Biofuel-related price volatility literature: a review and new approaches

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Abstract

In this article, a review of the price transmission literature addressing volatility interactions between biofuel and food and fossil fuel markets is presented. The data used, the modeling techniques and the main findings of this literature are discussed. Future extensions of this flourishing research area are proposed and late developments introduced.

Key words: time series, biofuels, volatility, literature review

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Introduction

The surge of the global biofuels industry during the 2000s decade has been mainly led by an array of government policies pursuing different objectives such as enhancing domestic energy security, combating the increasing global warming or the pollution derived from the use of harmful gasoline oxygenates, promoting economic growth in rural areas, or protecting fuel consumers against price increases. In 2009, world ethanol production reached roughly 20 billion gallons. The main ethanol producing countries were the United States (US), Brazil and the European Union (EU) with approximately 54%, 34% and 5% of global production, respectively (RFA, 2011). In the same year, the global biodiesel market was dominated by the EU, with 65% (9 million tons) of world output (EEB, 2010).

While cellulosic sources are projected to displace food crops as feedstocks for the biofuel industry sometime in the future, currently commercialized biofuels are, by and large, first-generation biofuels based on agricultural commodities. In the 2008-2010 period, coarse grains (specially corn) represented 51% of global ethanol output by feedstocks according to OECD-FAO (2011) estimates. During the same period, sugarcane accounted for 29% of global ethanol output. Biodiesel is mainly produced from vegetable oils (rapeseed oil in Europe and soybean oil in the US). Around 20 million hectares representing 1% of worldwide agricultural land, were estimated to be dedicated to grow biofuel feedstocks in 2008 (Scarlat and Dallemand, 2011). The fraction of global agricultural output devoted to fuel cars cannot be neglected: around 11% of coarse grain production, 13% of vegetable oil production and 21% of sugar cane production in the 2008-2011 period (OECD-FAO, 2011). Average figures however mask significant differences across countries and commodities. In 2010-2011 the US used 40% of its corn production to fuel cars (USDA, 2011), while Brazil distilled 55% of its sugarcane output into ethanol (Valdes, 2011).

Depending on technical restrictions, blending mandates, tax exemptions or subsidies, biofuels are usually commercialized blended with gasoline and diesel, but also in pure form (Chang et al., 2011). In 2009, ethanol displaced around half of the gasoline used for transportation in Brazil. In the US, however, ethanol only represented 5.5% of total gasoline consumption (RITA, 2011; REN21, 2010), while in the EU, biofuels represented around 4% of all fuels used for transportation purposes (EurObservr'ER, 2010).

There is certain consensus among academics that the outbreak of the global biofuels industry has altered the nature of the link between energy and agricultural markets. While traditionally, food and energy prices were mainly connected though the food supply chain, a stronger connection has been recently established through demand channels as the biofuel demand for food has increased (Taheripour and Tyner, 2008). This has spurred a number of research papers on the "food versus fuel" debate. The analysis of how biofuels affect fossil fuel prices has also focused some research efforts (Whistance and Thompson, 2010).

Volatility is generally characterized as a directionless variation in prices that cannot be predicted by market fundamentals (Prakash, 2011), or, more intuitively, it is a measure of the extent to which prices jitter. As noted by Andersen et al. (2003), assessments of price volatility should rely on high frequency data, both because high frequency volatility is easier to predict, and also because it has proven useful to forecast at longer horizons. Mainstream academic research on the economic impacts of biofuels has widely relied on structural partial and general equilibrium models that are usually calibrated using annual data. These models are thus unsuitable to investigate price volatility. As the availability of time-series data on biofuels has been growing, time-series econometric models studying price volatility have been flourishing.

Traditionally, reviews of the literature on the economic implications of biofuels have paid special attention to structural models (Kretschmer and Peterson, 2010; Rajagopal and Zilberman, 2007). More recently, Serra (2012) has conducted a broad review of the biofuel-related time-series literature. Most of this literature has investigated price level links and a majority of research studies support that either biofuel or crude oil prices affect food price levels in the long-run. This literature however has failed to provide supporting evidence that biofuels have a long-lasting impact on fossil fuel prices (Serra, 2012). The latter result is not surprising given the small size of the biofuels market relative to the fossil fuels market. Despite that price volatility has been shown to have relevant negative economic and social impacts (Prakash, 2011), less effort has been devoted to formally study price volatility interactions in the biofuel industry. The recent commodity price crisis, however, has encouraged research in this area.

Drawing from Serra's (2012) work, this article discusses what we know in the area of volatility in biofuel markets. The data used, the modeling techniques and the main findings of previous research are presented. This literature review is used to shed light on research gaps, raise suggestions for future research and present late research developments. The paper is organized as follows. In the next section a review of previous biofuel-related price volatility studies based on time-series econometrics is presented. Proposals for further research and new research approaches are discussed in the following section. A concluding remarks section closes the article.

Price volatility interactions in biofuel markets: a review of time-series literature

Time-series data properties are usually found to violate the most common assumptions of conventional statistical inference methods such as stationarity and homoskedasticity. As a result, application of these methods to investigate time-series data may produce completely spurious results. Apart from displaying time-varying and clustering volatility, time-series data are usually nonstationary and may share a tendency to co-move in the long-run (Deaton and Laroque, 1992; Myers, 1994; Stigler, 2011). The co-integration and error correction model (ECM) theory introduced by Engle and Granger (1987) formally characterizes nonstationarity and co-movements. Volatility is usually studied through autoregressive conditional heteroskedastic (ARCH) models (Engle, 1982) or their generalized version (GARCH) proposed by Bollerslev (1986). While most of the literature has focused on understanding the volatility of a single time-series variable, multivariate versions of GARCH (MGARCH) models have been proposed to investigate volatility interactions between related variables.

MGARCH models are usually composed of two sub-models: the conditional mean and the conditional covariance model. The first sub-model investigates price level behavior and its specification can range from a simple vector of constants, to more sophisticated forms including vector error correction models (VECM). The time-varying volatility property of time series violates the usual homoskedastic assumption in econometric analysis. The second MGARCH sub-model treats heteroskedasticity as a variance that can be modeled and predicted (Engle, 2001). The variance-covariance matrix is usually expressed as a function of its own lags and the lagged square residual matrix, which captures new market information.

With a few exceptions, the biofuel-related price volatility literature has relied on GARCH-type models. The following lines focus on this literature. We discuss the data used, modeling approaches and main results of nine recent empirical research articles that study volatility interactions between food and energy prices (Zhang et al., 2008, 2009; Busse et al., 2010; Du et al., 2011; Balcombe, 2011; Wu et al., 2011; Trujillo et al., 2011; Serra, 2011; and Serra et al., 2011). A schematic presentation of these articles is offered in table 1 below.

Regarding the data used, we classify the reviewed studies according to whether they use biofuel prices or not; whether the data are representative of US, Brazil, EU or world markets; and according to the frequency of the data. Out of nine reviewed articles, four have studied the links between biofuel, gasoline and/or crude oil and biofuel industry feedstock prices (Zhang et al., 2009; Trujillo et al., 2011; Serra, 2011; and Serra et al., 2011). Zhang et al. (2008) limited their analysis to assess ethanol-gasoline price links. Probably due to biofuel price data availability problems, the rest of the studies have narrowed their focus to a consideration of the relationship between fossil fuels and biofuel industry feedstock prices. These latter studies generally rely on the hypothesis that, to the extent that biofuels have strengthened the link between energy and food markets, a change in the food-fuel price relationship after the surge of the global biofuels industry may be reasonably attributed to the impact of biofuels. As noted by Busse et al. (2010), since fossil fuel prices determine the profitability of biofuel production, food-fossil fuel price links may reflect mid-term expectations of market changes rather than actual changes.

With more than half of the reviewed research papers looking into this market, the US biofuel industry has attracted most research attention (Zhang et al., 2008 and 2009; Wu et al., 2011; Trujillo et al., 2011; and Du et al., 2011). The Brazilian market follows the US market in terms of research interest (Serra et al. 2011; and Serra, 2011). EU's data is used by Busse et al. (2010), while Balcombe (2011) focuses on international markets. Regarding data frequency, a majority of the analyses rely on weekly data. Daily data are used in Busse et al. (2010) and Trujillo et al. (2011), while Zhang et al. (2008) focus on monthly data. Balcombe (2011) uses data at different frequencies.

Methodologically speaking and with some exceptions, most reviewed papers rely on VECM-BEKK-MGARCH models. While, relative to BEKK formulations, more parsimonious specifications of the conditional covariance function in GARCH models have been proposed, these may not allow to fully capture the dynamics in the covariance structure (Silvennoinen and Teräsvirta, 2005). More parsimonious specifications, for example, do not usually allow assessing volatility spillovers across related markets. While BEKK permits studying these spillovers, it does so at the cost of increasing convergence difficulties in the estimation process. Busse et al. (2010) use a parsimonious DCC-GARCH that does not allow drawing inferences regarding volatility causality links. Only correlation between different price volatilities can be measured. A stochastic volatility model with Merton jumps (SVMJ) is estimated by Du et al. (2011), while Balcombe (2011) relies on a random parameters model. While most modeling approaches used are, in principle, flexible enough to allow volatility spillovers to flow in any direction, some of the studies impose the direction of causality links. Wu et al. (2011) and Trujillo et al. (2011) force unidirectional spillovers from crude oil markets to food and biofuel markets, precluding the possibility that biofuel markets induce instability into crude oil markets.

Reviewed research articles can also be classified according to their results. Most of them not only study price volatility, but also price level behavior. Of those that assess long-run causality links flowing from biofuel (or crude oil) to feedstock price levels, the unanimous conclusion is that neither sugar, nor corn long-run price levels are driven by energy markets (Wu et al., 2011; Trujillo et al., 2011; Zhang et al., 2009; Serra, 2011; Serra et al., 2011). There are only a few studies that are able to provide a response to the issue of long-run causality links flowing from biofuel to crude oil price levels. Neither the Brazilian, nor the US biofuels industry are found able of shaping crude oil prices (Trujillo et al., 2011; Serra, 2011; Serra et al., 2011). These studies further conclude that long-run biofuel price levels are driven by feedstock prices.

While Brazilian and US biofuel industries have not been found able to drive corn and sugar price levels in the long-run, they are however capable of inducing volatility in feedstock markets (Wu et al., 2011; Trujillo et al., 2011; Serra, 2011; Serra et al., 2011; Balcombe, 2011). Evidence of causality in the opposite direction, which implies that turbulences in feedstock markets are passed on to biofuel markets is also provided both for Brazilian and US biofuel industries (Trujillo et al., 2011; Serra, 2011; Serra et al., 2011; Zhang et al., 2009). Finally, there is only mild evidence of the capacity of biofuel markets to induce instability in crude oil markets (Serra, 2011; Serra et al., 2011). This capacity is however found to be very small.

A summary of research results of the reviewed papers is presented in table 2 below, where it can be appreciated that, in spite of the differences between the Brazilian and ethanol industries, research findings show very small differences regarding price behavior. In the next section a discussion of the issues that remain uninvestigated is presented. Some new approaches are discussed.

Proposals for further research and new approaches

A majority of the studies reviewed in the previous section provide evidence that instability in energy markets is generally transferred to feedstock markets. Causality links also flow in the opposite direction. Further, the growth of the biofuels industry is usually found to have intensified these links. Since the biofuel-related price volatility literature is still very young, a number of research questions remain unanswered. Some of these literature gaps are discussed here. First, previous research papers have generally relied on a specification of the variance-covariance matrix that does not allow for asymmetric impacts of price increases and decreases on volatility. Hence, it is not yet clear if an increase in biofuel prices has a stronger impact on food price volatility than a biofuel price decline. Nor is obvious whether the biofuel price becomes more volatile during crude oil price increases than crude oil price declines. Asymmetric MGARCH or other nonlinear modeling approaches could be used to shed light on this question.

Linear forms have been used in the specification of the conditional mean model. While most of the price-transmission literature focusing on price level links concludes that energy prices drive long-run food price levels (Serra, 2012), volatility analyses reviewed in this article fail to provide evidence of this fact. Previous work has shown that linearities in price level links should not be expected to hold, either because changes in the economic or political framework could lead to structural breaks affecting price dynamics, or because prices respond nonlinearly, for example, to deviations from the long-run parity (Obstfeld and Taylor, 1997). Due to the existence of arbitrage or adjustment costs, prices may only adjust when the deviation from the equilibrium reaches a certain minimum magnitude. Failure to allow for these nonlinearities may lead to failure to identify long-run causality price links. While articles focusing on price level behavior have allowed for these nonlinearities, price volatility studies have not.

By focusing on biofuel, crude oil and feedstock price links, previous volatility studies have left the question of how volatility in energy markets is transmitted along the food marketing chain unanswered. Since biofuel feedstocks are not only used to fuel cars, but also to produce food products such as meat, flour, or beverages, a biofuel-induced change in feedstock prices may eventually affect food consumer prices. Investigating price volatility transmission along the food marketing chain could be accomplished by increasing the range of prices considered in the analysis.

Another characteristic common to volatility studies is that, with very few exceptions, they generally consider price volatility interactions across related markets and volatility clustering as the single cause of price instability. Previous research, however, has identified other possible volatility sources such as storage, changes in food demand, weather fluctuations, macroeconomic conditions, speculation in futures markets, etc. (Cooke and Robles, 2009; Wright, 2011; Balcombe, 2011). This raises questions such as what is the impact of biofuels on food price instability relative to other volatility causes?

While assessing price volatility transmission is, per se, and interesting exercise, mild volatility will not have the same economic impacts as extreme volatility (Ferderer, 1996; Vedenov et al., 2006). Future research should thus pay further attention, for example, to study whether the introduction of biofuels in the transportation fuel portfolio will help cushioning extreme fuel price changes. This could be easily studied, for example, through the use of copula modeling (Patton, 2006).

Another research question that remains unanswered is related to the role of industry characteristics and policy instruments in explaining price behavior in different biofuel markets. A comparative study between US, Brazilian and EU biofuel industries would shed light on this puzzle. Differences in methodological approaches and data used do not allow drawing reliable conclusions on this topic from available research papers. Further, EU markets should be studied in more depth given the scarcity of analyses focusing on this region.

Recent research has shed light on some of the unanswered questions presented above. Serra and Gil (2012a) provide supporting evidence that the capacity of biofuels to increase food price volatility may be small compared to the influence of other variables such as changes in commodity stock levels. Another recent study by Serra and Gil (2012b) maintains that promotion of biofuels can be a useful tool to reduce national economies' vulnerability to extreme crude oil price increases. The next two sub-sections are devoted to present the key findings of these two studies.

Are volatility spillovers from energy to food markets relatively important?

Serra and Gil (2012a) study US corn price volatility over the last two decades. Interest in the US corn market is justified both because the US is the major world producer and exporter of corn (one of the most relevant sources of world's food energy consumption); and because the US corn industry has recently undergone important changes related to the growth of the biofuels industry.

As noted above, while the economics literature has proposed a wide array of different justifications for recent increases in food price instability, biofuel-related time-series analyses have generally failed to compare the effects of energy prices on food price volatility with other possible volatility sources such as weather fluctuations, demand changes, stocks, interest rate instability, etc. Serra and Gil (2012a) identify lagged ethanol and corn price shocks and volatility, corn stocks and interest rate volatility as determinants of corn price instability. The empirical analysis is based upon monthly US corn and ethanol prices, US corn stocks-to-disappearance ratio forecasts for the subsequent end of season and the volatility of the 3-month US treasury bill interest rate, observed from January 1990 to December 2010.

Methodologically, the paper relies on a bivariate VECM-BEKK-MGARCH specification that models corn-ethanol price interactions allowing for exogenous variables in the conditional covariance model. The conditional mean and covariance models are specified as follows:

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha} ECT_{t-1} + \boldsymbol{\gamma} \Delta \mathbf{p}_{t-1} \tag{1}$$

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

where $\Delta \mathbf{p}_t$ is a (2×1) vector of corn and ethanol prices in first differences and ECT_{t-1} is the lagged error correction term derived from the corn-ethanol long-run relationship. The (2×1) $\boldsymbol{\alpha}$ matrix shows the adjustment of each price to deviations from the long-run parity, while $\boldsymbol{\gamma}$ (2×2) reflects short-run price dynamics. Matrix $\mathbf{A}$ (2×2) measures the influence of past market shocks on current price volatility, while $\mathbf{B}$ (2×2) informs on the influence of past volatility on current volatility. Elements c_{ij} in matrix $\mathbf{C}$ (2×2 lower triangular) are specified following Moschini and Myers (2002): $c_{ij} = z\delta_{ij}$, where $z = (1, z_1, z_2)$ is a vector of exogenous variables influencing price volatility, z_1 represents the corn stocks-to-use ratio forecasts, z_2 is the interest rate volatility, and δ_{ij} is a vector of parameters.

The VECM-BEKK-GARCH model is estimated using both conventional maximum likelihood (ML) parametric methods and by the semiparametric techniques proposed by Long et al. (2011) that involve the use of local smoothing methods. Cointegration analysis supports existence of an equilibrium relationship between corn and ethanol prices, being both prices endogenous for long-run parameters. Nonlinear parameter functions in the corn conditional variance equation provide evidence that volatility spillovers from ethanol to corn markets are of an indirect nature (through the covariance terms) (table 3). The exogenous variables are found to exert a statistically significant impact on corn price volatility (see Serra and Gil, 2012a for further detail).

To compare and assess the sign and the magnitude of the impact of different shocks on corn price volatility, the effects of a one-time 10% increase in the stocks-to-disappearance ratio forecast, interest rate and ethanol price volatility are simulated. Results are presented in figure 1 and show that while an increase in stock forecasts will reduce corn price instability, increases in interest rate and ethanol price volatility will bring about increased corn price fluctuations. The magnitude of the impacts of stock forecasts is relevant relative to the effects of interest rate and ethanol price volatility, specially in the very short-run. These figures thus suggest that, when compared to other sources of price volatility, biofuels may not have substantial impacts on food price instability.

The use of local smoothing techniques (Long et al., 2011) allows correcting the nonlinear parameter functions in the conditional corn variance equation for each observation in the sample. As a result, the semiparametric approach permits the predictions of the model to change according to the prevalent economic and regulatory conditions. The nonparametrically corrected marginal impacts of the corn stock forecasts on corn price volatility are derived for each observation in the sample and presented in figure 2, along with the evolution of the stocks-to-disappearance ratio itself. These figures provide evidence of a growing marginal impact over time, as stock forecasts have tended to decline. Hence, it is more effective, for the purpose of curbing down price fluctuations, to increase forecast levels when these are very low than when they are very high. To conclude this section, it is worth noting that Serra and Gil (2012a) results show the relevance of extending the studies on volatility spillovers between food and energy markets to a consideration of a wider array of explanatory variables.

Are biofuels a useful instrument to buffer the influence of extreme crude oil price changes?

Serra and Gil (2012b) asses the capacity of biofuels to reduce the exposure of national economies to extreme crude oil price fluctuations. Since biofuels are produced from renewable energy sources such as food crops, its price should be less subject to crude oil price volatility. As a result, the likelihood that extreme crude oil price increases are passed on to biodiesel or ethanol blends sold at the pump should be smaller than the likelihood that these increases are transmitted to pure gasoline and diesel prices.

Serra and Gil (2012b) shed light on this issue by focusing on the Spanish diesel and biodiesel markets. Spain concentrates 10% of EU's biodiesel production, being the third most relevant biodiesel producer after Germany and France. In 2009, Spain consumed 894 thousand toes of biodiesel and 152 thousand toes of bioethanol, being the biofuel market share of 3.4% (EurObserv'ER, 2010), the binding mandate set by the government (Orden ITC 2877/2008).

Serra and Gil's (2012b) empirical analysis is based on weekly international crude oil and Spanish diesel and biodiesel prices observed from November 2006 to October 2010. Links between crude oil and diesel, and crude oil and biodiesel prices during extreme market events are modeled through copulas. The copula approach to dependence modeling does not require any specific assumption on the joint distribution of the variables of interest. Copula modeling is rooted on the Sklar's (1959) theorem that states that an *n*-dimensional joint distribution characterizing dependence of *n* economic variables can be decomposed into *n univariate distributions* and a *copula* function. The latter fully describes the dependence structure between the variables. Let *F* and *G* be univariate distribution functions of two random variables *x* and *y*. *H* is assumed to represent the joint distribution function. There exists a unique copula *C* that can be expressed as:

$$H(x,y) = C\left(F(x), G(y)\right) = C(u,v) \quad (3)$$

The joint density can be expressed as:

$$h(x,y) = f(x)g(y)c\left(F(x), G(y)\right) = f(x)g(y)c(u,v) \quad (4)$$

where *c* is the copula density and *f*(*x*) and *g*(*y*) are univariate density functions.

The symmetrized Joe-Clayton (SJC) copula is chosen to measure the probability that the prices are in their lower or upper joint tails. In other words, the SJC copula measures the likelihood that relevant price declines and upsurges will occur together and can be expressed as follows:

$$C_{SJC}(u,v|\tau^U,\tau^L) = 0.5\left(C_{JC}(u,v|\tau^U,\tau^L) + C_{JC}(1-u,1-v|\tau^U,\tau^L) + u + v - 1\right) \quad (5)$$

where $C_{JC}(u,v|\tau^U,\tau^L) = 1-\left(1-\left\{\left[1-(1-u)^k\right]^{-\gamma} + \left[1-(1-v)^k\right]^{-\gamma} - 1\right\}^{-1/\gamma}\right)^{1/k}$ is the Joe-Clayton (JC) copula, $k = 1/\log_2(2-\tau^U)$, $\gamma = -1/\log_2(\tau^L)$, $\tau^U \in (0,1)$ and $\tau^L \in (0,1)$. Parameters τ^U and τ^L are measures of the tail dependence and are informative of variable dependence during extreme events. In contrast to the JC copula, the SJC allows for symmetric dependence as a special case.

The SJC is estimated following the two-stage procedure by Patton (2006) for the biodiesel – crude oil and the diesel – crude oil price pairs. In the first estimation stage, a univariate ECM-GARCH model is fit to each price. The standardized iid residuals from this first stage are then used in a second stage in which the copula is estimated using ML methods. The unconditional long-run variances derived from the ECM-GARCH model estimates in the first stage are 6.2e-5, 1.1e-4 and 1.7e-3 for biodiesel, diesel and crude oil, respectively. Hence, biodiesel long-run price volatility is smaller than diesel and crude oil price volatility.

Results from the SJC copula estimation are presented in table 4. The lower tail dependence between biodiesel and crude is 0.3 (τ^L) and is statistically significant. The upper tail dependence (τ^U) is 0.1 and is not significant. This involves that price declines are more prone to occur together than price increases. In other words, while extreme declines in crude oil prices are likely to be passed on to biodiesel prices, extreme increases are not. In contrast, for the diesel-crude price pair, the dependence is equally relevant for extreme downturns and upturns of the two markets. Thus, while biodiesel protects consumers against crude oil price spikes, diesel does not. This implies that biodiesel can be a useful tool to reduce national economies' vulnerability to crude oil price increases.

Concluding remarks

Recent commodity price volatility has turned the political and academic agenda onto the identification of its causes and consequences and its management. Since volatility is a measure of the extent to which prices jitter, analyses of price volatility should be based upon high frequency data (Andersen et al., 2003). To the extent that structural models are usually calibrated using annual data, volatility is best assessed using time-series models. The time-series econometrics literature has provided a wide array of techniques to model price volatility and volatility interactions.

Our literature review shows that biofuel-related price volatility studies have mainly focused on the assessment of volatility interactions between energy and food markets using GARCH-type of models. Some common shortcomings of these studies are that they don't shed light on how energy-induced food price volatility is transferred along the food marketing chain, whether biofuels are able to protect fuel consumers against extreme crude oil price spikes, whether the biofuel-induced food price volatility is relevant compared to other volatility sources, etc.

Recent advances in the literature show the relevance of extending mainstream GARCH modeling approaches to a consideration of a wider array of variables, or to model dependence during extreme market events. As the availability of time series data on biofuels grows, scientists should be able to pursue refined research objectives and implement better econometric techniques, which should improve our understanding and forecasting of price instability.

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Table 1. Review of the time-series literature assessing volatility in biofuel markets

		Zhang et al. (2008)	Wu et al. (2011)	Trujillo et al. (2011)	Zhang et al. (2009)	Du et al. (2011)	Serra (2011)	Serra et al. (2011)	Balcombe (2011)	Busse et al. (2010)
Time-series modeling approach		BEKK-MGARCH	Univariate TGARCH; Bivariate VECM-BEKK-MGARCH	Univariate TGARCH; Bivariate VECM-BEKK-MGARCH	VECM-BEKK-MGARCH	SVMJ	VECM-BEKK-MGARCH	VECM-BEKK-MGARCH	Random parameter model	DCC-MGARCH
Geographic area	**US**	X	X	X	X	X				
	Brazil						X	X		
	EU									X
	International								X	
Data used	**Biofuel**	X		X	X		X	X		
	Crude		X	X	X	X	X	X	X	X
	Gasoline	X			X					
	Feedstock		X	X	X	X	X	X	X	X
	Other		X			X			X	
Data freq.	**Daily**			X					Several frequencies	X
	Weekly		X		X	X	X	X		
	Monthly	X								
Period studied		May 1998 - Mar 2007	Jan 1992 - Jun 2009	Jul 2006 – Jan 2011	Mar 1989 – Dec 2007 Results discussed for Jan 2000 – Dec 2007	Nov 1998 – Jan 2009 Results discussed for Oct 2006 – Jan 2009	Jul 2000 – Feb 2008	Jul 2000 – Nov 2009	Variable, depending on commodity	1999 - 2009

Table 1. Review of the time-series literature assessing volatility in biofuel markets (continued)

		Zhang et al. (2008)	Wu et al. (2011)	Trujillo et al. (2011)	Zhang et al. (2009)	Du et al. (2011)	Serra (2011)	Serra et al. (2011)	Balcombe (2011)	Busse et al. (2010)
$P_B/P_E \rightarrow P_F$ (l/r)	yes									
	no		X	X	X		X	X		
	not studied	X				X			X	X
$P_B \rightarrow P_E$ (l/r)	yes				X					
	no			X			X	X		
	not studied	X	X			X			X	X
$P_F \rightarrow P_B$ (l/r)	yes			X			X	X		
	no				X					
	not studied	X	X			X			X	X
$\sigma_B/\sigma_E \rightarrow \sigma_F$	yes		X	X			X	X	X	
	no				X	X				
	not studied	X								X
$\sigma_B \rightarrow \sigma_E$	yes						X	X		
	no				X					
	not studied	Not discussed	X	X		X			X	X
$\sigma_F \rightarrow \sigma_B$	yes			X	X		X	X		
	no									
	not studied	X	X			X			X	X

Note: $P_B/P_E \rightarrow P_F$ (l/r) Do biofuel or energy prices drive long-run feedstock prices?
$P_B \rightarrow P_E$ (l/r) Do biofuel prices drive long-run fossil fuel prices?
$P_F \rightarrow P_B$ (l/r) Do feedstock prices drive long-run biofuel prices?
$\sigma_B/\sigma_E \rightarrow \sigma_F$ Do biofuel or energy prices transmit volatility to feedstock prices?
$\sigma_B \rightarrow \sigma_E$ Do biofuel prices transmit volatility to fossil fuel prices?
$\sigma_F \rightarrow \sigma_B$ Do feedstock prices transmit volatility to biofuel prices?

Table 2. Summary of the time-series literature assessing volatility in biofuel markets (continued)

	Brazilian ethanol industry	**US ethanol industry**
Price level		
Do biofuel (or energy) prices drive long-run feedstock prices?	NO	NO
Do biofuel prices drive long-run fossil fuel prices?	NO	NO
Do feedstock prices drive long-run biofuel prices?	YES	YES
Price volatility		
Do biofuel (or energy) prices transmit volatility to feedstock prices?	YES	YES
Do biofuel prices transmit volatility to fossil fuel prices?	YES*	NO
Do feedstock prices transmit volatility to biofuel prices?	YES	YES

(*) Only very small capacity is found

Table 3. Conditional corn variance equation

$h_{22t} =$	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

Note: *(**) denotes statistical significance at the 10% (5%) level.

Note: h_{11t} and h_{22t} represent ethanol and corn price volatility, respectively. r_{1t} and r_{2t} represent ethanol and corn market shocks, respectively

Source: Serra and Gil (2012a)

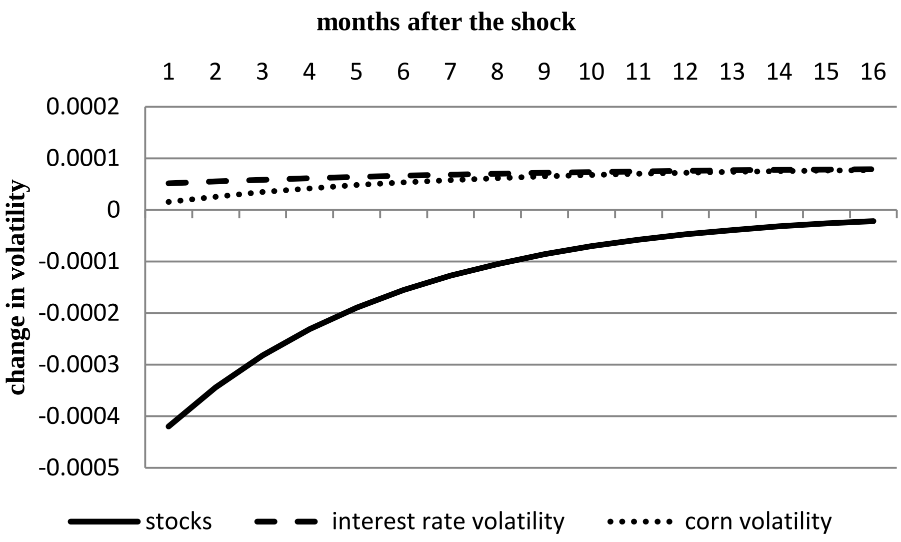
Table 4. Results for the SJC copula model

	Crude oil – Biodiesel price pair	Crude oil – Diesel price pair
	SJC copula	
τ^U	0.112	0.254**
	(0.114)	(0.117)
τ^L	0.312**	0.244**
	(0.079)	(0.097)
Copula likelihood	18.015	19.659

Note: *(**) denotes statistical significance at the 10% (5%) level.

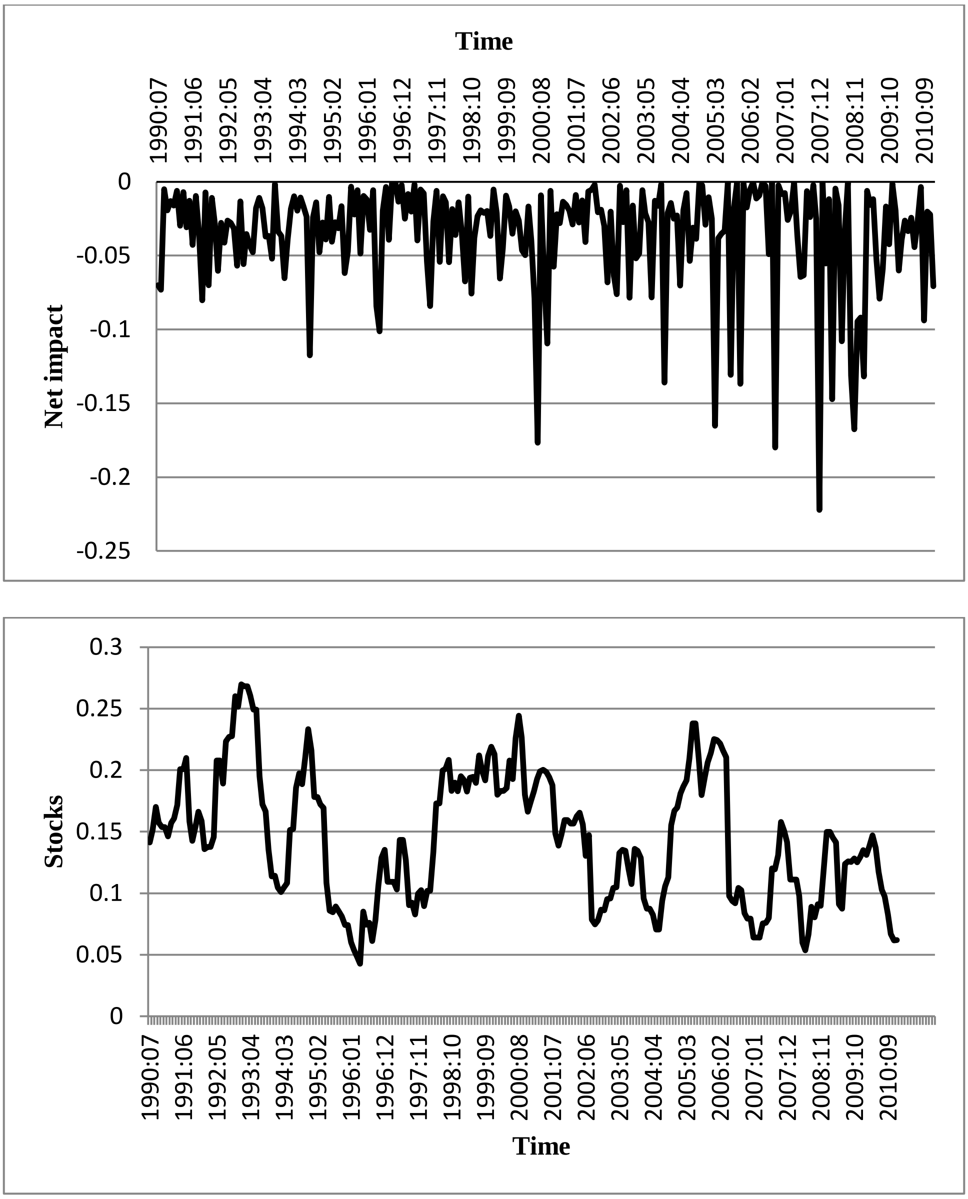
Source: Serra and Gil (2012b)

Fig 1. Corn volatility response to a one-time 10% increase in corn inventories, interest rate and corn price volatility



Source: Serra and Gil (2012a)

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



Source: Serra and Gil (2012a)