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Time-Frequency Dynamics of Biofuels-Fuels-Food System

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Keywords

JEL Classification

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Time-Frequency Dynamics of Biofuels-Fuels-Food System

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Abstract

For the first time, we apply the wavelet coherence methodology on biofuels (ethanol and biodiesel) and a wide range of related commodities (gasoline, diesel, crude oil, corn, wheat, soybeans, sugarcane and rapeseed oil). This way, we are able to investigate dynamics of correlations in time and across scales (frequencies) with a model-free approach. We show that correlations indeed vary in time and across frequencies. We find two highly correlated pairs which are strongly connected at low frequencies – ethanol with corn and biodiesel with German diesel – during almost the whole analyzed period (2003-2011). Structure of correlations remarkably changes during the food crisis – higher frequencies become important for both mentioned pairs. This implies that during stable periods, ethanol is correlated with corn and biodiesel is correlated with German diesel mainly at low frequencies so that they follow a common long-term trend. However, in the crisis periods, ethanol (biodiesel) is led by corn (German diesel) even at high frequencies (low scales), which implies that the biofuels prices react more rapidly to the changes in their producing factors.

Keywords: biofuels, prices, correlations, wavelet coherence
JEL codes: C22, Q16, Q42

1. Introduction

Relationship between biofuels and related fossil fuels and producing agricultural commodities and its analysis have become more challenging to study in recent years which experienced strongly varying prices of all mentioned commodities. The so-called "food crisis", which was characteristic by sharply increasing prices of agricultural commodities and crude oil as well as retail fuels and biofuels, captured a very wide academic and policy attention during 2008 and it continues to form policy attitude toward the biofuels versus food issues. The matter of food–fuels–biofuels interactions gained another dimension and a research on possible squeeze-out effect, i.e. whether the increasing prices of biofuels cause prices of related agricultural commodities to raise as well, has become very frequent since that time.

However, the results are in general quite ambiguous, which might be caused by the fact that the authors usually use different models with different assumptions and restricted commodity coverage coming to different results (Hochman et al., 2012; Janda et al., 2012; Zilberman et al., 2013). In this paper, we contribute to this discussion by providing a new comprehensive view on the price-correlation dynamics of food-biofuels-fuels system. Using the wavelet coherence analysis, we are able to capture complex price-correlation dynamics without restriction to ad-hoc specified time or frequency frameworks used in the previous literature. Additional advantage of our paper is a wide coverage of all biofuels related commodities including crude oil, fossil fuels, both main types of biofuels and major agricultural feedstocks for biofuels, which is a unique contribution to biofuels price transmission literature.

In the previous studies, Zhang et al. (2009, 2010) use VECM and mGARCH models to analyze the US ethanol connections with corn, soybeans and gasoline to find no long-range relationships. Also, they focus on Granger causality and uncover only weak short-term effects. McPhail (2011) uses structural VAR model to analyze relationship between the US ethanol, crude oil and gasoline to show that a policy-driven increase in demand for ethanol leads to lowering prices of both crude oil and gasoline. Busse et al. (2010) focus on German biodiesel and its connections to rapeseed oil, soy oil and crude oil between 2002 and 2009 and argue that crude oil strongly influenced the prices of biodiesel and biodiesel shocks transmitted into rapeseed oil prices. However, the results are regime-dependent.

A number of previous studies dealing with price transmission in food-energy systems do not consider the prices of biofuels at all. Instead they just consider crude oil prices and prices of agricultural commodities. Ciaian and Kancs (2011b) report cointegration between crude oil and a range of food commodities, some of them being used in the production of biofuels. Since their range of food commodities cointegrated with the prices of crude oil grows over time, they provide supporting evidence to the hypothesis of increasing importance of biofuels transmission channel in the link between energy and food markets (Tyner, 2010; Ciaian and Kancs, 2011a).

Serra et al. (2010, 2011) and Serra et al. (2011) focus on cointegration between crude oil, ethanol and related feedstock to find an equilibrium relationship between the commodities for the US market as well as the Brazilian market with a slower reaction to the

shocks found for the latter. Rajcaniova and Pokrivcak (2011) argue that the cointegration relationship between ethanol and related commodities exists only for years 2008 onwards, finding no statistically significant relationship in preceding years 2005–2008. Pokrivcak and Rajcaniova (2011) provide evidence for cointegration relationship between crude oil and gasoline prices but they do not find any cointegration between the prices of ethanol and gasoline, and ethanol and oil. The role of biofuel policies in determining which country is the biofuel price leader in world markets using a cointegration analysis and the Vector Error Correction (VEC) model is analyzed by Rajcaniova et al. (ming) with a more evidence on connection between policies and biofuels related prices being provided by de Gorter et al. (ming).

Focusing more on the relationships in the frequency domain, Kratschell and Schmidt (2012) utilize frequency domain Granger causality test to analyze short- and long-run causality between energy and food commodities prices to find that the causality comes from oil to food commodities but the relationship is profound mainly at low frequencies, i.e. the causality is evident mainly in the long-run. Kristoufek et al. (2012a, 2013) analyze the biofuels markets with a use of minimum spanning and hierarchical trees to show that biofuels are very weakly connected to fossil fuels and relevant agricultural commodities in short-term but become more interrelated in medium-term. The relations become stronger for the food crisis period onwards. Kristoufek et al. (2012b) study the same dataset as the previous reference and focus on elasticities and Granger causality and their price dependence. They find that corn causes changes in ethanol prices while both elasticity and causality are price-dependent, and they find biodiesel to be caused and elastic to the changes in German diesel prices and the effects are again price-dependent.

Evidently, the results differ considerably not only due to the model specifics but also due to the analysis of sometimes different time scales (the most frequently analyzed scales range from weekly to monthly or quarterly). Moreover, standardly used time series econometric methods usually consider the frequency and time components separately. In this paper, we utilize the wavelet approach, which allows to study the frequency components of time series without losing the time information. Moreover, the wavelet methodology is constructed to work with nonstationary data, which is a frequent issue in the financial time series modeling (Roueff and Sachs, 2011). In addition, the wavelet approach does not assume any specific model and it is thus model-free, which is an important advantage compared to the other methodologies discussed above. The wavelet methodology can be seen as a filter of the time series so that it is not degraded by the omitted variable bias, which can play an important role considering a potential complexity of the fuels–biofuels–commodities system compared to standard methods.

As confirmed by the most recent review of biofuel-related price transmission literature by Serra and Zilberman (2013), we are the first ones to apply the wavelet coherence analysis on biofuels (ethanol and biodiesel) and a wide range of related commodities (gasoline, diesel, crude oil, corn, wheat, soybeans, sugarcane and rapeseed oil). Wavelets have been used several times in the analysis of commodities and energy markets. Connor and Rossiter (2005) were among the first ones to use wavelets on the commodity markets. They studied price correlations using a discrete form of wavelet transform. Relations between oil prices

and economic activity with wavelets were studied by Naccache (2011). However, that study was focused on very long cycles. Recently, Vacha and Barunik (2012) applied continuous wavelet analysis to study dynamic dependence between energy commodities. The authors compared the wavelet methodology with multivariate concept of dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) and showed robustness of the wavelet coherence method.

We show that correlations indeed vary in time and across frequencies. We find two highly correlated pairs which are strongly connected during almost the whole analyzed period (2003-2011) at low frequencies – ethanol with corn and biodiesel with German diesel. This asymmetric behavior of ethanol and biodiesel is quite an interesting phenomenon since a simple technological reasoning could assume that both biofuels would have similar correlation structures with respect to their agricultural feedstock and appropriate fossil fuel substitute. However we show that this is not the case and that ethanol prices are primarily connected with the price of its major US feedstock while the biodiesel prices are most strongly connected with prices of its German fossil fuel substitute.

We discover that structure of correlations remarkably changes during the food crisis – higher frequencies become important for both mentioned pairs. This implies that during the stable periods, ethanol is correlated with corn and biodiesel is correlated with German diesel mainly at low frequencies so that they follow a common long-term trend. However, in the crisis periods, ethanol (biodiesel) is led by corn (German diesel) even at high frequencies (low scales), which implies that the biofuels prices react more rapidly to changes in their producing factors.

The rest of this paper is structured as follows. In Section 2, we provide the basic definitions of the wavelet analysis – wavelets, wavelet transforms and coherence. In Section 3, the analyzed dataset is described and the results of wavelet analysis are discussed. Section 4 concludes.

2. Methodology

In this part, we briefly introduce motivation why we use wavelet transform for studying relationships on biofuels markets. In economic analysis, the time or frequency domain approach is usually used separately but when these methods are applied to a real-world data, which are often non-stationary, the results my be flawed. For example, if a sudden change or a structural break occurs during the period we investigate, a classical time domain model with fixed parameters does not yield relevant results. In such case, we need a methodology that can localize such changes in economic relationships. Another problem arises when we use only the frequency domain approach, such as the Fourier transform, where we obtain information about the frequency components only and the time information is completely lost. Again, the stationarity of the examined time series is of great importance.

The wavelet transform decomposes the time series from the time domain to the time-frequency domain, i.e. using wavelets, we transform one dimensional time series into a two-dimensional space. Contrary to the Fourier transform, the wavelet transform uses a

localized function with a finite support – a wavelet – for the decomposition. For this reason, the wavelet transform has significant advantages over the Fourier transform mainly when the object under study is non-stationary, or only locally stationary (Roueff and Sachs, 2011). When a bivariate relation is studied, the same problem with time localization applies, see Gençay et al. (2002); Percival and Walden (2000); Ramsay (2002); Vacha and Barunik (2012) for details. The utilized wavelet analysis overcomes these issues. Since the biofuels markets are relatively new, their behavior is very dynamic and unstable as it is visible in the following sections. Thus the motivation for the localized time-frequency wavelet analysis is evident.

Another advantage of wavelets is the decomposition of the time series to frequency components, in wavelet terminology called scales. Decomposition to scales gives us an opportunity to study economic relationships on a scale-by-scale level which gives a broader picture than when only the aggregate time series is studied. Thus we are able to separate the short- and long-term behavior, in the bivariate case the short-term and long-term dependencies. Since the wavelet analysis uses localized functions we can also study dynamics of these relations in time.

On the other hand, the main disadvantage of the wavelets methodology comes in hand with the advantages – as the wavelets are practically filters, the methodology is not easily applicable for forecasting of future behavior of the series. Its utility thus mainly comes from a detailed description of relationships between variables.

2.1. The continuous wavelet transform

The continuous wavelet transform $W_x(u, s)$ is defined as a projection of a specific wavelet[1] $\psi(.) \in L^2(\mathbb{R})$ onto the examined time series $x(t) \in L^2(\mathbb{R})$,

$$W_x(u, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\psi\left(\frac{t-u}{s}\right)} dt, \tag{1}$$

where u determines the exact position of the wavelet[2]. Scale parameter s controls how the wavelet is stretched or dilated. If the scale is lower (higher), the wavelet is more (less) compressed and therefore it detects higher (lower) frequencies. After the continuous wavelet transform is performed on real time series of finite length $x(t)$, $t = 1, \ldots, N$, we obtain a matrix of wavelet coefficients with $u = 1, \ldots, N$ rows, and $s = 1, \ldots, J$ columns, representing a scale (or a frequency) and time position, where J is a maximum number of scales used for the wavelet decomposition. Wavelet coefficients $W_x(u, s)$ thus represent local energy (variance) at a specific scale (frequency) u at position s.

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[1] We use the Morlet wavelet that belongs to the family of complex wavelets. Complex, or analytical, wavelets have a real and an imaginary part, hence we can perform the phase analysis. The Morlet wavelet is defined as $\psi^M(t) = \frac{1}{\pi^{1/4}} e^{i\omega_0 t} e^{-t^2/2}$, where ω_0 denotes the central frequency of the wavelet. In our analysis, we set $\omega_0 = 6$, which is the value often used in the economic applications as it provides an optimal time-frequency balance (Rua and Nunes, 2009; Aguiar-Conraria et al., 2012).

[2] This parameter helps to perfectly localize the behavior of the time series under study. In other words, this is the extra parameter that we do not have in the Fourier transform.

Further, a wavelet must fulfill the admissibility condition: $C_\psi = \int_0^\infty \frac{|\Psi(f)|^2}{f} df < \infty$, where $\Psi(f)$ is the Fourier transform of a wavelet $\psi(.)$. The time series $x(t)$ can be then reconstructed using the wavelet coefficients as

$$x(t) = \frac{1}{C_\psi} \int_0^\infty \left[\int_{-\infty}^\infty W_x(u, s)\psi_{u,s}(t)du \right] \frac{ds}{s^2}, \quad s > 0. \tag{2}$$

Importantly, the continuous wavelet transform preserves energy of the analyzed time series, i.e. when the squared absolute value of the wavelet coefficients is summed through time and across scales, we get the total energy (variance) of the analyzed time series. This is a very important feature of the wavelet transform as we do not lose any information by applying the transform

$$\|x\|^2 = \frac{1}{C_\psi} \int_0^\infty \left[\int_{-\infty}^\infty |W_x(u, s)|^2 \, du \right] \frac{ds}{s^2}. \tag{3}$$

We use this key property for the definition of the cross wavelet power and subsequently of the wavelet coherence. For a more detailed introduction to wavelets, see Daubechies (1988); Percival and Walden (2000).
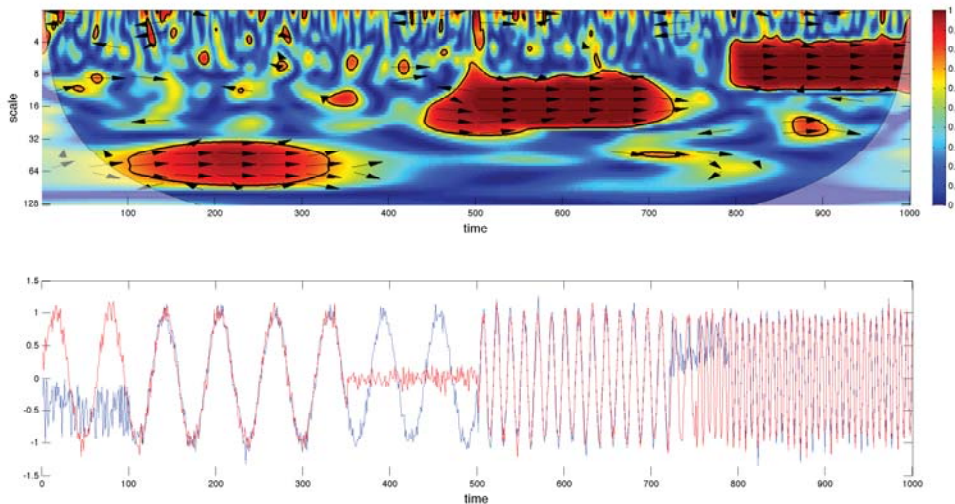

Figure 1: *Wavelet coherence example.* Two processes with changing level of correlation and changing frequency (lower chart) and corresponding evolution of the wavelet coherency in time (x-axis) and across scales/periods (y-axis). Perfect positive correlation is represented by red color and right-pointing arrows. Several artifacts occur due to finite sample fluctuations.

2.2. Wavelet coherence

Since we study the interactions between two time series, we introduce a bivariate setting called wavelet coherence. As the first step, we define the cross wavelet transform and subsequently the cross wavelet power.

6

The cross wavelet transform (Torrence and Compo, 1998) of two time series $x(t)$ and $y(t)$ is defined as

$$W_{xy}(u, s) = W_x(u, s)\overline{W_y(u, s)}, \tag{4}$$

where $W_x(u, s)$ and $W_y(u, s)$ denote the continuous wavelet transforms of $x(t)$ and $y(t)$, respectively, u defines a time position, and s denotes the scale parameter. The bar denotes complex conjugate. Further, using the cross wavelet transform, we obtain the cross wavelet power as $|W_{xy}(u, s)|$. The cross wavelet power represents the local covariance between the examined time series at the specific scale u. In other words, it indicates where the time series have high common power in the time-frequency domain.

Following Torrence and Webster (1999), we define the squared wavelet coherence coefficient as:

$$R^2(u, s) = \frac{|S(s^{-1}W_{xy}(u, s))|^2}{S(s^{-1}|W_x(u, s)|^2)S(s^{-1}|W_y(u, s)|^2)}, \tag{5}$$

where S is a smoothing operator[3]. The squared wavelet coherence coefficient is in the range $0 \leq R^2(u, s) \leq 1$. Values of the coherence close to one indicate strong correlation (red color) at a given scale, while values close to zero (blue color) indicate no correlation. The squared wavelet coherence can be perceived as a local linear correlation between two time series at a particular scale. Fig. 1 shows illustrative example of the wavelet coherence. In the lower part of the figure, two time series of thousand observations are depicted, the upper part shows the wavelet coherence. There are three periods where these two time series co-move together at the same frequency (approximately observations – I: 100-350, II: 500-720 and III: 800-1000 on x-axis). Between these three periods, one of the time series is only a noise. The time series in the period I co-move at low frequencies (high scales). This co-movement is described by high value of wavelet coherence that forms a red-colored region in the lower left corner. The third period of co-movement occurs at high frequencies (low scales), therefore the wavelet coherence displays the red region in the upper right corner. As the second period of co-movement is at the middle frequencies, it lies in the middle of the figure. In both cases, we have almost exact localization in time provided by values on the x-axis. This example shows the advantage of the wavelet methodology when the dependence between time series changes dynamically both in time and across frequencies, i.e. the time series are not stationary.

As the theoretical distribution for the wavelet coherence is not known, the statistical significance is tested using Monte Carlo methods. The testing procedure is based on the approach of Grinsted et al. (2004) and Torrence and Compo (1998). In the paper, we use the 5% significance levels. The significant areas of the wavelet coherence are bordered with the black thick contour.

Since wavelets are in fact filters, we have to deal with boundary conditions. This problem arises at the beginning and at the end of a dataset, where the filter analyzes nonexistent data. In our work, we solve this problem by augmenting the dataset with a

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[3]Smoothing is achieved by convolution in both time and scale, see Grinsted et al. (2004) for more details.

sufficient number of zeros. The area where we pad the dataset with zeros is called the cone of influence. It is graphically represented by a cone bordered by a bold black line in our figures. For more details, see Torrence and Compo (1998), Grinsted et al. (2004).
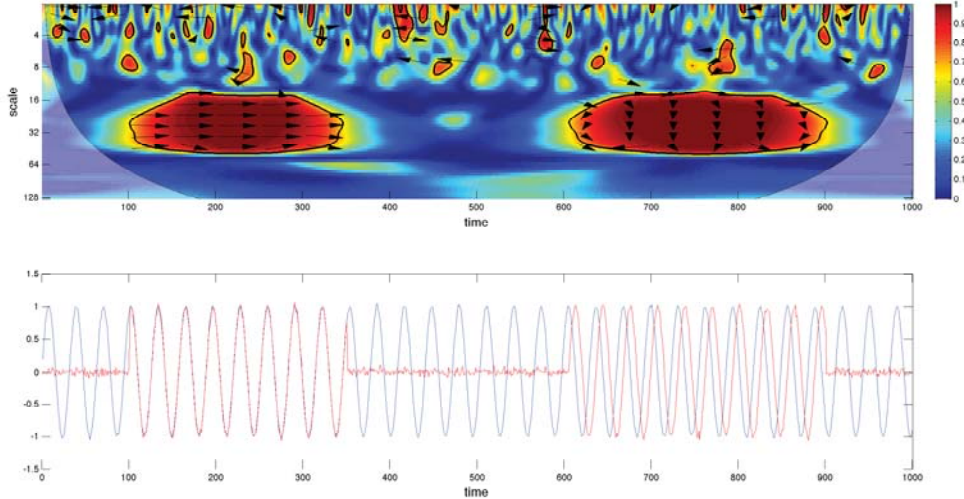

Figure 2: *Wavelet phase example.* Two processes with changing level of correlation and changing phase shift (lower chart) and corresponding evolution of the wavelet coherency in time (x-axis) and across scales/periods (y-axis). Perfect positive correlation with no lag/lead relationship is represented by red color and right-pointing arrows. Perfect positive correlation with the red series leading the blue series is represented by red color and down-pointing arrows. Several artifacts occur due to finite sample fluctuations.

2.3. Phase

As the wavelet coherence coefficient is squared, we cannot distinguish between negative and positive correlation. For this reason, we use the wavelet coherence phase differences which indicate delays in the oscillation between the two examined time series. Following Torrence and Webster (1999), we define the wavelet coherence phase difference as

$$\phi_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy}(u,s))\}}{\Re\{S(s^{-1}W_{xy}(u,s))\}}\right), \tag{6}$$

where $\Im$ and $\Re$ denote an imaginary and a real part operator, respectively. Phase differences are indicated by black arrows in our figures. In case the two examined time series move together, they have a zero phase difference on a particular scale and the arrows point to the right. If the time series are in anti-phase, i.e, they are negatively correlated, then the arrows point to the left. Arrows pointing down indicate that the first time series leads the second one by $\frac{\pi}{2}$, whereas arrows pointing up means that the second time series leads the first one by $\frac{\pi}{2}$. A mixture of positions is common. For example, an arrow pointing up and right means that the time series are in phase, with the second time series leading

8

the first one. As an illustration, see Fig. 2 where the case of zero phase difference and phase shift are depicted. In the lower part of the figure, there are two time series with two periods (I: 100-350 and II: 600-900) of a highly significant wavelet coherence, both with the same frequency. The difference between these two periods is the phase shift. In the first period, the time series are in phase (no phase difference) so that the arrows point to the right while in the second period, there is a phase shift of $\frac{\pi}{2}$, therefore the arrows point down. This example again demonstrates the ability of the wavelet analysis to cope with non-stationary time series.

3. Data and results

Table 1: Analyzed commodities

Commodity	Ticker	Contract type
Biodiesel	BIOCEUGE	Spot, Germany
Corn	C1	Futures, CBOT
Crude oil	CO1	Futures, ICE
Ethanol	ETHNNYPR	Spot, FOB
Rapeseed Oil	RPSOCRDU	Futures, EU Mill
Soybeans	S1	Futures, CBOT
Sugarcane	SB1	Futures, ICE
Wheat	W1	Futures, CBOT

We analyze time and frequency dependent correlations (wavelet coherence) between biofuels and related commodities. Since our focus is on biodiesel and ethanol, we include only relevant agricultural commodities, which are used for their production, and only relevant fossil fuels, which are their respective natural substitutes. Our dataset thus contains consumer biodiesel (BD), ethanol (E), corn (C), wheat (W), soybeans (S), rapeseed oil (RS), sugarcane (SC), crude oil (CO), German diesel (GD) and the US gasoline (USG). Corn, wheat and sugarcane are the feedstock for ethanol; soybeans and rapeseed oil are the feedstock for biodiesel. As ethanol is mainly the US domain and its natural substitute is gasoline, we include the US gasoline. In a similar way, biodiesel is predominantly the EU domain and its substitute is diesel, thence German (as the biggest EU economy) diesel is included. Crude oil (Brent) is included as well because it serves as a production factor for all fuels in our dataset, or at least indirectly. This basic structure of the biofuels system has been validated by our previous analysis in Kristoufek et al. (2012a). Majority of the dataset was obtained from the Bloomberg database (Table 1), rapeseed oil from the DataStream database, and the two fossil fuels were obtained from the U.S. Energy Information Administration and represent the countries' average price. As the price series of the biofuels are very illiquid, we analyze weekly data for a period between 24.11.2003 and 28.2.2011 (Monday closing prices).

Fig. 3 shows weekly logarithmic prices for all analyzed commodities. The retail fossil fuels are obviously highly correlated with crude oil and the normalized prices almost
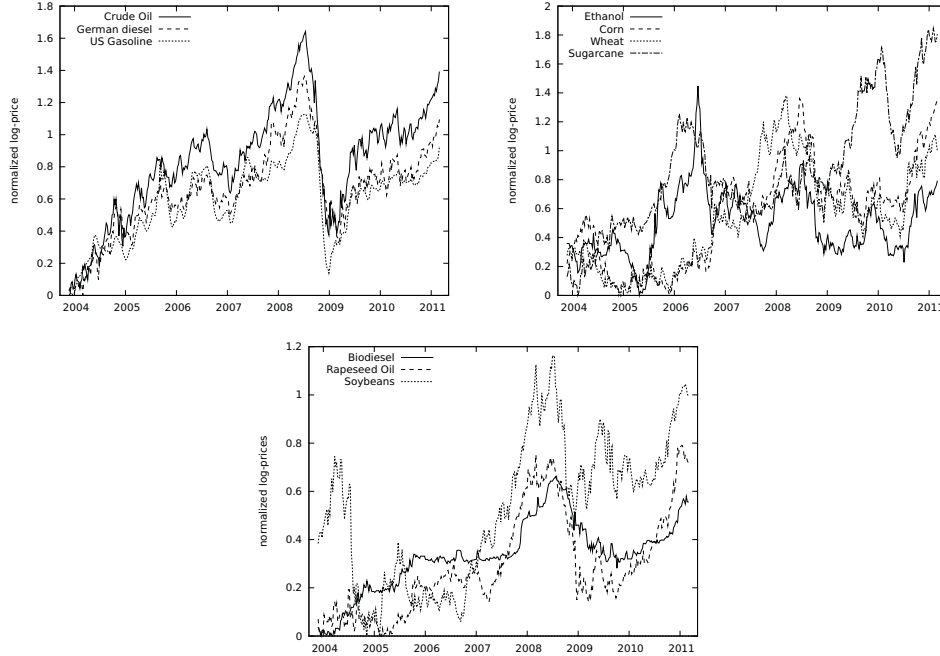
Figure 3: *Logarithmic prices.* Logarithmic prices are normalized so that the minimum value is subtracted making the series more easily comparable.

overlap. Strong increasing trend in prices is observed for the period between 2007 and a middle of 2008 which corresponds to the food crisis period (Hochman et al., 2011). For the ethanol and related agricultural commodities, the highest prices are connected to the half of 2008. Corn and wheat even reach their maxima in this period. Even though ethanol experienced increasing prices in the food crisis period, these prices are only mildly higher than the heights of 2007 and are even much lower than the maximum in 2006. Sugarcane seems rather unconnected with the rest of the ethanol feedstock commodities and shows the highest variability while reaching its maximum at the break of 2010 and 2011. For the biodiesel and its feedstock commodities, we observe that biodiesel itself has a relatively stable price with slow increasing trend between 2004 and the end of 2005 followed by the period between 2006 and the second half of 2007, where the prices remained very stable. During the food crisis, the price of biodiesel rocketed reaching the peak in the middle of 2008 and returning to the previous levels the following year. Rapeseed oil follows relatively similar path to biodiesel but is much more volatile while soybeans are even more variable in time. Again, the period of food crisis is connected to strong local maxima of the three commodities.

Out of all 45 possible pairs of commodities in our dataset, we focused only on two biofuels branches – the ethanol (ethanol, corn, wheat, sugarcane, crude oil and the US gasoline) and biodiesel branch (biodiesel, soybeans, rapeseed oil, crude oil and German diesel) – and analyzed only the relevant connections as a follow-up to our previous results (Kristoufek et al., 2012a). As we are primarily interested only in pairs including a biofuel, we were left

10

with 9 pairs to analyze. Wavelet coherence analysis is applied on the logarithmic returns of weekly prices. Due to the length of the analyzed data (380 observations), we utilize a maximum scale of 64 weeks (approximately 1.25 years)[4].

Starting with the ethanol branch, we found that out of five analyzed pairs, only the ethanol – corn pair shows economically interesting and statistically significant results. In Fig. 4, we present wavelet coherence for the ethanol branch. There are several features needing further description – the wavelet coherence can be seen as correlation between analyzed commodities and here, the hotter the color, the higher the correlation; regions of statistically significant correlations are bordered with a bold black line (against the null hypothesis of red noise, i.e. AR(1)-noise); and the direction of correlations is marked by an arrow as described in the previous section. From the picture, we can tell than in the first half of the analyzed sample, ethanol and corn are only weakly correlated and this statistically significant correlation occurs only for scales approximately between a quarter and one year in the period between half of 2005 and half of 2007. In this period, corn clearly leads ethanol. Note that when the arrow points straight upwards, then corn leads ethanol by $\frac{\pi}{2}$, i.e. by one quarter of the corresponding scale. With this in mind, we can say that corn leads ethanol by approximately two months in the second half of 2005 while the leading period, i.e. a lag between the two series, was decreasing from 2006 onwards and even reached insignificant correlations at all scales at the break of 2007 and 2008. Starting from 2008, we observe a rapid increase of correlations at almost all scales. Note that this period is connected to very high prices of all the analyzed commodities – the food crisis. For lower frequencies (higher scales), we observe that corn and ethanol are highly correlated but it is not clear which commodity is the leading one. The higher the frequency gets, the more visible it becomes that corn leads ethanol. Moving forward in time, we can see that from the beginning of 2009 onwards, the dominating frequencies lower considerably and the relationship becomes the most evident approximately between one and three quarters of the year. However, compared to the relationships before the food crisis, we find no dominance between the two. For the remaining pairs, i.e. E–W, E–CO, E–SC and E–USG, we find no economically interesting and significant relations between the series and if so, these are rather short-term and can be hardly distinguished from random occurrences as shown in Figs. 1-2.

Moving to the biodiesel branch, we find that the pair with the most pronounced interactions is the biodiesel and German diesel one. In Fig. 5, we can see that the most dominant scale is approximately 32 weeks for almost whole analyzed period. Biodiesel and German diesel are positively correlated and in majority of cases, German diesel is the leading series. However, the length of the lag between commodities is on average shorter than for E–C case, i.e. biodiesel reacts faster to changes in German diesel than ethanol does to the changes in corn. In the beginning of 2007, German diesel started a growth rally which culminated in a half of 2008. This period is connected with more complex dynamics

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[4]For higher scales, most of the wavelet coherence fall below the cone of influence so that the values would not be reliable.
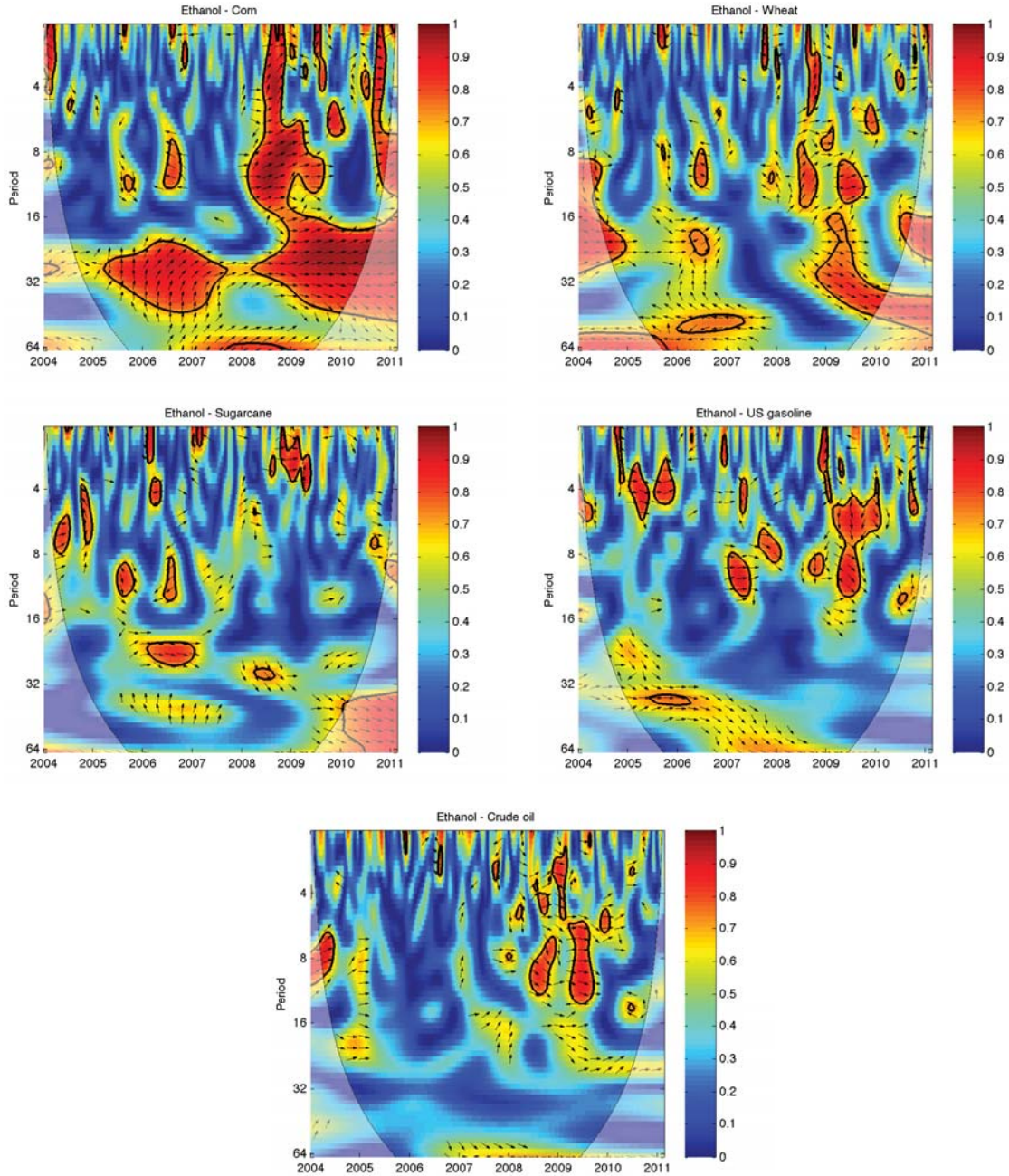
Figure 4: *Wavelet coherence for ethanol and related commodities.* Evolution of wavelet coherency in time between 2004 and 2011 (x-axis) and across scales/periods in weeks (y-axis). The color scale on the right of the charts shows the level of correlation, the hotter the color the higher the absolute value of correlation corresponding to $R^2(u,s)$ in Eq. 5. Significant correlations (at 5% level) tested against the AR(1)-noise are marked with a thick black line. Cone of influence is separated by paler colors in the lower left and lower right parts of the charts. Only periods up to 64 weeks (1.25 years) are shown as for the higher levels, most of the contour falls below the cone of influence.

of correlations between GD and BD with scales of significant correlations broadening to a range between 5 and 50 weeks. German diesel remains the leader of biodiesel for practically all significant scales in this period. For high frequencies between 5 and 10 weeks, we observe a strong leadership of German diesel where the leading period length gets as low as 1–2 weeks. This implies that when the price of German diesel is very high, biodiesel reacts to its changes very quickly. When prices of German diesel get back to the pre-crisis levels – from the beginning of 2009 onwards – the dominance of longer scales becomes apparent again. Similarly to the ethanol–corn case, when we compare the pre-crisis and post-crisis correlations at the low frequencies, we have German diesel as a clear leader in the former but no obvious leadership in the latter period. Quite similar, yet much weaker connections are observed for biodiesel and crude oil pair. However, significant connections are visible for only very specific time periods and compared to the BD–GD and E–C pairs, the coherence is much less evident. Nevertheless, crude oil is identified as a leading series of biodiesel for these significant periods and the series are positively correlated most of the time. The remaining pairs, i.e. BD–S and BD–RS, show practically no significant co-movements.

4. Conclusions and discussion

We analyzed the interconnections in ethanol and biodiesel systems with a use of the wavelet coherence analysis, which has never been done before. By doing so, we were able to uncover how correlations between pairs of commodities evolve in time and across frequencies. This way, we overcame the basic problem of standardly used methodologies, i.e. focusing on either the time or frequency domain.

Starting with a wide range of the biofuels-related commodities, and covering the most important producing factors and the fossil fuel substitutes for ethanol and biodiesel, we find that the only economically important and statistically significant connections come up between ethanol and corn, and German diesel and biodiesel. For both pairs, we find that the most dominant frequency is around 32 weeks, i.e. approximately half of a year, which holds for almost the whole analyzed period 2003–2011. We also find that a structure of correlations changes with respect to the food crisis between 2007 and 2008, which was connected to unprecedentedly high prices of almost all biofuels feedstock commodities. During this period, the strong interactions in the pairs broadened to higher frequencies as well and the leadership of the producing factors (corn and German diesel) became more apparent. In the crisis period, the leadership of corn relative to ethanol is apparent only for the short scales whereas the German diesel leadership with respect to biodiesel is visible at practically all significant scales.

Interesting distinction between the two pairs of commodities lies in the difference in leadership shifts before and after the food crisis. For ethanol, we observe that corn evidently leads the biofuel at lower frequencies for the pre-crisis period but after the crisis, we find no such strong leadership but only a strong positive correlation between the two. The structure of correlations thus visibly changed after the crisis. Quite similarly, the leadership of German diesel with respect to biodiesel differs before and after the crisis – the phase
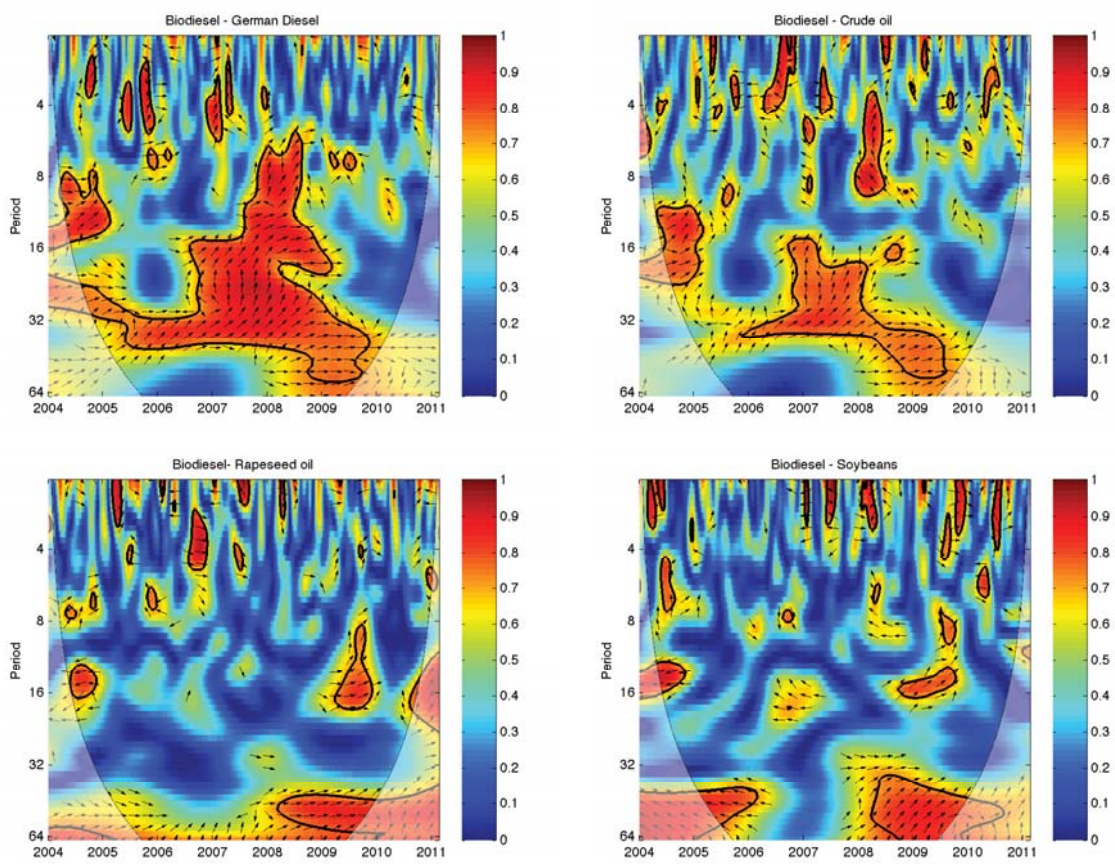
Figure 5: *Wavelet coherence for biodiesel and related commodities.* Labels from Fig. 4 hold.

shift between the two becomes weaker in time at low frequencies. However, the change is not as noticeable as for the ethanol–corn pair.

Importantly, we find no evidence for potential squeeze-out effect of agricultural commodities by biofuels, which is of high economic, political and also social interest. On contrary, we find that if some leader-follower relationship is found, the producing factor (corn and German diesel) is the leader of the biofuel (ethanol and biodiesel) in a majority of the cases (both in time and across frequencies), and not vice versa.

Note that results presented here nicely integrate and validate partial results of our previous research in Kristoufek et al. (2012a) and Kristoufek et al. (2012b). In Kristoufek et al. (2012a), we show that from the whole period 2003–2011 viewpoint, there are hardly any correlations between biofuels and the rest of the system at weekly frequency, which changes when we decrease the frequency to one month so that the correlations increase. Importantly, we show that correlations are much stronger for the crisis and post-crisis periods even for high frequencies. This is practically the same result we find with the wavelet coherence analysis. In Kristoufek et al. (2012b), we find that ethanol is led by corn and biodiesel is led by German diesel with a use of Granger causality tests, while other connections remain very weak. Again, this is what we show in this paper where we integrate separate correlation and causality techniques, which we used in the earlier papers, by wavelet coherence methodology. Summarizing the results together, we arrive at the very convincing evidence that ethanol (biodiesel) is mainly connected to and lead by corn (German diesel) while the intensity of leadership and magnitude of correlation vary in time and seem to be dependent on corn (German diesel) prices.

Our results show that the wavelet coherence technique is an exceptionally promising technique for analyzing not only biofuels but also the time and frequency dynamics of other commodities. While we introduce this technique in the price domain, it could be obviously used for equally interesting biofuels quantities related analysis as soon as the biofuels markets trading reach such maturity that sufficiently frequent quantity data would be available. Additionally, the results indicate that wavelets methodology applied on biofuels system can be further utilized as a tool in predictions and portfolio construction as they are nicely able to uncover the structure and dynamics of correlations.

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References

Aguiar-Conraria, L., M. Martins, and M. J. Soares (2012). The yield curve and the macroeconomy across time and frequencies. *Journal for Economic Dynamics and Control 36*, 1950–1970.

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.

Ciaian, P. and D. Kancs (2011a, October). Food, energy and environment: Is bioenergy the missing link? *Food Policy 36*(5), 571–580.

Ciaian, P. and D. Kancs (2011b, January). Interdependencies in the energy-bionergy-food price systems: A cointegration analysis. *Resource and Energy Economics 33*(1), 326–348.

Connor, J. and R. Rossiter (2005). Wavelet transforms and commodity prices. *Studies in Nonlinear Dynamics & Econometrics 9*(1).

Daubechies, I. (1988). Orthonormal bases of compactly supported wavelets. *Communications on Pure and Applied Mathematics 41*, 909–996.

de Gorter, H., D. Drabik, and D. R. Just (Forthcoming). How biofuels policies affect the level of grains and oilseed prices: Theory, models, and evidence. *Global Food Security*.

Gençay, R., F. Selçuk, and B. Whitcher (2002). *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics*. Academic Press.

Grinsted, A., J. C. Moore, and S. Jevrejeva (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Processes in Geophysics 11*, 561–566.

Hochman, G., S. Kaplan, D. Rajagopal, and D. Zilberman (2012). Biofuel and food-commodity prices. *Agriculture 2*(3), 275–281.

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.

Janda, K., L. Kristoufek, and D. Zilberman (2012). Biofuels: Policies and impacts. *Agricultural Economics 58(8)*, 372–386.

Kratschell, K. and T. Schmidt (2012). Long-run trends and short-run fluctuations – what establishes the correlation between oil and food prices? *Ruhr Economic Papers 357*, 1–21.

Kristoufek, L., K. Janda, and D. Zilberman (2012a). Correlations between biofuels and related commodities before and during the food crisis: A taxonomy perspective. *Energy Economics 34(5)*, 1380–1391.

Kristoufek, L., K. Janda, and D. Zilberman (2012b, August). Mutual responsiveness of biofuels, fuels and food prices. Working Paper 38, Centre for Applied Macroeconomic Analysis, Australian National University.

Kristoufek, L., K. Janda, and D. Zilberman (2013, February). Regime-dependent topological properties of biofuels networks. *European Physical Journal B 86*(2), Article 40.

McPhail, L. L. (2011). Assessing the impact of US ethanol on fossil fuel markets: A structural VAR approach. *Energy Economics 33*(6), 1177–1185.

Naccache, T. (2011). Oil price cycles and wavelets. *Energy Economics 33*(2), 338 – 352.

Percival, D. B. and A. T. Walden (2000). *Wavelet Methods for Time series Analysis*. Cambridge University Press.

Pokrivcak, J. and M. Rajcaniova (2011, August). Crude oil price variability and its impact on ethanol prices. *Agricultural Economics – Czech 57*(8), 394–403.

Rajcaniova, M., D. Drabik, and P. Ciaian (Forthcoming). How policies affect international biofuel price linkages. *Energy Policy*.

Rajcaniova, M. and J. Pokrivcak (2011). The impact of biofuel policies on food prices in the European Union. *Journal of Economics (Ekonomicky casopis) 59*(5), 459–471.

Ramsay, J. B. (2002). Wavelets in economics and finance: Past and future. *Studies in Nonlinear Dynamics & Econometrics 6*(3).

Roueff, F. and R. Sachs (2011). Locally stationary long memory estimation. *Stochastic Processes and their Applications 121*(4), 813 – 844.

Rua, A. and L. C. Nunes (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance 16*(4), 632 – 639.

Serra, T. and D. Zilberman (2013, May). Biofuel-related price transmission literature: A review. *Energy Economics 37*, 141–151.

Serra, T., D. Zilberman, and J. M. Gil (2011). Price volatility in ethanol markets. *European Review of Agricultural Economics 38(2)*, 259–280.

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 42*(1), 35–45.

Serra, T., D. Zilberman, J. M.Gil, and B. K. Goodwin (2010). Price transmission in the US ethanol market. In M. Khanna, J. Scheffran, and D. Zilberman (Eds.), *Handbook of Bioenergy Economics and Policy*, Natural Resource Management and Policy, Chapter 5, pp. 55–72. Springer.

Torrence, C. and G. P. Compo (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society 79*(1), 61–78.

Torrence, C. and P. J. Webster (1999). Interdecadal changes in the enso-monsoon system. *Journal of Climate 12*(8), 2679–2690.

Tyner, W. E. (2010, November). The integration of energy and agricultural markets. *Agricultural Economics 41*(s1), 193–201.

Vacha, L. and J. Barunik (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Economics 34*(1), 241–247.

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

Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein (2010). Food versus fuel: What do prices tell us. *Energy Policy 38*(1), 445–451.

Zilberman, D., G. Hochman, D. Rajagopal, S. Sexton, and G. Timilsina (2013). The impact of biofuels on commodity food prices: Assessment of findings. *American Journal of Agricultural Economics 95*(2), 275–281.