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Graph Theory Approach to Prices Transmission in the Network of Commonly Used Liquid Fuels

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Abstract:
We analyze the relationships within the liquid fuels system and its associated supply chain using innovative network filtering methods, namely the Minimum Spanning Tree and Triangulated Maximally Filtered Graph. Our findings reveal that biofuels form robust connections with their feedstocks that intensify during periods of economic or legislative uncertainty. Conversely, fossil fuels form detached clusters primarily influenced by global economic conditions. These insights significantly enhance our understanding of the liquid fuels market dynamics and suggest potential avenues for integrating additional liquid fuels into the supply chain network.

JEL: C38, Q41, Q55
Keywords: fossil fuels, biofuels, crude oil, complex network analysis, community detection, triangulated maximally filtered graph, minimum spanning tree, relationship analysis

1 Introduction

To explore the connections between commonly used liquid fossil fuels, biofuels, their supply chain commodities, and other possibly relevant commodities, we propose a graph theory network analysis methodology that provides us with the tools to explore the network and the groups (communities) of commodities or financial assets that may capture these formed relationships.

Using a novel methodological approach for the analysis of the fuel supply chain, we employ network filtering techniques like the Minimum Spanning Tree (MST) and Triangulated Maximally Filtered Graph (TMFG). These methods extract the network structure from the underlying data. Subsequently, the Louvain algorithm is utilized to scrutinize this structure, revealing the formation of asset groups (communities) within the network. These methods are applied to two types of correlation matrices characterizing the price transmission in the supply chain and the whole network of potentially related assets. These are either the full correlation matrix or the spectrally decomposed correlation matrix.

We build on the literature on network communities, as represented by Korbel, Jiang, and Zheng (2019), where spectral decomposition and network filtration methods were used to find clusters (communities) in complex network analysis of financial data. Previously, Kristoufek, Janda, and Zilberman (2012) or Janda, Krištoufek, Schererová, and Zilberman (2021) investigated the linkages of food and biofuels with the minimum spanning tree algorithm. Our approach is unique in keeping the focus on commonly used liquid fuels while considering a wide supply chain of 39 commodities and assets. The most simple supply chain we consider is an upstream relation between crude oil and gasoline in the sense of Bastianin, Galeotti, and Manera (2014b); Valenti, Bastianin, and Manera (2023). We also consider the related energy commodities of heating oil and natural gas similarly to Bastianin, Galeotti, and Polo (2019). However, our main extension of the simple liquid fuel supply chain is based on structural change (Beckman, Hertel, Taheripour, & Tyner, 2012) caused by extensive incorporation of biofuels into this supply chain since the beginning of 21st century, which received much attention in the past decade (Ciaian & Kancs, 2011; de Gorter, Drabik, & Just, 2015; Drabik, Ciaian, & Pokrivcak, 2016; Drabik, de Gorter, Just, & Timilsina, 2015; Drabik, de Gorter, & Timilsina, 2014; Rajcaniova, Drabik, & Ciaian, 2013; Rajcaniova & Pokrivcak, 2011; Reboredo, 2012a).

The inclusion of biofuels naturally leads to consideration of their feedstock (Bastianin, Galeotti, & Manera, 2016) and other agricultural commodities (Bastianin, Galeotti, & Manera, 2014a) which directly compete for the use of agricultural land (Rajcaniova, d'Artis Kancs, & Ciaian, 2014). While we should not expect as wide an expansion of biofuels as forecasted at the time when our dataset starts (2003), they are still a lasting part of the liquid fuels supply chain, driven both by their technological properties and policy support through US Renewable Fuel Standard (Taheripour, Baumes, & Tyner, 2022) and similar measures in other countries. In some segments like aviation, biofuels are still likely to stay as a primary pathway to decarbonization (Taheripour, Sajedinia, & Karami, 2022). An important part of our approach is also an inclusion of wider dimension of financial links, in particular stock exchange (Bastianin & Manera, 2018; Reboredo & Rivera-Castro, 2014; Reboredo, Ugolini, & Hernandez, 2021) and economic growth (Bastianin, Galeotti, & Manera, 2017; de Gorter, Drabik, Just, & Kliauga, 2013) connections of our supply chain. Because of the global nature of the fuels supply chain, we also have to consider exchange rates between the main currencies used for pricing the commodities covered in our model in a similar vein to (Reboredo, 2012b; Reboredo & Rivera-Castro, 2013; Reboredo, Rivera-Castro, & Zebende, 2014; Reboredo et al., 2021).

2 Methodology

A complex network of the supply chain of commonly used liquid fuels can be defined as a graph that exhibits significant non–trivial topological characteristics, such as the existence of highly interconnected nodes or the emergence of community structures, where the term "community structures" refers to a division of the nodes within a network into groups or clusters based on their connectivity. Networks like this are commonly utilized to represent real-world systems, such as biological systems (Costa, Rodrigues, & Cristino, 2008), transportation systems (Cheung & Gunes, 2012), and in our case, financial markets of fuels-related commodities. Complex networks have emerged as a versatile and intriguing tool for characterizing the structural dependencies among interacting units (Albert & Barabási, 2002).

2.1 Correlation matrix

The initial stage of our complex network analysis is to determine a suitable network representation for time series data. This involves implementing an algorithm to determine the network edges and, therefore, the position of the network vertices. Before that, we need to calculate a matrix from which a network structure emerges using a filtering algorithm. To measure the dependence between each time series of the dataset, we calculate the matrix of Pearson correlation coefficients, where the element on ith row and jth column in $\mathbb{C}_{i,j}$ matrix represents the cross-correlation between series $X_i(t)$ and $X_j(t)$ defined as:

$$\mathbb{C}_{i,j} = C_{X_i,X_j} = \frac{(X_i(t) - \mu_{X_i})(X_j(t) - \mu_{X_j})}{\sigma_X \sigma_Y} \tag{1}$$

where μ_{X_i} and μ_{X_j} are the unconditional means and we write σ_X and σ_Y as the respective standard deviations.

The square correlation matrix is used in the filtering algorithms for network construction and community detection and thus represents a finite graph. The rows and columns of the matrix correspond to the vertices of the graph, and the entries of the matrix represent the edges between the vertices (Singh & Sharma, 2012). When we have a correlation matrix from a finite sample of independent random variables, as is the case in our dataset, it may happen that the observed correlations in a finite sample may not perfectly represent the true population correlations. The sample size, as well as other factors such as sampling bias or outliers, can affect the accuracy and reliability of the estimated correlations (Girko, 1985). In order to filter these fluctuations, the spectral decomposition of a matrix can be used to transform the original correlation matrix, which is then decomposed into its eigenvectors and eigenvalues, and the resulting eigenvectors are used to represent the correlation between the nodes in the network. This method is also very useful to identify and separate the underlying sources of variation in the data. The spectrally decomposed correlation matrix is therefore defined as:

$$\mathbb{C} = \lambda_\alpha u_\alpha \otimes u_\alpha \tag{2}$$

where λ_α are the eigenvalues and u_α are eigenvectors.

The most important reason to apply spectral decomposition is the ability to filter out only the non-random structures (modes), as they are the modes that capture most of the variation in the data and provide the largest information-added value. These modes refer to the principal components or patterns that make up the data. The structures (modes) are ordered based on their significance, with the first mode capturing the largest amount of variation in the data, followed by the second mode, and so on. We distinguish the non-random modes by comparing the spectrum of their covariance matrix to one of purely random and uncorrelated processes. The null model, also known as Wishart matrix Q, is a correlation matrix of N time series in T finite time (where $N \to \infty$ and $T \to \infty$, $Q = \frac{T}{N} \gg 1$) where the distribution of eigenvalues is determined by

$$P(\lambda) = \frac{Q}{2\pi} \frac{\sqrt{(\lambda_{max} - \lambda)(\lambda - \lambda_{min})}}{\lambda} \tag{3}$$

where $\lambda_{min/max} = [1 \pm (\sqrt{\frac{1}{Q}})]^2$ is an interval known as Marchenko-Pastur band (Marchenko & Pastur, 1967). Therefore, we are able to distinguish the non-random modes by comparing the spectrum to a null model. Practically, we select the eigenvalues that do not belong to the Marchenko-Pastur range and reconstruct the new filtered correlation matrix, which is an approach pioneered by Plerou et al. (2002); Plerou, Gopikrishnan, Rosenow, Amaral, and Stanley (1999). In this study, we use both full correlation matrix as well as spectrally decomposed correlation matrix for network construction, as both methods may provide certain advantages. The main advantage of using spectral decomposition is that it may identify patterns that are not as apparent in the full correlation matrix as well as identify tight interconnections between the data. However, it is important to note that the use of a spectrally decomposed matrix that consists of eigenvalues and eigenvectors may also lead to a certain loss of information that was present in the original correlation matrix, as the eigenvectors are able only to capture a subset of the information, which may in some cases lead to less accurate network structure.

2.2 Network filtering methods

Subsequently, the matrix that remains still captures all connections in the network, not only the most important ones. Therefore, we use graph filtering methods to obtain a reasonable and understandable graph network that highlights the most important structures and connections in the analyzed network. In this study, we use the Minimum Spanning Tree method (Mantegna, 1999) and Triangulated Maximally Filtered Graph (Tumminello, Aste, Di Matteo, & Mantegna, 2005), which is basically an approximation of Planar Maximally Filtered graph (Camerini, 1978).

First, let us define a tree as an undirected graph in which any two vertices are connected by exactly one path, or equivalently, a connected acyclic undirected graph. Then a spanning tree T of a connected graph $G = (V, E)$, where V represents vertices and E represents edges, is a subgraph that is a tree and includes all the vertices of G. This means that spanning tree T is a connected acyclic graph that contains all the vertices of G and $|T| = |V| - 1$, where $|T|$ is the number of edges in T and $|V|$ is the number of vertices in G (Graham & Hell, 1985).

The vertices, in the case of the minimum spanning tree in our paper, are represented by the price time series, while the edges have to be calculated. The starting point for that is the calculation of the Pearson pairwise correlation coefficients $\rho_{i,j}$. The correlation coefficients depict the connections that are formed between the price time series of commodities that we work with. Correlation coefficients in the fuels and biofuels supply chain had previously been used in pioneering articles by Tyner and Taheripour (2008) and Tyner (2010) to demonstrate the integrated relationship between energy and agricultural markets. We convert the correlations of $\rho_{i,j}$ between variables i and j into distances. For this conversion we utilize the technique devised by Mantegna (1999), where we transform the Pearson correlation coefficients of $\rho_{i,j}$ into a measurement of distance by using the formula:

$$d_{i,j} = \sqrt{2(1 - \rho_{i,j})} \tag{4}$$

This means that the values of the Pearson correlation coefficient in the closed interval $[-1; 1]$ are now converted by the transformation into non-negative measures of distance $[0; 2]$, which are then used in the construction of the Minimum Spanning Trees (MSTs). When the Pearson correlation coefficient is used, it is necessary to test for the normality of the dataset (Schober, Boer, & Schwarte, 2018). The two tests employed are the Shapiro–Wilk (Shapiro & Wilk, 1965) and Jarque – Berra normality test (Jarque & Bera, 1987).

There are two widely used algorithms to construct a minimum spanning tree; Kruskal's algorithm (Kruskal, 1956), and Prim's algorithm (Prim, 1957). These algorithms, in general, do not lead to the same result – the MST created by one of these algorithms may be different from the one created by the other one. Kruskal's algorithm follows a bottom-up approach and uses a disjoint-set data structure to merge separate trees by adding edges in increasing order of weight. On the other hand, Prim's algorithm follows a top-down approach and uses a priority queue to select edges based on their weight that connects an existing vertex to a new vertex. Prim's algorithm has to find an arbitrary starting vertex from which it operates. This is not the case for Kruskal's algorithm, which orders the edges of the graph by their weights and sorts them. The weights are measures to determine how important each link is in the structure. For the purpose of this study, we use Kruskal's algorithm.

The idea behind this Kruskal's algorithm is to reduce the $\frac{n(n-1)}{2}$ number of pairs to only the $n-1$ most important connections with the whole system remaining connected, while the network must not be closed or create closed loops. If the next link were to create a loop, it would not be added to the network. It can be said that the algorithm removes the largest distances between the nodes, and the application of the steps culminates in the construction of a tree-like formation that depicts the most salient interconnections in a system of variables, in our case, the price time series of chosen commodities and assets.

This tree structure would contain N nodes and $N-1$ edges and maximizes the correlation between the nodes on the graph. However, as was already previously mentioned, the MST omits the connections that would result in the creation of a closed loop, which is why we also include another methodology that eliminates this limitation, resulting in the use of the Triangulated Maximally Filtered Graph (TMFG). In our case, we are not strictly interested in finding the "best" $N-1$ connections among our price time series. We are interested in the characterization of the most important connections in our system of price time series. So, we do not deem problematic having more than $N-1$ connecting edges, as long as our goal of "best" characterization of the structure of our widely considered supply chain of commonly used liquid fuels is achieved.

As the TMFG is an approximation of the Planar Maximally Filtered Graph (PMFG), we first briefly explain the basis of PMFG. PMFG may be seen as an extension of the previously mentioned MST method, which is based on the concept of a planar graph. A planar graph is a graph that we are able to draw on a plane without the edges of the graph intersecting (Tumminello et al., 2005). PMFG algorithm selects edges in a way that maximizes the degree (number of connections) of the nodes that one node has to other nodes in the network. The maximum number of edges that can be added to a planar graph with N nodes without creating a new face, which is a region bounded by edges in a planar graph, is $3(N-2)$. This stems from the Euler's formula (Funkenbusch, 1974). This Euler's formula states that for a connected planar graph with V vertices, E edges, and F faces, the following equation has to be satisfied: $V - E + F = 2$.

To generate the planar maximally filtered graph, a method similar to that of the minimum spanning tree (MST) approach can be used. Firstly, all the links in the initial graph, which is the graph that is constructed only based on the correlation matrix, must be sorted from largest to smallest weight according to their Pearson correlation coefficient. Next, an empty graph should be constructed with the same nodes as the initial graph, which is used as the filtered graph. Then, the algorithm iterates through the links in descending order of weight and adds each link to the graph. If the graph remains planar (there are no intersections of edges) after adding the link, the link should also be added to the filtered graph, hence the name – Planar Maximally Filtered Graph. The process is constantly repeated until all links have been considered. Each node should be a part of a clique, which is a fully connected subgraph or, in other words, a subset of nodes in a graph where every node is directly connected to every other node in the subset.

Since this process can be exceedingly slow for larger networks, as it requires a thorough examination of all the links in the graph while testing for planarity at each step, an alternative method was proposed. This alternative method is the Triangulated Maximally Filtered Graph and we use this method in our study. This method constructs a sparse graph that captures the essential features of a network while preserving its triangular motifs. It starts with a graph of all nodes; it then proceeds to identify four nodes with the highest sums of correlations to all other nodes, creating four main nodes of the network. For each main node, it selects three edges with the highest degree of correlation while iteratively removing all other edges that would create a cycle of length greater than three. The resulting graph is maximally triangulated, meaning that every cycle in the graph is a triangle (formed from the three selected edges). The algorithm then updates the network by removing all non-planar edges until only the maximum planar subgraph remains. The same formula gives the number of edges in the TMFG as for the PMFG i.e., $3(N-2)$ where N is the number of nodes in the network.

2.3 Community detection algorithm

To detect the communities (clusters of closely related nodes) in the complex networks that are created by filtering both types of correlation matrices with both the MST and TMFG methods, we use the Louvain algorithm introduced in Blondel, Guillaume, Lambiotte, and Lefebvre (2008). The Louvain algorithm finds communities that are formed by assets that show dense connections within the community while keeping the links to other assets very sparse. The community detection algorithm begins by initializing each node as a separate community. Next, it then identifies all the communities connected to the first detected note and proceeds to calculate the change in modularity by moving the second detected note to each neighboring community. In this case, modularity basically measures and compares how strongly are nodes from the same community interconnected. In the case of the Louvain algorithm, the modularity is calculated as

$$Q = \frac{1}{2m} \sum \left[d_{i,j} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j), \tag{5}$$

where Q represents the modularity, $d_{i,j}$ represents the edge weight of i and j. Further, k_x is the sum of weights attached to vertex x, c_i represents the community to which the vertex is assigned, δ represents a function that is evaluated as unity, if nodes belong to the same community and as zero otherwise. Constant m is computed as a deterministic function of elements of correlation matrix $\mathbb{C}_{i,j}$ in (1).

When a node is moved from one community to another, the modularity of the network changes. Therefore, the algorithm seeks to maximize the change in modularity by moving nodes between communities until an optimal partition of the network is obtained, resulting in a layer of community partition. Finally, the algorithm merges each community obtained into a new node, with the relationship between the new nodes being the relationship between the original communities. The algorithm repeats this process until all nodes are merged into one community, selecting the partition with the highest modularity as the final result of the community detection. By following these steps, the algorithm can obtain a multilevel community partition that accurately reflects the community structure of the network (Zhang, Fei, Song, & Feng, 2021). These communities are then visualized and analyzed, with the aim of discovering related commodities or assets that are influenced by common forces or behave in a similar way. We are interested mainly in the differences in the structure of the communities that each type of method (MST from full and spectrally decomposed correlation matrix and TMFG from full and spectrally decomposed correlation matrix) produces.

Following the approach of Kristoufek et al. (2012), Zilberman, Hochman, Rajagopal, Sexton, and Timilsina (2013), and Janda et al. (2021), we transform raw data entries to logarithmic returns since as the aforementioned works suggest, this provides a level of stationarity and symmetry to the dataset that we would not be able to achieve otherwise. So, we use this transformation:

$$r_t = log(\frac{P_t}{P_{t-1}}). \tag{6}$$

We test the stationarity with the standard pair of stationarity tests; Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The results confirm the usability of our data for the analysis performed in this study when we reject the alternative hypotheses of non-stationarity (or vice versa in the KPSS case) at a statistically significant level.

3 Data

The aforementioned methodology from the previous part is now applied to a dataset of 39 price time series. This dataset contains commodities connected to the fuel product chain and other assets that may have any kind of influence on the prices in the liquid fuel product chain. The definition of the set of the chosen commodities was taken from Janda et al. (2021) and was enriched by an additional time series of the Geopolitical Risk Index. The dataset was subsequently updated and now represents 39 weekly price time series spanning the period from November 21, 2003, until January 27, 2023, amounting to exactly 1002 observations. Weekly prices recorded at the market close on Friday were chosen for the construction of the dataset. In case Friday prices were for various reasons not available, the price from the previous close day was substituted.

Our data can be divided into groups based on their underlying features. The group of fossil liquid fuels includes gasoline, diesel, and upstream crude oil from which the formers are refined. It is important to note that Brazilian gasoline Gasolina Comun is mandatorily mixed with currently 12% of ethanol, while the Brazilian diesel Óleo Diesel is also mixed with 12% of biodiesel, according to the last mandate. Therefore, the price time series is the price of the mix of biofuels and crude oil. The same applies to the US prices of gasoline and diesel, where the US Premium Gasoline already contains the 10% mandated ethanol mixture, with diesel containing 2.5% of biodiesel. As for the European commodities, Unleaded Gasoline contains up to 10% of ethanol, fulfilling the minimum 7.5% requirement of the European Union. The EU diesel contains 6.25% of biodiesel.

The biofuels group consists of ethanol (New York Harbor Price Ethanol Index and Anhydrous ethanol index from CEPEA) and biodiesel (A.R.A. European Biodiesel and A.R.A. US Biodiesel). As in Zilberman et al. (2013), we also include an upstream part of the product chain, which in the case of ethanol is corn, wheat, sugar, sugar cane, and sugar beets, and for biodiesel, it represents rapeseed oil, soybean oil, palm oil, and sunflower seed (since the specific price series of sunflower seed oil was not available).

We also include heating oil and natural gas as substitutes for liquid fuels. The question of whether fuel prices influence food prices or even make food prices increase was discussed in large by Filip, Janda, Kristoufek, and Zilberman (2019); Tomei and Helliwell (2016) and recently by Zhang et al. (2021). In order to contribute to this ongoing discussion, we also include prices of other important agricultural commodities, such as rice, cocoa, coffee, and orange juice, which compete for the use of agricultural land with corn or other biofuel feedstock. To complement these commodities, we also consider the price of cotton and cattle feed.

In our supply chain model, we also consider financial assets such as exchange rates between countries with the biggest biofuels production and consumption rates, i.e., the U.S., Brazil, and Europe (hence we include USD/BLR and USD/EUR exchange rate time series), as well as main stock indices traded on relevant stock exchanges. We once again only look at the indices that come from previously mentioned countries, and we, therefore, include European indices such as Financial Time Stock Exchange 100 and Deutsche Boerse DAX index, American Dow Jones and Standard and Poor's 500 and finally also, stock index from Brazil in the form of Bovespa index (Bolsa de Valores do Estado de Sao Paul index) is included. To finalize the global financial outlook, we chose the two most important interest rates that influence the global economy at a large scale, the US Federal Fund Rate (FED) and the 3-month London Interbank Offered Rate (LIBOR).

In order to capture military conflicts and similar events possibly related to prices considered in our supply chain, we use the Geopolitical risk (GPR) index of Caldara and Iacoviello (2022). This GPR index is constructed through automated text-search results of the electronic archives of 10 major English language newspapers (Chicago Tribune, the Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, the Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post). Essentially, it calculates the number of articles related to adverse geopolitical events in each newspaper for each month. We used the daily calculation of the index since weekly calculation was not available, and we followed our convention of using Friday data as long as they were available.

To make the graphical display more visible, the nodes of the graphs representing each price time series were marked with specific colors according to the type of data group that they belong to – fossil fuels are marked with brown color, biofuels are highlighted with orange, their respective feedstock is marked with yellow for ethanol and red for biodiesel, other food commodities are green, financial indices are depicted in grey, interest rates and exchange rates in pink and blue respectively, and the newly added geopolitical risk index is highlighted in purple. The color distribution also helps the reader to be able to discover the clusters that are being formed at first glance; therefore, it helps with the analysis of the results.

4 Results

4.1 Community detection in MST

We first discuss Figure 1 with five communities that were created on the MST network filtered with a full correlation matrix. The MST communities provide a more straightforward relationship detection. The five communities created from the data series in our sample could be classified into groups of biofuels and their feedstocks marked as orange, crude oils marked as red, financial indices marked as grey, fossil fuels marked as brown, and community of Brazilian biofuel and feedstock and foods that are leading products that Brazil produces marked as green. The biofuels community is very straightforward, connecting all included non-Brazilian biofuels with their feedstocks (EU Biodiesel – Rapeseed, US Biodiesel – Soybean, US Ethanol – Corn). This community confirms, to some degree, the interconnectedness of biofuels and food prices and their influence on each other. We observe that commodities such as wheat, corn, and rice are present in this community, which relates to the results of Bilgili, Koçak, Kuşkaya, and Bulut (2020). The Geopolitical Risk Index is part of this community, which may suggest that out of our whole system, these assets are most prone to fluctuations during turbulent times. An intriguing community is that of sugars and crude oils, marked with red color. Sugar and oil prices may be perceived as correlated through the demand for their respective derivatives, leading to the seemingly unlikely price relationship between the two commodities.

The grey community of stock exchange indices is very straightforward. The only unexpected member of this commodity is the cattle price. Together with the dispersion of other major food commodities not used as feedstock for biofuels among different communities, this indicates that the price movement of individual food commodities is not so closely related that it would lead to the formation of separate food communities. Remembering that the community construction Louvain algorithm considers not only the strength of the relationship between members of a community but also their connection out of this community, we can classify cattle as a financialized commodity, related more to the financial stock exchanges community than to any commodity supply chains.

Another community shown in Figure 1 consists mainly of Brazilian commodities such as the ethanol–feedstock combination, along with most produced Brazilian agricultural commodities – coffee (Volsi, Telles, Caldarelli, & Camara, 2019) and orange juice (Neves, Trombin, Marques, & Martinez, 2020). It rather surprisingly involves Libor financial index. Lastly, the fossil fuels community exhibits strong co-movement, as is supported by the research of (Mutascu, Albulescu, Apergis, & Magazzino, 2022). All groups correspond well to the heuristic communities that one can expect. We argue that the full correlation matrix filtered by MST method provided a straightforward and intuitive description of the network and the created communities.

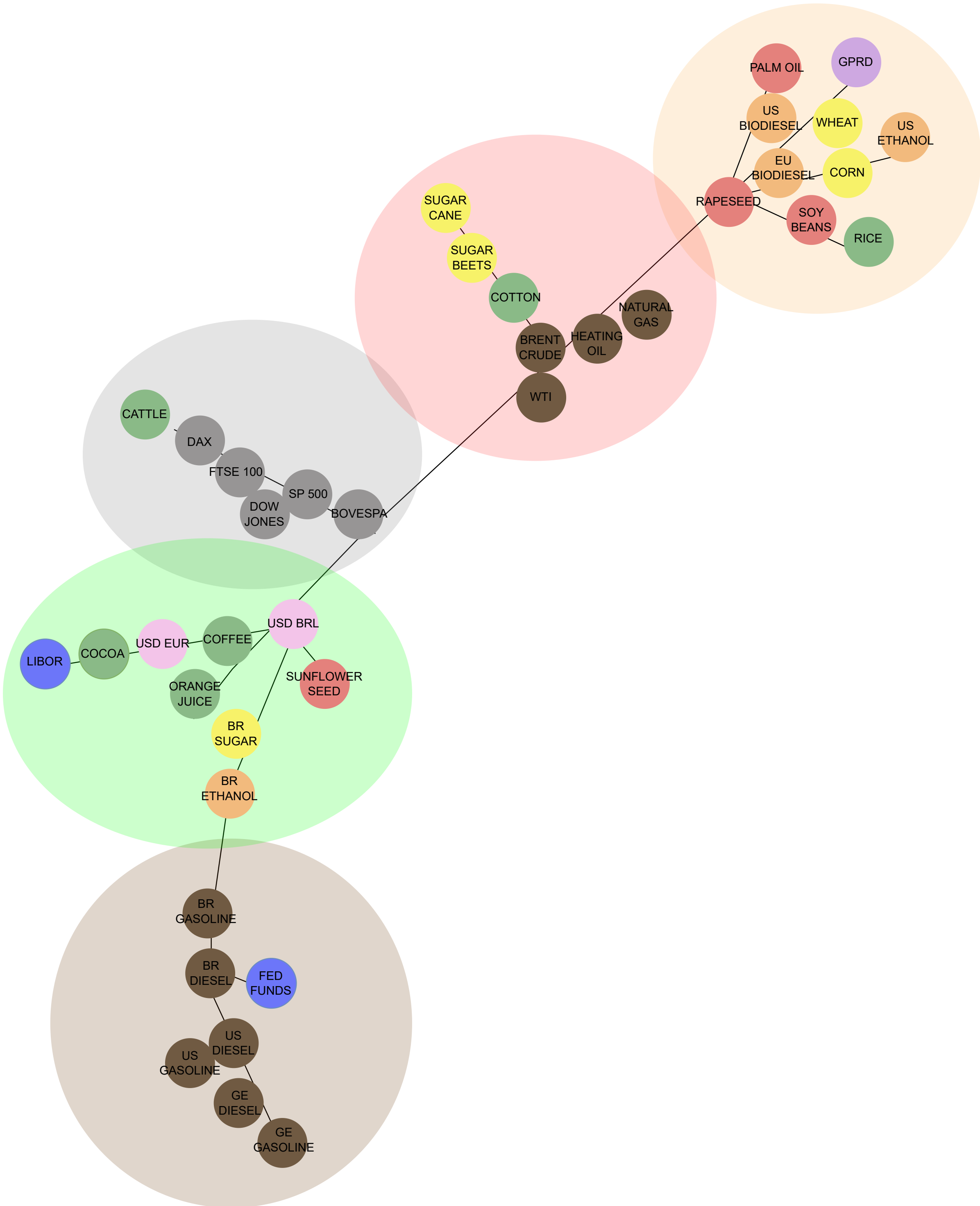

Figure 1: Community detection – Full correlation + MST

On the other hand, Figure 2 shows the spectral decomposition of the correlation matrix, which calculates different community relationships. This method used with the MST method detected one additional community, resulting in 6 communities, again with quite an intuitive interpretation. In this case, the brown gasoline community is only formed by German and American diesel, as in this case, the Brazilian fossil fuels seem to have deeper connections to Brazilian ethanol and sugar. This community creation can be partially explained by Chen and Saghaian (2015), who found that prices of oil, sugar, and ethanol in the Brazilian market were cointegrated in the second period (2008 – 2015) of their research.

Another interesting relationship is revealed in the connection of Brazilian commodities to interest rates, such as Libor and Fed Funds (in green). This could have been caused by agricultural credit policies (Meyer, 1977) such as Pronaf - National Program for Strengthening Family Agriculture, which is a program that provides credit and technical assistance to small family farmers in Brazil, and Plano Safra, which is an annual government plan that outlines the credit, marketing, and research policies for the agricultural sector that are still in place today.

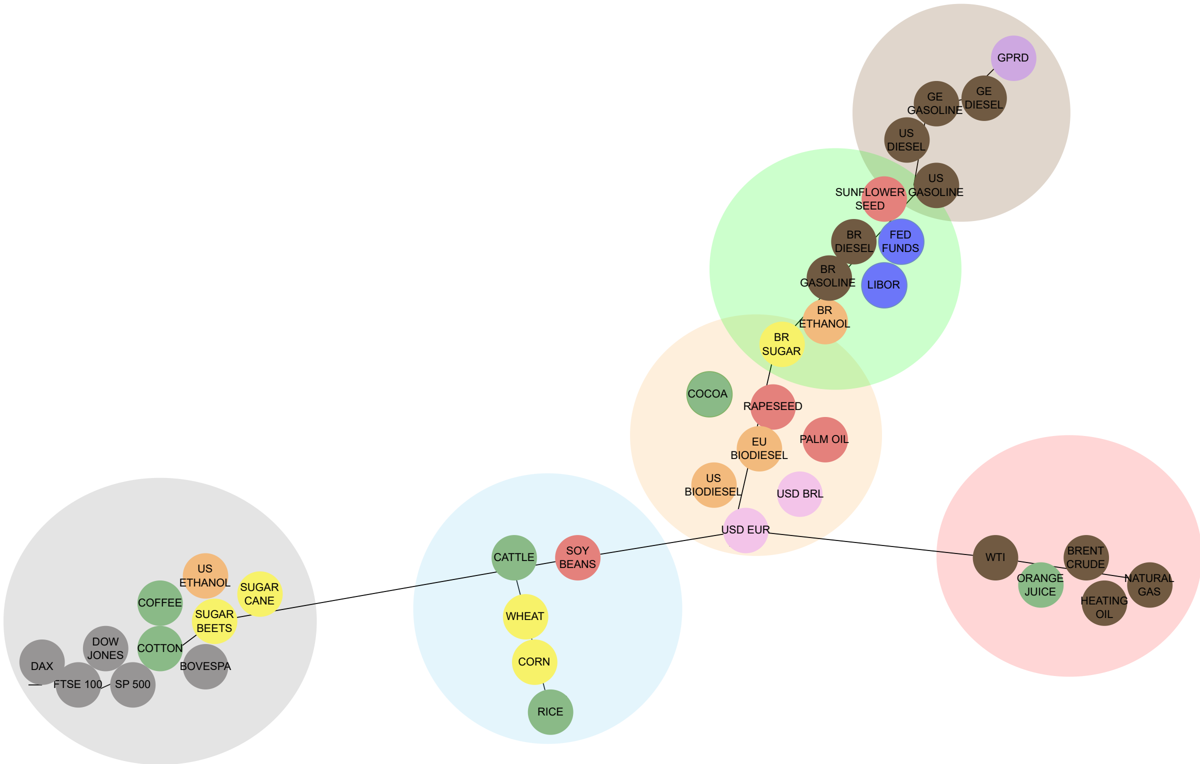

Figure 2: Community detection – Spectral decomposition + MST

We may argue that since interest rates reflect the borrowing costs of money the agricultural companies producing these commodities face, there may therefore be a relationship between interest rates and the prices of these commodities. Another interesting relationship revelation is in food commodities. While in Figure 1, the Brazilian food commodities remained together in one community, this time we observe a complete division – orange juice now forms a community with crude oils, which appears contra-intuitive. One might speculate that as crude oil may be used in the production, transportation, and even in the treatment (as a pesticide) of agricultural commodities, i.e., orange juice, there may be an underlying relationship that was revealed by the community detection algorithm. The biofuel community remained quite similar, with ethanol exiting the community, leaving only the biodiesels and the exchange rate present, which seems like a reasonable relationship as well. Only the inclusion of cocoa may seem rather random since Avalos and Lombardi (2015) found "no direct or indirect connection with the biofuel industry."

The U.S.-focused food community of cattle, soybeans, wheat, corn, and rice that is detected (in blue) is very intuitive, as the prices of food are very interconnected. This reflects the quintessential nature of the U.S. agricultural economy over centuries, without any regard to modern fuels or biofuel trends. In particular, the results suggest that biofuels, or other commodities out of agriculture for that matter, do not really capture the dynamics of U.S. agriculture.

Brown community consisting of crude oils and geopolitical risk index may indicate that crude oil prices are very sensitive to geopolitical tensions and are highly volatile in times of war and geopolitical conflicts, as reported by Zavadska, Morales, and Coughlan (2020). The grey community is quite unconventional, combining financial indices, sugars, and other foods along with US ethanol. As per the relationship between sugars and ethanol, it can be argued that the U.S. is a significant importer of Brazilian ethanol, which could imply that changes in Brazilian ethanol prices can also affect the cost of ethanol in the U.S. market, with the fluctuations in Brazilian sugar prices indirectly affecting American ethanol prices.

We could argue that while the filtration of the full correlation matrix provided us with sufficient results in the form of confirmation of expected communities, the filtered spectrally decomposed matrix revealed some interesting underlying connections, mainly the correlation between agricultural commodities and interest rates. Some of the unexpected connections, such as the inclusion of cocoa and orange juice with crude oils and biofuels, may be seen as the result of limited information caused by decomposition resulting in a less accurate representation of the network structure. Both the full correlation matrix and the spectrally decomposed matrix consistently revealed rather unexpected suggestions about the close connection of Brazilian markets and commodities with leading financial indicators – interest rates, both Fed Funds and Libor. Now with a spectrally decomposed matrix, we are better able to explain the unexpected separation of both of these variables into different communities in the previous (full correlation matrix-based) network. In that network, both Fed Funds and Libor were drawn towards Brazilian assets. However, because these Brazilian assets were divided into two communities, Fed Funds and Libor were separated. Now with the emergence of a unified Brazilian community in a spectrally decomposed matrix network, the Fed Funds and Libor are closely joined in one community, as we would ex ante expect. What is an original insight is that this community containing Fed Funds and Libor is closely associated not with the EU or U.S. but rather with Brazil.

4.2 Community detection in TMFG

The main difference between the minimum spanning tree and the triangulated maximally filtered graph methodology is that since the TMFG forms triangular cycles, it is then able to retain more information about the original network structure and, naturally, includes more edges than MST. TMFG should therefore provide a more nuanced and detailed representation of the relationships that are created. Also, the communities that are detected on these types of networks are more complex, which can be seen by the decreased number of communities that contain a much higher number of assets, resulting in more intricate groups. We first discuss the network that was created by filtering the full correlation matrix, which provides a more straightforward interpretation and is depicted in Figure 3. The orange community is virtually the same. The results that the more complex TMFG method detected in this community indicate that the biofuels community is very stable, strongly interconnected, and unchanged.

Another quite similar community is that of crude oils connected with sugars and, in this case, even more, food assets, including coffee, cotton, and cocoa, as well as sugars. Various research papers support these relationships, one example being the Esmaeili and Shokoohi (2011), who, by using principal component analysis, found that the oil price index has an influence on the food production index and, subsequently, crude oil prices have an indirect effect on food prices, which would provide an explanation for the red community forming. The brown fossil fuel community remains completely interconnected, which is a result consistent across the estimation methods.

One of the more interesting communities in Figure 3 is the green community. The MST with

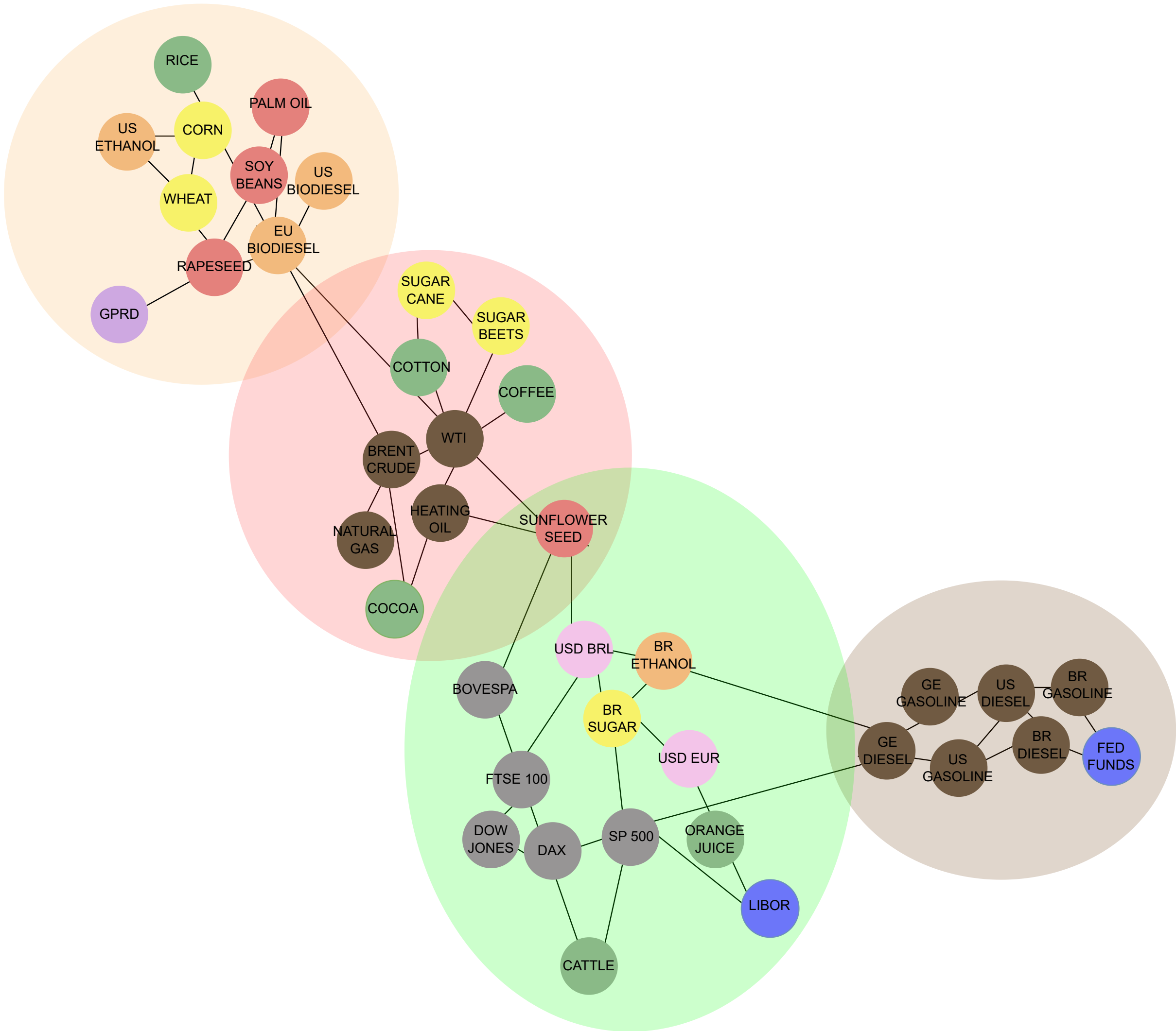

Figure 3: Community detection – Full correlation + TMFG

full correlation matrix in Figure 1 also detected this; however, probably because of the limitation of MTS for not being allowed to create a closed loop, these commodities were not able to create one single community but remained rather divided into the more obvious groups of financial markets and Brazilian commodities. However, in the case of TMFG, the more complex nature of the network was able to cluster these commodities into one community, possibly unveiling a relationship that would not be possible to detect only using the MST method. In this community, we observe the global influences of demand and supply in the form of the financial indices that interact with Brazilian commodity prices, which is very reasonable with Brazil being the second largest agricultural exporter (Hubbard, Garrod, & Alvim, 2017). As in the case of MST-based communities in Figure 1 and Figure 2, we again confirm close Brazilian connections of Fed Funds and Libor.

The spectral decomposition filtered by TMFG in Figure 4 showed certain similarities with the network filtered by MST in Figure 2. For example, the red community of crude oils and orange juice remained the same, as well as the biofuels–feedstock community. However, the other two communities perfectly display the additional use of TMFG in this study, which is not to capture the obvious, heuristic community distribution but to be able to discover complex relationships that may be seen in the representation of this graph. The community of diesel and gasoline that

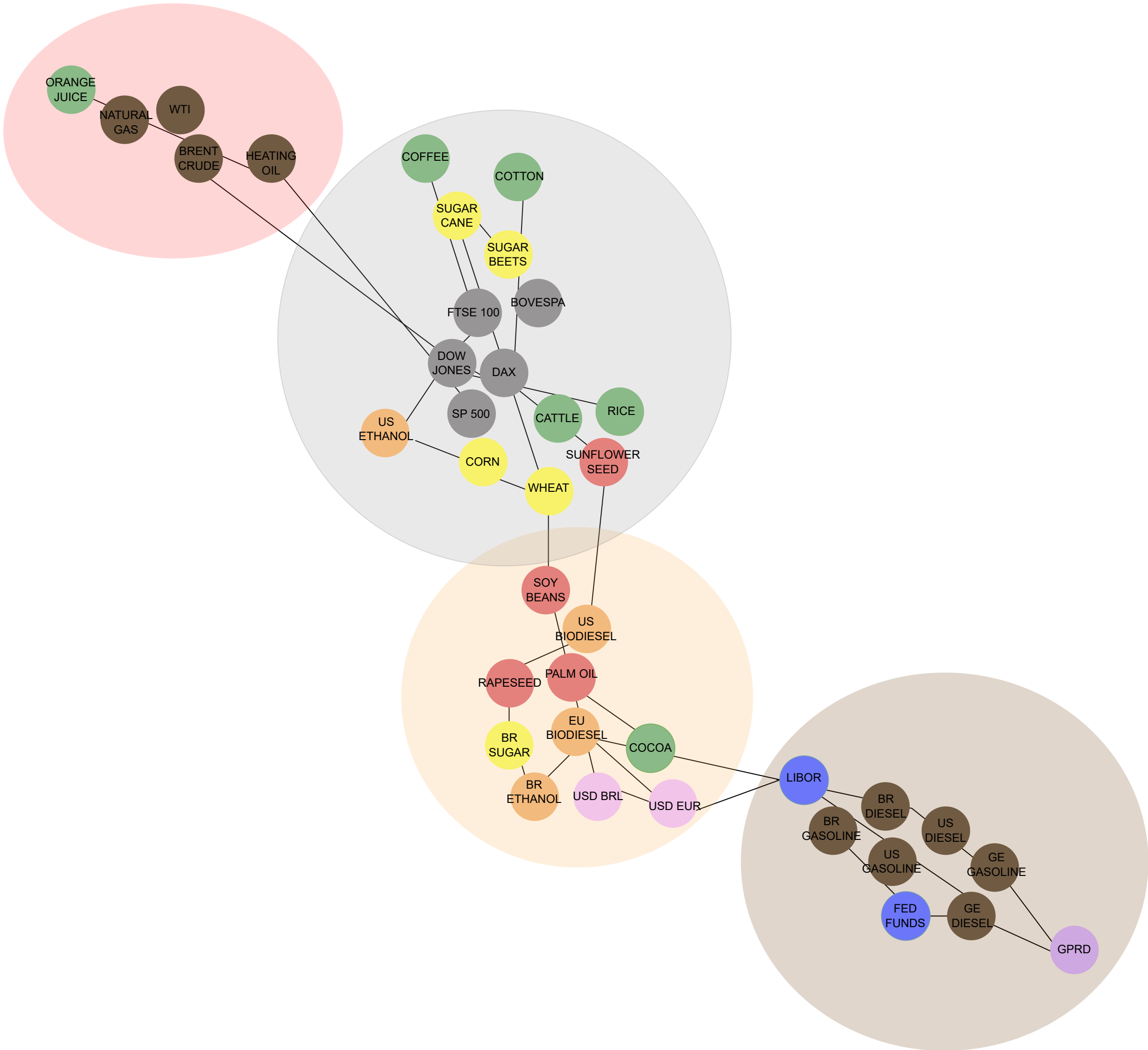

Figure 4: Community detection – Spectral decomposition + TMFG

connects fossil fuels with interest rates and geopolitical risk index provides a very useful example of the price movements observed lately as a result of the Covid-19 pandemic combined with the Russian invasion of Ukraine. In a time of such global turmoil, which is represented by the GPDR Index, the global economy experienced unprecedented rises in interest rates due to governmental policy against rising inflation (IMF, 2023)[1], which were followed by fuel prices that increased by 19.4% from December 2021 to December 2022 (U.S. Bureau of Labor Statistics, 2023).[2] The community detection was able to capture completely this interconnectedness, probably due to the use of more elaborated TMGF method and spectrally decomposed correlation matrix. This gasoline group manages again to unite Fed Funds and Libor in one community. While, as in the previous graphs, both interest rates have a clear Brazilian connection (in this case, through

[1]Available online at https://www.imf.org/en/Blogs/Articles/2023/04/11/global-financial-system-tested-by-higher-inflation-and-interest-rates

[2]U.S. Bureau of Labor Statistics. (2023). Import fuel prices up 19.4 percent from December 2021 to December 2022: The Economics Daily: U.S. Bureau of Labor Statistics. Available at: https://www.bls.gov/opub/ted/2023/import-fuel-prices-up-19-4-percent-from-december-2021-to-december-2022.htm

Brazilian fossil fuels), this is kind of hidden by an ex-ante expected complete international connectedness of all fossil fuels.

As for the last community, one may find it probably too complex and not completely accurate, as there is represented a mix of financial assets, biofuels, and foods, but there are various pieces of evidence that food prices are globally influenced, which would explain their community formation with global financial indices. As was highlighted by Algieri (2014) and Ulussever, Ertuğrul, Kılıç Depren, Kartal, and Depren (2023), local food prices may increase due to an increase in the exogenous variables such as the country risk, raw material prices, temperature, fertilizer prices, volatility index, oil prices, and FX rate. The studies also state that there is a causal interaction between the exogenous factors (domestic and international) and regional food prices, only supporting the community formed in our graph.

To conclude, both MST and TMFG seem to complement each other, with MTS being the more straightforward network filtration, revealing the expected and understandable relationships, while TMFG provides a more complex assessment of the network and yields very interesting results, mainly in the last Spectrally Decomposed TMGF graph.

Overall, we conclude that certain communities were more or less present throughout all four graphs, those being some variations of biofuels – feedstock pairs, crude oils, and fossil fuels with some other varying commodities as either connected food commodities or global influencers, i.e., interest rates and GDPR index. Financial indices have such a strong interconnectedness that they are either detected as a community on their own or in more complex methods, are connected mainly with food prices, which is reasonable considering that foods are global assets being imported and exported all the time, which makes them very influenced by global asset movements. The fact that in different graphs GDPR index was connected to different communities actually shows that all these communities are exposed to geopolitical risks. Depending on particular settings and emphasis in different analyzed networks, the marginal differences in geopolitical risk exposure of particular commodity and asset groups determine the attachment of GDPR to a particular community.

5 Conclusions and Policy Implications

Our study employs the Minimum Spanning Tree (MST) and Triangulated Maximally Filtered Graph (TMFG) filtration methods to analyze complex networks within the liquid fuels system. The TMFG method, by maximizing network triangular loops, uncovers additional, less apparent relationships between nodes, revealing intricate network structures. Conversely, the MST method provides a more direct view of the strongest node correlations. Further, we utilize a spectrally decomposed correlation matrix, revealing strong interconnections and patterns unobservable with a standard full correlation matrix.

Our findings indicate that biofuels consistently form communities with their respective feedstock, with these relationships intensifying during policy changes or crises. Unexpected community structures were found between Brazilian commodities and interest rates due to agricultural credit policies and between fossil fuels and the Geopolitical Risk Index, highlighting global price influences. On the other hand, fossil fuels form a detached cluster, primarily influenced globally, serving as a connecting piece between biofuels and fossil fuels clusters. This suggests that crude oil prices significantly impact the price competitiveness of biofuels and fossil fuels.

Our findings underscore the importance of considering the interconnectedness of commodities in the liquid fuels supply chain when formulating policies. Policymakers should be aware that changes in one area of the network can have far-reaching effects on other areas. Furthermore, the strong link between biofuels and their feedstock suggests that policies promoting the use of biofuels could also have significant impacts on the agriculture sector. Further, the results emphasize the importance of continued innovation and investment in biofuel production technologies. As biofuels form strong connections with their feedstocks, advancements in feedstock efficiency and processing could significantly impact the overall sustainability and economic viability of the biofuel sector.

From a general policy perspective, policymakers should consider providing incentives for research and development in biofuel production technologies. Policies could also be implemented to encourage the adoption of flexible fuel vehicles and the expansion of biofuel refueling infrastructure. However, regulations need to be put in place to ensure that the growth of the biofuel market does not negatively impact food supply chains, which are closely linked with biofuel feedstocks.

Despite the already large size (39 nodes) of our supply chain graph, there are still additional elements that may be included in the future extension of this research. In this paper, we did not explicitly consider the connection to gold (Mensi, Reboredo, & Ugolini, 2021) or other major traded commodities outside the fuels and food commodities network. Because of our focus on commonly used liquid fuels, we do not explicitly consider lignocellulosic second-generation biofuels (Boutesteijn, Drabik, & Venus, 2017) or hydrogen-based liquid fuels (Heidary & Janda, 2023). However, with the increase of their use and policy importance of these fuels, they would be natural candidates for an extension of our supply chain network in the middle or long run future. By design, we also strongly focus on liquid fuels and exclude an important and growing sector of electro-mobility and all supply chain extension in the direction of electricity generation, storage, and distribution (Rocha, Rotella, Aquila, & Janda, 2022; Zubi, Dufo-López, Carvalho, & Pasaoglu, 2018). Another area for future extension is the direct incorporation of environmental quality changes (Ciaian & Kancs, 2011) and technological progress (Taheripour, Scott, Hurt, & Tyner, 2021) in the context of energy systems (Ordonez, Cavalcanti, & Carvalho, 2022).

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