PRICE VOLATILITY IN FOOD MARKETS: CAN STOCK BUILDING MITIGATE PRICE FLUCTUATIONS?

Teresa Serra[1] and José M. Gil

Centre de Recerca en Economia i Desenvolupament Agroalimentaris (CREDA)-UPC-IRTA, Parc Mediterrani de la Tecnologia, Edifici ESAB, C/ Esteve Terrades 8, 08860 Castelldefels, Spain.

Abstract

This article studies US corn price fluctuations in the past two decades. Price volatility is explained by volatility clustering, the influence of energy prices, corn stocks and global economic conditions. A multivariate GARCH specification that allows for exogenous variables in the conditional covariance model is estimated both parametrically and semiparametrically. Findings provide evidence of price volatility transmission between ethanol and corn markets. They also suggest that macroeconomic conditions can influence corn price volatility and that stock building is found to significantly reduce corn price fluctuations.

Keywords: price volatility, corn, ethanol, stocks

JEL classification: c32, q11

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[1] Corresponding author:

Tel.: +34 935-521-209; fax: +34 935-521-121.

E-mail address: teresa.serra-devesa@upc.edu

1. Introduction

Over the last decade, global food markets have undergone a period of marked and persistent volatility. Market instability has been especially intensive since 2006, when inflation in food prices was relevant and led to unprecedented highs between 2006 and 2008. While in the second half of 2008 prices declined again, market turbulences returned in 2010 and 2011 (FAO-OECD, 2011). According to FAO-OECD (2011) forecasts, turbulences are likely to continue in the 2010 decade.

Agricultural price volatility not only affects the usually risk-averse producers and consumers in developed countries, but also undermines food security in poor nations where households spend a substantial portion of their income on food. Cereals, especially corn, represent the most relevant source of world's food energy consumption, being key to food security (Wright, 2011). Prakash (2011a) shows that corn price volatility has been growing over the last 50 years. Our analysis focuses on assessing volatility in the United States (US) corn market.

We focus on this market for two reasons. First, because the US is the major world producer and exporter of corn. US corn production represents 41 per cent of global corn output, while US corn exports represent around 54 per cent of total world exports (in 2010 production was in the order of 333 million metric tons, while exports were almost 50 million metric tons) (USDA, 2010). Second, it is interesting to study the US corn industry due to the important changes it has recently undergone, mainly related to the outburst of the biofuels industry involving an important shift in the demand for corn.

The threat that food price volatility poses for both developing and developed nations has risen social and political concerns regarding the causes of recent price instability, its socio-economic impacts and the instruments available to mitigate them. These socio-political concerns have influenced the academic agenda. A wide array of different justifications for recent increases in food price volatility have been proposed in the literature and include massive financial investments in food commodity markets, other macroeconomic factors such as interest or exchange rate fluctuations, public promotion of biofuels, climate and demographic changes, storage, etc.

While publications in scientific journals on this topic are still scarce, there have been a number of institutional initiatives worth mentioning. FAO (Prakash, 2011b) has recently published a monograph, aiming at shedding light on the causes and consequences of food price volatility and shaping the related policy debate. Recent EU calls for research and technological development (KBBE.2012.1.4-05 volatility of agricultural commodity markets) are an indicator that research in agrofood markets in the upcoming years will devote much attention to this issue. Our aim is to contribute to the food price volatility literature.

The scarce number of empirical research articles shedding light on food price volatility have focused on the dependence of prices across related markets (Natcher and Weaver, 1999; Apergis and Rezitis, 2003; Buguk et al., 2003; Rezitis and Stavropoulos, 2011). Along these lines of research, recent work has studied and found evidence of price volatility interactions between food and biofuel markets (Zhang et al., 2009; Serra et al., 2011a). While economic theory has suggested that stock building and macroeconomic conditions can play a key role in shaping price volatility, the empirical literature has paid little attention to this issue. The objective of our analysis is to study corn price volatility over the last two decades by allowing for price volatility transmission between biofuel and corn markets, as well as the impacts of corn stocks and macroeconomic conditions on corn price fluctuations. Our exercise should be taken as an empirical test of the relevance of different variables in explaining food price variability, but not as an empirical test of a specific structural model.

To achieve our objective, a multivariate generalized auto-regressive conditional heteroskedastic (MGARCH) model with exogenous variables in the conditional covariance model is used. The model is estimated using both well known parametric techniques and a recently proposed semiparametric approximation (Long et al., 2011) that overcomes the most relevant limitations attributed to parametric methods. The use of very innovative econometric techniques constitutes another contribution of our work to the literature.

2. Previous research

An active scholarly debate is being held on the role of stocks in cushioning food price volatility. The theoretical background for this debate includes the works by Gustafson (1958), Samuelson (1971), Scheinkman and Schechtman (1983), Williams and Wright (1991), Wright and Williams (1982 and 1984), or Deaton and Laroque (1992). This literature has focused on the competitive storage model that, under the assumption of rational expectations, views stocks as a key determinant of commodity price behaviour. According to this literature, when the current price is below the expected price (adjusted for financial and storage costs), storage will be used to sell the commodity in the future.

Conversely, when prices are expected to decline, there will be no incentives to store and the stock-out case will be predominant. In this latter framework, price behaviour will be entirely dependent on market shocks. The implications of the storage model are not yet well understood and widely accepted among researchers (Wright, 2011).

While the consequences of the storage model for price volatility are not clear cut (Stigler and Prakash, 2011), Williams and Wright (1991) and Wright (2011) postulate that, since stock building can contribute to mitigate dependency on demand and supply shocks, price volatility will increase as inventories decline. Starting on 1999/2000 the global stock-to-use ratio for major cereal grains has been declining. Aggregate stocks of the most relevant cereals reached minimum levels by 2007/2008 (Dawe, 2009; Wright, 2011). It is thus possible that late food price volatility bears some relationship to stock depletion.

While much discussion has been held on the links between stocks and price behaviour at the theoretical level, the scarcity of statistical data on public and private stocks has however limited the number of empirical applications. Shively (1996) fits a single-equation autoregressive conditional heteroskedasticity (ARCH) model to monthly wholesale maize prices in Ghana observed from January 1978 to July 1993. Annual production data, exchange rates and past prices (taken as a proxy for storage) are used as possible explanatory variables in the conditional mean and variance equations. Higher past prices are found to lead to higher current price volatility, which is consistent with the theory of competitive storage behavior under rational expectations (Deaton and Laroque, 1992). Kim and Chavas (2002) focus on the US non-fat dry milk market. A heteroskedastic Tobit model is fit to monthly data covering the period from January 1970 to July 2000, to represent price behavior in the presence of a price support program defining a floor price. Both the price mean and the price variance model are expressed as a function of lagged prices, public and private stocks and interest rates. Compatible with the theory of competitive storage, findings support that an increase in stocks and a decline in interest rates will reduce price volatility. The effects of private stocks are found to be stronger than public ones.

Balcombe (2011) studies the volatility of different world agricultural prices (cereals, vegetable oils, meat, dairy, cocoa, coffee, tea, sugar and cotton) observed monthly for different time periods. A random parameter model with time-varying volatility is used. Volatility is allowed to be a function of several exogenous variables (oil price volatility, stocks, yields, spillovers from other agricultural commodities, exchange and interest rate volatility, export concentration). Results suggest that volatility can be explained by spillovers from other agricultural commodities, oil price and exchange rate volatility, yields and stock levels, the latter having a downward impact on volatility. Stigler and Prakash (2011) model the role of stocks on price volatility in the US wheat market using a two-stage analysis. First, wheat price volatility is studied by means of a Markov-Switching GARCH model. Switching between regimes is controlled by a latent process following a first-order Markov process. In a second stage, a Probit model is estimated to assess whether regime-switching is associated with stocks. The empirical application is based upon daily wheat futures prices observed from January 1985 to January 2009 and on monthly stocks-to-disappearance forecasts. Two price regimes are identified, one being characterized by substantially higher volatility than the other. Stocks are found to be likely to generate regime-switching, with a decline in stocks leading to higher volatility.

Roache (2010) explains volatility in international food markets using a spline-GARCH approach that produces estimates of low frequency volatility. Estimates are then regressed against a set of possible explanatory variables: annual inventory to consumption ratios, crude oil price volatility, speculation, global weather patterns and a series of macroeconomic indicators. The empirical study is based on monthly prices observed from January 1875 to December 2009. The variables with the largest impacts on price volatility since the mid 1990s are the US inflation volatility and the US dollar (USD) exchange rate volatility. Inventories are not found to have a significant impact on price volatility. Dawe (2009) presents a descriptive analysis of the evolution of world stocks-to-use ratio for major cereal grains. He argues that a decline in this ratio could not have caused the 2007/2008 food price crisis, because world stocks mainly declined as a result of a stock drawdown in China, a country with a modest role in international food markets. World stocks excluding China did not reach particularly low levels before the crisis and their decline was certainly much slower. This leads the author to conclude that stocks did not exert a relevant influence on the evolution of the world food crisis.

While empirical research results are difficult to generalize due to differences in the food markets studied, data used and methodological approaches, a majority of previous analyses have provided evidence in favor of the competitive storage theory (Shively, 1996; Kim and Chavas, 2002; Balcombe, 2011; and Stigler and Prakash, 2011). Most of these studies rely upon single-equation specifications that do not allow for volatility spillovers across related markets. Allowing for volatility interactions between food and energy markets is especially relevant when assessing corn price behaviour, given the massive use of corn as a feedstock in the US ethanol industry.

There is an intensive debate on the impacts of biofuels on agricultural commodity prices. While previous research findings are rather dispersed, there seems to be a general agreement that public promotion of biofuels has strengthened the link between energy and agricultural markets. Most analyses that study the implications of biofuels for food prices have focused on price levels, ignoring the impacts on food price volatility (Serra, 2011). Balcombe and Rapsomanikis (2008) or Serra et al. (2011b) are not an exception to this rule. These authors show that an increase in energy prices will lead to an increase in Brazilian sugar and US corn prices, the link between the two markets being fuelled by the ethanol industry. Given previous research findings, it is interesting to assess to what extent volatility in energy prices can be transferred to US corn markets.

Macroeconomic conditions have been found to also explain price fluctuations by previous research (Roache, 2010; Balcombe, 2011). As noted by Frankel (2006), interest rates can affect commodity price volatility through different demand and supply channels. Roache (2010) finds interest rates to drive food price volatility. Other studies (Meyers and Meyer, 2008; Headey and Fan, 2008; Abbott et al., 2008; Mitchell, 2008; Baffes and Haniotis, 2010) attribute substantial influence of the USD exchange rate on food price behaviour. Financial investments have also been pointed out by Cooke and Robles (2009), Du et al. (2011), Baffes and Haniotis (2010), among others, as possible drivers of food price instability. The influence of macroeconomic variables will also be considered in our analysis to shed light on US corn price volatility.

3. Methods

Price volatility tends to vary over time and display a clustering behaviour (Myers, 1994), with periods of high (low) volatility tending to be followed by periods of high (low) volatility. To allow for this pattern, usually present in nonstationary time series, we measure volatility using GARCH models. GARCH models allow for volatility clustering by specifying current volatility as a function of past volatility.

Previous research findings support an increased link between food and energy prices fuelled by the biofuels industry. We expect ethanol prices to influence corn prices through the demand for corn to produce ethanol. Since feedstock costs represent the major ethanol production cost (OECD, 2006), we also expect ethanol prices to be influenced by corn prices. As explained in the literature review section, studies investigating the impacts of stocks on food price volatility have considered the former as an exogenous variable. We initially specified a more general model where stocks were allowed to be a regressand. Results, available upon request, however provided evidence that neither corn nor ethanol prices drive stock levels and their volatility. As a result, stocks can be considered a regressor. Our GARCH specification thus consists of two equations explaining corn and ethanol price levels and volatility.

GARCH models accommodate two sub-models: the conditional mean and the conditional covariance model. Economic theory (de Gorter and Just, 2008) suggests that demand forces in ethanol markets will ensure a co-movement of ethanol and feedstock prices, i.e., corn and ethanol prices are likely to be cointegrated. The conditional mean model is thus specified as a vector error correction model (VECM) which allows capturing both the short-run and the long-run dynamics of price series (equation 1). Since we are interested in assessing volatility spillovers between food and energy markets, a bivariate Baba-Engle-Kraft-Kroner (BEKK) GARCH specification (equation 2) is used for the conditional volatility model (Engle and Kroner, 1995).

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha} ECT_{t-1} + \sum_{i=1}^{n} \boldsymbol{\gamma}_i \Delta \mathbf{p}_{t-i} + \mathbf{r}_t \tag{1}$$

$$\mathbf{H}_{p,t} = \mathbf{CC}' + \mathbf{A}'\mathbf{r}_{t-1}\mathbf{r}'_{t-1}\mathbf{A} + \mathbf{B}'\mathbf{H}_{p,t\text{-}1}\mathbf{B} \tag{2}$$

where $\Delta \mathbf{p}_t$ is a 2×1 vector of corn and ethanol prices in first differences, ECT_{t-1} is the lagged error correction term derived from the cointegration relationship, $\boldsymbol{\alpha}$ is a 2×1 matrix showing price adjustment to deviations from the long-run parity, $\boldsymbol{\gamma}_i$ are 2×2 matrices representing short-run price dynamics, $\mathbf{r}_t$ is a 2-dimensional error vector and $t = 1, ..., T$. $\mathbf{H}_{p,t}$ is the parametric estimate of the residuals variance – covariance matrix. Matrix $\mathbf{A}$ (2×2) relates the influence of past market shocks on current price volatility, while $\mathbf{B}$ (2×2) relates the influence of past volatility on current volatility. $\mathbf{C}$ is a 2×2 lower triangular matrix.

Elements c_{ij} in matrix $\mathbf{C}$ in (2) are specified following Moschini and Myers (2002): $c_{ij} = \mathbf{z}_t \delta_{ij}$, where $\mathbf{z}_t = (1, z_1, ..., z_{r-1})$ is an *r*-dimensional vector of exogenous variables influencing price volatility and δ_{ij} is a parameter vector.[1] Parameterizing the conditional covariance matrix as a function of exogenous variables is a complex process, since the proposed specification needs to preserve the positive definiteness of the matrix. In contrast to most econometric specifications, Moschini and Myers (2002) do not restrict the sign of the effect of the exogenous variables on price volatility in order to ensure this positive definiteness.

[1] An alternative specification including $\mathbf{z}_t = (1, z_1, ..., z_{r-1})$ as regressors in the conditional mean equation was also considered, but not found to be statistically significant.

The conditional mean and covariance models are, in a first stage, jointly estimated under the assumption of normally distributed errors and using standard maximum likelihood procedures. Conventional parametric MGARCH models have been criticized for two main reasons: First, they usually rely upon the assumption of a normal distribution of the model errors and second, the conditional covariance matrix is usually assumed to be linear. Previous literature has found ample evidence against both the normality and linearity assumptions (Longin and Solnik, 2001; Richardson and Smith, 1993; Long et al., 2011). More flexible parametric specifications have been recently proposed to overcome these limitations (Capiello et al., 2003; Lai et al., 2009; Pelletier, 2006; Silvennoinen and Teräsvirta, 2005). Nonparametric and semiparametric methods can also play a role in overcoming parametric model misspecifications. Most approaches in this field have however been developed in the univariate context (Audrino, 2006; Härdle and Tsybakov, 1997). Long et al. (2011) have recently proposed a semiparametric estimator of the conditional covariance functional form in the MGARCH model.

In a second stage in our analysis, we adopt the proposal by Long et al. (2011) that consists of a nonparametric correction of the parametric conditional covariance estimator. Let's now assume that the 2-dimensional[2] vector of errors of the conditional mean model in (1), $\mathbf{r}_t = (r_{1t}, r_{2t})'$, follows the stochastic process $\mathbf{r}_t \big| \mathscr{F}_{t\text{-}1} \sim \mathbf{P}(\boldsymbol{\mu}_t, \mathbf{H}_t; \theta)$, where θ is a vector of distribution parameters, $\mathscr{F}_{t\text{-}1}$ is the information set at time $t-1$, $\boldsymbol{\mu}_t = E(\mathbf{r}_t \big| \mathscr{F}_{t\text{-}1}) = 0$, $\mathrm{H}_t = E(\mathbf{r}_t \mathbf{r}_t' \big| \mathscr{F}_{t\text{-}1})$ and $\mathbf{P}$ is the joint cumulative distribution

[2] While from a theoretical point of view Long et al.'s (2011) proposal can be extended to higher order settings, the 'curse of dimensionality' affecting local smoothing methods (Fan, 2000; Stone, 1980) drastically reduces the usefulness of these extensions.

function (CDF). In contrast to the parametric process, no specific assumption is made regarding the joint distribution of $\mathbf{r}_t$.

Vector $\mathbf{r}_t$ can be expressed as a function of a vector of standardized errors with $E(\mathbf{e}_t \vert \mathscr{F}_{t\text{-}1}) = 0$ and $E(\mathbf{e}_t\mathbf{e}_t{'} \vert \mathscr{F}_{t\text{-}1}) = \mathbf{I}_k$: $\mathbf{r}_t = \mathbf{H}_t^{1/2}\mathbf{e}_t$. No assumption on the distribution of $\mathbf{e}_t$ is necessary to derive the semiparametric estimator either. Matrix $\mathbf{H}_t^{1/2}$ is the symmetric square root of $\mathbf{H}_t$. The semiparametric estimator of the conditional covariance matrix is:

$$\mathbf{H}_t = \mathbf{H}_{p,t}^{1/2}(\theta)E\left[\mathbf{e}_t(\theta)\mathbf{e}_t(\theta)' \middle\vert \mathscr{F}_{t\text{-}1}\right]\mathbf{H}_{p,t}^{1/2}(\theta) \tag{3}$$

where matrix $\mathbf{H}_{p,t}(\theta)$ is the parametric estimator of $\mathbf{H}_t$ (equation 2) and $\mathbf{e}_t(\theta) = \mathbf{H}_{p,t}^{\text{-}1/2}(\theta)\mathbf{r}_t$ is the result of standardizing the errors from the parametric model. $E\left[\mathbf{e}_t(\theta)\mathbf{e}_t(\theta)' \middle\vert \mathscr{F}_{t\text{-}1}\right]$ is the nonparametric component of $\mathbf{H}_t$ and is derived under the assumption that the conditional expectation of $\mathbf{e}_t\mathbf{e}_t'$ depends exclusively on the current information set through the q-dimensional vector $\mathbf{x}_t = (x_{1t},..., x_{qt})'$. Hence,

$$E\left[\mathbf{e}_t\mathbf{e}_t' \middle\vert \mathscr{F}_{t\text{-}1}\right] = \mathbf{G}_{np}\left(\mathbf{x}_t\right). \tag{4}$$

By substituting (4) into (3), the following expression is derived:

$$\mathbf{H}_t = \mathbf{H}_{p,t}^{1/2}(\theta)\mathbf{G}_{np,t}\mathbf{H}_{p,t}^{1/2}(\theta) \tag{5}$$

In order to estimate $\mathbf{H}_t$ a two-step process is implemented. First, an estimate of θ , $\hat{\theta}$, is derived through the parametric estimation of the conditional covariance matrix described above. The errors from this estimation are then standardized as follows: $\hat{\mathbf{e}}_t = \hat{\mathbf{H}}_{p,t}^{-1/2}\mathbf{r}_t$. In the second stage, $E\left[\mathbf{e}_t\mathbf{e}_t^{'}\middle|\mathscr{F}_{t-1},\mathbf{x}_t = \mathbf{x}\right]$ is derived by means of the nonparametric Nadaraya-Watson estimator as detailed below:

$$\hat{\mathbf{G}}_{np,t}\left(\mathbf{x}\right) = \frac{\sum_{s=1}^{T}\hat{\mathbf{e}}_s\hat{\mathbf{e}}_s^{'}K_{\mathbf{h}}\left(\mathbf{x}_s - \mathbf{x}\right)}{\sum_{s=1}^{T}K_{\mathbf{h}}\left(\mathbf{x}_s - \mathbf{x}\right)} \tag{6}$$

where $K_{\mathbf{h}}\left(\mathbf{x}_s - \mathbf{x}\right) = \prod_{l=1}^{q} h_l^{-1}k\left(\left(x_{ls} - x_l\right)/h_l\right)$ is a multivariate multiplicative kernel, and $\mathbf{h} = \left(h_1,...,h_q\right)$ is the vector of bandwidth parameters. The semiparametric estimator of the conditional covariance matrix can thus be expressed as:

$$\hat{\mathbf{H}}_{sp,t} = \hat{\mathbf{H}}_{p,t}^{1/2}\hat{\mathbf{G}}_{np,t}\hat{\mathbf{H}}_{p,t}^{1/2} \tag{7}$$

We follow Long et al. (2011) and set $\mathbf{x}_t = \mathbf{r}_{t\text{-}1}$ in the empirical application. The kernel function is specified using the Gaussian form: $k(u) = \exp(-u^2/2)\big/\sqrt{2\Pi}$.[3] Following Long et al. (2011), $h_i = m_j \hat{\sigma}_i T^{-1/6}$ defines the bandwidth, $\hat{\sigma}_i$ represents the sample standard deviation of r_{it}, T denotes the number of observations and m_j is selected through a grid search process. The grid search minimizes the difference between the true conditional covariance matrix and its estimates. Because the true conditional covariance matrix is not known, the squared $\mathbf{r}_t$ vector is used as an approximation (Long et al., 2011; Awartani and Corradi, 2005; Pelletier, 2006; Zangari, 1997). If the parametric model is correctly specified, $\mathbf{H}_t = \mathbf{H}_{p,t}$ which involves that $\mathbf{G}_{np,t}$ is equal to the identity matrix. This allows testing for the null of correct specification of the parametric conditional covariance estimator ($H_0 : \mathbf{G}_{np,t}(\mathbf{x}_t) = \mathbf{I}_t$) against the alternative hypothesis $H_1 : \Pr\left(\mathbf{G}_{np,t}(\mathbf{x}_t) = \mathbf{I}_t\right) < 1$.[4]

4. Empirical application

The objective of this research is to explain US corn price volatility in the last 20 years. To do so, we use a two-dimensional GARCH model of corn and ethanol prices in which time-varying volatility is allowed to depend on a series of weakly exogenous variables

[3] This univariate Gaussian kernel is a component of the multivariate multiplicative kernel function in (6).

[4] See the paper by Long et al. (2011) for further details on this specification test.

($\mathbf{z}_t$). Based on previous research results summarized in the literature review section, several candidates were considered to be included in vector $\mathbf{z}_t$, but only stocks and interest rate volatility were found to be statistically significant. Among the exogenous variables taken into account, but finally discarded on the basis of statistical significance, are the interest rate in levels, the dollar exchange rate (considered both in levels and volatility), financial speculation in corn futures markets (defined using the speculation indices proposed by Du et al., 2011 and Cooke and Robles, 2009), or crude oil price variability.

Our empirical implementation is based on monthly nominal prices for corn and ethanol, observed from January 1990 to December 2010. Information on pure ethanol prices is obtained from the Nebraska Government (2011), while Nebraska corn prices received by farmers are derived from the National Agricultural Statistics Service (NASS, 2011).[5]

A key objective of this article is to model the impacts of corn stocks on price volatility. Since it is based upon the assumption that production occurs at every time period, the competitive storage model is only capable of explaining yearly price fluctuations (Wright, 2011). Working with annual data involves two main shortcomings. First, it substantially reduces the number of observations available for econometric estimation and, second, it ignores information contained in more frequent available data. As a result, we follow Stigler and Prakash (2011) who propose to study market

[5] With a correlation coefficient with the NASS US corn price of 0.997, Nebraska corn prices can be safely taken as representative of the country-level price. Further, since the US is the first worldwide producer and exporter of corn, US corn prices should be representative of the world market.

reactions to forecasts of the stocks-to-disappearance ratio[6] made by official organisms. Forecasts are likely to be more influential than ex-post annual stocks that are unknown by economic agents at the time of taking their decisions. Since forecasts can be claimed to have been used in actual trading decisions, they are more pertinent to explain price behaviour. Following Schwager (1984), what economic agents believe to be true may be more relevant for price determination than what is actually truth.

Our analysis uses monthly stocks-to-disappearance forecasts for the subsequent end-of-season published by the USDA (2011). These forecasts include both grain stored on farms for feed, seed, sale, or under government programs, and grain stored in commercial storage facilities. Forecasts are usually derived as a residual to balance supply and demand forecasts (USDA, 1999). The supply forecast is based upon acreage, on and off-farm stocks and yield information. An annual survey to farmers is conducted to collect information on planted and/or planned acreage, grain stocks held and livestock inventories. Off-farm stocks information is derived from a survey to commercial grain storage facilities. Yield forecasts are built upon both monthly farmers yield projections and objective field measurements. Demand forecasts, on the other hand, representing domestic use and exports, are built upon a range of information including reports on livestock and feed, news on crop prospects abroad or on biofuel markets, regulatory changes, global politics, etc. The published stock forecast from January to April is for the current year, while from May to December, forecasts are published for the following crop year.[7]

[6] The stocks-to-disappearance ratio is the ratio of stocks to domestic consumption plus exports.

[7] As noted by Stigler and Prakash (2011), economic agents may not give the same relevance to forecasts close to the end of season than to forecasts for longer horizons. This may create some heterogeneity in that forecasts published throughout the year may not have the same impacts on price behavior. In any

The influence of interest rate volatility is also considered. The six-month moving variance of secondary market rates for the 3-month US treasury bills is used in this analysis. Monthly interest rates are derived from the Board of Governors of the Federal Reserve System (2011). Figure 1 presents both summary statistics and the evolution of the time series studied over time.

A preliminary analysis of the price series showed that both corn and ethanol prices have a unit root. Johansen (1988) cointegration tests suggest that corn and ethanol markets maintain a long-run equilibrium relationship whereby the two prices are positively related.[8] This positive link is expected. Since feedstock prices represent the major ethanol production cost, an increase in corn prices will increase ethanol prices. Further, a relevant portion of US corn production is being used to fuel cars: around 35 per cent in the 2009-2010 marketing year (USDA, 2011). An increase in ethanol demand (and price) will tighten corn markets and set corn equilibrium price to a higher level. By normalizing with respect to ethanol price, the cointegration relationship can be expressed as follows, where numbers in parenthesis represent standard errors, p_1 is the ethanol price and p_2 is the corn price:

$$\begin{aligned} p_1 - \underset{(0.115)}{0.313} p_2 - \underset{(0.299)}{0.644} = 0 \end{aligned} \tag{8}$$

case, the flexible Long et al.'s (2011) MGARCH semiparametric model can accommodate any change in price behavior due to the reference period change.

[8] Details on unit root and cointegration testing are available from authors upon request.

Results of the estimation of the MGARCH model are presented in table 1.[9] We first interpret the conditional mean model that assesses price level behaviour and that, like the conditional covariance model, does not make any a priori assumption on causality links. Current ethanol price changes depend on their own lags, on past corn price changes and on the deviations from the long-run parity (equation 8). Current corn price changes also depend on their own lags and on departures from the equilibrium parity. Hence, both ethanol and corn are endogenous for long-run parameters, a result compatible with the findings of Serra et al. (2011b) and Balcombe and Rapsomanikis (2008). Our results, however, differ from those obtained by Zhang et al. (2009) who did not find US corn and energy markets to be related in the long-run after the outbreak of the US ethanol industry in 2006.[10]

We now move to the interpretation of the conditional covariance model. The Portmanteau test for autocorrelation and Long et al.'s (2011) misspecification test provide evidence that the model is correctly specified. Individual coefficients in the MGARCH parameterization cannot be directly interpreted. Inferences can be drawn from the nonlinear parameter functions in the conditional variance equations presented in table 2. Results suggest that ethanol price volatility (h_{11t}) is influenced by its own lags (higher volatility in the past, h_{11t-1}, leads to higher current volatility) and by past shocks in the ethanol market (r_{1t-1}^2). Corn influences h_{11t} indirectly through the interaction term $r_{1t-1}r_{2t-1}$. Corn price volatility (h_{22t}) is found to grow with its own

[9] The final selection of lags of the VECM was based upon the SBC information criteria.

[10] Differences in modeling approaches, the data used, the time span covered by the analysis and the markets studied can explain differences in research results.

lagged volatility (h_{22t-1}). Past volatility in ethanol markets influences corn volatility through the covariance term (h_{12t-1}).

Table 2 further shows that the influence of the stocks-to-disappearance forecasts (z_1) and interest rate variability (z_2) on corn price volatility is statistically significant. Conversely, the exogenous variables exert no significant effect on ethanol price variability. Table 3 presents the marginal effects of z_1 and z_2 on h_{11t} and h_{22t}. At the data means, the marginal impact of stocks-to-disappearance forecasts on ethanol price volatility is negative. This is compatible with the theory that stock building can reduce market dependency on shocks, and thus price instability (Williams and Wright, 1991; Wright, 2011). It is also compatible with the findings of Shively (1996), Kim and Chavas (2002), Balcombe (2011) or Stigler and Prakash (2011). An increase in interest rate volatility is found, at the data means, to have a positive influence on corn price volatility.

Another step in this article is to apply Long et al.'s (2011) nonparametric correction of the parametric conditional covariance estimator, in order to capture information still remaining in the residuals of the model and derive estimates that are robust to misspecification of the parametric model. Since the application of such methodology involves using local smoothing techniques, it allows correcting the nonlinear parameter functions in the conditional variance equations for each observation in the sample. As a result, the semiparametric approach permits the parameters and the predictions of the model to change according to the prevalent economic and regulatory conditions. The distributions of the localized nonlinear parameter functions in h_{22t} are not presented here for brevity, but are available from the authors upon request. These distributions do show very little variation in about half of the parameter estimates (where the most frequent value represents 80-90 per cent of the localized estimates) and more relevant variability in the other half (the most frequent value representing around 60 per cent of parameter estimates). In any case, the impacts of this variability are best appreciated by comparing predicted volatility under the parametric and semiparametric methods. Predicted corn price volatility under both approaches, presented in figure 2, is similar. The most relevant differences are observed during periods of relatively high volatility in corn markets, which indicates that the semiparametric approach may be more suited to forecast price behaviour during turbulent periods. Predicted corn price volatility is especially high from the second half of 2005 until the end of 2009. This time span coincides with the post 2005 Energy Policy Act period, a critical factor driving the US ethanol industry surge. The act contributed to increase US demand for ethanol by holding oil companies liable for Methyl Tertiary Butyl Ether (MTBE) pollution. This drove the gasoline industry to massively switch from MTBE to ethanol as an oxygenate additive. The act also originated the Federal Renewable Fuel Standard (RFS1) program, mandating 7.5 billion gallons of renewable fuel to be blended with regular gasoline by 2012. The scope of the RFS1 program was later expanded to 36 billion gallons by 2022 and 12.95 by 2010 by the Energy Independence and Security Act (EISA) of 2007. The surge in ethanol production led to increased demand for corn, increased corn prices and their volatility. The period of high corn price volatility also coincides with reduced stocks-to-disappearance forecast levels relative to historical values, as well as with increased macroeconomic instability, i.e., the eruption of the financial crisis in the late 2008 that lingered until mid 2009 and that led to the global recession. This macroeconomic instability also led to high interest rate volatility.

Under Long et al.’s (2011) approach, the marginal impacts of the exogenous variables on corn price volatility can also be derived for each observation in the sample.

We compare predicted marginal impacts under the parametric and semiparametric approaches. Recall that the parametric model has been found to have less predictive ability during high volatility episodes (i.e., periods with low stocks-to-disappearance forecasts and high interest rate volatility). Hence, differences between the two methods should be especially relevant when z_1 (z_2) levels are low (high). This is confirmed in figures 3 and 4 where, for comparison purposes, the evolution of z_1 and z_2 over time is also presented. Figure 3 suggests relevant differences between the two methodological approaches by the end of the sample period, coinciding with relatively low z_1 levels. Further, localized parameter estimates show that the marginal capacity of z_1 to reduce h_{22t} has tended to increase over time as z_1 has declined, i.e., an increase in stocks-to-use ratio forecasts is more effective to control corn price variability when forecast levels are low than when they are high.[11] In the same fashion, figure 4 compares the marginal impacts of z_2 under the two alternative estimation methods. As expected, the largest differences between the two predictions take place during periods of large interest rate fluctuations that in turn lead to higher corn price volatility.

In spite of the differences between parametric and semiparametric methods, and as noted above, Long et al.'s (2011) test for the null of correct specification of the parametric model does not allow rejecting the null. To better understand the impacts of stocks-to-disappearance forecasts and interest rate instability on corn price volatility and

[11] These results thus provide evidence that price behavior is indeed characterized by different regimes, depending on the size of the stocks-to-use ratio. In being more accurate than a threshold model, the semiparametric approach does not distinguish between two (or a few) price regimes, one below a threshold and another above this threshold. Instead, under Long et al.'s (2011) proposal estimates and predictions are adapted for each observation in the sample.

given the fact that the parametric model is found to be well specified, we simulate, based on this model, volatility responses to a one-time 10 per cent increase in the exogenous variables. The differences between the predicted corn variance with and without the shocks are presented in figures 5 and 6. For comparison purposes, the impact of a 10 per cent increase in ethanol price volatility is also presented in figure 7. A one-time increase in corn stocks-to-disappearance forecast involves a temporary decline in corn price volatility that stabilizes at a smaller value after about 15 months following the shock (figure 5). An increase in the interest rate variance produces a very small positive effect on corn price volatility that is completed after about one year following the shock (figure 6). An increase in ethanol price volatility stimulates an increase in corn price volatility that is also completed after a year (figure 7). It is noteworthy that the impacts of stock forecasts in the short-run (first 9 months following the shock) are very high relative to the impacts of interest rate and ethanol price volatility. In the medium-run, the ethanol price and the interest rate volatility gain more relevance. Hence, our results suggest that US corn price volatility is not only influenced by energy price volatility, but also by corn stock forecasts and prevalent macroeconomic conditions. While previous research has paid attention to volatility spillovers between food and energy markets, the influence of stocks and macroeconomic conditions has not been studied in depth. Our empirical results show the relevance of doing so.

5. Concluding remarks

The scarce literature on food price instability has mainly focused on price volatility transmission across interrelated markets (Natcher and Weaver, 1999; Apergis and Rezitis, 2003; Buguk et al., 2003). Along these research lines, recent articles on the impacts of biofuels on food price volatility have assessed and found evidence of volatility spillovers between food and energy markets (Zhang et al., 2009; Serra, 2011). While energy markets can contribute to explain food price volatility, the economics literature has suggested a number of other variables that can also be relevant. The competitive storage model views stocks as a key determinant of price behaviour. Macroeconomic variables representing global economic conditions have also been considered to explain market fluctuations.

We study US corn price volatility over the last two decades by allowing for the influence of ethanol markets, corn stocks-to-disappearance forecasts and macroeconomic conditions represented by fluctuations in interest rates. An MGARCH model which is estimated both parametrically and semiparametrically is used for this purpose. Our contribution to the literature is twofold: we add to the scarce literature on food price volatility and we apply very innovative semiparametric techniques.

In accordance with the competitive storage theory, stocks-to-disappearance forecasts are found to turn down corn price instability. Interest rate variability brings more volatile food prices. As expected, instability in ethanol markets destabilizes corn markets. The impacts of stocks-to-disappearance forecasts in the short-run are very high relative to the effects of energy price and macroeconomic instability. Managing expectations in the market (e.g. by releasing more information or details about the forecasts) can thus be a relevant tool to control price volatility. The semiparametric approach shows that the marginal impacts of stocks-to-disappearance forecasts are decreasing with forecast levels. Our results show the relevance of extending analyses of volatility spillovers between food and energy markets, to a consideration of a wider array of explanatory variables.

Our research has important policy implications. First, our results suggest that public stock management (or simply stock forecasts published by public institutions) appears to be a powerful tool to mitigate food price instability, especially in periods of low stocks. Further, public promotion of second generation biofuels that are not based on food commodities, may contribute to reduce energy-food price links, which may lead to more stable food prices. Any policy directed towards safeguarding macroeconomic stability is also likely to yield less volatile food prices.

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Table 1. Ethanol – corn MGARCH model: mean and variance equations

Short-run dynamic parameters: $\begin{pmatrix} \Delta p_{1t} \\ \Delta p_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} ECT_{t-1} + \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix} \begin{pmatrix} \Delta p_{1t\text{-}1} \\ \Delta p_{2t\text{-}1} \end{pmatrix}$		
	$i=1$	$i=2$
α_i	-0.031* (0.016)	0.028* (0.017)
γ_{1i}	0.233** (0.059)	0.100** (0.034)
γ_{2i}	-0.057 (0.048)	0.398** (0.059)
GARCH model parameters: $C = \begin{pmatrix} c_{111} & 0 \\ c_{211} & c_{221} \end{pmatrix} + \begin{pmatrix} c_{112}z_1 & 0 \\ c_{212}z_1 & c_{222}z_1 \end{pmatrix} + \begin{pmatrix} c_{113}z_2 & 0 \\ c_{213}z_2 & c_{223}z_2 \end{pmatrix}$, $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, and $B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$		
	$i=1$	$i=2$
c_{1i1}	0.009 (0.022)	
c_{2i1}	0.032 (0.091)	0.144** (0.025)
c_{1i2}	-0.121 (0.103)	
c_{2i2}	-0.127 (0.531)	-0.912** (0.129)
c_{1i3}	0.095** (0.031)	
c_{2i3}	-0.043 (0.045)	0.103** (0.032)
a_{1i}	0.375** (0.042)	-0.089** (0.042)
a_{2i}	0.080**(0.035)	0.089 (0.068)
b_{1i}	0.918** (0.016)	0.056** (0.019)
b_{2i}	-0.014 (0.015)	0.903** (0.018)
Portmanteau test (third-order autocorrelation)		4.762**
Long et al.'s (2011) test for the null of correct specification of the MGARCH model		0.259

* and ** denote statistical significance at the 10 and 5 per cent significance level, respectively

p_1 = ethanol price, p_2 = corn price, z_1 = corn stocks-to-use ratio, z_2 = interest rate volatility

Table 2. Conditional variance equations

h_{11t} =	8.886e-5	+0.015 z_1^2	+9.045e-3 z_2^2	-2.290e-3 z_1	+1.793e-3 z_2	-0.023 $z_1 z_2$
	+0.843** h_{11t-1}	-0.027 h_{12t-1}	+2.104e-4 h_{22t-1}	+0.141** r_{1t-1}^2	+0.060** $r_{1t-1} r_{2t-1}$	+6.391e-3 r_{2t-1}^2
h_{22t} =	0.022**	+0.848** z_1^2	+0.012 z_2^2	-0.271** z_1	+0.027** z_2	-0.177** $z_1 z_2$
	+3.124e-3 h_{11t-1}	+0.101** h_{12t-1}	+0.815** h_{22t-1}	+7.953e-3 r_{1t-1}^2	-0.016 $r_{1t-1} r_{2t-1}$	+7.978e-3 r_{2t-1}^2

* and ** denote statistical significance at the 10 and 5 per cent significance level, respectively

h_{11} = ethanol price variance, h_{22} = corn price variance, r_1 = ethanol market shocks, r_2 = corn market shocks, z_1 = corn stocks-to-use ratio, z_2 = interest rate volatility

Table 3. Marginal effects of the exogenous variables on price volatility at the data means

$\frac{\partial h_{11t}}{\partial z_1} =$	$+0.030\ z_1$	-2.290e-3	$-0.023\ z_2$	= -1.190e-4
$\frac{\partial h_{11t}}{\partial z_2} =$	$+0.018\ z_2$	+1.793e-3	$-0.023\ z_1$	= 0.930e-4
$\frac{\partial h_{22t}}{\partial z_1} =$	$+1.696^{**}\ z_1$	-0.271**	$-0.177^{**}\ z_2$	= -0.041
$\frac{\partial h_{22t}}{\partial z_2} =$	$+0.024\ z_2$	+0.027**	$-0.177^{**}\ z_1$	= 0.003

* and ** denote statistical significance at the 10 and 5 per cent significance level, respectively

h_{11} = ethanol price variance, h_{22} = corn price variance, z_1 = corn stocks-to-use ratio, z_2 = interest rate volatility

Fig1. Time series data

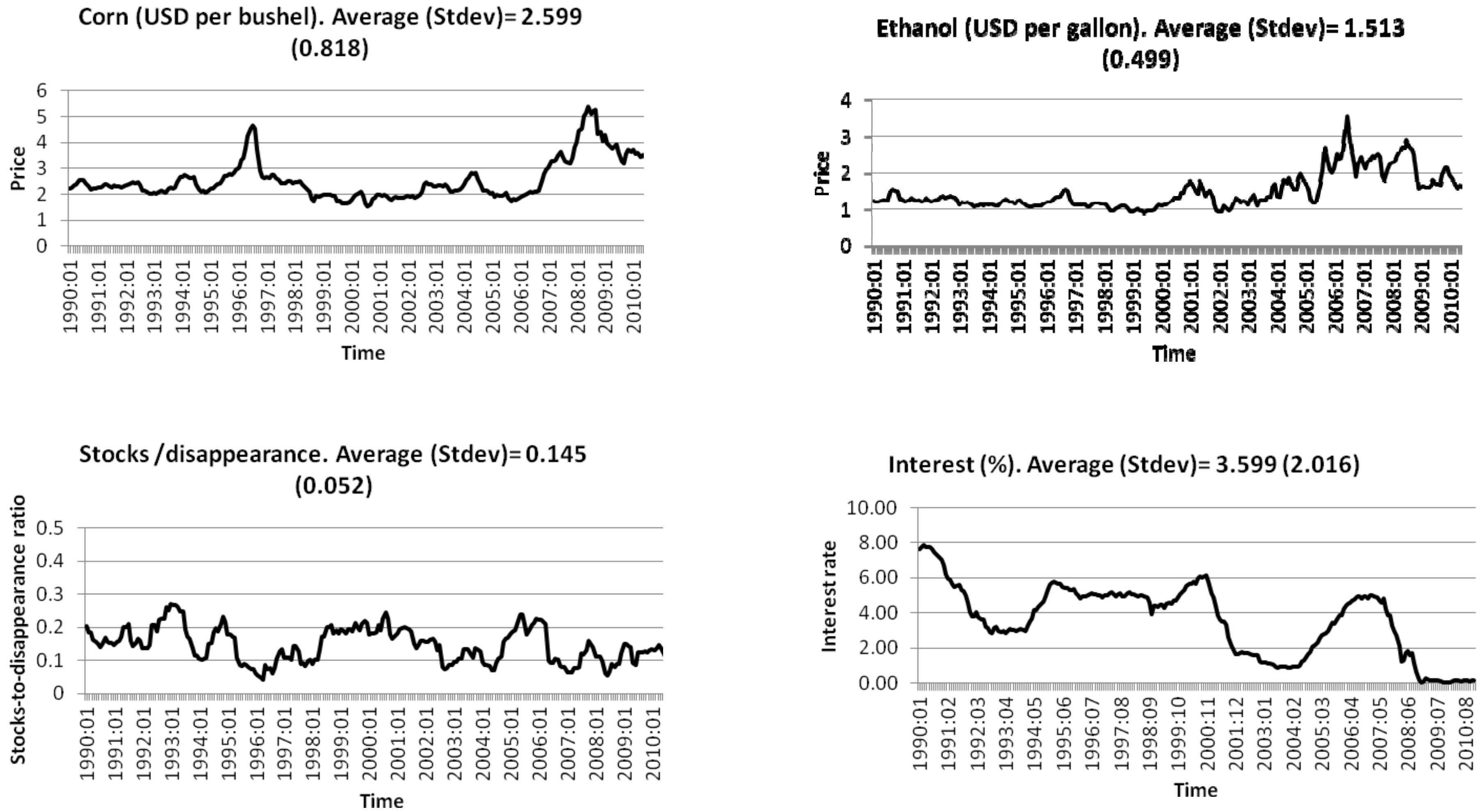


Fig 2. Predicted values for corn price volatility (h_{22t}) both under the parametric and the semiparametric approach

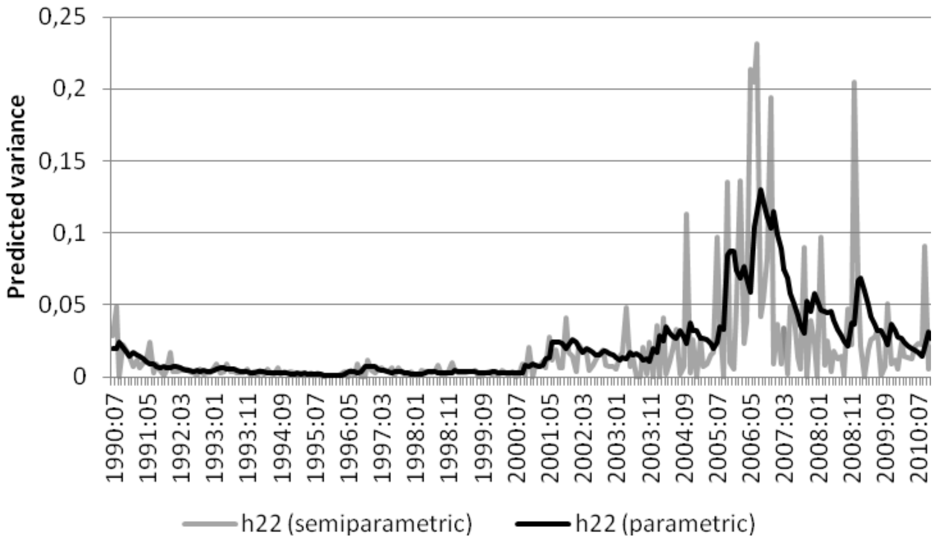


Fig 3. Parametric and semiparametric marginal effects of the stocks to disappearance ratio on corn price volatility (h_{22t}) and evolution of this ratio over time

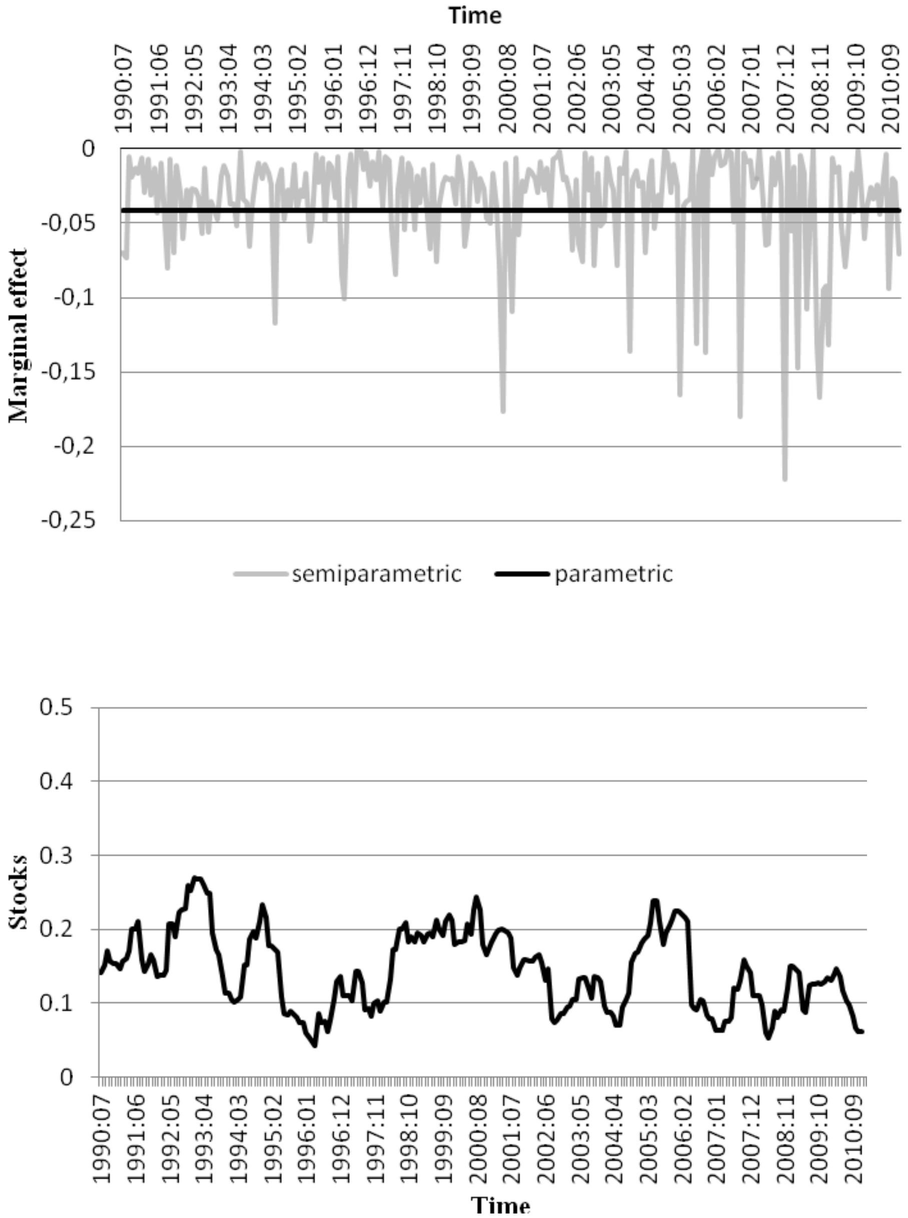
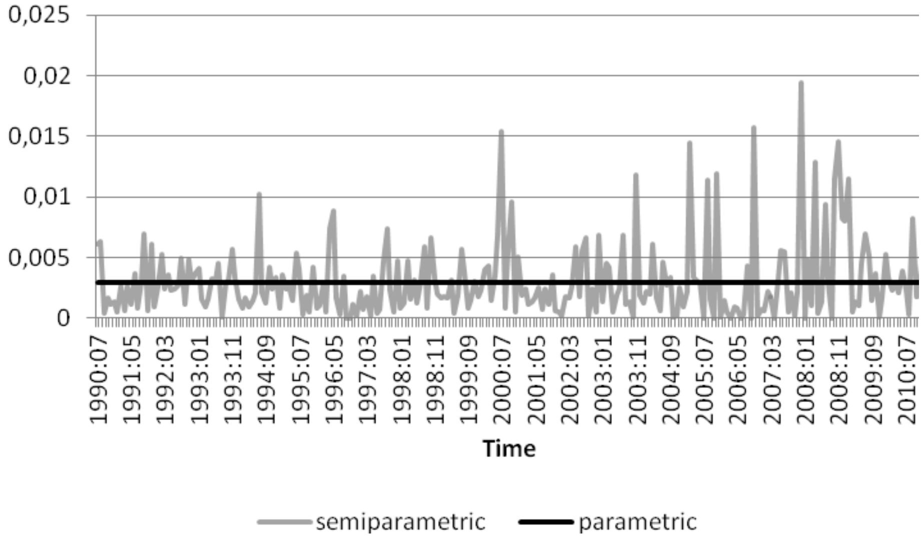


Fig 4. Parametric and semiparametric marginal effects of interest rate volatility on corn price volatility (h_{22t}) and evolution of interest rate volatility over time



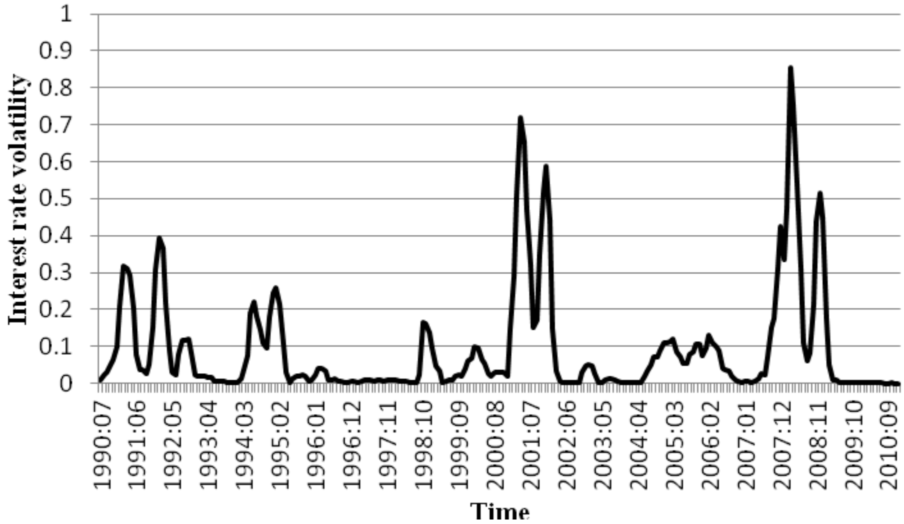


Fig 5. Corn volatility (h_{22t}) response to a one-time 10 per cent increase in corn stocks-to-use ratio

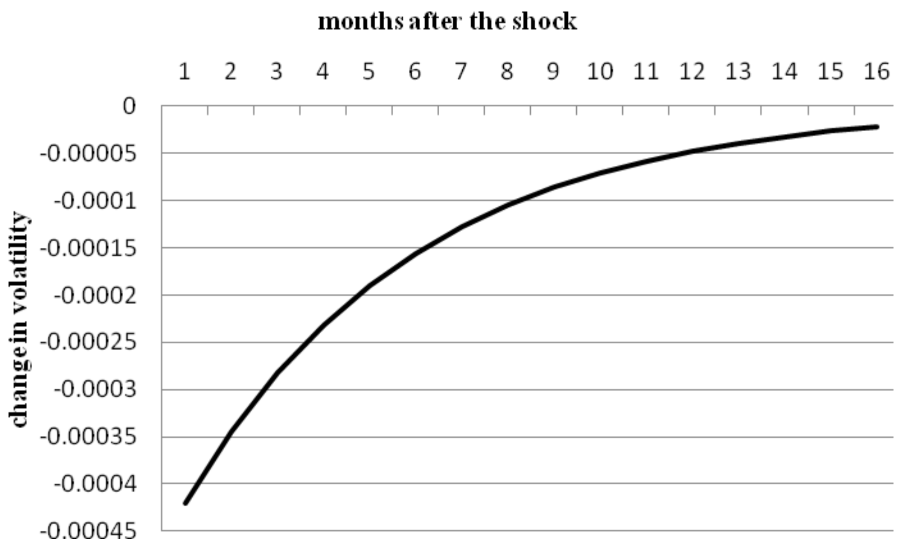


Fig 6. Corn volatility (h_{22t}) response to a one-time 10 per cent increase in the interest rate volatility

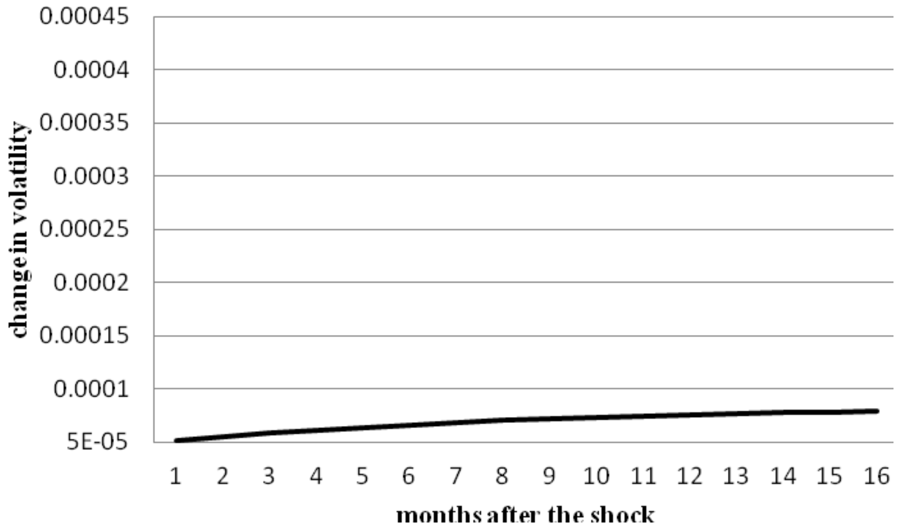


Fig 7. Corn volatility (h_{22t}) response to a one-time 10 per cent increase in ethanol price volatility