PRICE VOLATILITY IN ETHANOL MARKETS

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Abstract

Our paper looks at how price volatility in the Brazilian ethanol industry changes over time and across markets by using a new methodological approach suggested by Seo (2007). The main advantage of Seo's proposal over previously existing methods is that it allows to jointly estimate the cointegration relationship between the price series investigated and the multivariate GARCH process. Our results suggest that crude oil prices not only influence ethanol price levels, but also their volatility. Increased volatility in crude oil markets results in increased volatility in ethanol markets. Ethanol prices, on the other hand, influence sugar price levels and an increase in their volatility levels also impacts, though less strongly, on sugar markets.

Keywords: volatility, ethanol, GARCH, cointegration

JEL classification: Q11, C32

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1. Introduction

Ethanol is currently the major liquid biofuel produced around the world. Recent increases in worldwide ethanol demand and production can be partially attributed to international crude oil prices reaching historically high levels. This has created an incentive to use alternative energy sources and reduce the dependence on fossil fuels. Apart from high energy prices and their consequences, policy makers and society at large are also concerned about the relevant volatility in crude oil prices that may cause price spikes that are likely to harm the economy.

Highly volatile crude oil prices reduce crude oil competitiveness and represent a further incentive to adopt alternative energy sources (Vedenov *et al*., 2006). Since currently ethanol is mainly produced from food crops, the upward shift in ethanol demand has also increased social and political concerns on the effects of this shift on both food price levels and volatility.

While a few studies have econometrically assessed average price relationships within the Brazilian and North American ethanol industries (see Balcombe and Rapsomanikis, 2008; or Serra *et al*., 2008), to the best of our knowledge no previous published paper addresses the transmission of volatility within this industry.[1] Volatility in oil prices, for example, may spill over ethanol markets which in turn may induce volatility into the feedstock market.

[1] Vedenov *et al*. (2006) use a real-options pricing approach to assess whether volatility in gasoline markets creates incentives for adoption of alternative fuels. These authors however, do not study volatility interactions between oil, ethanol and feedstock markets, which is the objective of our research.

Our paper looks at how volatility in the Brazilian ethanol industry changes over time and across markets. Understanding volatility transmission over time and across markets is important for both market participants, who will adjust their investment and hedging decisions accordingly, as well as for policy makers who are more concerned about the macroeconomic and social welfare consequences of price links.

World ethanol production is dominated by the US and Brazil. In 2006 worldwide production totaled 13,489 million gallons, with the US and Brazil producing, respectively, a 36 and a 33% of this quantity. Although both countries produce a conspicuous part of worldwide ethanol, their industries are not equally developed: while the Brazilian market is starting to transform into a mature industry, the US industry is still in a more infant stage. We draw from the Brazilian experience to shed light on the issues raised above.

Modeling volatility in time series has received much attention in the economics and econometrics literature since the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) models in Engle's (1982) seminal paper and their generalized version (GARCH) by Bollerslev (1986). Although modeling volatility of a single time series has been the main focus of attention, the literature has also attempted at understanding volatility spillovers across different markets by making use of multivariate GARCH models (MGARCH). While modeling conditional heteroskedasticity, ARCH-type models do not explicitly estimate the long-run relationship between the prices being studied.

Demand and supply forces in the energy and food markets are likely to ensure that crude oil, ethanol and feedstock prices co-move in the long-run (Balcombe and

Rapsomanikis, 2008). Hence, when assessing price volatility changes and spillovers in the ethanol industry, one should also pay attention to the notion of cointegration introduced by Engle and Granger (1987) to capture the long-run or equilibrium relationships among different time series.

Until recently, the methods proposed to estimate cointegration relationships, have not explicitly considered time varying volatility in the data. Seo (2007) suggests an estimator of the cointegration vector that explicitly models conditional heteroskedasticity. More specifically, he proposes a maximum likelihood estimator that estimates the error correction model and the multivariate GARCH process jointly. We follow this proposal.

To the best of our knowledge, Seo's (2007) methodological approach has not yet been empirically implemented. Hence, our paper contributes to previous literature by studying volatility interactions and cointegration relationships in biofuels markets by making use of a new methodological approach. Although average price relationships have been assessed in this industry, no attempt has been made to explicitly model conditional heteroskedasticity in the data.

2. The Brazilian ethanol industry

The ethanol industry in Brazil was initially promoted through government intervention as a response to the petroleum shortage caused by the 1973 oil crisis (Goldemberg, 2006). Aggressive support measures aiming at stimulating both the demand and supply of ethanol and increase the share of domestically produced fuel in the transportation sector were provided in the framework of the Proálcool program. The relevance of sugarcane production in Brazil and the low sugar prices registered during the 1970s oil crisis, recommended developing a sugarcane-based ethanol industry. In 2005 more than half of Brazil's sugarcane output was being devoted to ethanol production (Perkins and Barros, 2006).

Apart from governmental support, the sugar-based Brazilian ethanol industry has also benefited from large amounts of land available for sugarcane cultivation, investments in new production facilities, and various technological developments. The latter have improved the processing of sugarcane into ethanol and have increased the industry flexibility to adapt to changes in relative market prices: a large number of Brazilian ethanol plants operate on a large scale and are dual, i.e., they can easily switch from ethanol to sugar production depending on the predominant economic conditions (Tokgoz and Elobeid, 2006).

Technological progress has also improved flexibility on the demand side, mainly through the introduction in 2003 of flex-fuel vehicles (FFVs) that can run on any ethanol-gasoline blend without affecting automotive performance. Since their introduction, the sales of FFVs have increased dramatically. By the end of 2005, they represented more than 70% of passenger car sales (Perkins and Barros, 2006). Success of FFVs is partially due to the legacy of the Proálcool program that provided Brazil with a sound infrastructure for ethanol handling and distribution. Nowadays virtually all of Brazil's gas service stations have ethanol pumps.

The Proálcool program was eliminated in the 1990s, but a combination of market regulation and tax incentives was still maintained. Transition to full liberalization took place between 1996 and 2000. Nowadays no direct control over ethanol production and trade exists, though several demand boosting incentives are still applied. An official blending ratio requires transport fuel to have 20-25% ethanol content, taxes on FFVs are lower than those on gasoline-powered vehicles and ethanol benefits from a favorable tax treatment at the pump relative to gasoline.

Technical change in the ethanol and automobile industry has increased efficiency and lowered ethanol costs below the regional supply costs of petrol (OECD, 2006; Hamelinck and Faaij, 2006). Compared to other ethanol producing countries, Brazil is estimated to have the lowest production costs (OECD, 2006; Martines-Filho *et al*., 2006). These developments have led ethanol to hold a larger market share than gasoline in the Brazilian transportation sector.

Recent increases in worldwide crude oil demand have stretched global crude oil production capacity near to its limits, resulting in the recent increases in crude oil prices. These have further improved ethanol competitiveness within the fuels market and have increased the amount of sugarcane diverted to ethanol production. In spite of more sugarcane being devoted to fuel production, demand increases have tightened the market causing important ethanol price increases.

Tightened markets are more likely to suffer from increased price volatilities because of their reduced flexibility in supply response. It is thus interesting to assess volatility changes and spillovers in the Brazilian ethanol market. Since we expect feedstock, crude oil and ethanol prices to co-move in the long-run, our analysis will also asses cointegration relationships.

3. Methodological approach

Most price time series possess common characteristics that must be considered for a sound econometric analysis of price relationships (Myers, 1994). Two of these characteristics are especially relevant to our empirical application. First, commodity prices are usually highly volatile and the volatility varies over time. Second, price series may share a tendency to move together over time.

Since the introduction of ARCH models by Engle (1982) and their generalized version (GARCH) by Bollerslev (1986), univariate volatility modeling has been an important research topic. More recently, multivariate GARCH (MGARCH) models have gained relevance as interest in understanding volatility spillovers across different markets has increased (Bollerslev *et al*., 1988; Engle and Kroner, 1995).

Co-movements in commodity price series can result from the existence of an equilibrium relationship between individual price series and have been formalized in the econometrics literature through the concept of cointegration (Engle and Granger, 1987). Several statistical methods for the analysis of cointegrated price systems have been devised in the literature. Until recently however, estimates of the cointegrating vector have not explicitly modeled conditional heteroskedasticity. Filling this gap in the literature, Seo (2007) develops a maximum likelihood estimator of the cointegrating vector that estimates the error correction model and the multivariate GARCH process jointly.

Consider a p-dimensional vector of cointegrated prices P_t. Assume that the cointegration rank is known and is equal to r. Further, assume the data are generated by the following error correction model (ECM):

$$\Delta P_t = \alpha \begin{pmatrix} I_r \\ \beta \end{pmatrix}' P_{t-1} + \sum_{i=1}^{l} \Gamma_i \Delta P_{t-i} + u_t \tag{1}$$

where α is the $p \times r$ adjustment matrix representing the speed of adjustment of each price to deviations from the long-run equilibrium relationship and β is a $(p-r)\times r$ cointegrating matrix. The cointegrating matrix is normalized with respect to the first r elements of P_t. As a result, the cointegration relationship can be expressed as: $w_t(\beta) = P_{1t} + \beta' P_{2t}$, where P_{1t} is r-dimensional and P_{2t} is $(p-r)$-dimensional.

Vector u_t is assumed to be a vector-valued Martingale difference sequence with $E\left(u_t \middle| \mathscr{F}_{t\text{-}1}\right) = 0$ and $E\left(u_t u_t' \middle| \mathscr{F}_{t\text{-}1}\right) = \Omega_t$, where $\mathscr{F}_{t\text{-}1}$ is the σ-field generated by P_{t-i} for $i = 0,1,2,\ldots$ Under the hypothesis that $u_t \middle| \mathscr{F}_{t\text{-}1} \sim N(0,\Omega_t)$ the log-likelihood function of model (1) is given by:

$$\mathscr{L}_n(\theta) = n^{-1}\sum_{t=1}^{n} l_t(\theta) \tag{2}$$

where

$l_t(\theta) = -0.5\log|\Omega_t(\theta)| - 0.5u_t^{'}(\theta)\Omega_t^{-1}(\theta)u_t(\theta)$. The ML estimator $\hat{\theta}_n$ can be defined as:

$$\hat{\theta}_n = \arg\max \mathscr{L}_n(\theta) \tag{3}$$

Seo (2007) recommends using White's robust covariance estimator for sound statistical inference. In order to allow for both time-varying volatility and volatility spillovers across different commodities, we define matrix Ω_t following the Baba-Engle-Kraft-Kroner (BEKK) GARCH specification (Engle and Kroner, 1995):

$$\Omega_t = CC' + A'u_{t-1}u'_{t-1}A + B'\Omega_{t-1}B \tag{4}$$

where C, A, and B are $p \times p$ parameter matrices and C is lower triangular. Restrictions for the identification of the parameters in the BEKK model proposed by Engle and Kroner (1995) are imposed. The BEKK model is covariance stationary if the eigenvalues of

$A \otimes A + B \otimes B$, where $\otimes$ denotes the Kronecker product of two matrices, are less than one in modulus.

As is well known, parameters in matrices C, A, and B cannot be interpreted on an individual basis. Instead, the nonlinear parameter functions in the conditional variance and covariance equations need to be derived and interpreted. In a 2-dimensional model for example, matrices C, A, and B can be expressed as $C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$, $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, and $B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$, and the conditional variance-covariance matrix can be written as[2] follows:

$$\Omega_t = \begin{bmatrix} h_{11t} & 0 \\ h_{12t} & h_{22} \end{bmatrix} = \begin{bmatrix} c_{11}^2 & 0 \\ c_{11}c_{21} & c_{21}^2 + c_{22}^2 \end{bmatrix} +$$
$$\begin{bmatrix} b_{11}^2 h_{11t-1} + 2b_{11}b_{12}h_{12t-1} + b_{21}^2 h_{22t-1} & 0 \\ b_{11}b_{12}h_{11t-1} + (b_{11}b_{22} + b_{12}b_{21})h_{12t-1} + b_{21}b_{22}h_{22t-1} & b_{12}^2 h_{11t-1} + 2b_{12}b_{22}h_{12t-1} + b_{22}^2 h_{22t-1} \end{bmatrix} + \qquad (5)$$
$$\begin{bmatrix} a_{11}^2 u_{1\,t-1}^2 + 2a_{11}a_{12}u_{1\,t-1}u_{2t-1} + a_{21}^2 u_{2\,t-1}^2 & 0 \\ a_{11}a_{12}u_{1\,t-1}^2 + (a_{11}a_{22} + a_{12}a_{21})u_{1\,t-1}u_{2t-1} + a_{21}a_{22}u_{2\,t-1}^2 & a_{12}^2 u_{1\,t-1}^2 + 2a_{12}a_{22}u_{1\,t-1}u_{2t-1} + a_{22}^2 u_{2\,t-1}^2 \end{bmatrix}$$

Parameters multiplying h_{ijt-1}, $i, j = 1, 2$, indicate direct and indirect volatility transmission between prices, and parameters representing u_{it-1} and $u_{1t-1}u_{2t-1}$ show how

[2] The standard error of each function of estimated coefficients can be derived by means of a first-order Taylor series expansion of the function around its mean.

price volatility is affected by market shocks. Results derived from model estimation are presented in the following section.

4. Results

Our empirical analysis uses weekly international crude oil prices and Brazilian ethanol and sugar prices. Prices are expressed in USD and observed from July 14, 2000 to February 29, 2008. Information on Brazilian ethanol and sugar prices was obtained from the Center for Advanced Studies on Applied Economics (2008) database, while international crude oil prices were derived from the Energy Information Administration (2008) dataset. Figure 1 plots the price series divided by their own mean.

Logarithmic transformations of the price series are used in the empirical implementation. A preliminary analysis of the prices is conducted in order to assess their time series properties. Standard augmented Dickey and Fuller (1979), KPSS (Kwiatkowski *et al*., 1992) and Perron (1997) tests confirm the presence of a unit root in all price series.[3]

Our analysis is of a pair-wise nature. Pair-wise analyses are very common in the price transmission literature and represent a natural avenue for studying price relationships (Goodwin and Piggott, 2001; Balcombe and Rapsomanikis, 2008). Since, as will be shown below, our results suggest a casual chain between the three prices running from oil to ethanol and finally to the sugar market, two pairs of prices: oil-ethanol (model 1) and ethanol-sugar (model 2), are considered.

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

Engle and Granger (1987) and Johansen (1988) cointegration tests provide evidence that the pairs of prices considered are cointegrated, with a cointegration rank $r = 1$. Results derived from the joint estimation of the error correction model and the multivariate GARCH process are presented in table 1 for the crude oil-ethanol pair of prices (model 1) and in table 2 for the ethanol-sugar pair (model 2). Tables 3 and 4 present the conditional variance and covariance equations for models 1 and 2 respectively. The covariance stationary condition is checked for both models and all eigenvalues are found to be less than one in modulus (see tables 1 and 2). Further, the residuals of the models are examined for autocorrelation by using the multivariate Portmanteau test (Bauwens *et al.*, 2005). Results indicate that both models are correctly specified (tables 1 and 2).

Model 1 estimation results (see table 1) include the parameters of the cointegration relationship (β). These parameters indicate that ethanol and crude oil prices are positively related in the long-run, which involves that the two products are substitutes.[4] This is compatible with ethanol tax incentives and recent crude oil price increases that have made ethanol a competitive substitute for gasoline. The α parameters also presented in table 1 suggest that while ethanol prices adjust to disequilibriums from the long-run parity, crude oil prices can be considered weakly exogenous. Parameters representing short-run dynamics, Γ, show that while first-order lags of price changes are useful in explaining current price changes, second-order lags are less relevant.

[4] A negative relationship would indicate a complementarity relationship.

As noted above, individual coefficients in the GARCH parameterization cannot be directly interpreted. Instead, we draw inferences from the nonlinear parameter functions in the conditional variance equations (see table 3). Our results indicate that volatility in the ethanol price (h_{22t}) is directly affected by its own volatility (h_{22t-1}) and by the volatility in the crude oil price (h_{11t-1}). Higher levels of conditional volatility in the past are associated to higher current conditional volatility. Since the coefficient of the term h_{12t-1} is statistically significant, there is an indirect volatility transmission from crude oil to ethanol through the covariance term. Our results also indicate that ethanol price volatility is directly and indirectly affected by shocks originating in either the oil or the ethanol markets (estimated coefficients on u_{1t-1}^2, u_{2t-1}^2 and $u_{1t-1}u_{2t-1}$ are all statistically significant).

The behavior of crude oil prices differs from the one displayed by ethanol prices. While volatility in crude oil price (h_{11t}) depends on its own lagged volatility (h_{11t-1}), it is only indirectly related to the ethanol price volatility through the covariance term (h_{12t}). Further, crude oil price volatility is independent on crude oil and ethanol market shocks. The fact that most parameters in the crude oil conditional variance equation are not statistically significant is not surprising, given that oil prices are weakly exogenous and thus are not determined by ethanol prices.

To better understand volatility spillovers between crude oil and ethanol markets, we simulate the ethanol volatility response to a shock to the crude oil market (figure 2). The value of the oil price series shock is set to 1 positive standard deviation of the series and the response of the conditional variances is simulated. The difference between the predicted ethanol variance with and without the shock is represented in figure 2. As can be seen, an increase in crude oil prices increases ethanol price volatility. The volatility response increases during the first four weeks following the shock to decrease thereafter and disappear after about 14 weeks.

Model 2 assesses price links between ethanol and sugar prices. Cointegration parameters (β) suggest that ethanol and sugar prices are positively related (see table 2). Hence, increases in ethanol prices are followed by increases in the feedstock price. α parameters presented in table 2 suggest that ethanol prices are weakly exogenous to sugar prices, while sugar prices are found to respond to deviations from the long-run parity. These results together with findings from model 1 suggest a casual chain running from crude oil to ethanol and finally to the sugar market. Coefficients representing the short-run dynamics show that while first-order lags of price changes are statistically significant, second-order lags are less relevant.

In table 4 we present the conditional variance-covariance equations for ethanol and sugar. Results indicate that sugar volatility increases with its own lagged variance. Sugar volatility is also influenced by the ethanol price volatility but only indirectly through the covariance term. This involves that while ethanol markets are able to induce increases in average sugar prices, they are less capable to transmit volatility to sugar markets. The volatility of ethanol prices is influenced by innovations occurring in ethanol markets and by the covariance term. Hence, and as is the case for sugar prices, only indirect volatility spillover effects are allowed.

In figure 3 we represent the result of simulating the sugar volatility response to a shock to the ethanol market. The value of the series-specific shock is set to 1 positive standard deviation of the series and the response of the conditional variances is simulated. As can be seen, an increase in ethanol prices increases the volatility of sugar prices though, as noted, only indirectly through the covariance term. The volatility shock increases during the first 6 weeks and decreases thereafter disappearing after about 35 weeks.

In figures 4 and 5 estimated volatility (Engle, 2001) for ethanol and sugar prices, the endogenous variables in models 1 and 2 respectively, are presented. As it can be seen, the models predict especially high volatility in these markets during the period 2002-2004. During this period, world crude oil markets experienced several changes that led to increased price levels and volatility. A key factor was probably the increase in crude oil demand, which was especially relevant in China. On the supply side, growth in production fell short of meeting increasing world needs. Both strong demand and insufficient supply tightened petroleum markets increasing price levels and volatility.

As it can be seen by comparing figures 1 and 4, the high volatility period coincides with a change in the crude oil prices trend from negative to positive. The change in crude oil prices trend brought about changes in the initially declining trends for ethanol and sugar prices and increased market volatility.

Apart from the economic changes, this period was also influenced by technological advances, most notably the introduction of FFVs by the automotive industry and the positive consumer response to the new product. Market adjustments to the new developments may also explain the high variances registered during the period. Consistently with ethanol price volatility, sugar prices are found to be highly volatile during the 2002-2004 period. The result is not surprising since ethanol prices are found to influence sugar price volatility through the covariance term h_{12t-1}.

5. Concluding remarks

We assess volatility spillovers in Brazilian ethanol markets by using Seo's (2007) maximum likelihood estimator that estimates the error correction model and the multivariate GARCH process jointly. To the best of our knowledge, Seo's (2007) methodological approach has not yet been empirically implemented. We use weekly international crude oil prices and Brazilian ethanol and sugar prices observed from July 2000 to February 2008. A pair wise analysis is carried out.

Results derived from the empirical analysis suggest a casual chain running from crude oil to ethanol and finally to the sugar market. An increase in crude oil price levels increases ethanol prices, which in turn causes sugar price levels to grow.

With regards to volatility spillovers, results suggest a direct and an indirect volatility transmission from crude oil to ethanol through the lagged crude oil variance and covariance terms. Conversely, sugar price volatility is only influenced by the ethanol price volatility indirectly through the covariance term. Predicted volatility for ethanol and sugar shows especially high volatility levels during 2002-2004 coinciding with a period of tightening crude oil markets and a change in the crude oil price trend.

Hence, our results suggest that crude oil prices not only influence ethanol price levels, but also their volatility. Increased volatility in crude oil markets results in increased volatility in ethanol markets. Ethanol prices, on the other hand, influence sugar price levels and an increase in their volatility levels also impacts, though less strongly, on sugar markets.

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Table 1. Crude oil (P_1)– ethanol (P_2) model results

Error correction model estimation		
Cointegration relationship: $P_2 = -2.860^{**} + 0.490^{**} P_1$ (0.063) (0.017)		
Short-run dynamics parameters: $\begin{pmatrix} \Delta P_{1t} \\ \Delta P_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} w_t(\beta) + \begin{pmatrix} \gamma_{111} & \gamma_{112} \\ \gamma_{121} & \gamma_{122} \end{pmatrix} \begin{pmatrix} \Delta P_{1t-1} \\ \Delta P_{2t-1} \end{pmatrix} + \begin{pmatrix} \gamma_{211} & \gamma_{212} \\ \gamma_{221} & \gamma_{222} \end{pmatrix} \begin{pmatrix} \Delta P_{1t-2} \\ \Delta P_{2t-2} \end{pmatrix}$		
Dependent variable	$P_i, i=1$	$P_i, i=2$
α_i	-0.004	-0.025**
	(0.008)	(0.005)
γ_{11i}	0.248**	0.046
	(0.044)	(0.052)
γ_{12i}	-0.029	0.523**
	(0.031)	(0.051)
γ_{21i}	-0.023	-0.088*
	(0.042)	(0.047)
γ_{22i}	-0.025	-0.035
	(0.0370)	(0.044)

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

Table 1. Crude oil (P_1)– ethanol (P_2) model results (continued)

GARCH model parameters: $C=\begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$, $A=\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, and $B=\begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$

Dependent variable		$P_i, i=1$			$P_i, i=2$
c_{1i}		0.0217**			
		(1.576E-6)			
c_{2i}		0.030**			9.807E-3**
		(0.001)			(2.296E-6)
a_{1i}		0.000			-0.138**
		(6.682E-5)			(0.026)
a_{2i}		-0.060			0.610**
		(0.060)			(0.030)
b_{1i}		0.277**			-0.365**
		(1.045E-3)			(0.017)
b_{2i}		-0.105**			0.675**
		(0.031)			(0.015)
Eigenvalues of $A\otimes A+B\otimes B$		0.935	0.163	0.140	0.039
Portmanteau test (third order autocorrelation)					1.365

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

Table 2. Sugar (P_1)– ethanol (P_2) model results

Error correction model estimation		
Cointegration relationship:	$P_2 = \text{-}5.553^{**} + 1.856^{**} P_1$ (1.318) (0.565)	
Short-run dynamics parameters:		

$$\begin{pmatrix} \Delta P_{1t} \\ \Delta P_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} w_t\left(\beta\right) + \begin{pmatrix} \gamma_{111} & \gamma_{112} \\ \gamma_{121} & \gamma_{122} \end{pmatrix} \begin{pmatrix} \Delta P_{1t-1} \\ \Delta P_{2t-1} \end{pmatrix} + \begin{pmatrix} \gamma_{211} & \gamma_{212} \\ \gamma_{221} & \gamma_{222} \end{pmatrix} \begin{pmatrix} \Delta P_{1t-2} \\ \Delta P_{2t-2} \end{pmatrix}$$

Dependent variable	$P_i, i=1$	$P_i, i=2$
α_i	0.030*	0.002
	(0.016)	(0.014)
γ_{11i}	0.597**	0.0512
	(0.084)	(0.072)
γ_{12i}	0.026	0.581**
	(0.090)	(0.095)
γ_{21i}	-0.162*	0.080
	(0.096)	(0.094)
γ_{22i}	0.012	-0.100
	(0.079)	(0.086)

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

Table 2. Sugar (P_1)– ethanol (P_2) model results (continued)

GARCH model parameters: $C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$, $A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, and $B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$

Dependent variable		$P_i, i=1$			$P_i, i=2$
c_{1i}		6.623E-3**			
		(8.440E-6)			
c_{2i}		-0.005			0.010**
		(0.004)			(7.659E-6)
a_{1i}		0.350**			-0.229*
		(0.012)			(0.137)
a_{2i}		-0.030			0.767**
		(0.109)			(0.124)
b_{1i}		0.657**			0.333*
		(0.029)			(0.178)
b_{2i}		0.281**			0.524**
		(0.141)			(0.167)
Eigenvalues of $A \otimes A + B \otimes B$		0.987	0.715	0.512	0.415
Portmanteau test (third order autocorrelation)					1.881

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

Table 3. Conditional variance and covariance equations. Crude oil (P_1)– ethanol (P_2) model

$h_{11t} =$	4.701E-4** +	0.077** h_{11t-1} -	0.202** h_{12t-1} +	0.010 h_{22t-1} +	0.000 u_{1t-1}^2 -	0.000 $u_{1t-1}u_{2t-1}$ +	3.572E-3 u_{2t-1}^2
$h_{22t} =$	9.753E-4** +	0.134** h_{11t-1} -	0.494** h_{12t-1} +	0.456** h_{22t-1} +	0.019** u_{1t-1}^2 -	0.169** $u_{1t-1}u_{2t-1}$ +	0.372** u_{2t-1}^2
$h_{12t} =$	6.428E-4** -	0.101** h_{11t-1} +	0.225** h_{12t-1} -	0.071** h_{22t-1} -	0.000 u_{1t-1}^2 +	8.278E-3 $u_{1t-1}u_{2t-1}$	-0.036 u_{2t-1}^2

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

Table 4. Conditional variance and covariance equations. Sugar (P_1)– ethanol (P_2) model

$h_{11t} =$	4.386E-5 +	0.431* h_{11t-1} +	0.438* h_{12t-1} +	0.080 h_{22t-1} +	0.122 u_{1t-1}^2 -	0.160 $u_{1t-1}u_{2t-1}$ +	9.179E-4 u_{2t-1}^2
$h_{22t} =$	1.248E-4** +	0.111 h_{11t-1} +	0.349** h_{12t-1} +	0.275 h_{22t-1} +	0.052 u_{1t-1}^2 -	0.351 $u_{1t-1}u_{2t-1}$ +	0.588** u_{2t-1}^2
$h_{12t} =$	-3.046E-5 +	0.219* h_{11t-1} +	0.438** h_{12t-1} +	0.147* h_{22t-1} -	0.080 u_{1t-1}^2 +	0.275** $u_{1t-1}u_{2t-1}$ -	0.023 u_{2t-1}^2

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

Figure 1. Price series

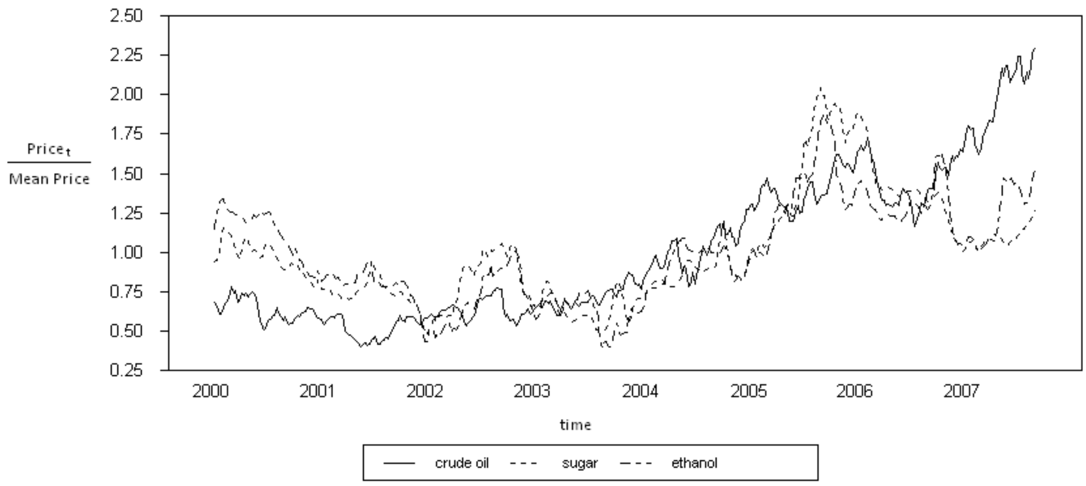

Figure 2. Ethanol volatility response to 1 positive standard deviation shock to the crude oil price

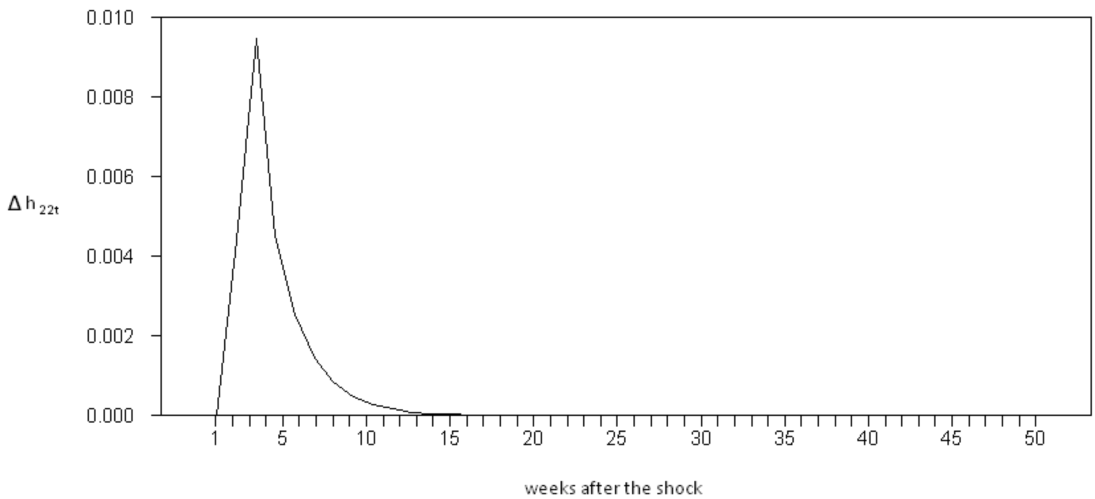

Figure 3. Sugar volatility response to 1 positive standard deviation shock to the ethanol price

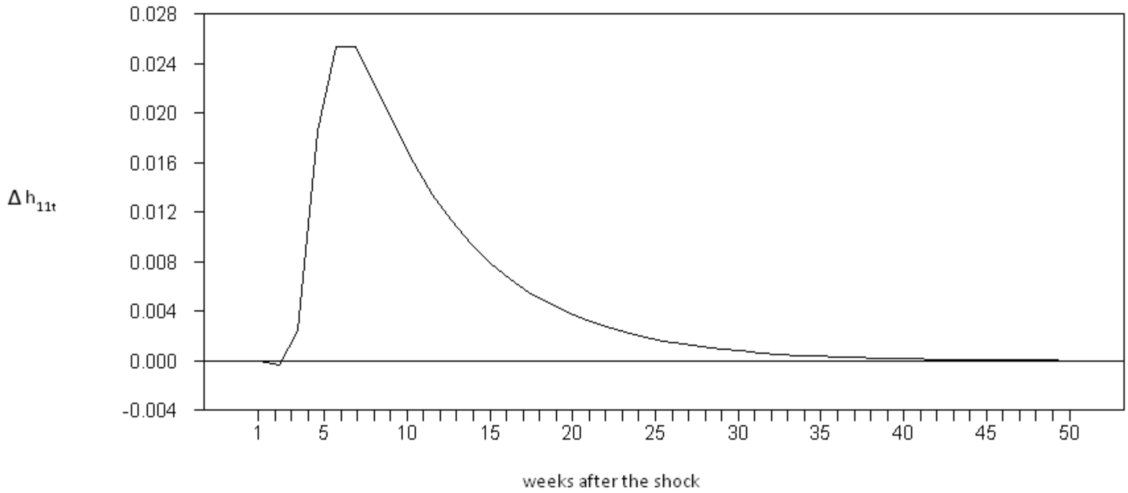

Figure 4. Predicted ethanol volatility

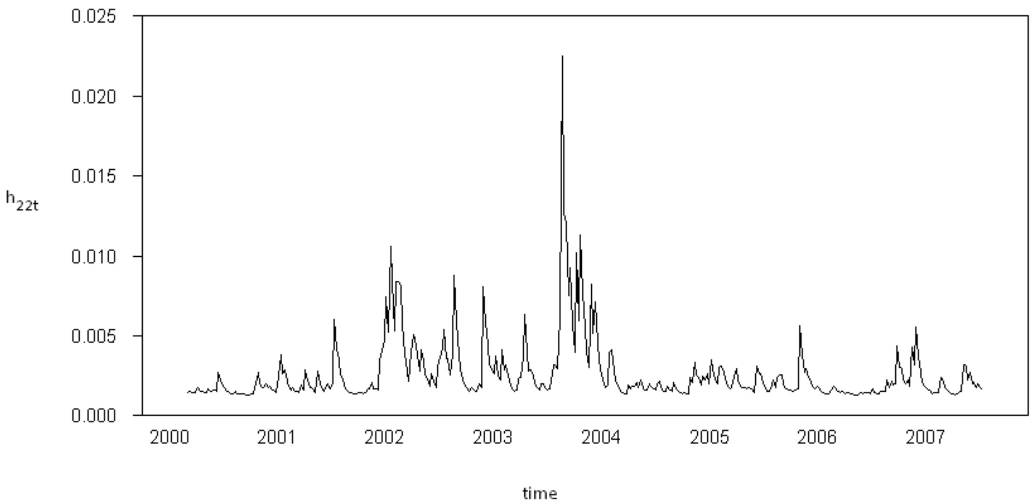

Figure 5. Predicted sugar volatility