Relationship Between Prices of Food, Fuel and Biofuel

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Annotation: In this paper, we analyze the relationships between the prices of biodiesel, ethanol and related fuels and agricultural commodities with a use of minimal spanning trees and hierarchical trees. To distinguish between short-term and medium-term effects, we construct these trees for different frequencies (weekly and monthly). We find that in short-term, both ethanol and biodiesel are very weakly connected with the other commodities. In medium-term, the biofuels network becomes more structured. The system splits into two well separated branches – a fuels part and a food part. Biodiesel tends to the fuels branch and ethanol to the food branch. As a part of this paper we also characterize the major biofuels and their agricultural feedstock and we outline their recent quantitative development.

Key words: biofuels, networks, minimal spanning tree, hierarchical tree.

1 Introduction

In this paper, we utilize a straightforward methodology of taxonomy standardly used in networks and complex systems analysis for clear identification of relationships between components of the system. We apply the methodology on the system of biofuels and related agricultural and fuel commodities. We quantify these relationships over different market phases and time dimensions using a graphical display of price transmission network. In this way, we contribute to important policy discussion about impact of biofuels and energy prices on food prices.

Biofuels became of high interest after the oil crisis of the 1970s as a possible replacement for fossil liquid fuels used in transportation. Increased interest in climate and environmental issues in last three decades also contributed to the popularity of biofuels as alternative fuels. Global production of biofuels experienced a rapid increase since then, especially during the last decade. The main drivers behind this growth are government policies such as mandates, targets and subsidies which have been justified on the grounds of energy security and climate change considerations. However, the concerns raised by the global food crisis in 2007/2008 and ambiguity with respect to environmental impact of biofuels led many government to reconsider their earlier optimism with respect to biofuels.

Very important factor leading to expansion of ethanol was a phase-out of the gasoline additive methyl tertiary butyl ether (MTBE) which was used as an oxygenate to raise the octane number. MTBE was banned or restricted in multiple US states (California, New York, etc.) since it was found to contaminate ground water where it leaked from tanks and pipelines. Unlike other ingredients contained in gasoline fuel, MTBE dissolves in water during the gasoline spills and moves away from spill sites with water flow. MTBE was classified as a possible carcinogen. The fuel industry therefore substituted ethanol as an alternative source of oxygen for fuel blends.

Biofuel production has increased continuously worldwide over the last years. In 2009, global ethanol production reached nearly 75 billion liters in more than 40 countries. That year, the ethanol production was 40 billion liters in the USA, 26 billion liters in Brazil and 3 billion liters in the EU. Global biodiesel production totaled almost 19 billion liters worldwide in 2009. The biodiesel production reached 2.2 billion liters in the USA, 1.5 billion liters in Brazil and 9.4 billion liters in the EU. The FAPRI biofuel production forecasts for 2019 are 65 and 5.4 billion liters of ethanol and biodiesel, respectively for the USA, 52 and 2.9 billion liters of ethanol and biodiesel, respectively for Brazil, 6.9 and 13.1 billion liters of ethanol and biodiesel, respectively for the EU. The land used for biofuels was estimated in 2008 at around 20 million ha worldwide, or around 1% of the global agricultural land, of which about 8 million ha was used for sugarcane plantation in Brazil. The share of ethanol on the US total gasoline motor transportation fuel use measured in gasoline-equivalent gallons was 6.5% in 2010. Corresponding share of biodiesel on the US diesel transport fuel use was 0.8% in 2010. Since the US use of diesel as transportation fuel at less than 50 billion gallons yearly is equal to approximately 1/3 of gasoline use, the overall share of biofuels on the US transportation fuel use was 5.1% on an energy-equivalent basis in 2010. This relatively small share sharply contrasts with a very large contribution in Brazil, where ethanol from sugar cane replaced already 50 percent of gasoline for transport in 2009.

Biofuel use represents an important share of global cereal, sugar and vegetable oil production. According to 2010 Agricultural Outlook of OECD-FAO, sugarcane will remain the single most biofuel-oriented commodity. Its global share to be used for the ethanol production is expected to rise to 35% in 2019 as opposed to 20% in the baseline period of 2007-2009. The next most used category is molasses with the expected share of slightly less than 25% as compared to slightly less than 20% in the baseline period. Vegetable oil and coarse grains, which have the same share of 9% of their production being used for biofuels in the baseline period, are predicted to diverge somehow with about 13% of the global production of coarse grains being used to produce ethanol in 2019, while the corresponding forecast for vegetable oil conversion to biodiesel is 16%. For sugar beets, a modest increase from currently less than 10% biofuel utilization to about 11% utilization is expected in 2019. Relatively high rate of increase of the biofuel utilization is expected for wheat. But given its low baseline share about 1%, only about 3-4% of its 2019 production is expected to be used for biofuels.

The economics of biofuels constitutes a very active and growing research area as documented in recent review article by Janda et al. (2012). Simulation models of economic impacts of biofuels, which are based on long-run parameters (the leading source being GTAP database of Thomas Hertel and his collaborators, for recent references see Beckman et al. (2011)) and on partial or general equilibrium economic theory, assume links between prices of food, biofuels and fossil fuels. But empirical evidence for these links is largely inconsistent.

Current empirical research on biofuels and fuels price dynamics varies widely from Value-at-Risk estimation (Chang et al., 2011) to various cointegration estimations (Peri and Baldi, 2010) to volatility spillovers (Serra, 2011) and wavelet coherence analysis (Vacha and Barunik, 2012) and others. The common feature of this research is growing sophistication of econometric estimation which usually comes at the cost of imposing many structural or distributional assumptions on the processes underlying the interactions between the prices of biofuels and related commodities. In this article, we present different methodological approach to this problem. We analyze connections between biofuels and related commodities (energy-related and food-related) with a use of minimal spanning trees (MST) and hierarchical trees (HT) to uncover the most important connections in the network of commodities.

MST and HT are methodologically very straightforward approaches using only simple correlations as a starting point with no additional prior assumptions. The MST and HT methods are now being increasingly used for analysis of stocks connections (Bonanno et al., 2004; Tumminello et al., 2007), foreign exchange rates (Jang et al., 2011), import/export networks (Kantar et al., 2011), interest rates systems (Tabak et al., 2009), portfolio selection (Onnela et al., 2002) as well as commodities networks (Tabak et al., 2010; Lucey et al., 2011), yet mainly in the journals of interdisciplinary physics, specifically econophysics.

This paper presents the first MST and HT analysis applied on the network containing biofuels. The advantage of our approach is a natural possibility to include simultaneously different biofuels and many different related commodities into our analysis. This contrasts with previous time-series econometric studies which usually focus only on a small selected group of commodities. Our analysis allows the integration of the principal findings in the literature on price transmission between food, fuels and biofuels markets in a clear and elegant way. The correlation clusters formed as results of our analysis may serve as good starting points for further econometric analysis of the price interactions within these clusters. Indeed, the fact that the MST and HT methodology is very straightforward is not only its advantage but of course its limitation as well – we are not able to comment on causality between commodities, the methodology does not take into consideration possible cointegration or lagged values of variables of interest. Further, as the methodology is constructed for the stationary series, we might loose information if the analyzed series need to be first-differenced to attain stationarity, which is the case for all stationarity-assuming approaches.

In this paper, we focus on the most popular biofuels – ethanol and biodiesel. Ethanol is mainly produced from crops rich in sugar and starch like sugarcane and corn. Biochemical technologies for conversion of sugar and starch are the most technologically and commercially mature today. Biodiesel is produced from oilseed crops like soybean, rapeseed, and oil palm. Therefore, we are mainly interested whether a dynamic behavior of ethanol and biodiesel forms clusters with food commodities and/or energy commodities. Moreover, we want to analyze the behavior at different frequencies (weekly and monthly) to see whether the relationships apply in short and/or medium term. Further, the connections between the commodities might vary for different phases of the market depending on binding regulatory or technological constraints and market development.

The rest of the paper is structured as follows. In Section 2, we present a brief review of a current research dealing with links among biofuels and related commodities. In Section 3, we describe the basic notions of the used methodology. In Section 4, the data choice and description is given. Section 5 presents the results of our analysis. Section 6 concludes.

2 The relation to current research

In this section, we briefly review most recent time-series studies on links between prices of biofuels and related commodities. More detailed recent reviews are provided by Janda et al. (2012) and Zilberman et al. (2012).

Zhang et al. (2009) focus on volatility of ethanol and commodity prices using cointegration, vector error corrections models (VECM) and multivariate generalized autoregressive conditional heteroskedasticity (mGARCH) models. The authors analyze weekly wholesale price series of the US ethanol, corn, soybean, gasoline and oil from the last week of March 1989 through the first week of December 2007. They find that there are no long-run relations among fuel (ethanol, oil and gasoline) prices and agricultural commodity (corn and soybean) prices in recent years.

The same authors further analyze long and short-run interactions with a use of cointegration estimation and vector error corrections model with Granger-type causality tests (Zhang et al., 2010). They examine corn, rice, soybeans, sugar, and wheat prices along with prices of energy commodities such as ethanol, gasoline and oil from March 1989 through July 2008. They find no direct long-run price relations between fuel and agricultural commodity prices and only limited if any direct short-run relationships.

Tyner (2010b) finds that since 2006, the ethanol market has established a link between crude oil and corn prices that did not exist historically. He finds that the correlation between crude oil and corn prices was negative (-0.26) from 1988 to 2005; in contrast, it reached a value of 0.80 during the 2006-2008. However, only the price series are analyzed, which rises serious questions about stationarity of the data.

Du et al. (2011) investigate the spillover of crude oil price volatility to agricultural markets (specifically corn and wheat). They apply stochastic volatility models on weekly crude oil, corn and wheat futures prices from November 1998 to January 2009. Their model parameters are estimated using Bayesian Markov Chain Monte Carlo methods. They find that the spillover effects are not statistically significant from zero over the period from November 1998 to October 2006. However, the results indicate significant volatility spillover from the crude oil market to the corn market between October 2006 and January 2009.

In a pair of papers focusing on the cointegration of prices for oil, ethanol and feedstocks, Serra, Zilberman and co-authors study the US (Serra et al., 2011) and Brazilian (Serra et al., 2011) ethanol markets. In the case of the US, they find the existence of a long-term equilibrium relationship between these prices, with ethanol deviating from this equilibrium in the short term. Further for the US, they find the prices of oil, ethanol and corn to be positively correlated as might be expected. The authors estimate that a 10% perturbation in corn prices boosts ethanol prices by 15%. From the other side, they find that a 10% rise in the price of oil leads to a 10% rise in ethanol. In terms of temporal response time, they find that the response to corn prices is much quicker (1.25 months to full impact) than for an oil price shock (4.25 months). For Brazil, the relevant feedstock is sugarcane. The authors find that sugar and oil prices are exogenously determined and focus their attention on the response of ethanol prices to changes in these two exogenous drivers. The authors conclude that ethanol prices respond relatively quickly to sugar price changes, but more slowly to oil prices. A shift in either of these prices has a very short run impact on ethanol price volatility as well. These commodity markets are not as quick to achieve long-run equilibrium again as those in the US according to these two studies.

Rajcaniova and Pokrivcak (2011) analyze the relationship between fuel prices (oil, gasoline, ethanol) and prices of food (corn, wheat, sugar) serving as ethanol feedstock. They do not find any cointegration in the period January 2005 – July 2008, while they find cointegration among majority of their price time series for more recent time period of August 2008 – August 2010. Pokrivcak and Rajcaniova (2011) investigate the relationship among the prices of ethanol, gasoline and crude oil in a vector autoregression and impulse–response framework. Their results confirm the usual finding in the literature that the impact of oil price shock on transport fuels is considerable larger than vice versa.

The interaction between monthly prices of crude oil, the US gasoline and the US ethanol between 1994 and 2010 is investigated in a joint structural vector auto regression (SVAR) model by McPhail (2011). His structural VAR model allows to decompose price and quantity data into demand and supply shocks. Since the US ethanol demand is driven mainly by government support through blending mandates and tax credits, he assumes that ethanol demand reflects primarily changes in government policy. As opposed to policy driven demand, ethanol supply shocks are determined by changes in feedstock prices. The author shows that policy-driven ethanol demand expansion leads to statistically significant decrease in real crude oil prices and the US gasoline prices. He also shows that ethanol supply expansion does not have a statistically significant influence on real oil prices.

Ziegelback and Kastner (2011) investigate the relationship between the futures prices of European rapeseed and heating oil. They use 2005-2010 daily data to show the asymmetry in price movements. The results of their three-regime threshold cointegration model are similar to the results of Peri and Baldi (2010). Related paper by Busse et al. (2010) deals with the connections between prices of rapeseed oil, soy oil, biodiesel and crude oil during the rapid growth of German biodiesel demand from 2002 until its decline in 2009. They found an evidence for a strong impact of crude oil price on German biodiesel prices, and of biodiesel prices on rapeseed oil prices. However, in both cases, the price adjustment behavior was found to be regime-dependent.

Different results with respect to mutual interactions between the prices of biofuels and related commodities may be due to a number of factors. In our research, we focus on the differences in investment horizon (comparing different frequencies), on the role of technological and regulatory constraints and also on geographic factors of the US and European biofuels markets.

Besides time-series models of interactions between biofuels, agricultural commodities, fosil fuels and raw oil, there is a number of other structural models. Conceptually most simple type of structural models are engineering-like cost accounting models which are used to estimate profitability of an activity for a single price-taking agent, such as an individual farmer or a processor. The production function in such models is typically assumed as a fixed-proportion one. Classical representatives of this class of models are crop budget models which have been used to estimate profitability of cultivation of energy crops based on assumptions about yield, output prices, cost of production and other technological and economic parameters.

More theory-based economic studies, which evaluate the impact of biofuels, are based on partial equilibrium or computable general equilibrium (CGE). These models explain the interaction among supply, demand, and prices through the market clearance using a system of equilibrium equations.

In the partial equilibrium structural models, which are also labeled as sector models, clearance in the market of a specific good or sector is obtained under the assumption that prices and quantities in other markets remain constant. Partial equilibrium models are therefore suitable for providing good indication of short-term response to shocks. Partial equilibrium models often provide a detailed description of the specific sector of interest but do not account for the impact of expansion in that sector on other sectors of the economy. The examples of partial equilibrium models used in the assessment of the impact of biofuel development include AGLINK/COSIMO model developed by OECD and FAO, ESIM model, which was developed by the Economic Research Service of the US Department of Agriculture and which is used by the European Commission since 2001, FAPRI model of the Food and Agricultural Policy Research Institute, and the IMPACT model of the International Food Policy Research Institute.

A number of smaller partial equilibrium models are used for analysis of specific questions related to biofuels. An example of this type of models is GLOBIOM model, which is a global recursive dynamic partial equilibrium model integrating the agricultural, bioenergy and forestry sectors.

CGE structural models compute equilibrium by simultaneously taking into account the linkages between all sectors in the economy. The CGE modeling framework provides an understanding of the impact of biofuels on the whole economy by taking into account all the feedback relations between biofuels and other markets. The most well known CGE studies of biofuels are based on variants of GTAP model which is under continuous development under the leadership of Thomas Hertel since 1991.

The major disadvantage of CGE approach to modeling biofuels is that global CGE models are much stronger in a treatment of the developed countries than in the treatment of the developing countries. In the case of biofuels, this is a serious deficiency since the developing countries are expected to be a big supplier of biofuels in the future. They are also currently a focus of the debate about social and environmental consequences of biofuels production and of the fuel versus food discussion.

3 Methodology

In this section, we describe the basics of construction of minimal spanning trees and hierarchical trees. As this methodology is not well known in the economics literature, we present quite careful description of the methods. For the first application of minimal spanning trees and hierarchical trees to the financial time series and a more detailed description, see Mantegna (1999).

3.1 Distance measure

The interconnections in a group of assets are standardly measured by sample correlation coefficients. For a pair of assets i and j with values X_{it} and X_{jt} and $t = 1,\ldots,T$, the sample correlation coefficient $\hat{\rho}_{ij}$ is calculated as

$$\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T}(X_{it} - \overline{X_i})(X_{jt} - \overline{X_j})}{\sqrt{\sum_{i=1}^{T}(X_{it} - \overline{X_i})^2 \sum_{i=1}^{T}(X_{jt} - \overline{X_j})^2}}, \tag{1}$$

where $\overline{X_i} = \frac{\sum_{t=1}^{T} X_{it}}{T}$ and $\overline{X_j} = \frac{\sum_{t=1}^{T} X_{jt}}{T}$ are respective time series averages. Linear correlation ρ_{ij} ranges between -1 (perfectly anti-correlated) and 1 (perfectly correlated) with $\rho_{ij} = 0$ meaning that the pair is uncorrelated. Note that it only makes sense to estimate correlations for the series with well defined means and variances, i.e. weak stationarity of the series is needed.
For a portfolio of N assets, we obtain $N(N-1)/2$ pairs of correlations. Mantegna (1999) showed that the correlation coefficients can be transformed into distance measures, which can in turn be used to describe hierarchical organization of the group of analyzed assets. Distance measure

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \tag{2}$$

is constructed so that it fulfills three axioms of a metric distance:

- $d_{ij} = 0$ if and only if $i = j$;
- $d_{ij} = d_{ji}$;
- $d_{ij} \le d_{ik} + d_{kj}$ for all k

From the definition of the correlation coefficient, the distance ranges between 0 and 2, while $d_{ij} \to 0$ means that the pair is strongly correlated, $d_{ij} \to 2$ implies strongly anti-correlated pair and $d_{ij} = \sqrt{2}$ characterizes an uncorrelated pair.

3.2 Minimal spanning tree and hierarchical tree

Minimal spanning tree (MST) is used to extract the most important connections in the whole network. For our purposes, the connections are characterized by correlation coefficients between pairs of assets. The basic idea behind MST is to reduce the number of $N(N-1)/2$ pairs to only the $N-1$ most important connections while the whole system remains connected. The procedure is very straightforward and in detail described in Mantegna (1999). In short, we transform the correlation matrix C into a distance matrix D, discarding the diagonal elements (containing zero distances). We then find the closest pair of assets, which creates the first two nodes in the network connected by the first link (with a weight equal to the distance d_{ij}). Each node now has a single edge (the link connected to the node). We proceed to the second closest pair which creates the second pair of nodes. At this point, if a node from the second pair is already present in the network, the new node is simply connected to the existing pair. The steps are repeated until $N-1$ links are reached, while the network must not be closed or create closed loops. If the link would create a loop, it is not added into the network. We use Kruskal's algorithm in our application (Kruskal, 1956).

MST helps us to construct hierarchical trees (HT) which are important for the analysis of clusters. With a use of HT, it has been shown that stocks form clusters based on the industrial branches (Mantegna, 1999; Tabak et al., 2010) and that foreign exchange rates create clusters with respect to the geographical location (Mizuno et al., 2006; Keskin et al., 2011; Jang et al., 2011). In order to construct HT with a use of MST and distance matrix D, we first need to determine the subdominant ultrametric distance matrix D^*. The elements of the matrix D^* are defined as the subdominant ultrametric distances d_{ij}^*. Such a distance is equal to the maximal weight of the link which needs to be taken to move from node i to node j in the MST. More formally, $d_{ij}^* = \max(d_{kl})$, where k and l stand for all nodes connecting i and j (including i and j) in the corresponding MST. In matrix D^*, we find the minimal distance d_{ij}^* and create the first pair of assets. We follow in connecting the assets and if we find more assets with same d_{ij}^*, we connect the clusters together. In the end, we obtain the whole HT which clearly separates clusters of the analyzed variables (Mantegna, 1999). For illustration, consider three commodities a, b and c, which form MST such that $a—b—c$ with $d_{ab} = 0.4$ and $d_{bc} = 0.7$. Since the lowest distance is d_{ab}, then the ultra metric distance is $d_{ab}^* = 0.4$. The second lowest distance is d_{bc} which implies $d_{bc}^* = 0.7$. Now, we need to find d_{ac}^*. To get from c to a in this simple MST, we need to cross b. d_{ac}^* is then a maximum of distances between $a—b$ and $b—c$, i.e. $d_{ac}^* = \max(d_{ab}, d_{bc})$. We arrive at $d_{ab}^* = 0.4$ and $d_{ac}^* = d_{bc}^* = 0.7$, which means that a and b are connected and form a pair while c is separated from this simple cluster as it has the same ultra metric distance from both a and b, and we are able to construct the hierarchical tree. The procedure will be better illustrated on the analyzed dataset arriving at more complicated hierarchical structures in the following sections.

Depending on the structure of HT, we can discuss interconnections between specific clusters or separate assets and commodities. In general, HT translates relatively unstructured MST and creates a unique hierarchical structure. From the point of view of our research and focus on clusters in biofuels and related commodities, HT gives a more informative picture of existing clusters. Without HT, MST would give only limited information.

3.3 Stability of links

The major weakness of the described methodology lies in the fact that the calculated MST and HT might be unstable. Moreover, without further statistical analysis, we cannot be sure whether the links present in the MST are actually the important links in the network or are rather a statistical anomaly, i.e. whether the results are sensitive to the sampling. To deal with the problem, we use a bootstrapping technique proposed by Tumminello et al. (2007) specifically for MST and HT analysis.

In the procedure, we first construct the original MST and HT. Then, we construct a bootstrapped time series from the original while keeping the time series length fixed (i.e. the observations may repeat in the bootstrapped sample). MST and HT are then constructed for the bootstrapped time series and links are recorded. It is then checked whether the connections in the original MST are also present in the new MST based on bootstrapped time series. We repeat such procedure 1,000 times so that we can distinguish whether the connections in the original MST and HT are the strong ones or statistical anomalies (Keskin et al., 2011). The share of the bootstrapped cases, where the link appears between nodes i and j, will be labeled as b_{ij} with an obvious range $0 \le b_{ij} \le 1$.

4 Data

Biofuels represent a wide range of fuels which are in some way derived from biomass. The wide definition of biofuels covers solid biomass, liquid fuels and various biogases. In the further text, we concentrate on liquid biofuels.

The biofuels are generally classified as conventional (the first generation) biofuels and advanced biofuels (the second, third, and fourth generations). The first generation biofuels are made from food crops rich in sugar or starch or vegetable oil. The most common types of the first generation biofuels are bioalcohols (especially ethanol) and biodiesel. The second generation biofuels are produced from residual non-food parts of current crops, such as stems, leaves and husks that are left behind once the food crop has been extracted, as well as other crops that are not used for food purposes, such as switchgrass, jatropha, miscanthus and cereals that bear little grain, and also industry waste such as wood chips, skins and pulp from fruit pressing etc. The third generation biofuels are obtained from algae. Biofuels created from processes other than the first generation ethanol and biodiesel, the second generation cellulosic ethanol, and the third generation algae biofuels are referred to as the fourth generation biofuels. Fourth generation biofuels are highly experimental and have not yet been even clearly defined. Some fourth generation technologies are: decomposition of biofuels at high temperatures, artificial photosynthesis reactions, known as solar-to-fuel, and genetically modifying organisms to secrete hydrocarbons.

Crops rich in sugar and starch like sugarcane and corn (maize), respectively, supply almost all the ethanol that is produced today. Other major crops being used include wheat, sorghum, sugar beet, and cassava. Biochemical technologies for conversion of sugar and starch are also the most technologically and commercially mature today. Currently prevailing fermentation technologies are based on an extraction of simple sugars in sugar crops, their yeast-fermentation and distillation into ethanol. Starches crops require an additional technological step. They are initially converted into simple sugars through an enzymatic process under high heat. This conversion requires additional energy and leads to an increase in the cost of production. The major drawback of the first generation biofuel crops is that they are important food crops and their use for fuel can have adverse impacts on food supply. Another drawback is that these crops are intensive in the use of one or more inputs such as land, water, fertilizers, pesticides, etc., which have other environmental implications. In the future, the cellulosic sources are expected to displace such crops as the major second-generation source of ethanol. While the first generation ethanol is produced from the sugar or starch part of the plant, which comprises only a small percentage of the total biomass of the plant, the second-generation conversion of lignocellulosic biomass leads to the full use of lignocellulosic material contained in many biomass sources like waste seed husks and stalks and fast growing grasses and trees. Lignocellulosic biomass is composed of polysacharides (cellulose and hemicellulose), which are converted into sugars through hydrolysis or chemical (or combined) processes. The sugar is then fermented into ethanol using the technologies already utilized for the first generation biofuels.

In contrast to ethanol, biodiesel is produced from oilseed crops like soybean, rapeseed, and oil palm. The most common method of producing biodiesel is transesterification. It is a chemical process by which vegetable oils (like soy, canola, palm, etc.) can be converted to methyl or ethyl esters of fatty acids also called biodiesel. Biodiesel is physically and chemically similar to petro-diesel and hence substitutable in diesel engines. Transesterification also results in the production of glycerin, a chemical compound with diverse commercial uses.

In this paper we analyze weekly and monthly prices of Brent crude oil (CO), ethanol (E), corn (C), wheat (W), sugar cane (SC), soybeans (S), sugar beets (SB), consumer biodiesel (BD), German diesel and gasoline (GD and GG), and the US diesel and gasoline (UD and UG) from 24.11.2003 to 28.2.2011. While the majority of our data were obtained from the Bloomberg database, gasoline and diesel prices were obtained from the U.S. Energy Information Administration and they present average prices of the countries. We use both the US and the German prices to uncover potential connection to ethanol and biodiesel as biodiesel production used to be rather a European activity while ethanol production is more an American activity. Ethanol price is the New York Harbor price for ethanol according to ASTM D4806 specification. This is a denaturated anhydrous fuel ethanol for blending with gasoline. Crude oil price refers to current pipeline export quality Brent blend as supplied at Sullom Voe. Corn price is for Corn No. 2 Yellow. Wheat price is for various types of wheat (No. 2 Soft Red Winter Wheat, No. 2 Hard Red Winter Wheat, No. 2 Dark Northern Spring Wheat, and No. 2 Northern Spring Wheat at par (contract price); and No. 1 Soft Red Winter Wheat, No. 1 Hard Red Winter Wheat, No. 1 Dark Northern Spring Wheat and No. 1 Northern Spring Wheat at 3 cents per bushel over contract price.) Sugar price is for raw centrifugal cane sugar based on 96 degrees average polarization. Soybeans price is for Soybeans No. 2 Yellow. Sugar beets price is for white beet or cane crystal sugar or any other refined sugar. Biodiesel price is for commodity type consumer biodiesel, as reported by F.O. Licht. Daily data are not used in our analysis as the spot markets (ethanol and biodiesel) are not liquid enough and the analysis would not be meaningful.

Taking X_t as Monday closing prices, we analyze returns $r_t = \log(X_t - X_{t-1})$. As we analyze the structure of distances, which are simply transformed correlations, between the commodities, stationarity of the series becomes crucial. The results for three stationarity tests – ADF test with a constant, ADF test without a constant and KPSS test are quite straightforward – all the logarithmic returns are stationary, which implies that we can proceed to the estimation of correlation coefficients and distances from the logarithmic returns series without further adjustments. Note that we try to keep the methodology as straightforward as possible. To do so, we present only the results for unadjusted logarithmic returns, which is standardly done in the literature. We also applied the methodology on AR(1)-GARCH(1,1)-filtered series, i.e. the estimated correlations were robust to autocorrelation and heteroskedasticity in the processes. However, the sample correlations differ only a little for the adjusted series and the resulting MSTs and HTs are qualitatively the same as the ones presented in this paper. Again, the methodology can be extended to various frameworks modeling time-dependent correlations (Long et al., 2011) or even time- and frequency-dependent correlations (Vacha and Barunik, 2012).

5 Results

In this section, we present and comment on the results of the minimal spanning trees and hierarchical trees for the studied network of commodities[1].

We start with the first few steps of construction of minimal spanning tree for weekly returns to illustrate the procedure. The pair with the highest correlation coefficient – and thus the closest one – consists of German diesel and German gasoline with $d_{ij} = 0.5330$. Therefore, the first connected nodes of the MST are GD—GG. The second lowest distance is the one between US gasoline and US diesel ($d_{ij} = 0.6563$). We now have two pairs of nodes GD—GG and UD—UG in the MST. The next lowest distance is found for SB—SC pair ($d_{ij} = 0.7671$). The MST now contains three separate pairs of nodes – GD—GG, UD—UG and SB—SC. We proceed to the fourth lowest distance and obtain a next pair created by corn

[1] All calculations and construction of MST and HT have been conducted and coded in TSP 5.0.

and wheat ($d_{ij} = 0.8848$). Again, neither corn nor wheat are connected to the other nodes already present in the MST which implies that the MST is now made of four separate pairs. In the next step, we find that the fifth lowest distance in the distance matrix D is for the German and US gasolines ($d_{ij} = 0.9181$). Both of the nodes are already present in the MST so that we just connect the nodes GG and UG. The MST is now created by two pairs C—W, SB—SC and one quadruple GD—GG—UG—UD. Next pair is formed by soybeans and corn with $d_{ij} = 0.9369$. Corn is already a part of the MST so that soybeans are just connected to the existing couple C—W. The MST is now formed by a pair SB—SC, a triple C—W—S and a quadruple GD—GG—UG—UD. The next closest pair is the one of German gasoline and US diesel. Both nodes are already present in the MST. Moreover, they are both a part of the quadruple GD—GG—UG—UD and are therefore already connected. If we added a new link GG—UD, we would create a loop, which is not desirable. Eventually, no new link is added for this pair. Following these simple rules, we arrive at the final MST presented in Fig. 1a.

In the similar way, we describe the construction of the hierarchical tree for the weekly returns. We start with finding the closest pair in the MST – that is GG—GD pair, which in turn forms the first pair in the HT. Next is the UG—UD pair, which again forms a pair in the HT. In the same way, the C—W and SC—SB pairs are formed. The next lowest distance is between GG—UG link. Now, both nodes are already present in the HT so that we connect the pairs GG—GD and UG—UD but assign the distance $d^*_{ij} = 0.9181$ to all pairs which might be formed by these four nodes. Therefore, the distance between the pairs is now 0.9181. This is graphically shown in Fig. 1b. The next lowest distance in the MST is present for C—S pair. Corn is already a part of the HT and forms a pair with wheat. We now check what the maximum distance between soybeans and wheat is and we find that it is the distance between corn and soybeans. In turn, we assign $d^*_{ij} = 0.9369$ to both possible pairs formed from the three. Graphically, we connect S to the pair C—W. Again, if we follow these simple rules, we finally arrive at the HT presented in Fig. 1b. In the same way, we constructed the HT for monthly frequency.

Let us first focus on the minimal spanning trees for a higher frequency – a trading week. It is clearly visible that the minimal spanning tree is formed from two parts – a food part (SC, SB, W, C, S) and a fuels part (CO, GD, GG, UG, UD, E, BD). In the MST charts, we also show the distances d_{ij} between nodes (regular font) as well as a bootstrapped value b_{ij} (italics in brackets). The bootstrapped value represents the proportion of times when the specific link has been present in the bootstrapped MST. For example, the value of 0.783 for S—CO link means that out of 1,000 bootstrapped realization, the S—CO link has been found in 783 final MSTs. Using these values, we can comment on a strength or a stability of a link in the MST. In the food part of the MST, we observe a triple W—C—S and a pair SC—SB which have been found in all bootstrapped realizations. These links are thus very stable. The connection between the triple and the pair is quite weaker ($b_{ij} = 0.428$). We can see similarly strong connections in the fuels part of the MST, mainly for a foursome GD—GG—UG—UD which has been found in almost all the bootstrapped cases. Both biofuels are linked to the US fuels. Relatively low bootstrapped value for CO—GD link ($b_{ij} = 0.388$) is caused mainly by the fact that crude oil is correlated to GG, GD, UD and UG at similar levels so that the links alter between the four in the bootstrapped cases.

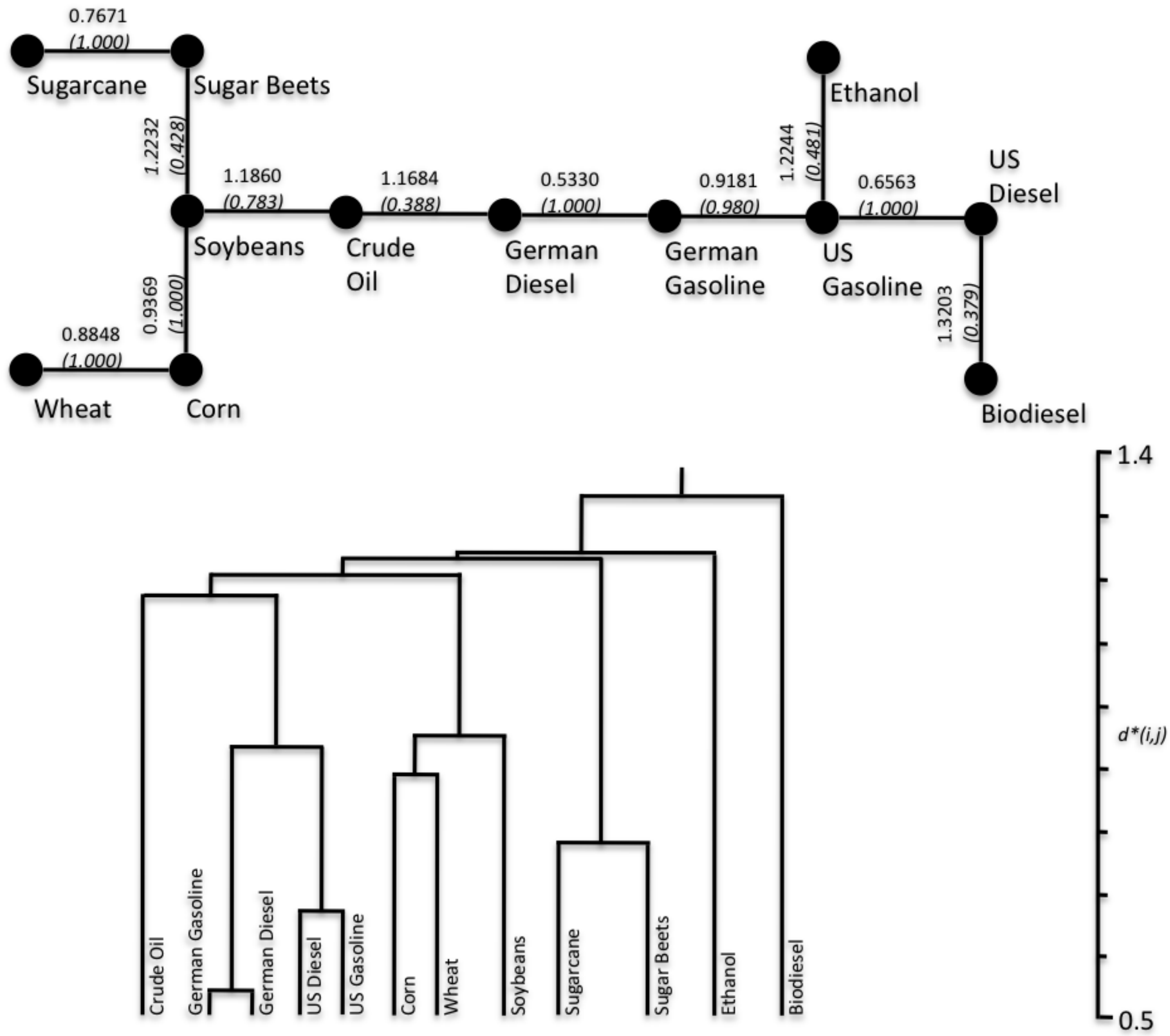

Figure 1a, b. ***Minimal spanning tree (upper picture) and hierarchical trees (lower picture) for network of returns with weekly frequency***

Very similar results can be read from the HT. Here, we can see that there are several clusters – a fuels cluster, a sugar cluster and a fodder cluster. The other commodities – crude oil, ethanol and biodiesel – are quite far from these clusters and thus do not interact much in the short term. Importantly, the biofuels are quite remote from the rest of the network, which can be interpreted in a way that in a short term horizon, the behavior of these biofuels is not dependent on the other analyzed commodities.

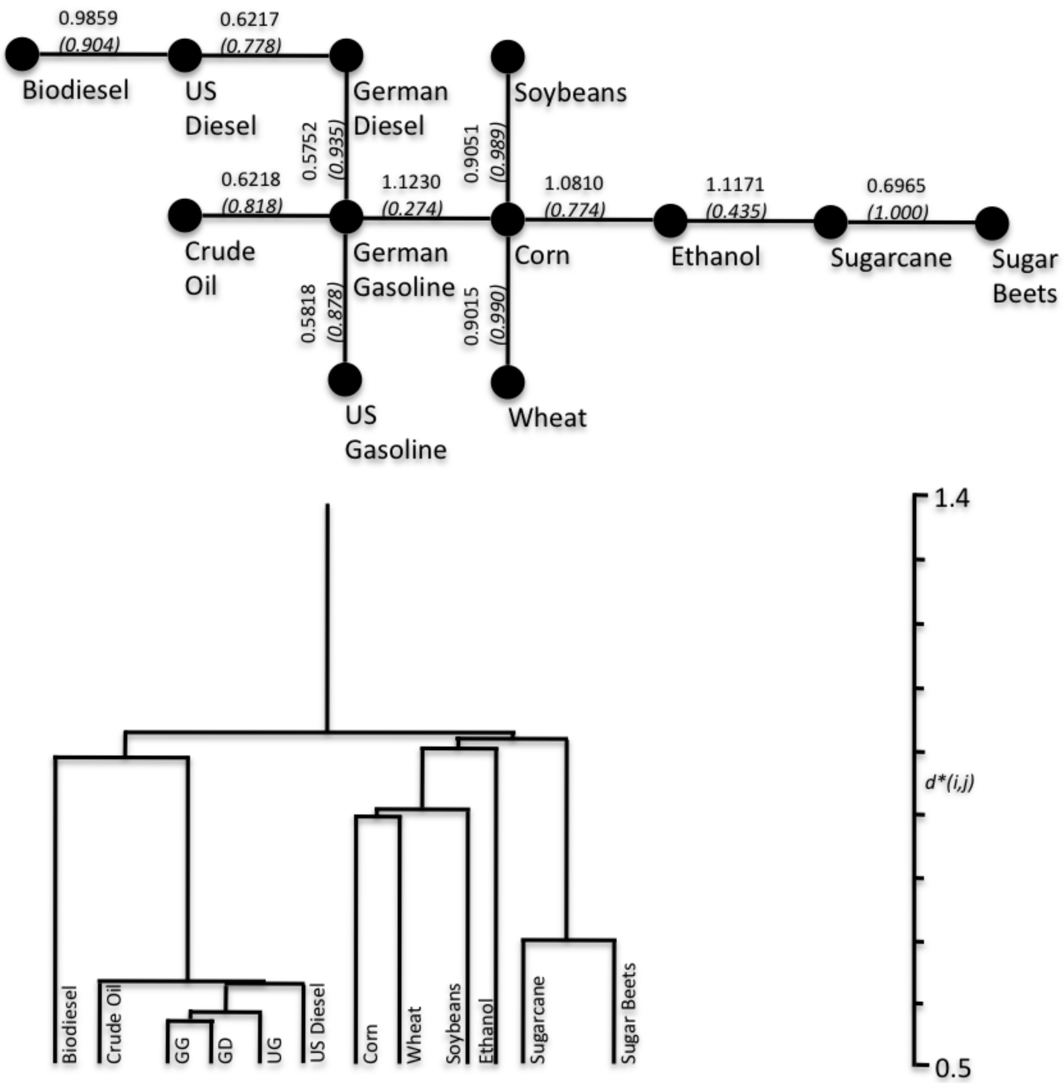

Figure 1c, d. ***Minimal spanning tree (upper picture) and hierarchical trees (lower picture) for network of returns with monthly frequency***

When we look at the relationships between commodities at the lower (monthly) frequency, both MST and HT are getting more structured. The core of the connections remains the same – we still have the three clusters. However, the behavior of the biofuels changes. Ethanol becomes more connected with the food part and biodiesel with the fuels part. Interestingly, the whole network practically splits into two branches – one branch contains all the retail fuels, crude oil and biodiesel and the other branch includes all the analyzed food and ethanol. However, it has to be noted that a distance between the branches is quite low so that the whole system is well correlated. Moreover, difference in the distances between ethanol and C—W—S cluster, then SC—SB from C—W—S—E cluster and then between the whole food cluster and the fuels cluster is very small (all three ultrametric distances are between 1.08 and 1.12), which means that this separation is very unstable. Nevertheless, the average distance between the analyzed commodities decreases from 0.98 for the weekly frequency to 0.84 for the monthly frequency, which implies that the system gets more interconnected with the lower frequency. Apart from the connections of the biofuels to the rest of the network, we observe some other interesting features. First, compared to the weekly frequency, where the GG—GD and UG—UD clusters were well separated, this separation almost disappears for the monthly frequency. This implies that in a short term, behavior of the retail fuels is dominated by geographical features but in medium term, this separation vanishes. Second, crude oil is very well connected to the retail fuels cluster in the medium term, which was not the case for the short term. This implies that it takes several weeks until the effect of the price change of crude oil is reflected in the prices of retail fuels. And last, the feedstock and sugar clusters are well separated for both frequencies.

To summarize the most important findings for ethanol and biodiesel returns with respect to different frequencies, we can say that in the short term, both of these are very weakly connected with the other commodities. Moreover, there is no clear inclination to either of fuels or food parts of the network. In the medium term, biodiesel becomes connected to the fuels section of the system, whereas ethanol gets more connected to the food branch of the system.

Unfortunately, the MST and HT analysis is not capable to find the direction of the effects, i.e. whether the effect comes from food to ethanol or the other way around. However our supplementary follow-up analysis of Granger-causality based on the whole sample of data used in this paper shows that prices of corn Granger-cause prices of ethanol in both short and medium term. We found out that this effect is positive, so that increase in price of corn leads to increase in price of ethanol in relatively short time and the effect disappears quite quickly since the aggregate effect is insignificant starting by the 12th week. We did not find statistically significant Granger causality in the other direction (from ethanol to corn). This is in agreement with the findings of Wixson and Katchova (2012) who show on monthly US data from 1995 to 2010 that price of corn Grange-causes price of ethanol and that ethanol does not Grange-cause wheat. Similar results are reported by Saghaian (2010) who shows that corn price Granger-causes price of ethanol with statistical significance on all conventional levels, but the reversed direction of Granger causality is statistically significant only on 10 percent significance level.

However there also exist studies indicating different causality patterns. For example Zhang et al. (2009) did not find any long-run causality relation between prices of ethanol and corn while in the short-run they found out that prices of ethanol Granger-cause the price of corn. Serra et al. (2011) show that positive causal relationship from ethanol prices to corn prices does not only prevail in the short-run but also in the longer term. However they also show that a shock to corn price when the ethanol price is far away from its equilibrium level will cause an adjustment in the ethanol price in the same direction.

An important starting point for further discussion of our results is the comparison of two major biofuels markets covered in our analysis - US and EU. The EU is historically the largest producer, consumer and importer of biodiesel, which is the most important biofuel in EU. According to Flach et al. (2011) on energy basis biodiesel represents about 80 percent of the total EU biofuels market in the transportation sector. Biodiesel was the first biofuel developed and used in the EU in the transport sector in the 1990s. At the time, the rapid expansion was driven by an increasing crude oil price, the Blair House Agreement of 1992 between US and EU on export subsidy and domestic subsidy reduction and resulting provisions of the EU's set-aside scheme, and generous tax incentives mainly in Germany. The Blair House Agreement allowed the EU to produce oilseeds for non-food use of up to 1 million MT of soybean equivalent. EU biofuels goals set in directive 2003/30/EC (indicative goals) and in the RED 2009/28/EC (mandatory goals) further pushed the use of biodiesel. In addition, the Fuel Quality Directive gave the industry considerable latitude to market higher blends in the fuel supply. This means that the EU orientation on biodiesel was very much induced by public policies originating in 1990s. On the contrary to the EU situation, the US biofuels markets are dominated by ethanol.

The EU policy of setting a single target for all types of biofuel provides a flexibility for EU fuel markets to select a cost-effective biofuels types and technologies. The US approach of sectoral targets is missing this market flexibility, but it may provide market players a long-term confidence for introducing new investments in a broad range of renewable energy sources. More detailed comparison of the US and EU biofuels markets and policies is provided by Tyner (2010a) and Ziolkowska et al. (2010). Because of crucial determining role of government policies in biofuel markets development both in US and EU, it is important to realize that US biofuels mandate was designed in volumes while the EU targets are in energy units. This means that in the US a liter of ethanol was equivalent to a liter of biodiesel as far as volumetric mandates were concerned, while in the EU a kilojoule of ethanol is equivalent to kilojoule of pure biodiesel. According to Tyner (2010a) 1.65 liters of ethanol have an energy equivalent of 1 liter of biodiesel which means that EU system provides an incentive for private sector to use the biodiesel in order to meet the biofuels mandates while the US policy is biased towards the use of ethanol.

Another important difference among EU and US motor fuel markets is much higher share of diesel-engined cars in Europe than in US. This historical difference was again caused by government policies, primarily by taxation of motor fuels. Since the fuel taxes in US were historically much lower than in Europe, the higher fixed cost of diesel engines, as compared to gasoline engines, were more important than variable cost advantage of diesel fuel. In addition the relative tax differences among diesel and gasoline in Europe and US meant that over the period covered in our paper the consumer price of a liter of diesel was higher than that of gasoline in US and vice versa in EU.

From economic point of view, our results show that short-term adjustments, which correspond more to random changes than systematic forces, do not form strong price links in the whole system of biofuels and related commodities. The picture changes by extending the analyzed horizon to one month since the MST and HT constructed with monthly data exhibit considerably more complex structure.

While some earlier evaluations (Mitchell, 2008) pointed to biofuels as a major cause of 2007/2008 food crisis, subsequent research of Hochman et al. (2011) and other authors shows that biofuels were only one of many contributors of price increase. Majority of this research dealing with the role of biofuels in the 2007/2008 food crisis concentrates on ethanol and main agricultural commodities (corn, soybean, rice, wheat) and concludes that the role of biofuels in the price increase was noticeably stronger for corn than for soybeans, with soybean prices driven primarily by the increase in demand due to economic growth. This is in line with our results separating soybeans into a “food subgroup” of MST/HT and placing biodiesel into a distinctive “fuels group” as opposed to ethanol with strong connections to food commodities.

An important policy lesson of our analysis is to emphasize that the general statements about biofuels driving up the prices of agricultural commodities miss a critical distinction between different biofuels. We show that ethanol prices and biodiesel prices have clearly different places in a wide system of biofuels-related commodities. Our results confirm that discussion about food and biofuels prices is primarily relevant for ethanol, but not so much for biodiesel. While we present a strong correlation between prices of ethanol and its major feedstock corn and to a lesser extent other feedstocks, we do not obtain such results for biodiesel. The close connection of major biodiesel feedstock – soybeans – with corn and other grains shows that pricing of soybeans is more driven by its competition with corn for land and water resources and as major components of animal feed in livestock production in US and abroad, especially in China.

6 Conclusions and suggestions for further research

We analyzed the relationships between biodiesel, ethanol and related fuels and agricultural commodities with a use of minimal spanning trees and hierarchical trees. To distinguish between short-term and medium-term effects, we constructed the trees for different frequencies (weekly and monthly).

We found that in the short term, both analyzed biofuels are very weakly connected with the other commodities. In the medium term, the network structure becomes more interesting. The system practically splits into two branches – a fuels part and a food part. Biodiesel tends to the fuels branch and ethanol to the food branch.

Our results contributed to the policy debate about biofuels as possible (major) source of rises in food prices leading to food crises. We confirmed positive correlations among the prices of biofuels and food, but we shoved that the distinction should be made between different biofuels. The policy recommendation of carefully distinguishing between different biofuels is not new to the biofuels and food debate, but so far the distinction was drawn primarily between first generation and second generation biofuels with emphasis on ethanol related feedstock. Our contribution is in highlighting the differences among biodiesel and ethanol with respect to co-movements with food commodity prices and to emphasize time-varying nature of these co-movements. The investigation of time and price varying dynamic causal relations among prices of various biofuels and related commodities is a topic of our further ongoing research in this food-policy relevant area.

Finally, even though the methodology of taxonomy for economic time series is very simple and only transforms the correlations into distances, we were able to find several important results. We identified different biofuel prices network clusters corresponding to different binding constraints for the biofuels price equilibrium formation. The connections among different elements of biofuels network identified in this paper may be used as starting points for more detailed econometric time series investigations (identification of the most important connections in the system, identification of potential collinearity, or even a basis for an optimal portfolio construction). The simplicity of the minimal spanning trees and hierarchical trees methodology allows to include a large number of prices and we therefore expect future research to expand our analysis both in terms of goods and locations in more detail. This will eventually create a good picture of how the relative food and fuel prices relate over space and time.

The taxonomy methodology opens new possibilities for further research. First, a broader range of commodities and assets which might be important in the biofuels discussion – exchange rates, interest rates, commodities futures, stocks, climate conditions, exports and many others – can be included in the MST and HT analysis. A range of possible factors influencing clustering of commodity prices is suggested by Savascin (2011). Second, the proposed methodology can be accompanied by principal component analysis (Pearson, 1901) to give a more complex view on the cluster analysis. Third, conditional (time-varying) correlations can be taken into consideration and incorporated into MST/HT methodology to better describe the evolution in time. However, this would impose a specific model on the data-generating process of the analyzed series, which we wanted to avoid in this paper. Fourth, the time-dependent correlations analysis can be expanded to the frequency domain through wavelets which are able to separate time and frequency characteristics of the series (Vacha and Barunik, 2012). Discrete wavelets and corresponding coherences can be incorporated into the proposed methodology as well while still keeping the framework model-free. And fifth, the biofuels network can be analyzed with a 3D generalization of MST/HT methodology proposed by Song et al. (2011). As a starting point, the proposed methodology and obtained results uncover new frontiers in the biofuels systems research.

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References

[1] Beckman, J., T. Hertel, and W. Tyner (2011). Validating energy-oriented CGE models. Energy Economics (5), 799–806.

[2] Bonanno, G., G. Caldarelli, F. Lillo, S. Micciche, N. Vandewalle, and R. Mantegna (2004). Networks of equities in financial markets. European Physical Journal B, 363–371.

[3] Busse, S., B. Brummer, and R. Ihle (2010). Interdependencies between fossil fuel and renewable energy markets: the German biodiesel market. DARE Discussion Paper 1010, Georg-August University of Gottingen, Department of Agricultural Economics and Rural Development.

[4] Chang, T.-H., H.-M. Su, and C.-L. Chiu (2011). Value-at-risk estimation with the optimal dynamic biofuel portfolio. Energy Economics (2), 264–272.

[5] Du, X., C. L. Yu, and D. J. Hayes (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. Energy Economics (3), 497–503.

[6] Flach, B., S. Lieberz, K. Bendz, and B. Dahlbacka (2011, June). EU-27 annual biofuels report. GAIN Report NL1013, USDA Foreign Agricultural Service.

[7] Hochman, G., D. Rajagopal, G. Timilsina, and D. Zilberman (2011, August). Quantifying the causes of the global food commodity price crisis. Policy Research Working Paper 5744, World Bank.

[8] Janda, K., L. Kristoufek, and D. Zilberman (2012). Biofuels: Policies and impacts. Agricultural Economics, Forthcoming.

[9] Jang, W., J. Lee, and W. Chang (2011). Currency crises and the evolution of foreign exchange market: Evidence from minimum spanning tree. Physica A , 707–718.

[10] Kantar, E., B. Deviren, and M. Keskin (2011). Hierarchical structure of Turkey's foreign trade. Physica A (20), 3454–3476.

[11] Keskin, M., B. Deviren, and Y. Kocakaplan (2011). Topology of the correlation networks among major currencies using hierarchical structure methods. Physica A , 719–730.

[12] Kruskal, J. (1956). On the shortest spanning subtree of a graph and the traveling salesman problem. Proceedings of the American Mathematical Society (1), 48–50.

[13] Long, X., L. Su, and A. Ullah (2011). Estimation and forecasting of dynamic conditional covariance: a semiparametric multivariate model. Journal of Business and Economic Statistics, 109–125.

[14] Lucey, B. M., G. G. Gilmore, and M. Boscia (2011). Comovements in commodity markets: A minimum spanning tree analysis. Presentation for Midwest Finance Conference, 2012.

[15] Mantegna, R. (1999). Hierarchical structure in financial markets. European Physical Journal B , 193–197.

[16] McPhail, L. L. (2011). Assessing the impact of US ethanol on fossil fuel markets: A structural VAR approach. Energy Economics (6), 1177–1185.

[17] Mitchell, D. (2008, July). A note on rising food prices. World Bank Policy Research Working Paper 4682, World Bank – Development Economics Group.

[18] Mizuno, T., H. Takayasu, and M. Takayasu (2006). Correlation networks among currencies. Physica A, 336–342.

[19] Onnela, J.-P., A. Chakraborti, K. Kaski, and J. Kartesz (2002). Dynamic asset trees and porfolio analysis. European Physical Journal B, 285–288.

[20] Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. Philosophical Magazine (6), 559–572.

[21] Peri, M. and L. Baldi (2010). Vegetable oil market and biofuel policy: An asymmetric cointegration. Energy Economics (3), 687–693.

[22] Pokrivcak, J. and M. Rajcaniova (2011). Crude oil price variability and its impact on ethanol prices. Agricultural Economics – Czech (8), 394–403.

[23] Rajagopal, D., S. Sexton, G. Hochman, D. Roland-Holst, and D. Zilberman (2009). Model estimates food-versus-biofuel trade-off. California Agriculture (4), 199–201.

[24] Rajcaniova, M. and J. Pokrivcak (2011). The impact of biofuel policies on food prices in the European Union. Journal of Economics (Ekonomicky casopis) (5), 459–471.

[25] Saghaian, S. H. (2010, August). The impact of the oil sector on commodity prices: Correlation or causation? Journal of Agricultural and Applied Economics (3), 477–485.

[26] Savascin, O. (2011, November). The dynamics of commodity prices: A clustering approach. University of North Carolina, Chapel Hill.

[27] Serra, T. (2011). Volatility spillovers between food and energy markets: A semiparametric approach. Energy Economics (6), 1155–1164.

[28] Serra, T., D. Zilberman, and J. M. Gil (2011). Price volatility in ethanol markets. European Review of Agricultural Economics (2), 259–280.

[29] Serra, T., D. Zilberman, J. M.Gil, and B. K. Goodwin (2011, January). Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system. Agricultural Economics (1), 35–45.

[30] Song, W.-M., T. Di Matteo, and T. Aste (2011). Nested hierarchy in planar graphs. Discrete Applied Mathematics , 2135–2146.

[31] Tabak, B., T. Serra, and D. Cajueiro (2009). The expectation hypothesis of interest rates and network theory: The case of Brazil. Physica A , 1137–1149.

[32] Tabak, B., T. Serra, and D. Cajueiro (2010). Topological properties of commodities networks. European Physical Journal B , 243–249.

[33] Tumminello, M., T. Di Matteo, T. Aste, and R. Mantegna (2007). Correlation based networks of equity returns sampled at different time horizons. European Physical Journal B, 209–217.

[34] Tyner, W. E. (2010a). Comparison of the US and EU approaches to stimulating biofuels. Biofuels (1), 19–21.

[35] Tyner, W. E. (2010b). The integration of energy and agricultural markets. Agricultural Economics (s1), 193–201.

[36] Vacha, L. and J. Barunik (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. Energy Economics (1), 241–247.

[37] Wixson, S. E. and A. L. Katchova (2012, February). Price asymmetric relationships in commodity and energy markets. Presentation at 123rd EAAE seminar in Dublin.

[38] Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein (2009). Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. Energies (2), 320–339.

[39] Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein (2010). Food versus fuel: What do prices tell us. Energy Policy (1), 445–451.

[40] Ziegelback, M. and G. Kastner (2011). European rapeseed and fossil diesel: Threshold cointegration analysis and possible implications. Presentation at GEWISOLA conference in Halle, Germany.

[41] Zilberman, D., G. Hochman, D. Rajagopal, S. Sexton, and G. Timilsina (2012). The impact of biofuels on commodity food prices: Assessment of findings. American Journal of Agricultural Economics, Forthcoming.

[42] Ziolkowska, J., W. H. Meyers, S. Meyer, and J. Binfield (2010). Targets and mandates: Lessons learned from EU and US biofuels policy mechanisms. AgBioForum (4), 398–412.