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Article

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Asymmetric Spillover Effects between Agricultural Commodity Prices and Biofuel Energy Prices

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ABSTRACT

This study addresses the problem of causal price relationships of biofuels for an enhanced group of agricultural commodities to capture possible asymmetric causal effects. It investigates the long-run equilibrium and assumes that an adjustment process toward this equilibrium exists. The adjustment process can be non-linear, implying that we can identify critical thresholds that determine regions in the sample that once exceeded, price inter linkages may vary. The empirical results indicate that there are commodity prices that have strong causal (asymmetric) relationship with biofuel energy prices.

Keywords: Biofuels Energy Prices, Agricultural Prices, Asymmetric Cointegration, Asymmetric Causality
JEL Classification: Q16

1. INTRODUCTION

Over the last four decades the agricultural production has been characterized by falling real prices (Schmidhuber, 2006) and this is primarily the result of the lowering production costs due to the adoption of new technologies. However, the very recent years we have witnessed an increase in prices and this comes out as the result of several factors. There is an ongoing debate starting with the agricultural commodity price spikes in 2007/2008 and more recently in 2010/2011. One of the most frequently mentioned factors of soaring agricultural prices (and hence food prices) is the use of food crops for the production of biofuels. Though, the increasing production of biofuels puts considerable concerns for the future developments in food prices and the food security levels worldwide. These concerns necessitate a review of the policies on biofuel production and the use of land for biofuels feedstock.

Biofuels are promoted as one of the most significant substitutes of fossil fuels with a considerable share growth in recent years. They are environmental friendly, targeting to the reduction of the greenhouse gas emissions, produced primarily by feedstocks as they are sugarcane and maize (corn), and used mainly in the transportation sector. Insofar, nevertheless, only few countries have special interests in biofuels. Our endeavor focuses on the effect of food price competition with emphasis (which is the main novelty of this work) given on the presence of potential asymmetries in the nexus between agricultural and biofuel prices. Specifically, the question we like to address is: Why biofuels prices have recently increased strongly, following strong energy prices, despite the decrease of feedstock prices (mainly sugar and corn)? It seems that biofuels, though an imperfect substitute of diesel and gasoline, are considerably related to crude oil prices and the scope of our analysis is to shed light to potential asymmetries between agricultural and biofuel prices. We are expecting that our findings could contribute to the policy debate about biofuels as possible (major) source of rises in food prices leading to food crises. Moreover, there is eventually a break-even point where the land competition makes the land use for biofuels a welfare worsening option. The technologies that use biofuels may become non-competitive with adverse effects in the industry. Cost efficiency is an important factor for adopting the biofuels technology and the presence of asymmetries in the relationship that links agricultural and biofuel prices may deter the further development of biofuels use.

Section 2 presents the literature review related to in this paper, while Section 3 presents the model specification followed in the empirical analysis. Section 4 presents the data used, including data on biofuel prices, as well as data on non-energy (agricultural) commodities. Section 5 documents the empirical results, while

the paper concludes with Section 6 that provides a summary of the main results.

2. LITERATURE REVIEW

There are several studies that have examined the spillovers between the biofuels' expansion and the price of agricultural feedstock. The general outcome seems to support the argument of competition for land use between the production of food and biofuels feedstock. The implied land use substitutability raises more questions on the price formation of food products. For instance, a significant question is related to the effect on income distribution and the social welfare. Low income households spend disproportionately higher share of their income on food expenditures, making them more vulnerable to food price volatility. As a result, households reduce their savings to meet their nutrition needs and once their savings are drained they switch their diet to less nutritious foods or they become undernourished.

The way biofuels energy prices are channeled on food prices can be identified at the upstream level, in feedstocks supply. Biofuels are competing food stuffs for the same crops of feedstocks, i.e., wheat, corn etc. However, this is not always the case, since many times the varieties used for distilling biofuels are not recommended for food production or animal feed. Schmidhuber (2006) suggests that the competing crops are not an unsolvable problem and that there are both floor and ceiling prices in agriculture; however, these prices are endogenous to fossil energy prices. This comes out from the high dependency of biofuels energy prices on fossil energy prices.

The idea of asymmetric links between fossil prices and agricultural commodity prices is related to the crop re-allocation and switching costs issues. According to Ajanovic (2011) the most suitable land for biomass production is already in use. In 2006, about 1% of the world's arable land was used for the production of biofuels. Insofar, only a 1% of biofuels serve the transportation sector worldwide, and if we are to double this production level, this can be happen either if the fuel demand is to be reduced or if the land productivity is to dramatically increase. If neither scenario occurs, the land use competition will push thing to a land use substitution against food production.

The relatively constant supply of land, in combination with the biofuel policies that push demand for biofuels upwards, engenders a land use substitution to crops that may be used as biofuel feedstock. That means that less land will become available for staple crops that can alternatively be used for biofuel feedstock, and taking into account the limitations of yield increases due to technological constraints, the supply of many food crops will inevitably be reduced. Moreover, it will prompt the conversion of pasture and forest lands to croplands. The idea behind this substitution effect is simple. Farmers and land managers would change their crop to other staple crops that can be used as biofuels feedstock once the demand is not coming only for food but also from the biofuels production. Prices are partly driven by the biofuels policies and are anticipated to increase rapidly, creating opportunities for significant profitability. The incurring costs by the switch may be significant as well but once the potential profits amortize the necessary fixed costs in a short period, the investment decision becomes viable.

The year 2008 was characterized by soaring food prices and increasing volatility. The International Monetary Fund's (IMF's) index of internationally traded food commodity prices soared by 56% from January 2007 to June 2008 (Mitchell, 2008). These developments are attributed in several factors, among others, the increasing demand for food items originated from emerging economies, i.e., mainly India and China. From the supply side, we highlight the increased crude oil prices as well as the increased share of first generation biofuels. Energy accounts for an important share in the overall cost of food products and energy price hikes transmitted to the intermediate production levels of food products, primarily in production and transportation. Onour and Sergi (2011) indicate that shocks in oil markets have permanent effect on food commodity price changes and evidenced that this effect may occur either directly or indirectly via the cost of fertilizers. They also illustrate that the increased demand for feedstock for biofuels had had also an important role in the volatility of food prices. Mitchell (2008) provides some illuminating numbers for the effect of biofuels. In 2007, about 7% of global vegetable oil used for biodiesel production while for the period 2004-2007, the one third of the consumption increase was due to the demand for biodiesel. For the same period (2004-2007) the increase in maize production was absorbed by 70% for ethanol production. In the U.S. the rapid demand for maize displaced the soybean production, contributing by 75% to the rise of soybean prices in 2007-2008. In the E.U., respectively, the oilseed production displaced wheat, lowering the wheat stocks. Timilsina and Shrestha (2010) survey extensively the existing literature on the impact of biofuels on food crisis of 2008. They highlight that most studies agree on the role of the expanded biofuel production as one of the main drivers of food prices hikes in 2008. However, they stress that the interdependence with other drivers, as they are fossil oil prices, ought not to be neglected. Baier et al. (2009) show that the biofuel production was responsible for the rises in food prices by 17% in corn, 14% in soybean and 100% in sugar. The result for corn prices is in accordance with Lazear (2008) for the US market ethanol production. He finds that US ethanol increase was due for the 20% of the increase in corn prices. Glauber (2008) finds that US biofuel production accounted for about 25% of the rise in corn prices. The interested reader is also advised to turn to two great survey papers by Zilberman and Serra (2013) and Zilberman et al. (2013) who provide an extensive literature review on the rapidly growing biofuel-related time-series studies that have been carried out. Such energy prices drive long-run agricultural price levels, while the presence of instability in these biofuels energy markets is transferred to food markets. These surveys highlight, however, that biofuels have not been the most dominant driver to the recent food-price inflation, while different types of biofuels have different impacts. Finally, Abderladi and Serra (2015) explore the proportion of agricultural production spent for biofuels purposes in the case of Spain. In particular, they explore the presence of asymmetric volatility spillovers between food and biofuel prices. Through an asymmetric MGARCH model their findings highlight the bidirectional and asymmetric volatility spillovers between the two variables under study.

3. MODEL SPECIFICATION

The main hypothesis posits that a linear model describing the nexus between agricultural commodity markets and biofuels is specified as follows:

$$\ln COM_t = b_0 + b_1 \ln BIO_t + u_t \quad (1)$$

Where BIO is the price of biofuels, COM is the price of non-energy commodity prices described below, ln denotes the natural logarithm, and u is the error term. The coefficient b_1 measures the impact of biofuel prices on non-energy commodity prices; it is expected to be positive. In other words, an increase (decrease) in biofuel prices is expected to lead to higher (lower) non-energy commodity prices due to a rise (decline) in the cost of production.

4. DATA

We obtained daily data on biofuel prices (i.e., seasonal biodiesel prices-FAME) as well as on seven non-energy commodities. However, all prices do not cover the same time span. The details about biofuels, non-energy commodities, their definition and their time span, are provided in the Appendix 1 of this study. Data were obtained from Bloomberg. To avoid the impact of seasonality and given that energy demand exhibits seasonal fluctuations due to changing climate conditions, such as temperature and the number of daylight hours, as well as that supply side also can show seasonal variations in output, we need to seasonally adjust our biofuels data sample by making use of the moving average (MA) methodology recommended by Weron (2006). To this end we considered the MA-6 model as a good method for seasonal adjustment for our daily biofuels prices data. In terms of the agricultural daily prices data, the same procedure considers different MA models (depending upon the nature of the agricultural commodity) that deals with seasonality. The results recommended: A MA(7) model for corn, a MA(7) model for sugar cane (sc), a MA(4) model for soybeans oil (sboil), a MA(6) model for sunflowers oil (sfoil), a MA(18) model for palm oil (poil), a MA(7) model for camelina oil (coil), and a MA(7) model for sugar. In addition, we further filter out agricultural prices data by using the Kalman filter to filter out estimates of convenience yields.

5. EMPIRICAL ANALYSIS

5.1. The Non-linear-asymmetric Case

First, we examine for the presence of non-linearities in relevance to model equation (1). To this end, this part of the empirical analysis makes use of the non-linearity test proposed by Hamilton (2001), which investigates the null hypothesis that the true relationship between biofuels and agricultural prices is linear. Hamilton's (2001) v^2-statistic has an asymptotic $\chi^2(1)$ distribution under the null hypothesis of linearity. The results are reported in Table 1. These findings document that the null hypothesis that the relationship between biofuels and agricultural prices (across all agricultural products considered here) is linear is rejected.

Next, we explore the number of relevant regimes driving the time series under investigation. To this end, we allow for a Markov-switching model that allows for multiple regime shifts (Nason, 2006; Stock and Watson, 2007). The main distinguishing feature of the model is the allowance for possible discrete regime shifts by letting the model parameters depend on an N-state Markov-switching variable with fixed transition probabilities. For such Markov-switching models, the null hypothesis tests for the number of regimes which are confounded by identically zero scores at the null and the presence of nuisance parameters under the alternative (Hansen, 1992; Garcia, 1998). Thus, the test addresses the question of how many regimes to include in the modeling approach. First, we consider model selection based on the Akaike information criterion (AIC). Second, we verify our model selection results by conducting residual diagnostic tests. Specifically, we consider whether a given model captures all of the serial correlation and heteroskedasticity in the data using the modified Ljung-Box portmanteau tests for the standardized residuals and squared standardized residuals. Looking at the results in Table 2, AIC selects two regimes instead of three (or more).

Zivot and Andrews (1992) propose a testing procedure where the time of the break is estimated, rather than assumed as an exogenous phenomenon. The null hypothesis in their method is that the variable under investigation contains a unit-root with a drift that excludes any structural break, while the alternative hypothesis is that the series is a trend stationary process with a one-time break occurring at an unknown point in time. Table 3 summarizes the result of the Zivot and Andrews (1992) test in the presence of structural break allowing for a change in both the intercept and trend. In this model, the break point is endogenously determined

Table 1: Non-linearity tests (bivariate model)

Variables	v^2-statistic	P-value
corn	8.71	0.00
sc	9.95	0.00
sboil	7.48	0.01
sfoil	8.65	0.00
poil	6.99	0.01
coil	6.53	0.02
sugar	7.38	0.01

Table 2: Number of regimes tests (two vs. three regimes)-the bivariate model

Lag	Standardized residuals		Squared standardized residuals	
	Q*-statistic	P-value	Q*-statistic	P-value
corn				
4	0.091	0.75	0.016	0.91
sc				
3	0.056	0.84	0.011	0.97
sboil				
3	0.039	0.96	0.006	0.99
sfoil				
2	0.064	0.78	0.028	0.86
poil				
4	0.048	0.89	0.035	0.8
coil				
3	0.073	0.71	0.051	0.69
sugar				
3	0.05	0.86	0.032	0.83

The Q*-statistic refers to the modified Ljung-Box portmanteau test statistic

by running the model sequentially allowing for this break point to be any day within a 15% trimming region. The optimal lag length is determined on the basis of the Schwartz-Bayesian Criterion. Using the Zivot and Andrews (1992) procedure, the time of the structural changes (impacting on both the intercept and the slope of each series) for each of the variables is detected and the results are also presented in Table 3. As shown, the most significant structural breaks occur around January 2008. This date corresponds broadly to the pronounced structural changes associated with the 2008 food crisis. Nevertheless, the results document the presence of stationarity only in the first differences of the variables under study.

In the next step, we test for unit root tests through non-linear threshold autoregressive (TAR) unit root tests, recommended by Caner and Hansen (2001), in relevance to the hypothesis of no threshold effect and in relevance to the above results reported in Table 3. Non-linearities can arise because small deviations are not considered important by participants in the relevant energy and non-energy commodity markets, whereas for larger deviations, the pressure from these markets to return adjustable prices near the equilibrium value becomes larger (Taylor and Peel, 2000). Alternatively, non-linearities can also arise as a consequence of transaction costs and market frictions (Dumas, 1992). The conventional linear unit root tests are biased against rejecting nonstationarity when the true process is non-linear.

The non-linear (asymmetric) model is a two-regime symmetric TAR model with an autoregressive root that is local-to-unity. Table 4 reports the bootstrap P-values for threshold variables of the form $Z_t=x_t-x_{t-m-1}$ for delay parameters m from 1 to 8 and where x is either the biofuel energy or the non-energy commodity price. Because the delay parameter (m) is generally unknown, we let it be endogenously determined. The ordinary least squares estimate of the delay parameter (m) is chosen so that it minimizes the residual variance for the TAR model of each deviation series. The entries of the table are P-values obtained using 10,000 bootstrap simulations (replications). These P-values correspond to the delay parameters that minimize the residual variances across the two regimes. The insignificance of such P-values indicates the presence of a unit root. In addition, the least squares estimates of m is shown in Table 3. For these delays parameters the bootstrap P-values indicate that for the levels of all the variables under examination the no threshold effect hypothesis is strictly rejected in all cases. By contrast, for the variables in first differences, the bootstrap P-values are significant, implying that we should reject the null hypothesis of the unit root and accept stationarity of all the variables under study. To discriminate between pure nonstationarity and partial nonstationarity, we employ test statistics t_1 and t_2. The results provide strong evidence that all prices under examination are nonstationary across both regimes.

Kunitomo (1996) explains that in the presence of a structural change, traditional cointegration tests may produce spurious evidence concerning cointegration or the lack of cointegration. Saikkonen and Lütkepohl (2000a; 2000b; 2000c) propose a test for cointegration analysis that allows for possible shifts in the mean of the data-generating process. They argue that researchers should make appropriate adjustments if structural shifts are known.

Table 3: Zivot-Andrews unit root tests with breaks in the intercept and trend

Variable	k	t_a	Break
bio	5	−3.26	January 20, 2008
Δbio	4	−6.39	
corn	4	−3.71	January 12, 2008
Δcorn	3	−6.30	
sc	6	−4.02	January 23, 2008
Δsc	5	−7.28	
sboil	5	−3.58	February 02, 2008
Δboil	3	−6.35	
sfoil	6	−3.63	January 18, 2008
Δsfoil	4	−6.90	
poil	6	−4.24	February 05, 2008
Δpoil	5	−7.41	
coil	5	−3.82	January 21, 2008
Δcoil	3	−6.63	
sugar	4	−4.12	February 17, 2008
Δsugar	3	−7.24	

t_a is the estimated t-statistic related to the null hypothesis of the presence of a unit root under a break and k is the number of lags in the test. Critical values at 1%, 5% and 10% levels are−5.57, −5.08 and−4.82, respectively

Table 4: Non-linear unit root tests

Variable	m	t_1	t_2
bio	2	0.42	0.19
Δbio	2	0.01	0.00
corn	1	0.38	0.27
Δcorn	1	0.00	0.00
sc	2	0.37	0.26
Δsc	2	0.02	0.03
sboil	3	0.24	0.11
Δboil	2	0.01	0.00
sfoil	3	0.49	0.25
Δsfoil	1	0.00	0.04
poil	2	0.40	0.21
Δpoil	1	0.03	0.00
coil	2	0.56	0.28
Δcoil	1	0.02	0.01
sugar	1	0.44	0.25
Δsugar	1	0.00	0.01

Δ denotes first differences. Figures for t_1 and t_2 denote P values were obtained from 10,000 replications. Estimations stand for the inclusion of both constant and trend terms, m is the delay parameter, t_1 stands for the unit root test in regime 1, t_2 stands for the unit root test in regime 2

According to Saikkonen and Lütkepohl (2000b) and Lütkepohl and Wolters (2003), an observed n-dimensional time series $y_t=(y_{1t},\ldots,y_{nt})$, y_t is the vector of observed variables (t=1,…,T) which are generated by the following process:

$$y_t=\mu_0+\mu_1 t+\delta_0 Dt_{0t}+\delta_1 Du_{1t}+x_t \quad (2)$$

Where Dt_{0t} and DU_{1t} are the respective impulse and shift dummies which account for the presence of structural breaks, Dt_{0t} is equal to one when $t = t_0$, and zero otherwise and the step (shift) dummy (DU_{1t}) is equal to one when ($t > t_1$), and zero otherwise. The parameters μ_0, μ_1, δ_0 and δ_1 are associated with the deterministic terms.

The possible options in the Saikkonen and Lütkepohl (2000a; 2000b; 2000c) procedure, as for Johansen's approach, are threefold: A constant, a linear trend term, or a linear trend orthogonal to the cointegration relations. For the empirical purposes of this research,

the optimal number of lags to be included is searched up to 10 lags and determined by the Schwartz Baysian information criterion, while the timing of the most significant structural breaks has been determined above using the Zivot and Andrews (1992) procedure. We also consider dummies with trend and intercept included into the cointegration relation.

The null hypothesis of a no long-run relationship between biofuel prices and agricultural commodity prices is tested and the results are reported in Table 5. The empirical results indicate that the null hypothesis of no cointegration is rejected at the 1% level of significance. In other words, there is evidence of a stable long-run relationship between biofuel prices and agricultural commodity prices across the entire spectrum of agricultural commodities considered as long as allowance is made for significant structural changes in the agricultural commodity prices regime in 2008. Put differently, since the long-run biofuel prices and the agricultural commodity prices move together, biofuel prices are mutually interacted with the prices of the primary agricultural commodities used for the production of biofuels.

Next, we estimate a threshold error correction model (TECM) across all pairs between biofuel energy prices and non-energy (agricultural) commodity prices. To this end, this study adopts the method of Hansen and Seo (2002) to obtain a consistent estimate of the threshold by applying maximum likelihood. This particular methodology generates substantially consistent results for the case of bi-variate models. The consistent threshold estimate can be obtained by ordering the ε_t (the residuals from cointegration) sequence in ascending order, such that $\varepsilon_1<\varepsilon_2<\ldots<\varepsilon_T$, where T is the number of usable observations, while truncating the upper and lower 15%, leaves 70%. Substituting this 70% into the model, the estimated threshold yielding the lowest residual sum squares is the consistent estimate of the threshold. Based on the unit root tests allied previously which identified the presence of two regimes, the transmissions are tested using the TECM. The estimated two-regime TECM results are presented in Table 6. These findings identify two regimes across all cases under investigation with statistically different EC coefficients (Wald tests). The first regime matches the period prior to the commodity price spikes, while in the majority of the cases the magnitude of the EC term turns out to be larger (indicating faster adjustment toward equilibrium) in the first regime (the one that led to the commodity price spike around 2008).

Table 5: Saikkonen and lutkephol cointegration test results (bivariate model)

r_0	LR	P-value
corn		
0	59.84	0
1	1.19	0.64
sc		
0	63.49	0
1	1.05	0.77
sboil		
0	52.74	0
1	0.97	0.83
sfoil		
0	48.96	0
1	0.71	0.89
poil		
0	60.92	0
1	1.14	0.71
coil		
0	42.85	0
1	0.68	0.9
sugar		
0	55.03	0
1	1.26	0.57

Cointegration results indicate that the corresponding null of no cointegration is rejected at the 1% level. Critical values are tabulated by Saikkonen and Lutkephol (2000b). The optimal number of lags (searched up to 10 lags) is determined by the Schwartz Baysian information criterion

Across all equations, the adjustment parameters are statistically significant, implying that both biofuel energy prices and agricultural prices drive agricultural prices and biofuel energy prices, respectively, toward the equilibrium level. For instance, in the case of corn, over the first regime period, the magnitude of the corn EC coefficient (−0.128) indicates slower adjustment to long-run equilibrium, whereas in the second regime the adjustment is faster (−0.181). In other words, the convergence to long-run equilibrium is not uniform over the time span under study, i.e., it is faster when the deviation from equilibrium is above the critical threshold, while in terms of the biofuel energy price equation, the results highlight the different speed of adjustment toward equilibrium across the two regimes (−0.151 vs. −0.166), with the speed also being faster in the second regime. The presence of the regimes along with the different speeds of adjustment toward equilibrium across regimes documents that both corn prices and biofuel energy prices are more vulnerable to biofuel energy prices and corn prices, respectively, compared to the past. The results remain robust in the remaining markets. Overall, the convergence to long-run equilibrium is not uniform, i.e., it is characterized by an asymmetric behavior, while it turns out to be faster when the deviation from equilibrium is above the critical threshold. These findings could potentially indicate that the presence of such asymmetries are likely due to the availability of alternative feedstocks in the market, along with the reluctance of biodiesel producers to increase food prices when feedstocks become more expensive.

5.2. Robustness Check: The Case of a Multivariate Model

To investigate the robustness of our results, we also include the U.S. dollar exchange rate in the modeling analysis, as there is strong evidence that commodity prices have been sensitive to the U.S. dollar over a long period (Chen et al., 2008; Clements and Fry, 2008; Roache, 2008). Roache (2008) argues that commodities are often viewed as a hedge against U.S. dollar depreciation versus other major currencies with large financial market-related turnover, such as the yen, the Euro and the pound sterling. The IMF nominal effective exchange rate (with data obtained from the IFS database) index provides clean exposure to these currencies. In addition, our robust modeling approach considers the role of oil prices (data obtained from Bloomberg). Hanson et al. (1993) argue that increases in crude oil prices are followed by higher costs, resulting in rising agricultural prices, which are also expected to affect biofuels prices. Dramatic increases in crude oil prices contribute to further rising food prices, as well as to a closer link

Table 6: Two-regime TECM results (bivariate model)

Corn equation regime	**I (EC_{t-1}≤−4.55)**	**II (EC_{t-1}>−4.55)**	**Wald-test**
Constant	−0.471(_0.48)	−1.238(−0.99)	[0.01]
EC_{t-1}	−0.128(−5.13)*	−0.181(−6.38)*	
$\Delta corn_{t-1}$	−0.346(−4.38)*	−0.393(−4.63)*	
$\Delta corn_{t-2}$	−0.118(−4.31)*	−0.210(−4.55)*	
$\Delta corn_{t-3}$	−0.088(−6.22)*	−0.163(−4.38)*	
Δbio_{t-1}	−0.227(−4.29)*	−0.177(−5.40)*	
Δbio_{t-2}	−0.162(−3.93)*	−0.142(−3.68)*	
Δbio_{t-3}	−0.133(−3.52)*	−0.159(−4.32)*	
Biofuel equation regime	**I (EC_{t-1}≤−4.55)**	**II (EC_{t-1}>−4.55)**	**Wald-test**
Constant	0.338 (0.37)	−0.541(−0.78)	[0.00]
EC_{t-1}	−0.151(−5.74)*	−0.166(−5.28)*	
$\Delta corn_{t-1}$	−0.277(−4.05)*	−0.428(−4.90)*	
$\Delta corn_{t-2}$	−0.160(−3.84)*	−0.274(−4.24)*	
$\Delta corn_{t-3}$	−0.105(−4.38)*	−0.181(−4.27)*	
Δbio_{t-1}	−0.271(−4.93)*	−0.238(−4.29)*	
Δbio_{t-2}	−0.185(−4.11)*	−0.129(−3.86)*	
Δbio_{t-3}	−0.129(−3.91)*	−0.107(−4.71)*	
Sugarcane equation regime	**I (EC_{t-1}≤−3.72)**	**II (EC_{t-1}>−3.72)**	**Wald-test**
Constant	−1.552(−1.13)	−1.008(−1.72)**	[0.02]
EC_{t-1}	−0.139(−4.84)*	−0.167(−5.41)*	
Δsc_{t-1}	−0.301(−4.71)*	−0.422(−5.06)*	
Δsc_{t-2}	−0.149(−4.06)*	−0.262(−4.09)*	
Δsc_{t-3}	−0.126(−5.36)*	−0.192(−4.23)*	
Δbio_{t-1}	−0.211(−3.84)*	−0.164(−4.33)*	
Δbio_{t-2}	−0.133(−3.66)*	−0.120(−3.82)*	
Δbio_{t-3}	−0.074(−3.61)*	−0.133(−4.71)*	
Biofuels equation regime	**I (EC_{t-1}≤−3.72)**	**II (EC_{t-1}>−3.72)**	**Wald-test**
Constant	−0.772(−0.92)	−1.338(−0.91)	[0.01]
EC_{t-1}	−0.342(−5.21)*	−0.396(−6.14)*	
Δsc_{t-1}	−0.334(−4.46)*	−0.449(−3.95)*	
Δsc_{t-2}	−0.201(−3.99)*	−0.338(−4.11)*	
Δsc_{t-3}	−0.183(−4.91)*	−0.152(−4.83)*	
Δbio_{t-1}	−0.297(−4.26)*	−0.271(−4.83)*	
Δbio_{t-2}	−0.155(−4.48)*	−0.133(−3.91)*	
Δbio_{t-3}	−0.104(−3.67)*	−0.121(−5.22)*	
Soybean oil equation regime	**I (EC_{t-1}≤−4.03)**	**II (EC_{t-1}>−4.03)**	**Wald-test**
Constant	−0.853(−0.74)	−1.237(−1.14)	[0.00]
EC_{t-1}	−0.172(−4.22)*	−0.241(−5.04)*	
$\Delta sboil_{t-1}$	−0.344(−5.31)*	−0.471(−5.46)*	
$\Delta sboil_{t-2}$	−0.171(−4.63)*	−0.281(−4.35)*	
$\Delta sboil_{t-3}$	−0.148(−4.82)*	−0.211(−4.71)*	
Δbio_{t-1}	−0.228(−4.13)*	−0.188(−4.52)*	
Δbio_{t-2}	−0.138(−3.91)*	−0.128(−4.02)*	
Δbio_{t-3}	−0.108(−4.16)*	−0.148(−4.46)*	
Biofuels equation regime	**I (EC_{t-1}≤−4.03)**	**II (EC_{t-1}>−4.03)**	**Wald-test**
Constant	−0.641(−0.74)	−1.109(−0.83)	[0.01]
EC_{t-1}	−0.156(−4.62)*	−0.183(−4.87)*	
$\Delta sboil_{t-1}$	−0.368(−4.72)*	−0.483(−4.55)*	
$\Delta sboil_{t-2}$	−0.243(−4.53)*	−0.384(−4.52)*	
$\Delta sboil_{t-3}$	−0.196(−4.53)*	−0.170(−4.94)*	
Δbio_{t-1}	−0.319(−4.64)*	−0.323(−4.46)*	
Δbio_{t-2}	−0.173(−4.77)*	−0.151(−4.05)*	
Δbio_{t-3}	−0.129(−4.12)*	−0.139(−4.82)*	
Sunflower oil equation	**I (EC_{t-1}≤−5.01)**	**II (EC_{t-1}>−5.01)**	**Wald-test**
Constant	−1.004(−0.63)	−1.127(−1.08)	[0.00]
EC_{t-1}	−0.136(−4.13)*	−0.175(−4.35)*	
$\Delta sfoil_{t-1}$	−0.284(−4.27)*	−0.328(−4.21)*	
$\Delta sfoil_{t-2}$	−0.127(−4.11)*	−0.214(−4.14)*	
$\Delta sfoil_{t-3}$	−0.094(−4.25)*	−0.127(−4.26)*	
Δbio_{t-1}	−0.213(−3.94)*	−0.136(−4.06)*	
Δbio_{t-2}	−0.125(−3.88)*	−0.113(−4.14)*	
Δbio_{t-3}	−0.102(−4.06)*	−0.088(−4.05)*	
Biofuels equation regime	**I (EC_{t-1}≤−5.01)**	**II (EC_{t-1}>−5.01)**	**Wald-test**
Constant	−0.557(−0.53)	−1.009(−0.77)	[0.00]

(*Contd...*)

Table 6: (*Continued*)

Biofuels equation regime	**I (EC_{t-1}≤−5.01)**	**II (EC_{t-1}>−5.01)**	**Wald-test**
EC_{t-1}	−0.142(−4.15)*	−0.166(−5.12)*	
$\Delta sfoil_{t-1}$	−0.305(−4.46)*	−0.349(−4.17)*	
$\Delta sfoil_{t-2}$	−0.221(−4.13)*	−0.251(−4.11)*	
$\Delta sfoil_{t-3}$	−0.136(−4.22)*	−0.152(−4.28)*	
Δbio_{t-1}	−0.285(−4.28)*	−0.287(−4.16)*	
Δbio_{t-2}	−0.146(−4.19)*	−0.148(−4.27)*	
Δbio_{t-3}	−0.107(−4.02)*	−0.104(−4.16)*	
Palm oil equation regime	**I (EC_{t-1}≤−3.34)**	**II (EC_{t-1}>−3.34)**	**Wald-test**
Constant	−0.573(−0.46)	−1.118(−1.21)	[0.00]
EC_{t-1}	−0.158(−4.59)*	−0.183(−4.71)*	
$\Delta poil_{t-1}$	−0.349(−4.38)*	−0.325(−4.43)*	
$\Delta poil_{t-2}$	−0.262(−4.25)*	−0.241(−4.21)*	
$\Delta poil_{t-3}$	−0.148(−4.19)*	−0.130(−4.09)*	
Δbio_{t-1}	−0.272(−4.16)*	−0.142(−4.15)*	
Δbio_{t-2}	−0.155(−3.95)*	−0.109(−4.36)*	
Δbio_{t-3}	−0.122(−4.47)*	−0.073(−4.11)*	
Biofuels equation regime	**I (EC_{t-1}≤−3.34)**	**II (EC_{t-1}>−3.34)**	**Wald-test**
Constant	−0.662(−0.73)	−1.127(−1.23)	[0.00]
EC_{t-1}	−0.234(−6.07)*	−0.328(−5.15)*	
$\Delta poil_{t-1}$	−0.289(−4.24)*	−0.302(−4.47)*	
$\Delta poil_{t-2}$	−0.231(−4.84)*	−0.216(−4.22)*	
$\Delta poil_{t-3}$	−0.157(−4.38)*	−0.162(−4.09)*	
Δbio_{t-1}	−0.263(−4.33)*	−0.283(−4.69)*	
Δbio_{t-2}	−0.171(−4.20)*	−0.156(−4.97)*	
Δbio_{t-3}	−0.116(−4.32)*	−0.129(−4.42)*	
Canelina oil equation regime	**I (EC_{t-1}≤−2.84)**	**II (EC_{t-1}>−2.84)**	**Wald-test**
Constant	−1.095(−0.91)	−1.084(−0.91)	[0.03]
EC_{t-1}	−0.145(−4.24)*	−0.211(−4.54)*	
$\Delta coil_{t-1}$	−0.295(−4.11)*	−0.311(−4.63)*	
$\Delta coil_{t-2}$	−0.188(−4.52)*	−0.209(−4.46)*	
$\Delta coil_{t-3}$	−0.126(−4.58)*	−0.152(−4.13)*	
Δbio_{t-1}	−0.255(−4.27)*	−0.142(−4.95)*	
Δbio_{t-2}	−0.163(−4.09)*	−0.120(−4.35)*	
Δbio_{t-3}	−0.137(−4.59)*	−0.094(−4.57)*	
Regime	**I (EC_{t-1}≤−2.84)**	**II (EC_{t-1}>−2.84)**	**Wald−test**
Constant	−0.904(−0.83)	−1.110(−1.13)	[0.01]
EC_{t-1}	−0.134(−4.14)*	−0.205(−4.54)*	
$\Delta coil_{t-1}$	−0.276(−4.17)*	−0.316(−4.37)*	
$\Delta coil_{t-2}$	−0.216(−4.83)*	−0.219(−4.96)*	
$\Delta coil_{t-3}$	−0.147(−4.66)*	−0.127(−4.28)*	
Δbio_{t-1}	−0.252(−4.13)*	−0.254(−4.68)*	
Δbio_{t-2}	−0.175(−4.28)*	−0.122(−4.37)*	
Δbio_{t-3}	−0.118(−4.29)*	−0.101(−4.09)*	
Sugar equation regime	**I (EC_{t-1}≤−3.15)**	**II (EC_{t-1}>−3.15)**	**Wald-test**
Constant	−0.548(−0.82)	−0.483(−0.48)	[0.00]
EC_{t-1}	−0.292(−5.61)*	−0.372(−5.82)*	
$\Delta sugar_{t-1}$	−0.448(−6.38)*	−0.384(−4.92)*	
$\Delta sugar_{t-2}$	−0.375(−5.93)*	−0.274(−5.27)*	
$\Delta sugar_{t-3}$	−0.268(−5.18)*	−0.226(−4.85)*	
Δbio_{t-1}	−0.362(−4.83)*	−0.276(−5.38)*	
Δbio_{t-2}	−0.285(−4.66)*	−0.204(−4.96)*	
Δbio_{t-3}	−0.235(−5.17)*	−0.148(−4.83)*	
Biofuels equation regime	**I (EC_{t-1}≤−3.15)**	**II (EC_{t-1}>−3.15)**	**Wald-test**
Constant	−0.749(−0.61)	−0.483(−0.92)	[0.00]
EC_{t-1}	−0.149(−5.55)*	−0.187(−6.31)*	
$\Delta sugar_{t-1}$	−0.294(−4.77)*	−0.376(−5.83)*	
$\Delta sugar_{t-2}$	−0.226(−4.52)*	−0.274(−4.93)*	
$\Delta sugar_{t-3}$	−0.178(−4.61)*	−0.227(−4.61)*	
Δbio_{t-1}	−0.283(−4.28)*	−0.281(−4.94)*	
Δbio_{t-2}	−0.192(−4.82)*	−0.225(−4.81)*	
Δbio_{t-3}	−0.137(−4.59)*	−0.214(−5.69)*	

Figures in parentheses denote t-statistics estimated using Eicker–White standard errors (Eicker, 1967; White, 1980), while those in brackets denote P values. The Wald test explores the null hypothesis of the equality of the two EC coefficients across the two regimes. **Denote significance at the 10% levels, respectively. TECM: Threshold error correction model

between energy and agriculture (Cooke and Robles, 2009). Based on the above discussion, we repeat the empirical analysis in terms of the following model:

$$\ln COM_t = b_0 + b_1 \ln BIO_t + b_2 \ln POIL_t + b_3 \ln E_t + v_t \quad (3)$$

Where POIL is the international oil prices, E is the US effective exchange rate index, and v is the new error term. The remaining variables are defined similarly to those in Equation (1). To avoid seasonality the oil prices are described through a MA(4) model, while the exchange rate through a MA(5) model.

Once again we begin with exploring the presence of non-linearities in relevance to model Equation (3). The new results are reported in Table 7 and they highlight that the null hypothesis that the relationship between biofuels and agricultural prices (across all agricultural products under study) is linear is rejected again.

In terms of testing for the number of relevant regimes, the new findings reported in Table 8 indicate (once again) the presence of two regimes versus the case of three regimes.

Following the identification of the number of regimes, we next test for unit root tests through non-linear TAR unit root tests. Table 9 reports the bootstrap P-values for threshold variables for delay parameters m from 1 to 8. The entries of the table are again P-values obtained using 10,000 bootstrap replications. The insignificance of such P-values indicates the presence of a unit root. The bootstrap P-values indicate that for the levels of all the variables under examination the no threshold effect hypothesis is strictly rejected in all cases, while for the variables in first differences, the bootstrap P-values are significant, implying that we should reject the null hypothesis of the unit root and accept stationarity of all the variables under study. According to the new results, the two new variables under examination are nonstationary in their levels across both regimes.

In the next level of the robustness analysis, we apply Saikkonen and Lütkepohl (2000a; 2000b; 2000c) cointegration tests that consider dummies with trend and intercept included into the cointegration relation. The null hypothesis of a no long-run relationship between biofuel prices and agricultural commodity prices is tested and the new results are reported in Table 10. The empirical results indicate that the null hypothesis of no cointegration is rejected at the 1% level of significance, thus, confirming the presence of a stable long-run relationship between biofuel prices, agricultural commodity prices, oil prices and the US real exchange rate. In other words, once again long-run biofuel prices and agricultural commodity prices move together, with biofuel prices being mutually interacted with the prices of the primary agricultural commodities used for the production of biofuels.

Finally, Table 11 provides estimates of a TECM across all non-energy (agricultural) commodity prices based on Hansen and

Table 7: Non-linearity tests (multivariate model)

Variables	v^2-statistic	P-value
corn	9.63	0.00
sc	11.58	0.00
sboil	9.81	0.00
sfoil	8.94	0.00
poil	7.62	0.00
coil	7.14	0.01
sugar	7.89	0.00

Table 8: Number of regimes tests (two vs. three regimes)-the multivariate model

Lag	Standardized residuals		Squared standardized residuals	
	Q*-statistic	P-value	Q*-statistic	P-value
corn				
5	0.083	0.81	0.019	0.88
sc				
3	0.047	0.88	0.015	0.94
sboil				
4	0.032	0.98	0	0.99
sfoil				
4	0.051	0.69	0.036	0.82
poil				
4	0.037	0.94	0.054	0.68
coil				
5	0.065	0.78	0.046	0.74
sugar				
4	0.043	0.91	0.022	0.94

Similar to Table 2

Table 9: Non-linear unit root tests (multivariate model)

Variable	m	t_1	t_2
poil	2	0.35	0.17
Δpoil	2	0.00	0.00
e	2	0.29	0.22
Δe	2	0.00	0.00

Similar to those in Table 3. Estimations stand for the inclusion of both constant and trend terms, m is the delay parameter, λ stands for the threshold variable, t_1 stands for the unit root test in regime 1, t_2 stands for the unit root test in regime 2

Table 10: Saikkonen and Lutkephol cointegration test results (multivariate model)

r_0	LR	P-value
corn		
0	52.47	0
1	1.06	0.69
sc		
0	58.72	0
1	1.13	0.71
sboil		
0	63.49	0
1	0.76	0.91
sfoil		
0	52.38	0
1	0.86	0.78
poil		
0	50.23	0
1	1.02	0.82
coil		
0	49.53	0
1	0.61	0.94
sugar		
0	50.48	0
1	1.17	0.64

Similar to those in Table 5

Table 11: Two-regime TECM results (multivariate model)

Corn equation regime	I (EC_{t-1}≤−4.16)	II (EC_{t-1}>−4.16)	Wald-test
Constant	−0.386 (−0.59)	−0.894 (−0.71)	[0.00]
EC_{t-1}	−0.115 (−4.62)*	−0.167 (−5.84)*	
$\Delta corn_{t-1}$	−0.310 (−4.19)*	−0.360 (−4.72)*	
$\Delta corn_{t-2}$	−0.106 (−4.12)*	−0.206 (−4.38)*	
Δbio_{t-1}	−0.211 (−4.05)*	−0.194 (−5.52)*	
Δbio_{t-2}	−0.108 (−3.58)*	−0.126 (−4.17)*	
$\Delta poil_{t-1}$	0.188 (−4.26)*	0.198 (−5.24)*	
$\Delta poil_{t-2}$	0.113 (−4.19)*	0.131 (−4.73)*	
Δe_{t-1}	−0.175 (−4.61)*	−0.190 (−5.62)*	
Δe_{t-2}	−0.116 (−4.38)*	−0.143 (−5.19)*	
Sugarcane equation regime	**I (EC_{t-1}≤−3.55)**	**II (EC_{t-1}>−3.55)**	**Wald-test**
Constant	−1.263 (−1.02)	−0.862 (−1.29)	[0.01]
EC_{t-1}	−0.125 (−4.42)*	−0.178 (−6.13)*	
Δsc_{t-1}	−0.274 (−4.66)*	−0.380 (−5.25)*	
Δsc_{t-2}	−0.161 (−4.52)*	−0.294 (−5.48)*	
Δsc_{t-3}	−0.101 (−4.61)*	−0.163 (−4.58)*	
Δbio_{t-1}	−0.238 (−4.46)*	−0.179 (−4.82)*	
Δbio_{t-2}	−0.151 (−4.27)*	−0.128 (−4.21)*	
Δbio_{t-3}	−0.115 (−3.93)*	−0.102 (−4.10)*	
$\Delta poil_{t-1}$	0.255 (−4.72)*	0.241 (−5.29)*	
$\Delta poil_{t-2}$	0.142 (−4.78)*	0.169 (−4.88)*	
$\Delta poil_{t-3}$	0.101 (−3.96)*	0.115 (−4.32)*	
Δe_{t-1}	−0.203 (−4.93)*	−0.199 (−4.95)*	
Δe_{t-2}	−0.142 (−4.75)*	−0.122 (−4.18)*	
Δe_{t-3}	−0.119 (−4.32)*	−0.095 (−4.53)*	
Soybean oil equation regime	**I (EC_{t-1}≤−3.78)**	**II (EC_{t-1}>−3.78)**	**Wald-test**
Constant	−0.639 (−0.46)	−0.915 (−0.82)	[0.00]
EC_{t-1}	−0.159 (−4.48)*	−0.236 (−5.42)*	
$\Delta sboil_{t-1}$	−0.317 (−5.14)*	−0.419 (−5.68)*	
$\Delta sboil_{t-2}$	−0.226 (−4.99)*	−0.315 (−5.50)*	
Δbio_{t-1}	−0.251 (−4.82)*	−0.197 (−4.68)*	
Δbio_{t-2}	−0.169 (−4.25)*	−0.130 (−4.26)*	
$\Delta poil_{t-1}$	0.184 (−4.68)*	0.191 (−5.11)*	
$\Delta poil_{t-2}$	0.116 (−4.12)*	0.113 (−4.74)*	
Δe_{t-1}	−0.203 (−5.15)*	−0.219 (−5.63)*	
Δe_{t-2}	−0.138 (−4.74)*	−0.152 (−4.90)*	
Sunflower oil equation regime	**I (EC_{t-1}≤−4.82)**	**II (EC_{t-1}>−4.82)**	**Wald-test**
Constant	−0.837 (−0.52)	−0.716 (−0.84)	[0.00]
EC_{t-1}	−0.149 (−4.48)*	−0.183 (−4.81)*	
$\Delta sfoil_{t-1}$	−0.260 (−4.35)*	−0.301 (−4.62)*	
$\Delta sfoil_{t-2}$	−0.171 (−4.30)*	−0.252 (−4.49)*	
Δbio_{t-1}	−0.234 (−4.41)*	−0.168 (−4.62)*	
Δbio_{t-2}	−0.157 (−4.19)*	−0.132 (−4.26)*	
$\Delta poil_{t-1}$	0.214 (−4.63)*	0.189 (−4.55)*	
$\Delta poil_{t-2}$	0.152 (−4.27)*	0.131 (−4.19)*	
Δe_{t-1}	−0.236 (−4.91)*	−0.249 (−4.84)*	
Δe_{t-2}	−0.149 (−4.30)*	−0.182 (−4.25)*	
Palm oil equation regime	**I (EC_{t-1}≤−3.19)**	**II (EC_{t-1}>−1.19)**	**Wald-test**
Constant	−0.438 (−0.62)	−0.874 (−0.95)	[0.00]
EC_{t-1}	−0.146 (−4.39)*	−0.192 (−4.65)*	
$\Delta poil_{t-1}$	−0.316 (−4.94)*	−0.359 (−5.16)*	
$\Delta poil_{t-2}$	−0.229 (−4.18)*	−0.236 (−4.70)*	
Δbio_{t-1}	−0.255 (−4.61)*	−0.239 (−4.72)*	
Δbio_{t-2}	−0.138 (−3.56)*	−0.127 (−4.12)*	
$\Delta poil_{t-1}$	0.218 (−5.20)*	0.247 (−4.92)*	
$\Delta poil_{t-2}$	0.157 (−4.39)*	0.163 (−4.71)*	
Δe_{t-1}	−0.244 (−5.01)*	−0.276 (−5.28)*	
Δe_{t-2}	−0.140 (−4.92)*	−0.158 (−4.49)*	

(*Contd...*)

Table 11: (*Continued*)

Canelina oil equation regime	I (EC_{t-1}≤−2.62)	II (EC_{t-1}>−2.62)	Wald-test
Constant	−0.914 (−0.75)	−0.826 (−0.83)	[0.01]
EC_{t-1}	−0.159 (−4.62)*	−0.204 (−5.16)*	
$\Delta coil_{t-1}$	−0.268 (−4.37)*	−0.291 (−4.75)*	
$\Delta coil_{t-2}$	−0.159 (−4.23)*	−0.211 (−4.18)*	
$\Delta coil_{t-3}$	−0.102 (−4.04)*	−0.119 (−3.84)*	
Δbio_{t-1}	−0.271 (−4.69)*	−0.246 (−4.53)*	
Δbio_{t-2}	−0.138 (−4.13)*	−0.147 (−4.14)*	
Δbio_{t-3}	−0.095 (−4.01)*	−0.115 (−4.26)*	
$\Delta poil_{t-1}$	0.292 (−4.94)*	0.303 (−5.14)*	
$\Delta poil_{t-2}$	0.182 (−4.47)*	0.182 (−4.52)*	
$\Delta poil_{t-3}$	0.124 (−4.30)*	0.128 (−4.65)*	
Δe_{t-1}	−0.284 (−4.92)*	−0.269 (−4.75)*	
Δe_{t-2}	−0.163 (−4.52)*	−0.179 (−4.48)*	
Δe_{t-3}	−0.099 (−4.13)*	−0.120 (−4.35)*	
Sugar equation regime	**I (EC_{t-1}≤−3.02)**	**II (EC_{t-1}>−3.02)**	**Wald-test**
Constant	−0.436 (−0.66)	−0.419 (−0.37)	[0.00]
EC_{t-1}	−0.261 (−5.14)*	−0.299 (−5.26)*	
$\Delta sugar_{t-1}$	−0.385 (−5.82)*	−0.419 (−5.96)*	
$\Delta sugar_{t-2}$	−0.286 (−5.14)*	−0.295 (−4.81)*	
Δbio_{t-1}	−0.355 (−4.48)*	−0.296 (−5.11)*	
Δbio_{t-2}	−0.263 (−4.19)*	−0.225 (−4.68)*	
$\Delta poil_{t-1}$	0.259 (−5.06)*	0.271 (−4.58)*	
$\Delta poil_{t-2}$	0.214 (−4.68)*	0.225 (−4.09)*	
Δe_{t-1}	−0.226 (−4.71)*	−0.248 (−4.52)*	
Δe_{t-2}	−0.178 (−4.19)*	−0.216 (−4.18)*	

Similar to those in Table 6. TECM: Threshold error correction model. *: significance at 1%

Seo (2002) methodological approach. To focus on the impact of biofuel prices on agricultural prices, the findings report only the estimations of the agricultural prices equations (the estimations for the remaining equations are available upon request).

Across all equations, the adjustment parameters are statistically significant, implying that biofuel energy prices, oil prices and the US real exchange rate drive agricultural prices toward the equilibrium level. Once again, the findings provide solid evidence that over the first regime period, the size of the EC coefficient indicates slower adjustment to long-run equilibrium vis-à-vis the EC coefficient over the second regime. In terms of the new control variables, oil prices are shown to exert a positive effect on agricultural prices, while a real appreciation of the dollar has a negative impact on those prices. These results are similar to those reached by Nazioglu and Soytas (2012). Overall, the findings from the multivariate model illustrate that the convergence process to long-run equilibrium is not uniform across both regimes, thus confirming the results from the bivariate model. However, now these findings include potential sources explaining the presence of such asymmetries, oil prices and a strong or a weak dollar, being the factors that drive biodiesel producers to change food prices when feedstocks become more or less expensive.

6. CONCLUSION

This empirical paper provided new empirical insights into the analysis of the causal relationships between biofuel energy prices and a number of commodity (agricultural) prices when considering a sample of daily prices.

A number of tests, able to capture the presence of any potential non-linearities, showed the presence of the non-linear nature of such price relations over the period under investigation. Threshold analysis displayed the presence of asymmetric movements in the prices between the two markets, supporting the role of a threshold defining two different regimes. In all cases, biofuel energy prices drive commodity prices, while the reverse is also true in the majority of the cases, to the long-run equilibrium. This non-linear association clearly documents that all commodity prices under examination are very vulnerable to biofuel energy price shocks compared to the past. At the same time, biofuel energy prices also receive influence from shocks occurring across all commodity markets used in this research paper. The results receive robust support from both a bivariate and a multivariate model in which both oil prices and the US real exchange rate are playing their own role in explaining the link between biofuels and agricultural prices.

The growth of the renewable (bio)fuels industry has had tremendous implications for agriculture commodity markets and opened up many new opportunities for agricultural commodity producers. In other words, our empirical findings highlighted the fact that agricultural policy makers need to consider the new role of agricultural crops and their new emerging role in forming the dynamics of biofuel energy prices. However, these new opportunities introduce new sources of risk as the market prices of agricultural commodities may become more dependent on fossil energy prices. Moreover, commodity oil traders and biofuel producers must reduce the risk associated with price fluctuations and, therefore, have to manage all different commodity oils (Liu, 2008).

A thorough understanding of the interrelationships among the prices of agricultural commodities and biofuel energy prices is essential for producers, policy makers and traders to make informed decisions. With respect to traders in international markets, the presence of our causality results imply informational benefits across markets that lead to stronger portfolio diversification, better forecasting ability, and, potentially, to higher profits. In addition, the increasing demand for biofuels is expected to stimulate the conversion of land-use from undisturbed ecosystem to biofuel-related crops, leading to higher levels of carbon debts, a fact expected to nullify the environmental benefit associated with renewable energy sources (Fargione et al., 2008). It is in association with this risk that has made the European Commission to propose a regulatory framework for biofuel, which exemplifies environmental sustainability along with biofuel production guidelines.

Moreover, the food inflation over the last years highlights the importance of a proactive inventory management policy as well as the need for mechanisms that usually compensate the poor when price increases reach abnormally high levels or alternatively tend to reduce spikes in prices. In that sense, the mechanisms essentially must adjust biofuel policies to any changes in food markets as well as to any changes in inventory management policies. In addition, agricultural supply should be further supported through a higher volume in research and development and mainly through the introduction of enhanced regulatory activities that allow the presence of more effective utilization of present technological approaches as well as more investments in outreach and infrastructure that lead to higher productivity, with the latter contributing to the deletion of food price spikes.

Finally, the asymmetric pattern we identified in the empirical section between biofuel energy and commodity prices is expected to play a substantial role in forming the properties of an efficient energy portfolio. In particular, even that non-renewable energy is cheaper vis-à-vis renewable energy, high non-renewable price fluctuations impose a risk on individuals as well as on societies. By contrast, the higher price stability with respect to renewable energy sources provides a clear benefit in forming less expensive energy portfolios (Awerbuch and Berger, 2003).

Far from being conclusive, this study allows us to open new research directions in the assessment of energy type policies and technological innovation in the energy sector. Future research should expand our analysis in terms of volatility. Further applications of this empirical framework could be the estimation of short and long-run causalities related to disaggregated sectors. Working with specific sectors allows the existence of divergent trends to be considered even in a quite homogeneous international commodity markets sample.

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APPENDIX

Appendix 1: Data description

Definition	Unit	Time span	
Biofuel energy prices (on a daily basis)			
Fame (seasonal biodiesel)	Liter	2007-2011	
Agricultural commodity prices (on a daily basis)			
Corn	US	US cents per bushel	2007-2011
Sugarcane (sc)	Brazil	US cents per pound	2007-2011
Soybean oil (sboil)	Dutch ports	$ per metric ton	2008-2011
Sunflower oil (sfoil)	EU (NW EU ports)	$ per metric ton	2008-2011
Palm oil (poil)	Malaysia (Rotterdam)	$ per metric ton	2007-2011
Camelina oil (coil)	Any origin	$ per metric ton	2007-2011
Sugar	Brazil	US cents per pound	2008-2011