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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 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.

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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                                                                                                                                |
|--------------------------------------------------------------------------|--------------------------------------------------|----------------|-----------|---------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Neutrality hypothesis</i>                                             |                                                  |                |           |                                                                                                                                             |
| 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, 2SLS, 3SLS                    | OLS, 1971-2008 | Quarterly | Economic activity, monetary expansion and exchange rate fluctuations lead to higher food prices.                                            |
| Nazlioglu and (2011)                                                     | Soytas causal-ity, 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. |
| <i>Crude oil/energy prices affect prices of agricultural commodities</i> |                                                  |                |           |                                                                                                                                             |
| 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 is small and statistically insignificant.           |
| Ciaian and Kancs (2011b) | VECM                    | 1994-2008 | Weekly    |                                                                                                                                                                    |

|                               |                           |           |         |                                                                                                                                                                                  |
|-------------------------------|---------------------------|-----------|---------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 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 sur-passes 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 Soytaş (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 are attributed to the global financial crisis due to the increasing use of agricultural commodities as financial assets. |
| Han et al. (2015)            | Multivariate normal mixture models | 2000-2014 | Daily     |                                                                                                                                                                                     |
| Nagayev et al. (2016)        | MGARCH-DCC                         | 1999-2015 | Daily     |                                                                                                                                                                                     |

(B) Biofuel data used

| Reference                    | Modeling Approach     | Period    | Frequency | Key Findings                                                                                                        |
|------------------------------|-----------------------|-----------|-----------|---------------------------------------------------------------------------------------------------------------------|
| <i>Neutrality hypothesis</i> |                       |           |           |                                                                                                                     |
| 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, mMGARCH | 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.<br>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 Rapso-manikis (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.                                                                                              |
| Abdelradi and Serra (2015)      | Correlation | 1988-2009 | Monthly | Correlation among crude oil and corn prices by 2006-2008.                                                                                                           |
|                                 | MGARCH      | 2008-2012 | Weekly  | Significant asymmetries in volatility spillovers between biodiesel and rapeseed oil prices.                                                                         |

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*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):

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

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

1. no restrictions on  $\pi$  and  $\delta$ , i.e. the trend and intercept are unrestricted;
2.  $\tau = 0$  but  $\gamma$ ,  $\mu$  and  $\rho$  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<sup>1</sup>:

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

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<sup>1</sup>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<sup>2</sup>. 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<sup>3</sup> as all but one logarithmic price series are detected as unit roots. Only for the soybeans series, the time trend needs to be included

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<sup>2</sup>The dataset is provided in a separate file attached to this paper.

<sup>3</sup>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<sup>4</sup>. 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<sup>5</sup>. In Tab. 5, we present the results of the forecasting error variance decomposition based on the VECM

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<sup>4</sup>We stick to the presentation of the original paper which shows the forecasting error variance decomposition after five periods (months).

<sup>5</sup>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<sup>6</sup>. 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<sup>7</sup>. 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.

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<sup>6</sup>The extended dataset is provided in a separate file attached to this paper.

<sup>7</sup>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, “ $\times$ ” 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 par-

ticular 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.

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

$$y_t = \beta_0 + \beta_1 x_t + \epsilon_t \quad (\text{A.1})$$

for which  $\epsilon_t$  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  $\epsilon_t$  is stationary ensures that series  $y_t$  and  $x_t$  do not wander far away from one another. In fact, their difference is mean-reverting with a mean of  $\beta_0$ .

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

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

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  $\eta$  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

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

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

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<sup>8</sup>

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

where  $\Delta X_t$  is a vector ( $N \times 1$ ) of differenced series at time  $t$ ,  $\Delta X_{t-1}$  is a vector ( $N \times 1$ ) of lagged differenced series at time  $t - 1$  and  $\varepsilon_t$  is a vector of random shocks at time  $t$ . The parameters of interest are represented by matrix  $\phi$  ( $N \times N$ ), matrix  $\Pi$  ( $N \times N$ ), vector  $\pi$  ( $N \times 1$ ) and vector  $\gamma$  ( $N \times 1$ ). The vector  $\pi$  represents the constant terms for each endogenous variable and the vector  $\gamma$  represents the time trend for each endogenous variable. The matrix  $\phi$  reflects the short-term lagged interactions between endogenous variables and the matrix  $\Pi$  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  $\Pi$  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

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<sup>8</sup>We limit ourselves to one lag, i.e.  $\Delta X_{t-1}$ , 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) | <i>p</i> -value | ADF (trend) | <i>p</i> -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) | <i>p</i> -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) | <i>p</i> -value | ADF (trend) | <i>p</i> -value | KPSS (constant) | <i>p</i> -value | KPSS (trend) | <i>p</i> -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,  $\times$  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/ $\times$ / $< 0.01$    | 0.097/ $\times$ / $\times$     | $< 0.01$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $< 0.0992$ / $\times$ |
| Brent               | 0.0311/ $< 0.01$ / $\times$    | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ /0.0533/ $\times$     | $\times$ / $\times$ /0.0118      |
| EU diesel           | $< 0.01$ /0.0059/ $\times$     | $\times$ /0.0138/0.0385        | $\times$ / $\times$ / $\times$ | $\times$ /0.0310/ $\times$     | 0.0550/ $\times$ / $\times$      |
| DAX/FTSE100         | $\times$ / $\times$ / $\times$ | 0.0887/ $\times$ / $\times$    | 0.0103/0.068/ $\times$         | 0.0132/0.0052/0.0074           | $\times$ /0.0067/0.0259          |
| USD/EUR             | $\times$ / $\times$ /0.009     | $\times$ / $\times$ /0.0854    | $\times$ / $\times$ / $\times$ | $\times$ /0.0947/ $\times$     | $\times$ / $\times$ / $\times$   |
| LIBOR               | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ /0.0376    | $\times$ / $\times$ / $\times$   |
| soybeans            | $\times$ / $\times$ / $\times$ | $< 0.01$ / $< 0.01$ / $< 0.01$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$   |
| sunflower           | 0.0499/ $\times$ / $< 0.01$    | $\times$ /0.087/ $\times$      | $< 0.01$ / $< 0.01$ / $< 0.01$ | $\times$ / $\times$ / $\times$ | 0.0509/ $\times$ / $\times$      |
| rapeseed            | $\times$ / $\times$ /0.0052    | $\times$ / $\times$ /0.0082    | $\times$ / $\times$ / $\times$ | $< 0.01$ / $< 0.01$ / $< 0.01$ | $\times$ /0.0907/ $\times$       |
| palm oil            | $\times$ /0.0378/ $\times$     | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $< 0.01$ / $< 0.01$ / $< 0.01$   |
| Short-run causality |                                |                                |                                |                                |                                  |
| EU biodiesel        | $< 0.01$ / $< 0.01$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $< 0.01$ / $\times$ / $\times$ | $\times$ / $\times$ /0.0391      |
| Brent               | $\times$ / $\times$ / $\times$ | 0.039/ $\times$ / $\times$     | $\times$ / $\times$ / $\times$ | 0.0271/ $\times$ / $\times$    | 0.0369/ $\times$ / $\times$      |
| EU diesel           | $\times$ / $\times$ / $\times$ | $\times$ / $< 0.01$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ /0.0072/ $\times$     | $\times$ / $\times$ / $\times$   |
| DAX/FTSE100         | $\times$ / $\times$ /0.0246    | 0.0481/ $\times$ / $\times$    | 0.0571/ $\times$ / $\times$    | 0.0268/ $\times$ /0.0907       | $\times$ / $\times$ / $\times$   |
| USD/EUR             | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ /0.0410/ $\times$     | $\times$ /0.0451/ $\times$     | $\times$ / $\times$ / $\times$   |
| LIBOR               | $\times$ / $< 0.01$ / $\times$ | $\times$ /0.0224/ $\times$     | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$   |
| soybeans            | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ /0.0219    | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$   |
| sunflower           | $\times$ / $\times$ /0.0145    | $\times$ / $\times$ / $\times$ | 0.0223/ $\times$ / $\times$    | $\times$ /0.0739/ $\times$     | $\times$ / $\times$ / $\times$   |
| rapeseed            | 0.0198/ $\times$ / $< 0.01$    | $\times$ / $\times$ /0.0124    | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$   |
| palm oil            | $\times$ /0.0979/ $\times$     | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | $\times$ / $\times$ / $\times$ | 0.0289/0.0326/ $\times$          |

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

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       |