Non-parametric and Parametric Modeling of Biodiesel - Sunflower Oil - Crude Oil Price Relationships

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Abstract
Multivariate local linear regression and parametric error correction models are applied to assess price linkages and price transmission patterns between food and energy prices in Spain. Weekly biodiesel, sunflower and crude oil prices observed from November 2006 to October 2010 are used in the empirical analysis. Results suggest the existence of a long-run equilibrium relationship between the three prices studied. Biodiesel is the only variable that adjusts to deviations from this long-run parity. Local linear regression techniques show that the speed of adjustment of biodiesel prices is higher when biodiesel is cheap than when it is expensive. Energy prices are also found to influence sunflower oil prices through the short-run price dynamics.

Key words: Price transmission, local linear regression, biodiesel, Spain

1. Introduction

The rapid growth in worldwide biofuel production over the last decade has been mainly motivated by an array of policies targeting different objectives such as the reduction of the energy dependence on fossil fuels, the diversification of energy supply sources, the promotion of economic development in rural areas, or the reduction of greenhouse gas emissions and other sources of environmental degradation (Rajagopal and Zilberman, 2007).

World biofuel market is dominated by biodiesel and ethanol. While ethanol is mainly produced by the US and Brazil, the EU is considered as the major producer of biodiesel in the world, representing about 65% of global output. Within the EU, Spain occupies the third position as the largest EU biodiesel producer behind Germany and France (EBB, 2010). While allowing to reduce foreign energy dependence, improve rural economies and achieve environmental goals, increased use and production of biofuels poses however important challenges. The major feedstocks in the biofuels industry are agricultural commodities that can be alternatively used to produce food. In Spain, for example, sunflower oil represents the most relevant raw material used for biodiesel production. The demand for sunflower oil to produce biodiesel directly competes with its use to produce food or animal feed. This raises social and political concerns about the relationship between food and energy prices. It is thus important to determine to what extent energy (biodiesel) markets have the potential to increase food (sunflower oil) prices.

Our paper sheds light on this issue. While previous literature has focused on studying price linkages and price transmission patterns between energy and feedstock markets in the US and Brazil (Balcombe and Rapsomanikis, 2008; Zhang et al., 2009; Serra et al., 2010 and 2011), European markets have not yet received any attention. This research aims at filling this gap in the literature by assessing the relationship between biodiesel, sunflower and crude oil prices in Spain, one of the most relevant biodiesel producers within Europe.

To achieve the aforementioned objective, two different time series models are considered. First, we estimate a parametric Vector Error Correction Model (VECM) that studies the short-run and long-run dynamics of price transmission among the markets studied. This parametric approach requires assumptions about the nature of price behavior that may be too restrictive and lead to misleading results. More specifically, VECM are based upon the assumption that price links are of a linear nature. In order to study to what extent the linearity hypothesis and the results obtained from the parametric VECM are reliable, a non-parametric model is also fit to the data. Unlike parametric methods, non-parametric techniques such as Multivariate Local Polynomial Regression (MLPR) methods, are data driven and do not require any assumption about the nature of price transmission. Thus, they are robust to misspecification issues. To our knowledge, no previous study has utilized non-parametric modeling to assess the relationships between energy and feedstock prices, which represents another important contribution of our work to the existing literature.

The rest of the paper is organised as follows. Section 2 presents an overview of the EU and the Spanish biodiesel industry. After offering a brief review of the literature, in section 4 we describe both the parametric and non-parametric methods used to assess the nature of price transmission. The results are discussed in section 5. Finally, the paper ends with the concluding remarks section.

2. The EU and the Spanish biodiesel industry

Recent increases in crude oil prices as well as the fact that oil reserves are limited, have been the main drivers for industrialized countries to promote alternative energy sources such as biofuels to diversify energy supplies, and thus reduce the dependency on fossil fuels. Biofuels are transportation fuels that are mainly produced from agricultural inputs. Biodiesel and ethanol are the most common biofuels utilized in the transportation section worldwide.

In the EU, biofuels have experienced a dynamic development over the recent years. Biofuel use for transportation in the EU grew by 30.3% between 2007 and 2008. In 2009, consumption continued to increase, but at less buoyant rate than in 2008 (18.7%). As a result, the share of biofuels in total EU consumption of road transportation fuels increased from 3.3% in 2008 to 4% in 2009. More specifically, in 2009 the EU consumption of biofuels reached almost 12.1 million tons of oil equivalent (toe), of which 9.6 million tons were biodiesel and 2.3 million tons were ethanol. The predominance of biodiesel is due to the relevance of diesel consumption in the EU compared to gasoline (EurObserv'ER, 2010).[2]

With a consumption of almost 1.05 million toe in 2009, of which 894 thousand toe were biodiesel and 152 thousand toe ethanol, Spain was the fourth most relevant EU consumer of biofuels, behind Germany, France and Italy. The biofuel consumption growth has mainly benefited biodiesel with an increase of almost 72% in 2009 compared to 2008.

The implementation of the EU biofuels policy, which aimed at replacing, by the end of 2010, 5.75% of the non-renewable energy used in transportation by biofuels (Directive 2003/30 EC), as well as the recent increases in crude oil prices, have positively affected the development of the EU biofuels industry, motivating the increase of both EU biofuels production and production capacity. The expansion has been specially evident in the biodiesel industry.

The EU biodiesel industry plays a major role both at EU and at the international levels, in terms of production and production capacity. According to the European Biodiesel Board (EBB, 2009), EU biodiesel production capacity increased from 16 million tons to 21 million tons between 2008 and 2009 (a 31% increase). In spite of the progress made, the EU industry remains uncompetitive in relation to the American and Brazilian industries, that show much lower production costs. The low price of the biodiesel imported from the US causes significant damage to the EU biodiesel industry, particularly in terms of profitability and return on investments. To face up to increasing international competition and to equilibrate markets, duties on imports of US biodiesel were applied in 2009.

Nowadays, the EU is considered as the biggest producer of biodiesel in the world, representing about 65% of worldwide output (EBB, 2010). Biodiesel production rose by 16.6% (9 million tons) between 2008 and 2009, against 35.7% (7.7 million tons) between 2007 and 2008 and 54% (5.7 million tons) between 2006 and 2007, leaving almost half of the production capacity unused. In 2009, biodiesel represented almost 75% of the biofuels produced in the EU. Despite biodiesel production being below production capacity, the EU's renewable energy policy that aims to ensure that fuels sold in the EU contain a minimum 20% of renewable energy by 2020, as well as the duties against US biodiesel imports, are expected to positively affect the EU biofuels industry.

In Spain, according to the EBB (2010), biodiesel production increased from 207 thousand tons in 2008 to 859 thousand in 2009, representing the third largest biodiesel production in the EU after Germany and France. Currently, there are 46 biodiesel production plants in Spain with a total production capacity of over 4.2 million tons, leaving almost four fifths of the production capacity unused (APPA, 2010a). The excess production capacity can be mainly explained by the expectations created by the Directive 2003/30 EC (APPA, 2010b). In contrast to the EU, where the majority of the biodiesel is produced from rapeseed oil, sunflower oil constitutes the major feedstock of the biodiesel industry in Spain.

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[2] Unless otherwise indicated, the information presented in this section was obtained from EurObserv'ER (2010).

In 2009, the Spanish oilseed production registered an increase of 5% reaching 886 thousand tones, of which 851 thousand were sunflower oil, 32 thousand rapeseed oil and 3 thousand soybean oil, respectively (Agrocope, 2009). The area used to produce oilseeds in 2009 increased by 15%, representing 871 thousand hectares, of which, 852 thousand hectares were used for sunflower production (Alimentación en España, 2009).

The recent rapid growth in biodiesel production registered in the EU and in Spain have raised concerns about the impact that biodiesel can have on agricultural commodity prices. In this paper, we focus on assessing the links between food and energy prices within the Spanish biodiesel industry.

3. Literature review

Even though a large number of studies and reports on biofuels have been made available recently, the literature that empirically assesses the dynamic relationships between energy and commodity prices is relatively poor. A few notable studies on this topic are reviewed below. Balcombe and Rapsomanikis (2008) examine the nature of the relationships between crude oil, ethanol and sugar prices in Brazilian markets. A Bayesian approach is used in order to test for non-linear price-adjustments. They find that oil prices are the main drivers of both sugar and ethanol prices. Specifically, they show that a causal hierarchy runs from oil to sugar and to ethanol, and that non-linearities characterize price adjustment processes of sugar and ethanol prices to the oil price.

Zhang et al. (2009) investigate the impact that ethanol markets have on price levels and volatilities of agricultural commodities in the US. In doing so, they use cointegration, vector error correction and Multivariate Generalized Autoregressive Conditional Heteroskedascity (MGARCH) models. Their results indicate that although short-run links exist, no long-run links between fuel and food prices exist.

Serra et al. (2010) utilize a Smooth Transition Vector Error Correction Model (STVECM) in order to study the relationships among oil, ethanol, gasoline and corn prices within the US market. They find two equilibrium relationships between the four prices studied. Adjustment towards long-run equilibrium is found to occur in a non-linear fashion. Serra et al. (2010) further find that an increase in energy prices increases corn prices, being the ethanol market the main responsible for the strong link between food and energy prices.

The analysis by Serra et al. (2011) studies how price volatility in the Brazilian ethanol industry changes over time and across markets. Seo's (2007) maximum likelihood approach is used for such purpose, which allows estimating a VECM and a MGARCH model jointly. Their results suggest a strong link between food and energy markets, both in terms of price levels and volatility.

The literature review presented above shows that the dynamic links between food and energy markets have been mainly assessed for the major ethanol markets in the world, i.e., Brazil and the US. Emergent biofuel markets in Europe have, however, been ignored. Our paper aims at filling this gap in the literature by focusing on Spain, a relevant biofuel market within Europe.

Unlike the existing literature, which reveals that the analyses of the dynamic relationships among energy and agricultural commodity prices have been typically based on parametric models, we are interested in studying the relationships between biodiesel, sunflower and crude oil prices in Spain by using multivariate local polynomial regression (non-parametric) models, which represents another contribution of our work to the literature. Non-parametric techniques are data-driven methods that do not require any assumptions about the functional form characterizing price behavior and are thus robust to misspecification issues (Fan and Gijbels, 1996; Li and Racine, 2007). The results of non-parametric techniques are compared with the ones derived from a parametric VECM.

4. Methodology

As previously mentioned, in this paper we study the relationships between biodiesel, sunflower and crude oil prices in Spain. To do so, we use both a parametric VECM and a non-parametric MLPR model and compare the results obtained from both models. An interesting issue is the complementarity between non-parametric and parametric techniques. Specifically, MLPR and VECM can be applied to similar situations, but they serve different analytical purposes. While the parametric approach focuses on estimating and making inferences on the parameters of the model, MLPR concentrates on exploring data non-parametrically, which can help visualize data effects and can thus be considered as a powerful tool for data exploration and feature discovery that might otherwise be missed. It is thus interesting to apply both parametric and non-parametric techniques. Below we present the details of both techniques.

4.1 Vector Error Correction Model

Myers (1994) explains that price series have different common characteristics that are important for sound statistical analysis. Two of these characteristics are especially relevant to our analysis. First, individual commodity price series generally contain stochastic trends and are non-stationary. Second, commodity prices may tend to move together over time. In other words, though individual price series may be non-stationary, price series of interrelated markets are likely to contain the same stochastic trends. Hence, the co-movements of these variables may prove to be stationary. Co-movements among non-stationary prices are known in the econometrics literature through the concept of cointegration. VECM allow assessing both short-run price dynamics and the adjustment of individual prices to deviations from the cointegration relationship.

Assume that equation (1) represents the cointegration relationship between the prices studied:

$$P_{B,t} - \beta P_{S,t} - \beta P_{C,t} = v_t \tag{1}$$

Where $P_{B,t}$, $P_{S,t}$, $P_{C,t}$ are the prices of biodiesel, sunflower oil and crude oil at time *t*, respectively and v_t represents the deviation from the equilibrium relationship, i.e., the error correction term. Once the three series are found to be cointegrated, and following Engle and Granger (1987), a VECM can be expressed as follows:

$$\begin{aligned}
\Delta P_{B,t} &= \alpha_1 + \lambda_B v_{t-1} + \sum_{i=1}^{n} \alpha_{11}(i)\Delta P_{B,t-i} + \sum_{i=1}^{n} \alpha_{12}(i)\Delta P_{S,t-i} + \sum_{i=1}^{n} \alpha_{13}(i)\Delta P_{C,t-i} + \varepsilon_{P_{B,t}} \\
\Delta P_{S,t} &= \alpha_2 + \lambda_S v_{t-1} + \sum_{i=1}^{n} \alpha_{21}(i)\Delta P_{B,t-i} + \sum_{i=1}^{n} \alpha_{22}(i)\Delta P_{S,t-i} + \sum_{i=1}^{n} \alpha_{23}(i)\Delta P_{C,t-i} + \varepsilon_{P_{S,t}} \\
\Delta P_{C,t} &= \alpha_3 + \lambda_C v_{t-1} + \sum_{i=1}^{n} \alpha_{31}(i)\Delta P_{B,t-i} + \sum_{i=1}^{n} \alpha_{32}(i)\Delta P_{S,t-i} + \sum_{i=1}^{n} \alpha_{33}(i)\Delta P_{C,t-i} + \varepsilon_{P_{C,t}}
\end{aligned} \tag{2}$$

where Δ is a first difference operator; $\varepsilon_{P_{B,t}}$, $\varepsilon_{P_{S,t}}$ and $\varepsilon_{P_{C,t}}$ are white noise disturbances; v_{t-1} is the lagged error correction term, the alphas are all short-run dynamics parameters; and λ_B, λ_S and λ_C, known as the speed of adjustment parameters, measure the rate at which prices adjust to disequilibria from the long-run equilibrium relationship. It is important to note that all the variables in the VECM are stationary.

Parameters λ_B, λ_S and λ_C offer particularly valuable information and should not be simultaneously equal to zero. In particular, at least one of the speed of adjustment terms must be nonzero for the long-run equilibrium relationship between prices to exist. If λ_B, λ_S and λ_C are all equal to zero, the long-run equilibrium relationship does not exist. Nevertheless, it is possible to find only one of the speed of adjustment parameters to be significantly different from zero, indicating that there is only one price that does all the adjustment towards the long-run parity. The VECM can be estimated by the seemingly unrelated regressions technique.

Before estimating the VECM, standard unit root and cointegration tests were conducted in order to determine whether price series are stationary and whether they are cointegrated, respectively. In particular, standard Dickey and Fuller (1979) tests, their augmented version and

Perron tests (1997) were applied to each price series. Johansen (1988) test for cointegration was then used to evaluate long-run price links.

4.2 Multivariate local polynomial fitting

Though parametric models are the workhorse of applied data analysis, they require specifying the exact functional form of the model prior to estimation. A parametric model that is not exactly specified leads to misleading results. Non-parametric regression models do not impose any restriction on the functional form and thus allow exploring the data in a more flexible way. Local polynomial techniques are widely used to estimate regression functions in a non-parametric fashion, where data are segmented into small overlapping sections (Fan and Gijbels, 1996).

To formally study the relationship between biodiesel, sunflower and crude oil prices in Spain, we apply a multivariate local polynomial regression to estimate a non-parametric version of the VECM. Three non-parametric error correction equations are estimated, one for each equation in the VECM. Consider a set of scatter points $(Y_t, \mathbf{X}_{t-1})$ for $t = 1,...,n$ from a population $(Y, \mathbf{X}_{-1})$, where $Y_t = \Delta P_{it}$, $Y_t \in \mathbb{R}$, represents price *i* in first differences, *i*= *B*, *S*, *C* is an index representing biodiesel, sunflower oil and crude oil respectively, and $\mathbf{X}_{t-1} = (\Delta P_{Bt-1}, \Delta P_{St-1}, \Delta P_{Ct-1}, v_{t-1})$, $\mathbf{X}_{t-1} \in \mathbb{R}^d$ is a vector containing lagged price differences of biodiesel, sunflower and crude oil prices, and the lagged error correction term, being $d = 4$. Of interest is to estimate the multivariate non-parametric regression problem $m(\mathbf{x}_k) = E(Y_t \mid \mathbf{X}_{t-1} = \mathbf{x}_k)$.

The main idea behind local fitting is to estimate function m at point $\mathbf{x}_k$, i.e. $\hat{m}(\mathbf{x}_k)$, using the observations that are relatively close to $\mathbf{x}_k$. To estimate the whole function $\hat{m}(\mathbf{X}_{t-1})$, the process described in the previous sentence is then repeated for a number of grid values of $\mathbf{X}_{t-1}$ (Serra et al., 2006). Since function $m(\mathbf{x}_k)$ is not specified, a Taylor expansion is used to approximate it by a simple polynomial model:

$$m(\mathbf{x}) \approx \sum_{j=0}^{p} \boldsymbol{\beta}_j^{'} (\mathbf{x} - \mathbf{x}_k)^j \tag{3}$$

where local parameter vector $\boldsymbol{\beta}_j = m^{(j)}(\mathbf{x}_k)/j!$ depends on $\mathbf{x}_k$. The $m^{(j)}$ is the jth derivative of function m. Previous literature argues that odd order polynomial fits are preferable to even order polynomial fits. Moreover, several authors recommend choosing a polynomial of order $p = 1$, which leads to the Multivariate Local Linear Regression Estimator (MLLRE), an estimator that has been shown to provide adequate smoothed points and computational ease (Cleveland, 1979).

The observations with most information about $m(\mathbf{x}_k)$ should be those at locations closest to $\mathbf{x}_k$ compared with remote points. Weighted least squares is used to give more weight to neighborhood observations than to more distant ones. Weights are assigned through kernel functions as follows:

$$\sum_{t=1}^{n} (Y_t - \beta_0 - \boldsymbol{\beta}_1^{'}(\mathbf{X}_{t-1} - \mathbf{x}_k))^2 K_{\mathbf{h}}(\mathbf{X}_{t-1} - \mathbf{x}_k) \tag{4}$$

where $K_{\mathbf{h}}(\mathbf{X}_{t-1} - \mathbf{x}_k) = \prod_{j=1}^{d} K\left(\frac{X_{j,t-1} - x_{j,k}}{h_j}\right) h_j^{-1}$ is a multivariate multiplicative kernel function assigning weights to each datum point and $K\left(\frac{X_{j,t-1} - x_{j,k}}{h_j}\right)$ is a univariate kernel function. The bandwidth h_j controls for the size of the local neighborhood (Fan and Gijbels, 1996) and is equal to $h_j = h_{base} s_x n,^{-1/5}$ where s_x is the standard deviation of the covariate and n is the number of observations (Serra and Goodwin, 2009). The local linear estimate of $m(\mathbf{x}_k)$ is $\hat{\beta}_0$, while the gradient vector $m'(\mathbf{x}_k)$ is $\hat{\boldsymbol{\beta}}_1$.

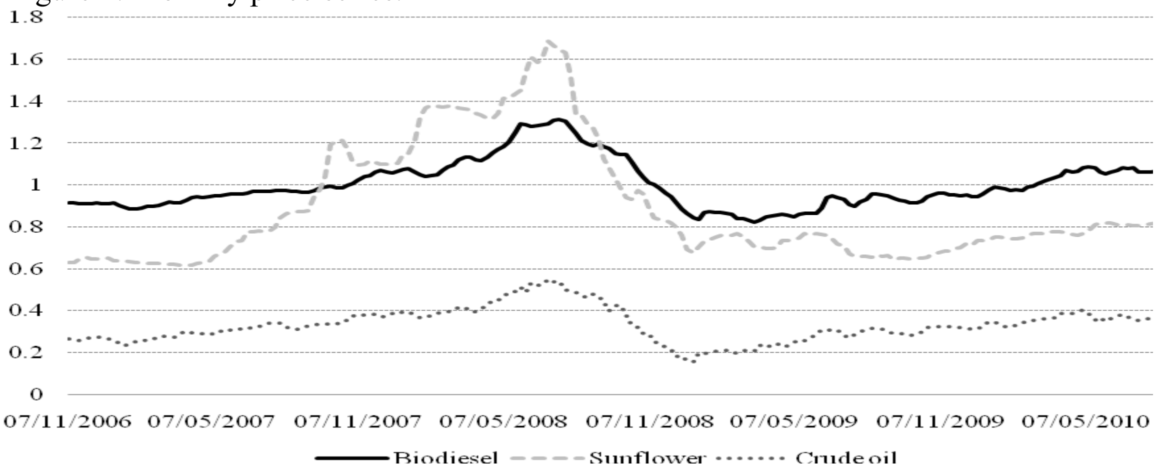
Previous literature argues that selecting an appropriate bandwidth is a key issue of multinomial local polynomial fitting. Specifically, selecting a large bandwidth may lead to an important modeling bias, while selecting a small bandwidth may result in noisy estimates. In order to find a balance in the bias-variance trade-off, we select an optimum constant base bandwidth h_{base} using the least squares cross-validation method. This commonly used method (Fan and Gijbels, 1996; Li and Racine, 2007) determines a smoothing bandwidth matrix that leads to the minimization of the squared prediction error: $\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2$. In our analysis and following Kumbhakar et al. (2007), the predicted values for Y_t are obtained using the leave one out version of the local linear estimator.[3] We refer to the authors for further details.

Another issue in multivariate local polynomial fitting is the choice of the kernel function. Fan and Gijbels (1996) argue that the choice of the kernel function is less crucial since the modeling bias is primarily controlled by the bandwidth. However, they recommend using the Epanechnikov kernel which is shown to be an optimal weight function.

5. Results

Our empirical analysis utilizes weekly prices for refined sunflower oil, biodiesel and crude oil observed from November 7, 2006 to October 5, 2010, giving a total of 205 observations. Sunflower, biodiesel and crude oil prices are expressed in euros per 100 kg, euros per litter and dollars per barrel, respectively. Data on refined sunflower oil prices were taken from the Spanish Ministry of the Environment and Rural and Marine Affairs (2010), biodiesel prices were obtained from the Spanish Ministry of Industry, Tourism and Trade (2010) and crude oil prices from the US Energy Information Administration (2010) data set. Crude oil prices were converted into euros per liter using the European Central Bank (ECB, 2010) exchange rates. Sunflower oil prices were also converted into euros per kg. Price series used in our analysis are presented in Figure 1.

Figure 1. Monthly price series.



Logarithmic transformations of the price series were used in the empirical analysis. A preliminary analysis of the time series data was carried out to assess their characteristics. In

[3] This method has been used by Kumbhakar et al. (2007) and Serra and Goodwin (2009) in a multivariate framework.

particular, standard augmented Dickey and Fuller (1979) and Perron tests (1997) were applied to each price series in order to determine whether or not they have a unit root. Results confirm the presence of a unit root in all price series.[4]

Johansen's (1988) method was then applied in order to test for log-run links among the prices studied. Results suggest the existence of a single cointegration relationship between sunflower oil and the energy price series (see Table 1). As will be seen below with the results of the VECM, sunflower and crude oil prices are weakly exogenous for long-run parameters, which implies that they do not react to deviations from the long-run parity. Only the biodiesel price responds to deviations from this parity. Hence, the cointegration relationship should be interpreted as the parity that biodiesel prices should maintain with sunflower and crude oil prices for the Spanish biodiesel industry to be in equilibrium. Long-run relationships between crude oil, ethanol and feedstock prices in the US and Brazil have been identified by Balcombe and Rapsomanikis (2008), Serra et al. (2010) and Serra et al. (2011), respectively.

Table 1. Johansen λ_{trace} test for cointegration and cointegration relationship.

Ho	Ha	λ_{trace}	P-value
$r=0$	$r>0$	121.461	0.000
$r\leq 1$	$r>1$	12.211	0.443
$r\leq 2$	$r>2$	1.798	0.811
Cointegration relationship (standard errors in parenthesis)			
$P_B-0.079^{**}P_S-0.398^{**}P_C-0.465^{**}=Ect$			
(0.019) (0.020) (0.021)			

Note: r is the cointegration rank.
** denotes statistical significance at the 5 % level.

The cointegration relationship suggests a positive correlation in the long-run between biodiesel and sunflower and crude oil prices. More specifically, the cointegration relationship suggests that an increase in crude oil (sunflower oil) prices on the order of 10% will be followed by an increase in biodiesel prices on the order of 4% (0.8%). The positive relationship between biodiesel and sunflower oil prices is expected, given that feedstock costs represent a considerable part of biodiesel production costs. Feedstock costs are specially relevant within the Spanish biodiesel industry, that has higher production costs than other more competitive industries such as the US industry. The imposition by the EU countries of import duties on US biodiesel imports in 2009 may contribute to perpetuate the lack of competitiveness of the Spanish market. The long-run positive link between biodiesel and crude oil prices is not surprising either and is due to the fact that biodiesel is not usually used in pure form, but blended with petroleum diesel that comes from refined crude oil.

Results derived from the VECM estimation are presented in Table 2. The coefficients showing price adjustments to the long-run parity suggest that while biodiesel prices adjust to correct disequilibriums from this parity, sunflower and crude oil prices do not adjust. The biodiesel price is thus the only variable that responds to deviations from the biodiesel, sunflower oil and crude oil prices long-run equilibrium and moves to re-equilibrate the price system (-6.7%). These results are not surprising and are compatible with previous research (Balcombe and Rapsomanikis, 2008; Serra et al., 2011). Further, parameter estimates show that crude oil prices have the capacity to influence biodiesel prices not only through the long-run price dynamics, but also through the short run price links. While energy prices are not found to influence sunflower prices through the long-run parity, they have the capacity to increase sunflower oil prices through the biofuel market by means of short-term price dynamics.

[4] Results are available from the authors upon request.

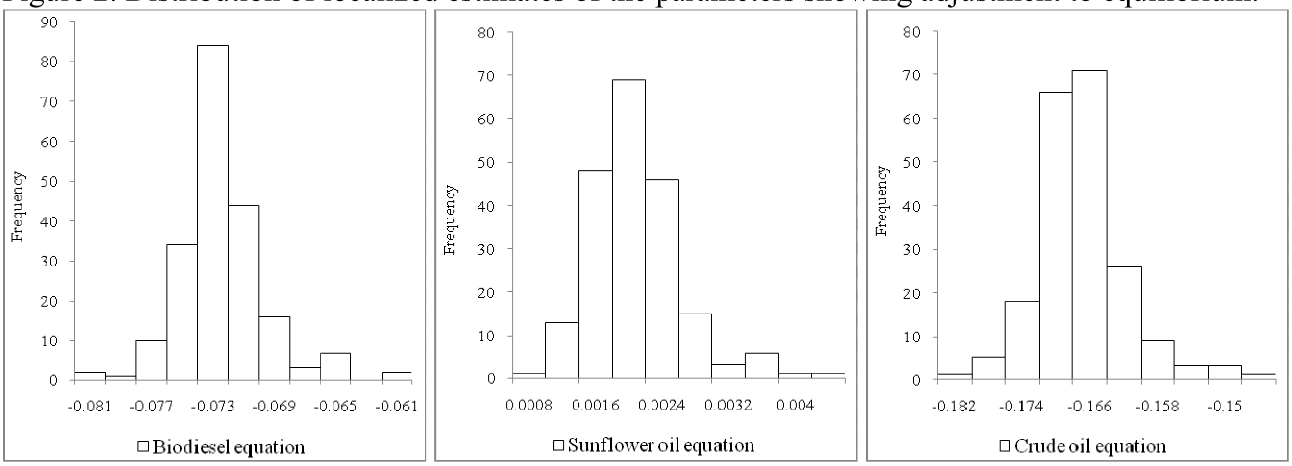
Table 2. Estimation of the Vector Error Correction Model.

Dependent variable	Biodiesel price equation	Sunflower oil price equation	Crude oil price equation
ΔLP_{Bt-1}	0.293**(0.453)	0.335** (0.149)	-0.061(0.270)
ΔLP_{St-1}	0.000 (0.019)	0.452** (0.064)	0.171(0.115)
ΔLP_{Ct-1}	0.157**(0.014)	0.030 (0.046)	0.057(0.084)
Constant	-0.000 (0.000)	0.001 (0.002)	0.000(0.003)
v_{t-1}	-0.067**(0.017)	0.003 (0.056)	-0.167(0.102)

Notes: Numbers in parentheses are standard errors.
** denotes statistical significance at the 5 per cent level.

The VECM imposes a linear adjustment of the variables being studied. However, the existing literature on price transmission within biofuel markets has generally allowed for and confirmed the existence of nonlinear price adjustments. Unlike parametric methods, non-parametric regression models are data driven and thus do not make any assumption about the functional form characterizing price links. Multivariate local linear regression is then applied in order to determine whether price dynamics are linear or whether they would be best modelled using a different functional form. The most relevant results are graphed in Figure 2. The figure shows the variation of the local estimates of the parameters representing the adjustment of biodiesel, sunflower and crude oil prices to deviations from the long-run parity.[5] Non-parametric results suggest a relatively small variation of parameter estimates, thus supporting the existence of linear price adjustments as modeled by the parametric model. This conclusion is further supported by the fitting of a smooth transition vector error correction model (STVECM) to the data (Luukkonen et al., 1988; Teräsvirta, 1994) that showed that the speed of transition parameter is not statistically different from zero.[6]

Figure 2. Distribution of localized estimates of the parameters showing adjustment to equilibrium.



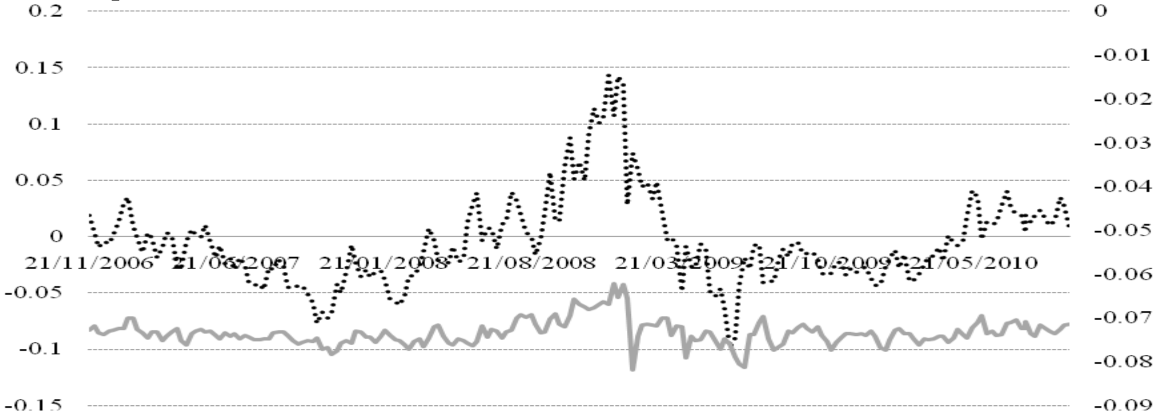
We now focus on the discussion of the parameter showing the adjustment of the biodiesel price to the long-run equilibrium relationship, as the adjustment of the sunflower and crude oil prices was not found to be statistically significant. Non-parametric results indicate that biodiesel price responses to long-run disequilibriums, can range from 6.1% to 8.1%. Figure 3 shows that the magnitude of the adjustment depends on the magnitude and sign of the disequilibrium. In general, when the error correction term is positive, the biodiesel price rate of adjustment to long-run equilibrium is on the order of almost 6%. The response is quicker, almost 8%, when the error

[5] Results of localized short-run parameters are available from the authors upon request.

[6] Results are available upon request.

correction term values are lower than zero. These different responses in biodiesel prices are found to have very important implications for market equilibrium. Positive values of the error correction term involve that biodiesel is too expensive and thus that its price has to decline for the market equilibrium to be maintained. Conversely, negative error correction values imply that the biofuel is too cheap and its price should be increased. Hence, shocks that increase biodiesel prices will trigger quicker responses than shocks that reduce biodiesel prices.

Figure 3. Evolution over time of the error correction term and the parameter showing adjustment of biodiesel price to this term.



Notes: The error correction term v_{t-1} is represented by the continuous silver line and is plotted on the left-hand side axis. The error correction parameter, presented by the doted black line, is plotted on the right-hand side axis.

Given the reliability of the parametric VECM model as shown by the small variation of localized parameter estimates, and to better understand the dynamic relationships between biodiesel, sunflower and crude oil prices, an impulse response analysis is conducted. Impulse Response Functions (IRFs) provide useful information by illustrating the evolution over time of the response of one variable to a shock in another variable in the system (see Lütkepohl, 2005). Since sunflower and crude oil markets are exogenous with respect to the error correction term, only the IRFs showing the biodiesel price adjustment to system shocks are presented. Figures 4 and 5 illustrate the results of simulating biodiesel price responses to a positive one standard deviation shock to the crude and sunflower oil prices, respectively. Figure 4 shows that an increase in crude oil prices generates a response in the biodiesel price in the same direction. The response increases during the first two weeks following the shock and decreases thereafter, disappearing after about 8 weeks. A positive sunflower oil price shock is also seen to induce an increase in the biodiesel price. This increase gains strength during the first 3 weeks and shrinks thereafter, disappearing after about 12 weeks (see Figure 5). Hence, biodiesel producers pass on an increase in feedstock costs more slowly than an increase in the price of crude oil.

Figure 4. Biodiesel response to a positive one standard deviation shock to the crude oil price.

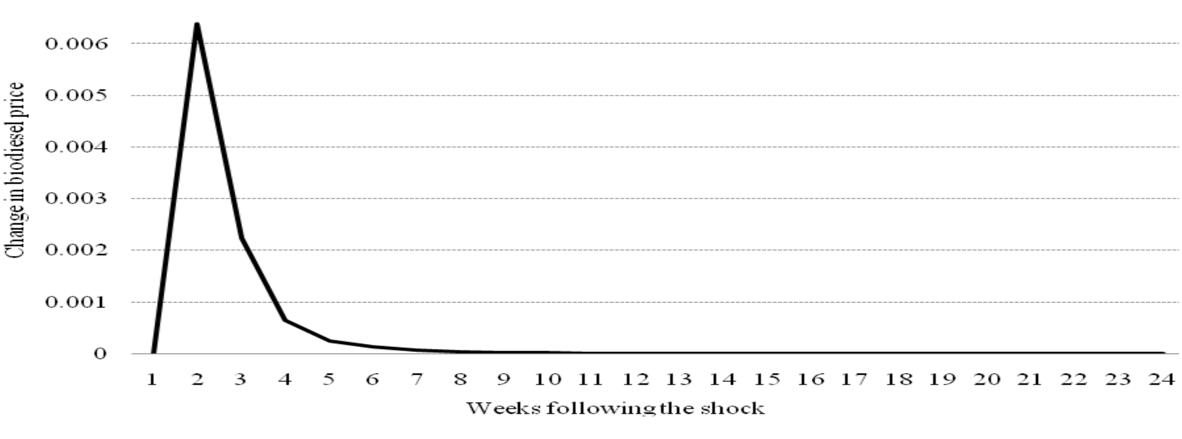
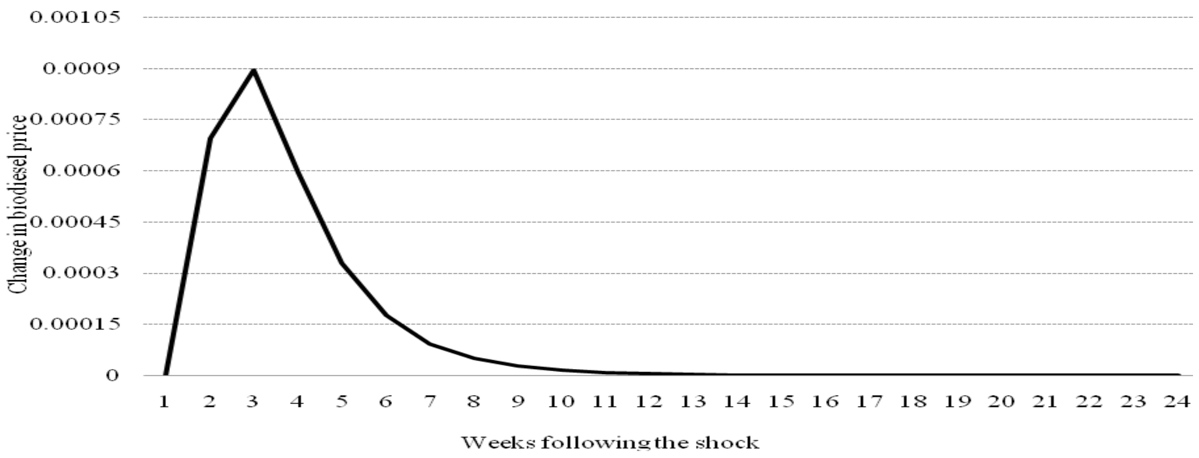


Figure 5. Biodiesel response to a positive one standard deviation shock to the sunflower oil price.



6. Concluding remarks

Recent increases in biofuel production to reduce the dependence on crude oil, diversify energy supplies, support rural economies and reduce greenhouse gas emissions, have generated social and political concerns with regards to the links between energy and food price levels. Currently, food inputs represent the main feedstocks used in biofuel production. In this paper we shed light on this issue by assessing price linkages and price transmission patterns between biodiesel, sunflower and crude oil prices in Spain.

To achieve the aforementioned objective, a parametric vector error correction model and its multivariate local polynomial version are estimated and compared. To the best of our knowledge, no previous study has utilized non-parametric modeling to assess the relationships between energy and feedstock prices, which represents a contribution of our research to previous literature. Weekly world crude oil prices, and Spanish biodiesel and sunflower oil prices observed from November 2006 to October 2010 are used.

Cointegration tests provide evidence of a single long-run equilibrium relationship between biodiesel, sunflower and crude oil prices. This cointegration relationship suggests a positive correlation between biodiesel and sunflower and crude oil prices. Results obtained from the parametric VECM provide evidence that biodiesel is the only variable that adjusts to deviations from the long-run equilibrium relationship. This finding is expected and is compatible with previous research (Balcombe and Rapsomanikis, 2008; Serra et al, 2011). Multivariate local linear regression shows that the speed of this adjustment will be larger when biodiesel is too cheap than when it is too expensive. Variation in the local estimates of the VECM parameters is however small, which provides evidence that price adjustments are well represented by a linear model. Generalized impulse response functions suggest that shocks to both sunflower and crude oil prices cause changes in biodiesel prices in the same direction.

References

Agrocope, 2009. La producción de oleaginosas aumentará un 7%. Accessed December 2010, available at http://www.agrocope.com/noticias.php?id=102858&comu=&ztipo= .

Alimentacíon en España, 2009. Principales resultados macroeconómicos de la agricultura y la ganadería en 2009. Accessed January 2011, available at http://www.munimerca.es/mercasa/alimentacion_2010/pdfs/pag_028-033_02-01_resultados.pdf .

APPA, 2010a. El 75% de las plantas españolas de biodiésel están paradas, mientras una avalancha de importaciones argentinas inunda el mercado. Accessed December 2010, available at http://www.appa.es/descargas/Biocarburantes-Situacion_Biocarburantes_Espana-Julio2010.pdf .

APPA, 2010b. El Congreso de los Diputados aprueba la obligación de biocarburantes para España. Accessed January 2011, available at http://www.appa.es/descargas/prensa/Congreso_Diputados.pdf .

Balcombe, K. and Rapsomanikis, G., 2008. Bayesian estimation of nonlinear vector error correction models: the case of sugar-ethanol-oil nexus in Brazil. *American Journal of Agricultural Economics* 90 (3), 658-668.

Cleveland, W.S., 1979. Robust locally-weighted regression and smoothing scatterplots. *Journal of American Statistical Association* 74, 829-836.

Dickey, D.A. and Fuller, W.A., 1979. Distribution of the estimators for autoregressive time Series with a unit root. *Journal of the American statistical Association* 74, 427-431.

Engle, R.F. and Granger, C.W.J., 1987. Co-integration and error correction: representation, estimation and testing. *Econometrica* 55, 251-276.

EurObserv'ER, 2010. Biofuels Barometer. Accessed December 2010, available at http://www.eurobserv-er.org/pdf/baro198.pdf .

European Biodiesel Board (EBB), 2009. Press Release. Accessed December 2010, available at http://www.ebb-eu.org/EBBpressreleases/EBB%20press%20release%202008%20prod%202009%20cap%20FINAL.pdf .

European Biodiesel Board (EBB), 2010. Press Release. Accessed December 2010, available at http://www.ebb-eu.org/EBBpressreleases/EBB%20press%20release%202009%20prod%202010_capacity%20FINAL.pdf .

European Central Bank (ECB), 2010. Dataset. Accessed October 2010, available at http://www.ecb.int/home/html/index.en.html .

Fan, I. and Gijbels, I., 1996. *Local Polynomial Modeling and Its applications*. London, UK: Chapman and Hall.

Hansen, H. and Johansen, S., 1999. Some tests for parameter constancy in cointegrated VAR-models. *Econometrics Journal* 2, 306-333.

Johansen, S., 1988. Statistical analysis of cointegration vectors. *Johansen of Economics Dynamics and Control* 12, 231-254.

Kumbhakar, S.C., Park, B.U., Simar, L. and Tsionnas. E.G., 2007. Nonparametric stochastic frontiers: A local maximum likelihood approach. *Journal of Econometrics* 137, 1-27.

Li, Q. and Racine, J.S., 2007. *Nonparametric Econometrics: Theory and Practice*. Princeton University Press: Princeton, NJ.

Luukkonen, R., Saikkonen, P. and Teräsvirta, T., 1988. Testing linearity against smooth transition autoregressive models. *Biometrika* 75, 491-499.

Lütkepohl, H., 2005. *New introduction to multiple time series analysis*. Springer-Verlag, Berlin.

Myers, R.J., 1994. Time series econometrics and commodity price analysis: a review. *Review of marketing and agricultural economics* 62, 167-181.

Nadaraya, E.A., 1964. On estimating regression. *Theory of probability and its Applications* 9,141-142.

Perron, P., 1997. Further Evidence on Breaking Trend Functions in Macroeconomics Variables. *Journal of Econometrics* 80, 355-85.

Rajagopal, D. and Zilberman, D., 2007. Review of Environmental, Economic and Policy Aspects of Biofuels. Policy Research Working paper WPS4341. The World Bank Development Research Group, September.

Seo, B., 2007. Asymptotic distribution of the cointegrating vector estimator in error correction models with conditional heteroskedasticity. *Journal of Econometrics* 137, 68-111.

Serra, T. and Goodwin, B.K., 2009. The efficiency of Spanish arable crop organic farms, a local maximum likelihood approach. *Journal of Productivity Analysis* 31, 113-124.

Serra, T., Gil, José M. and Goodwin, B.K., 2006 Local polynomial fitting and spatial price relationships: price transmission in EU pork markets. *European Review of Agricultural Economics* 33, 415-436.
Serra, T., Zilberman, D. and Gil, J.M., 2011. Price volatility in ethanol markets. *European Review of Agricultural Economics*, 1-21.
Serra, T., Zilberman, D., Gil, J.M. and Goodwin, B.K., 2010. Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system. *Agricultural Economics* 42, 35-45.
Spanish Ministry of Industry, Tourism and Trade, 2010. Dataset. Accessed October 2010, available at http://geoportal.mityc.es/hidrocarburos/eess/# .
Spanish Ministry of the Environment and Rural and Marine Affairs, 2010. Dataset. Accessed October 2010, available at http://www.marm.es/index_en.htm .
Teräsvirta, T., 1994. Specification, estimation, and evaluation of smooth transition autoregressive models. *Journal of the American Statistical Association* 89, 208-218.
US Energy Information Administration, 2010. World crude oil prices. Dataset. Accessed October 2010, available at http://tonto.eia.doe.gov/dnav/pet/pet_pri_wco_k_w.htm.
Watson, G.S., 1964. Smooth regression analysis. *Sankhya: The Indian Journal of Statistics, Series* A 26, 359-372.
Zhang, Z., Lohr, L., Escalante, C. and Wetzstein, M., 2009. Ethanol, Corn, and Soybean Price Relations in a Volatile Vehicle-Fuels Market. *Energies* 2, 320-339.