Price volatility in food markets: can stock building mitigate price fluctuations?

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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 instability can increase corn price volatility. Finally, stock building is found to significantly reduce corn price fluctuations.

Keywords: corn price, ethanol, stocks, garch.

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Introduction

Over the last decade, global food markets have undergone a period of marked and persistent volatility. Market instability has been specially 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 it also undermines food security in poor nations where households spend a substantial portion of their income on food. Cereals, specially corn, represent the most relevant source of world's food energy consumption and thus are key to food security (Wright 2011). Prakash (2011a) shows that corn price volatility has been growing over the last 50 years. Our analysis will focus on assessing volatility in the US corn market.

We focus on this market for two main reasons. First, because the US is the major world producer and exporter of corn. US corn production represents 41% of global corn output, while US corn exports represent around 54% of total world exports (in 2010 production was on 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 outbreak of the biofuels industry that has involved 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 enhanced price instability, its socio-economic impacts and the instruments available to mitigate them. These sociopolitical concerns have influenced the academic agenda. A wide array of different justifications for the recent increases in food price volatility have been proposed in the literature and include, among others, massive financial investments in food commodity markets, macroeconomic factors such as interest or exchange rate fluctuations, recent 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 that are 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, Arpegis and Rezitis 2003, Buguk et al. 2003). 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 the theoretical literature has suggested that stock building can play a key role in shaping price volatility, the empirical literature has paid little attention to this issue. Our analysis not only allows for price volatility transmission between biofuel and food markets, but also studies the impacts of corn stocks on corn price fluctuations, thus contributing to the scarce literature on this topic.

As will be explained in detail below, 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 fit using both well known parametric techniques and a recently proposed semiparametric approximation (Long et al. 2011) that overcomes the most relevant limitations that have been attributed to parametric methods. The use of very innovative econometric techniques to assess price volatility constitutes another contribution of our work to the literature.

Previous research

An active scholar debate is being held on the role that commodity stocks can play 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). The theoretical literature has focused most of its attention on the competitive storage model that views stocks as a key determinant of commodity price behavior and assumes that economic agents have rational expectations. When the current price is below the expected price (adjusted for financial and storage costs), storage will be used by economic agents in order 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 behavior will be entirely dependent on supply shocks. As noted by Wright (2011) the implications of the storage model are not yet well understood and widely accepted among researchers.

While the implications of the storage model for price volatility are not clear cut (Stigler and Prakash 2011), Williams and Wright (1991) and Wright (2011) postulate that price volatility will increase as inventories decline. While in the absence of stocks prices will fluctuate according to supply and demand shocks, stock building can contribute to mitigate dependency on these shocks. 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 price volatility in food prices bears some relationship to stock depletion.

While much discussion has been held on the links between stocks and price behavior at the theoretical level, the scarcity of statistical data on public and private stocks has however limited the number of empirical applications. Empirical research results are not conclusive. While Shively (1996), Kim and Chavas (2002), Balcombe (2011) and Stigler and Prakash (2011) provide empirical evidence of a significant influence of stocks on market price behavior, Dawe (2009) and Roache (2010) find a rather weak effect of stocks on price volatility. Most of these studies rely upon univariate generalized auto-regressive conditional heteroskedastic (GARCH) models that do not allow for volatility spillovers across related markets. Allowing for volatility interactions between food and energy markets is specially relevant when assessing corn price behavior, given the massive use of corn as a feedstock in the US ethanol industry. Our objective is to assess to what extent stocks have an influence on US corn price volatility using a MGARCH approach that allows for volatility transmission between US corn and ethanol markets.

There is an ample debate on the impacts of biofuels on agricultural commodity prices. While previous research findings are rather disperse, there seems to be a general agreement that public promotion of biofuels has strengthened the link between energy and agricultural markets. As been pointed out by Serra (2011), most analyses that study the implications of biofuels for food prices have focused on price levels, ignoring the impacts on food price volatility. Balcombe and Rapsomanikis (2008) or Serra et al. (2011b) are not an exception to this rule. These authors show that an increase in energy price levels will lead to an increase in Brazilian sugar and US corn prices, the link between the two markets being fueled by the ethanol industry. Given these 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 by previous research to also explain price fluctuations (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 have an impact on food price volatility. The influence of macroeconomic variables such as interest rate instability will also be considered in our analysis to shed light on US corn price volatility.

Methods

Previous research has shown that price volatility tends to vary over time and to display a clustering behavior (Myers 1994), with periods of high (low) volatility tending to be followed by periods of high (low) volatility. To allow for this pattern, which is 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.

In light of previous research findings, supporting an increased link between food and energy prices fueled by the biofuels industry boom, our GARCH model will be of a bivariate nature to include US corn and ethanol prices.[1] We expect ethanol prices to influence corn prices due to the biofuel-induced demand for corn to produce ethanol. Further, and since feedstock costs represent a conspicuous part of total ethanol producing costs (OECD 2006), we also expect ethanol prices to be influenced by corn prices.

As is well known, GARCH models accommodate two sub-models: the conditional mean and the conditional covariance model. Since prices of related markets are usually cointegrated (Myers 1994), mean models in price-series econometrics are usually specified as a vector error correction model (VECM) which allows to capture both the short-run and the long-run dynamics of price series (equation 1).[2] Since we are

[1] By suggesting that the supply of ethanol is derived from the supply of feedstock, the economic theory (de Gorter and Just, 2008) suggests that demand forces in ethanol markets will ensure a co-movement of ethanol and feedstock prices.

[2] The final selection of lags of the VECM was based upon statistical significance and parsimony.

interested in assessing volatility spillovers between food and energy markets, a multivariate Baba-Engle-Kraft-Kroner (BEKK) GARCH specification (equation 2) is used for the conditional volatility model (Engle and Kroner 1995).

$$\Delta \mathbf{p}_t = \alpha ECT_{t-1} + \gamma \Delta \mathbf{p}_{t-1} \quad (1)$$

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

where $\Delta \mathbf{p}_t$ is a 2×1 vector of prices in first differences, ECT_{t-1} is a lagged error correction term derived from the cointegration relationship, α is a 2×1 matrix that shows the adjustment of each price to deviations from the long-run parity, and γ is a 2×2 matrix showing the short-run price dynamics. Matrix $\mathbf{A}$ is a 2×2 parameter matrix that 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): $c_{ij} = z_t \delta_{ij}$, where $z_t = (1, z_1, ..., z_{r-1})$ is an *r*-dimensional vector of exogenous variables influencing price volatility. Parametrizing 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) proposal does not restrict the sign of the impact that the exogenous variables can have on price volatility in order to ensure this positive definiteness.

The conditional mean and covariance models are, in a first stage, jointly estimated under the assumption of normally distributed errors using standard maximum likelihood procedures. Conventional parametric MGARCH models have been criticized for two main reasons. First, because they usually rely upon the assumption of a normal distribution of the model errors and second, because the conditional covariance matrix is 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 misspecifications of the distribution errors and the conditional covariance functional forms. Most approaches in this field have been mainly developed in the univariate context (Audrino 2006, Härdle and Tsybakov 1997). Long et al. (2001) have however proposed a semiparametric estimator of the conditional covariance functional form in the MGARCH model.

In a second stage in our analysis, we adopt the semiparametric multivariate volatility model proposed by Long et al. (2011) that basically consists of a nonparametric correction of the parametric conditional covariance estimator. Let's now assume that the 2-dimensional[3] vector of errors of the conditional mean model in (1), $\mathbf{r}_t = (r_{1t}, r_{2t})'$, $t = 1,...,T$, 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 $t-1$,

[3] 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.

$\boldsymbol{\mu}_t = E(\mathbf{r}_t | \mathscr{F}_{t\text{-}1}) = 0$, $\mathrm{H}_t = E(\mathbf{r}_t \mathbf{r}_t ' | \mathscr{F}_{t\text{-}1})$ and $\mathbf{P}$ is the joint cumulative distribution function (CDF). In contrast to the parametric process followed above, no specific assumption is now 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 $E(\mathbf{e}_t | \mathscr{F}_{t\text{-}1}) = 0$ and $E(\mathbf{e}_t \mathbf{e}_t ' | \mathscr{F}_{t\text{-}1}) = \mathbf{I}_k$: $\mathbf{r}_t = \mathbf{H}_t^{1/2} \mathbf{e}_t$. No assumption on the distribution of $\mathbf{e}_t$ is necessary to derive the semiparametric estimator either. The matrix $\mathbf{H}_t^{1/2}$ is the symmetric square root of $\mathbf{H}_t$. The semiparametric estimator of the conditional covariance matrix is presented in (3):

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

where matrix $\mathbf{H}_{p,t}(\theta)$ is the parametric estimator of $\mathbf{H}_t$ (equation 2) and $\mathbf{e}_t(\theta) = \mathbf{H}_{p,t}^{-1/2}(\theta) \mathbf{r}_t$ is the result of standardizing the errors from the parametric model. $E\left[\mathbf{e}_t(\theta) \mathbf{e}_t(\theta)' | \mathscr{F}_{t\text{-}1} \right]$ 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,

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

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 following 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: $k(u) = \exp(-u^2/2)\big/\sqrt{2\Pi}$.[4] Following Long et al. (2011), $h_i = c_j \hat{\sigma}_i T^{-1/6}$ defines the bandwidth, $\hat{\sigma}_i$ represents the sample standard deviation of r_{it}, T denotes the number of observations and c_j is selected through a grid search process from 0.2, 0.6,…,5. The grid search aims at minimizing 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).

Empirical application

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).

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

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

model estimation and, second, it involves losing information contained in more frequent and available data. As a result, we follow Stigler and Prakash (2011) who propose to study market reactions to the forecasts on the stocks to disappearance ratio made by official organisms. As argued by these authors, forecasts are likely to be more influential than ex-post annual stocks that are unknown by economic agents at the time. 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[5] for the subsequent end-of-season published by the USDA (2011). The published forecast from January to April is for the current year, while from May to December, forecasts are published for the following crop year. 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.

As noted above, since previous research has found macroeconomic variables to be relevant to explain price behavior, the influence of the 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.[6] Monthly interest rates are derived from the Board of Governors of the Federal Reserve System (2011).

A preliminary analysis of the price time-series studied suggested that both corn and ethanol prices have a unit root. Johansen (1988) cointegration tests suggest that

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

[6] The same variable in level form as well as US dollar exchange rates both in levels and in variance form were considered, but not found to be statistically significant.

corn and ethanol markets maintain a long-run equilibrium relationship whereby these two prices are positively related.[7] As will be seen below, both ethanol and corn prices respond to deviations from this parity (table 1). A long-run positive link between the two prices is not surprising and is related to the fact that feedstock prices represent the major ethanol production cost. Hence, an increase in feedstock prices will yield an increase in ethanol prices. Such positive link is also due to the relevant portion of US corn production being transformed into ethanol in the US: around 35% in the 2009-2010 marketing year (USDA 2011). An increase in ethanol prices is an indicator of an increase in ethanol demand, which in turn tightens corn markets and sets corn equilibrium price to a higher level. By normalizing with respect to the 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:

$$\begin{array}{l} p_1 - 0.313 p_2 - 0.644 = 0 \\ \qquad (0.115) \quad (0.299) \end{array} \tag{8}$$

The results of the estimation of the MGARCH model with exogenous variables are presented in table 1. We first interpret the conditional mean model that assesses price level behavior and that, like the conditional covariance model, does not make any a priori assumption on casuality links among the variables considered. Current ethanol price changes depend on their own lags, on past corn price changes and on the deviations from the long-run parity presented in (8). Current corn price changes also

[7] Details on unit root and cointegration testing are not presented here, but are available from the authors upon request.

depend on their own lags and on disequilibriums from the corn-ethanol long-run 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 do not find US corn and energy markets to be related in the long-run after the outbreak of the US ethanol industry in 2006.

We now move to the interpretation of the conditional covariance model. The BEKK model is covariance stationary since the eigenvalues of $\mathbf{A} \otimes \mathbf{A} + \mathbf{B} \otimes \mathbf{B}$, where $\otimes$ denotes the Kronecker product, are less than one in modulus. As is well known, individual coefficients in the MGARCH parametrization cannot be directly interpreted. Inferences, however, 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 conditional volatility in the past, h_{11t-1}, leads to higher current volatility), as well as with past shocks in the ethanol market (r_{1t-1}^2). Corn influences ethanol price volatility indirectly through the interaction term $r_{1t-1}r_{2t-1}$. Corn price volatility (h_{22t}) is found to grow with its own lagged volatility (h_{22t-1}), while past volatility in ethanol markets influences corn volatility through the covariance term (h_{12t-1}).

Table 2 further shows the influence of stocks and interest rate variability on corn price volatility. To draw more specific conclusions on this issue, the net effects of these two variables on the variances of the two prices studied are presented in table 3. More specifically, table 3 shows the net impacts of corn inventories, z_1, and interest rate volatility, z_2, on corn and ethanol price volatility. We present both the first derivatives of h_{11t} and h_{22t} with respect to z_1 and z_2, as well as the value of these derivatives computed at the data means. Results suggest that, at the data means, the net impacts of stocks on price volatilities are 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). The parameters in the ethanol price volatility equation, however, are not statistically different from zero, thus indicating that corn stock building's impacts on ethanol price volatility are not significant. An increase in interest rate volatility, which can be understood as an increase in economic instability, is found to have a positive influence on ethanol and corn price volatility. Once more, the parameters in the ethanol price variance equation are not statistically significant.

Another step in this article is to apply the nonparametric correction proposed by Long et al. (2001) to 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, the whole set of conditional covariance parameter estimates is derived for each observation in the sample. In figure 1 we show the variability of the localized nonlinear parameters in the conditional variance equation for corn. The variability is relevant in about half of the parameters, where the most frequent value represents around 60% of localized parameter estimates. For the rest of the parameters, the variability is much less and the most frequent value represents between 80 and 90% of the localized estimates. This variability has implications for the estimation of the net impacts of stocks and interest rates on price volatility: the semiparametric model allows deriving these net impacts for each observation in the sample. Figure 2 presents the evolution over time of the first derivative of corn price volatility with respect to stocks (computed at the data means). For comparison purposes, the evolution of the stocks to disappearance ratio is also presented. This figure shows that the marginal capacity of stocks to reduce corn price volatility has tended to increase over time as stocks have declined, i.e., an increase in stocks is more effective to control price variability when stock levels are low than when they are high. Figure 3 presents the evolution over time of the first derivative of corn price variance with respect to interest rate volatility (computed at the data means). The evolution of the interest rate volatility is also graphed. The graphs provide evidence that usually the net impacts of interest rate volatility are specially relevant during periods of high interest rate fluctuations. In spite of the variation in the localized parameter estimates, the test for the null of correct specification of the parametric covariance estimator proposed by Long et al. (2011) suggests that the parametric model can be trusted.[8]

To better understand the impacts of stocks and macroeconomic instability on corn price volatility and given the fact that the parametric model is found to be well specified, we simulate volatility responses to a one-time 10% increase in the exogenous variables. The differences between the predicted corn variance with and without the shocks are presented in figures 4 and 5. For comparison purposes, the impact of a 10% increase in ethanol price volatility is also graphed and computed in figure 6. Figure 4 shows that a one-time increase in corn stocks involves a temporary decline in corn price volatility that stabilizes at a smaller value after about 15 months following the shock. An increase in the interest rate variance causes a very small positive effect on corn price

[8] Details on this test can be found in Long et al. (2011). Results are not presented here, but are available from the authors upon request.

volatility that is completed after about one year following the shock (figure 5). An increase in ethanol price volatility causes an increase in corn price volatility that is also completed after a year (figure 6). It is noteworthy that the impacts of stocks in the short-run (first 9 months following the shock) are very high relative to the impacts of interest rate and ethanol price volatility. However, in the long-run, the ethanol price first and the interest rate volatility second are found to have the strongest influence. Hence, our results suggest that US corn price volatility is not only influenced by energy price volatility, but also by corn stocks, as well as by the prevalent macroeconomic conditions. While previous research has paid special 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.

Concluding remarks

The scarce literature on food price instability has mainly focused on price volatility transmission across interrelated markets (Natcher and Weaver 1999, Arpegis and Rezitis 2003, Buguk et al. 2003). Along these research lines, recent literature on the impacts of biofuels on food price volatility has assessed and found evidence of volatility spillovers between food and energy markets (Zhang et al. 2009, Serra 2011). While price transmission from energy to food 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 agricultural price behavior. Macroeconomic variables representing global economic conditions have also been considered to explain market fluctuations.

This article studies US corn price volatility over the last two decades by allowing for the influence of ethanol markets, corn stocks and global economic conditions as represented by fluctuations in the interest rate. An MGARCH model which is estimated both parametrically and semiparametrically is used for this purpose. Our contribution to the literature is twofold. One the one hand we add to the scarce literature on the effects of stocks and macroeconomic conditions on market instability and on the other, we apply very innovative semiparametric techniques to assess food price fluctuations.

In accordance with economic theory, stock building is found to turn down corn price instability. Economic instability brings more volatile food prices. As expected, an increase in ethanol price volatility causes an increase in corn price volatility. While the impacts of stocks in the very short-run are very high relative to the effects of energy price and macroeconomic instability, in the long-run the ethanol price and interest rate volatility are found to have the strongest impacts. The localized parameter estimates derived from the semiparametric approach show that the marginal impacts of stocks are decreasing with stock levels, i.e., it is more effective, for the purpose of curbing down price fluctuations, to increase stocks when these are very low than when they are very high. 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 appears to be a powerful tool to mitigate food price instability, specially 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 (p_1) – corn (p_2) 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: $C=\begin{pmatrix}c_{111} & 0\\ c_{211} & c_{221}\end{pmatrix}+\begin{pmatrix}c_{112} & 0\\ c_{212} & c_{222}\end{pmatrix}\begin{pmatrix}z_1 & 0\\ z_1 & z_1\end{pmatrix}+\begin{pmatrix}c_{113} & 0\\ c_{213} & c_{223}\end{pmatrix}\begin{pmatrix}z_2 & 0\\ z_2 & z_2\end{pmatrix}$, $A=\begin{pmatrix}a_{11} & a_{12}\\ a_{21} & a_{22}\end{pmatrix}$, 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)
Eigenvalues of $\mathbf{A}\otimes\mathbf{A}+\mathbf{B}\otimes\mathbf{B}$		0.989 0.870 0.836 0.835

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

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

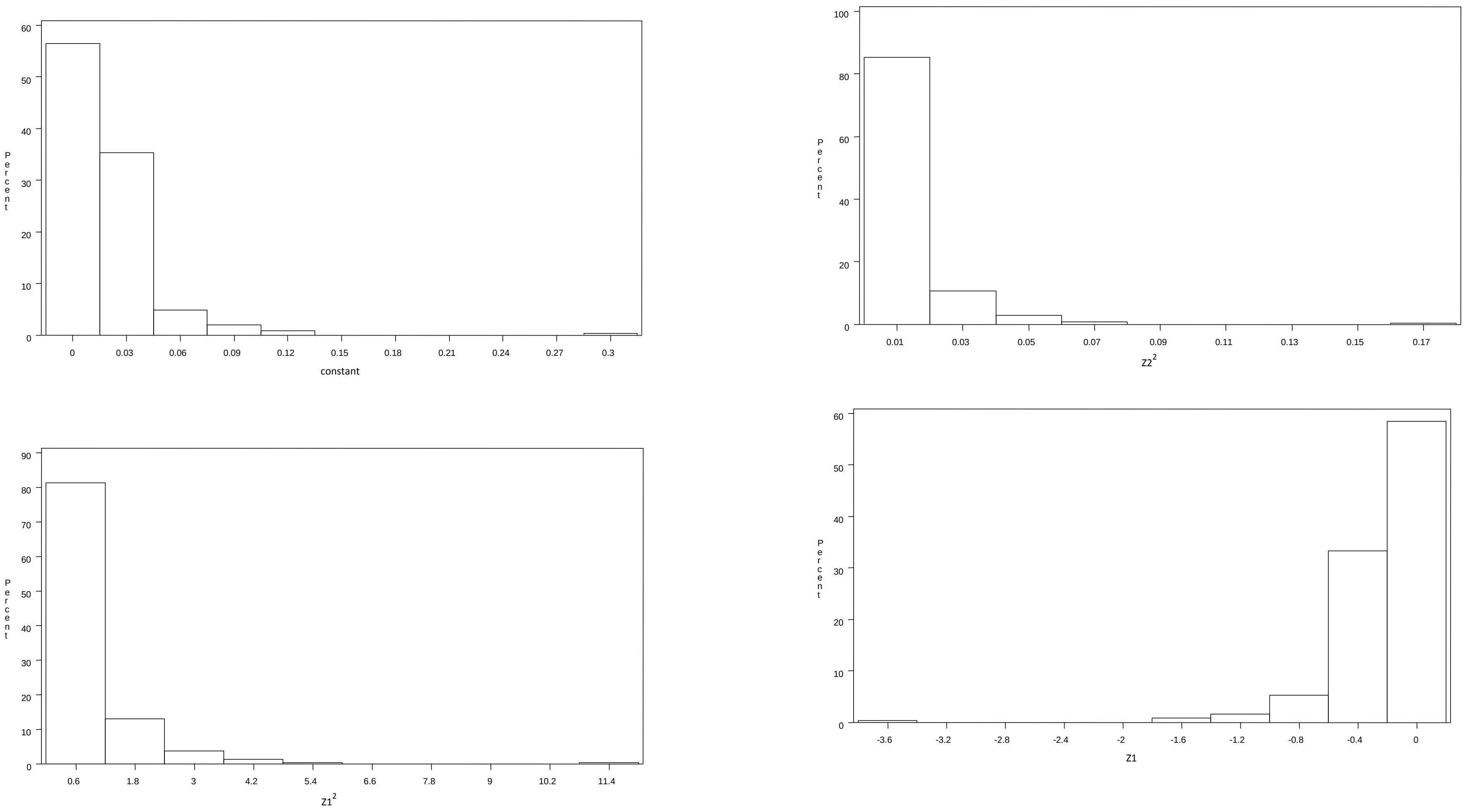
*(**) denotes statistical significance at the 10(5) per cent significance level

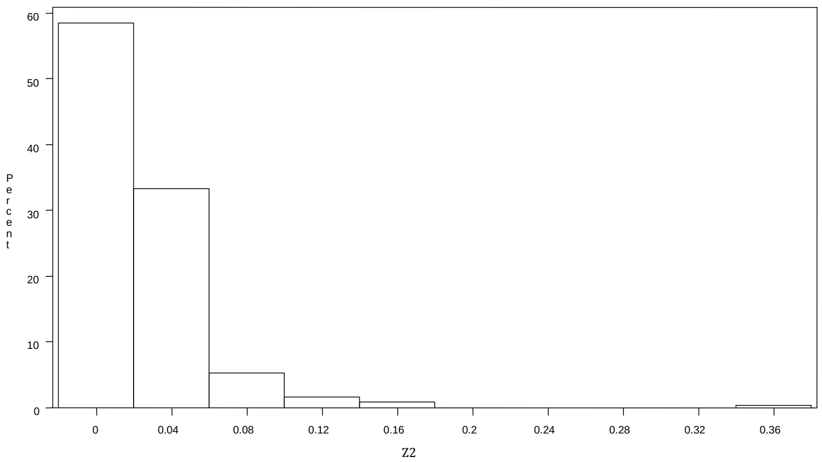
Table 3. Net effects of the exogenous variables on price volatility at the data means

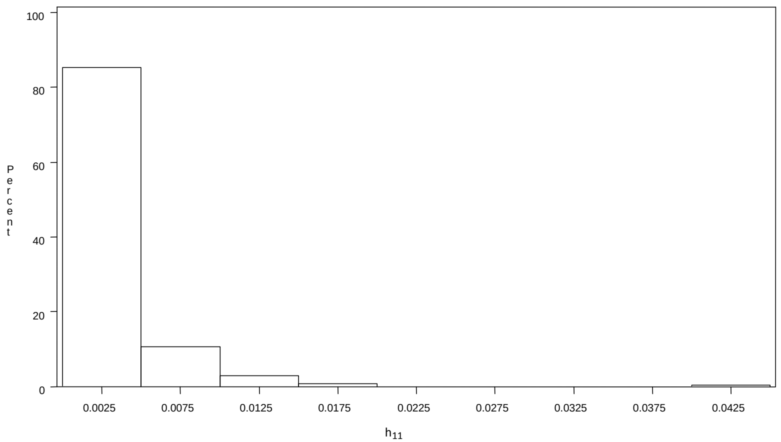
$\frac{\partial h_{11t}}{\partial z_1} =$	+0.030 z_1	-2.290e-3	-0.023 z_2	= -1.190e-4
$\frac{\partial h_{11t}}{\partial z_2} =$	+0.018 z_2	+1.793e-3	-0.023 z_1	= 0.930e-4
$\frac{\partial h_{22t}}{\partial z_1} =$	+1.696** z_1	-0.271**	-0.177** z_2	= -0.041
$\frac{\partial h_{22t}}{\partial z_2} =$	+0.024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

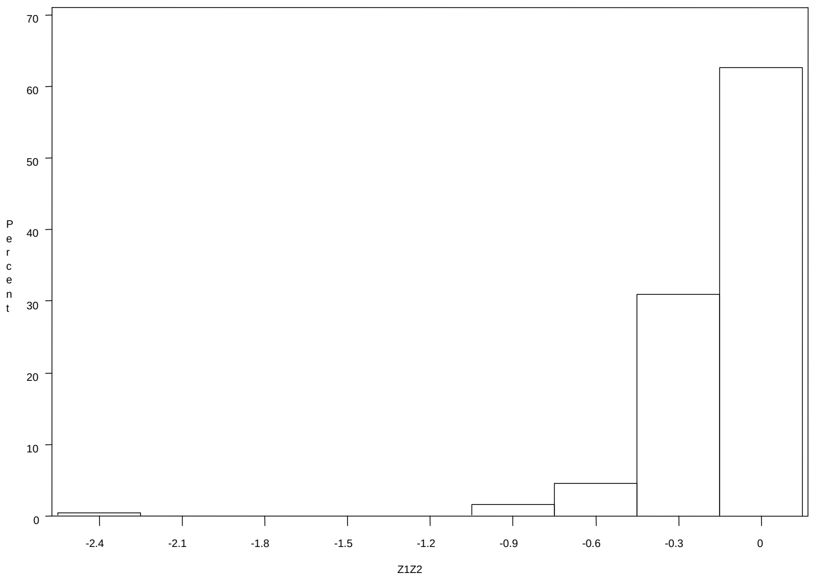
*(**) denotes statistical significance at the 10(5) per cent significance level

Fig 1. Histograms of the localized parameter estimates for h_{22t}




Percent
Z2


Percent
h_{11}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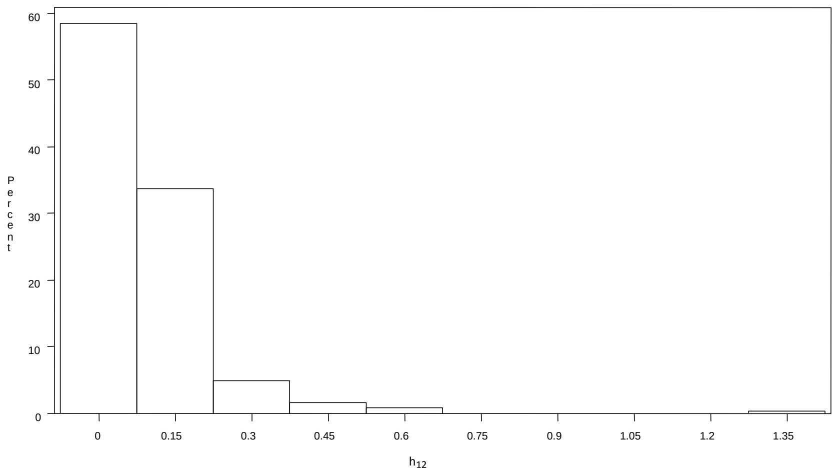
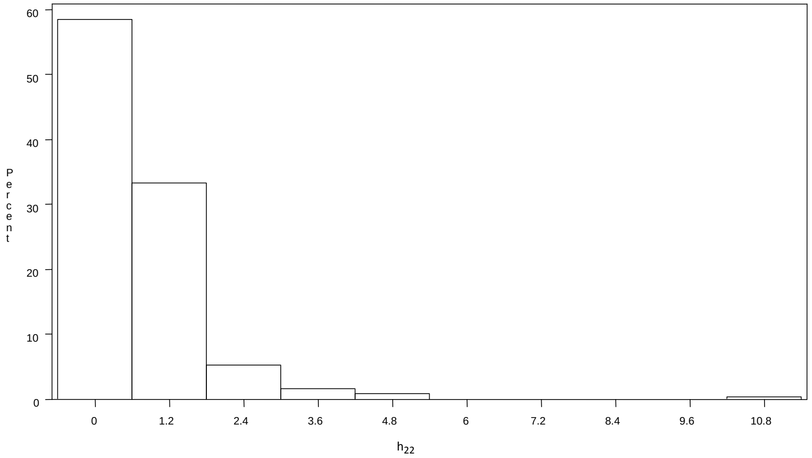
Z1Z2


Percent
h_{12}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20
30
40
50
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0
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2.4
3.6
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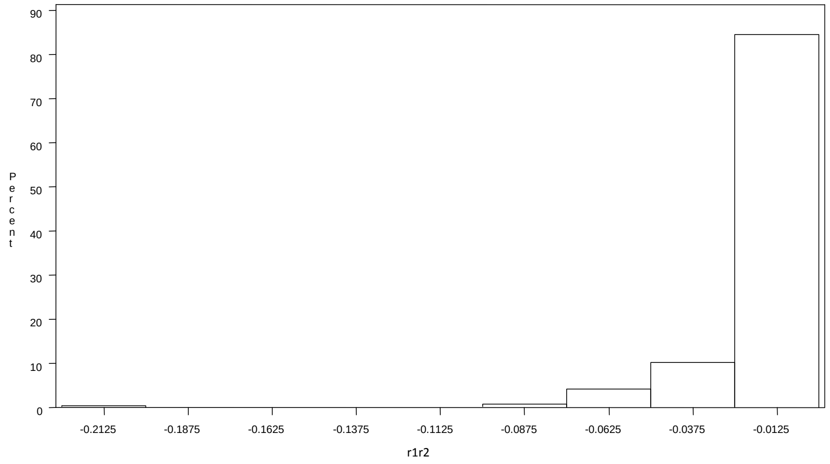
6
7.2
8.4
9.6
10.8
h22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30
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70
80
90
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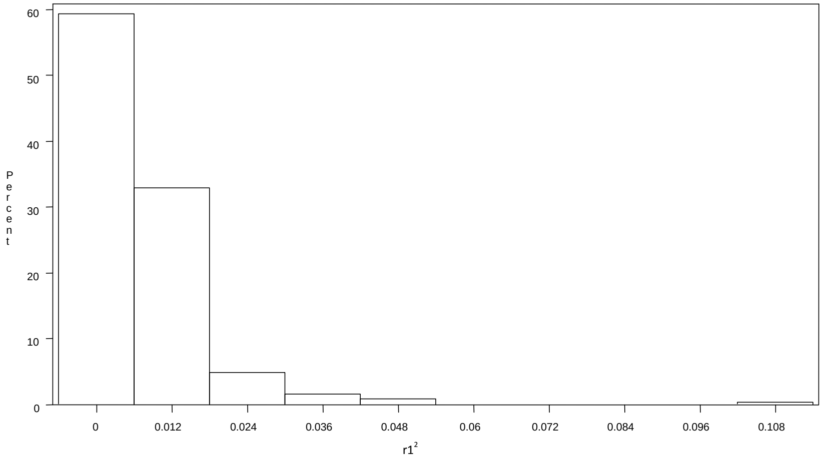
-0.0125
r1r2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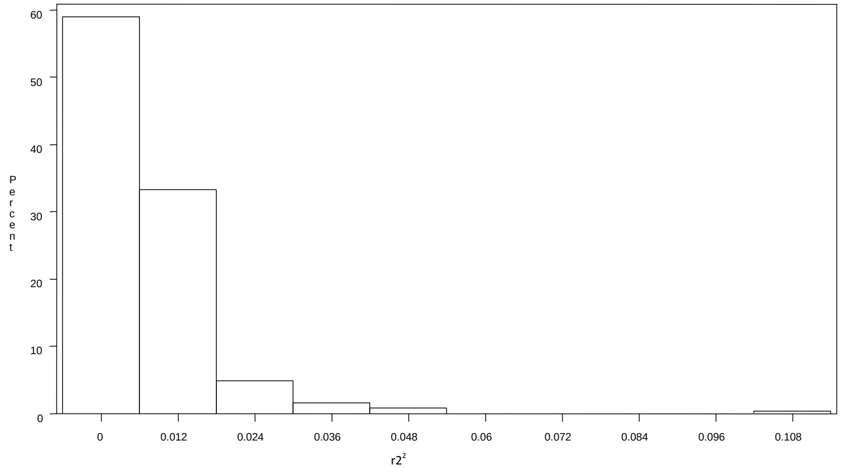
0.096
0.108
r1²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0.036
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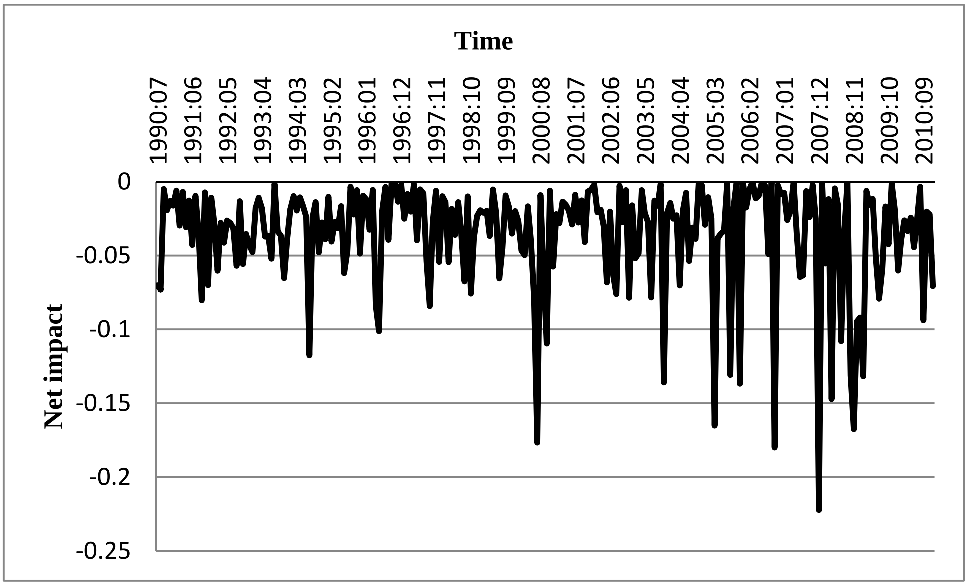
0.084
0.096
0.108
r2²

Fig 2. Localized net effects of the stocks to disappearance ratio on corn price volatility and evolution of this ratio over time



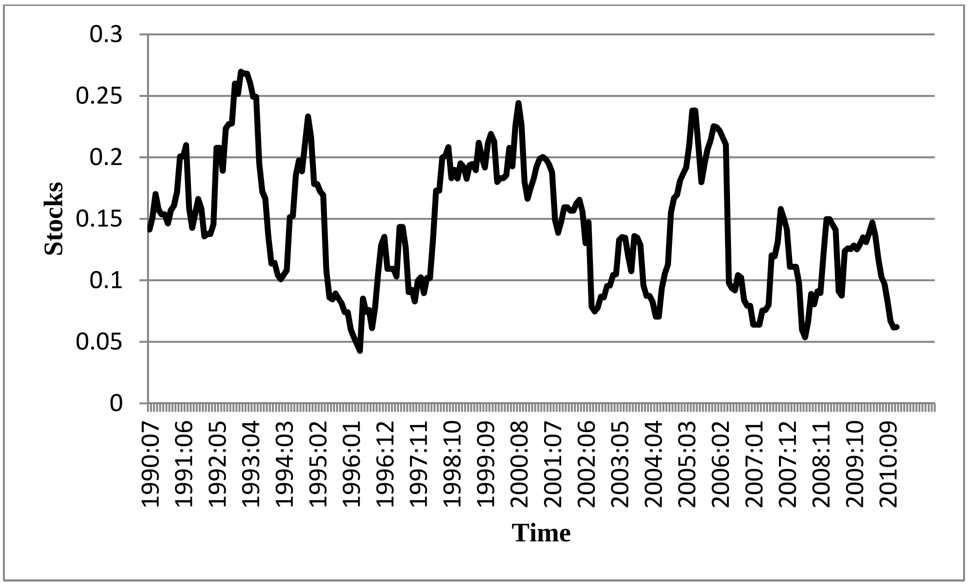
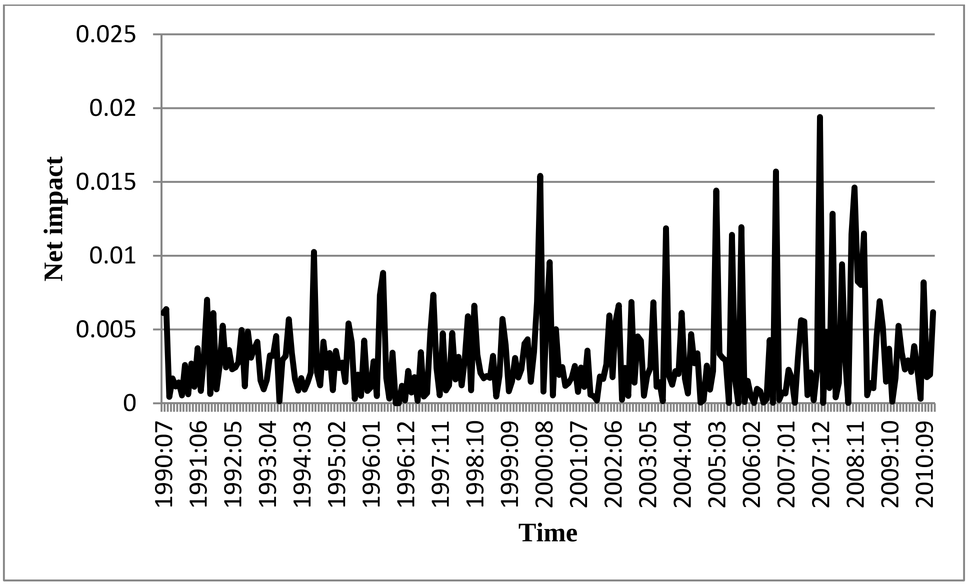


Fig 3. Localized net effects of interest rate volatility on corn price volatility and evolution of interest rate volatility over time



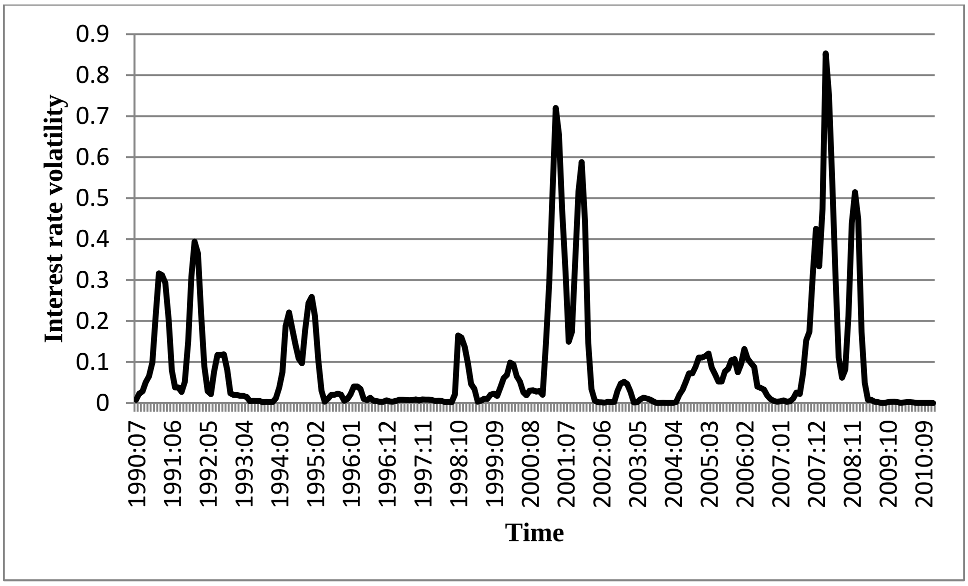


Fig 4. Corn volatility response to a one-time 10% increase in corn inventories

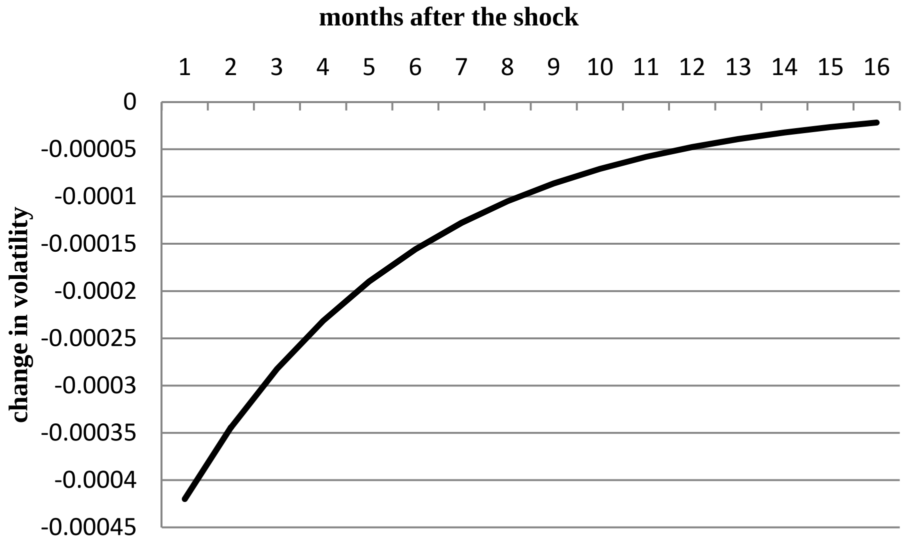


Fig 5. Corn volatility response to a one-time 10% increase in the interest rate volatility

Fig 6. Corn volatility response to a one-time 10% increase in ethanol price volatility