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

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Abstract:

This paper 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. These results suggest that speculation and uncertainty are drivers of the sharp slump in commodity prices synchronization.

1. Introduction and motivation

Commodities are frequently the most important source of export foreign revenues for many developing and some developed countries. Additionally, trading in commodities, in both derivatives and cash markets, has become an important investment asset alternative to traditional stocks and bond portfolios[1]. Movements in commodity prices therefore affect both policy-makers 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 and, therefore, puts permanent pressure on the balance of payments position; 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.

From a more global point of view, the importance of commodity price fluctuations lies in their interaction with the transmission of business cycles and in affecting inflation rates not only in developing countries (Borenzstein and Reinhart, 1994). During the last spike in commodity prices during 2007-2008, commodity-importing low and middle income countries suffered current account deterioration, rising inflation and higher interest rates, which have negatively impacted poor rural areas, increasing the number of people living in extreme poverty.

Commodity price fluctuations have recently attracted the attention of policy-makers, researchers and the general public, as the world economy has (over the past decade) experienced the longest commodity price boom since the Second World War. 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%. If we look at the IMF commodity price index for developing countries, the comparison is even more striking: during the 1990s, commodity prices for developing countries dropped 8% while in the next decade the increase was 190% in nominal terms. Moreover, as observed in figure 1, the highest increase in commodity prices occurred after 2007 whereas most commodity prices were either stagnant or on a downward trend during the

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[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, Ciner and Lucey, 2010)

1980s and 1990s. Therefore, the current boom is broader-based and longer-lasting than those in the past (see Helbling et al., 2008).

Taking into account the economic importance of fluctuations in commodity prices and their huge spike during the last few years, it is not surprising that this topic has attracted much attention among academics and policy-makers. There are two main strands of interest in the recent literature. One of them has placed attention on commodity prices' time series properties to examine the duration, magnitude and volatility in world commodity cycles (e.g., Cuddington, 1992; Deaton, 1999; Cashin et al., 2002; Roberts, 2009; Chen, 2010). Some results arise from this literature: firstly (and probably most important for policy advice), 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 the existence of long-term trends in commodity prices (Cashin et al., 2002; Roberts, 2010) 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, 1999; 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., Pindyck and Rotemberg, 1990; Cashin et al. 2002; Jerret and Cuddintong, 2008; Vansteenkiste, 2009; Lombardi et al., 2010; Byrne et al., 2011)[2]. 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 real interest rate (e.g., Frankel, 2008; Calvo, 2008), the importance of permanent or temporal shifts in global supply and demand patterns (e.g., Helbling et al., 2008), the importance of uncertainty with respect to economic outcomes (particularly for investment, see e.g., Dixit and Pyndick, 1994)), and the role of speculation in both cash and derivatives

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[2] 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.

markets (e.g., Helbling et al., 2008). 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 (Pindyck and Rotemberg, 1990; Labys et al., 1999).

Both strands of interest in the literature share an interesting shortcoming. Results from some studies that have included a broad range of commodities clearly point to the existence of a striking degree of heterogeneity with respect to co-movement among different commodity prices (e.g., Byrne et al., 2011; Lombardi et al., 2010; Cashin et al., 2002). Such heterogeneity indicates that measurement and characterization of commodity price cycles may prove difficult. Likewise, 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 metal cycles which was possible due to the availability of comprehensive time series data (e.g., Jerret and Cuddington, 2008; Chen, 2010; Roberts, 2009; Labys et al., 1999).

We tackle this shortcoming by employing 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 of the overall co-movements involved in the commodity price markets. Hence, our principal aim in this study is to present a better description of the existing heterogeneity in the extent and evolution of the international economic co-movements in the commodity prices. Our approach utilizes complex networks and cluster analysis to properly describe the architecture and evolution of the temporal structure in commodity price dynamics. Such an approach is in line with existing work from fields that study financial markets, synchronization of business cycles or international integration of trade flows (e. g., Mantegna, 1999; Miskiewicz and Ausloos, 2010; Reyes, Schiavo and Fagiolo, 2010; Matesanz et al., 2011).

We apply our methodology to a group of 32 oil and non-oil commodity prices. Using monthly data, we first 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 and other commodities that seem to be more isolated in terms of price dynamics. Once we have uncovered this topology, we measure the evolution of the co-movements inside the identified groups and the evolution of the 32 commodities as a whole. Finally, we observe the evolution of the importance of each commodity in the network to further analyse how specific shocks in one commodity can spread through the commodity topology.

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 are able to isolate 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, we introduce a network importance analysis that will potentially allow identification of spill-over effects in commodity price markets. Fourthly, through the identification of similar co-movement groups, we improve economic policy decisions regarding the reduction of risks associated with selection of a more diversified[3] commodities set.

The rest of the article is organized as follows. The next section describes the dataset and the numerical methods we have employed. Section three presents and discusses the results. Finally, the paper 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://www.imfstatistics.org/imf/about.asp. 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 33 commodity prices (CP) included in the study.

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[3] Diversification in terms of the set of common factors affecting variations in commodity prices.

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 33 columns (number of commodities). Because the paper is focused on the structure and evolution of the topology and hierarchy of the commodity price market system, we have not deflated our time series. Finally, our time sample covers almost the last 20 years, taking into account declining 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 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* indexes.

[figure 1 around here]

2.2 Numerical methods

2.2.1 Hierarchical analysis

To quantify the degree of co-movement between two or more time series, we used 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 time window of N_{win} is defined as

$$\rho_{i,j} = \frac{\sum_{k=1}^{N_{win}}(x_i(k) - \bar{x}_i)(x_j(k) - \bar{x}_j)}{\sqrt{\sum_{k=1}^{N_{win}}(x_i(k) - \bar{x}_i)^2 \sum_{k=1}^{N_{win}}(x_j(k) - \bar{x}_j)^2}} \qquad (1)$$

In our particular case, $\bar{x}_i = x_i(k), k = 1, N_{dat}$ corresponds to each of the $rCP_i(k)$ time series. Therefore, $1 \le i \le 33$ is the number of commodity prices and $1 \le k \le N_{win}$ is the number of months. To transform correlations, $\rho_{i,j}$, into distances, we follow Gower

(1966) and define the distance $d(i,j)$ between the evolution of the two time series x_i and x_j as

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

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

- $d(i,j) = 0$ if and only if $i = j$
- $d(i,j) = d(j,i)$

- $d(i,j) \leq d(i,l) + d(l,j)$ \qquad (3)

At this stage, we have a distance matrix representing all possible pairs of metric distances in the selected commodity prices. Based on nodes (commodities) and links (distances) between them, we are able to directly obtain topological and hierarchical 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, and then linking the remaining commodity prices according to their closeness to the previously connected commodities. In the distance matrix, the next 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 with soy. Proceeding in the above manner, we finally construct a tree with the 33 commodities and 32 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. We can then calculate the "cost" of the MST by summing up all the links among all the MST nodes. MST cost sheds light on the degree of correlation (or synchronization) among the whole set of elements in the network: the lower the cost, the smaller the distance between MST members and therefore the tighter the links among them. The MST cost therefore

gives information regarding synchronization of the most important links for every commodity.

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 dendogram 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 & 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. There are several algorithms aimed to detect communities in a network (Boccaletti et al., 2006). The simplest of these is based on the analysis of the dendogram, because a simple horizontal cut of a hierarchical tree at a particular distance automatically yields clusters/communities of tightly connected members. In the rest of the paper, we will use a more refined method (Langfelder et al., 2008) to extract communities from a hierarchical tree. This method analyses the structure of the hierarchical tree dynamically and extracts from it the relevant clusters/communities[4].

2.2.2. Time 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[5].

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

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[4] To check for robustness on the obtained clusters, we have additionally used the Kendall non-linear 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 every other ones. 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.

[5] Results arising from different time windows yield similar results. 18 and 24-time windows results can be obtained by directly contacting the authors.

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.

3. Empirical results

3.1. Commodity hierarchical structure

Figures 2(a) and 2(b) show the MST and HT respectively, covering the entire sample 1992(M12) to 2010 (M7). Figure 2(a) 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, oil and grains, and oilseeds. Within these groups, the oil groups identified by BREND 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 including aluminum, copper, tin, lead and nickel has shown

higher distances amongst the various components than has previous groups. In addition, gold and 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 A1 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. Therefore, the intensity of co-movement in prices is related to sectoral groups of commodities rather than general co-movements.

[figure 2 around here]

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 twelve 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 blue 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.

The normalized correlation coefficients for "metal" 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.

[figure 3 around here]

Finally, to determine the temporal importance of our set of countries 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). Therefore, 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 figure 4, each square therefore represents the number of connections weighted by their intensity over the past twelve months. Higher values (blue) represent more connected commodity prices while lower value (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" behaviour 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.

[figure 4 around here]

4. Conclusions and policy implications

During the last few years, the world economy has experienced the longest commodity price boom since the Second World War. This has attracted academic and policy

attention regarding the duration, magnitude, volatility and co-movements in world commodity cycles (e. g., Cuddington, 1992; Cashin et al., 2002; Byrne et al., 2011). In this study we have focused on 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 us to endogenously reveal groups of commodities with similar synchronization patterns. This feature is important as it indicates sets of commodities for use in empirical studies that will obtain more accurate results. 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. Oilseeds, metals and oil have shown homogenous price movements 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.

Our results suggest that the excess of co-movement for unrelated commodity prices is more driven by speculation and uncertainty than by permanent shifts in global supply and demand patterns (in line with Dixit and Pyndick,1994; Labys et al., 1999; Helbling et al., 2008). Additionally, identifying groups of commodities with similar price movement behaviour suggests that they are affected by common factors, and indicates where there may be more specific factors affecting the prices of other commodities. 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.

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Annex

List of commodities

Aluminum, Bananas, Barley, Beef, Coal, Coffeebrazil, Copper, Cotton, Gold, Hides, Lamb, Lead, Maize, Naturalgas, Nickel, Palmoil, Brent, Texas, Rice, Rubber, Silver, Soybeans, Soybeansrot, Soybeanmeal, Soybeanoil, Sugar, Tea, Tin, Tobacco, Wheat, Wool, Zinc.
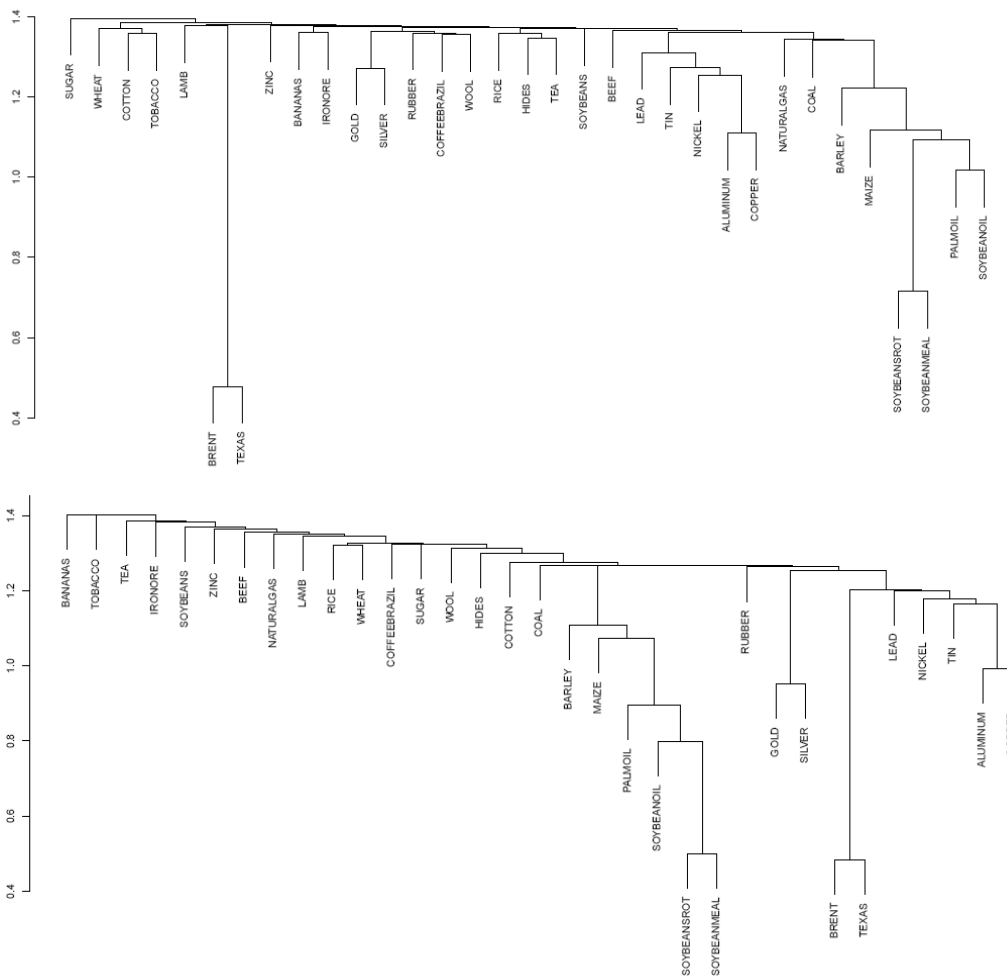

Figure 1A. Hierarchical Tree, 33 commodities. (a) 1993 (January) - 2001 (December). (b) 2001 (January) - 2010 (July).
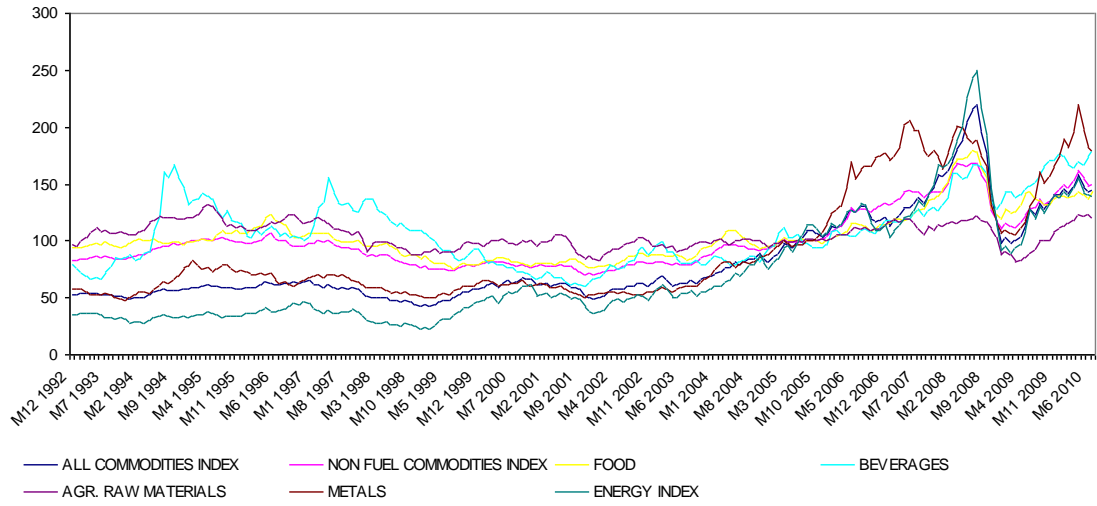
Figure 1. Commodity prices, Price Index, 2005=100, December 1992 – July 2010.
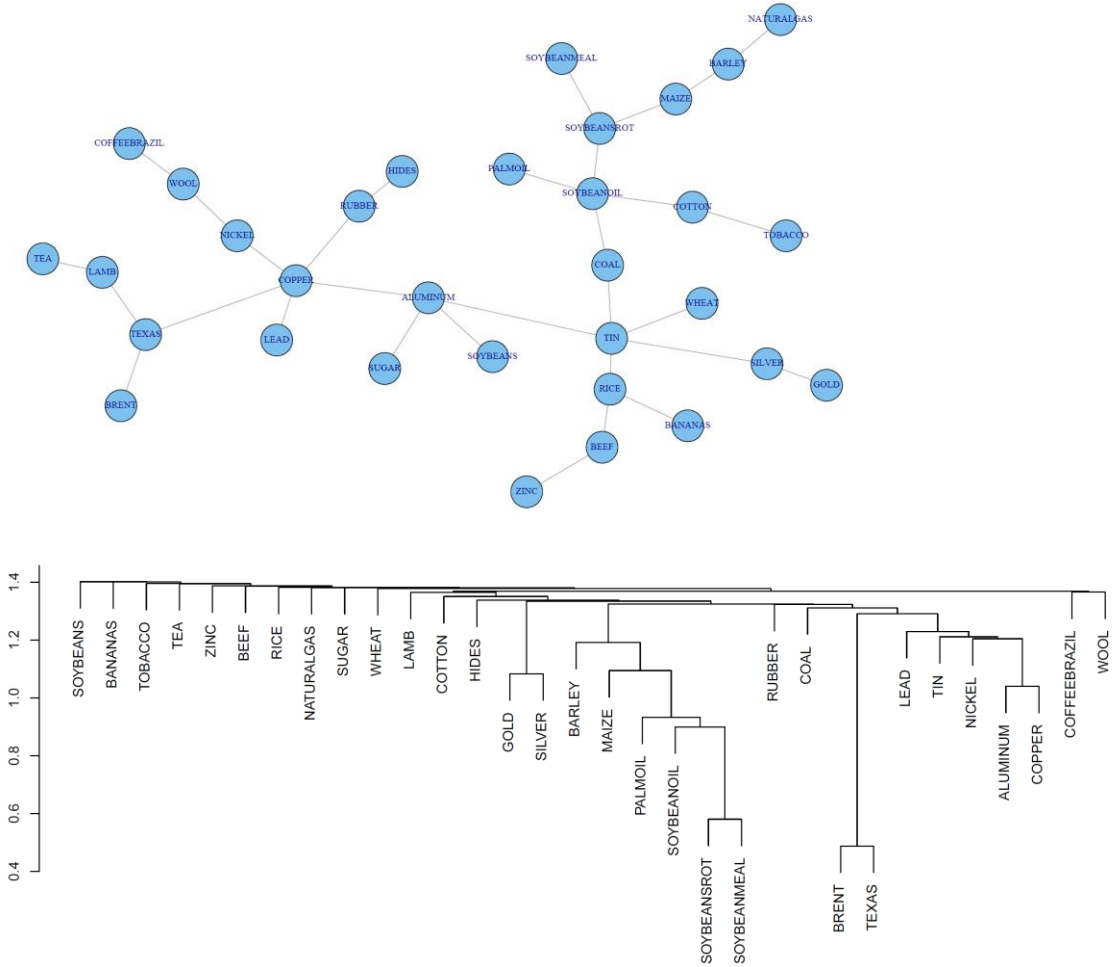Source: IMF.

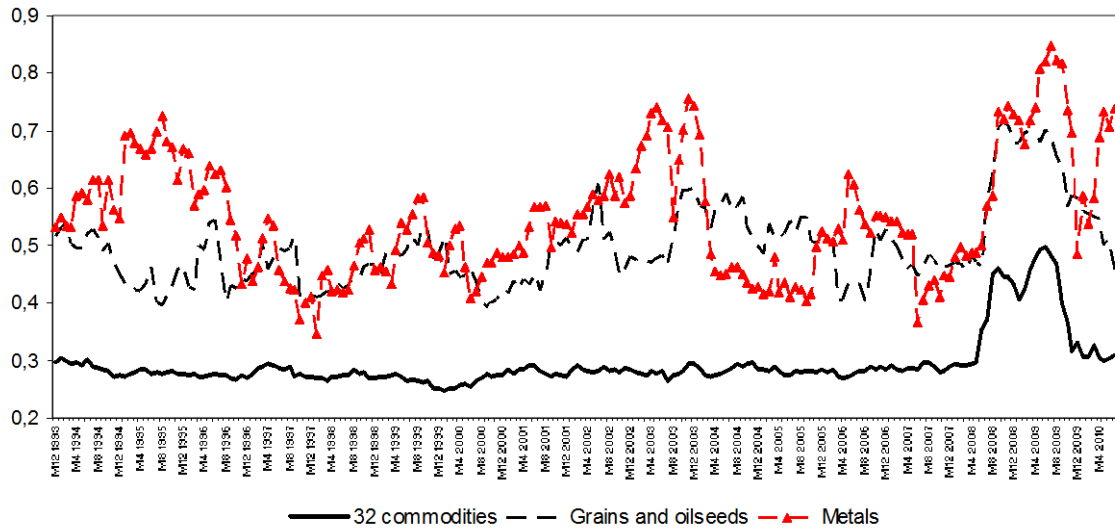**Figure 2**. MST (a) and HT(b): 1993–2010 using 33 commodities.

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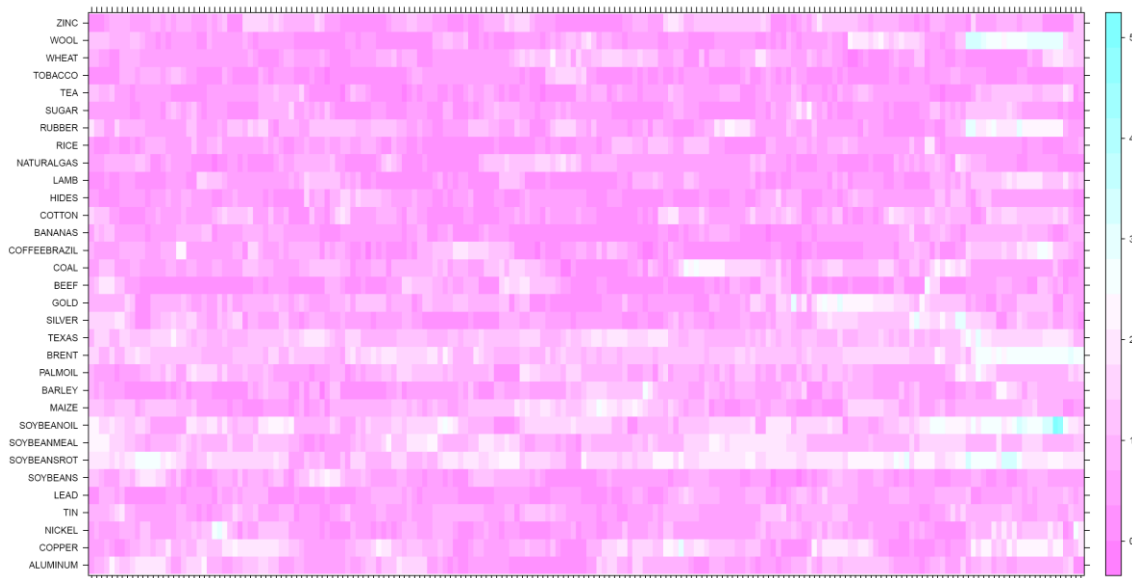

Figure 4. Intensity of connections inside the MST. 33 commodities. MST is built over 10-year overlapping windows.