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Co-movements of Ethanol Related Prices: Evidence from Brazil and the USA

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Keywords

ethanol, corn, sugar, oil, wavelet coherence

JEL Classification

C22, Q16, Q42

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Co-movements of Ethanol Related Prices: Evidence from Brazil and the USA

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Abstract

We use the wavelet coherence methodology to investigate relations between prices of ethanol and its feedstocks. Our continuous wavelet framework allows for discovering price connections and their evolution in both time and frequency domain in the most important ethanol markets – Brazil and the USA. For both of these markets we show that the long-run relationship between prices of ethanol and corn (in USA) or sugar (in Brazil) is positive, strong and stable in time. Importantly, we show that the prices of feedstock lead the prices of ethanol and not the other way around. The price lead of feedstock is documented for both short and long run horizons. Our qualitative results hold true even when the influence of crude oil prices is accounted for by utilizing partial wavelet coherence approach.

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1. Introduction

As biofuels are produced from agricultural crops, there is a persistent concern that biofuels compete with food production and that this competition drives up food prices and so causes hunger around the world. In particular, this argument assumes that increasing biofuels prices lead to an increase of the agricultural commodity prices. Rigorous clarification of this intuitive argument is a common theme of recent active research in bioenergy (Hochman et al., 2014; Kristoufek et al., 2014), agricultural (Myers et al., 2014), and energy (Bastianin et al., 2014a) oriented leading academic journals. This paper contributes to this discussion by analyzing the most recent price development in the most developed biofuels markets using a novel analytical framework.

Our results show that the prices of ethanol feedstock both in Brazil and the USA lead the prices of ethanol (supporting the earlier results of Saghaian (2010), Serra et al. (2011), Wixson and Katchova (2012)) and not the other way around. Our more recent data and analysis therefore reject earlier findings of no long run relationship among prices of ethanol, corn and gasoline reported by Zhang et al. (2009, 2010). Our qualitative results hold true for our data for both short run and long run horizons. Importantly, it is also true when consider crude oil prices influence.

Our study covers 84% of the world ethanol production, with 57% due to the USA and 27% due to Brazil (RFA, 2014). These shares of the year 2013 are quite representative for a longer period, as since 2010, the worldwide and the U.S. ethanol production levels have essentially stabilized after several years of rapid growth. In the light of recent biofuels development, it may be expected that the U.S. ethanol production will not change significantly while the Brazil ethanol production has a realistic potential for a slight increase. Besides an important issue of the policy regulation of biofuels, a viability of the prevailing first generation ethanol biofuel crucially depends on its pricing relative to the prices of its feedstock and the prices of crude oil.

The U.S. ethanol is produced mainly from corn. According to the FAO (2014) 2014/15 forecast, out of the expected 365 647 thousand tonnes of the U.S. corn production, 36 % (130 180 thousand tonnes) is forecast to be used for the ethanol fuel. This share of ethanol in the range of 35-43 % is stable over the whole period since the 2009/2010 crop year. With a relatively stable ethanol fuel use in the range of 116 616-130 180 thousand tonnes over this period, the naturally variable corn harvests mean that the highest share of ethanol occurs during the years with the lowest corn harvest.

During the recent food crises, the difference between the U.S. corn production and the fuel ethanol use was about 250 000 thousand tonnes in 2007/08 and about 160 000 thousand tonnes in 2012/13 (FAO, 2014). This may be compared to the total U.S. corn production in the pre-biofuels era, which was on the level of about 230 000-250 000 thousand tonnes during the 1996-2003 period and with occasionally low harvests of 106 031 (1983), 125 194 (1988), 160 986 (1993), 187 970 (1995) thousand tonnes (Indexmundi, 2015). These data indicate that ethanol boom with associated increase in the profitability of corn farmers has not lead to a large absolute decrease in the U.S. corn production used for non-ethanol purposes. An analysis based on the U.S. data (Oladosu et al., 2011) suggests that the corn use for ethanol has resulted in large reductions in its use for livestock within the U.S., and in an increased corn production.

The Brazilian ethanol is produced primarily from sugar cane, where the utilization of sugar cane is in long term relatively equally divided between sugar and ethanol. As sugar is not such a staple food product as is corn, the diversion of the Brazilian sugar cane production into ethanol is not perceived as such a menace for the world food situation as it is in the case of the U.S. corn. However, the land use and possible expansion of arable land due to biofuels is an important issue in Brazil (Rajcaniova et al., 2014).

The absolute sizes of the U.S. corn production or the Brazilian sugar production are not the main factors in the determination of the biofuels impact on food security and related issues. What matters for the global and regional food security the most is the price level of basic food staples around the world, which is influenced by ethanol related price transmission channeled through international trade prices. Carter et al. (2013) estimate that corn prices were 34 percent higher between 2006 and 2012 because of the U.S. ethanol mandate.

While the U.S. and European ethanol markets are investigated in many studies such as Serra et al. (2011), Sexton and Zilberman (2011), Pokrivcak and Rajcaniova (2011), Trujillo-Barrera et al. (2012), Kristoufek et al. (2012), Kristoufek et al. (2013), Rajcaniova et al. (2013), and de Gorter et al. (2013), the Brazilian sugarcane ethanol market has received less attention. The papers dealing with Brazilian biofuels include Serra et al. (2011), Drabik et al. (2015), and Capitani (2014).

Here, we study the Brazilian and the U.S markets and prices utilizing the continuous wavelet framework which was introduced into the biofuels literature by Vacha et al. (2013) and is applied across a wide range of disciplines (Lachaux et al., 2002; Klein et al., 2006; Vacha and Barunik, 2012; Sankari and Adeli, 2011; Holman et al., 2011; Keissar et al., 2009; Kirby and Swain, 2008; Cazelles et al., 2005; Kareem and Kijewski, 2002; Cohen and Walden, 2010). This approach allows for examining dynamics of correlations in time as well as across frequencies while providing an optimal balance between the time and frequency resolution (Rua, 2010). In addition, the continuous wavelet framework does not require further data transformation to achieve stationarity as it is not limited by the covariance-stationarity assumption for the underlying process (Raihan et al., 2005). The framework is especially useful in analyses of connections between time series which have likely undergone dramatic changes in their structure. Additionally to this time domain localization, the framework also provides information about the frequency domain specifics. It is thus possible to study differences between connections at various time scales. Specifically here, we comment on the changing interconnections between ethanol and producing factors prices, specifically sugar for Brazil and corn for the USA. Moreover, the newly utilized methodology of partial wavelet coherence also allows for filtering out the effects of other selected variables, which was not considered earlier (Vacha et al., 2013). In our case, we are primarily interested in controlling for the possible effect of the crude oil prices on the whole dynamics. The results indicate that both markets share several common features in the dynamics between ethanol and its producing factors.

Our paper contributes to the time series empirical econometrics literature dealing with the biofuels connected price links. The results of this rapidly growing literature on the biofuels related time series price transmission are summarized by Serra and Zilberman (2013) and Zilberman et al. (2013) while the general review of the economics of biofuels is provided by Janda et al. (2012) and by Timilsina and Zilberman (2014). The theoretical calibrated models (Hochman et al., 2014; Drabik et al., 2014) which provide rationale and evidence for the co-movement of prices of agricultural commodities and their feedstock emphasize that the strength and direction of this co-movement changes over time. While the nonlinear time dependent price transmission between biofuels related commodities is investigated by Kristoufek et al. (2014), our new continuous wavelet framework allows us to integrate these results with the analysis of long and short run co-movements, as undertaken recently by Myers et al. (2014).

2. Materials and methods

2.1 Data description

Studying the relationship between biofuels and relevant factors of its price dynamics is frequently limited by the biofuels prices data availability. Both length and frequency of the series pose difficulties during the analysis. To this end, we focus on the longest available data series of ethanol prices for the Brazilian and the U.S. markets. However, each market provides quite different data series to be studied.

For the Brazilian market, the time series are provided by the Center for Advanced Studies on Applied Economics (CEPEA) and they go back to 29.11.2002 for the spot ethanol (both anhydrous and hydrous) prices with a weekly frequency. Brazilian ethanol is first produced as a hydrous ethanol (E100) which is directly used by the ethanol-only and flex fuel vehicles. This hydrous ethanol may be further processed and transformed into an anhydrous ethanol, which is used for blending with pure gasoline to obtain the blended fuel (E25 in the case of Brazil). The additional processing cost forms a technologically based price wedge between the hydrous and anhydrous ethanol. The main producing factor for the Brazilian ethanol is sugarcane so that we include the sugar spot prices, which are again provided by CEPEA. To control for possible effect of the crude oil, we use the spot prices of the WTI crude oil provided by the U.S. Energy Information Administration (EIA). All series were downloaded on 17.4.2014.

For the U.S. market, we use the ethanol (only the anhydrous ethanol is used in the USA) and corn (the major producing factor for the U.S. market) prices provided by the Center for Agricultural and Rural Development (CARD) at Iowa State University. The prices are based on the futures contracts so that we use the Light-Sweet (Cushing, Oklahoma) crude oil front (i.e. with the earliest delivery date) futures prices from EIA to control for possible interconnections. The ethanol and corn prices were obtained on 8.4.2014 and the crude oil prices on 7.5.2014. All analyzed series go up to the end of March 2014.

2.2 Wavelets framework

Wavelet framework allows studying behavior of interdependence between series and how it varies in time and across scales. Contrary to the Fourier analysis, which utilizes a combination of sine and cosine functions, the wavelet analysis is based on a projection of a wavelet function onto the studied series. A wavelet $\psi(t)$ is a real-valued or a complex-valued (depending on the type of analysis) square integrable function which is further specified by scale s and location u parameters at time t so that we have

$$\psi_{u,s}(t) = \frac{\psi\left(\frac{t-u}{s}\right)}{\sqrt{s}}.$$

When the assumptions about the wavelet function are met (see Daubechies (1992) for more details), any series $\{x_t\}$ can be reconstructed back from its continuous wavelet transform $W_x(u,s)$ defined as

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

where the asterisk sign marks a complex conjugate operator, so that there is no information loss induced by the transformation (Percival and Walden, 2000; Grinsted et al., 2004). In our analysis, we use the Morlet wavelet with a central frequency of six as it provides a good balance between time and frequency localization. Moreover, the Morlet wavelet is a member of the complex-valued wavelets family which allows for examination of the bivariate (or even multivariate) relationships between series (Grinsted et al., 2004; Aguiar-Conraria et al., 2008). Specifically, the Morlet wavelet with a central frequency $\omega_0 = 6$ is defined as

$$\psi(t) = \pi^{-1/4} e^{t(6i-t)/2},$$

The complex-valued wavelets allow for a generalization into the bivariate setting. The cross-wavelet transform is then defined as

$$W_{xy}(u,s) = W_x(u,s)W_y^*(u,s)$$

where $W_x(u,s)$ and $W_y(u,s)$ represent the continuous wavelet transforms of series $\{x_t\}$ and $\{y_t\}$, respectively (Torrence and Compo, 1998). $W_{xy}(u,s)$ is in general complex and thus hard to interpret. For this point, the cross-wavelet power $|W_{xy}(u,s)|$ is standardly used as a measure of interdependence between series. In applications, the cross-wavelet power is usually interpreted as a covariance localized in time and at a specific scale. In other words, the cross-wavelet power identifies regions in the time-frequency space which are characteristic for both series. Therefore, if the dominating scales (or frequencies) of both series overlap at a given time, the cross-wavelet power is able to uncover it. This is an important improvement over the Fourier analysis of multivariate series, i.e. the cross-spectrum analysis, which limits itself to the relationships over different scales but leaves the time domain intact (McCarthy and Orlov, 2012). The cross-wavelet power is not bounded so that in the same way as for the standard covariance measure, it is difficult to detect whether the co-movement is strong or not.

To overcome this issue, the squared wavelet coherence is introduced in the following form

$$R_{xy}^{2}(u,s)=\frac{\left|S\left(\frac{1}{s}W_{xy}(u,s)\right)\right|^{2}}{S\left(\frac{1}{s}\left|W_{x}(u,s)\right|^{2}\right)S\left(\frac{1}{s}\left|W_{y}(u,s)\right|^{2}\right)}$$

where S is a smoothing operator (Grinsted et al., 2004; Torrence and Webster, 1998). The squared coherence is bounded between 0 and 1 and it is usually interpreted as a squared correlation for the specific time and scale. As the squared coherence loses the complex information about direction, the phase difference is studied as well and it is defined as

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

where $\Im$ and $\Re$ represent an imaginary and a real part operator, respectively.

The wavelet analysis thus provides a complete picture of the dependence between two series in the time-frequency space. In practice, the analysis is compressed into a single two-dimensional chart. On the axes, the time and scale are shown and the values themselves are represented by the contour plot of the squared wavelet coherence. The hotter the color of the contour is, the higher the coherence is as well. Statistical significance of the coherence is tested by the Monte Carlo simulation against the red noise null hypothesis. A black border highlights the significant regions and directional arrows represent the phase difference (or simply the phase). When the arrow points to the east, the analyzed series are positively correlated with no series being a leader. Westward pointing arrow indicates a negative relationship with no series as a leader. The southward oriented arrow tells that the first analyzed series leads the second one by $\pi/2$ whereas the northward pointing one shows the opposite. The phase difference represented by these arrows provides essential information about the relationship between the examined series. Importantly, the phase is not based on any prior assumption about the relationship between the studied series. Even more, it can serve as a starting point and an identification tool for a follow-up models construction.

The wavelet analysis is restricted by the boundary conditions as the wavelet is stretched to cover the given scale. Therefore, the results are less reliable at the beginning and at the end of the series. To separate the regions, the cone of influence is introduced into the chart. The paler colors show the less reliable region and the brighter colors cover the reliable region. The ability to analyze the interconnection at different scales thus comes at a cost of limited reliability of the analysis at high scales (low frequencies). Nonetheless, this is an apparent characteristic of any frequency domain instrument. The principle is better understood with specific results which are presented in the Results section. For a more detailed description, please refer to Grinsted et al. (2004), and for a more detailed description of the wavelets environment with an application to biofuels and related commodities, please refer to Vacha et al. (2013).

The wavelet coherence is limited in the same way as the standard correlation – it does not control for a possible influence of other variables and it is thus prone to the omitted variable bias, i.e. the reported high coherence between series X and Y might be due to a strong relationship between X and Z as well as Z and Y. As a parallel to the partial correlation, the partial wavelet squared coherence is defined as

$$RP^2_{y,x_1,x_2} = \frac{\left| R_{yx_1} - R_{yx_2} R^*_{yx_1} \right|^2}{\left(1 - R^2_{yx_2}\right)^2 \left(1 - R^2_{x_2x_1}\right)^2}$$

which quantifies the relationship between the series $\{y\}$ and $\{x_1\}$ controlling for the effect of $\{x_2\}$ (Mihanovic et al., 2009; Ng and Chan, 2012). The interpretation is parallel to the squared partial correlation.

We thus utilize a complete framework for a multivariate analysis of connections between series which allows for an inspection of its evolution in time and across frequencies (scales). This allows us to comment on dynamics of correlations and compare among short-term, medium-term and long-term effects as well as their stability in time, and possible breaking points connected to global or local events on the markets. Moreover, the partial coherence controls for possible spurious results due to multivariate correlations. In addition, the wavelets are very useful for possibly non-stationary or trending series without a need for any further specification during the estimation process (Raihan et al., 2005; Grinsted et al., 2004; Aguiar-Conraria et al., 2008; Torrence and Compo, 1998). The described framework thus provides a robust and flexible environment for studying evolution of correlations and transmission between ethanol and related commodities.

3. Results

3.1 Basic dynamics

In theory, when agricultural crops are used for biofuels, the first-order, direct, impact is to reduce the food and feed availability. This leads to increasing prices as users and various types of demand compete for the same available supplies. If that were the only effect, the commodity price would then rise rather steeply according to consumers' highest willingness to pay under the constraint of available supply. This is, however, not what we observe because of two feedback effects involving feedstock consumption and production, in addition to the possibilities of substitutions between foods and feedstocks, at the demand and production levels, in the food and fuel markets.

The first feedback effect is at the level of demand, where the price increase forces people to consume less food and, indirectly, less feed. The second feedback effect is at the level of production, where the high price encourages farmers to increase production and therefore supply. If the increase in production corresponds sufficiently closely to the increasing demand, price increases will be limited to the marginal rise in production costs associated with reaching higher yields or with using additional lands. Since demand for biofuel results from government policies, it is a demand that can be anticipated by agricultural producers and incorporated into planting decisions. To what extent farmers can reply to such new conditions by increasing supply is key to the net effect of biofuels on the prices of food commodities.

These impacts might be different both qualitatively (the sign) and quantitatively (the size) in the short versus the long term. In the short run, supply in particular is less responsive because farmers face obvious constraints to expand their production within a year or two. In fact, within a few months, the only supply response may come from increased sales by commodity stockholders. Such short-term limitations on the supply response imply that prices have the potential to rise more in the short run than the long run, when the incentive to invest and increase the production will be materialized. On the demand side, the responsiveness (elasticity) to price changes can also adjust with time as income conditions and habits evolve or as social protection programs and interventions are introduced. Also, we may expect asymmetric reactions to downside and upside price shocks (Bastianin et al., 2014b; Kristoufek and Lunackova, 2015).

Observed price developments of ethanol and its main feedstocks have differed in Brazil and the USA (Fig. 1). Both markets were struck by the food crisis between 2007 and 2008. However, the effects were different. In Brazil, the crisis was mainly reflected in an increased price of crude oil whereas prices of sugar and both types of ethanol remained relatively stable. The local heights had already been reached at the break of 2005 and 2006. Nonetheless, all the analyzed Brazilian commodities (anhydrous and hydrous ethanol, sugar and crude oil) started an increasing trend in prices in 2009 which held up to the break of 2011 after which the prices were stagnating until the end of the analyzed period. The food crisis had a stronger effect on the U.S. market. Prices of all the analyzed commodities (ethanol, corn and crude oil) had reached their local peak in the middle of 2008. At the break of 2009, the prices were back to the pre-crisis levels. Similarly to the Brazilian market, the U.S. commodities were then appreciating until the middle of 2011 after which the prices were quite stable until the end of the analyzed period.

We observe that commodities move together quite strongly and apart from the crude oil divergence in the Brazilian market around the time of the food crisis, the prices follow very similar trends. Even though the correspondence is not perfect, the prices are visually tightly linked together. To see whether this is in fact true and which series is the leading one in the pair, we utilize the wavelet coherence framework described in the previous section. We are first interested in the coherence between ethanol and its producing factor in each market and then we control for a possible influence of the crude oil dynamics to see whether the initial relationship remains strong. If it does, we report a strong relationship between ethanol and its producing factor regardless of the crude oil influence and possible indirect correlation.

3.2 Brazil

Fig. 2 shows the wavelet coherence and the partial wavelet coherence between sugar and anhydrous ethanol in Brazil. In the left panel, the wavelet coherence is presented and we can see its evolution in time (horizontal axis) and across scales or periods measured in weeks (vertical axis). Statistically significant regions are marked by a thick black curve. Low coherence is shown in cold colors which become hotter as the coherence increases. Most of the significant regions are thus in a red color. The most dominant region of significant relationship between the two series is between approximately 60 and 100 weeks, i.e. between 1 and 2 years. The band of statistically significant wavelet coherence suggests a remarkably stable relationship in time and it tells that the prices of sugar and anhydrous ethanol are tightly intertwined in the long-term horizon. The dominant scale slightly decreases in time which suggests that the reaction time of prices shortens slightly. However, such a change in the dynamics is very slow. Apart from this long-term relationship, there are only few periods when the coherence is statistically significant which indicates that there are only several short-lived episodes when the prices were reactive to one another in a shorter term.

Orientation of the phase arrows provides evidence of a lead-lag relationship between sugar and anhydrous ethanol. Most of the arrows in the significant region between 60 and 100 weeks are pointing to the right and more or less downwards. The direction to the right indicates that the series are positively correlated and the downward direction indicates that the sugar series leads ethanol. Therefore, in the long-term, sugar prices are positively correlated with ethanol prices while sugar is the leader of the relationship. Note that this relationship is again very stable in time. To control for the effect of crude oil, we present the partial wavelet coherence between sugar and anhydrous ethanol in the right panel of Fig. 2. Qualitatively, most of the dynamics remains unchanged. Even though crude oil has drawn a portion of the correlation away, the relationship still remains strong and our main findings stay unchanged. The relationship between sugar and hydrous ethanol (Fig. 3) is in the same line as the previous case. In fact, the interconnection seems to be even stronger for the hydrous ethanol compared to the anhydrous one. Nonetheless, the results remain practically unchanged, qualitatively.

The mechanism leading our observable results is consistent with a diversion of large amounts of sugar to ethanol production leading, everything else being equal, to an increase in the price of sugar relative to what it would have been without ethanol. However, given the overall increase in sugar cane production, the total effect has been mild and, in the Brazilian market, world sugar and oil prices influence ethanol prices more than the reverse.

3.3 United States

For the U.S. market, we study the relationship between ethanol and corn. Moreover, data are available on the daily basis rather than weekly as in the case of Brazil. Fig. 4 summarizes the results which allows for a more detailed analysis. The dynamics is more complex than in the case of Brazil. We again see a stable long-term positive relationship between the commodities represented by the statistically significant wavelet coherence at the high scales. Specifically, corn prices lead the ethanol prices at the scales above one trading year represented by a dominant orientation of the phase arrows to the southeast, which is in accordance with the Brazilian market. However, there are also more dominant episodes of statistically significant dynamics at lower scales. During the food crisis, the corn prices led the ethanol prices with a higher leading period which is represented by the arrows pointing more southwards at scales approximately between a trading month and half a year between 2008 and 2009. The extremely high prices thus seem to be connected with a stronger relationship between the U.S. ethanol and its producing factor. The same behavior is observed between 2012 and 2013, which is again connected to extremely high prices of corn. Even though the filtering out of the crude oil influence (the right panel of Fig. 4) seems to have consumed more of the correlations than in the case of Brazil, the base qualitative results remain unchanged.

4. Discussion

4.1 Comparison

A number of studies have investigated the biofuels related prices utilizing time series econometrics techniques. A representative review by Serra and Zilberman (2013) reports 51 such studies using different commodities, sample periods, data frequencies and techniques which were published over the period 2006–2012. Out of these studies, 20 support an existence of the link between biofuels or energy prices and feedstock prices, 13 do not support it and 18 focus on different topics.

Ciaian and Kancs (2011a,b) show that interdependence among the prices of crude oil and agricultural commodities was increasing over the 1993–2010 period, especially after 2005. Similarly, Rausser and de Gorter (2014) show that the global prices and price volatilities for food-grain commodities have spiked frequently and dramatically since 2006. We bring the results of these previous analyses further by utilizing additional data and by expanding the analytical techniques.

We have studied the relationship between ethanol and its producing factors in the two biggest ethanol markets – Brazil and the USA. Using the continuous wavelets framework, we have uncovered the interconnections and their evolution both in time and across frequencies. Even though the producing factors differ for each market – sugar for Brazil and corn for the USA – the qualitative results coincide. Overall, there are several important findings that hold for both analyzed markets. First, the long-term relationship between ethanol and its producing factors is positive, strong and stable in time. Second, the prices of the producing factors lead the prices of ethanol and not the other way around. Third, there are episodes at lower scales, mainly connected to extremely high prices of the producing factors, for which the strong relationship emerges as well. Moreover, the leading position of the producing factors becomes even more prominent. And fourth, these findings are only slightly altered when we control for the effect of crude oil prices and possible indirect correlations.

Our results provide a support to the argument in favor of economic feasibility of global ethanol market. The similarities in the behavior of the U.S. and Brazilian ethanol markets, which we present in this paper, indicate a possibility for overcoming an existing agricultural commodity fragmentation of the ethanol trade. Nonetheless, an emergence of a truly global ethanol market, in parallel to the global crude oil market or the world market for individual agricultural commodities, is still an open topic for the future development, especially because of the underdeveloped institutional framework (Hira, 2011; Ackrill and Kay, 2011).

Our confirmation that the ethanol prices lag behind the feedstock prices at any regime in which we are able to identify co-movement of these prices supports the recent results of Bastianin et al. (2014a). In addition to confirming their results (based on predictability in distribution) for the USA, our wavelet coherence analysis extends the global coverage to Brazil, providing the evidence which is missing in majority of the recent studies focusing on the U.S. biofuels or on the marginal markets in Africa, the EU or Asia. However, our analysis provides much deeper insights into the dynamics of the dependence.

4.2. Limitations

White (2006) describes the wavelets as a particularly powerful class of functions that need not be orthogonal and the author also discusses some further limitations of the framework in the context of other alternative nonlinear methods. Some useful references, which provide a more detailed treatment of specific issues, are reviewed there as well. Dekel and Leviatan (2003) show that wavelets do not perform well in capturing singularities around curves and they prefer nonlinear piecewise polynomial approximations in this specific case. The issue of the wavelets and Fourier series performance in the presence of singularities is further discussed by Candes (1999) who suggests using ridgelets as an optimal tool for smoothing multivariate functions. Candes (2003) further discusses the properties of ridgelet estimators and compares their properties with kernel smoothing and various wavelet thresholding methods. In addition to these issues of the wavelets framework, there are few potential weaknesses connected to the characteristics of the dataset we analyze.

In general, due to a wavelet function stretching in the wavelet powers calculation, the results are less reliable for higher scales and close to the beginning and the end of the analyzed period which is represented by the cone of influence in the figures. It is thus possible that the relationship is strong even for higher scales than reported. However, we report a strong and stable relationship for scales outside the unreliable region so that such issue limits our conclusions only marginally. In addition, the wavelet analysis is partly prone to arbitrariness due to a need to select a specific wavelet with given parameters. In our case, we use the Morlet wavelet with a specified central frequency. Note that the results do not change qualitatively even for other wavelet choices. And lastly, even though the utilized framework allows for multivariate control variables, the possibilities are of course limited by data structure and availability, which we now discuss in more detail.

The most evident omission in our dataset is a measure of economic activity (or some other demand factor) for the studied countries. Hypothetically, an increased economic activity drives up demand for both ethanol and its producing factors. This might create an omitted variable bias and the reported results could be biased upwards as we would assume positive correlation between the economic activity and each of ethanol and its producing factors. However, a quarterly nature of economic activity measures restricts the analysis, as such measures cannot be straightly imported into the multivariate wavelet coherence framework. To partially control for the possible bias, we examine the correlation between gross domestic product (GDP) of Brazil and the USA, and sugar and corn as the relevant producing factors, respectively. We use quarter-to-quarter real gross domestic product per capita growth provided by the World Bank (data.worldbank.org). We report the correlation coefficient between the economic activity and the ethanol producing factors at very low levels (0.21 for Brazil and 0.11 for the USA) and statistically insignificant with *p*-values well above 0.1 (we calculate average quarterly prices of sugar and ethanol to further obtain quarter-to-quarter growth rates, which are then compared with GDP of the relevant countries). Even though the linear correlation coefficient does not control for possible variation across scales, it provides information about overall dependence between series. Analysis of the dependence and its evolution in time and across scales using quarterly data with such a restricted time frame would not yield reliable results. Therefore, our results are not biased by a strong connection between the economic activity and studied commodities.

4.3. Policy implications

The partial wavelet coherence, applied for the first time to biofuel price system in this paper, clearly identifies the important structural break associated with the global food crisis around 2008. At that time, we observe the short-run positive co-movements of prices of ethanol and its feedstock replacing the long-run stable relationship which prevailed for the rest of the analyzed period. Characteristically, the following period of high prices around 2011 did not display this change in the long-run co-movement of ethanol and its producing factors, which confirms a fundamental difference between these two periods of high prices around 2008 and 2011.

Our major confirmation of the stable positive long run relationship among prices of ethanol and related agricultural commodities indicates that (at least) two years of record high harvests of biofuels feedstock in 2013 and 2014 should have a significant long run impact on the economics of biofuels. According to the United Nations (FAO, 2014), the expected 2014 world coarse grains production is virtually matching the 2013 record high of 1,308 million tonnes. World sugar production is forecast to reach 183.9 million tonnes in 2014/15 (FAO, 2014), which represents a modest 0.9 percent increase over the 2013/14 season, but still the second largest harvest in history. These high harvests and more importantly increasing levels of stock of these major ethanol related agricultural commodities obviously lead to lower commodity prices both in the short and middle run as well as to the long run price stabilization effect. While the decrease in the costs of main ethanol feedstocks clearly improves the competitiveness of ethanol, the concurrent decrease in the oil prices (EIA, 2014) works in the other direction. However, the results of our wavelet coherence analysis controlling for the price of crude oil suggest that the direct effect of lower prices of agricultural commodities will prevail and the ethanol producers are likely to benefit.

Obviously, an important side effect of good agricultural seasons of 2013 onwards is the changed short run public perception of dangers of food shortages and widespread starvation. This may positively influence the public attitudes towards biofuels. However, as shown in the recent World Bank research (Ivanic and Martin, 2014), the relation between food prices and livelihood of rural population may be more complicated than previous models based only on the concept of net food sellers/buyers suggest. Ivanic and Martin (2014) show that while low food prices lower global poverty in the short run, the high food prices lower global poverty in the long run. Therefore, the links between biofuels, food prices and global poverty are more complicated than those considered during the heated public debate during and immediately after the 2007-2008 food crisis.

Our results open further research possibilities and bring new challenges for modeling and possible forecasting. The findings indicate that adequate models should control for both time and frequency variability of dependence between ethanol and its producing factors. Even though the long-term relationship seems to be rather stable in time, the short-term and medium-term dynamics progress quite freely and react to an actual market situation. Such models should thus encompass long-run equilibrium relationship between variables with impulses coming from the producing factors to ethanol. In addition, the models should allow for time-varying parameters of the short-run dynamics. On the one hand, the long-term dynamics between ethanol and the producing factors suggest that the pairs could be used for long-term hedging (with opposing contracts) or pairs trading. On the other hand, the short-term trading strategies do not promise a simple solution due to strong time dependence of the correlations. The eventual solution is thus much more complex than usually presented in the applied literature studying the relationships between biofuels and related commodities.

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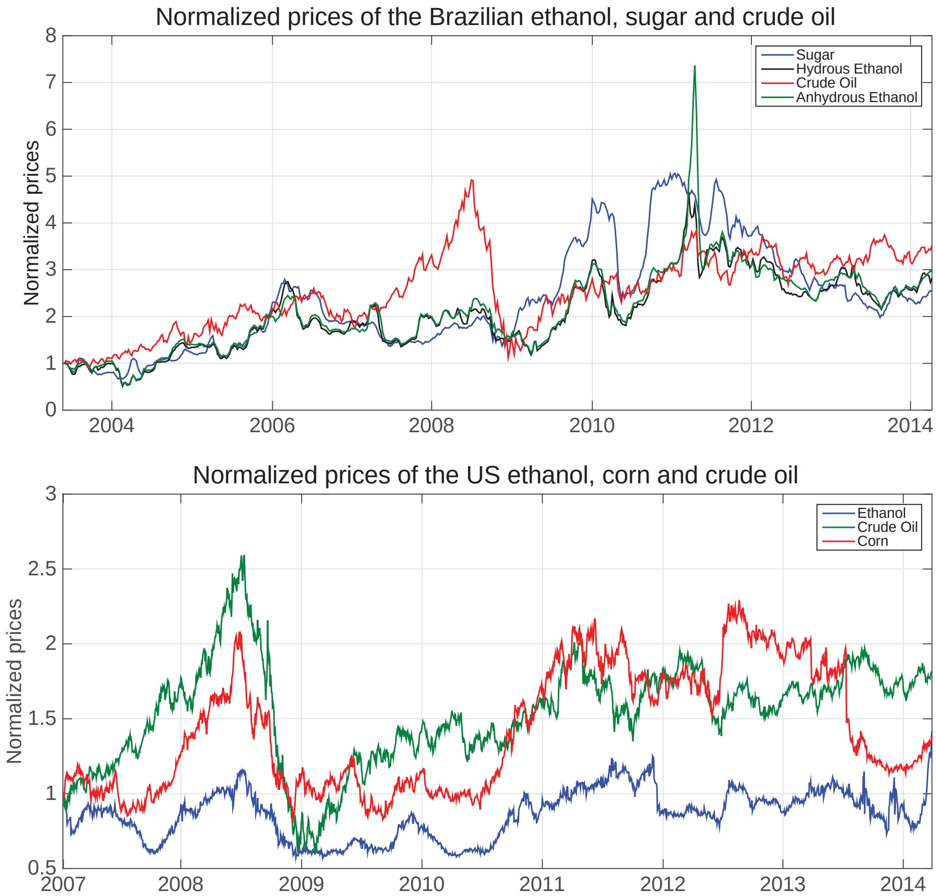

Figure 1: **Price evolution of ethanol and connected commodities for Brazil and the USA.** The prices are normalized using the first observation for a better comparison.

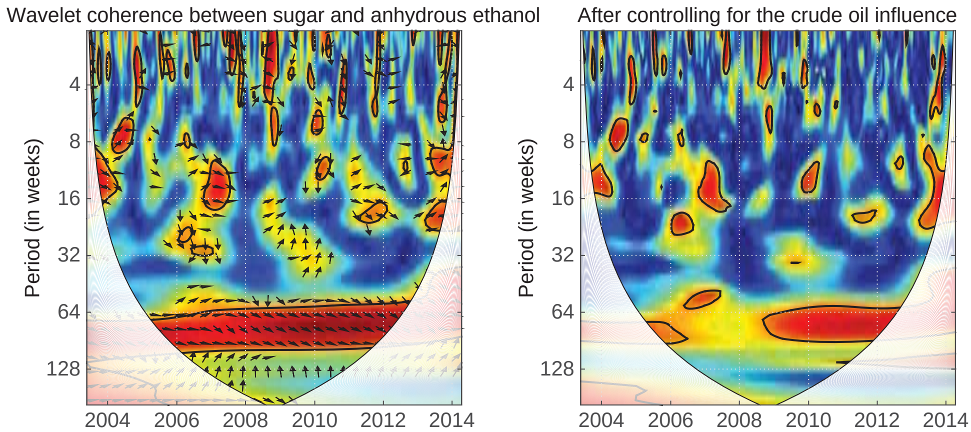

Figure 2: **Wavelet coherence for Brazilian anhydrous ethanol.** Wavelet squared coherence between sugar and anhydrous ethanol (left) together with the partial wavelet coherence controlling for crude oil (right) are shown. The hotter colors indicate higher coherence, the significant regions are marked by a thick black curve and the phase differences are represented by the directed arrows. The cone of influence separating the plane into reliable and less reliable regions is represented by bright colors for the former case and pale colors for the latter one. The most dominant region of significant relationship between the two series is between approximately 60 and 100 weeks, i.e. between 1 and 2 years. The band of statistically significant wavelet coherence suggests a remarkably stable relationship in time and it tells that the prices of sugar and anhydrous ethanol are tightly intertwined in the long-term horizon. Orientation of the phase arrows provides evidence of a lead-lag relationship between sugar and anhydrous ethanol. Most of the arrows in the significant region between 60 and 100 weeks are pointing to the right and more or less downwards. The direction to the right indicates that the series are positively correlated and the downward direction indicates that the sugar series leads ethanol. Therefore, in the long-term, sugar prices are positively correlated with ethanol prices while sugar is the leader of the relationship.

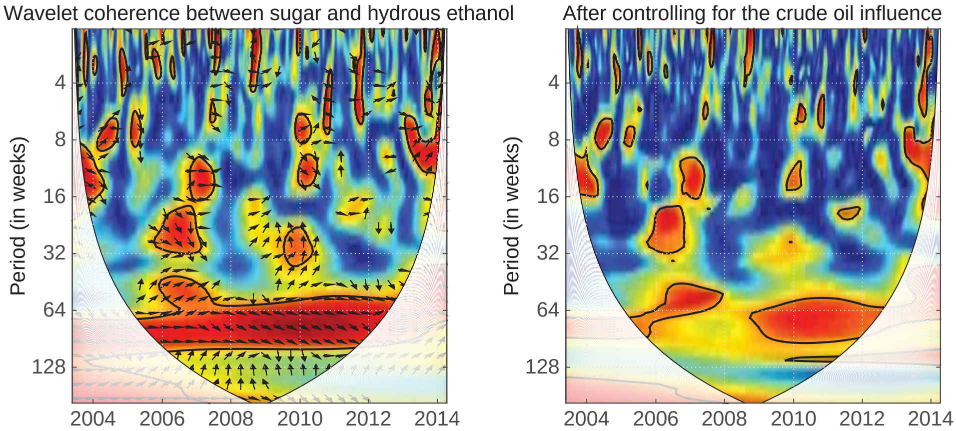

Figure 3: **Wavelet coherence for Brazilian hydrous ethanol.** Wavelet squared coherence between sugar and hydrous ethanol (left) together with the partial wavelet coherence controlling for crude oil (right) are shown. The rest of the notation holds from the previous figure. The results are in hand with ones for anhydrous ethanol.

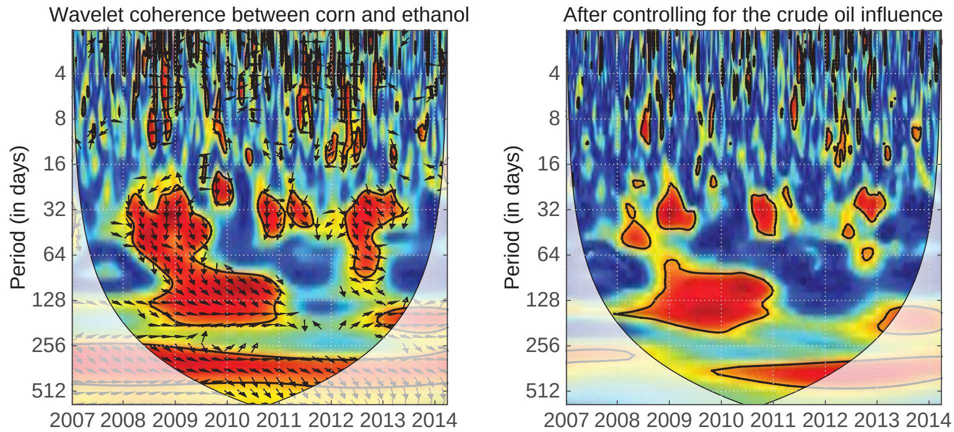

Figure 4: **Wavelet coherence for the U.S. ethanol.** Wavelet squared coherence between corn and ethanol (left) together with the partial wavelet coherence controlling for crude oil (right) are shown. The rest holds from the previous figure. The dynamics is more complex than in the case of Brazil. Corn prices lead the ethanol prices at the scales above one trading year represented by a dominant orientation of the phase arrows to the southeast. There are also more dominant episodes of statistically significant dynamics at lower scales. During the food crisis, the corn prices led the ethanol prices with a higher leading period which is represented by the arrows pointing more southwards at scales approximately between a trading month and half a year between 2008 and 2009. The extremely high prices thus seem to be connected with a stronger relationship between the U.S. ethanol and its producing factor. The same behavior is observed between 2012 and 2013, which is again connected to extremely high prices of corn.