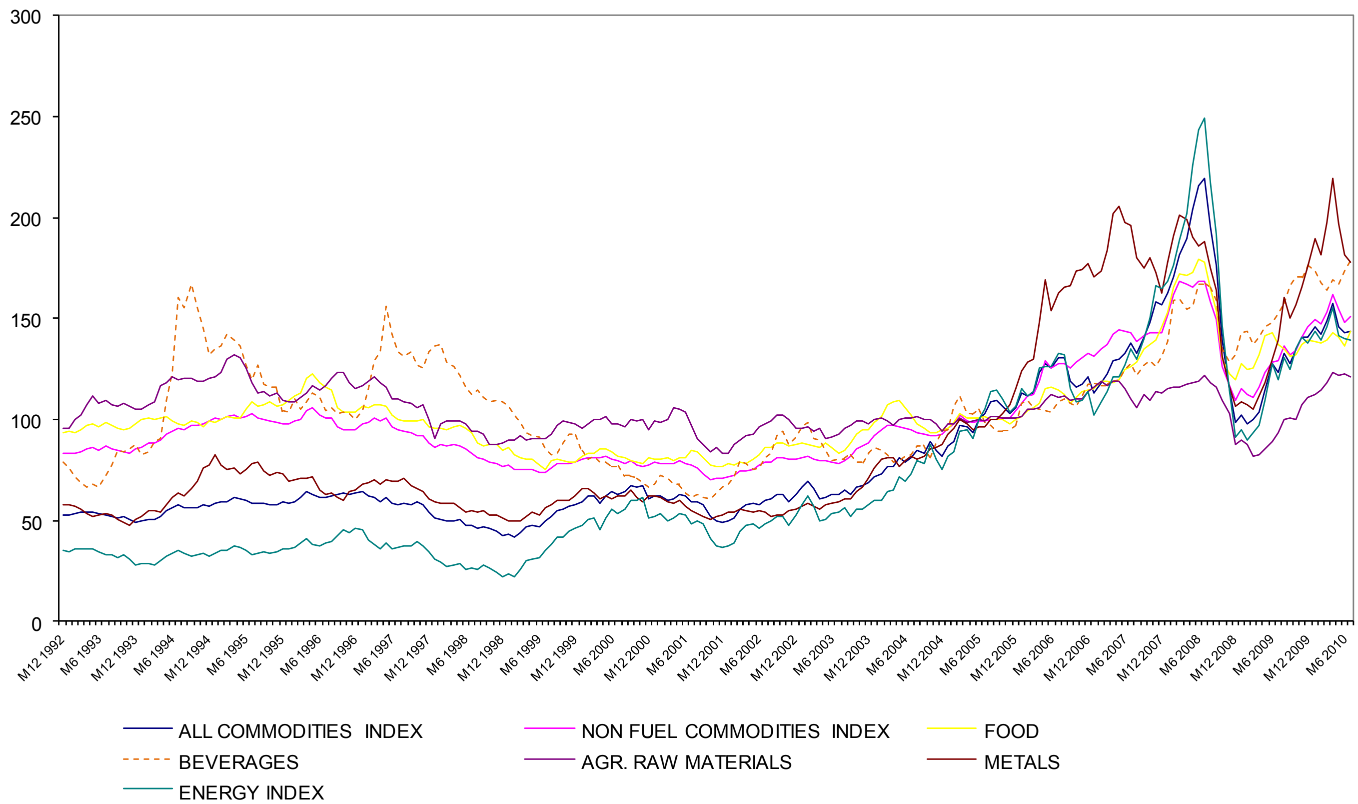

Fig. 1. Commodity prices, Price Index, 2005 = 100, December 1992 – July 2010. Source: IMF.

including a wide range of agricultural and nonagricultural commodities that employs this network approach.

We apply this methodology to a group of 32 agricultural, metals, and oil commodities. Using monthly data, we construct correlation and distance matrices for these commodities over the period 1992–2010. Based on these matrices, we build nested hierarchical structures of interactions that enable us to identify groups of commodity prices that have exhibited similar co-movement dynamic patterns.

This study contributes to the existing literature in several ways. Firstly, we measure the co-movement of commodity prices using a process that takes into account the overall dynamic connections involved in the price system. Secondly, we endogenously identify groups of commodities with similar co-movement patterns and more isolated commodity dynamics. This approach permits a better selection of commodity sets which will improve outcomes and knowledge in both commodity cycles and common factor analysis for future studies. Thirdly, the network analysis we introduce will potentially allow identification of spill-over effects inside and across groups of commodity prices.

The rest of the article is organized as follows. The next section describes the dataset and the numerical methods we employ. Section three presents and discusses the results. Finally, the article concludes with a brief summary and some policy implications.

2. Data and methodology

2.1. Data

This study considers a wide range of monthly commodity price indexes starting from December 1992 until July 2010. Our time series are taken from the International Monetary Fund database available online at http://elibrary-data.imf.org/. This dataset is selected as it includes an entire sample that measures different types of commodity prices. More specifically, we have used four main categories: food, agricultural raw materials, metals, and oil. Appendix A lists the 32 commodity prices (CP) included in the study.

The monthly rate of growth, *rCP*, is calculated in the usual way; therefore our complete dataset conforms to a matrix of 211 rows (monthly rates of growth) and 32 columns (number of commodities). Our time sample covers almost the last 20 years, taking into account declining nominal commodity prices during the 1990s, and then a permanent upward trend observable in the 2000s. Figure 1 represents commodity indexes since 1992. As can be observed, during the 1990s the path of most indexes is relatively stable and almost flat. Following this, an upward trend with two important spikes in the middle of 2008 and 2010

Additionally, a larger and more heterogeneous group of commodities has been included in our work.

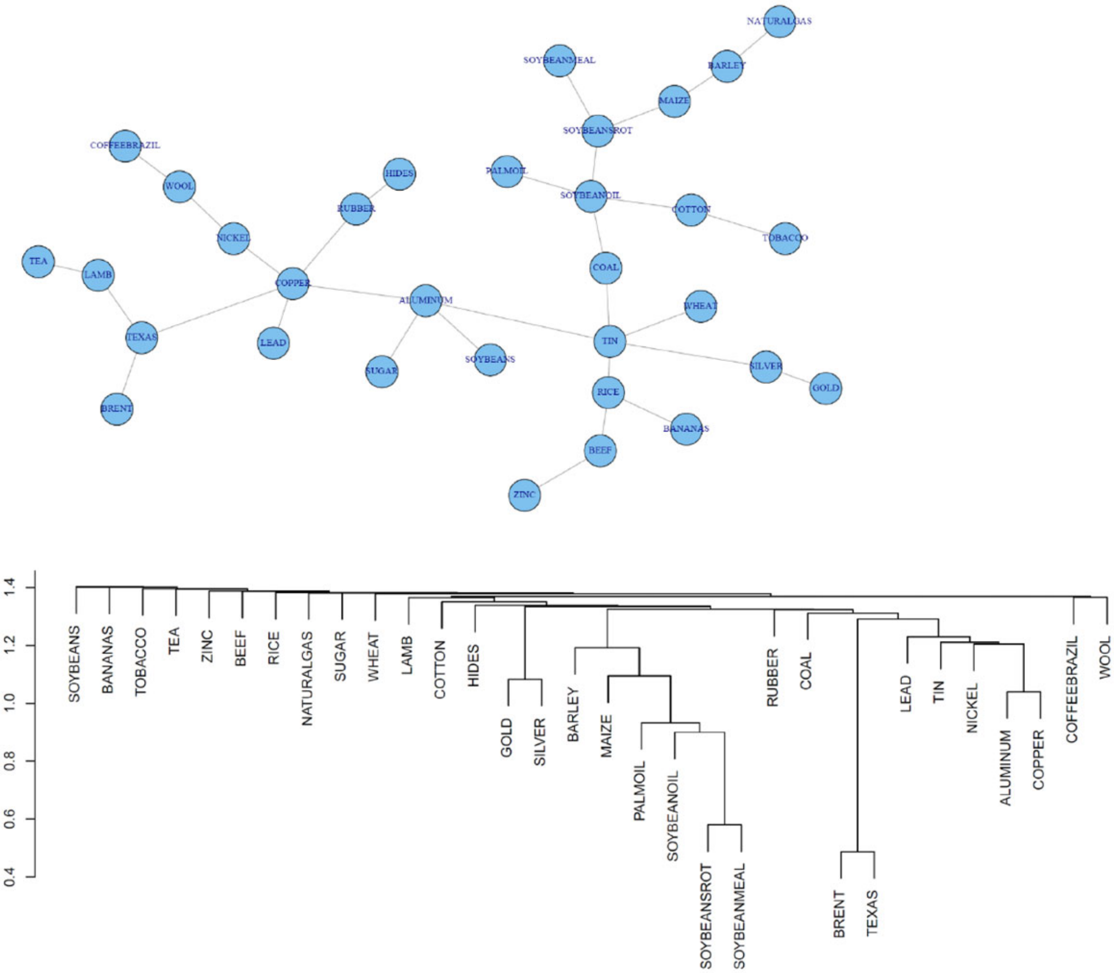

Fig. 2. MST (upper) and HT (lower): 1993–2010 using 33 commodities.

is observed. A certain degree of co-movement is apparent at the end of the period, and is especially intense between the *energy* and the *all commodities* index.

2.2. Numerical methods

2.2.1 Hierarchical analysis

To quantify the degree of co-movement between two or more time series, we employ the most commonly used linear measure in the economic literature: the Pearson cross-correlation coefficient, ρ.

Given two time series, $\bar{x}_i = x_i(k), k = 1, N_{win}$ and $\bar{x}_j = x_j(k)$, $k = 1$, N_{win}, the Pearson correlation coefficient between country *i* and country *j* in a temporal window of N_{win} data points is defined as

$$\rho'_{i,j} = \frac{\sum_{k=1}^{N_{win}} (x_i(k) - \overline{x_i})(x_j(k) - \overline{x_j})}{\sqrt{\sum_{k=1}^{N_{win}} (x_i(k) - \overline{x_i})^2 \sum_{k=1}^{N_{win}} (x_j(k) - \overline{x_j})^2}} \tag{1}$$

where, $\bar{x}_i$ is the mean value of $x_i(k)$ in the period considered and $k = 1$, N_{win} corresponds to each of the $rCP_i(k)$ time series. Taking into account all possible pair of commodities a diagonal correlation matrix is formed. Because a metric distance is actually needed to construct an appropriate taxonomy, following Gower (1966) we define the distance *d(i,j)* between the evolution of the two time series x_i and x_j as

$$d(i, j) = \sqrt{\rho_{i,i} + \rho_{j,j} - 2\rho_{i,j}} = \sqrt{2(1 - \rho_{i,j})} \tag{2}$$

where $\rho_{i,j}$ is the absolute value of the Pearson correlation coefficient $\rho'_{i,j}$, and $d(i, j)$ fulfils the three axioms of a distance:

- $d(i, j) = 0$ if and only if $i = j$
- $d(i, j) = d(j, i)$
- $d(i, j) \leq d(i, l) + d(l, j)$ (3)

In this way the distance, $d(i, j)$, shows similarities in co-movements between two different prices such that two synchronized commodities are close one from each other (small distance) while two independent prices are far one from each other (large distance).

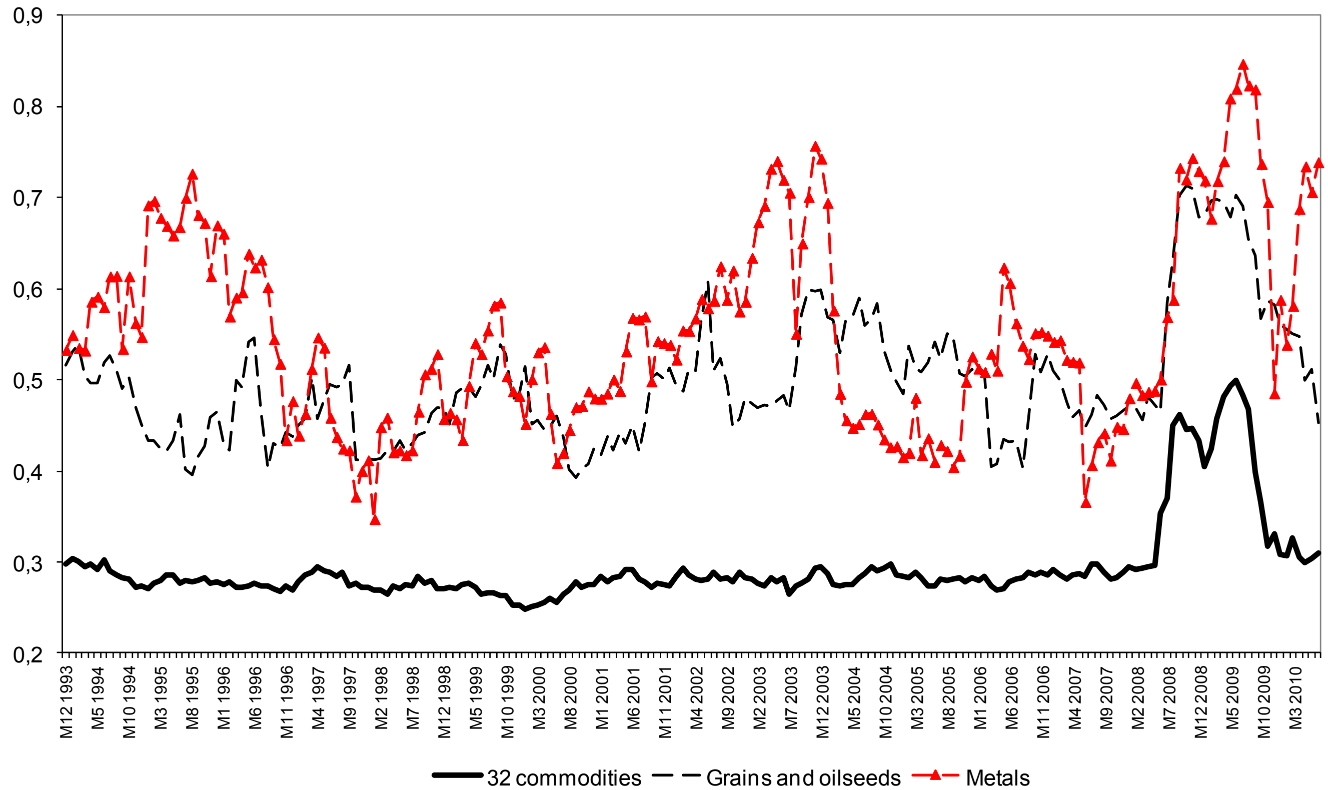

Fig. 3. Normalized correlation coefficients: 12-month overlapping windows. 1993–2010. Metals (aluminum, copper, nickel, tin, and lead) oilseeds (barley, maize, palmoil, soybean oil, soybean rot, soybean meal).

At this stage, we have a matrix representing all possible pairs of metric distances in the selected commodity prices. Based on the metric distances between commodities, we are able to directly obtain networks inside the matrix.

By using the Kruskal algorithm (Kruskal, 1956), the so-called minimum spanning tree (MST) is constructed in a straightforward manner. The process begins with connecting the closest commodity prices given by their shortest metric distance, $d(i,j)$, in this case, BREND and TEXAS. The following shortest distance is SOYBEANSROT and SOYBEANMEAL, which create another cluster followed by SOYBEANOIL that is directly linked to the previous cluster. At this stage we already have two clusters, the OIL cluster and the one related to soy. By linking the remaining commodity prices according to their closeness to the previously connected commodities, we finally construct a tree with the 32 commodities and 31 links among them. Figure 2 shows the complete MST given by the distance matrix $d(i, j)$. The interaction in the MST is a simple loop-free network that can comprehensively display the most important links and communities in a complex network.

It is also possible to construct a hierarchical organization, hierarchical tree (HT), using the single-linkage clustering algorithm (Johnson, 1967) in which "similar" objects (i.e., single commodities or group of commodities) are clustered in each step according to their characteristics. This classical agglomerative single-linkage algorithm enables the construction of a hierarchical dendrogram to illustrate the clustering characteristics of the data organization. In fact, clustering data into groups of members with tight connections among them is a usual way to define *communities* (Wasserman and Faust, 1994) in a complex network of interactions, where each member of a particular community shares some characteristics with other members of the same community. In this sense, by means of the MST and the HT we are extracting commodity clusters from the correlation matrix that have shown similar price dynamics.[6]

[6] To check for robustness on the obtained clusters, we have additionally used the Kendall nonlinear measure as a quantifier of co-movement in our time series. This measure summarizes the number of times every pair of data series moves in the same direction from every point in time to the next one, regardless of the intensity of the movement itself. In this spirit, we have also employed an "average" algorithm for clustering commodity prices. This clustering method takes into account not only the most important connection for every commodity price as the Kruskal´s algorithm does but their average distance to everyone else. Results from this additional checking roughly yield the same communities, which supports the robustness of the present calculations. These additional results can be obtained by directly contacting the authors.

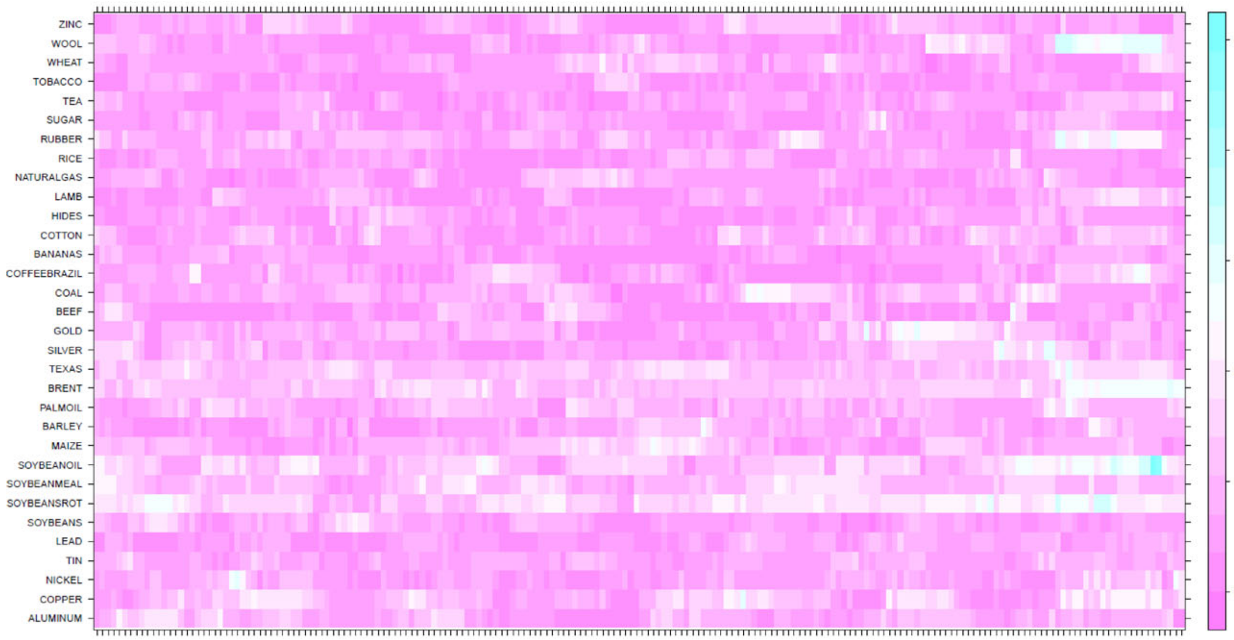

Fig. 4. Intensity of connections inside the MST. 33 commodities. MST is built over 12-month overlapping windows.

2.2.2. Temporal windows analysis

To examine the temporal behavior of interdependence relations among commodity prices, we also calculate distance correlation matrices for overlapping windows of 12, 18 and 24 months forward in time. We cover the whole sample by moving each temporal window 1-month at a time beginning in 1992. For simplicity of exposition we will only report the results with the 12-month window.[7]

In each time window matrix we create two synchronization measures. We label the first as *global correlation.* It is the sum of all pairs of correlations in the matrix. To enable comparisons among different clusters of unequal numbers of commodities, we sum the matrix coefficients for each window and normalize them to the number of commodities. Each dataset thus represents the sum of the distances among all commodity pairs in the past time window. We also calculate the corresponding MSTs in every window. By summing all distances in the tree and normalizing them using the same method, we build a measure that we term *MST cost*. This is our second synchronization measure.

The *global correlation* represents the interdependence among all commodities, while the *MST cost* shows the evolution of the interdependence of the closest connections. The higher the value of the normalized correlation coefficients, the tighter the coupling inferred among all commodities. Conversely, the smaller the value of the sum of distances represented in the MST cost, the tighter the co-movement of the first distances between commodity prices.

[7] As noted, we have repeated these calculations in different temporal windows to check for robustness and stability on the results. Results arising from these checking calculations yield similar results. Eighteen and 24-time windows results can be obtained by directly contacting the authors.

3. Empirical results

3.1. Commodity hierarchical structure

Figures 2a and 2b show the MST and HT respectively, covering the entire sample 1992 (M12) to 2010 (M7). Figure 2a shows a structure based on the metric distance matrix among all commodities, providing a rough idea of the topological organization where more synchronized commodity prices are connected by a direct link between them. In this manner, we are only able to observe which commodities prices are more connected with others and which ones seem to have a more specific price path of their own. Part (b) permits analysis of the hierarchy in that structure according to the proximity in the price dynamics. Therefore, the HT distinguishes between groups of commodities with similar price dynamics and commodities with more isolated paths. Moreover, the HT shows the intensity of price connections (co-movement) for the endogenously created clusters of commodities, which is something that MST is not able to display.

Figure 2 shows an important heterogeneity in the topological structure. In our set of commodities, three different groups appear: metals (copper, tin, nickel, lead, and aluminum), oil (Brent and Texas), and thirdly grains and oilseeds (soy and soy-derivatives, maize, barley, and palmoil). Within these groups, the oil group identified by BRENT and TEXAS show the shortest distance in our data set (which is as expected due to their ability to be substituted). Grains and oilseeds is the next group with a closer correlation in their price dynamics. Finally, the metal group has shown higher distances amongst the various components than previous groups have. In addition, gold and

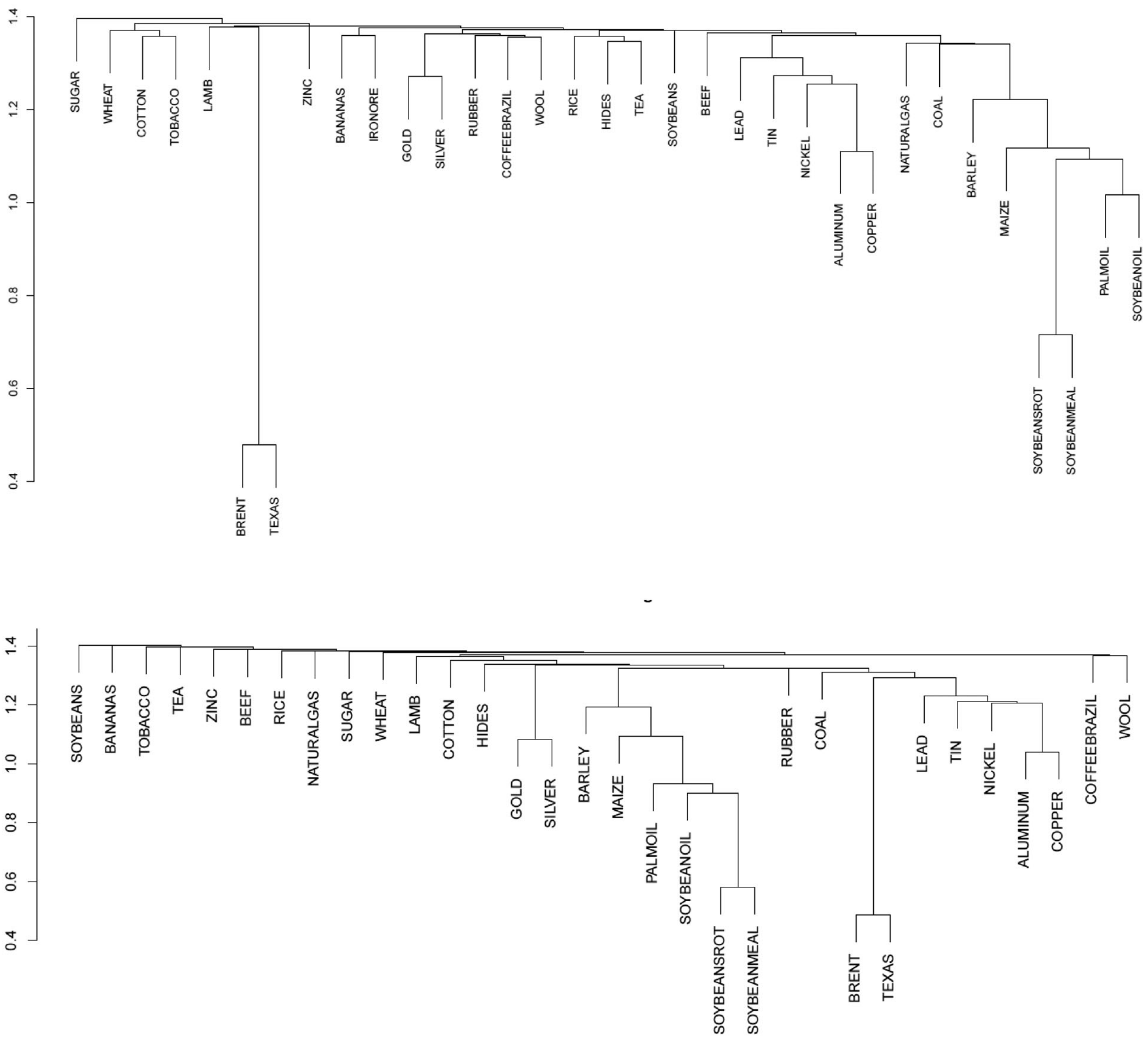

Fig. 5. Hierarchical Tree, 33 commodities. (upper) 1993 (January) – 2001 (December). (lower) 2001 (January) – 2010 (July).

silver are also aligned in their price synchronization, but present higher distances than the previous groups of commodities.

However, there are still an important number of commodity prices with no apparent price co-movements. Some of the commodity prices that are not highly connected are sugar, lamb, beef, rice, tobacco, and coffee. Therefore, there exists an important degree of heterogeneity in the price dynamics for our commodity dataset. Several of the price dynamics seem to move by their own while others co-move, forming sectoral groups. To check for robustness we split our time sample into two periods; 1993–2001 and 2001–2010. In figure 5 in the Annex, both HTs are displayed. Both of them show that the previous structure remains fairly stable in both periods. The same three groups are clearly identified. Consequently, the intensity of co-movement in prices is related to sectoral groups of commodities rather than general co-movements.

3.2. *Time windows analysis*

Figure 3 shows the normalized correlation coefficients for all commodity prices. In this figure each data point represents the normalized correlation coefficients over the past 12 months. As already explained, this analysis summarizes interactions between all pairs of commodity prices, giving information of co-movements in the whole price system. The bold line shows co-movements for the whole group of commodities. It is clear that the dynamics of co-movements have remained stable across the whole sample period. There is only one period beginning in the middle of 2008 for which a sharp increase in synchronization can be observed. This sharp change in price interactions lasted till the end of 2009, at which point the price synchronization in our group of commodities returned to previous levels. During this short period, global correlation coefficients increased more than 50%, reaching values close to 0.5. To some extent, the synchronization in commodity prices indicates that the 2008–2009 period is an outlier in the last 20 years. Hence, the rise in co-movements has not been a structural and permanent feature in the commodity cycle.[8]

The normalized correlation coefficients for "metals" and "grains and oilseed" groups are plotted in the same figure. Both groups show higher correlation coefficients than the overall group of 32 commodities. In fact, correlation coefficients are almost double the size of the overall group. Furthermore, the dynamics of the synchronization differ in both groups across the period sampled and only during 2008–2009 do we observe that co-movements increase for both groups.

Finally, to determine the temporal importance of our set of commodities in the network, we calculate an "intensity" measure based on the number of connections for each country inside the MST, weighted by the metric distance of these connections (intensity of the synchronization). We compute the number of connections divided by their metric distances, which reveals not only how every country moves within the network throughout time but also shows if they become more or less synchronized. To investigate the time sample evolution, we conduct the calculations as before, using overlapping windows of 12 months. In Fig. 4, each square represents the number of connections weighted by their intensity over the past 12 months. Higher values (blue) represent more connected commodity prices while lower values (pink) represent less connected commodity prices.

Two main results arise from this analysis: firstly, tighter and more permanent connections are observed in the oilseed group, particularly in soy prices. For metals, copper seems to be the most connected price in this group. In this sense, copper and soy represent some sort of "leader" behavior in their respective groups. Secondly, there is a clearly observable increase in the intensity of connections at the end of the time sample. This increase affects most of the commodities, coinciding with the most synchronized commodity prices period we have previously shown and therefore supports conclusion made beforehand.

4. Conclusions and policy implications

In this study we have studied co-movements in a wide group of commodity prices during the sample period 1992–2010. We summarize synchronization and interdependence by means of network analysis, describing topology and hierarchy in co-movements dynamics. Furthermore, we are able to capture the existing heterogeneity in the degrees of synchronization between commodity prices. This methodology permits us to overcome two shortcomings in the related literature. First, it allows to endogenously revealing groups of commodities with similar synchronization patterns. This feature is important as it indicates sets of commodities to be used in empirical studies that will obtain more accurate results, to analyze, for instance, common factors driving prices. In addition, this methodology summarizes the interaction of all commodity prices, taking into account the existing heterogeneity and complexity presented in the price system.

Two main results arise from this study. Firstly, the hierarchical structure has displayed three groups of sectoral commodity prices which have demonstrated similar price dynamics. Metals, oil, and oilseeds and grains have shown homogenous price movements inside these groups while other commodities have observed more specific patterns. A second key finding is that we do not observe a persistent increase in the degree of co-movement of the commodity prices over our sample period. On the contrary, co-movements have remained stable in the last 20 years and we only observe an excess of co-movement between mid 2008 to the end of 2009. After this short period, co-movements returned to previous levels. In this sense, we should consider this high co-movement period as an outlier in the last 20 years rather than a permanent change in commodity price dynamics.

Therefore, our results suggest that the excess of co-movement for unrelated commodity prices seem not to be driven by permanent shifts in global supply and demand patterns as commodity price synchronization quickly returned to previous levels after 2009 (in line with Helbling et al., 2008; Dixit and Pyndick, 1994; Labys et al., 1999). Even highly speculative, these results support the idea that the intense uncertainty occurred at the beginning of the global financial crisis by mid 2008 might be a more plausible reason for this excess of co-movement. Moreover, it might be reflecting the time confluence and the interlinkage of the food, energy, and financial crises by mid 2008 (e.g., Headey and Fun, 2008; Headey et al., 2010).

Additionally, identifying groups of commodities with similar price movement behavior suggests that they are affected by common factors, and indicates where there may be more specific factors affecting the prices of other commodities as the literature on the issue has tended to emphasize especially in food commodities (e.g., Headey and Fun, 2008; Headey et al., 2010; Mitchell, 2008; Piesse and Thirtle, 2009, among many others) or metals (e.g., Batten et al., 2010; Chen, 2010). In this sense, our hierarchy shows the intense heterogeneity in commodity price dynamics, which is useful for evaluating diversification risks arising from both production specialization patterns and portfolio optimization.

[8] Results from the synchronization measure MST cost show the same shape than those obtained in the global correlation. Unless not presented in the article they can be directly obtained from the authors.

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