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Food versus fuel: An updated and expanded evidence

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Abstract

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Keywords

Biofuels, fuels, food, cointegration

JEL Classification

Q16, Q42, Q56

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Food versus fuel: An updated and expanded evidence*

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Abstract

This paper replicates and extends the study of Zhang *et al.* (2010): "Food versus fuel: What do prices tell us?" *Energy Policy 38, pp. 445-451.* We confirm the findings of the original paper that there was only a weak relationship between ethanol and food commodities in the period between March 1989 and July 2008. In addition, we extend that study and examine the cointegration relationship between biofuels and related commodities for a considerably enlarged dataset (3 vs. 1 market, 26 vs. 8 commodities, analysis up till 2017 vs. 2008, weekly vs. monthly data frequency). Focusing on the biofuel markets of Brazil, the EU and the USA in the three separate periods before, during, and after the food crisis of 2007 and 2008, we show that studying the time variation of the relationships plays an essential role in their proper understanding. Our results help to clarify the wide extensive discussion about the role of biofuels prices in food shortages manifested particularly during the food crises. In agreement with the original study, we confirm that price series data do not support strong statements about biofuels uniformly serving as main leading source of high food prices and consequently the food shortages.

Keywords: biofuels; fuels; food; cointegration
JEL Codes: Q16, Q42, Q56

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1 Introduction

While the food versus fuels issue was introduced to the economic literature already by Barnard (1983) at the onset of the modern biofuels era and by Rajagopal et al. (2007) right before the world food crisis of 2007/2008 and while the most influential paper on this topic was Mitchel (2008), the most cited article dealing explicitly with the relationship between prices of biofuels and related fossil fuels and agricultural commodities is Zhang et al. (2010). In our paper, we replicate and extend their results.

The main result of Zhang et al. (2010) has been the absence of long-run price relations between the fuel and agricultural commodity prices, and a very limited short-run relationships. Even though we use essentially the same econometric techniques as Zhang et al. (2010), we perform additional testing and we include a step-by-step guide how to approach such analysis in this specific setting, allowing for possible future replication of our own results. In addition, we significantly extend the data set both in time and in the number of covered commodities. In the replication part of our article, we confirm the Zhang et al. (2010) results that there is no strong statistical evidence that ethanol would drive food prices or vice versa in the period between 1989 and 2008. However, in the extension part of our paper, we find statistically significant co-movement between time series of prices of biofuels and the related food commodities.

The results obtained in our paper are time and market dependent. Therefore, our major conclusion is that Zhang et al. (2010) analysis provides a good characterization of the U.S. ethanol market in the period up to the world food crisis. With the full development of the U.S. ethanol market, which coincides with the 2007/2008 world food crisis, we observe a fundamental change in the relationship between the prices of fossil fuels, agricultural commodities and biofuels. While the development of biofuels facilitated this price transmission on the U.S. ethanol and the European biodiesel markets, on the Brazilian ethanol market, which had reached the stage of mature development already before 2008, the ethanol leads short-run changes in sugar price quite strongly both in the pre-crisis and post-crisis periods.

The replicated article of Zhang et al. (2010) belongs to a series of research agenda-defining papers (Zhang et al., 2007, 2008, 2009, 2010) dealing with biofuels related price co-movements. This early price transmission literature is reviewed by Serra and Zilberman (2013) and Zilberman et al. (2013). More recent comprehensive literature reviews of the food versus fuels debate are provided by de Gorter et al. (2015) and by Hochman and Zilberman (2016). In our article, we present a structured review of the relevant literature in Tab. 1.

The rest of the paper is organized as follows. Section 2 describes the utilized methodology (cointegration and vector error-correction model) in detail. Sections 3 and 4 introduce the original dataset and replicate the results of the original study. Sections 5 and 6 present the expanded dataset and its results for three time periods (before, during and after the world food crisis) and three biofuel markets (the U.S., the EU and Brazil). Section 7 concludes.

Table 1: Summary of literature review

(A) Biofuel data not used

Reference	**Modeling Approach**	**Period**	**Frequency**	**Key Findings**
Neutrality hypothesis				
Fowowe (2016)	ECM, Nonlinear causality	2001-2014	Weekly	No price transmission from crude oil to agricultural commodities. Agricultural prices are neutral to oil prices.
Reboredo (2012)	Copulas	1998-2011	Weekly	The price rise of corn, soybean and wheat was not attributed to extreme changes in crude oil prices.
Gilbert (2010)	Granger causality, OLS, 2SLS, 3SLS	1971-2008	Quarterly	Economic activity, monetary expansion and exchange rate fluctuations lead to higher food prices.
Nazlioglu and Soytas (2011)	Toda-Yamamoto causality, Generalized impulse-responses	1994-2010	Monthly	Prices of agricultural commodities respond weakly to crude oil price variations in the short-run.
Yu et al. (2006)	Cointegration	1999-2006	Weekly	The influence of crude oil price on edible oil prices is not significant over the studied period.
Zhang and Reed (2008)	VARMA	2000-2007	Monthly	Influence of crude oil price was not significant over the studied period. The pork demand and supply result in the skyrocketing pork price.
Crude oil/energy prices affect prices of agricultural commodities				
Baffes (2007)	OLS	1960-2005	Annual	Agricultural price index increases by 1.8 per cent in response to the 10 per cent hike in crude oil prices.

Cha and Bae (2011)	SVAR	1986-2008	Quarterly	Increased crude oil price augments bioethanol demand which in turn raises the corn prices in the short run.
Chang and Su (2010)	EGARCH	2004-2008	Daily	Prices spill over from crude oil to corn and soybeans.
Chen et al. (2010)	ARDL	1983-2010	Weekly	Crude oil price changes significantly influence the prices of soybeans, corn, and wheat during 2005-2008.
de Nicola et al. (2016)	MV-GARCH	1970-2013	Monthly	Strong correlation between prices of crude oil and agricultural commodities (soybean corn, rice, wheat, sugar).
Koirala et al. (2015)	Copulas	2011-2012	Daily	Corn and soybean prices are correlated with energy prices.
Obadi and Korcek (2014)	VECM, Granger causality	1975-2013	Monthly	Prices of corn, wheat, rice, barley and palm oil are affected by the crude oil price movements.
Ibrahim (2015)	NARDL	1971-2012	Annual	Asymmetry in food price changes to crude oil price shocks.
Pal and Mitra (2016)	QADL	2004-2014	Monthly	Soybean price fluctuations react strongly to diesel price in the upper quantiles in comparison to the lower quantiles.
Rafiq and Bloch (2016)	NARDL	1971-2012	Annual	Corn reacts asymmetrically to crude oil price shocks.
Zhang and Qu (2015)	ARMA-GARCH	2004-2014	Daily	Crude oil price shocks have asymmetric impact on corn, soybean, and wheat price changes.
Campiche et al. (2007)	VECM	2003-2007	Weekly	No cointegration during the 2003-2005 time frame; however, corn prices and soybean prices are cointegrated with crude oil prices during the 2006-2007 time period.
Ciaian and Kancs (2011a)	VECM	1993-2010	Weekly	Prices of crude oil and agricultural commodities are interdependent. Indirect input price transmission channel
Ciaian and Kancs (2011b)	VECM	1994-2008	Weekly	is small and statistically insignificant.

Natanelov et al. (2011)	VECM, TVECM	1989-2010	Monthly	Co-movement is dynamic. Biofuel policy buffers the co-movement of crude oil and corn until crude oil price surpasses certain threshold.
Nazlioglu (2011)	TY and DP causality tests	1994-2010	Weekly	Nonlinear relationships between oil and agricultural prices. A persistent unidirectional nonlinear causality running from the oil prices to the corn and to the soybeans prices.
Nazlioglu and Soytas (2012)	Panel cointegration, VECM	1980-2010	Monthly	Strong evidence on the impact of world oil price on agricultural commodity prices, positive impact of weak dollar on agricultural prices.
Peri and Baldi (2010)	TVECM	2005-2007	Weekly	Rapeseed oil price adjusts rapidly to its long-run equilibrium determined by fossil diesel prices.
Rosa and Vasciaveo (2012)	VECM	2002-2010	Weekly	Causality in US markets with exogeneity of the oil on the US agricultural commodities, cointegration between US and Italian commodities.
Ziegelback and Kastner (2011)	TVECM	2005-2010	Daily	Asymmetric movements and presence of a threshold defining three different regimes of the rapeseed price adjustment.
Lucotte (2016)	VAR	1990-2015	Monthly	Strong positive co-movements between crude oil and food prices in the aftermath of the commodity boom. No statistically significant co-movements over the pre-boom period.
Other research focus				
Cooke and Robles (2009)	VAR	2002-2009	Monthly	Financial activity in futures markets and/or speculation in these markets help explain the behavior of agricultural prices in recent years.

Esmaeili and Shokoohi (2011)	VAR, PCA	1961-2005	Monthly	The crude oil price has indirect effect on the world GDP via its impacts on food production index.
Adams and Gluck (2015)	SDSVaR	1994-2013	Quarterly	Price links between crude oil and agricultural commodities
Han et al. (2015)	Multivariate normal mixture models	2000-2014	Daily	are attributed to the global financial crisis due to the increasing use of agricultural commodities as financial
Nagayev et al. (2016)	MGARCH-DCC	1999-2015	Daily	assets.

(B) Biofuel data used

Reference	**Modeling Approach**	**Period**	**Frequency**	**Key Findings**
Neutrality hypothesis				
Hassouneh et al. (2012)	VECM & MLPR	2006-2010	Weekly	Long-run equilibrium relationship between the three studied prices.
Myers et al. (2014)	VECM	1990-2010	Monthly	No indication of long-run cointegration between crude oil, ethanol, corn and soybean prices.
Zhang et al. (2010)	VECM	1989-2008	Monthly	No long-run price linkage between crude oil and agricultural commodities (corn, soybean, and wheat).
Qiu et al. (2012)	Structural VAR	1994-2010	Monthly	Biofuel production does not cause long run food price shifts. Oil, gasoline, and ethanol market shocks do not spillover to grain prices.
Cabrera and Schulz (2016)	VECM, MGARCH, mM-GARCH	2003-2012	Weekly	Biodiesel production cannot adequately explain the price co-movement between crude oil and agricultural feedstocks.

Bastianin et al. (2016)	Granger causality	1987-2012	Monthly	Ethanol returns do not Granger cause food price variations. Ethanol is Granger caused by returns on corn.
Bastianin et al. (2014)	Predictability in distribution	1987-2012	Monthly	Ethanol does not predict field crops or cattle, but field crops predict ethanol.
Biofuel/energy prices affect prices of agricultural commodities/feedstock				
Kristoufek et al. (2016)	Wavelet	1990-2011	Weekly	Ethanol price co-moves with corn (US) and sugar (Brazil).
Mallory et al. (2012)	VECM	2006-2010	Daily	Without structural breaks: no long-run relationship between energy and agricultural prices. With structural breaks: such long-run relationships exist and even intensified during last decade.
Natanelov et al. (2013)	VECM	2005-2011	Daily	Crude oil price is strongly linked to corn and ethanol prices.
Saghaian (2010)	VECM, Granger causality	1988-2002	Monthly	Crude oil price changes Granger cause fluctuations in ethanol, corn, soybean, and wheat prices.
Vacha et al. (2013)	Wavelet	2003-2011	Weekly	Ethanol prices co-move with corn prices; however, the correlation varies over time and frequency.
Balcombe and Rapsomanikis (2008)	Taylor series expansion of VECM, AVECM, TVECM	2000-2006	Weekly	Crude oil price fluctuations carry asymmetric impact on ethanol and sugar price variations in the long-run.
Serra et al. (2011)	STVEC	1990-2008	Monthly	Corn prices adjust nonlinearly to crude oil price changes.
Busse et al. (2012)	MS-VECM	2002-2008	Weekly	Before 2005 and after 2007, strong orientation of biodiesel towards diesel prices. Between 2005 and 2007, biodiesel and rapeseed oil prices are mutually interdependent.

Rajcaniova and Pokrivcak (2011)	VECM	2005-2010	Weekly	Long-run cointegrating relationship among the selected time series in the later years while the interrelationship among the variables was weaker in earlier period.
Rapsomanikis and Hallam (2006)	TVECM	2000-2006	Weekly	Both sugar and ethanol prices are found to be determined by oil prices and no evidence for a causal relationship that runs from oil to ethanol to sugar is found.
Wixson and Katchova (2012)	TVECM	1995-2010	Monthly	Asymmetric price changes do occur in the commodity and energy markets.
	Correlation	1988-2009	Monthly	Correlation among crude oil and corn prices by 2006-2008.
Abdelradi and Serra (2015)	MGARCH	2008-2012	Weekly	Significant asymmetries in volatility spillovers between biodiesel and rapeseed oil prices.
Other research focus				
Kristoufek et al. (2012)	Minimal spanning trees and hierarchical trees	2003-2011	Monthly/weekly	In the short-term, both ethanol and biodiesel are very weakly connected with other commodities. In the 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.
Kristoufek et al. (2014)	VAR	2003-2011	Weekly	Ethanol and biodiesel prices are responsive to their production factors as well as to their substitute fossil fuels.

McPhail (2011)	Structural VAR	1994-2010	Monthly	A policy-driven ethanol demand expansion causes a statistically significant decline in real crude oil prices. Ethanol supply expansion does not have a statistically significant impact on real oil prices.
Pokrivcak and Rajcaniova (2011)	VECM	2000-2009	Weekly	Cointegration relationship between oil and gasoline prices, but no cointegration between ethanol, gasoline and ethanol, oil prices.

2 Methodology

We follow the procedure of Zhang et al. (2010) and utilize the vector error-correction model to study both the long-term relationship represented by the cointegration relationship and the short-term connections represented by the lagged variables in the vector autoregression representation. More details can be found in the Appendix. We specifically use the representation of Hendry and Juselius (2001):

$$\Delta X_t = \phi \Delta X_{t-1} + \alpha\beta X_{t-1} + \alpha\mu + \gamma + \alpha\rho t + \theta t + \epsilon_t \tag{1}$$

Defining $\pi \equiv \alpha\mu + \gamma$ and $\delta \equiv \alpha\rho + \tau$, we obtain five possible cases:

1. no restrictions on π and δ, i.e. the trend and intercept are unrestricted;
2. $\tau = 0$ but γ, μ and ρ remain unrestricted, i.e. the trend is restricted to lie in the cointegration space;
3. $\delta = 0$, i.e. there are no linear trends in the differenced series and the constant term is unrestricted;
4. $\delta = 0$, $\gamma = 0$ but $\mu \neq 0$, i.e. the constant term is restricted to lie in the cointegration space;
5. $\delta = 0$ and $\pi = 0$, i.e. the model excludes all deterministic components.

Correct identification of one of the above cases is crucial for obtaining meaningful results. For more details, theoretical background and caveats, please refer to Banerjee and Hendry (1992), Ericsson et al. (1998), Hendry and Juselius (2001), Juselius (2006) and Hoover et al. (2008).

The procedure of finding a correct model can be rather complicated. To ensure that each model we consider here is treated on the same grounds, we apply the following step-by-step procedure[1]:

1. Test for unit roots in the original data with the lag selection based on the Bayesian information criterion (Schwarz, 1978) with the maximum lag of 12. If the series are unit roots, we can proceed. If the time trend needs to be added into the model, it suggests the unrestricted trend version of the original model.
2. Find the optimal number of lags by estimating Eq. A.5. The selection is again based on the Bayesian information criterion (BIC), i.e. parsimony is preferred, with the maximum lag of 12.
3. Check whether the time trend is significant (utilizing the heteroskedasticity and autocorrelation consistent (HAC) standard errors) in the model estimated in the previous step. If the time trend is

[1] All the models and procedures are estimated in gretl 1.9.92 and RStudio 1.0.136. The following step-by-step guide ensures that these can be easily replicated.

significant in the model, we consider either the restricted trend or unrestricted trend version of the final model.

4. Run the Johansen test (both trace and L_{max}) for preselected specifications (Johansen, 1991, 1995).
5. Estimate a specific version of the vector error-correction model with setting according to the previous steps.
6. Test the error-correction terms of the final model for unit roots. If these are rejected, we arrive at the final model.

After arriving at the final model, we can comment on interconnections (both short-term and long-term) between series using the standard procedures such as the Granger causality and forecast error-variance decomposition so that we can compare our results with the original ones of Zhang et al. (2010) and later extend them.

3 Original dataset

The original dataset of Zhang et al. (2010) contains the monthly prices of crude oil, gasoline, ethanol, corn, soybeans, wheat, sugar and rice between March 1989 and July 2008. We are thankful to the authors for providing us with the original series of crude oil and gasoline but the rest of the dataset is proprietary and could not be shared. Therefore, we have been forced to collect the data from various other sources. Eventually, we have been able to get the same time series (the same data specifications) as in the original paper. The analyzed series are listed and described in Tab. 2. The data sources are quite broad and we have utilized neo.ne.gov, quandl.com, koema.com and indexmundi.com to get the whole dataset[2]. To check whether the obtained series are close to the ones of the original dataset, we compare the basic descriptive statistics of the series presented in Zhang et al. (2010) and ours in Tab. 3. The comparison shows that the series are not exactly the same but very close so that the results should be easily comparable.

Tab. C.1 presents the results for the Augmented Dickey-Fuller test (Dickey and Fuller, 1979) for logarithmic prices and their first differences. We stick to the logarithmic transformations as these are closer to the Gaussian distribution as shown in Tab. 3 using the Jarque-Bera (J-B) test (Jarque and Bera, 1981) and to follow the original study. The results are quite straightforward[3] as all but one logarithmic price series are detected as unit roots. Only for the soybeans series, the time trend needs to be included

[2]The dataset is provided in a separate file attached to this paper.

[3]The outcomes have been confirmed by the ADF-GLS tests as well (Elliott et al., 1996; Elliott, 1998). The same is true for the ADF tests on the expanded dataset later.

to get the unit root. This suggests that there might be a need for the trend effect in the cointegration relationship. After first differencing, the unit root is rejected for all the series. Therefore, we can proceed with the cointegration testing. Note that the soybeans issues are not present in the original study of Zhang et al. (2010) which only confirms that the datasets are not exactly the same. Again, this should not limit our replication as the soybeans series is unit root after controlling for the time trend.

4 Replication results

Following the steps of the procedure listed above, we proceed with finding the optimal lag of the VECM model of Eq. A.5. For the original dataset, an optimal lag of one is detected for both models with and without a time trend. In Zhang et al. (2010), the optimal lag of four is used based on the Akaike information criterion (AIC) (Akaike, 1974) and Final Prediction Error (FPE) (Ljung, 1999). It is not surprising that BIC delivers lower optimal lag as it prefers parsimony over overfitting. Nevertheless, the authors note that the results they present are practically the same regardless choosing four lags or one. For our estimation, the time trend is statistically significant for the oil and sugar series which leads to the model with (possibly restricted) time trend.

The Johansen tests in Tab. 4 suggest five cointegration vectors which is in hand with the original analysis of Zhang et al. (2010). Tab. C.2 shows that the error-correction terms of the VECM do not contain unit roots. These results are valid for the VECM with the restricted time trend and one lag in the short-term components. Note that the unit root of the error-correction terms is not rejected for the unrestricted trend model variant. This confirms that our model selection is valid. It is not possible to directly compare the final model we have arrived at with the one of the original study as it is not explicitly stated which of the five variants of the VECM is used in the original study. However, based on an inspection of the presented results (primarily Tab. A1 and Eqs. 1a-1e of the original paper), it seems that the final model of the original study includes an intercept in the cointegration relationship but no time trends anywhere which yields the VECM with the restricted constant, i.e. the case number four in our list. Time trends seem to be not tested for at all in the original paper of Zhang et al. (2010).

The Granger causality tests of the original study find several causal pairs. Even though the test specifications are not clear, we stick to the standards and apply the Toda and Yamamoto (1995) test for the long-run causality and joint significance tests of the short-term VAR components of the VECM for the short-run causality. The original study finds a bidirectional causality between gasoline and crude oil, which is in hand with expectations (Baumeister et al., 2017). Then there are several unidirectional causalities – from gasoline to ethanol, from sugar to oil, from sugar to corn, from sugar to soybeans, from sugar to wheat, from sugar to rice, and from soybeans to corn and rice. This shows a rather unexpectedly strong role of the sugar prices in the system, and also quite unexpectedly weak role of crude oil. Crude oil Granger causes gasoline prices, which is not surprising, but it is also caused by gasoline and sugar. In Zhang et al. (2010), this strong role of sugar in the whole system is attributed to it being a proxy for economic indicators. In our replication and extended study as well, we add more variables into the system to control for such effects. Quite interestingly, the dominant role of sugar is not reflected in the forecast error variance decomposition (FEVD) presented in the original paper as the contribution of sugar shocks towards other variables never exceeds 10%. The only markable contribution off the diagonal is the one of oil towards gasoline as oil contributes around 80% towards the gasoline variance[4]. Apart from this one, the cross-effects are minute, i.e. there is no interesting interaction between ethanol and either its producing factors or crude oil or gasoline.

Replicating these results, we also find several pairs with statistically significant Granger causality but these are mostly different from the ones in the original analysis. For both short-run and long-run causality tests, the optimal number of lags is detected to be one (with respect to BIC). In the long-run, wheat causes gasoline and oil, gasoline causes ethanol and wheat, sugar causes soybeans and wheat, and ethanol causes wheat. In the short-run, wheat causes gasoline and oil, rice causes oil, sugar causes soybeans, corn causes wheat, and ethanol causes wheat, i.e. most of the short-run causalities overlap with the long-run ones. Nevertheless, the trouble with crude oil being Granger caused by agricultural commodities remains. We attribute this to an under-identification of the original model and possibly endogeneity issues, or more precisely the omitted variable bias. There surely are other variables that might be important for the system dynamics and are not included in the estimated model. Therefore, it would be helpful to enlarge the dataset.

As for the forecasting error variance decomposition (FEVD), the results cannot be directly replicated as the original paper does not state the variables ordering (Cholesky factoring) which plays an essential role in the final FEVD (Gentle, 1998). We proceed with the FEVD based on the generalized VAR as proposed by Pesaran and Shin (1998) and further developed by Dees et al. (2007) and Diebold and Yilmaz (2012), which does not require specific ordering and it is thus robust to errors due to incorrect ordering[5]. In Tab. 5, we present the results of the forecasting error variance decomposition based on the VECM

[4]We stick to the presentation of the original paper which shows the forecasting error variance decomposition after five periods (months).

[5]For a detailed procedure and code, please refer to Barunik and Krehlik (2015) and the appended R-package.

specification with restricted trend and one lag of the VAR terms. Our results show that all the agricultural commodities react mostly to their own shocks (with the proportion around 80% and more), i.e. there is strong autocorrelation present in their variance process with only weak cross-correlation effects. Similarly to the original study, we find that gasoline responds to the oil shocks quite strongly (43% compared to 78% in the original study) but also ethanol reacts to oil (22% compared to 15% in the original paper) and gasoline (over 5% compared to 4% in the original study). Other than these, there are no effects exceeding 10%. From the perspective of the main question of the original paper, i.e. whether there is a strong link between ethanol and related agricultural commodities, the results of the original paper and our replication suggest the same – there is no strong connection between them and there is no strong statistical evidence that ethanol would drive food prices or vice versa.

5 Expanded dataset

Since the publication of the Zhang et al. (2010) article, the availability of the biofuels-related data has improved markedly. Even though the data coverage does not (or even cannot) go too far into the past, the coverage improves substantially for the more recent years. To further expand on the results of the replicated paper, we provide a similar study conducted on a considerably enlarged dataset. Namely, we cover the three largest biofuel markets – Brazil (ethanol), the EU (biodiesel), and the USA (ethanol). For these markets, we have collected a comprehensive dataset (unprecedented in the topical literature) of weekly nominal prices of biofuels, its producing factors (agricultural commodities), crude oil and competing fossil fuels as well as relevant financial variables. This gives us a total of 26 series covering the period between Nov 24, 2003 and May 16, 2016. Specifically for these three markets, we covered the following time series:

- biofuels: Brazilian ethanol, EU biodiesel, US ethanol
- crude oil: Brent, WTI
- (competing) fuels: Brazilian gasoline, EU diesel, US gasoline
- stock indices: DJI, S&P500, FTSE100, DAX, BOVESPA
- interest rates: Fed Fund rates, LIBOR
- exchange rates: USD/EUR, USD/BRL
- biofuels-relevant agricultural commodities: corn, wheat, sugarcane, sugar beets, Brazilian sugar, soybeans, sunflower, rapeseed, palm oil

The data has been obtained from Bloomberg, Thomson Reuters Eikon, Centro de Estudos Avancados em Economica Aplicada (CEPEA), US Energy Information Administration (EIA), National Agency of Petroleum, Natural Gas and Biofuels – Agencia Nacional do Petroleo, Gas Natural e Biocombustiveis (ANP Brazil), US Federal Reserve, European Central Bank (ECB), and ECONSTATS databases[6]. Detailed description of the dataset and its sources is provided in Tab. 6.

In order to account for episodes of various market environments, we split the whole period into three subperiods. As a benchmark for the division, we use the FAO Food Price Index – a weighted average of five commodity group price indices. Upward sloping values of the index culminated during the 2007-2008 world food crisis with the index value peaking in June 2008. Subsequently, the agricultural prices fell, bottoming in September 2009 before catching up again for a new food commodity prices rally. The index reached its new peak in February 2011 followed by a stable price decrease. We set the two index peaks to be the breaking points. Our dividing points exactly correspond to the World Bank terminal points of the two global food crises in 2008 and 2011. As summarized by Cuesta et al. (2014), the World Bank developed a methodological approach to identify a situation leading to a potential food crisis. To check whether the two breaking points are in fact empirically valid, we utilize the methodology of Joyeux (2007) for each market. The breaking points are confirmed[7]. This finally gives us three subperiods:

- Period I: November 24, 2003 - June 30, 2008
- Period II: July 7, 2008 - February 28, 2011
- Period III: March 7, 2011 - May 16, 2016

As earlier demonstrated by Kristoufek et al. (2012), Vacha et al. (2013), Kristoufek et al. (2016) and Filip et al. (2016), the effect of time development seems to be crucial. These earlier studies of ours have repeatedly found a causal relationship between prices of biofuels and their production factors. However, these relationships experience a notable development in time. Thus, we believe that extending the original paper both in terms of data and time frame coverage may considerably contribute to the quality and correct interpretability of the obtained results.

[6]The extended dataset is provided in a separate file attached to this paper.

[7]Specifically, we extend Eq. 1 by adding dummy variables for the breaking points and also the interaction term dummies with the time trend. For each market, the optimal lag based on the BIC is identified as one. The null hypothesis of the specified dates not being the breaking points is confidently rejected with $\chi^2(28) = 136.20$ ($p < 0.0001$) for Brazil, $\chi^2(40) = 175.37$ ($p < 0.0001$) for the EU, and $\chi^2(40) = 154.86$ ($p < 0.0001$) for the US.

6 Results

We follow the same procedure of model selection and following analysis as for the original dataset. As the new dataset has been markedly enlarged, we now estimate three models – for the EU biodiesel, US ethanol, and Brazilian ethanol – for three separate periods – before, during, and after the food crisis which gives nine models in total. The model specification procedure is described in the Appendix and the resulting models are summarized in Tab. 7.

6.1 Short-term dynamics

Short-term interactions between series are easily uncovered using the Granger causality test in the VAR specification of the VECM model (if the cointegration relationship has been found) or in VAR itself (for no cointegration found). The results of the short-run Granger causality tests are summarized in Tabs. C.4-C.6. The tables summarize results for all three markets and all three analyzed periods. Specifically, the p-values of the Granger test are reported. In fact, as the optimal lag size has been detected as one for all the models and all the periods, these are in fact p-values for t-statistics in the VAR models. For a better orientation in the tables, we report only the p-values that are lower than 0.1, i.e. only when the "no Granger causality" null hypothesis is rejected at at least 90% significance level. Otherwise, "×" is reported. Also, to stick to the motivation of the original paper, we report only the pairs where either a biofuel or its producing factor is affected/caused by another variable in the specific market.

For the EU biodiesel market (Tab. C.4), we find that the results vary across the time periods and there are several interesting findings on the short-term interactions. First, biodiesel is Granger caused by at least one of its producing factors in each period. The strongest evidence is found during the post-crisis period when biodiesel is strongly driven by sunflower and rapeseed. The weakest short-term interactions between biodiesel and its producing factors are found for the food crisis where only palm oil causes biodiesel but only at the 90% significance level. Second, the biodiesel producing factors interact between one another quite frequently. The least interacting food factor is palm oil. Third, the producing factors are quite strongly affected by Brent crude oil prices (this is true for soybeans, rapeseed and palm oil in the pre-crisis period) and the stock markets (this is true for soybeans, sunflower and rapeseed in the pre-crisis period). Third, the effect of biodiesel price changes towards its producing factors is rather limited and there are only two commodity/period combinations when the effect is statistically significant (for rapeseed before the food crisis and for palm oil in the post-crisis period).

The results are more straightforward for the US ethanol market (Tab. C.5). Ethanol is driven by corn (its main US producing factor) in the pre-crisis and crisis period. However, this short-term effect vanishes after the food crisis. The ethanol producing factors are primarily driven by other economic/financial variables, i.e. WTI crude oil, gasoline, stock market, and exchange rates (this is true mainly for the pre-crisis and crisis periods). There is no strong evidence of ethanol causing changes in its producing factors.

For the Brazilian ethanol market (Tab. C.6), there is no evidence of sugar driving the dynamics of ethanol in the short-term. On the contrary, ethanol leads changes in sugar prices quite strongly (the evidence is found for the pre-crisis and post-crisis periods). For sugar prices, the currency strength evidently plays a strong role as well.

6.2 Long-term dynamics

To analyze the long-term connections between commodities, we follow the steps of the Zhang et al. (2010) study and, in addition to the long-run causality tests, we also provide the results for the forecasting error-variance decomposition. For each market, we primarily focus on the results for biofuels and their producing factors. The results of the long-run Granger causality tests based on the methodology of Toda and Yamamoto (1995) are summarized in Tabs. C.4-C.6. For the EU biodiesel market (Tab. C.4), the long-run dynamics is quite similar to the short-run dynamics as biodiesel prices are driven by at least one of its producing factors in each of the studied periods. In addition, biodiesel is also strongly driven by Brent crude oil and diesel prices before and during the food crisis. The food commodities are strongly driven by the stock markets and only slightly by biodiesel, crude oil and diesel. From the long-run perspective, the US ethanol market (Tab. C.5) is driven by corn and wheat before and during the food crisis. For the food commodities, the results are mixed and there are no obvious patterns. And for the Brazilian market (Tab. C.6), ethanol is driven by sugar only before and during the food crisis. After the crisis, the exchange rate is the main factor. From the other side, sugar is driven by ethanol only during the periods of relatively stable prices, i.e. before and after the food crisis. During such times, it is also strongly driven by crude oil and exchange rate between the US dollar and Brazilian real.

In the original study, the forecast error-variance decomposition, i.e. the effect of shocks in one commodity on variance of another, is studied five months after the shock. With the weekly data, we keep this timing and study the effects after twenty weeks. The results are summarized in Tabs. C.7-C.9.

For the EU biodiesel market (Tab. C.7), biodiesel is strongly driven by other commodities. In the pre-crisis period, more than 40% of the biodiesel variance is driven by Brent crude oil and retail diesel. The producing factors play no important role here. During the food crisis period, more than 40% of biodiesel variance accounts towards the agricultural commodities. Other economic factors play an important role as well, namely the stock market (20%), exchange rate (12%) and diesel (10%). After the food crisis, the influence of other financial factors decreases to around 30% overall and the effect of the agricultural commodities drops below 20%. From the other side, biodiesel does not play a major role in variance of the agricultural commodities in the long run (never exceeding a 15% contribution to the error-variance).

In the US ethanol market (Tab. C.8), the results are more direct. Before the food crisis, ethanol is only mildly affected by other analyzed assets. But during and after the food crisis, it is strongly driven by its producing food factors (with an aggregate contribution over 40% in both periods). From the other direction, ethanol does not influence the food commodities before the food crisis, but again during and after the crisis, the effect increases. During the crisis, ethanol explains around 15% of the corn variance and around 5% for the other food commodities. And after the crisis, the effect is rather uniform around 10%. Even though these are not huge contributions, they are not negligible. Our results therefore serve as ex-post correction for the suggestions of Mitchel (2008) and Wright (2014) about dramatic effects of introduction of biofuels on food prices. After the immediate impact of ethanol prices on food commodity prices during the 2008 food crisis, this effect had gradually decreased, and during the post-crisis period 2011-2016, the influence of ethanol prices on corn prices was not stronger than influence of financial factors like stock indexes and exchange rates.

The development of the long-term relationship between Brazilian ethanol and sugar is quite straightforward (Tab. C.9). In the pre-crisis period, there is practically no long-term interaction between ethanol and sugar. Around 40% of the ethanol variance is formed by the summed effects of stock market, crude oil, exchange rate, and gasoline. During the food crisis period, sugar slightly (13%) affects ethanol. From the other economic variables, the effects of stock market and exchange rate are worth mentioning. This is true for both ethanol and sugar. Ethanol has no notable influence on sugar prices. The sugar effect rises markedly to 30% after the crisis while ethanol does not affect sugar much (less than 5%). We thus observe an increasing influence of sugar on ethanol in the long run in the Brazilian market but not vice versa.

7 Final notes

Our results help to clarify the wide extensive discussion about the role of biofuels prices in food shortages manifested in particular during 2008 and 2011 food crises. In agreement with Zhang et al. (2010), we confirm that price series data do not support strong statements about biofuels uniformly serving as main leading source of high food prices and consequently the food shortages. However, we show that in particular markets and in particular periods, there exist statistically significant price transmissions between the agricultural commodities and fuels which have been facilitated by the development of biofuels price transmission channel (de Gorter et al., 2013; Drabik et al., 2016) which has been enabled by the biofuels supporting government policies (de Gorter et al., 2013; Drabik et al., 2014, 2015; Rajcaniova et al., 2013). This price transmission is not purely technologically based, it also includes the influence of financial markets.

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Table 2: **Original dataset description and sources.**

Commodity	Specification	Source
Crude oil	Average of Brent, WTI and Dubai Fateh crude oil prices	Zhang et al. (2010)
Gasoline	US wholesale spot prices	Zhang et al. (2010)
Ethanol	Fuel ethanol average rack prices, FOB Omaha, Nebraska	neo.ne.gov
Corn (maize)	US No. 2 Yellow, FOB Gulf of Mexico, US price	quandl.com
Soybeans	Chicago Soybean futures contract (first contract forward) No. 2 yellow and par	knoema.com
Wheat	Wheat, No. 1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico	indexmundi.com
Sugar	CSCE contract no. 11 nearest future position	quandl.com
Rice	5 percent broken milled white rice, Thailand nominal price quote	indexmundi.com

Table 3: **Descriptive statistics of the original dataset.** J-B stands for the Jarque-Bera testing statistic, the significance levels are labelled as ***, **, and * for 99%, 95%, and 90%, respectively. For the prices, the values in brackets represent the values in the original study of Zhang et al. (2010). As the logarithmic prices and differences of the logarithmic prices are derived from these, we report only our values.

	Average	SD	Skewness	Ex. kurtosis	Min.	Max.	J-B
prices							
oil	30.66 (30.67)	22.14 (22.14)	2.19 (2.21)	5.13 (5.27)	10.41 (10.41)	132.55 (132.55)	442.86***
gasoline	89.86 (89.86)	59.13 (59.13)	1.88 (1.89)	3.17 (3.26)	29.27 (29.27)	339.65 (339.65)	235.07***
ethanol	1.45 (1.43)	0.48 (0.46)	1.71 (1.98)	2.61 (4.46)	0.90 (0.97)	3.58 (3.78)	179.22***
corn	118.93 (115.31)	36.07 32.69)	2.01 (2.50)	4.33 (7.44)	75.06 (75.06)	287.11 (287.11)	339.25***
soybeans	223.00 (223.92)	39.00 (65.40)	0.91 (2.45)	1.02 (7.79)	158.31 (158.00)	363.55 (554.15)	41.95***
wheat	161.52 (161.52)	54.18 (54.18)	2.57 (2.59)	8.01 (8.21)	102.16 (102.16)	439.72 (439.72)	879.32***
sugar	10.03 (10.03)	2.75 (2.75)	0.34 (0.34)	-0.31 (-0.29)	5.11 (5.11)	18.05 (18.05)	5.49*
rice	282.26 (282.26)	104.40 (104.40)	4.25 (4.27)	24.78 (25.34)	162.10 (162.10)	1015.20 (1015.21)	6661.05***
log-prices							
oil	3.25	0.55	1.03	0.29	2.34	4.89	42.36***
gasoline	4.34	0.52	0.94	0.08	3.38	5.83	34.39***
ethanol	0.33	0.28	1.11	0.57	-0.11	1.28	51.33***
corn	4.74	0.25	1.32	1.40	4.32	5.66	86.46***
soybeans	5.39	0.17	0.40	0.10	5.06	5.90	6.23**
wheat	5.04	0.27	1.38	2.64	4.63	6.09	141.99***
sugar	2.27	0.28	-0.25	-0.57	1.63	2.89	5.70*
rice	5.60	0.27	1.34	5.53	5.09	6.92	366.42***
log-differences							
oil	0.01	0.08	0.39	3.60	-0.25	0.46	131.44***
gasoline	0.01	0.11	0.05	0.30	-0.25	0.36	0.97
ethanol	0.00	0.08	0.22	0.89	-0.23	0.28	9.41*
corn	0.00	0.06	-0.81	2.93	-0.25	0.17	108.41***
soybeans	0.00	0.06	-0.04	2.32	-0.25	0.27	52.29***
wheat	0.00	0.06	0.31	1.49	-0.19	0.23	25.16***
sugar	0.00	0.07	0.02	0.43	-0.25	0.22	1.83
rice	0.00	0.07	1.32	9.03	-0.28	0.41	855.16***

Table 4: **Johansen tests for the original dataset.** Both tests (trace test and L_{max}) are based on one lag as identified using the Bayesian information criterion. p-values are corrected for the finite sample size. The VECM specification is the option of the restricted trend based on the previous analysis.

rank	Eigenvalue	Trace test	p-value	L_{max}	p-value
0	0.27809	257.12	< 0.01	257.12	< 0.01
1	0.20441	181.84	0.0002	181.84	0.0003
2	0.14608	129.02	0.0069	129.02	0.0096
3	0.12940	92.542	0.0243	92.542	0.0295
4	0.11880	60.533	0.0909	60.533	0.1001
5	0.067435	31.318	0.4321	31.318	0.4439
6	0.042434	15.190	0.5658	15.190	0.5715
7	0.022148	5.1736	0.5795	5.1736	0.5806

Table 5: **Forecast error variance decomposition of the original model (5 months ahead).** Rows represent a response variable and columns are impulse variables.

	oil	gasoline	ethanol	corn	soybeans	wheat	sugar	rice
oil	0.5348	0.3935	0.0415	0.0017	0.0153	0.0064	0.0024	0.0044
gasoline	0.4309	0.4719	0.0518	0.0038	0.0180	0.0184	0.0025	0.0028
ethanol	0.2219	0.2670	0.4561	0.0008	0.0104	0.0011	0.0367	0.0060
corn	0.0101	0.0014	0.0570	0.8653	0.0101	0.0030	0.0352	0.0179
soybeans	0.0034	0.0070	0.0491	0.0878	0.7858	0.0184	0.0063	0.0423
wheat	0.0081	0.0026	0.0046	0.0204	0.0120	0.9369	0.0092	0.0062
sugar	0.0010	0.0013	0.0089	0.0115	0.0056	0.0735	0.8033	0.0949
rice	0.0178	0.0010	0.0210	0.0057	0.0355	0.0556	0.0298	0.8336

Table 6: **Description of the extended dataset.**

Asset	**Ticker**	**Source**	**Type**
US Ethanol	ETHNNYPR Index	Bloomberg	Spot, FOB, anhydrous ethanol
Brazilian Ethanol	-	CEPEA	Anhydrous ethanol
EU Biodiesel	BIOCEUGE Index	Bloomberg	German biodiesel, spot
	BIOD0CFTFO	Thomson Reuters Eikon	Argus Biodiesel FAME 0C CFPP RED ARA Range Barge FOB
Corn	C 1 Comdty	Bloomberg	1st month futures, CBOT
Wheat	W 1 Comdty	Bloomberg	1st month futures, CBOT
US Sugarcane	SB1 Comdty	Bloomberg	1st month futures, ICE
US Sugar Beets	QW1 Comdty	Bloomberg	1st month futures, LIFFE
Brazilian Sugar	-	CEPEA	Spot USD Price
Rapeseed Oil	IJ1 Comdty	Bloomberg	1st month futures
Soybean Oil	S 1 Comdty	Bloomberg	1st month futures, CBOT
Sunflower Seeds	SU1	Bloomberg	1st month futures
Palm Oil	KO3 Comdty	Bloomberg	1st month futures
Brent Crude Oil	CO1 Comdty	Bloomberg	1st month futures, ICE
WTI Crude Oil	CL1 COMB Comdty	Bloomberg	1st month futures, Nymex
EU Diesel	-	EIA	Retail Diesel Prices
US Gasoline	-	EIA	Retail Premium Gasoline
Brazilian Gasoline	-	ANP Brazil	Weighted av. consumer price
Dow Jones	DJI Index	Bloomberg	US Dow Jones Ind. Average
S&P 500	SP1 Index	Bloomberg	US S&P 500 Index
FTSE 100	UKX Index	Bloomberg	British FTSE 100 Index
DAX	DAX Index	Bloomberg	German DAX Index
BOVESPA	IBOV Index	Bloomberg	Brazilian BOVESPA
Federal Funds	-	Federal Reserve	US Fed Funds Rate
LIBOR	-	ECONSTATS	3 months USD LIBOR
USD/EUR	-	ECB	
USD/BRL	-	Federal Reserve	

Table 7: **Model selection summary table.** Model specification procedure is summarized here. First, the optimal lags are selected based for Eq. A.5 utilizing the Bayesian information criterion. Second, the time trend significance is checked for the same equation. Third, stability of the model is checked via the inverse roots location with respect to the unit circle. Fourth, number of cointegration vectors is identified using the Johansen tests – trace and L_{max}. And fifth, the final model is reported together with assurance that the model is properly specified via unit root testing on the error-correction terms.

	Period 1			Period 2			Period 3		
Criterion/Market	EU biodiesel	US ethanol	Brazilian ethanol	EU biodiesel	US ethanol	Brazilian ethanol	EU biodiesel	US ethanol	Brazilian ethanol
VECM optimal lag no trend (BIC)	1	1	1	1	1	1	1	1	1
VECM optimal lag trend (BIC)	1	1	1	1	1	1	1	1	1
significant trend	yes	yes	yes	yes	yes	no	yes	yes	yes
VECM inverse roots inside unit circle	yes	yes	yes	yes	yes	yes	yes	yes	yes
trace test (restr. constant)	x	x	x	x	x	2	x	x	x
L_{max} test (restr. constant)	x	x	x	x	x	2	x	x	x
trace test (unrestr. constant)	x	x	x	x	x	0	x	x	x
L_{max} test (unrestr. constant)	x	x	x	x	x	0	x	x	x
trace test (restr. trend)	3	0	1	4	2	2	2	1	2
L_{max} test (restr. trend)	3	1	1	2	2	2	2	1	2
trace test (unrestr. trend)	2	0	1	4	2	x	3	1	2
L_{max} test (unrestr. trend)	2	1	1	1	2	x	3	1	2
final model	VECM restr. trend	VAR with trend	VECM restr. trend	VECM restr. trend	VECM restr. trend	VAR with trend	VECM restr. trend	VECM restr. trend	VECM restr. trend
EC terms no unit root	yes	x	yes	yes	yes	x	yes	yes	yes

Appendices

A Cointegration and vector error-correction model

In its simplest form, the bivariate cointegration relationship arises when for two unit-root series, i.e. integrated of order one $I(1)$, there exists a relationship

$$y_t = \beta_0 + \beta_1 x_t + \epsilon_t \tag{A.1}$$

for which ϵ_t is a stationary process (specifically for the classical cointegration, stationary process with weak memory, i.e. integrated of order zero $I(0)$). Eq. A.1 represents a long-term relationship between series, and the fact that ϵ_t is stationary ensures that series y_t and x_t do no wander far away from one another. In fact, their difference is mean-reverting with a mean of β_0.

As the original series in Eq. A.1 are unit roots, their first differences are by definition stationary. Considering the error-term ϵ_t as a deviation from the long-term equilibrium, the equation can be utilized into the error-correction model

$$\Delta y_t = \omega_0 + \omega_1 \Delta x_t + \eta(y_{t-1} - \widehat{y_{t-1}}) + \epsilon_t \tag{A.2}$$

where $\widehat{y_{t-1}}$ is a lagged fitted value from Eq. A.1. The term $y_{t-1} - \widehat{y_{t-1}}$ represents the lagged deviation from the long-term equilibrium. When the parameter η is negative, the deviation from the equilibrium is dynamically corrected and hence the name of the model. If the parameter is not negative, the series are not cointegrated.

The more standard way to represent the error-correction model is using the vector autoregression (VAR) representation, i.e. controlling for both short-term dynamics (VAR) and long-term dynamics (cointegration). Eq. A.2 then changes to

$$\Delta x_t = \omega_{10} + \omega_{11} \Delta x_{t-1} + \omega_{12} \Delta y_{t-1} + \eta_1 (y_{t-1} - \widehat{y_{t-1}}) + \epsilon_{1t} \tag{A.3}$$

$$\Delta y_t = \omega_{20} + \omega_{21} \Delta x_{t-1} + \omega_{22} \Delta y_{t-1} + \eta_2 (y_{t-1} - \widehat{y_{t-1}}) + \epsilon_{2t} \tag{A.4}$$

The system and its representation gets more complicated for a general case of multiple endogenous variables. Let us have a system with N endogenous variables and T observations such that[8]

$$\Delta X_t = \phi \Delta X_{t-1} + \Pi X_{t-1} + \pi + \gamma t + \varepsilon_t \tag{A.5}$$

where ΔX_t is a vector ($N \times 1$) of differenced series at time t, ΔX_{t-1} is a vector ($N \times 1$) of lagged differenced series at time $t-1$ and ε_t is a vector of random shocks at time t. The parameters of interest are represented by matrix ϕ ($N \times N$), matrix Π ($N \times N$), vector π ($N \times 1$) and vector γ ($N \times 1$). The vector π represents the constant terms for each endogenous variable and the vector γ represents the time trend for each endogenous variable. The matrix ϕ reflects the short-term lagged interactions between endogenous variables and the matrix Π reflects the long-term cointegration relationships. In fact, Eq. A.5 can be seen as a vector autoregression with endogenous terms X_{t-1} (Hendry and Juselius, 2001). The crucial step in the analysis is finding whether the system is in fact cointegrated, estimation of the matrix Π and identifying the correct restrictions in the model.

B Model specifications for the extended dataset

The stationarity testing is summarized in Tab. C.3. We provide the results for a combination of the ADF test together with the KPSS test (Kwiatkowski et al., 1992) for stationarity, each test is applied both excluding and including the time trend (when necessary). The results of the KPSS tests are provided only when the unit roots are rejected for the original series. In this context and to follow the original research by Zhang et al. (2010), we study the logarithmic transformations of the series with an exception of the interest rates which are utilized in their original form (as they are already reported in percentage points). The results are quite straightforward – the unit root dynamics is not rejected for vast majority of the series, and if it is, stationarity is rejected as well, which implies that the series are not far away from the unit root behavior. We can thus proceed with the series as they are.

The whole model selection procedure is summarized in Tab. 7. There are several patterns in the final model specifications. First, we identified only one lag as the optimal one for all nine estimated models, which suggests that the short-term interactions are in fact rather short-lived. Second, the time trend was found significant for practically all VAR representations of the VECM specifications, i.e. the trend factor is important for the final analysis. Third, all estimated models are stable in the sense that the inverse roots of the VAR representation of VECM are inside the unit circle. Even though this is a rather technical

[8]We limit ourselves to one lag, i.e. ΔX_{t-1}, in this representation for brevity but in general, there can be numerous lags in the model.

finding, it validates the final models. And fourth, in seven out of nine cases, the VECM specification with a restricted trend was found to be the best model with stationary error-correction terms. In two cases (the US ethanol in the pre-crisis period and the Brazilian ethanol in the food crisis period), the cointegration relationship was not supported by the VECM analysis. Therefore, we used the VAR model for these two specific cases to be able to understand the short-term relationships between series as the variables do not tend towards long-run equilibrium.

C Tables

Table C.1: **Augmented Dickey-Fuller test results for the original dataset.** Optimal lag is selected based on the Bayesian information criterion (BIC).

	ADF (constant)	p-value	ADF (trend)	p-value
log-prices				
oil	0.6898	0.9920	-1.7461	0.7307
gasoline	0.2695	0.9768	-1.3486	0.8755
ethanol	-1.2929	0.6352	-2.4437	0.3567
corn	-1.9882	0.2923	-2.2210	0.4772
soybeans	-3.0820	0.0293	-3.0222	0.1284
wheat	-1.2518	0.6540	-1.8177	0.6964
sugar	-2.4237	0.1351	-2.3073	0.4294
rice	-0.4778	0.8932	-0.3700	0.9886
log-differences				
oil	-11.7984	< 0.01	-8.6488	< 0.01
gasoline	-3.9700	0.0016	-4.2706	0.0034
ethanol	-12.6368	< 0.01	-12.6811	< 0.01
corn	-5.8794	< 0.01	-5.8572	< 0.01
soybeans	-15.2683	< 0.01	-15.2588	< 0.01
wheat	-11.6541	< 0.01	-11.7451	< 0.01
sugar	-12.2266	< 0.01	-12.2340	< 0.01
rice	-10.3004	< 0.01	-10.5090	< 0.01

Table C.2: **Augmented Dickey-Fuller tests for the error-correction terms of the original model.** ADF tests use the optimal lags based on the Bayesian information criterion. Non-rejection of the null hypothesis would suggest that the cointegration (and the connected VECM) relationship is not well specified.

	ADF (constant)	p-value
EC1	-3.2349	0.0181
EC2	-3.2311	0.0183
EC3	-3.2525	0.0172
EC4	-3.0221	0.0329
EC5	-3.1602	0.0224

Table C.3: **Stationarity tests results for the logarithmic prices of the expanded dataset.** KPSS test results are shown only when a connected ADF test rejects the null hypothesis of the unit root. Otherwise, "×" is shown.

	ADF (constant)	p-value	ADF (trend)	p-value	KPSS (constant)	p-value	KPSS (trend)	p-value
Period 1								
EU biodiesel	0.3150	0.9791	-1.1677	0.9159	×	×	×	×
US ethanol	-2.0677	0.2580	-2.7302	0.2242	×	×	×	×
BR ethanol	-1.4109	0.5786	-2.2888	0.4395	×	×	×	×
Brent crude oil	-0.4466	0.8976	-1.9962	0.6001	×	×	×	×
WTI crude oil	-0.5465	0.8783	-2.0975	0.5442	×	×	×	×
US gasoline	-1.7610	0.4004	-4.0510	0.0074	×	×	0.2032	0.0180
EU diesel	-0.4783	0.8917	-2.3063	0.4285	×	×	×	×
BR gasoline	-1.4753	0.5446	-1.5624	0.8049	×	×	×	×
DJI	-1.8086	0.3758	-2.0213	0.5863	×	×	×	×
S&P500	-2.0129	0.2812	-2.1332	0.5242	×	×	×	×
FTSE100	-1.7255	0.4171	-1.7924	0.7056	×	×	×	×
DAX	-1.3743	0.5947	-1.3948	0.8604	×	×	×	×
BOVESPA	-0.7040	0.8424	-3.8688	0.0148	×	×	×	×
fed funds	-2.1309	0.2325	-2.0168	0.5916	×	×	×	×
LIBOR	-1.5815	0.4921	0.4474	0.9992	×	×	×	×
USD EUR	-0.2004	0.9352	-1.3819	0.8640	×	×	×	×
USD BRL	-0.0960	0.9473	-3.2801	0.0721	×	×	×	×
corn	0.9585	0.9961	-0.6889	0.9721	×	×	×	×
wheat	-0.0616	0.9509	-1.9553	0.6222	×	×	×	×
sugarcane	-1.8387	0.3611	-1.6778	0.7583	×	×	×	×
sugar beets	-1.8201	0.3702	-1.7306	0.7347	×	×	×	×
sugar brazil	-1.8892	0.3377	-1.5856	0.7990	×	×	×	×
soybeans	0.3814	0.9818	-0.6674	0.9736	×	×	×	×
sunflower	0.5570	0.9883	-1.4453	0.8452	×	×	×	×
rapeseed	0.7710	0.9934	-1.9097	0.6464	×	×	×	×
palm oil	0.5634	0.9885	-1.4242	0.8542	×	×	×	×
Period 2								
EU biodiesel	-2.0544	0.2636	-1.2533	0.8985	×	×	×	×
US ethanol	-2.1806	0.2144	-2.7401	0.2224	×	×	×	×
BR ethanol	-0.5253	0.8840	-2.1278	0.5296	×	×	×	×
Brent crude oil	-1.9997	0.2868	-3.1166	0.1066	×	×	×	×
WTI crude oil	-2.3368	0.1620	-2.9794	0.1418	×	×	×	×
US gasoline	-2.2313	0.1952	-2.8428	0.1818	×	×	×	×
EU diesel	-2.5287	0.1109	-2.9367	0.1544	×	×	×	×
BR gasoline	-1.5138	0.5238	-1.6762	0.7567	×	×	×	×
DJI	-1.2217	0.6640	-2.4491	0.3529	×	×	×	×
S&P500	-1.3266	0.6161	-2.5179	0.3192	×	×	×	×
FTSE100	-1.2739	0.6406	-2.8528	0.1814	×	×	×	×
DAX	-1.0913	0.7182	-2.7265	0.2278	×	×	×	×
BOVESPA	-1.2419	0.6551	-2.7638	0.2133	×	×	×	×
fed funds	-11.8623	< 0.01	-11.6888	< 0.01	0.4853	0.0470	0.1853	0.0280
LIBOR	-1.9771	0.2972	-1.7927	0.7086	×	×	×	×
USD EUR	-2.6125	0.0929	-2.3582	0.3997	×	×	×	×
USD BRL	-1.4197	0.5710	-2.7558	0.2164	×	×	×	×
corn	-1.4842	0.5388	-2.2419	0.4624	×	×	×	×
wheat	-1.8030	0.3778	-2.0510	0.5680	×	×	×	×
sugarcane	-0.4939	0.8878	-1.7440	0.7263	×	×	×	×
sugar beets	-0.8004	0.8156	-2.1145	0.5328	×	×	×	×
sugar brazil	-1.0135	0.7507	-2.9908	0.1347	×	×	×	×
soybeans	-2.6105	0.0933	-3.1219	0.1054	×	×	×	×
sunflower	-1.7555	0.4012	-2.1772	0.4980	×	×	×	×
rapeseed	-0.9711	0.7624	-2.6878	0.2434	×	×	×	×
palm oil	-1.4833	0.5392	-3.7553	0.0220	×	×	0.4340	< 0.01
Period 3								
EU biodiesel	-1.3744	0.5948	-2.8440	0.1829	×	×	×	×
US ethanol	-2.0825	0.2520	-3.5360	0.0376	×	×	1.3830	< 0.01
BR ethanol	-2.9080	0.0444	-5.1143	0.0001	6.1353	< 0.01	0.4767	< 0.01
Brent crude oil	-0.4622	0.8949	-1.8246	0.6902	×	×	×	×
WTI crude oil	-0.7600	0.8281	-1.6652	0.7640	×	×	×	×
US gasoline	-1.1580	0.6947	-2.4667	0.3449	×	×	×	×
EU diesel	-0.3327	0.9168	-1.8602	0.6723	×	×	×	×
BR gasoline	-0.0144	0.9556	-2.8418	0.1837	×	×	×	×
DJI	-1.1657	0.6915	-2.5104	0.3230	×	×	×	×
S&P500	-0.8956	0.7903	-2.3397	0.4117	×	×	×	×
FTSE100	-2.0126	0.2815	-2.2771	0.4460	×	×	×	×
DAX	-1.2065	0.6724	-2.7956	0.2002	×	×	×	×
BOVESPA	-2.9371	0.0425	-3.6953	0.0243	7.3098	< 0.01	0.2171	< 0.01
fed funds	-0.5574	0.8775	-1.3515	0.8747	×	×	×	×
LIBOR	-1.7014	0.4306	-1.6970	0.7529	×	×	×	×
USD EUR	-1.0882	0.7211	-1.8524	0.6763	×	×	×	×
USD BRL	-0.3843	0.9085	-2.1371	0.5223	×	×	×	×
corn	-1.2579	0.6496	-2.3675	0.3958	×	×	×	×
wheat	-1.7117	0.4242	-2.8491	0.1812	×	×	×	×
sugarcane	-2.2059	0.2048	-2.7429	0.2203	×	×	×	×
sugar beets	-2.0159	0.2799	-2.2929	0.4359	×	×	×	×
sugar brazil	-2.1483	0.2258	-2.0789	0.5570	×	×	×	×
soybeans	-1.3265	0.6178	-1.9868	0.6055	×	×	×	×
sunflower	-0.7420	0.8329	-1.7590	0.7219	×	×	×	×
rapeseed	-1.7935	0.3833	-2.3559	0.4020	×	×	×	×
palm oil	-2.5583	0.1031	-2.4216	0.3675	×	×	×	×

Table C.4: **Granger causality testing for EU biodiesel market.** "No Granger causality" null hypothesis is tested here. p-values are reported for all three periods in the form of Period1/Period2/Period3. When the null hypothesis is not rejected, × is reported. Columns represent a response variable and rows are impulse variables.

	EU biodiesel	soybeans	sunflower	rapeseed	palm oil
Long-run causality					
EU biodiesel	0.0215/×/< 0.01	0.097/×/×	< 0.01/×/×	×/×/×	×/0.0992/×
Brent	0.0311/< 0.01/×	×/×/×	×/×/×	×/0.0533/×	×/×/0.0118
EU diesel	< 0.01/0.0059/×	×/0.0138/0.0385	×/×/×	×/0.0310/×	0.0550/×/×
DAX/FTSE100	×/×/×	0.0887/×/×	0.0103/0.068/×	0.0132/0.0052/0.0074	×/0.0067/0.0259
USD/EUR	×/×/0.009	×/×/0.0854	×/×/×	×/0.0947/×	×/×/×
LIBOR	×/×/×	×/×/×	×/×/×	×/×/0.0376	×/×/×
soybeans	×/×/×	< 0.01/< 0.01/< 0.01	×/×/×	×/×/×	×/×/×
sunflower	0.0499/×/< 0.01	×/0.087/×	< 0.01/< 0.01/< 0.01	×/×/×	0.0509/×/×
rapeseed	×/×/0.0052	×/×/0.0082	×/×/×	< 0.01/< 0.01/< 0.01	×/0.0907/×
palm oil	×/0.0378/×	×/×/×	×/×/×	×/×/×	< 0.01/< 0.01/< 0.01
Short-run causality					
EU biodiesel	< 0.01/< 0.01/×	×/×/×	×/×/×	< 0.01/×/×	×/×/0.0391
Brent	×/×/×	0.039/×/×	×/×/×	0.0271/×/×	0.0369/×/×
EU diesel	×/×/×	×/< 0.01/×	×/×/×	×/0.0072/×	×/×/×
DAX/FTSE100	×/×/0.0246	0.0481/×/×	0.0571/×/×	0.0268/×/0.0907	×/×/×
USD/EUR	×/×/×	×/×/×	×/0.0410/×	×/0.0451/×	×/×/×
LIBOR	×/< 0.01/×	×/0.0224/×	×/×/×	×/×/×	×/×/×
soybeans	×/×/×	×/×/0.0219	×/×/×	×/×/×	×/×/×
sunflower	×/×/0.0145	×/×/×	0.0223/×/×	×/0.0739/×	×/×/×
rapeseed	0.0198/×/< 0.01	×/×/0.0124	×/×/×	×/×/×	×/×/×
palm oil	×/0.0979/×	×/×/×	×/×/×	×/×/×	0.0289/0.0326/×

Table C.5: **Granger causality testing for US ethanol market.** "No Granger causality" null hypothesis is tested here. p-values are reported for all three periods in the form of Period1/Period2/Period3. When the null hypothesis is not rejected, × is reported. Columns represent a response variable and rows are impulse variables.

	US ethanol	corn	wheat	sugarcane	sugar beets
Long-run causality					
US ethanol	< 0.01/< 0.01/< 0.01	×/×/×	×/0.0755/×	0.0793/×/×	×/×/0.0530
WTI	×/×/×	×/×/×	0.0253/×/×	×/0.0722/0.0349	×/×/×
US gasoline	×/×/×	0.0443/×/×	×/×/×	×/×/×	×/< 0.01/×
DJI/S&P500	×/×/×	0.0814/×/0.0915	×/×/×	×/×/×	×/×/×
Fed Funds	×/×/×	×/×/×	×/0.0250/×	×/×/×	×/×/×
USD/EUR	×/×/×	0.098/×/×	×/×/×	< 0.01/×/×	0.0157/×/×
corn	0.0721/0.087/×	< 0.01/< 0.01/< 0.01	×/×/×	×/×/×	×/×/×
wheat	×/0.0272/×	×/×/×	< 0.01/< 0.01/< 0.01	×/×/×	×/×/×
sugarcane	×/×/×	×/×/×	×/×/×	< 0.01/< 0.01/< 0.01	×/×/×
sugar beets	×/×/×	×/×/0.0146	×/×/×	×/×/0.0208	< 0.01/< 0.01/< 0.01
Short-run causality					
US ethanol	×/×/×	×/×/×	×/0.0818/×	×/×/×	×/×/×
WTI	×/×/×	0.0422/×/×	< 0.01/×/×	×/×/×	×/×/0.0694
US gasoline	×/×/×	×/0.0546/×	×/×/×	×/×/×	×/×/×
DJI/S&P500	×/×/×	×/0.0910/×	×/×/×	×/×/0.0808	×/×/×
Fed Funds	×/×/×	×/×/×	×/×/×	×/×/×	×/×/×
USD/EUR	×/×/×	×/×/×	×/×/×	0.0129/×0.0511	0.0321/×/×
corn	0.0397/0.0353/×	×/×/×	×/×/×	×/×/×	×/×/×
wheat	×/×/×	×/×/×	×/×/×	×/×/×	×/×/×
sugarcane	×/×/×	×/×/0.0829	×/×/×	×/×/××	×/×/×
sugar beets	×/×/×	×/×/< 0.01	×/×/×	×/×/×	×/×/×

Table C.6: **Granger causality testing for Brazilian ethanol market.** "No Granger causality" null hypothesis is tested here. p-values are reported for all three periods in the form of Period1/Period2/Period3. When the null hypothesis is not rejected, $\times$ is reported. Columns represent a response variable and rows are impulse variables.

	Brazilian ethanol	Brazilian sugar
Long-run causality		
Brazilian ethanol	$< 0.01/< 0.01/< 0.01$	$0.0171/\times/< 0.01$
WTI	$\times/\times/\times$	$0.0326/\times/0.0427$
Brazilian gasoline	$< 0.01/\times/\times$	$< 0.01/\times/\times$
BOVESPA	$\times/\times/\times$	$\times/\times/\times$
LIBOR	$\times/\times/\times$	$\times/\times/\times$
USD/BRL	$\times/\times/< 0.01$	$< 0.01/\times/< 0.01$
Brazilian sugar	$0.0546/< 0.01/\times$	$< 0.01/< 0.01/< 0.01$
Short-run causality		
Brazilian ethanol	$< 0.01/0.0857/< 0.01$	$< 0.01/\times/< 0.01$
WTI	$\times/\times/0.0974$	$\times/\times/\times$
Brazilian gasoline	$\times/0.0832/\times$	$\times/\times/\times$
BOVESPA	$\times/\times/\times$	$\times/\times/\times$
LIBOR	$\times/\times/\times$	$0.0860/\times/\times$
USD/BRL	$\times/\times/< 0.01$	$< 0.01/< 0.01/< 0.01$
Brazilian sugar	$\times/\times/\times$	$< 0.01/< 0.01/< 0.01$

Table C.7: **Forecast error variance decomposition of EU biodiesel (20 weeks ahead).** Rows represent a response variable and columns are impulse variables.

	FTSE100/DAX	Brent	USD/EUR	LIBOR	DE diesel	biodiesel	soybeans	sunflower	rapeseed	palm oil
Period 1										
FTSE100	0.5076	0.1903	0.0212	0.0100	0.0058	0.0437	0.0445	0.0086	0.0524	0.1158
Brent	0.0068	0.8196	0.0076	0.0127	0.0875	0.0138	0.0130	0.0122	0.0130	0.0138
USD/EUR	0.0001	0.0831	0.7138	0.0566	0.0789	0.0259	0.0082	0.0104	0.0051	0.0181
LIBOR	0.0073	0.1462	0.0477	0.2657	0.0021	0.0054	0.0790	0.0401	0.0750	0.3316
DE diesel	0.0106	0.6355	0.0427	0.0293	0.2011	0.0169	0.0052	0.0289	0.0232	0.0066
biodiesel	0.0192	0.4386	0.0210	0.0727	0.1416	0.2256	0.0058	0.0142	0.0368	0.0244
soybeans	0.0195	0.0097	0.0050	0.0014	0.0252	0.0068	0.5932	0.0010	0.1885	0.1496
sunflower	0.0429	0.0793	0.0010	0.0007	0.0040	0.0827	0.0066	0.6025	0.0834	0.0970
rapeseed	0.0773	0.0317	0.0001	0.0021	0.0414	0.0321	0.1314	0.0077	0.4960	0.1803
palm oil	0.0326	0.0300	0.0011	0.0213	0.0756	0.0161	0.0866	0.0487	0.1233	0.5647
Period 2										
DAX	0.4297	0.1372	0.0683	0.0279	0.0982	0.0099	0.0864	0.0034	0.0426	0.0965
Brent	0.2964	0.2220	0.0623	0.0355	0.0143	0.0013	0.1255	0.0018	0.1550	0.0856
USD/EUR	0.1861	0.0411	0.5088	0.0957	0.0231	0.0077	0.0771	0.0105	0.0086	0.0415
LIBOR	0.0055	0.0004	0.0172	0.8392	0.0106	0.0546	0.0271	0.0085	0.0094	0.0275
DE diesel	0.3568	0.1400	0.0972	0.0236	0.1383	0.0120	0.0720	0.0087	0.0865	0.0649
biodiesel	0.2096	0.0245	0.0041	0.1261	0.0840	0.1074	0.1110	0.0082	0.1978	0.1273
soybeans	0.1623	0.0629	0.0476	0.0707	0.0016	0.0324	0.3304	0.0186	0.1619	0.1117
sunflower	0.0189	0.0002	0.0258	0.0202	0.1062	0.0076	0.0695	0.5882	0.1320	0.0315
rapeseed	0.1262	0.0520	0.0001	0.0326	0.0016	0.0174	0.1969	0.0347	0.4216	0.1170
palm oil	0.2171	0.0818	0.0167	0.0474	0.0015	0.0058	0.1409	0.0027	0.1546	0.3314
Period 3										
FTSE100	0.6384	0.158	0.0011	0.0399	0.0611	0.0188	0.032	0.0087	0.0387	0.0033
Brent	0.1859	0.5552	0.0053	0.0234	0.0871	0.0246	0.0233	0.0637	0.0206	0.0110
USD/EUR	0.0124	0.0619	0.7644	0.0267	0.0179	0.095	0.0056	0.0012	0.0036	0.0114
LIBOR	0.0287	0.0498	0.0008	0.8461	0.0118	0.0004	0.0113	0.0193	0.0145	0.0173
DE diesel	0.1796	0.5121	0.0021	0.0168	0.1153	0.0351	0.0469	0.0474	0.0379	0.0068
biodiesel	0.0505	0.1251	0.0863	0.0057	0.0461	0.5053	0.0684	0.048	0.0442	0.0204
soybeans	0.0101	0.0277	0.0012	0.0047	0.0052	0.1383	0.4589	0.0471	0.2188	0.088
sunflower	0.0104	0.0289	0.0602	0.0004	0.0483	0.0413	0.0715	0.632	0.0207	0.0862
rapeseed	0.0088	0.0088	0.0267	0.0061	0.0443	0.0464	0.1273	0.0028	0.6756	0.0532
palm oil	0.0028	0.0141	0.0438	0.0244	0.0813	0.0368	0.1058	0.0074	0.0507	0.6329

Table C.8: **Forecast error variance decomposition of US ethanol (20 weeks ahead).** Rows represent a response variable and columns are impulse variables.

	DJI/S&P500	WTI	USD/EUR	Fed funds	US gasoline	US ethanol	corn	wheat	sugarcane	sugar beets
Period 1										
DJI	0.8641	0.0463	0.0125	0.0414	0.0048	0.0033	0.0094	0.0012	0.0148	0.0023
WTI	0.0234	0.8140	0.0171	0.0021	0.0732	0.0082	0.0142	0.0107	0.0251	0.0120
USD/EUR	0.0109	0.0194	0.8851	0.0002	0.0549	0.0029	0.0138	0.0020	0.0066	0.0043
Fed funds	0.0347	0.0033	0.0003	0.9060	0.0016	0.0084	0.0113	0.0144	0.0074	0.0126
US gasoline	0.0120	0.1954	0.0368	0.0011	0.6760	0.0504	0.0050	0.0063	0.0011	0.0160
US ethanol	0.0082	0.0255	0.0036	0.0001	0.0709	0.8171	0.0190	0.0148	0.0191	0.0218
corn	0.0052	0.0231	0.0126	0.0072	0.0073	0.0094	0.7115	0.1984	0.0168	0.0084
wheat	0.0007	0.0180	0.0014	0.0112	0.0045	0.0086	0.1991	0.7295	0.0240	0.0030
sugarcane	0.0002	0.0155	0.0132	0.0057	0.0003	0.0139	0.0153	0.0164	0.6472	0.2725
sugar beets	0.0019	0.0080	0.0107	0.0107	0.0099	0.0128	0.0087	0.0031	0.2761	0.6580
Period 2										
DJI	0.3358	0.3065	0.0509	0.0085	0.0081	0.0648	0.0661	0.0810	0.0606	0.0177
WTI	0.1448	0.1919	0.0825	0.0352	0.2377	0.0614	0.1169	0.0929	0.0158	0.0210
USD/EUR	0.0316	0.0937	0.4103	0.0589	0.0645	0.1685	0.0680	0.0360	0.0609	0.0075
Fed funds	0.0317	0.1251	0.0445	0.3896	0.1358	0.0135	0.1280	0.1029	0.0048	0.0239
US gasoline	0.1135	0.1408	0.0798	0.0376	0.3496	0.0346	0.1225	0.0932	0.0088	0.0195
US ethanol	0.0413	0.0601	0.0459	0.0007	0.0264	0.3777	0.2633	0.1373	0.0225	0.0247
corn	0.0362	0.0445	0.0311	0.0185	0.0715	0.1631	0.4065	0.1857	0.0249	0.0180
wheat	0.0156	0.0772	0.0448	0.0295	0.0145	0.0557	0.2435	0.4585	0.0364	0.0243
sugarcane	0.0255	0.0012	0.0039	0.0004	0.0112	0.0587	0.0385	0.0247	0.4901	0.3458
sugar beets	0.0154	0.0020	0.0030	0.0214	0.0546	0.0668	0.0419	0.0145	0.3135	0.4668
Period 3										
S&P500	0.2902	0.0388	0.3129	0.0283	0.0193	0.0830	0.0760	0.0025	0.0043	0.1447
WTI	0.0480	0.0987	0.4178	0.0030	0.0273	0.1585	0.0849	0.0076	0.0134	0.1409
USD/EUR	0.0916	0.0683	0.7274	0.0013	0.0057	0.0550	0.0204	0.0133	0.0028	0.0142
Fed funds	0.0025	0.0531	0.0593	0.7151	0.0701	0.0417	0.0041	0.0087	0.0060	0.0393
US gasoline	0.1153	0.0988	0.4449	0.0025	0.0687	0.1409	0.0435	0.0082	0.0039	0.0733
US ethanol	0.1150	0.0249	0.0794	0.0168	0.0372	0.3044	0.1307	0.0132	0.0874	0.1910
corn	0.1041	0.0371	0.1421	0.0162	0.0099	0.1050	0.2904	0.0037	0.1474	0.1440
wheat	0.0486	0.0040	0.0022	0.0332	0.0145	0.0894	0.1183	0.3988	0.2309	0.0600
sugarcane	0.0825	0.0172	0.0482	0.0014	0.0045	0.1152	0.1952	0.0031	0.3477	0.1850
sugar beets	0.0834	0.0079	0.1588	0.0124	0.0365	0.1036	0.1360	0.0117	0.0919	0.3578

Table C.9: **Forecast error variance decomposition of Brazilian ethanol (20 weeks ahead).** Rows represent a response variable and columns are impulse variables.

	BOVESPA	WTI	USD/BRL	LIBOR	BR gasoline	BR ethanol	sugar brazil
Period 1							
BOVESPA	0.5580	0.0020	0.2102	0.0007	0.0011	0.0631	0.1649
WTI	0.0231	0.8099	0.0311	0.0030	0.0413	0.0911	0.0005
USD/BRL	0.1957	0.0196	0.5758	0.0079	0.0259	0.0030	0.1720
LIBOR	0.0090	0.0055	0.0127	0.8514	0.0606	0.0395	0.0214
BR gasoline	0.0163	0.0017	0.0024	0.0176	0.9096	0.0229	0.0294
BR ethanol	0.0870	0.1229	0.0085	0.0057	0.1341	0.6325	0.0093
sugar brazil	0.1031	0.0613	0.0428	0.0039	0.1309	0.0122	0.6459
Period 2							
BOVESPA	0.5207	0.1246	0.2007	0.0041	0.0031	0.0457	0.1010
WTI	0.1408	0.5728	0.1773	0.0074	0.0057	0.0046	0.0914
USD/BRL	0.1594	0.1323	0.4177	0.0595	0.0012	0.0751	0.1548
LIBOR	0.0058	0.0387	0.0974	0.7927	0.0015	0.0399	0.0241
BR gasoline	0.0110	0.0513	0.0144	0.0015	0.9117	0.0016	0.0084
BR ethanol	0.0627	0.0408	0.1278	0.0326	0.0051	0.5951	0.1361
sugar brazil	0.0945	0.0773	0.1705	0.0129	0.0035	0.0290	0.6125
Period 3							
BOVESPA	0.5890	0.1413	0.1271	0.0615	0.0046	0.0019	0.0746
WTI	0.1589	0.6964	0.0826	0.0260	0.0225	0.0043	0.0094
USD/BRL	0.0694	0.0351	0.5017	0.0453	0.0102	0.0235	0.3147
LIBOR	0.1829	0.1068	0.1674	0.4292	0.0577	0.0517	0.0041
BR gasoline	0.0331	0.0029	0.0121	0.0392	0.8880	0.0201	0.0045
BR ethanol	0.0125	0.0667	0.0978	0.0547	0.0694	0.3895	0.3094
sugar brazil	0.0084	0.0047	0.1167	0.0013	0.0009	0.0310	0.8371