VOLATILITY SPILLOVERS BETWEEN FOOD AND ENERGY MARKETS, A SEMIPARAMETRIC APPROACH

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Abstract

Previous literature on volatility links between food and energy prices is scarce and mainly based on parametric approaches. We assess this issue by using a semiparametric GARCH model recently proposed by Long et al. (2009), which is essentially a nonparametric correction of the parametric conditional covariance function. We focus on price links between crude oil, ethanol and sugar prices in Brazil. Results suggest strong volatility links between the prices studied. They also suggest that parametric approximations of the conditional covariance matrix may lead to misleading results and can be improved using nonparametric techniques.

Keywords: biofuels, feedstocks, price volatility interactions, semiparametric GARCH
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1. Introduction

The global emergence of biofuel production has been a disruptive event for energy and agricultural markets, causing significant changes in the liquid fuels market and in the demand for food products that are used to provide a portion of worldwide liquid fuel supply. Several research papers have attempted to characterize the nature of this event from an economic point of view by assessing, among other topics, the effects of the ethanol industry on economic welfare (Babcock, 2008), agricultural land allocation and values (Henderson and Gloy, 2009), and agricultural commodity prices (Balcombe and Rapsomanikis, 2008; de Gorter and Just, 2008; McNew and Griffith, 2005).

Because of its social and political relevance, the link between energy and agricultural commodity prices has received considerable attention. Most research has shown that the outbreak of the ethanol industry has strengthened the links between food and energy prices. Most of the analyses working on this topic are methodologically founded on standard supply and demand frameworks and partial or general equilibrium models calibrated to current conditions (Babcock, 2008; Giesecke et al., 2009). A rather common characteristic of these analyses is that they focus on price-level links. The studies of price volatility interactions between energy and food markets are, however, very scarce.

An increased correlation between food and energy prices is likely to yield stronger volatility spillovers between these prices. Further, changes in price levels and volatility may render traditional risk management tools unuseful and may require higher economic margins to compensate for increased risk levels. It is thus relevant to assess the impacts of the emergence of ethanol, not only on price level links, but also on price variability relationships.

McPhail and Babcock (2008) develop a stochastic equilibrium model of the U.S. corn market to assess the impacts of the ethanol industry on prices and welfare. They conclude that ethanol markets have increased corn price levels and volatility. Zhang et al. (2009) model price volatility interactions between U.S. food and energy markets using a MGARCH model. They find that while ethanol price volatility is influenced by the feedstock price volatility, corn price levels and volatility do not depend on ethanol's. The work by Serra et al. (2010) assesses volatility interactions within the Brazilian ethanol markets by using Seo's (2007) parametric MGARCH model. They find relevant volatility spillovers across markets flowing in multiple directions.

Both Serra et al. (2010) and Zhang et al. (2009) articles model volatility of multiple economic time-series using parametric MGARCH models that have two characteristic features. First, they assume a normal distribution of the model errors and second, the conditional covariance matrix is assumed to be linear. The literature on economic data volatility has widely rejected normality (Longin and Solnik, 2001). Further, nonlinear patterns in conditional covariance have been widely observed in the financial literature (Long et al., 2009). Asymmetric volatility responses to positive and negative market shocks have also been identified.

Several non-linear volatility functions have been proposed to allow for non-constant, non-linear conditional correlations over time. The works by Cappiello et al. (2003), Lai et al. (2009), Pelletier (2006) are built upon parametric nonlinear GARCH models. Nonparametric and semi-parametric approximations to GARCH modeling have also been proposed (Audrino, 2006; Härdle and Tsybakov, 1997). Long et al. (2009) developed a semiparametric multivariate volatility model that consists of a nonparametric correction of the parametric conditional covariance estimator. In contrast with previous non and semi-parametric research, Long et al. (2009) jointly model multivariate volatilities. The proposal is robust to potential misspecifications of the error density and the parametric conditional covariance function.

We study volatility interactions between energy and food prices by using Long et al.'s (2009) proposal. In a first stage, the reliability of a parametric approximation to the conditional covariance functional form is assessed. In the second stage, such parametric estimator is adjusted using Long et al.'s (2009) nonparametric correction. We focus on the Brazilian ethanol industry. While the U.S. is currently leading worldwide ethanol production, the Brazilian case allows assessing price links within a more consolidated and mature industry, thus yielding results that are less dependent on conjunctural events. We contribute to the literature on volatility interactions between energy and food markets by using a semi-parametric method that overcomes two of the most important shortcomings of traditional MGARCH models: the assumption of normally distributed errors and linearity of the conditional covariance matrix.

Global ethanol markets have recently been affected by important market shocks. Worldwide ethanol demand surged in the mid 2000s partly as a result of major U.S. refiners switching from MTBE to ethanol, used as an oxygenate additive. High crude oil prices also contributed to increased ethanol demand. More recently however, weak oil prices and the global financial crisis have undermined investments in ethanol projects and reduced the ethanol-derived demand for feedstocks. The semi-parametric model proposed by Long et al. (2009) allows for changing behavior of volatility relationships depending on the state of the world, or the prevailing economic regime.

2. The sugarcane ethanol industry

The global ethanol industry experienced an outbreak by mid 2000s due to a policy-driven surge in U.S. demand. Other ethanol demand boosting incentives include crude oil prices that reached historical highs in the second half of the 2000s and motivated the use of alternative fuels, the worldwide promotion of policies to address global warming by increasing the use of renewable fuels, or the endorsement of biofuels as a means of increasing energy security, promoting economic growth and rural development.

Brazil is currently the leading worldwide sugarcane ethanol producer. The ethanol industry was initially supported by the ProÁlcool program, a government reaction to the petrol shortage during the 1973 oil crisis (Goldemberg, 2006) and that provided different policy measures to stimulate both the demand and the supply of ethanol. The program was eliminated in the 1990s and currently, though demand incentives are still applied, no direct control over ethanol production or trade exists.

The Brazilian ethanol industry is estimated to have the lowest ethanol production costs in the world (Martines-Filho et al., 2006; OECD, 2006). These costs are strongly determined by the costs of sugarcane production and processing and the rate of sugarcane conversion into ethanol. Investments in sugarcane agronomic research that have led to increased sugarcane yields and quality, have played a key role in reducing ethanol production costs. The use of sugarcane bagasse as an energy source by the ethanol industry instead of fossil fuels, also contributes to reduced costs.

The Brazilian ethanol industry is not only characterized by its competitiveness, but also by its flexibility. A large number of ethanol plants operate on a large scale and use a dual technology that allows switching from ethanol to sugar production and vice-versa, depending on market prices. A sound infrastructure for handling and distributing ethanol and the steady increase in flex fuel vehicle (FFV) sales, allow consumers to shift from high to low ethanol-gasoline blends depending on the prices at the pump.

Both the outburst of the international ethanol market and the strong internal demand for ethanol, mainly driven by the development and consumer acceptance of flex-fuel vehicles, have led to an expansion of ethanol production in Brazil (De Almeida et al., 2007). In 2007, 491 million tons of sugarcane were harvested in Brazil from 6,5 million hectares. About 70% of sugarcane is directly cultivated by the sugar and ethanol mills in Brazil (around 370), while the remaining 30% is cultivated by around 70 thousand independent farmers. A strong ethanol demand and less attractive sugar prices have led the industry to divert increasing quantities of sugarcane to ethanol production. In the 2007/08 marketing year, on the order of 55% of sugarcane was processed into ethanol (USDA, 2008). About 65% of sugar production is exported to international markets where Brazil plays a leading role. Brazil ethanol production in the 2007/08 marketing year was on the order of 22,4 billion liters. Brazilian ethanol exports were around 3.6 billion liters, with the U.S. and Europe being the main destinations.

While until 1997 ethanol prices were heavily controlled by the government, from 2002 on they fluctuate freely. These prices, however, receive government incentives in the form of tax exemptions that enhance ethanol competitiveness (De Almeida et al., 2007). The Brazilian ethanol price has a strong dependence on sugarcane harvest and harvest yields. It also depends heavily on crude oil prices. During the last decade, specially in the second half of the 2000s, Brazilian ethanol prices have experienced considerable changes. Relevant drivers of these changes are the increases in worldwide and internal ethanol demand, as well as the important changes in oil prices.

Our analysis focuses on assessing volatility links between the prices of oil, sugar and ethanol in the period from July 2000 to November 2009. The period studied comprises the ethanol boom in the mid 2000s. From mid 2008 on, the economic scene was characterized by an economic and financial crisis. The collapse in crude oil prices in the second half of 2008 constrained ethanol demand and weakened ethanol prices. Ethanol prices recovered during 2009 as a result of global sugar production being unable to cope with demand and resulting in strong increases in sugar prices. The decline in crude oil prices, the economic crisis and the high feedstock prices, have mined the short-term forecasts of ethanol with millers currently focusing on more attractive returns from export sugar (International Sugar Organization, 2009). As noted above, the flexible semi-parametric techniques employed in this research, are specially suited to allow for time-changing price behavior.

3. Methodology

Our methodological approach to assessing volatility links within the Brazilian ethanol industry is based on Long et al.’s (2009) semiparametric GARCH model. The application of an innovative methodology to shed light on ethanol industry price behavior is a contribution of our work. The semiparametric estimator consists of a nonparametric correction of the parametric estimator of the conditional covariance. Suppose that the *k*-dimensional vector of time series $\mathbf{r}_t = (r_{1t},...,r_{kt})'$, $t = 1,...,T$, follows the stochastic process $\mathbf{r}_t | \mathcal{F}_{t\text{-}1} \sim \mathbf{P}(\boldsymbol{\mu}_t, \mathbf{H}_t; \theta)$, where $\mathcal{F}_{t\text{-}1}$ is the information set at time $t-1$, $\boldsymbol{\mu}_t = E(\mathbf{r}_t | \mathcal{F}_{t\text{-}1})$, $\mathrm{H}_t = E(\mathbf{r}_t \mathbf{r}_t' | \mathcal{F}_{t\text{-}1})$, $\mathbf{P}$ is the joint cumulative distribution function (CDF) of $\mathbf{r}_t$, and θ includes the distribution parameters.

It is assumed that $\boldsymbol{\mu}_t$ is zero (or that standardization has been applied). The model for $\mathbf{r}_t$ can be written as $\mathbf{r}_t = \mathbf{H}_t^{1/2}\mathbf{e}_t$, being $\mathbf{e}_t = \mathbf{H}_t^{-1/2}\mathbf{r}_t$ a standardized error with $E(\mathbf{e}_t | \mathcal{F}_{t\text{-}1}) = 0$ and $E(\mathbf{e}_t \mathbf{e}_t' | \mathcal{F}_{t\text{-}1}) = \mathbf{I}_k$. No assumption on the distribution of $\mathbf{e}_t$ is necessary to derive the semiparametric estimator. Matrix $\mathbf{H}_t^{1/2}$ is the symmetric square root of $\mathbf{H}_t$.

Let a parametric estimation of $\mathbf{H}_t$ be denoted by $\mathbf{H}_{p,t}(\theta)$. The semiparametric estimator of the conditional covariance matrix is obtained as follows $\mathbf{H}_t = \mathbf{H}_{p,t}^{1/2}(\theta)E\left[\mathbf{e}_t(\theta)\mathbf{e}_t(\theta)'\middle|\mathscr{F}_{t\text{-}1}\right]\mathbf{H}_{p,t}^{1/2}(\theta)$, where $\mathbf{e}_t(\theta) = \mathbf{H}(\theta)_{p,t}^{-1/2}\,\mathbf{r}_t$ is the standardized error derived from the parametric model. $E\left[\mathbf{e}_t(\theta)\mathbf{e}_t(\theta)'\middle|\mathscr{F}_{t\text{-}1}\right]$ is the nonparametric component of $\mathbf{H}_t$ which is derived assuming that the conditional expectation of $\mathbf{e}_t\mathbf{e}_t'$ depends on the current information set only through the q-dimensional vector $\mathbf{x}_t = (x_{1t},...,x_{qt})' \in \mathscr{F}_{t\text{-}1}$. Hence, $E\left[\mathbf{e}_t\mathbf{e}_t'\middle|\mathscr{F}_{t\text{-}1}\right] = \mathbf{G}_{np}(\mathbf{x}_t)$.

The semiparametric estimator can thus be expressed as: $\mathbf{H}_t = \mathbf{H}_{p,t}^{1/2}(\theta)\mathbf{G}_{np,t}\mathbf{H}_{p,t}^{1/2}(\theta)$ To estimate $\mathbf{H}_t$, the following two stage method is implemented. First, an estimate of θ, $\hat{\theta}$, is obtained by parametrically estimating the conditional covariance matrix $\mathbf{H}_{p,t}(\theta)$. The standardized residuals are then defined as $\hat{\mathbf{e}}_t = \hat{\mathbf{H}}_{p,t}^{-1/2}\mathbf{r}_t$. In the second stage, $E\left[\mathbf{e}_t\mathbf{e}_t'\middle|\mathscr{F}_{t\text{-}1}, \mathbf{x}_t = \mathbf{x}\right]$ is obtained using the nonparametric Nadaraya-Watson estimator as follows: $\hat{\mathbf{G}}_{np,t}(\mathbf{x}) = \sum_{s=1}^{T}\hat{\mathbf{e}}_s\hat{\mathbf{e}}_s' K_{\mathbf{h}}(\mathbf{x}_s - \mathbf{x}) \Big/ \sum_{s=1}^{T} K_{\mathbf{h}}(\mathbf{x}_s - \mathbf{x})$, where $K_{\mathbf{h}}(\mathbf{x}_s - \mathbf{x})$ is a multiplicative kernel function, and $\mathbf{h} = (h_1,...,h_q)$ is a vector of bandwidth parameters. The semiparametric estimator of the conditional covariance matrix is defined as $\hat{\mathbf{H}}_{sp,t} = \hat{\mathbf{H}}_{p,t}^{1/2}(\theta)\hat{\mathbf{G}}_{np,t}\hat{\mathbf{H}}_{p,t}^{1/2}(\theta)$.

The empirical implementation sets $\mathbf{x}_t = \mathbf{r}_{t\text{-}1}$ and uses a Gaussian kernel. The bandwidth is defined as $h_i = c_j\hat{\sigma}_i T^{-1/6}$, where $\hat{\sigma}_i$ is the sample standard deviation of r_{it}, T is the number of observations and c_j is selected from 0.5, 0.6,…,5 through a grid search process that minimizes the minimum sum of squares (MSE) loss function. This function is a measure of the difference between the true conditional covariance matrix and its estimates. Since the true conditional covariance matrix is not known, Long et al. (2009) use the squared $\mathbf{r}_t$ vector.

Based on the semiparametric estimator, Long et al. (2009) propose a test for the correct specification of the parametric conditional covariance estimator. If the parametric model was correctly specified, $\mathbf{H}_t = \mathbf{H}_{p,t}$ and according to (2) matrix $\mathbf{G}_{np,t}$ would be equal to the identity matrix. Long et al. (2009) test the null hypothesis $\mathbf{G}_{np,t}(\mathbf{x}_t) = \mathbf{I}_t$ against the alternative $H_1 : \Pr\left(\mathbf{G}_{np,t}(\mathbf{x}_t) = \mathbf{I}_t\right) < 1$.

4. Results

Our empirical analysis is based on logarithmic transformations of weekly international crude oil prices (p_1), as well as on Brazilian ethanol (p_2) and sugar (p_3) prices. Data sources are the Center for Advanced Studies on Applied Economics that provided Brazilian ethanol and sugar prices, and the U.S. Energy Information Administration that facilitated crude oil prices. All prices are expressed in U.S. dollars and are observed from July 2000 to November 2009.

Our analysis is of a pair-wise nature. Pair-wise analyses are very common in the price transmission literature and are further justified because of the “curse of dimensionality” that affects nonparametric estimators (Fan, 2000). We consider two pairs of prices: oil-ethanol (model 1) and ethanol-sugar (model 2). Standard unit root tests confirm the presence of a unit root in each price series. Engle and Granger (1987) and Johansen (1988) tests provide evidence that the pairs of prices are cointegrated. By normalizing with respect to the ethanol price, cointegration relationships can be expressed as follows (where numbers in parenthesis are standard errors):

$$\underset{}{p_2} - \underset{(0.022)}{0.453 p_1} + \underset{(0.083)}{2.872} = 0; \qquad p_2 - \underset{(0.022)}{0.777 p_3} + \underset{(0.057)}{3.161} = 0 \tag{1}$$

The positive long-run relationship between ethanol and sugar prices is expected given the fact that sugar represents a conspicuous part of ethanol production costs. Further, the long-run positive link between ethanol and crude oil prices is also expected given the use of fossil fuel as an input into blended gasoline.

The semiparametric estimator of the conditional covariance matrix is derived in two stages. In the first stage a MGARCH model is estimated parametrically. A vector error correction model is used to examine the conditional mean (equation 2) and a multivariate BEKK-GARCH specification (Engle and Kroner, 1995) is employed to analyze the conditional heteroscedasticity (equation 3). Conditional mean and heteroscedasticity equations are expressed as follows:

$$\Delta \mathbf{p}_t = \alpha ECT_{t-1} + \gamma_1 \Delta \mathbf{p}_{t-1} + \gamma_2 \Delta \mathbf{p}_{t-2} \tag{2}$$

$$\mathbf{H}_{p,t} = \mathbf{CC'} + \mathbf{A'r}_{t-1}\mathbf{r'}_{t-1}\mathbf{A} + \mathbf{B'H}_{p,t\text{-}1}\mathbf{B} \tag{3}$$

where $\Delta \mathbf{p}_t$ is a 2×1 vector of prices in first differences, ECT_{t-1} is a lagged error correction term, α (2×1) shows the adjustment of each price to deviations from the long-run parity and γ_i, $i=1,2$ (2×2) shows the short-run price dynamics. Matrix $\mathbf{A}$ (2×2) captures the influence of past market shocks on price volatility, while $\mathbf{B}$ (2×2) models the influence of past volatility on current volatility. $\mathbf{C}$ is a 2×2 lower triangular matrix. The conditional mean and variance models are jointly estimated using standard maximum likelihood procedures. The errors of the parametric model are then used in a second stage to derive the standardized errors necessary to build the semiparametric estimator.

The conditional mean equations derived from the estimation of the BEKK model are presented in tables 1 and 2 for the crude oil-ethanol (model 1) and the sugar – ethanol (model 2) pairs of prices, respectively. Tables 3 and 4 present the conditional variances for these models. The covariance stationarity condition is checked for both models and all eigenvalues are found to be less than one in modulus. The α parameters that are presented in table 1 suggest that, while ethanol price levels adjust to correct disequilibriums from the oil – ethanol long – run parity, crude oil prices can be considered as weakly exogenous, which is compatible with findings in Balcome and Rapsomanikis (2008) and Serra et al. (2010). This result is expected since, relative to the international crude oil market size, the Brazilian ethanol market is small.

The conditional variance equations are presented in table 3. Crude oil price volatility h_{11t} increases with its own lagged volatility (h_{11t-1}) and with shocks occurring in the crude oil market (r_{1t-1}^2). Lagged ethanol price volatility does not have an influence on crude oil price volatility. Further, lagged ethanol market shocks only affect crude oil price volatility indirectly through the term $r_{1t-1}r_{2t-1}$. The small influence of ethanol on crude oil price instability is not surprising given the weak exogeneity of crude oil with respect to the equilibrium relationship. The volatility in ethanol prices (h_{22t}) is found to increase with increases in its own lagged volatility (h_{22t-1}), as well as with shocks occurring in the crude oil and ethanol markets (r_{1t-1}^2 , r_{2t-1}^2 and $r_{1t-1}r_{2t-1}$ are significant).

The Long et al.'s (2009) test for the correct specification of the parametric conditional covariance estimator, that takes the value of 0.76, allows rejecting the null of correct specification at the 8% significance level, and motivates the use of the semiparametric estimator so as to capture information still remaining in the residuals of the parametric model. Figures 1 and 2 show, respectively, to what extent the parameters in h_{11t} and h_{22t} can vary depending on the prevalent economic conditions. More specifically, these figures present the histogram of the nonparametric correction of the parameters for h_{11t-1}, h_{22t-1}, r_{1t-1}^2 and r_{2t-1}^2 that show the direct volatility links between crude oil and ethanol markets.

Figure 1 confirms the relevance of using the nonparametric correction proposed by Long et al. (2009) through the heterogeneity in the localized parameter estimates in the crude oil price variance (h_{11t}). Parameter heterogeneity reduces the reliability of previous research estimates fully based on parametric methods. While the parametric BEKK model suggests that an increase in one unit in past crude oil price volatility contributes to increase current crude oil price volatility by 0.88, figure 1a shows that the resulting increase can indeed fluctuate from 0 to 3. The effects of crude oil market shocks on crude oil price volatility (figure 1c) are also rather disperse. Figures 1b and 1d confirm parametric results by suggesting, through the magnitude of the parameters, a small capacity of ethanol markets to induce volatility in crude oil prices.

Parameter dispersion is less acute in the ethanol price variance equation (h_{22t}). The parametric analysis shows a statistically significant impact of crude oil on ethanol price variability through crude oil market shocks. Figure 2c shows that the most frequent effect of past crude oil market shocks on ethanol price volatility is on the order of 0.05, though the value can fluctuate from 0 to 0.5. Figure 2b suggests that an increase in one unit in past ethanol price volatility can result in an increase in current volatility that ranges between 0 to 5, with the most frequent value being 0.5.

The α parameters in model 2 (table 2) suggest that the sugar price can be considered as weakly exogenous with respect to the ethanol – sugar long – run parity. Hence, it is the ethanol price that reacts to re-equilibrate the system. This result is compatible with Balcome and Rapsomanikis' (2008) and Serra et al.'s (2010) results. The exogeneity of sugar with respect to the long-run parity is an indicator that sugar prices lead ethanol prices. Sugar prices in Brazil have a very strong dependence on agricultural yields, as well as on international sugar prices. This helps to explain the decline in Brazilian ethanol production after the increase in international sugar prices in 1988 that led sugarcane mills to divert their production to sugar. Sugar prices were not affected by the decline in energy prices during part of the year 2008 thanks to tight worldwide sugarcane supplies that supported sugar prices. Hence, the finding that sugar prices are weakly exogenous for long-run parameters can also be explained through the relevance of Brazilian sugar exports and the dominant role that Brazil plays in the international sugar market (according to the USDA Foreign Agricultural Service, Brazilian exports represented more that 40% of world's sugar exports in 2006).

The conditional variance equations for model 2 are presented in table 4. Results suggest that volatility in the sugar price h_{33t} increases with its own lagged volatility. An increase in ethanol price volatility only affects h_{33t} indirectly through the covariance term. Shocks originating in the sugar market have also an influence on sugar price volatility, while ethanol market shocks only have an indirect influence through $r_{3t-1}r_{2t-1}$. Lagged instability in sugar and ethanol markets (h_{33t-1}, h_{22t-1} and h_{32t-1}) is found to increase ethanol price volatility (h_{22t}). Shocks occurring either in the sugar or ethanol markets are also found to have an impact on ethanol price volatility.

Long et al.'s (2009) test for the correct specification of the parametric conditional covariance estimator, that takes the value of 15.01, allows rejecting the null of correct specification at the 2% significance level suggesting, once more, that relying on parametric MGARCH models to assess volatility interactions can lead to misleading results. Figures 3 and 4 show to what extent the parameters in h_{33t} and h_{22t} from model 2 can vary depending on the prevalent economic conditions. While the parametric model suggests that an increase in past sugar volatility in one unit will cause an increase in current volatility equal to 0.78, figure 3a shows that the resulting increase can indeed fluctuate from 0.50 to 2.90, being the most frequent increase around 0.70. Figures 3b and 4d confirm, in accordance with the parametric results and through the small parameter values, the reduced capacity of ethanol markets to influence sugar price volatility. Figures [4a] (4c) show that the impact of [sugar price volatility] (sugar market shocks) on ethanol's can range from [0.05 to 1.15] (0 to 1.95).

5. Concluding remarks

We assess volatility spillovers in Brazilian ethanol markets by using Long et al.'s (2009) semiparametric estimator of the conditional covariance matrix. We use weekly international crude oil prices and Brazilian ethanol and sugar prices observed from July 2000 to November 2009. A pair wise analysis is carried out to avoid the "curse of dimensionality" affecting nonparametric estimators.

Our results suggest that ethanol and crude oil, as well as ethanol and sugar price levels are linked in the long-run by an equilibrium parity. These long-run price links show that ethanol prices increase with an increase in both crude oil and sugar prices. Further, while ethanol prices react to deviations from each long-run parity and respond to re-equilibrate the market, sugar and crude oil prices are weakly exogenous for long-run parameters. Crude oil and sugar prices thus determine ethanol prices.

With regards to volatility spillovers, parametric results suggest that crude oil market shocks can increase ethanol price volatility. Further, the ethanol price volatility is influenced by the sugar price volatility through the variance term. Shocks affecting the sugar market have also an impact on ethanol price volatility. Compatible with crude oil and sugar price levels being exogenous for long-run parameters, ethanol markets are found to have a reduced capacity to increase instability in sugar and crude oil markets. Another important result from our paper is that an assessment of volatility links based solely on parametric MGARCH models can lead to misleading results. We show the relevance of using the nonparametric correction proposed by Long et al. (2009) through the heterogeneity in the localized parameter estimates.

Our results have important policy implications. Ethanol markets are unable to affect feedstock price levels in the long-run. Hence, ethanol prices do not seem to induce an increase in food prices, for the markets and time period considered. This is compatible with large amounts of land being available for sugarcane cultivation in Brazil. Consistently with these results, we show that ethanol markets have a small capacity to induce volatility in feedstock prices, thus reducing the likelihood of instability transmission from energy to food markets. Hence, concerns regarding Brazilian ethanol markets bringing higher and more volatile food prices do not seem founded in light of our results.

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Table 1. Crude oil (p_1) – ethanol (p_2) MGARCH model: mean equation

Short-run dynamics parameters:

$$\begin{pmatrix}\Delta p_{1t}\\ \Delta p_{2t}\end{pmatrix}=\begin{pmatrix}\alpha_1\\ \alpha_2\end{pmatrix}ECT_{t-1}+\begin{pmatrix}\gamma_{111} & \gamma_{112}\\ \gamma_{121} & \gamma_{122}\end{pmatrix}\begin{pmatrix}\Delta p_{1t\text{-}1}\\ \Delta p_{2t\text{-}1}\end{pmatrix}+\begin{pmatrix}\gamma_{211} & \gamma_{212}\\ \gamma_{221} & \gamma_{222}\end{pmatrix}\begin{pmatrix}\Delta p_{1t\text{-}2}\\ \Delta p_{2t\text{-}2}\end{pmatrix}$$

	$i=1$	$i=2$
α_{i}	-6.786e-4 (0.007)	-0.023** (0.006)
γ_{11i}	0.243** (0.045)	0.048 (0.042)
γ_{12i}	-0.045 (0.034)	0.531** (0.049)
γ_{21i}	-0.006 (0.042)	-0.082* (0.043)
γ_{22i}	0.013 (0.036)	-0.017 (0.049)
Test for the correct specification of the parametric conditional covariance estimator (p value)		0.763 (0.080)

*(**) denotes statistical significance at the 10(5) per cent significance level

Table 2. Sugar (p_3) – ethanol (p_2) MGARCH model: mean equations

Short-run dynamics parameters:

$$\begin{pmatrix}\Delta p_{3t}\\ \Delta p_{2t}\end{pmatrix}=\begin{pmatrix}\alpha_3\\ \alpha_2\end{pmatrix}ECT_{t-1}+\begin{pmatrix}\gamma_{133} & \gamma_{132}\\ \gamma_{123} & \gamma_{122}\end{pmatrix}\begin{pmatrix}\Delta p_{3t\text{-}1}\\ \Delta p_{2t\text{-}1}\end{pmatrix}+\begin{pmatrix}\gamma_{233} & \gamma_{232}\\ \gamma_{223} & \gamma_{222}\end{pmatrix}\begin{pmatrix}\Delta p_{3t\text{-}2}\\ \Delta p_{2t\text{-}2}\end{pmatrix}$$

	$i=3$	$i=2$
α_{i}	-0.001 (0.006)	-0.025** (0.008)
γ_{13i}	0.650** (0.046)	-0.011 (0.034)
γ_{12i}	0.035 (0.060)	0.573** (0.048)
γ_{23i}	-0.144**(0.044)	0.065* (0.033)
γ_{22i}	0.150** (0.053)	-0.107** (0.038)
Test for the correct specification of the parametric conditional covariance estimator (p value)		15.015 (0.020)

*(**) denotes statistical significance at the 10(5) per cent significance level

Table 3. Conditional variance equations. Crude oil (p_1)– ethanol (p_2) model

$h_{11t}=$	9.423e-5**	+0.879** h_{11t-1}	-0.056 h_{12t-1}	+7.001e-4 h_{22t-1}	+0.053** r_{1t-1}^2	+0.101** $r_{1t-1}r_{2t-1}$	+8.516e-3 r_{2t-1}^2
$h_{22t}=$	2.896e-4**	+8.819e-4 h_{11t-1}	-0.041 h_{12t-1}	+0.482** h_{22t-1}	+0.048** r_{1t-1}^2	-0.252** $r_{1t-1}r_{2t-1}$	+0.328** r_{2t-1}^2

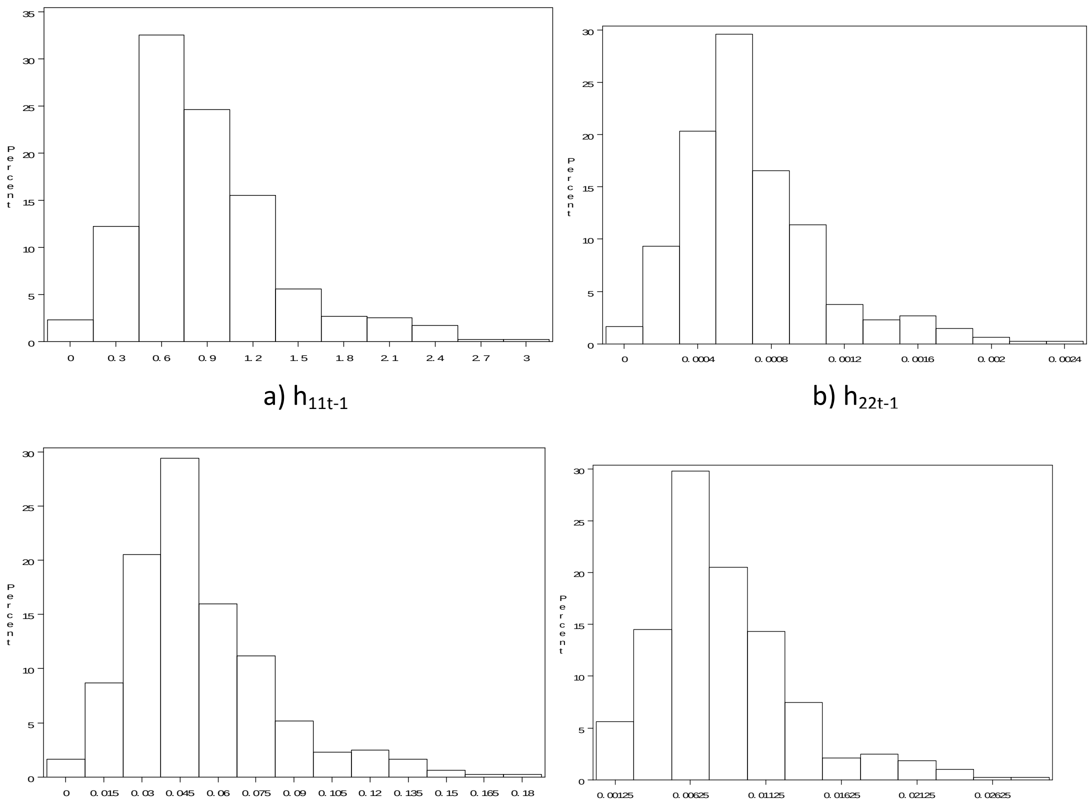
*(**) denotes statistical significance at the 10(5) per cent significance level

Table 4. Conditional variance. Sugar (p_3)– ethanol (p_2) model

$h_{33t}=$	4.022e-5**	+0.779** h_{33t-1}	+0.557** h_{32t-1}	+1.331e-3 h_{22t-1}	+0.124** r_{3t-1}^2	-0.290** $r_{3t-1}r_{2t-1}$	+1.100e-4 r_{2t-1}^2
$h_{22t}=$	2.506e-4**	+0.099* h_{33t-1}	+0.317** h_{32t-1}	+0.254** h_{22t-1}	+0.169** r_{3t-1}^2	-0.692** $r_{3t-1}r_{2t-1}$	+0.707** r_{2t-1}^2

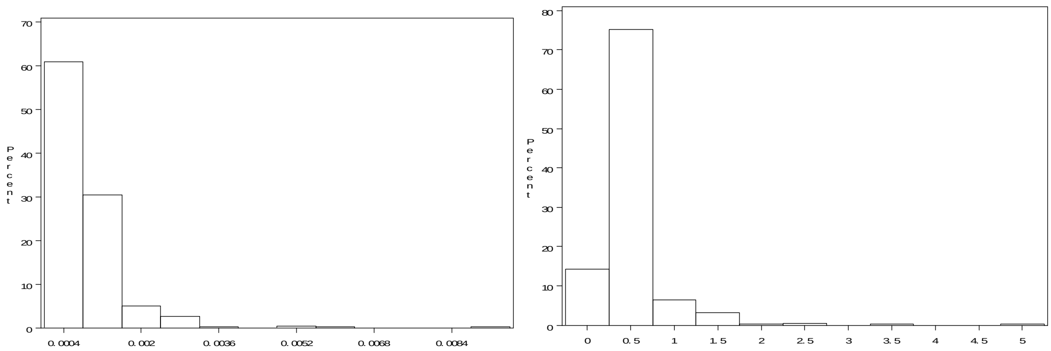
*(**) denotes statistical significance at the 10(5) per cent significance level

Figure 1. Distribution of localized estimates of the parameters of the conditional variances. Crude oil (p_1)– ethanol (p_2) model. Crude oil price variance h_{11t}

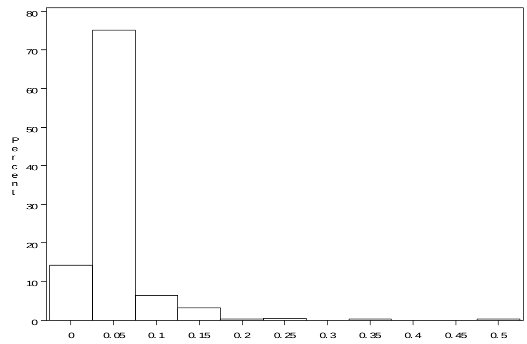


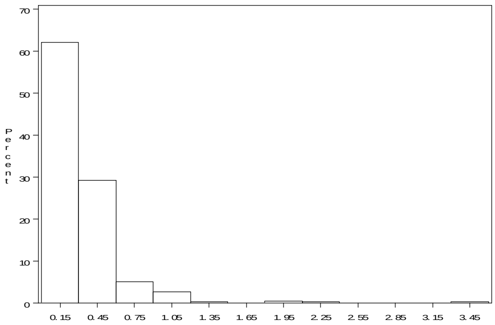
a) h_{11t-1} b) h_{22t-1} c) r^2_{1t-1} d) r^2_{2t-1}

Figure 2. Distribution of localized estimates of the parameters of the conditional variances. Crude oil (p_1)– ethanol (p_2) model. Ethanol price variance h_{22t}



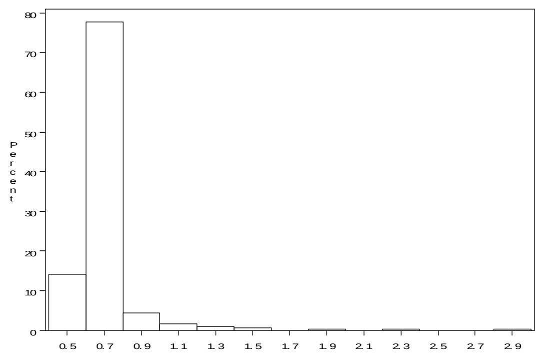
a) h_{11t-1} b) h_{22t-1}

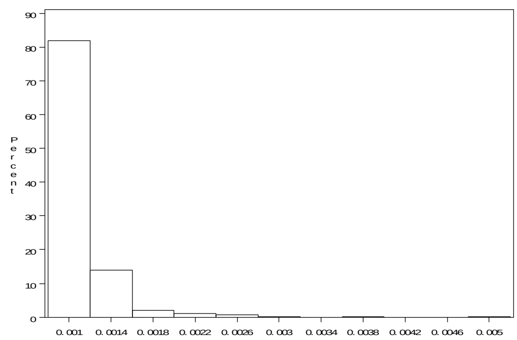




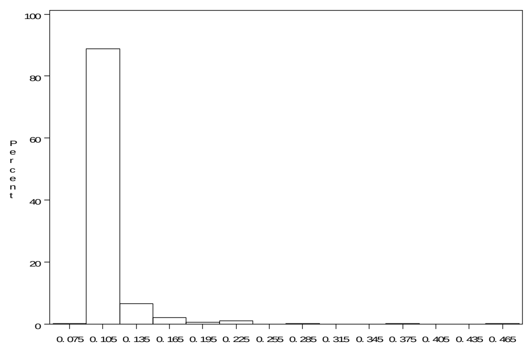
c) r^2_{1t-1} d) r^2_{2t-1}

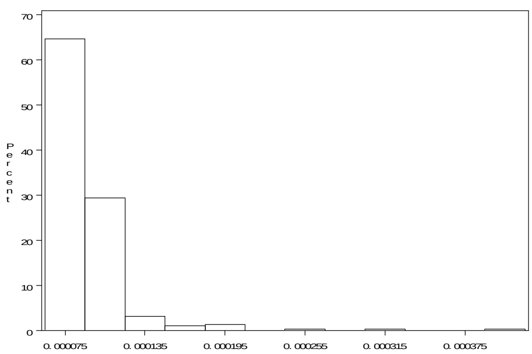
Figure 3. Distribution of localized estimates of the parameters of the conditional variances. Sugar (p_3)– ethanol (p_2) model. Sugar price variance h_{33t}





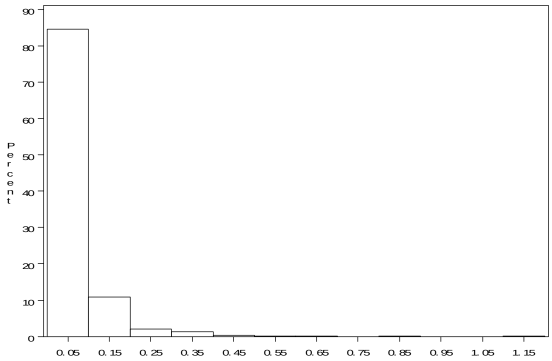
a) h_{33t-1} b) h_{22t-1}



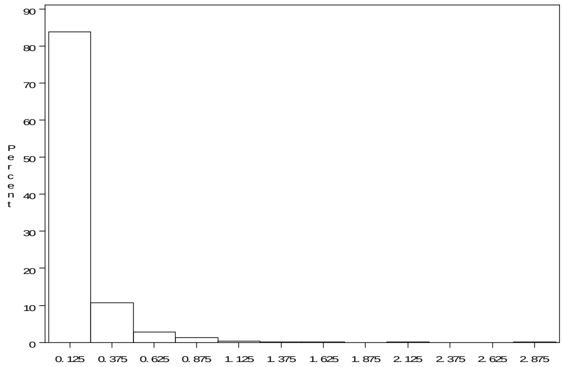


c) r^2_{3t-1} d) r^2_{2t-1}

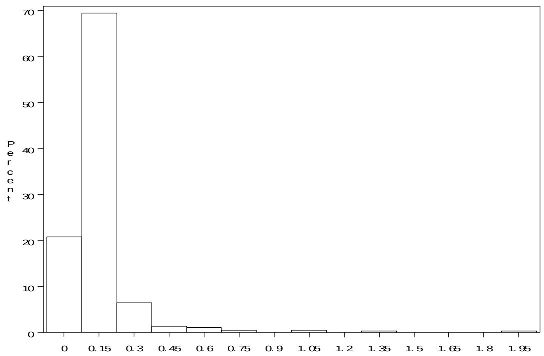
Figure 4. Distribution of localized estimates of the parameters of the conditional variances. Sugar (p_3)– ethanol (p_2) model. Ethanol price variance h_{22t}



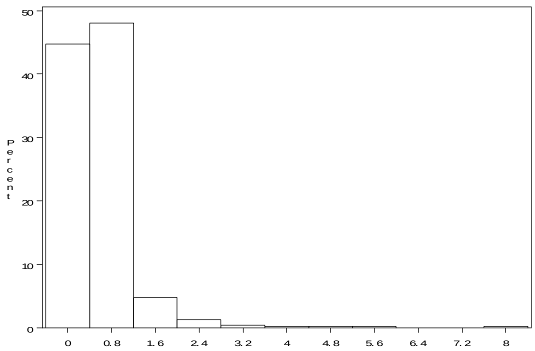
a) h_{33t-1}



b) h_{22t-1}



c) r^2_{3t-1}



d) r^2_{2t-1}