NONLINEAR COINTEGRATION IN THE FOOD-ETHANOL OIL SYSTEM: EVIDENCE FROM SMOOTH THRESHOLD VECTOR ERROR CORRECTION MODELS

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Contents

Abstract

We examine the nature of relationship between prices of crude oil, ethanol and grains (maize, wheat and rice). Our working hypothesis is that profit maximization, the US biofuel policies and automotive engine technology give rise to a nonlinear relationship between oil and ethanol prices, and by extension between oil and grains prices. While legislation sets a floor in the ethanol market, engine technology, which shapes fuel substitution, sets a ceiling. We explore price relationships in the food-ethanol-oil nexus by applying both discrete and smooth threshold error correction models. First, we find that oil prices are the long run drivers of ethanol and grains prices. Second, ethanol prices co-move with oil prices in the long run. However, in the short run, oil and ethanol prices are linked in a nonlinear manner. Ethanol prices appear to drift apart from the path as this is determined by oil prices, due to policy changes. Adjustment back to the long run equilibrium the path is rapid, less than two months, when the deviations are small. Large deviations take more time to be corrected.

1. Introduction

Since 2000, global production of ethanol, the most widely used transport renewable fuel, more than quadrupled, reaching in 2011 a total of 84.6 billion litres. Together, the US and Brazil produce 87 percent of the world's ethanol. In Brazil, approximately half of the sugarcane crop is processed into ethanol, while in the US ethanol is produced from maize. Approximately 40 percent of the maize crop in the US, the world's largest maize producer and exporter, is used to produce ethanol. With such a proportion of the crop destined to satisfy the new and increasing derived industrial demand for maize by the ethanol sector, it may not be surprising that maize prices can be subject to frequent surges and significant volatility. However, the role of energy market forces and of the policies that encourage biofuel production in determining prices, not only of maize, but of other agricultural commodities remains contentious. If the global energy market is indeed closely integrated with the global food market through the production of biofuels, oil price volatility can be spilled-over on food markets exerting pressure on food prices and changing their time series characteristics.

In this paper we examine the nature of the relationship between crude oil, ethanol and the prices of maize, wheat and rice. We join the debate on the role of energy prices in determining agricultural and food commodity prices and their volatility. Since both energy and food or feed utilise the same input, for example maize, increases in the price of oil, can lead to increases in the production of ethanol with the possibility of reducing the supply of food and thus resulting in increases in its price. This relationship between the prices of oil, biofuels and crops can arise due to the fact that, in the short run, the supply of crops cannot be expanded to meet the demand by both food and energy consumers.

Nevertheless, the role of biofuels in food price surges remains controversial. A number of authors stress that the demand for biofuels is a determining factor of both food prices long run trends and their volatility (Mitchell, 2008; Nazlioglu and Soytas, 2012). The evidence provided by modelling, both time series and simulation models is, with few exceptions, either unconvincing or does not shed light to the underlying relationships. For example, Enders and Holt (2012) implement methods for detecting multiple structural breaks in time series data and stress that demand growth in emerging economies and the increasing utilization of certain crops for biofuels production have contributed to the recent price surges. McPhail (2011) argues on the basis of Granger-causality tests that ethanol prices are the main drivers of oil prices. Serra et al. (2011) estimate nonlinear cointegration models and find strong linkages between maize and energy prices which are related in a nonlinear manner.

Profit-maximising behaviour, policies, such as the Renewable Fuels Standards mandates and other measures, and technology, that is the US automotive fleet composition give rise to a complex relationship between food and energy markets and they shape the link between the prices of maize, ethanol and oil. In this paper, we assess the relationship between the price of oil, the price of ethanol, and the prices of maize, wheat and rice. We postulate that production costs for the conversion of maize

to ethanol, as well as policies, such as the mandated volumes, and technology give rise to nonlinear adjustment of ethanol and crop prices towards long run equilibrium. Price adjustment in the oil, ethanol and, by extension in the crop markets, may depend on the level of disequilibria with the correction towards the long run path occurring when price spreads move outside a certain threshold, or when policies allow.

We test for linear co-movement between oil, ethanol and food prices, as well as nonlinear adjustment to the long run equilibrium. Our objective is to explore the nature of energy and food price relationships, and especially the role of profit maximising behaviour, in terms of substituting one fuel for another, and that of biofuel policies in the US, in determining both ethanol and crop prices. Biofuel mandates, other policies and automobile engine technology do alter the relationship between fuels. Oil and ethanol can be substitutes, complements or can be completely unrelated, and their prices can move either together, or apart. As a result, the price of maize, the allocatable input between the food and energy markets in the US, can be determined by either food market fundamentals, or by the forces of demand and supply in both the food and energy markets, with shocks in the latter being transmitted in the former.

We apply an exhaustive battery of tests on energy and crop prices and estimate a number of specifications: cointegration, in order to test for long run equilibrium between energy and food prices, vector error correction models, to assess speed of adjustment and weak erogeneity of prices, as well as nonlinear vector error correction models, with both discrete and smooth adjustment specifications, to capture the behaviour of oil, ethanol and food price movements.

The paper starts by discussing the US biofuel policy and market. In the following sections, we introduce both discrete threshold and smooth transition vector error correction models, discuss their specifications and the estimation methods. We apply these models on the world market prices of oil, ethanol, maize, wheat and rice. We find that oil prices are the main drivers of both ethanol and grains prices and our results support nonlinear behaviour in the oil-ethanol price system.

2. The US Ethanol Market and Policies

The growth of the US ethanol sector has been supported by a range of policy measures, such as the Renewable Fuels Standard (RFS) mandates, under the Energy Independence and Security Act of 2007 (EISA), subsidies to blenders and import tariffs. Since 2007, these incentives contributed significantly to the development of the ethanol market in the US. Before the Act of 2007, legislation encouraging the production of ethanol from maize was in place since the late 1970s (Abbott, 2012). Since 2005, together with a mandated minimum level of ethanol production, the legislation included tax credits to fuel blenders and an import tariff on ethanol. Currently, the RFS mandates, specified each year for

different biofuels, are the only significant policy instrument affecting the market, with the objective to reduce emissions of greenhouse gasses. Tax credits for blending ethanol and biodiesel and the import tariff on ethanol were eliminated at the end of 2011.

Each year, the RFS mandates[1] set a floor on the volume of renewable fuels that have to be consumed by requiring a specific amount to be blended into petrol, or diesel. Given projections of annual consumption of petrol and diesel, this requirement is reflected by the blending ratio, a percentage of ethanol, or biodiesel in the final blended fuel, which is used to determine each individual company's volume obligation. For example, the 2012 blending ratio for total renewable fuels was set as 9.23 percent. For each individual refiner, blender or importer of fuel, this blending rate sets their mandated biofuels obligation in terms of volume, as a percentage of their annual fuels sales.

Implementation of the mandates is facilitated by a system of identification numbers, the renewable identification numbers (RINs), which are assigned to biofuels at the point of production or importation. Each gallon of biofuel has its own unique RIN and blenders have to purchase biofuels and demonstrate their compliance with the mandates on the basis of the RINs. In addition to identifying compliance, RINs are also used for credit trading, thus facilitating the implementation of the mandates where there are regional differences in the consumption of fuels. For example, a blender who has used more biofuels than the mandated volume and has a surplus of RINs, can sell them to another blender who has not reached the mandate and has a deficit of RINs. A market of RINs has been developed as the consumption of fuels varies over time and across regions, with the price of RINs reflecting both transaction costs, but also overall compliance prospects.

While the RFS mandates set a floor to the consumption of ethanol, the blend wall, that is the maximum capacity of the market to use ethanol, sets a ceiling. The blend wall is the upper limit of ethanol that can be blended into petrol and consumed by the US automotive fleet (McPhail and Babcock, 2012). The demand of ethanol depends on the composition of the automotive fleet, as well as the availability of pumps offering different ethanol blends. The fleet, in its greater part, comprises of E10 cars which can consume fuel blends with up to 10 percent ethanol. E85 cars, which run on blends with 85 percent of ethanol, and flex-fuel cars, that can use any blend, are few and are served by a limited number of pumps. Constraints in the substitution of one fuel (petrol) for another (ethanol) put an upper limit in the demand for ethanol, as well as for the industrial derived demand for maize.

The profit-maximising behaviour of the energy market participants, policies (the RFS mandates), and technology (the automotive fleet composition and the blend wall) give rise to a complex relationship between food and energy markets and, more specifically, between the prices of maize, ethanol and oil.

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[1] The renewable fuels mandate includes: biomass-based biodiesel, cellulosic and agricultural waste-based fuel, advanced biofuels and total renewable fuels. Maize starch ethanol qualifies for the mandate of total renewable fuels, while imported sugarcane ethanol from Brazil qualifies for the mandate of advanced biofuels.

Maize, the input which is to be allocated between the food and the energy markets, is quasi-fixed in the short run, as its supply cannot be increased significantly by expanding the cultivated area. This gives rise to jointness in the production of maize and ethanol and a relationship between the marginal cost of maize and the quantity of ethanol produced and *vice versa*, establishing a link between the food and energy markets (Moschini, 1989). Given this, an increase in the price of oil relative to the production costs of ethanol, will make the maize's marginal value product in the energy market exceed that in the food market, resulting in more maize being supplied for the production of ethanol and in an increase in its marginal cost (Balcombe and Rapsomanikis, 2008).

Nevertheless, although profit maximising behaviour can shape the integration of the energy and food markets and establish a link between food and energy prices, policies and technology restrict this relationship. The implications of policies and technology on the relationship between prices of maize, ethanol and oil is better explained by Figure 1 which presents the demand curve for ethanol subject to the RFS mandate and the blend wall, as well as the total demand for maize by both the food and the ethanol sectors.

The RFS mandate and the blend wall give rise to a kinked derived demand curve for ethanol. The demand for ethanol destined to comply with the RFS mandate is fixed and represented by the totally inelastic part of the curve, D_m. Neither the price of ethanol, nor that of oil has an impact in determining the mandated volume Q_m, as the industry is obligated to comply with the regulations. Above the mandated volume, the demand for ethanol is determined by market forces, and is elastic as shown by segment D_e. Once the mandated volume has been exceeded, an increase in the price of oil can result in blenders and consumers of fuel switching to ethanol, subject to the possibilities of substituting one fuel for another. Oil and ethanol become substitutes in the production of fuel and oil price increases will be transmitted to ethanol and possibly maize prices.

The total demand for maize, that is the aggregate demand by ethanol and food consumers, is also kinked, corresponding to the demand for ethanol with segments that are less elastic determined by the price elasticities of the demand for ethanol, and that for food and feed.

Substitution possibilities determine the extent to which the segment D_e of the demand for ethanol remains elastic. If the automotive fleet was mainly comprised by E10 cars, as currently in the US, and the mandated blending rate is close to 10 percent, there is limited scope to substitute ethanol for petrol, making this segment of the demand curve less elastic. If the mandated blending rate was well below 10 percent, the scope for substitution of oil with ethanol is greater, shaping a more elastic demand curve. If the automotive fleet comprised mainly by E85 or flex fuel cars, as this is the case in Brazil, ample substitution possibilities would give rise to an elastic demand curve.

The demand for ethanol and maize

Ethanol market   Maize market
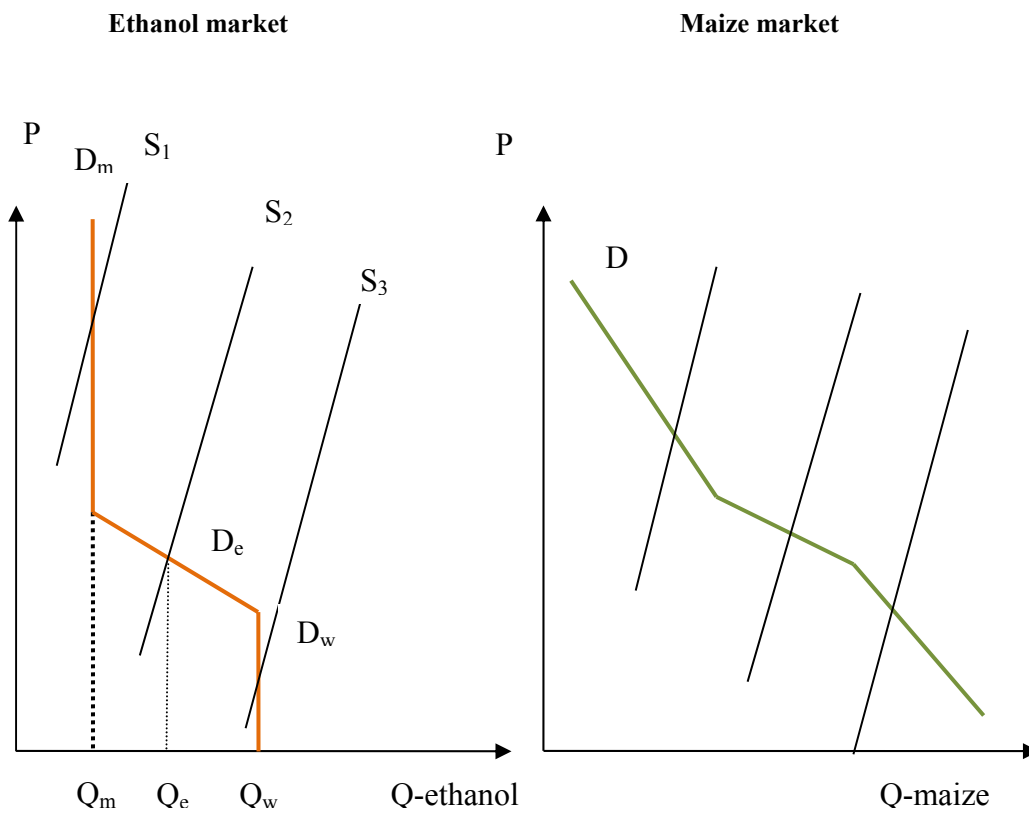
In the US, automobile engine technology constrains the substitution between fuels. Once petrol contains more than10 percent of ethanol, most car engines may be subject to corrosion due the water affinity properties of ethanol, resulting in car manufacturers' warranties not covering fuel blends with more ethanol. Beyond this point, when demand for ethanol runs up against the 'blend wall', that is the maximum volume of ethanol, the US automotive fleet can use in fuel blends, substitution possibilities cease to exist, making the segment of the demand curve for ethanol totally inelastic (D_w). Only technology improvements which allow more substitution can make the derived demand curve for maize more elastic. Once the blend wall is binding, and depending on how close the blending rate is to the wall, oil and ethanol can be either substitutes or complements.[2]

The above discussion highlights two important issues:

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[2] For example, with a blend wall of 10 percent, and a mandated blending rate of 8 percent, increases in the oil price can strengthen the demand for ethanol and that of maize and bring about increases in the price of maize. In a different case, with a blending rate of, say 9.5 percent, there is little scope for substitution with oil and ethanol becoming complements – an increase in the price of oil will result in decreases in the demand for oil, ethanol and, consequently, maize.

i.   First, policies and automobile engine technology give rise to a complex relationship between fuels. Oil and ethanol can be substitutes, complements or can be completely unrelated, and their prices can move either together, or apart. The relationship between oil, ethanol and maize prices depends entirely on which constraint is binding (Abbott, 2012). Binding constraints, either the RFS mandate, or the blend wall, also determine the extent to which demand is inelastic. As a result, the price of maize, the allocatable input between the food and energy markets, can be determined by either food market fundamentals, or by the forces of demand and supply in both the food and energy markets, with shocks in the latter being transmitted rapidly in the former.

ii.   Second, due to the constraints arising from the RFS mandate and the limited substitution possibilities in the consumption of fuel, the demand for ethanol and the derived demand for maize are kinked. This can contribute to high and persistent price volatility. As maize can be substitutable in consumption in food and feed markets, price volatility can spill-over to other crops, such as wheat, or rice.

Abbott (2012) identifies several regimes between 2005 and 2012, based on which of the constraints is binding. For example, in 2005-06, low maize prices in conjunction with high oil prices, led to an expansion of the ethanol production sector, suggesting that constrains were non-binding. In early 2008, high oil prices strengthened the demand for ethanol and the derived demand for maize above the mandate, but below the blend wall, indicating substitution possibilities between fuels and thus price transmission between food and energy markets. Currently, the price of RINs, the tradable instrument that ensures compliance to the mandate across regions in the US, has increased dramatically by about 1,400 percent from March 2012 to March 2013, indicating that the RFS mandate is not far below the ceiling set by the blend wall (Thompson et al., 2012).

3. Methodology

The presence of different regimes in the relationship between oil, ethanol and food crops lends itself to a nonlinear cointegration in the Vector Error Correction Model (VECM) framework. Market forces in the food and energy markets may result in the prices of oil and crops moving together within a specific regime which is determined by policies and technology. Outside this regime, price relationships are altered, giving rise to non linearities. These issues have been addressed in different ways by a growing literature that encompasses discrete and smooth threshold VECMs and Markov-chain VECMs, classical and Bayesian estimation and inference.

Nonlinear time series models have been widely applied to model complex economic phenomena mainly associated with multiple equilibria and nonlinearities between variables. The increasing interest in nonlinear VECMs has also resulted in contributions that developed an analogue to

Granger's representation theorem for nonlinear vector autoregressions (see Corradi et al., 2000; Escribano and Mira, 2002; Bec and Rahbec, 2004; Saikkonen, 2005).

There is a number of important issues related to nonlinear VECMs. These include testing for the null hypothesis of linear cointegration against the alternative of threshold/smooth cointegration, the identification and estimation of parameters that govern regime switching, as well as of the model's slope parameters and the provision of the corresponding standard errors. Applied nonlinear VECM research was originally instigated by the work of Balke and Forby (1997), and is based on one of three main approaches: Markov-chain VECMs, threshold VECMs and smooth transition VECMs.

Nonlinear models are characterised by an indicator, or transition function, either discrete, or continuous, that determines regime switches. For models that are based on discrete indicator functions, the literature divides into two main methodologies, the Markov-switching models (MS) and the threshold VECMs (TVECMs). Both strains evolved from their corresponding univariate counterparts. MS models were originally applied by Hamilton (1989) in a business cycle context and were extended to a multivariate application in a form of an MS-VECM by Krolzig (1998). Threshold cointegration has been discussed by Balke and Forby (1997) and TVECMs have been initially applied by Hansen and Seo (2002), having their origin in the Self-Exciting Autoregressive model (SETAR) of Tong (1983). The main difference between these two methodologies lies in the treatment of the indicator function and the related switching variables that are assumed to be unobservable and determined by a latent stochastic process in the MS literature, whilst they are observable determinants in the TVECM methodology.

MS-VECMs are well suited for modelling the changing relationship between economic variables in the context of business cycles, mainly because regimes and their corresponding probabilities and duration, can be readily associated with periods of recession, or high growth (see Krozig and Clements, 2002 and Clements and Krolzig, 2001). However, the explicit estimation of threshold parameters is, in many cases, preferable to identifying the probability that a certain regime occurs at a particular point in time. Depending on the application, thresholds can be rationalised in a number of ways. In testing the Law of One Price, deviations between prices of assets traded in different markets may occur due to many reasons including transaction costs, adjustment costs and capital constraints. Such factors give rise to thresholds with arbitrage opportunities being realised when the deviation in prices is high. The estimation of threshold parameters enables the researcher to calculate the magnitude of the price spread above which prices adjust to their long run equilibrium.

In TVCEMs, threshold effects follow variants of the specification of Balke and Fomby (1997) where the rate of adjustment to the long run equilibrium of two cointegrated variables $y_t' = (y_{1,t}, y_{2,t})$ differs between regimes as follows:

$$\Delta y_t = \mu_t + F(e_{t-1}) + \sum_{i=1}^{k} \varphi_i \Delta y_{t-i} + u_t \tag{1}$$

$$F(e_{t-1}) = \delta \alpha_1 e_{t-1} + (1 - \delta)\alpha_2 e_{t-1}$$

$$\delta = \begin{cases} 1 \ if \ e_{t-1} \leq \lambda_1 \\ 0 \ if \ e_{t-1} > \lambda_2 \end{cases}$$

where t=*1,...,n,* and *F(e_{t-1})* is an indicator function of the error correction e_{t-1} which is assumed to be covariance stationary with zero mean. Vectors $\alpha_i' = (\alpha_{1,i}, \alpha_{2,i})$ and $\varphi_i' = (\varphi_{1,i}, ..., \varphi_{k,i})$ are adjustment and short run dynamic parameters. As in linear VECMs, the error correction term is defined as:

$$e_{t-1} = y_{1,t-1} - \beta_1 y_{2,t-1} - \beta_o - \beta_2 t, \tag{2}$$

while the parameters β_o and β_2 may assume values equal to zero. The TVECM errors u_t are assumed to be an *i.i.d.* Gaussian sequence with a finite covariance matrix, $\Sigma = E\{u_t u_t'\}$. Models such as (1) with $\lambda_1 \leq \lambda_2$ allow for a Band TVECM specification, where there is no adjustment inside the threshold, when the error abides by $\lambda_1 < e_{t-1} \leq \lambda_2$, whilst a simple two-regime threshold model is specified with $\lambda_1 = \lambda_2$. Other popular threshold models, such as the Momentum Threshold Autoregressive models of Granger and Lee (1999), Enders and Granger (1998) and Escribano and Pfann (1997) allow for the variables to adjust differently depending on whether the disequilibria are negative or positive.

More general specifications give rise to a variety of non linear behaviour that can be characterised by more than one threshold, as well as by attractor mechanisms to the long equilibrium relationship different than the adjustment coefficients. Balke and Forby (1997) view cointegration as a global characteristic of the series, whilst threshold behaviour consists a local characteristic and conduct estimation in two steps. The first step comprises of testing for non cointegration and the estimation of the cointegrating vector. As a second step, tests for nonlinearity are conducted on the residuals of the cointegrating regression, by means of cumulative least squares tests, as well as tests developed by Tsay (1989). Such an estimation procedure is not optimal if threshold behaviour was present, since the likelihood function, on which the estimates of the cointegrating vector are based, depends on the threshold parameters.

In general, the inequality constraints implied by the threshold behaviour are difficult to enforce within the classical estimation framework. Maximum Likelihood Estimation (MLE) is complex, as the

likelihood function is not differentiable, rendering optimisation methods that are based on derivatives inadequate and, in general, making inference difficult. In addition, the threshold parameter is not identified under the null hypothesis, implying the distribution of likelihood ratio statistics is non-standard (Andrews and Ploberger, 1994). Hansen and Seo (2002) propose a quasi-MLE method based on a grid-search over the cointegrating vector and the threshold parameter, in conjunction with a 'fixed regressor' bootstrap to test for threshold effects. For a two-regime threshold model, the procedure provides estimates of the cointegrating vector and the threshold parameter λ that maximise the likelihood function, starting the evenly grid-search with consistent estimates of the cointegrating vector from the linear model, whilst inference is based on conventional standard errors.

A Lagrange Multiplier (LM) test for threshold effects is also proposed to test the null hypothesis of a linear cointegrating relationship against the alternative of threshold cointegration. As the parameter λ is not identified under the null, Hansen and Seo (2002) rely on the supremum of the LM test over the parameter space. The distribution of the test is approximated by means of a fixed regressor bootstrap as in Hansen (1996). In this line, the test is based on the restriction that the adjustment coefficients are equal, $\alpha_1 = \alpha_2$, whilst the threshold parameter is treated as fixed to its maximum likelihood value. Seo (2004) stresses that this procedure is not optimal, as cointegration tests are subject to power loss when the alternative is threshold cointegration. Seo examines a two-regime Band TVECM with a pre-specified cointegration vector and proposes a Wald test with the null hypothesis of no cointegration, providing a formal treatment of its asymptotic distribution.

Rapsomanikis and Hallam (2006) and Balcombe and Rapsomanikis (2008) explore the integration of oil, ethanol and sugar markets in Brazil, by estimating TVECMs, thus allowing for cointegration between oil, ethanol and sugar prices with the dynamic adjustments being nonlinear functions of the disequilibrium errors. Their results suggest that the long run drivers of Brazilian sugar prices are the prices of oil and that there are threshold effects in the adjustment process of sugar and ethanol process to oil prices arising due to the ethanol's production costs.

Although TVECMs postulate that switches from one regime to another are sudden, in actual fact, switches can be gradual, as economic agents may need time to adjust to changes in the economic environment, or policies. A smooth TVECM (STVECM) is obtained by replacing the indicator function by a smooth function defined over the unit interval. The choice of this function often falls on exponential or logistic functions which give rise to smooth adjustments based on inverted normal density function and cumulative logistic distribution, respectively. In this paper, we model the relationship between oil, ethanol and food markets using bivariate STVECM (see, for example, van Dijk et al. 2002):

$$\Delta y_t = \left(\mu_{1,0} + \alpha_1 e_{t-1} + \sum_{j=1}^{p-1} \varphi_{1,j} \Delta y_{t-j} \right)(1-F) + \left(\mu_{2,0} + \alpha_2 e_{t-1} + \sum_{j=1}^{p-1} \varphi_{2,j} \Delta y_{t-j} \right)(F) + u_t$$

$$F = G(s_{t-d}; \gamma, c) \tag{3}$$

where y_t, Δy_t, α and φ are as in (1), and the variables y_t are cointegrated. The distinctive feature of this model is the regime-switching indicator function $F = G(s_{t-d}; \gamma, c)$. This function G is continuous and bounded between 0 and 1, allowing for two regimes associated with these values, while the transition from one regime to another is smooth, giving rise to a 'continuum' of regimes each reflected by a different value of $G(s_{t-d}; \gamma, c)$ over the time of transition (van Dijk et al. 2002). This function G depends on the transition variable s_{t-d}, where d is a delay period. It is common practice, as the variables y_t are integrated to use the deviations from the long run equilibrium e_{t-d} as a transition variable. In particular, in our analysis the transition variable s_{t-d} is a lagged residual from an error correction term[3]. The parameters c and γ have to be estimated and reflect the average location of the adjustment (or the threshold between regimes) and the speed of transition from one regime to another respectively. Most of the STVECM are interpreted as giving rise to two regimes $G_{t-d} = 0$ and $G_{t-d} = 1$, while the system moves continuously and smoothly from one regime to another. Different specifications, such as the exponential or the logistic functions, produce different types of regime switching behaviour.

For this work, we consider an exponential specification for the smooth transition variable as in Serra et al. (2011):

$$G(s_{t-d}; \gamma, c) = 1 - exp\left\{ -\gamma \frac{(s_{t-d}-c)^2}{\sigma^2(s_{t-d})} \right\}, \quad \gamma > 0. \tag{4}$$

s_{t-d} and c are normalised by $\sigma^2(s_{t-d})$ which is the variance of the transition variable to become scale free. The choice of the exponential function is motivated by van Dijk et al. (2002) who proposed that this specification is appropriate when regimes are associated with small and large absolute values of s_{t-d} relative to the threshold parameter c, while the adjustment is symmetric around this threshold. Large (small) values of the parameter γ, which determines the speed of transition from one regime to another, reflect quick (slow) switching between the regimes. As the variables in y_t are cointegrated and in a long-run equilibrium relationship, the adjustment towards this equilibrium, as specified by (3) is nonlinear, switching from one regime to another smoothly, depending on the deviations from the long run equilibrium relative to the threshold.

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[3] After several specification tests the delay period d has been set to 1.

The test for the null hypothesis of linearity is complicated due to the presence of unidentified nuisance parameters under the null hypothesis (Andrews and Ploberger, 1994). In particular, the derivation of the asymptotic null distribution of the classical Likelihood Ratio, the Lagrange Multiplier and the Wald type tests is difficult. A practical way to perform this test is provided by Saikkonen and Luukkonen (1988) and Luukkonen et al. (1988), who propose that the test for the null hypothesis of linearity against the alternative of smooth transition is equivalent to testing $\gamma = 0$. A simple way to carry out this test is to replace the transition function by a suitable Taylor series approximation (first or third order) around $\gamma = 0$ and then perform a classical Lagrange Multiplier test using an auxiliary regression.

The estimation of parameters γ and c , jointly with other model parameters is also difficult, as γ tends to inflate to infinity (Haggan and Ozaki, 1981; Terasvirta, 1994). Kapetanios et al. (2006) specify a STVECM in which the adjustment function follows the exponential smooth transition autoregressive functional form (ESTAR). Their method consists of the estimation of the cointegrating regression and the residuals, as a first step and the estimation of a STVECM in which the exponential adjustment function is approximated by a first-order Taylor approximation. Their specification allows the development of a test for the null hypothesis of no cointegration against the alternative of non linear ESTAR cointegration that is analogous to the Engel and Granger (1987) test for linear cointegration. However, no threshold parameters are estimated. Seo (2004) focuses on both exponential and logistic functional forms and develops a LM test for smooth adjustment nonlinearity, the associated asymptotic theory and bootstrap inference. Seo's work can be viewed as a generalisation of Hansen and Seo (2002) to smooth threshold models. Likewise, the test is based on fixing the smooth transition parameters to their maximum likelihood value, based on a grid-search, whilst no distribution theory for the estimates is provided.

Serra et al. (2011) evaluate price linkages and transmission patterns in the U.S. ethanol industry during 1990-2008, a period characterized by significant changes in the U.S. ethanol and related markets. Smooth TVECM allowed to analyse long-run relationship among ethanol, maize, oil and gasoline, as well as for non linear adjustment toward their long-run equilibrium. In contrast with previous price analyses, they found strong linkages between maize and energy market. More specifically, energy prices cause the price of maize, with this causal effect being realized through the ethanol market, while price relationships were found to be nonlinear.

Smooth transition VECMs are estimated by traditional Maximum Likelihood. Clearly, the MLE leads to an efficient estimation strategy. There are a number of numerical challenges arising due to the flatness of the criterion function and the choice of the parameters' initial values which may have serious consequences for optimization. In practice, reliable numerical optimization has to be based on starting points that can be obtained by a grid search algorithm. Our grid search algorithm follows

Yang (2013), in which the starting points are obtained through a constrained optimisation. In particular, we construct a two dimensional grid and search over the domain of γ and c smooth transition parameters, performing for each point of the grid a constrained optimisation of the likelihood function in which the two smooth transition parameters are set equal to the corresponding point of the grid. We considered ten grid points for each parameter, obtaining in total one hundred grid points.

In order to improve the performance of the grid search we also consider the possibility of zooming. We split the grid search algorithm into several sequential stages that analyze specific portion of the parameter space. Yang (2012) proposed a numerically stable zig-zag algorithm that optimizes the regression parameters, given the transition parameters and *vice versa*, exploiting the closed-form expression of the maximum of the conditional criterion functions in these two cases. However, this estimation technique leads to inconsistent estimates if the two set of parameters are not orthogonal.

4. Application and results

We estimate three classes of models to explore the relationship between prices of oil, ethanol, maize, wheat, and rice prices: linear VECMs, threshold VECMs (equation (1)) and smooth transition VECMs (equations (3) and (4)). We use the logarithmic transformations of prices from January 1980 to April 2012 (Figure 2). Data on prices for oil, maize, wheat and rice are collected from the International Financial Statistics of the International Monetary Fund. The information on ethanol prices was obtained from the Nebraska Government website.[4]

The time-series properties of the data are assessed through standard ADF (Dickey and Fuller, 1979), Elliot (1999), Elliot et al. (1996), KPSS (Kwiatlowski et al., 1992), and Phillips-Perron (Phillips and Perron, 1988) tests. All statistics suggest the presence of unit roots in all price series.[5]

Non cointegration is tested and linear VECMs are estimated with the standard Johansen (1988) approach that is based on MLE and likelihood ratio tests. Lag length is selected by means of the Akaike and Swartz-Bayes criteria. We take the first lag of the error correction term (equation (2)), as *a priori* known for our work on the TVECMs and STVECMs. We follow the Hansen and Seo (2002) approach to test for linear adjustment versus threshold adjustment to the long run equilibrium, as in Rapsomanikis and Hallam (2006).

The tests for non cointegration suggest the presence of long run equilibrium relationships among the price pairs ethanol-oil, ethanol-maize, maize-oil, wheat-oil, rice-oil (see Table 1).[6] These results

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[4] http://www.neo.ne.gov/
[5] Results of this preliminary analysis are not present here but are available from the authors upon request.

suggest that maize price, but also the prices of wheat and rice co-move with the price of oil in the long run. Although they can drift apart in short run, market forces will ensure that prices will move together in the long run. For maize prices, co-movement with oil prices can be attributed to the industrial demand for maize by the ethanol industry. For prices of crops that are not used to produce ethanol, such as rice, co-movement may be the result of the substitution between crops in food consumption. In addition, as production technologies are similar and common inputs are used, one would expect unit costs to go up more or less uniformly across the crops. However, empirical evidence suggests that even unrelated commodity prices tend to move together being driven by non-market fundamental factors, such as money supply (Pindyck and Rotemberg, 1990).

Figure 2

Food and energy prices, January 1980 – April 2012
(logarithmic transformations)
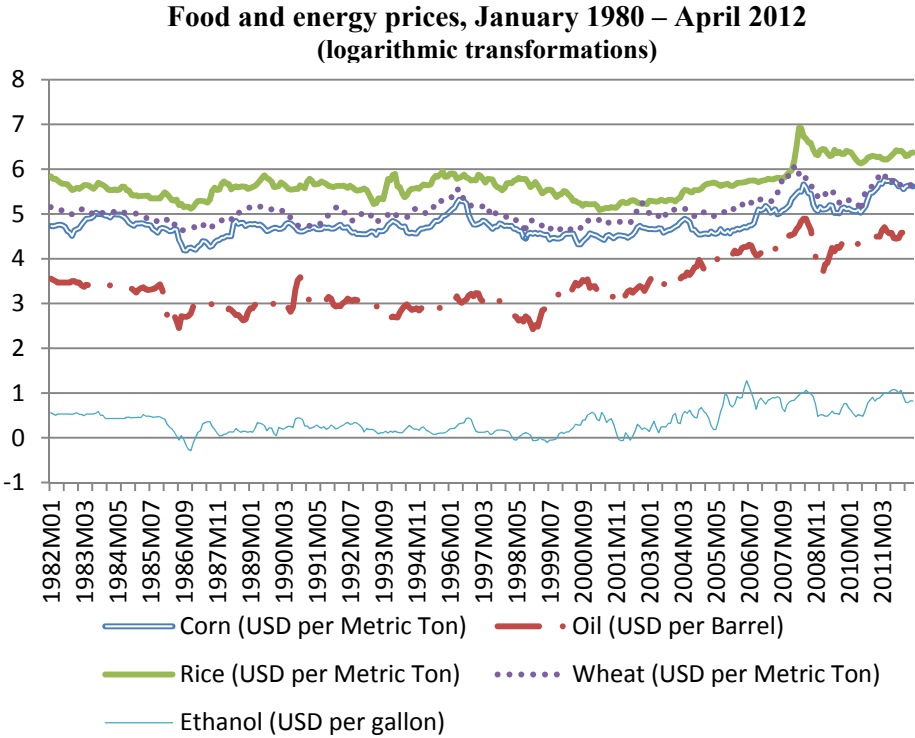
Source: **IMF and Nebraska Government website.**

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[6] We also run Johansen tests for daily and weekly transformation of the series and found no evidence of cointegration in these cases probably due to the high frequency of the data.

Table 1

Johansen tests for non cointegration

	Maximum Eigenvalue test		Number of cointegrating relationships	
	0 versus 1 cointegrating vector	**1 versus 2 cointegrating vectors**		
Ethanol-Oil	44.89	1.83	1	***
Maize-Ethanol	22.03	2.87	1	***
Maize-Oil	16.02	1.04	1	**
Wheat -Oil	17.3	1.22	1	**
Rice - Oil	14.73	1.15	1	*
Note: critical values 15.57(5%) and 13.75(10%) for H^0: r=0				
For H^0: r<=1, critical values are 7.52 (10%) 9.24 (5%)				

For the ethanol-oil price pair the cointegrating parameter is 0.45, implying that a 10% increase in the price of oil will bring about, in the long run, a 4.5% increase in the price of ethanol (Table 2). Maize prices are found to co-move with the prices of ethanol, with a 10% increase in ethanol prices resulting in a 14.2% increase in the prices of maize in the long run. The results for the maize-oil price pair confirm the long run relationship between maize, ethanol and oil prices. The estimated linear VECMs shed light on the causal effects between prices. The adjustment parameter of the ethanol error correction model is negative and statistically significant, indicating that oil is the dominant market, with ethanol prices adjusting to a long run path that is determined by oil prices. Likewise, the long run path of maize, wheat and rice prices is determined by the price of oil. Maize prices are determined by ethanol prices and *vice versa*, with a long run bi-directional causal effect which runs from one price to another.[7] This is not surprising, as maize is a quasi-fixed input in the production of ethanol, and thus its price can influence the price of ethanol.

The adjustment parameters also reveal the time that is necessary for the food prices to adjust to their long run path, which is determined by oil prices. Wheat and rice prices adjust to a change in oil prices by 5% and 4% in one month respectively. Ethanol prices respond to changes in oil prices fast and adjust to their oil price-determined long run path by 18% each month. Full adjustment of ethanol prices to their long run equilibrium is achieved in less than 4 months. Adjustment in the maize-ethanol system is considerably slower. Given a change in the ethanol (maize) price, market forces in the ethanol-maize system correct the disequilibrium by adjusting the maize price (ethanol price) by 2% (5%) in one month.

The adjustment of food and ethanol prices towards their long run equilibrium, as this is determined by the price of oil, may be nonlinear due to the limited possibilities in the substitution of oil for ethanol in the US transport fuel market, or due to the policies that shape ethanol production and consumption

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[7] The statistical significance and negative sign of the adjustment parameters suggests that oil (ethanol) prices are weakly exogenous in the econometric sense in the oil-food price (maize-ethanol) VECMs (Granger, 1988).

discussed in Section 2. Co-movement may be inactive during specific periods, or adjustment may depend on the level of disequilibria from the long run path, and may be either discrete with the adjustment taking place when price spreads move outside a certain threshold, or smooth and continuous, as market agents take time to adjust to changes in prices.

Table 3 presents a series of tests for linear adjustment to the long run equilibrium: test for linear against the alternative of discrete adjustment (Hansen and Seo, 2002) and Table 4 the tests for linear against smooth transition to the long run equilibrium (Luukkonen, 1988). The tests provide no evidence for discrete adjustment to long run equilibrium for all price-pairs. Nevertheless, in one case, for the price pair of ethanol-oil, there is evidence adjustment is nonlinear and smooth.

Table 2

Linear Vector Error Correction models (VECMs)

	Ethanol-Oil price pair				Maize-Oil price pair		
	Ethanol		**Oil**		**Maize**		**Oil**
e_{t-1}	-0.19	***	-0.04	e_{t-1}	-0.04	***	0.02
	0.03		0.03		0.01		0.02
ΔEthanol	0.29	***	-0.04	**ΔMaize**	0.31	***	-0.02
	0.05		0.06		0.05		0.07
ΔOil	0.07		0.30 ***	**ΔOil**	-0.05		0.31 ***
	0.05		0.06		0.04		0.05
Cointegrating vector	$e_{t-1} = E_{t-1} - 0.45O_{t-1} + 1.18$			**Cointegrating vector**	$e_{t-1} = M_{t-1} - 0.54O_{t-1} - 2.95$		

	Maize-Ethanol price pair				Wheat-Ethanol price pair		
	Maize		**Ethanol**		**Wheat**		**Ethanol**
e_{t-1}	-0.02	*	0.05 ***	e_{t-1}	-0.02	*	0.07 ***
	0.01		0.01		0.01		0.02
ΔMaize	0.31	***	0.21 **	**ΔWheat**	0.28	***	0.10
	0.05		0.07		0.05		0.07
ΔEthanol	-0.09	*	0.28 ***	**ΔEthanol**	0.01		0.30 ***
	0.04		0.05		0.04		0.05
Cointegrating vector	$e_{t-1} = M_{t-1} - 1.42E_{t-1} - 4.26$			**Cointegrating vector**	$e_{t-1} = W_{t-1} - 1.19E_{t-1} - 4.63$		

	Wheat-Oil price pair				Rice - Oil price pair		
	Wheat		**Oil**		**Rice**		**Oil**
e_{t-1}	-0.05	***	0.04 *	e_{t-1}	-0.04	***	0.02
	0.01		0.02		0.01		0.02
ΔWheat	0.27	***	-0.05	**ΔRice**	0.36	***	-0.07
	0.05		0.07		0.05		0.07
ΔOil	-0.00		0.31 ***	**ΔOil**	-0.01		0.31 ***
	0.04		0.05		0.04		0.05
Cointegrating vector	$e_{t-1} = W_{t-1} - 0.45O_{t-1} - 3.54$			**Cointegrating vector**	$e_{t-1} = R_{t-1} - 0.54O_{t-1} - 3.83$		

We proceed to the estimation of STVECMs with an exponential transition function, as in equations (3) and (4). We choose the errors of the ethanol-oil cointegrating regression as the transition variable s_{t-d} with $d = 1$. We allow all coefficients, that is the constant μ, the short run dynamics parameters φ, and the adjustment parameters α to switch between regimes in line with exponential transition function G. Table 4 presents our results for the ethanol-oil price pair for the two regimes which correspond to the values which bound the exponential function, namely 0 and 1. These regimes are determined by the parameter c, the threshold over (under) which adjustment to long run equilibrium differs, and the estimate of γ which reflects the speed of transition from one regime to another.

Table 3

Test of linear versus threshold cointegration (Hansen and Seo, 2002)

	Test statistics	10%	5%	p-value
Ethanol-Oil	20.79	23.89	25.44	0.31
Maize-Ethanol	14.66	23.13	24.47	0.93
Maize-Oil	21.91	23.47	24.34	0.21
Wheat -Oil	21.85	24.20	25.26	0.23
Rice - Oil	22.73	23.61	24.66	0.17

Note: Number of bootstrap replications 100

Table 4

Tests for linear against nonlinear adjustment

	Test statistics	p-value	Test statistics	p-value
	Ethanol-Oil		**Wheat-Oil**	
Taylor expansion 1st order	13.37	0.04	5.81	0.45
Taylor expansion 3rd order	35.35	0.01	27.66	0.07
	Maize-oil		**Wheat-Ethanol**	
Taylor expansion 1st order	13.05	0.04	4.61	0.60
Taylor expansion 3rd order	30.26	0.04	43.94	0.02
	Maize -Ethanol		**Rice-Oil**	
Taylor expansion 1st order	11.41	0.08	10.42	0.11
Taylor expansion 3rd order	36.53	0.01	20.33	0.32
12.59 (critical value for 1st order expansion)		*28.869 (critical value for 1st order expansion)*		

The threshold c is estimated at -0.38 (Table 5). The exponential transition function takes values associated with large and small disequilibria and has the property that $G(s_{t-d}; \gamma, c) \to 1$ both as

$s_{t-1} \rightarrow -\infty$ and $s_{t-1} \rightarrow +\infty$. This property means that values of the ethanol-oil disequilibria in proximity to the threshold $c = -0.38$ place the price system in a 'typical' regime where $G(s_{t-d}; \gamma, c) = 0$. As disequilibria become larger than the threshold, the function places the system towards an 'extreme' regime where $G(s_{t-d}; \gamma, c) = 1$. High negative disequilibria, over the threshold, are associated with oil prices surging, or falling fast and ethanol prices following at a much slower rate. As the disequilibria move over the threshold, -0.38, ethanol prices follow oil prices more closely, or deviate from them increasing (falling) at a relative faster (slower) rate, rendering the disequilibria positive.

The parameter γ is estimated to be equal to 0.26, a relatively slow speed of transition between regimes reflecting the extent to which rigidities in the ethanol-oil system, which arise due to policies and limited substitution between fuels, affect transition and adjustment.[8] The exponential transition function suggests that the oil-ethanol price system moves between regimes smoothly but slowly, while most of its values are estimated between 0.7 and 1 falling well within the higher regime (see Figure 3).

Table 5

Ethanol-Oil price pair: smooth transition vector error correction model estimates

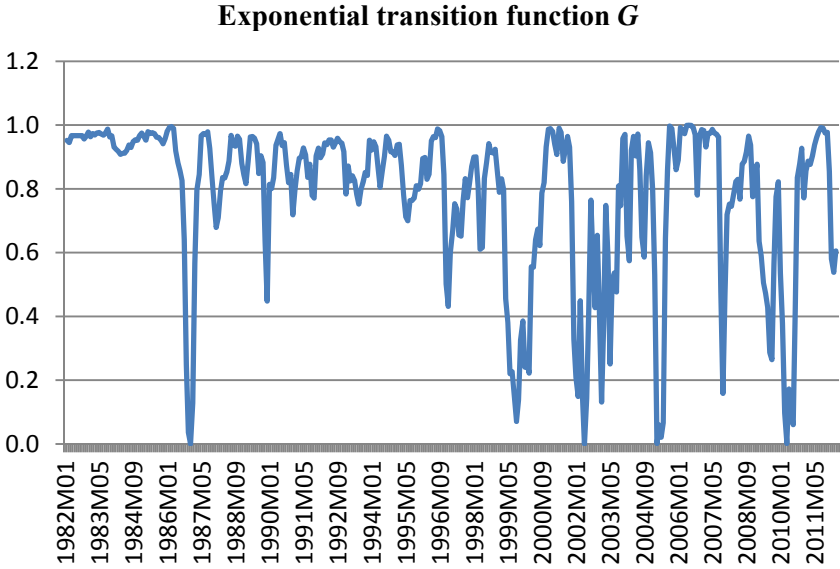| Equation	Regime $G = 0$		Regime $G = 1$	
	Ethanol	**Oil**	**Ethanol**	**Oil**
e_{t-1}	-0.54 **	0.33	-0.29 ***	0.15
	0.33	0.46	0.09	0.13
ΔEthanol	0.60 ***	-0.01	0.18 ***	-0.08
	0.26	0.18	0.08	0.08
ΔOil	-0.29 **	-0.39	0.17 ***	0.46 ***
	0.21	0.38	0.08	0.10
Speed of transition and threshold variable		**Parameter estimate**		
γ		0.26		
c		-0.38		

(*) Denotes statistical significance at 5(10)% significance level

The estimated ethanol-oil price STVECM captures the behaviour of ethanol and oil prices better relative to the linear model. The estimates suggest asymmetric adjustment behaviour for small and large disequilibria relative to the threshold. As in the linear VECM, the estimates suggest that oil prices are weakly exogenous and the long-run drivers of ethanol prices. In the ethanol price smooth error correction model, the adjustment parameters α are statistically significant and differ considerably between regimes. In the typical regime, where $G=0$, the estimate of the adjustment parameter is -0.54, suggesting that when disequilibria are in proximity to the threshold, ethanol price adjusts to changes in the price of oil rapidly, with about 54 percent of the disequilibrium corrected within the period of one month. Within this regime, it takes less than 2 months for the price of ethanol to fully adjust to its long

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[8] Parameter γ is positive and also tends to infinity, thus a value of 0.26 is considered low. High values of would mean that the transition from one regime to another can take place instantaneously.

run equilibrium. Once prices deviate from the long run path and the associated disequilibria are becoming larger relative to the threshold, the adjustment of ethanol price to oil price changes is much weaker. Under the extreme regime, where $G=1$, the estimated parameter α suggests that about 29 percent of the disequilibria are corrected within the period of one month, with full adjustment been achieved by 2 to 3 months.

Figure 3

Exponential transition function *G*

Figure 4

Ethanol-oil error correction model adjustment parameter
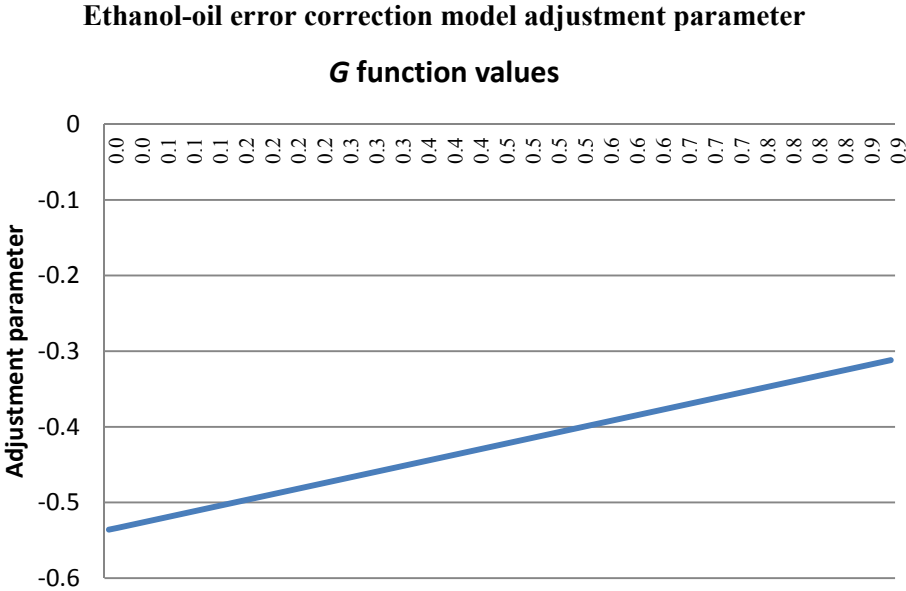
***G* function values**

These differences in the adjustment can be attributed to the rigidities in the oil-ethanol price system introduced by the RFS mandate and the blend wall, but also other policy changes. Rapid adjustment of ethanol price to oil prices can take place when the substitution of one fuel for another is possible – at the elastic segment of the demand curve for ethanol in Figure 1. Slower adjustment, such as that estimated to take place within the extreme regime, may be the result of the ethanol quantity produced being determined either by the RFS mandate, the blend wall, or other policies that influence the ethanol market. Nevertheless, an adjustment parameter of -0.29 does not reflect a situation where substitution possibilities between ethanol and oil have ceased to exist. It may be that petrol blenders continue to utilise ethanol in their fuel blends either for exportation or storage.
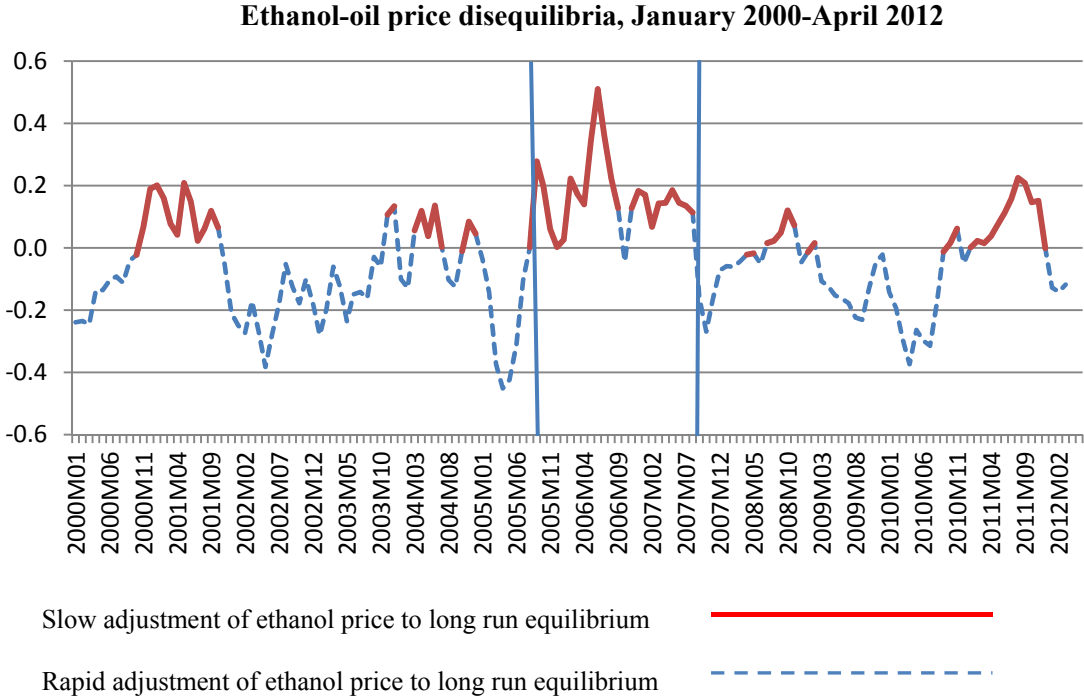
Between these two regimes, the adjustment of ethanol price to disequilibria changes in a smooth and continuous manner. The exponential function G changes the strength of the short run relationship between the prices of oil and ethanol through changing the corresponding adjustment coefficients. Figure 4 shows the smooth transition of the adjustment parameter from one regime, where disequilibria are small and adjustment of the ethanol price is fast $(\alpha = -0.54, \ G = 0)$ to the other regime, where disequilibria are large and adjustment is slower$(\alpha = -0.29, \ G = 1)$.

Figure 5 presents the disequilibria of the ethanol-oil price cointegrating regression, used as the transition variable in estimating the ethanol-oil price STVECM for the January 2000 – April 2012 period. In order to better explain the influence of policy measures on the relationship between ethanol and oil prices, we arrange the disequilibria in two groups: those that correspond to $G \geq 0.8$ that is the large disequilibria, and those for which $G < 0.8$ Most of the large disequilibria, which result in slow adjustment with the corresponding parameter decreasing towards -0.287, are positive. This reflects that ethanol prices drift away from their long-run path, as this is determined by the prices of oil, either by increasing faster than oil prices, or by falling at a slower rate that oil prices.

The differences in the adjustment of ethanol prices to their long run equilibrium can be used to identify a number of periods. Prior to 2005, a combination of high crude oil prices and relatively low maize prices provided strong incentives to ethanol producers, resulting in a rapid adjustment of ethanol prices to their long run equilibrium for most of this period, as shown in Figure 5 by the path dotted line. The period from the summer of 2005 to that of 2007 is characterized by a rapid expansion in the ethanol production capacity, as well as a series of policy events (Period I, Figure 5). The implementation of RFS mandates in conjunction with high oil and low maize prices continued to encourage increases in ethanol production capacity. However, in 2006, the use of fuel oxygenates (MTBEs) in petrol was banned, in order to protect surface and ground water from releases from storage, pipelines and marine engines. Since the 1990s, MTBEs were added to petrol to increase its oxygen content and reduce carbon monoxide and ozone levels. The ban in 2006 resulted in strengthening the demand for ethanol and in increasing its price above its long-run equilibrium level,

resulting in a slow adjustment to crude oil prices. The period from the summer of 2007 to the autumn of 2008 is characterized by the commodity price surge. With persistently increasing prices of oil and maize, ethanol prices adjusted rapidly to the trend, following closely oil prices and, up to a certain extent influencing the prices of maize (Period II, Figure 5). For most of this period, both production capacity and the blend wall have not being binding, allowing substitution between fuels.

Figure 5

Ethanol-oil price disequilibria, January 2000-April 2012

Slow adjustment of ethanol price to long run equilibrium

Rapid adjustment of ethanol price to long run equilibrium

Source: **Authors own calculations.**

Period III, from late 2008 to July 2010, is marked by the end of the commodity price surge, the financial crisis and the onset of the economic recession. During this period, ethanol prices adjust rapidly to the declining oil prices. This adjustment started becoming progressively slower in the beginning of period IV, as ethanol producers expected that the blend wall will bind by the end of 2010, adjusted their production and increased exports. Again, in 2011, ethanol prices increased above their long run equilibrium path, adjusting slowly to oil prices, prior to the elimination of subsidies, as blenders strengthened their demand for ethanol, blending fuel and putting it in storage in order to benefit from the subsidies.

5. Conclusions

We examined the nature of relationship between prices of crude oil, ethanol and grains (maize, wheat and rice). Our working hypothesis was that profit maximization, the US biofuel policies and

automotive engine technology give rise to a nonlinear relationship between oil and ethanol prices, and by extension between oil and grains prices. The Renewable Fuels Standards mandates set a floor in the ethanol market – blenders have to comply with the mandate and use a specific minimum volume of ethanol whatever the price. Up to this volume, the demand for ethanol is inelastic and oil and ethanol prices can be unrelated. Above the mandate, relative costs will determine ethanol demand with blenders substituting an expensive fuel (e.g. petrol) with a cheaper one (e.g. ethanol). Substitution possibilities link the price of ethanol, and possibly the price of maize and other grains, with the price of oil. Nevertheless, substitution possibilities cease to exist over a certain threshold, called the 'blend wall', as the US automotive fleet is composed, in its greater part, by vehicles which can run on blends that contain up to 10 percent of ethanol. Over this threshold, the link between oil, ethanol and grains prices breaks.

We explored price relationships in the food-ethanol-oil nexus with time series models, both linear and nonlinear. We found that oil prices are the long run drivers of ethanol and grains prices. This may not be only due to biofuels. Commodity prices tend to move together being driven by non-fundamentals, such as money supply. In the long run, ethanol prices co-move with oil prices. A change in the price of oil will make the price of ethanol adjust. Full adjustment to the long run path takes place quickly in a period less than four months. Maize and ethanol prices form a system, with one price adjusting to the other. Not only the ethanol price drives that of maize, but also *vice versa*.

Surprisingly, we found that in the short run, the speed of adjustment is low: maize (ethanol) prices will respond to a change in ethanol (maize) prices and will adjust fully in about 17 (12) months. This finding suggests that ethanol, as well as oil prices determine the long run path of maize (and of the other grains), but have a relatively small impact in the short run. This weak link between energy and grains prices in the short run may be the result of the constraints put on ethanol use by cap for ethanol in the biofuels mandate, the blend wall and the limited substitution possibilities in the consumption of fuels.

In the short run, oil and ethanol prices were found to be linked in a nonlinear manner. Although, they co-move in the long run, ethanol prices appear to drift apart from the path, mainly due to policy changes. Adjustment back to the long run equilibrium the path is rapid, less than two months, when the deviations are small. Large deviations take more time to be corrected, between 2 and 3 months. During the period under consideration, ethanol production capacity, the ban of fuel oxygenates (MTBEs) in petrol, the elimination of subsidies and the substitution possibilities at the pump, shape the adjustment of ethanol price to oil price changes.

21

References

Abbott, P., 2012. Biofuels, Binding Constraints and Agricultural Commodity Price Volatility. NBER Working paper No. 18873

Akaike, H., 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control, 19: 716–723.

Andrews, D. W. K., and W. Ploberger, 1994. Optimal Tests When a Nuisance Parameter Is Present Only under the Alternative. Econometrica, 62(6): 1383-1414.

Balcombe, K. and G. Rapsomanikis, 2008. Bayesian Estimation and Selection of Nonlinear Vector Error Correction Models: The Case of the Sugar-Ethanol-Oil Nexus in Brazil. American Journal of Agricultural Economics, 90(3): 658-668.

Balke, N.S. and T.B. Fomby, 1997. Threshold Cointegration. International Economic Review 38: 627-645.

Bec, F., and A. Rahbek, 2004. Vector Equilibrium Correction models with Nonlinear Discontinuous Adjustments. Econometrics Journal 7:628-651.

Clements, M.P. and H.-M. Krolzig, 1998. A comparison of the forecast performance of Markov-switching and threshold autoregressive models of US GNP. Econometrics Journal, 1: C47-C75.

Clements, M.C. and Krolzig, H.-M., 2001. Modelling Business Cycle Features Using Switching Regime Models. Economics Series Working Papers 9958, University of Oxford, Department of Economics.

Corradi, V., N. Swanson, and H. White, 2000. Testing for Stationarity Ergodicity and for Comovements between Nonlinear Discrete Time Markov Processes. Journal of Econometrics 96:39-73.

Dickey, D.A. and W.A. Fuller, 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74: 427–431.

Elliott, G., 1999. Efficient tests for a unit root when the initial observation is drawn from its unconditional distribution. International Economic Review, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, vol. 40(3): 767-83

Elliott, G., Rothenberg, T., and Stock, J., 1996. Efficient tests for an autoregressive unit root. Econometrica, 64, 813-836.

Enders, W., and C.W.J. Granger, 1998. Unit Root Tests and Asymmetric Adjustment with an Example Using the Term Structure of Interest Rates. Journal of Business and Economic Statistics 16: 304-311.

Enders, W. and Holt, M.T., 2012. Sharp breaks or smooth shifts? An investigation of the evolution of primary commodity prices. American Journal of Agricultural Economics 94:659-673.

Engle, R.F. and C.W.J. Granger, 1987. Cointegration and Error-correction: Representation, Estimation and Testing. Econometrica 55: 251-276.

Escribano, A., and S. Mira, 2002. Nonlinear Error Correction Models. Journal of Time Series Analysis 23:509-522.

Escribano, A., and G.A. Pfann, 1998. Nonlinear Error Correction, Asymmetric Adjustment and Cointegration. Economic Modelling 15:197-216

Granger C.W.J., and T.H. Lee, 1989. Investigation of Production Sales and Inventory Relationships using Multicointegration and Non-symmetric Error Correction Models. Journal of Applied Econometrics, 4, (Supplement: Special Issue on Topics in Applied Econometrics):S-145-S-159.

Haggan, V. and T. Ozaki, 1981. Modeling nonlinear vibrations using an amplitude-dependent autoregressive time series model. Biometrika 68: 189-196.

Hamilton, J. D., 1989. A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrica, 57(2): 357-84.

Hansen, B.E., 1996. Inference when a Nuisance Parameter is not Identified Under the Null Hypothesis. Econometrica 64: 413-430.

Hansen, B., and B. Seo, 2002. Testing for Two-Regime Threshold Cointegration inVector Error-Correction Models. Journal of Econometrics 110:293-318.

Johansen, S., 1988. Statistical analysis of cointegrating vectors. Journal of Economic Dynamics and Control 12: 231-254.

Kapetanios, G., Y. Shin, and A. Snell, 2006. Testing for Cointegration in Nonlinear Smooth Transition Error Correction Models. Econometric Theory, 22:279-303.

Krolzig, H.M., 1998. Econometric Modelling of Markov-Switching Vector Autoregressions using MSVAR for Ox. Institute of Economics and Statistics and Nuffield College, Oxford. December 15.

Krolzig, H.M. and M.P. Clements, 2002. Can oil shocks explain asymmetries in the US Business Cycle? Empirical Economics, 27(2): 185-204.

Kwiatkowski, D., P.C.B. Phillips, P. Schmidt, Y. Shin, 1992. Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root. Journal of Econometrics, 54, pp. 159-178.

Luukkoven, R., Saikkoven P., Teräsvirta T., 1988. Testing linearity against smooth transition autoregressive models. Biometrika 75: 491-499.

McPhail, L., 2011. Assessing the impact of US ethanol on fossil fuel markets: A structural VAR approach. Energy Economics 33:1177-1185.

McPhail, L. L. and B.A. Babcock, 2012. Impact of US Biofuel Policy on US Corn and Gasoline Price Variability. Staff General Research Papers 34892, Iowa State University, Department of Economics.

Mitchell, D., 2008. A note on rising food prices. World Bank, Washington DC.

Moschini, G., 1989. Modeling the Supply Response of Supply-Managed Industries: A Review of Issues. Canadian Journal of Agricultural Economics/Revue Canadienne d'Agroeconomie, 37(3): 379-392.

Nazlioglu, S. and Soytas, U., 2012. Oil price, agricultural commodity prices and the dollar: A panel cointegration and causality analysis. Energy Economics 34:1098-1104.

Ng S. and P. Perron, 2001. LAG Length Selection and the Construction of Unit Root Tests with Good Size and Power. Econometrica, 69(6): 1519-1554.

Phillips, P.C.B and P. Perron, 1988. Testing for a Unit Root in Time Series Regression. Biometrika, 75, 335–346

Pindyck R.S., and J. J. Rotemberg, 1990. The Excess Co-Movement of Commodity Prices. The Economic Journal, 100(403): 1173-1189.

Rapsomanikis, G., Hallam, D., 2006. Threshold cointegration in the sugar-ethanol-oil price system in Brazil: Evidence from nonlinear vector error correction models. FAO Commodity and Trade Policy Research Papers 22, FAO, Rome. Available at ftp://ftp.fao.org/docrep/fao/009/ah471e/ah471e00.pdf, accessed January 2013.

Saikkonen, P. and Luukkonen, R., 1988. Lagrange multiplier tests for testing nonlinearities in time series models. Scandinavian Journal of Statistics 15(1):55–68.

Saikkonen, P., 2005. Stability Results for Nonlinear Error Correction Models. Journal of Econometrics 127:69-81.

Seo, B., 2004. Testing for Nonlinear Adjustment in Smooth Transition Vector Error Correction Models. Econometric Society, Far Eastern Meetings.

Serra, T., Zilberman, D., Gil, J. M. and Goodwin, B. K., 2011. Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system. Agricultural Economics, 42: 35–45

Terasvirta T., 1944. Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models. Journal of the American Statistical Association 89 (425): 208-218.

Thompson, W., S. Meyer, P. Westhoff, and Jarrett Whistance, 2012. A Question Worth Billions: Why Isn't the Conventional RIN Price Higher? FAPRI-MU Report 12-12, FAPRI, University of Missouri, Columbia, Missouri, December.

Tsay, R.S., 1989. Testing and Modelling Threshold Autoregressive Processes. Journal of the American Statistical Association, 84:231-240.

Tong, H. 1983. Threshold Models in Nonlinear Time Series Analysis: Lecture Notes in Statistics, 21. Berlin: Springer.

van Dijk, D., and T. Terasvirta and P. H. Franses, 2002. Smooth Transition Autoregressive Models — A Survey Of Recent Developments. Econometric Reviews, Taylor and Francis Journals, 21(1): 1-47.

Yang Y.K., 2012. Modelling Nonlinear Vector Economic Time Series. PhD Thesis, Business and Social Sciences, Aarhus University.