
# Examining the relationship between biofuel and food crops markets in Brazil

*E. Silva[1]; R. Lima[2]*

*1: Federal Rural University of Pernambuco, , Brazil, 2: Federal University of Pernambuco, , Brazil*

*Corresponding author email: eduardaferreiragf@gmail.com*

***Abstract:***

*The objective of this article is to discuss the relationship between biofuels and food crop markets in Brazil, from August 2004 to August 2017. Prices of ethanol and food commodities (sugar, soybean and corn) were used to estimate a Vector Error Correction Model (VECM). The system also included Real/Dollar exchange rate, policy and seasonal dummies, and an exogenous variable representing international oil price. The results suggest the occurrence of linkages between biofuel and food commodity markets in Brazil. Thus, it is crucial that the development of public policies to pursue the objective of increasing the supply of renewable and less pollutant fuel do not conflict with the goals of food security.*

*Acknowledegment:*

**JEL Codes:** Q02, Q01

#2611

## INTRODUCTION

With the oil shocks of 1973 and 1979, energy costs in Brazil increased sharply. At the time, the country imported about 80% of its oil consumption (IPEA, 2010). After the first shock, import expenditures increased from US$ 600 million in 1973 to US$ 2.5 billion in 1974, causing a deficit of US$ 4.7 billion in the Brazilian trade balance. This deficit increased the external debt and caused a rise in inflation from 19% to 34% between 1973 and 1974 (ALCARDE, 2008). In its quest to become less dependent on imported oil, Brazilian government created a national ethanol program (Proálcool) in 1975, with the objective of stimulating renewable fuel production.

In its initial phase, the program was intended to produce mainly anhydrous ethanol. From 1975 to 1979, biofuel supply in Brazil increased from 600 million liters/year to 3.4 billion liters/year (Alcarde, 2008). The next phase of Proálcool began in 1980, shortly after the second oil shock when fossil fuel prices had tripled. Brazilian government allocated public resources to stimulated ethanol production, and the number of cars powered by ethanol alone increased, reaching 95.8% of the total fleet in 1985 (Barros, 2007). During that period, ethanol production reached 12.3 billion liters/year. In 1986, oil prices gradually returned to levels before the first oil shock, dropping from US$ 40/barrel to US$ 12/barrel (Alcarde, 2008). In the third phase, the program experienced stagnant ethanol production. Also, sugar prices were recovering in the international market, and ethanol production became less price attractive for producers (Kohlhepp, 2010). Then, Brazil substantially reduced incentives for Proálcool resulting in a domestic supply decrease. With the objective of meeting domestic demand, the government imported fuel alcohol and promoted substitution of anhydrous ethanol to methane in the gasoline mixture (IPEA, 2010). As a result, consumers and vehicle manufacturers once again prioritized gasoline-powered cars, and mill owners produced more sugar for the international market. After 2002, international oil prices rose again, causing a further increase in gasoline prices. Consumers, in turn, became again interested in the use of ethanol. However, the lack of confidence in the biofuel supply caused ethanol-powered cars sales to be stagnant. In 2003, flex-fuel engines, which used any quantities of gasoline and ethanol in the mixture, started to be commercialized in Brazil. In 2006, the country became self-sufficient in oil production, but large-scale ethanol making continued increasing (Kohlhepp, 2010).

Considering that Brazil is the world's largest producer of sugarcane, and the second largest producer of ethanol, the debate about the influence of biofuel production on food security became recurrent in recent years (Capitani, 2014; Monteiro, Altman and Lahiri, 2012; FGV, 2008). Hence, the objective of this paper is to provide empirical evidence on the relationship between prices of sugarcane ethanol and prices of selected food crops in Brazil. The study also considers the influence of the real/dollar exchange rate, and the international oil prices, on food and biofuel markets. The period considered for the analysis was from August 2004 to August 2017.

## LITERATURE REVIEWED

The latest phase of the Brazilian fuel alcohol program, especially since the introduction of flex-fuel engines in 2003, was followed in the United States by the Renewable Fuel

Standard-RFS program, established as an amendment to the Clean Air Act in 2005. The law forced the use of a minimum volume of ethanol in the mixture with gasoline, which was aimed to increase annually. Between 2003 and 2014, ethanol production in Brazil almost doubled, while it increased more the fivefold in the United States over the same period. With this expansion, the debate on the relationship between food security and biofuel production has grown and gained interest from the academic community.

Several researchers examined the relationship between biofuel and food markets via prices causality. Bastianin, Galeotti, and Manera (2013) using Granger´s methodology found a causal relationship of corn prices to ethanol prices, but not the reverse in Nebraska, the second largest producer of biofuels in the U.S. In conclusion, the study found no evidence in favor of the food-biofuels linkage. Myers et al. (2014) analyzed comovements between energy commodity prices (oil, gasoline, and ethanol) and the prices of agricultural commodities used in biofuel production (maize and soybean) in the U.S. with an error correction model. The paper, however, found no statistical evidence of cointegration between fuel and food prices.

Du and McPhail (2012), using a Vector Autoregression model (VAR), divided the studying period in two: 2005 to 2008 (years following the 2005 Clean Air Act) and 2008 to 2011 (more recent period). Only in the second period was the relationship between food prices and biofuels statistically significant. Chen, Kuo, and Chen (2010) investigated the relationship between oil and food commodities prices in the United States using a Distributed Lags Model. The results indicated that changes in international oil prices would have exerted higher influence on prices of agricultural commodities if it was not for the development of the biofuels program in that country

Using a Vector Error Correction Model (VECM), Capitani (2014) examined the price impact of ethanol and sugarcane on selected food crops in Brazil. Results indicated that price of ethanol exerts statistically significant influence on sugar and sugarcane prices. The study, however, concluded that despite the recent expansion of sugar and ethanol production in Brazil, food commodities market in the country do not seem to have been affected by the growth of the biofuels production.

Monteiro, Altman, and Lahiri (2012) examined the influence of the United States and Brazil, the world's largest ethanol producers, on food commodity prices Using linear regression models. The study found that an increase in the share of Brazilian biofuel production, in respect to the U.S., is related to rising food prices. However, there was no statistically significant causal relationship between the expansion of areas for planting biofuels crops in both countries and food prices. On the contrary, an increase in sugarcane areas in Brazil showed to exert a negative influence on the price of food. According to the authors, a possible explanation is that the areas planted with sugarcane, destined for ethanol, expanded along with the areas of sugarcane intended to produce sugar. As a consequence, the price of sugar tended to fall, pushing down food price index.

The reviewed literature is not conclusive regarding the impacts of biofuel production on food security. Most studies, however, are also unable to ensure that there is no causal link between the bio-based energy markets and food commodities. It is therefore crucial that further studies examine the relationship between these markets to find elements that help to formulate public policies capable of encouraging the production of biofuels without endangering food security.

## METHODOLOGY

### Data

The data used in the empirical model were related to ethanol prices, prices of a selected group of Brazilian agribusiness food commodities (sugar, soy, and maize), the real/dollar exchange rate and the international oil price. The oil price entered the system as an exogenous variable since, by assumption, it could affect prices formation in Brazilian agribusiness, but it is not likely to be affected by it. Dummy variables were also used to mark regime changes (structural breaks) and seasonal periods. The data used were monthly, covering the period from August 2004 to August 2017. The use logarithmic transformation in the data improved model's fit. Table 01 details the nature of the data and its sources.

**Table 01** – Variables Description

| Variable | Description | Source |
|---|---|---|
| *ETH* | Monthly ethanol price (US$/liter) | CEPEA/USP |
| *SUG* | Monthly sugar price (US$/50 kg bags) | CEPEA/USP |
| *SOY* | Monthly soybean price (US$/60 kg bags) | CEPEA/USP |
| *COR* | Monthly corn price (US$/60 kg bags) | CEPEA/USP |
| *EXC* | Nominal monthly exchange rate (R$/US$) | IPEA |
| *OIL* | Brent crude oil – FOB, Europe (US$/Barrel) | U.S. EIA |

### Empirical Strategy

The VECM models estimated in the present study used the following endogenous variables described in the previous section:

$$\boldsymbol{y_t} = (ETH_t, SUG_t, SOY_t, COR_t, EXC_t)$$

Also, the model included dummy variables, seasonal dummy variables, and the international oil price (OIL) as an exogenous variable. Variables stationarity was checked using ADF (Augmented Dickey-Fuller) and KPSS (Kwiatkowski, Phillips, Schmidt and Shin) tests (Dickey and Fuller, 1981; Kwiatkowski, 1992); the occurrence of structural breaks was examined using Bai-Perron method (Bai and Perron, 1998).

As a first step for model estimation, statistical tests using Akaike (AIC), Hannan-Quinn (HQ), Schwarz (SC), and Akaike´s Final Prediction Error (FPE) criterions examined system´s lag order (Enders, 2004; Pfaff, 2015). Then, two causality tests were performed to check if variables in $\boldsymbol{y_t}$ were endogenous. The first was a Granger Causality F-test and the second a Wald-type test for nonzero correlation between the error processes of the cause and effect variables (Pfaff, 2008). A Johansen test examined the number of cointegration relations ($r$) amongst nonstationary variables of the same order (Juselius, 2006).

The Vector Error Correction Model (VECM) was defined according to Johansen and Juselius (1992), Juselius (2006), and Kilian and Lütkepol (2017) as follows:

$$\Delta \boldsymbol{y}_t = \Pi \boldsymbol{y}_{t-1} + \Gamma_1 \Delta \boldsymbol{y}_{t-1} + \cdots + \Gamma_{p-1} \Delta \boldsymbol{y}_{t-p+1} + b\Delta \boldsymbol{x}_t + \mu + cD_t + \varepsilon_t \qquad (1)$$

Where $\boldsymbol{y_t}$ represents the vector of endogenous variables; $\boldsymbol{y_{t-1}}$ is the cointegration vector; $\boldsymbol{x}_t$ is a vector of possible exogenous variables; $\Gamma_i$ represents $\Delta \boldsymbol{y}_{t-i}$ coefficients; $D_t$ is a vector *dummy* variable; $\mu$ is a constant; $b$ and $c$ are, respectively, $\Delta x_t$ and $D_t$ coefficients; and $\varepsilon_t$ is the model´s error term. Π is the cointegration vector coefficient, which also signifies the variables' speed of adjustment to the long run equilibrium. Empirically, a low speed of adjustment may indicate the existence of short-term factors that keep the variable out of long-run equilibrium, such as over-regulation and other adjustment costs (Johansen and Juselius, 1992). A statistically non-significant speed of adjustment may suggest that the dependent variable in the VECM equation is weakly exogenous; that is, it does not respond to discrepancies regarding the long-term equilibrium (Enders, 2004).

The VECM model examined the residuals concerning serial autocorrelation, normality, and heteroscedasticity. The residuals serial autocorrelation was examined by a Portmanteau (Ljung-Box) test defined as:

$$Q_h = T \sum_{j=1}^{h} tr(\hat{C}_j' \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}),$$

With $\hat{C}_i = \frac{1}{T} \sum_{t=i+1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_{t-1}'$. For $K$ endogenous variables, $Q_h$ has approximate $\chi^2(K^2 h - n^*)$ distribution, where $h$ is the lag memory of the error term regression used in the test, and $n^*$ is the number of coefficients excluding deterministic terms of the model. The tests of residual normality were Jarque-Bera univariate (for the residues of each equation), Jarque-Bera multivariate (for the residuals of the system as a whole), asymmetry (multivariate) and kurtosis (multivariate). The Jarque-Bera test is approximate distributed as $\chi^2$ (2*K*) and the asymmetry and kurtosis are approximate distributed as $\chi^2$ (*K*). The test for residuals heteroscedasticity was univariate and multivariate ARCH (Lagrange Multiplier), with $\chi^2(qK^2(K+1)^2/4)$ approximate probability distribution (Pfaff, 2008).

## Results

ADF and KPSS tests showed that all variables in the VECM system were nonstationary integrated of order 1, and the causality tests confirmed endogeneity of variables in vector $\boldsymbol{y_t}$.[1] Table 02 shows the results of Johansen cointegration test for the trace statistic. The null hypothesis of $r = 0$ was rejected, while the null hypothesis of $r <= 1$ could not be rejected at the significance levels considered. Hence, the system was found to have one cointegration vector.

[1] See tables 01, 02, 03 and 04 in the appendix.

**Table 02** – Johansen Cointegration Test

| $H_0$ | Test Statistic | Critical Values 10% | 5% | 1% |
|---|---|---|---|---|
| $r <= 4$ | 0.02 | 6.5 | 8.18 | 11.65 |
| $r <= 3$ | 6.39 | 15.66 | 17.95 | 23.52 |
| $r <= 2$ | 22.11 | 28.71 | 31.52 | 37.22 |
| $r <= 1$ | 42.71 | 45.23 | 48.28 | 55.43 |
| $r = 0$ | 117.31 | 66.49 | 70.6 | 78.87 |

The VECM model estimation, therefore, included one cointegration vector in the system. Table 03 shows the cointegration vector with Student *t* statistics in parenthesis. Results confirmed statistical significance of all elements in $\hat{\beta}$ vectors at 5% level. Cointegration vector coefficients were used to calculate variables´ speeds of adjustment in respect to the long run equilibrium (Johansen and Juselius, 1992)

**Table 03** – Cointegration Vector

| Vector | $ETH_{t-1}$ | $SUG_{t-1}$ | $SOY_{t-1}$ | $COR_{t-1}$ | $EXC_{t-1}$ |
|---|---|---|---|---|---|
| $\hat{\beta}'$ | 1,000 | -0.518 | 0,162 | -0.127 | -0.508 |
| | | (-19.613) | (3.321) | (-2.362) | (-10.774) |

Note: *t* statistics in parenthesis

Table 04 shows the speeds of adjustment of the VECM variables to the long run equilibrium, and the respective standard errors, student *t* statistics, and p-values. Speeds of adjustment were negative and between 0 and 1 for the price of ethanol, sugar, soybean, and corn, as expected, and positive for the exchange rate.

**Table 04** – Speeds of Adjustment

| Variable | Speeds of Adjustment | Standard Error | t value | Pr (>\|t\|) |
|---|---|---|---|---|
| ***ETH*** | -0.575 | 0.101 | -5.679 | 9.76e-08 *** |
| ***SUG*** | -0.349 | 0.091 | -3.851 | 0.0002 *** |
| ***SOY*** | -0.257 | 0.068 | -3.807 | 0.0002 *** |
| ***COR*** | -0.382 | 0.085 | -4.500 | 1.59e-05 *** |
| ***EXC*** | 0.247 | 0.036 | 6.792 | 4.62e-10 *** |

*** p-value lower than 0.001.

The price of ethanol (*ETH*) exhibited the highest speed of adjustment in absolute value amongst VECM variables. A possible reason was that on the demand side ethanol consumers have the option of using gasoline in flex-fuel cars when prices increase. On the supply side, when ethanol prices fall mills can shift to sugar production. That is, ethanol prices are very likely to return to long-run equilibrium quickly once disturbed by shocks. Soybean price exhibited the lowest speed of adjustment, which can be related to a higher price rigidity in the Brazilian soybean market.[2] Exchange rate was the only variable to show positive speed of adjustment, which may describe an overshooting behavior of the variable (Juselius, 2006).

International oil price (*OIL*) entered the model as an exogenous variable since it is not likely to be impacted by changes in Brazilian food price. Table 05 shows parameter estimates of the variable *OIL* in each of the food price equation, along with the respective p-values. The results showed a higher impact of international oil price on the domestic price of ethanol, which is a reasonable result given that gasoline and ethanol are close substitutes. The impact on food commodities may be due to transportation and input costs.

**Table 05** – Oil Price Impact on Commodities Price

| Variable | Parameter | P-value |
|---|---|---|
| ***ETH*** | 0.00369 | 9.76e-07 *** |
| ***SUG*** | 0.00176 | 0.006804 ** |
| ***SOY*** | 0.00162 | 0.000962 *** |
| ***COR*** | 0.00216 | 0.000469 *** |

*** p-value lower than 0.001, ** p-value lower than 0.01

Table 06 shows the forecast error variance decomposition of ethanol price for 24 steps after a shock. Almost 24% of the *ETH* variance was explained by *SUG* variance 24 months after a shock. Ethanol price variance also was shown to be highly dependent on the exchange rate.

**Table 06** – Forecast error variance decomposition of ethanol price

| Period | $\varepsilon_t^{ETH}$ | $\varepsilon_t^{SUG}$ | $\varepsilon_t^{SOY}$ | $\varepsilon_t^{COR}$ | $\varepsilon_t^{EXC}$ |
|---|---|---|---|---|---|
| [1] | 1 | 0 | 0 | 0 | 0 |
| [4] | 0.745 | 0.037 | 0.004 | 0.001 | 0.213 |
| [8] | 0.569 | 0.120 | 0.013 | 0.002 | 0.295 |
| [12] | 0.491 | 0.179 | 0.011 | 0.006 | 0.313 |
| [16] | 0.441 | 0.205 | 0.010 | 0.006 | 0.338 |
| [20] | 0.410 | 0.221 | 0.009 | 0.007 | 0.352 |
| [24] | 0.386 | 0.236 | 0.008 | 0.007 | 0.363 |

[2] Hassouneh *at al.*(2015) found price rigidity in specialized and concentrated food markets, which is the case of Brazilian soybean industry.

Table 07 shows the forecast error variance decomposition of sugar price for 24 steps ahead of the shock. Sugar price own variance accounted for 68% of the total variance after 24 months, while ethanol variance influence on sugar variance was only 7.4%.

**Table 07** – Forecast error variance decomposition of sugar price

| Period | $\varepsilon_t^{ETH}$ | $\varepsilon_t^{SUG}$ | $\varepsilon_t^{SOY}$ | $\varepsilon_t^{COR}$ | $\varepsilon_t^{EXC}$ |
|---|---|---|---|---|---|
| [1] | 0.179 | 0.821 | 0.000 | 0.000 | 0.000 |
| [4] | 0.167 | 0.707 | 0.002 | 0.004 | 0.120 |
| [8] | 0.136 | 0.628 | 0.001 | 0.015 | 0.219 |
| [12] | 0.098 | 0.675 | 0.002 | 0.027 | 0.198 |
| [16] | 0.088 | 0.673 | 0.002 | 0.034 | 0.204 |
| [20] | 0.080 | 0.678 | 0.002 | 0.036 | 0.204 |
| [24] | 0.074 | 0.681 | 0.002 | 0.038 | 0.205 |

Results in Tables 06 e 07 suggested an asymmetry on the relationship between sugar and ethanol prices. Sugar price influence on ethanol price was stronger than the other way around. A possible explanation is that changes in the ethanol price are partially absorbed on the demand side through substitution effect, and its ability to influence sugar price was limited by a fast adjustment to the long-run equilibrium. Sugar prices, on the other hand, were more rigid to the influence of domestic factors due to its stronger link to international market.[3]

**Table 08** – Forecast error variance decomposition of soybean price

| Period | $\varepsilon_t^{ETH}$ | $\varepsilon_t^{SUG}$ | $\varepsilon_t^{SOY}$ | $\varepsilon_t^{COR}$ | $\varepsilon_t^{EXC}$ |
|---|---|---|---|---|---|
| [1] | 0.003 | 0.085 | 0.911 | 0.000 | 0.000 |
| [4] | 0.237 | 0.043 | 0.715 | 0.002 | 0.003 |
| [8] | 0.332 | 0.034 | 0.631 | 0.001 | 0.002 |
| [12] | 0.338 | 0.031 | 0.628 | 0.001 | 0.001 |
| [16] | 0.332 | 0.027 | 0.638 | 0.001 | 0.001 |
| [20] | 0.331 | 0.025 | 0.642 | 0.001 | 0.001 |
| [24] | 0.330 | 0.024 | 0.644 | 0.001 | 0.001 |

Table 08 shows the forecast error variance decomposition of soybean price for

[3] In the 2016/2017 harvest 70% of Brazilian sugar was exported, while only 30% were consumed. During the same period, ethanol had only 6% of all its production shipped to international market (https://www.economiaemdia.com.br/EconomiaEmDia/pdf/infset_acucar_etanol.pdf)

24 periods subsequently to a shock. After eight periods, about 33% of the soybean price variance is due to the ethanol price variance. This result can be regarded as evidence of linkage between the two markets. Brazil is one of the biggest soybean end ethanol producer in the world, and this link may be due competition for the resource to produce those commodities.

**Table 09** – Forecast error variance decomposition of corn price

| Period | $\varepsilon_t^{ETH}$ | $\varepsilon_t^{SUG}$ | $\varepsilon_t^{SOY}$ | $\varepsilon_t^{COR}$ | $\varepsilon_t^{EXC}$ |
|---|---|---|---|---|---|
| [1] | 0.019 | 0.044 | 0.183 | 0.754 | 0.000 |
| [4] | 0.069 | 0.018 | 0.097 | 0.795 | 0.022 |
| [8] | 0.094 | 0.034 | 0.117 | 0.678 | 0.078 |
| [12] | 0.106 | 0.037 | 0.152 | 0.611 | 0.093 |
| [16] | 0.111 | 0.035 | 0.165 | 0.592 | 0.098 |
| [20] | 0.110 | 0.034 | 0.174 | 0.583 | 0.099 |
| [24] | 0.110 | 0.033 | 0.178 | 0.577 | 0.102 |

Table 09 shows the forecast error variance decomposition of corn price for 24 periods subsequently to a shock. After twelve periods, about 11% of the corn price variance are due to the ethanol price variance. The influence of ethanol price variance on corn price variance is around one third when comparing to soybean price variance.

Figure 01 presents Impulse-response functions between ethanol and food commodity prices with 95% bootstrap confidence interval for 100 runs. The orthogonal response of a unit impulse in ethanol price on sugar price was positive, exhibited the highest value in the first six months after the shock and stabilized at a lower level. The impulse caused by a unit change in sugar price on ethanol price increased up to the ninth month after the shock and stabilized at a lower level. The impulse impact of sugar price on ethanol price, however, was higher than the other way around. This result was consistent with the variance decomposition, which showed sugar variance exerts a higher influence on ethanol price variance than the inverse.

The responses of one-unit impulse of ethanol on soybean and corn were similar. In both cases, a unit increase in ethanol price provoked a fall in soybean and corn prices, which is consistent with results found by Capitani (2014). On the other hand, impulses of soybean and corn price caused only a slight disturbance in ethanol price in the beginning, stabilizing close to zero for the rest of the period. One possible explanation is that biofuel production and food crop production may compete to the use of resources. When diverting resources from the sugar/ethanol production to food commodity production (corn and soybean), an increase in ethanol price and a decrease in food commodity price is likely to happen *via* supply effect. Diverting resources from the food commodity sector to ethanol/sugar industry would provoke an opposite effect, with the difference that ethanol price adjusts quickly to its historical level due to substitute effect on the fuel demand market. That is, in this latter case, prices of food commodities raise, but prices of ethanol fall in the beginning and quickly adjusts.

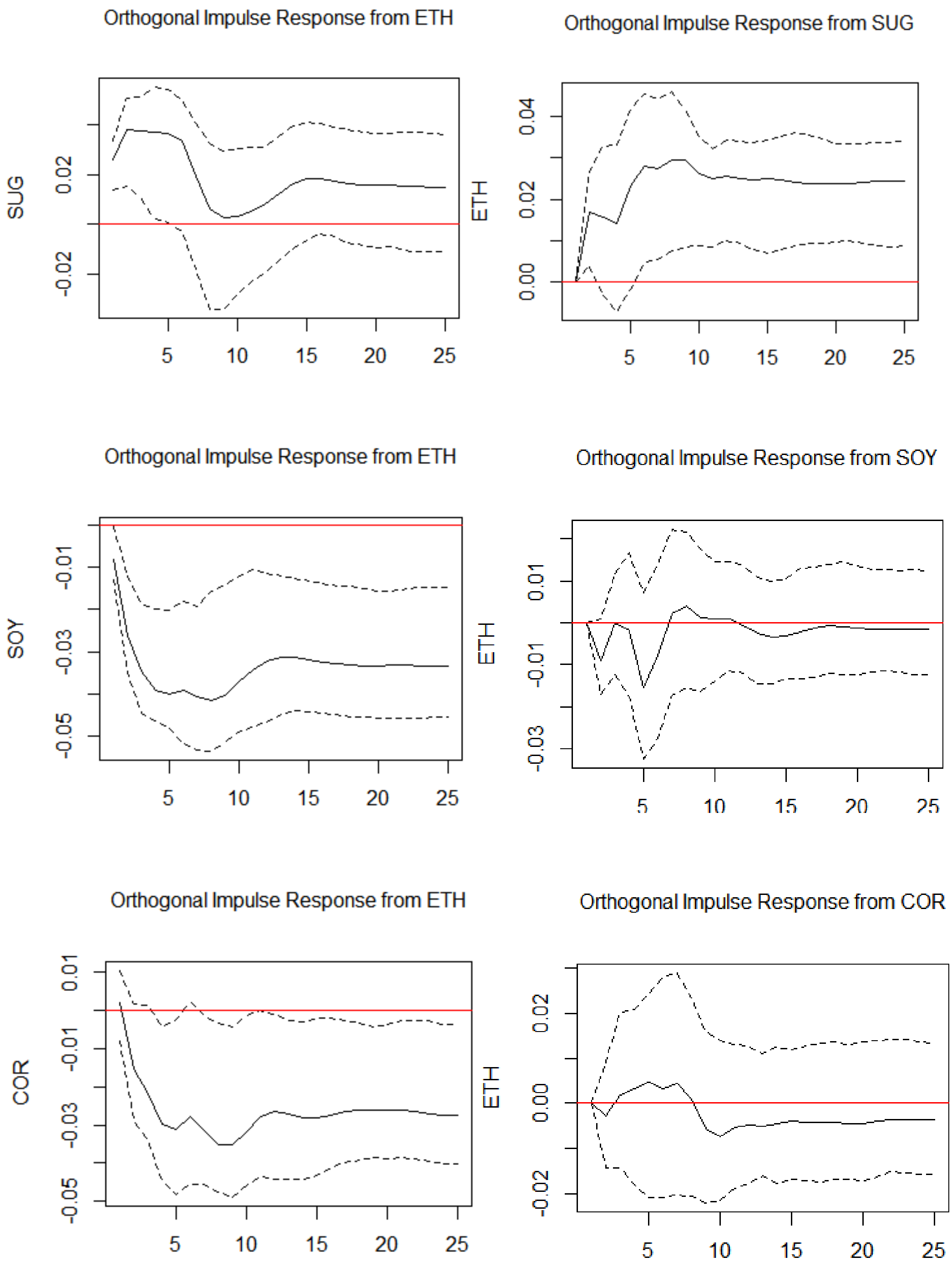


Figure 01 – Impulse-response functions between ethanol and food commodity prices with 95% bootstrap confidence interval for 100 runs.

Table 10 shows the model´s diagnostic test for residuals serial autocorrelation, normality and heteroscedasticity. The Ljung-Box test (portmanteau) failed to reject the null hypothesis of no serial autocorrelation of the residuals, but a Jarque-Bera test rejected the null hypothesis of residuals normality. Errors, however, did not showed kurtosis. ARCH test failed to reject the null hypothesis of conditional heteroscedasticity.

**Table 10** – Model diagnostics

| **Diagnostics** | **Test** | $\chi^2$ | **P-valor** | **Conclusion** |
|---|---|---|---|---|
| Residuals autocorrelation | Ljung-Box (16) | 292.14 | 0.054 | No autocorrelation |
| Residuals normality | Jarque-Bera | 21.69 | 0.016 | Non-normal |
| | Skewness | 11.22 | 0.047 | Skewness |
| | Kurtosis | 10.47 | 0.063 | No kurtosis |
| Conditional Heteroscedasticiy | ARCH | 1170.2 | 0,170 | No heteroscesticity |

## CONCLUSIONS

This article examined the relationship between biofuel and food markets in Brazil, modeling the Vector Error Correction system using ethanol, sugar, soybean, corn and Real/Dollar exchange rates as endogenous variables, and international oil price as an exogenous variable. The statistical test detected one cointegration vector in the model, which represented a trend along which the endogenous variables will move in the long run. That is, the existence of a cointegration relation in the model could be evidence of linkage between biofuel and food markets. The sign, magnitude, and statistical significance of the variable coefficients in the cointegration vector strengthened such hypothesis. The forecast error variance decompositions and the impulse response functions show an asymmetric relationship between sugar and ethanol prices, but there appears to be a significant link between those markets. Also, results showed considerable impacts of ethanol prices on food commodity prices and vice-versa, even though the intensity of such impacts was not the symmetric. In summary, the results seem to support the hypothesis of economic linkages between biofuel and food commodity markets in Brazil. It is essential, however, to expand this study using biodiesel, and other food commodities in the country. As a policy implication, it is crucial that public sector in Brazil pursue the objective of increasing the supply of renewable and less pollutant fuel observing the goals of food security.

## REFERENCES


Alcarde, A.R. 2008. "From Proalcool to flexfuel, ethanol has migrated from the State to the market." *Visão Agrícola,* (8).

Bai, J., and P. Perron. 1998. "Estimating and Testing Linear Models with Multiple Structural Changes." *Econometrica,* 66(1):47–78.

Barros, R. 2007. "Energy for a new world." Rio de Janeiro: CREA-RJ: 160.

Bastianin, A., M. Galeotti, and M. Manera. 2013. "Biofuels and Food Prices: Searching for the Causal Link." *Working Paper Series,* 55.

BRADESCO – DEPEC (Department of Research and Economic Studies). "Sugar and Ethanol." Available at: www.economiaemdia.com.br/EconomiaEmDia/pdf/infset_acucar_etanol.pdf/. [Accessed July 1, 2017].

CAPITANI, D. H. D. 2014. "Biofuels versus food: How much Brazilian ethanol production can affect domestic food prices?" Selected paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN.

Chen, S. T., H. I. Kuo, and C. C. Chen. 2010. "Modeling the relationship between the oil price and global food prices." *Applied Energy,* 87(8):2517–2525.

Dickey, D. A., and W.A. Fuller. 1981. "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root." *Econometrica,* 49(4):1057–1072.

Du, X., and L. L. Mcphail. 2012. "Inside the Black Box: the Price Linkage and Transmission between Energy and Agricultural Markets." *The Energy Journal,* 33(2).

Enders, W. 2004. *Applied econometric time series.* 2nd ed. Wiley.

FGV (Getúlio Vargas Foundation). 2008. "Determining Factors of Food Prices: The Impact of the Biofuels." Rio de Janeiro: FGV Projects.

Hassouneh, I., C. Holst, T. Serra, S.V. Cramon-Taubadel, and J.M. Gil. 2015. "Overview of Price Transmission and Reasons for Different Adjustment Patterns across EU Member States." *Food Price Dynamics and Price Adjustment in the EU*:51-64.

IPEA (Institute of Applied Economic Research). 2010. "Biofuels in Brazil: Ethanol and Biodiesel." Communcation from IPEA (53), Brasília, DF.

Johansen, S. R., and K. Juselius. 1992. "Testing structural hypotheses in a multivariate cointegration analysis of the PPP and the UIP for UK." *Journal of Econometrics,* 53(1-3):211–244.

Juselius, K. 2006. *The cointegrated VAR model: methodology and applications.* Oxford University Press.

Kilian, L., and H. Lütkepohl. 2017. *Structural Vector Autoregressive Analysis.* Cambridge University Press.

Kohlhepp, G. 2010. "Analysis of the situation of ethanol and biodiesel's production in Brazil." *Estudos Avançados,* 24(68):223–253.

Kwiatkowski, D., P.C. Phillips, P. Schmidt, and Y. Shin. 1992. "Testing the null hypothesis of stationarity against the alternative of a unit root." *Journal of Econometrics,* 54(1-3):159–178.

Monteiro, N., I. Altman, and S. Lahiri. 2012. "The impact of ethanol production on food prices: The role of interplay between the U.S. and Brazil." *Energy Policy,* 41:193–199.

Myers, R. J., S. R. Johnson, M. Helmar, and H. Baumes. 2014. "Long-run and Short-run Co-movements in Energy Prices and the Prices of Agricultural Feedstocks for Biofuel." *American Journal of Agricultural Economics,* 96(4):991–1008.

Pfaff, B. 2008. *Analysis of integrated and cointegrated time series with R*. Springer.

Pfaff, B. 2015. "Package vars". Available at: http://www.pfaffikus.de/. [Accessed June 18, 2017].

# APPENDIX

**Table 01 -** Augmented Dickey-Fuller Test

| Variables | Deterministic terms | Lags | P-value | Critical Values | | | Result |
|---|---|---|---|---|---|---|---|
| | | | | 1% | 5% | 10% | |
| **SUG** | $a_0$, $t$ | 12 | -15,443 | -3,99 | -3,43 | -3,13 | I (1) |
| **Δ SUG** | $a_0$ | 12 | -67,493 | -3,46 | -2,88 | -2,57 | I (0) |
| **ETH** | $a_0$, $t$ | 12 | -2,561 | -3,99 | -3,43 | -3,13 | I (1) |
| **Δ ETH** | $a_0$ | 12 | -90,044 | -3,46 | -2,88 | -2,57 | I (0) |
| **COR** | $a_0$, $t$ | 12 | -29,049 | -3,99 | -3,43 | -3,13 | I (1) |
| **Δ COR** | $a_0$ | 12 | -59,587 | -3,46 | -2,88 | -2,57 | I (0) |
| **SOY** | $a_0$, $t$ | 12 | -27,335 | -3,99 | -3,43 | -3,13 | I (1) |
| **Δ SOY** | $a_0$ | 12 | -65,311 | -3,46 | -2,88 | -2,57 | I (0) |
| **EXC** | $a_0$, $t$ | 12 | -22,251 | -3,99 | -3,43 | -3,13 | I (1) |
| **Δ EXC** | $a_0$ | 12 | -67,908 | -3,46 | -2,88 | -2,57 | I (0) |

**Table 02** – KPSS Test

| Variables | Lags | P-Value | Critical Value | | | | Result |
|---|---|---|---|---|---|---|---|
| | | | 1% | 2.50% | 5% | 10% | |
| **SUG** | 12 | 0.188 | 0,216 | 0,176 | 0,146 | 0,119 | I(1) |
| **ETH** | 12 | 0.198 | 0,216 | 0,176 | 0,146 | 0,119 | I(1) |
| **COR** | 12 | 0.2 | 0,216 | 0,176 | 0,146 | 0,119 | I(1) |
| **SOY** | 12 | 0.247 | 0,216 | 0,176 | 0,146 | 0,119 | I(1) |
| **EXC** | 12 | 0.27 | 0,216 | 0,176 | 0,146 | 0,119 | I(1) |

**Table 03** – Granger Causality Test

| Variables | P-Value |
|---|---|
| **SUG** | 0.003616 |
| **ETH** | 0.003877 |
| **COR** | 0.5439 |
| **SOY** | 0.1521 |
| **EXC** | 0.0000296 |

**Table 04** - Instantaneous Causality Test (Wald)

| Variables | P-valor |
|---|---|
| SUG | 9.96E-07 |
| ETH | 5.62E-07 |
| COR | 8.26E-08 |
| SOY | 5.38E-08 |
| EXC | 1.88E-05 |