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Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets

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ABSTRACT

This paper examines volatility transmission in oil, ethanol and corn prices in the United States between 1997 and 2011. We follow a multivariate GARCH approach to evaluate the level of interdependence and the dynamics of volatility across these markets. The estimation results indicate a higher interaction between ethanol and corn markets in recent years, particularly after 2006 when ethanol became the sole alternative oxygenate for gasoline. We only observe, however, significant volatility spillovers from corn to ethanol prices but not the converse. We also do not find major cross-volatility effects from oil to corn markets. The results do not provide evidence of volatility in energy markets stimulating price volatility in the US corn market.

1. Introduction

The rapid and continuous increase in the use of ethanol as a fuel alternative and its potential impact on agricultural markets has received much attention in the past years (Rajagopal and Zilberman, 2007). Ethanol is currently the major liquid biofuel produced worldwide with a global production of over 23,000 million gallons in 2010, almost double the amount produced in 2005 and four times the amount produced in 2000. While, traditionally, agricultural prices have been affected by energy (oil) prices through production and transportation costs, the increased demand for the agricultural production of ethanol (e.g., corn in the United States, sugarcane in Brazil) has raised concerns about a stronger relationship between energy and agricultural markets, and the likely impact of increasing fuel prices on agricultural price volatility.[1] In addition, the recent spikes of agricultural prices during 2007–2008, in 2010 and 2011, and the prevailing high price volatility in agricultural commodities have reinforced global fears about energy prices stimulating agricultural price volatility and their potential impacts on the economy.

These impacts affect different factors at various levels. First, more volatile crop prices increase costs for farmers to manage price risks (Wu et al., 2011), altering hedging and investment decisions. Second, volatility spillovers from oil prices to agricultural commodity prices are problematic for financial trade portfolios. In recent years agricultural commodities have been included more and more in financial investment portfolios. However, if oil and agricultural price volatilities co-move this may worsen portfolio diversification. Third, increased price volatility of agricultural commodities used for biofuels may also spill over to other agricultural commodities such as wheat or soybeans since these prices are connected to each other via substitution in supply (acreage) and demand (substitution in animal fodder). Resulting price volatility in wheat is problematic for importing countries whose consumers still spend a large share of their incomes on food. At the macro-level Byrne et al. (2011) indicate that increased agricultural price volatility also affects the design and effectiveness of price stabilization policies. Ultimately, increasing food price volatility is of great concern for policymakers as it constitutes a major threat to food security of the poor (FAO-OECD, 2011).

Economic theory based on market fundamentals and arbitrage activities suggests that oil, ethanol and corn (sugar) prices are interrelated (de Gorter and Just, 2008). Increasing crude oil prices directly affect agricultural prices through higher input and transportation costs and create an incentive to use alternative energy sources like biofuels. An upward shift in ethanol demand, in turn, may indirectly stimulate food prices as ethanol is mainly produced from fodder

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[1] Ethanol production is dominated by the United States and Brazil with 54 and 34% of global production.

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crops. These potential relationships may also be exacerbated or weakened by biofuel mandates, subsidies, and the so-called blending wall. Consequently, understanding the extent of the oil–ethanol–corn price relationships, particularly the dynamics of volatility transmission between these prices, requires additional investigation.

Based on previous studies which suggest the existence of different interdependencies in the relation between oil, ethanol and corn prices (see, e.g., Meyer and Thompson, 2010; Babcock, 2011), this paper follows a multivariate GARCH (MGARCH) approach to examine the dynamics and cross-dynamics of price volatility in oil, ethanol and corn markets in the United States between 1997 and 2011. We evaluate the magnitude and source of interrelation between markets and, in particular, whether energy price volatility stimulates price volatility in the US corn market, either directly from oil to corn, or indirectly via the oil–ethanol–corn nexus. The period of analysis further helps us to examine if the degree of interdependence across markets has changed over time, and whether changes in biofuel mandates have affected the nature of the links between energy and agricultural markets. The analysis is complemented with a suitable test for structural breaks in volatility for strongly dependent processes.

As noted by Serra (2011), studies on volatility transmission between energy and agricultural markets are still scarce. Previous work has mainly focused on assessing price level links based on standard supply and demand frameworks and partial/general equilibrium models (e.g., Babcock, 2008; Luchansky and Monks, 2009) or based on vector error correction models (e.g., Balcombe and Rapsomanikis, 2008; Serra et al., 2011b). However, there are a few studies that explicitly focus on volatility transmission between energy and agricultural commodity prices. Zhang et al. (2009) examined price volatility interactions between the US energy and food markets between 1989 and 2007 using the BEKK model suggested by Engle and Kroner (1995). Serra et al. (2011a) also used a standard BEKK model to analyze volatility interactions between crude oil, ethanol and sugarcane prices in Brazil for the period 2000–2008. In another study on volatility in the Brazilian ethanol–sugarcane nexus, Serra (2011) used semi-parametric MGARCH models. Wu et al. (2011) estimated a restricted asymmetric MGARCH model using the US corn and oil prices from 1992 to 2009 to investigate oil price volatility spillover to corn price volatility. Trujillo-Barrera et al. (2012) estimated a similar model using futures prices for crude oil, ethanol and corn from 2006 to 2011. Du et al. (2011) used futures market prices for crude oil, corn and wheat from 1998 to early 2009 to estimate a stochastic volatility model in order to investigate oil price volatility spillovers to corn and wheat price volatility. Finally, Nazlioglu et al. (2012) used univariate GARCH models and causality in variance tests to examine volatility transmission between oil and wheat, corn, soybean, and sugar prices.

Our study contributes to this literature in two ways. First, we implement two different MGARCH specifications to provide an in-depth analysis of the dynamics and cross-dynamics of price volatility across crude oil, ethanol and corn prices in the United States. As shown by Gallagher and Twomey (1998), modeling volatility spillovers provides better insight into the dynamic price relationship between markets, but inferences about the interrelationship depend importantly on how we model the cross dynamics in the conditional volatilities of the markets.[2] Therefore, we first estimate a BEKK model, which is suitable to examine volatility transmission across markets since it is flexible enough to model own- and cross-volatility spillovers and persistence between markets. We estimate the model using a Student's t density (so called T-BEKK model). The use of Student's t density is to account for the leptokurtic distribution of the series we work with, something which is not accounted for in some of the above-mentioned studies that also estimated a BEKK model (e.g., Serra et al., 2011a; Zhang et al., 2009).[3] We further derive impulse–response functions for the estimated conditional variances, which help to better illustrate the cross-volatility dynamics between markets, and we formally account for potential breaks in our data. Next, we estimate a Dynamic Conditional Correlation (DCC) model based on Engle (2002), which has the advantage of parameter parsimony and permits to analyze volatility interdependence across time between markets. This is very useful since energy and agricultural commodity markets have been in substantial turmoil in recent years. As far as we know this MGARCH specification has not been applied before in analyzing volatility interactions between energy and agricultural commodity prices. We also use a Student's t density for the estimation of the DCC model.

Our second contribution regards the data we use to analyze volatility interactions. Our analysis is based on the weekly US spot prices for crude oil, ethanol, and corn for the period September 1997 through October 2011. With this data we are able to overcome some of the shortcomings of the previous studies. First, the selected sample period permits us to examine whether there have been important changes in the dynamics of volatility during periods of special interest with major structural and regulatory changes in the US biofuel industry. In particular, our sample covers both the years before and during the ethanol boom with important changes in energy policies promoting the use of biofuels and significant improvements in bioenergy technologies; it also covers the recent food price crises of 2007–2008 and 2011, periods of particular interest with strong price variations. Most of the studies reviewed above did not use data from recent years (e.g. Du et al., 2011; Serra et al., 2011a; Wu et al, 2011; Zhang et al., 2009) or did not include data from before the US biofuel boom (e.g. Trujillo-Barrera et al., 2012). Second, we include ethanol prices in our analysis of price volatility interactions. In order to disentangle direct price volatility spillovers of crude oil to corn, via input and transportation costs, from indirect volatility interactions via the biofuel channel, it is essential to include ethanol prices in the analysis. Studies that did not include ethanol prices (e.g. Du et al., 2011; Nazlioglu et al., 2012; Wu et al., 2011; Zhang et al., 2009) cannot distinguish between direct and indirect effects. Third, in contrast to studies that use futures prices (e.g. Du et al., 2011; Trujillo-Barrera et al., 2012) we use spot prices to analyze volatility interactions. Futures prices are partly driven by other factors than market conditions (speculation, herd behavior, scalping, etc.). In order to avoid these additional sources of volatility interactions it is better to use spot prices.

The remainder of the paper is organized as follows. Section 2 provides an overview of direct and indirect relations between energy and corn prices and their volatility with specific attention to biofuel policies. Section 3 presents the empirical approach used to examine volatility transmission between energy and corn markets. Section 4 describes the data. Section 5 presents and discusses the estimation results. Section 6 concludes.

2. Interdependencies between energy and corn markets and US biofuel policies

Energy prices relate to corn prices in various ways. This shapes the relationship between energy price levels and corn price levels, but also has implications for the interrelationship between energy and corn price volatility. In this section we first discuss direct relations between energy prices and agricultural commodity prices and their volatility levels. Next, we focus on the indirect relation between energy and corn prices via biofuels. As Meyer and Thompson (2010) have argued, there are different interdependencies between crude oil,

[2] We do not implement more flexible models, like the semiparametric MGARCH model recently proposed by Long et al. (2011) and applied by Serra (2011), because this would require separate pairwise analyses of markets due to the inherent “curse of dimensionality” in nonparametric methods. Our analysis is more in line with studies by Karolyi (1995) and Worthington and Higgs (2004) on volatility transmission in stock markets and with Hernandez et al. (in press) who studied volatility spillovers in agricultural futures markets.

[3] For further details on MGARCH modeling with a Student's t density see Fiorentini et al. (2003).

ethanol, and corn prices, which motivate why volatility spillovers between energy and corn prices may vary.

2.1. Direct links between oil and agricultural commodity prices

Baffes (2011) warns that when focusing on biofuels when investigating the relation between energy prices and agricultural prices one should not forget that energy prices also have direct impacts on agricultural prices. Many inputs used in crop production are energy intensive, in particular nitrogen fertilizer, so that increases in energy prices raise the cost of production. Moreover, transportation costs increase in oil prices, which may also lead to higher commodity prices. Agricultural commodity prices do not only rise when oil prices increase, but the relationship between these prices also intensifies at higher prices. Baffes (2011) shows that the elasticity of food prices with respect to oil prices is higher if the recent 2005–2010 period (with relatively high crude oil prices) is considered in estimation. A stronger relationship between oil and food prices implies that volatility shocks in oil prices will also lead to bigger shocks in food price volatility. A few studies exist that investigate the relation between oil prices and agricultural prices in the absence of biofuel effects. Babula and Somwaru (1992) show that oil price shocks have substantial impact on the prices of fertilizer and pesticides. Chaudhuri (2001) concludes that many agricultural commodity export prices adjust to oil price shocks. Alghalith (2010) focused on the effects of oil price levels and oil price volatility on food prices and found that both lead to higher food prices.

2.2. Variations in the crude oil, ethanol, and corn price relationship

The recent boom in biofuel production has renewed attention for the links between energy and food prices, leading to a number of studies on this relationship. Many of these studies use time-series econometric techniques to quantify the relation between oil, ethanol, and food prices in levels (e.g., Balcombe and Rapsomanikis, 2008; Serra et al., 2011b) or their volatility interactions (e.g., Serra, 2011; Serra et al., 2011a; Zhang et al., 2009).

When analyzing price volatility interactions it is important to realize that the relations between crude oil, ethanol and corn prices are not constant. Meyer and Thompson (2010) argue that there are different sources of ethanol demand leading to a highly non-linear ethanol demand curve with a varying price elasticity. One source of ethanol demand stems from the addition of ethanol as oxygenate to gasoline. This kind of demand is price inelastic with respect to ethanol and gasoline prices. A second source of ethanol demand arises when ethanol prices are on par with gasoline prices so that ethanol is a competitive substitute for gasoline leading to price elastic demand for ethanol. In this range the ethanol price is driven by the oil price. Finally, the maximum amount of ethanol that can be absorbed by the market due to maximum blending (the so-called blending wall) and the number of flex-fuel cars, marks the transition to a third regime of ethanol demand. In this regime ethanol demand is again price inelastic with respect to ethanol and crude oil prices.

Ethanol supply, which is a function of ethanol prices and corn prices, also has different price elasticity regimes (Meyer and Thompson, 2010). When ethanol production capacity is not fully used, supply is somewhat elastic with respect to corn and ethanol prices. However, when the sector operates at full capacity supply is highly price inelastic in the short-run.

The values of both price elasticities for ethanol demand and supply eventually determine what the effect of oil price shocks is on ethanol and corn prices. Since these elasticities vary over time, the effect of oil price shocks on other markets will also differ. The fluctuating relation between crude oil, ethanol and corn prices is further complicated by biofuel policies such as mandates and tax credits. For example, the well-known replacement of MTBE by ethanol as an oxygenate which culminated in 2006 led to a substantial increase in demand for ethanol that raised ethanol prices sharply and made ethanol demand more price inelastic, and disconnected ethanol prices from gasoline prices in the short run. In the corn market, prices rose mildly as ethanol only constituted 14% of the total US corn demand in 2005/2006 (Meyer and Thompson, 2010). However, with the share of corn used for ethanol rising to 40% in 2012 (USDA, 2012), the effect of ethanol price changes on corn prices can be much stronger. For an overview of biofuel policies see Sorda et al. (2010).

In short, the relationship between oil, ethanol and corn prices varies over time due to different price regimes and policies. Therefore, a proper econometric analysis of price volatility interactions should examine these potential variations in volatility dynamics between markets across time.

3. Methodology

We follow a MGARCH approach to examine the level of interdependence and the dynamics of volatility between oil, ethanol and corn markets in the United States. In particular, we estimate both a T-BEKK model and a DCC model. The BEKK model is suitable to characterize volatility transmission across markets since it is flexible enough to account for own- and cross-volatility spillovers and persistence between markets. The DCC model approximates a dynamic conditional correlation matrix, which permits to evaluate whether the level of interdependence between markets changes across time.[4]

Consider the following model,

$$r_t = \gamma_0 + \sum_{j=1}^{p} \gamma_j r_{t-j} + \varepsilon_t, \quad \varepsilon_t | I_{t-1} \sim (0, H_t), \tag{1}$$

where r_t is a 3×1 vector of price returns for oil, ethanol and corn, γ_0 is a 3×1 vector of long-term drifts, γ_j, with $j = 1,...,p$, are 3×3 matrices of parameters, and ε_t is a 3×1 vector of forecast errors for the best linear predictor of r_t, conditional on past information denoted by I_{t-1}, and with corresponding variance–covariance matrix H_t. As in a standard VAR representation, the elements of γ_j, $j = 1,...,p$, provide measures of own- and cross-mean spillovers between markets.

In the BEKK model with one time lag, the conditional variance–covariance matrix H_t is given by

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'H_{t-1}G, \tag{2}$$

where C is a 3×3 upper triangular matrix of constants c_{ij}, A is a 3×3 matrix containing elements a_{ij} that measure the degree of innovation from market i to market j, and the elements g_{ij} of the 3×3 matrix G show the persistence in conditional volatility between markets i and j. This specification guarantees, by construction, that the covariance matrices are positive definite. The conditional variance–covariance matrix defined in Eq. (2) permits us to analyze the direction, magnitude and persistence of volatility transmission across markets. In particular, it allows us to derive impulse–response functions for the conditional volatilities to show how a shock originated in a market may affect the other markets under analysis.

In the DCC model, which assumes a time-dependent conditional correlation matrix $R_t = (\rho_{ij,t})$, $i, j = 1, \ldots, 3$, the conditional variance–covariance matrix H_t is defined as

$$H_t = D_t R_t D_t \tag{3}$$

where

$$D_t = diag\left(h_{11,t}^{1/2} \ldots h_{33,t}^{1/2}\right), \tag{4}$$

[4] For detailed surveys of MGARCH models see Bauwens et al. (2006), or Silvennoinen and Teräsvirta (2009).

$h_{ii,t}$ is defined as a GARCH(1,1) specification, i.e. $h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}$, $i = 1, \ldots, 3$, and

$$R_t = diag\left(q_{ii,t}^{-1/2}\right) Q_t diag\left(q_{ii,t}^{-1/2}\right) \tag{5}$$

with the 3×3 symmetric positive-definite matrix $Q_t = (q_{ij,t})$, $i, j = 1, \ldots, 3$, given by

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \tag{6}$$

and $u_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$. $\overline{Q}$ is the 3×3 unconditional variance matrix of u_t, and α and β are non-negative adjustment parameters satisfying $\alpha + \beta < 1$. Q_t basically resembles an autoregressive moving average (ARMA) type process which captures short-term deviations in the correlation around its long-run level. The variance–covariance matrix defined in Eq. (3) permits us, then, to model the degree of volatility interdependence between markets across time.

4. Data

The data used for the analysis are weekly prices for US crude oil, ethanol and corn from September 1997 through October 2011. As noted above, the sample period covers both the pre- and ethanol boom periods with significant changes in biofuel use mandates. Oil prices are West Texas Intermediate crude oil FOB spot prices from the Energy Information Administration (EIA). Ethanol prices are denatured fuel ethanol spot prices for blending with gasoline from the Chicago Board of Trade (CBOT).[5] Corn prices are No.2 yellow corn FOB Gulf prices reported by the Food and Agriculture Organization. Table A.1 in the Supplementary Appendix provides further details on the sources of information used.

Fig. 1 shows the evolution, in real terms, of crude oil, ethanol and corn prices and their volatility during the sample period. As observed, price movements in the three markets seem to be highly correlated, with important price spikes during the food crisis of 2007–2008 and in the past year. The price spike in ethanol in 2006, the year where MTBE was effectively banned in the United States, is also remarkable. A third observation is that corn prices have increased rapidly since mid-2010, whereas ethanol and crude oil prices rose more gradually. The correlation across markets is further corroborated when comparing the volatility in prices (measured using a moving monthly standard deviation). Again, a few observations can be made. Up to 2000, ethanol and crude oil prices were very stable and only corn prices showed some volatility. Between 2005 and 2007 there were huge fluctuations in ethanol prices, whereas corn prices and crude oil prices fluctuated very mildly. In 2008 corn prices fluctuated a lot, crude oil prices only by the end of the year, but ethanol prices did not show much volatility then. After a rather quiet period around 2010 for all three prices, particularly corn prices started to fluctuate again, and to a lesser degree crude oil prices. Fluctuations in ethanol are not much different from the average volatility since 2000. Overall, the figure suggests not only some connections between unconditional volatility, but also periods with weaker or absent co-movement in volatility.

Table 1 provides additional insight about the potential interdependencies between the three markets. The table reports Pearson correlations of weekly price returns for different sample periods. The returns are defined as $y_t = \log(P_t/P_{t-1})$, where P_t is the price of oil, ethanol or corn at week t.[6] We subdivide our sample period in 1997–2005 and 2006–2011 considering the major demand expansion for ethanol in 2006 after MTBE was effectively banned as an oxygenate for gasoline in the United States.[7] A comparison across periods indicates that energy and corn markets have become more interconnected in recent years. We find a statistically significant positive correlation in all returns for 2006 onwards; the correlation between corn and ethanol returns is also stronger than the correlation between the other price returns. Prior to 2006, we only observe a significant correlation between oil and ethanol returns. A first look at the data suggests that energy and corn markets in the United States appear to be interrelated, particularly during more recent years. Yet establishing sources of interdependence on price volatility transmission requires further analysis as discussed below.

Turning to the statistical properties of the return series, Table 2 presents descriptive statistics for the price returns in each market (multiplied by 100). Several patterns emerge from the reported statistics. First, oil returns are roughly 2.5–3 times higher than the returns in ethanol and corn. The average weekly return in this market is 0.17% versus 0.06% in ethanol and 0.07% in corn. Second, the returns in the three markets appear to follow a non-normal distribution. The Jarque–Bera statistic rejects the null hypothesis that the returns are well approximated

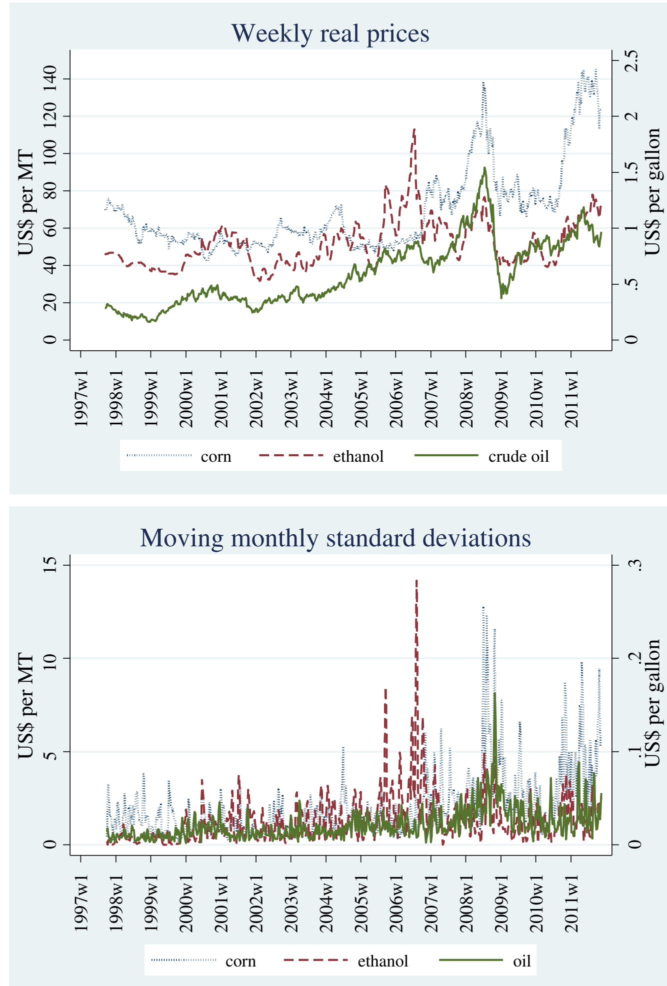

Fig. 1. Oil, ethanol and corn prices and volatility, 1997–2011. Note: Prices deflated by CPI (1982–84 = 100). Monthly volatility based on real weekly prices.

[5] We also identified average ethanol rack prices in Nebraska, starting on July 2003, from the Nebraska Ethanol Board; this state is the second largest ethanol producer in the United States after Iowa. We find a 0.96 correlation between these prices and the CBOT ethanol prices used in the analysis.

[6] This logarithmic transformation is a good approximation for net returns in a market and is usually applied in empirical finance to obtain a convenience support for the distribution of the error terms.

[7] A test for structural breaks in volatility, discussed below, also suggests an important shift during mid-2006 in the dynamics of ethanol price returns.

Table 1
Correlation of weekly returns, 1997–2011.

Commodity	1997–2005			2006–2011			Total sample		
	Oil	Ethanol	Corn	Oil	Ethanol	Corn	Oil	Ethanol	Corn
Oil	1.000	0.166*	−0.010	1.000	0.268*	0.278*	1.000	0.217*	0.143*
Ethanol		1.000	0.029		1.000	0.381*		1.000	0.240*
Corn			1.000			1.000			1.000
# observations			433			304			737

Note: The correlations reported are the Pearson correlations. The symbol (*) denotes significance at 5% level.

by a normal distribution. The kurtosis in all markets exceeds three, pointing to a leptokurtic distribution. We therefore estimate both the BEKK and DCC models assuming a Student's t density for the innovations.[8] Third, while the Ljung–Box (LB) statistics for up to 6 and 12 lags reject the null hypothesis of no autocorrelation for both oil and ethanol returns, they uniformly reject the null hypothesis for the squared returns in all three markets. This autocorrelation in the weekly squared returns is indicative of nonlinear dependency in the returns, probably due to time varying conditional volatility, as observed in Fig. 2 which plots the three weekly returns series. These patterns motivate the use of a MGARCH approach to model the interdependencies in the first and second moments of the returns within and across markets. Finally, proper specification of the mean equation in an MGARCH model requires investigating whether the returns series are non-stationary in order to account for potential long-run relationships between them. Therefore, we applied augmented Dickey–Fuller tests with non-stationarity as null hypothesis and KPSS tests that have stationarity as null hypothesis. The last block in Table 2 shows that both tests confirm the stationarity of the three returns series.

5. Results

This section presents the estimation results of the MGARCH models used to examine the level of interdependence and volatility transmission between energy and agricultural markets in the United States. We first present the estimation results of the T-BEKK and DCC models using the full sample, which constitute our base results. The T-BEKK model allows us to analyze volatility spillovers and persistence effects between oil, ethanol and corn prices, while the DCC model permits us to evaluate if the degree of interdependence between these markets has changed across time. We then present the estimation results of the T-BEKK model for different sample periods in light of potential shifts in the dynamics of volatility across these markets due to changes in biofuel policies and the recent food price crisis of 2007–2008.

5.1. Base results

Table 3 reports the coefficient estimates for the conditional mean return equation (top panel) and the conditional variance–covariance matrix (bottom panel) of the T-BEKK model. This model allows for own- and cross-volatility spillovers and persistence between markets. The lag length (one lag) corresponds to the optimal number as determined by the Schwarz's Bayesian information criterion or SBIC (equal to 15.8). The residual diagnostic tests reported at the bottom of the table support the adequacy of the model specification. The Ljung–Box (LB), Lagrange Multiplier (LM) and Hosking Multivariate Portmanteau (HM) test statistics for up to 6 and 12 lags show no evidence of autocorrelation, ARCH effects and cross-correlation in the standardized squared residuals of the estimated model. The estimated degrees of freedom parameter (v) is also small (6.4), further supporting the appropriateness of the estimation with a Student's t distribution.

In the conditional mean equation, the γ_{1ii} coefficients, $i = 1, \ldots, 3$, capture own-market dependence, i.e. the dependence of the return in market i on its lagged value, while the γ_{1ij} coefficients capture cross-market dependence, i.e. the dependence of the return in market i on the lagged return in market j. The results indicate that there are no cross-market mean spillovers between oil, ethanol and corn markets. The observed mean return in a market is only influenced by the lagged return in the same market but not by the lagged returns in the other markets. In sum, energy and agricultural markets do not seem to be interrelated at the mean level.[9] In addition, while energy markets (especially ethanol) exhibit strong and positive own-mean spillovers, corn markets show negative own-mean spillovers. The latter finding can be explained from substitution effects in demand. A high return for corn is connected to an increase in corn prices, which may dampen demand for corn and raise demand for substitutes (e.g. soybeans as animal fodder) leading to lower corn returns the next period, and vice versa. This demand substitution is less relevant for crude oil and ethanol, where returns are more driven by slowly changing macro-economic conditions.

Turning to the conditional variance–covariance equation, the diagonal a_{ii} coefficients, $i = 1, \ldots, 3$, capture own-volatility spillovers, i.e. the effect of lagged innovations on the current conditional return volatility in market i, and the diagonal g_{ii} coefficients capture own-volatility persistence, i.e. the dependence of volatility in market i on its own past volatility. The results reveal significantly large own-volatility effects in the three markets, indicating the presence of strong GARCH effects. Own-volatility spillovers have a higher initial effect in ethanol than in crude oil and corn, but the ethanol market also exhibits the lowest own-volatility persistence. This suggests that while own information shocks have a relatively important, short-term effect on the volatility of ethanol price returns, the returns in this market derive at the same time less of their volatility persistence from their own market, as compared to oil and corn returns where own volatility shocks have a more persistent effect over time.

Regarding the cross-dynamics, it is important to distinguish between direct and full effects across markets. In particular, the off-diagonal a_{ij} and g_{ij} coefficients measure direct spillover and persistence effects between markets. The a_{ij} coefficients capture the direct effects of lagged innovations originating in market i on the current conditional volatility in market j, while the g_{ij} coefficients capture the direct dependence of volatility in market j on that of market i. Yet, to analyze full interactions across markets we need to account for both direct and indirect effects.

[8] It is worth noting that we find qualitatively similar results when estimating the BEKK model using a quasi-maximum likelihood (QML) method with a normal distribution of errors. Bollerslev and Wooldridge (1992) show that this method can result in consistent parameter estimates if the log-likelihood function assumes a normal distribution while the series are skewed and leptokurtic.

[9] Although not reported, a comparison of these mean spillover results with the results of a standard VAR model suggests that the dynamics of the conditional volatility processes builds important structure into the first moment relationships. More specifically, the VAR estimates indicate some mean-spillovers from oil to ethanol returns, which disappear after we allow for cross-volatility dynamics between markets.

Table 2
Summary statistics for weekly returns.

	Crude oil	Ethanol	Corn
Statistic			
Mean	0.165	0.061	0.077
Median	0.492	0.000	−0.065
Minimum	−19.261	−19.748	−13.796
Maximum	24.768	19.855	18.931
Std. Dev.	4.585	3.415	3.759
Skewness	−0.312	−0.007	0.194
Kurtosis	5.623	7.936	4.923
Jarque–Bera	222.28	748.30	118.20
p-value	0.00	0.00	0.00
# observations	737	737	737
Returns correlations			
AC (lag = 1)	0.122*	0.436*	−0.092*
AC (lag = 2)	−0.089*	0.261*	0.033
Ljung–Box (6)	24.37*	201.18*	11.00
Ljung–Box (12)	46.27*	214.69*	18.03
Squared returns correlations			
AC (lag = 1)	0.244*	0.226*	0.119*
AC (lag = 2)	0.257*	0.038	0.041
Ljung–Box (6)	177.85*	43.93*	57.49*
Ljung–Box (12)	257.08*	98.32*	111.71*
Tests for stationarity			
ADF (lag = 13)	−5.964*	−7.353*	−6.134*
KPSS (lag = 6)	0.038	0.032	0.179

Note: The symbol (*) denotes rejection of the null hypothesis at the 5% significance level.
AC is the autocorrelation coefficient.
Lags in ADF test based on significance in auxiliary regression.
Lags in KPSS test based on Schwert criterion.

Markets in a BEKK model may be directly interrelated through the conditional variance and indirectly related through the conditional covariance. Hence, the dynamics of volatility across markets ultimately comprises all off-diagonal a_{ij} and g_{ij} coefficients.

The Wald test reported in Table 3 rejects the null hypothesis that the cross effects (i.e. off-diagonal coefficients a_{ij} and g_{ij}) are jointly equal to zero with a 99 percent confidence level. The cross effects, however, are generally smaller in magnitude than the own effects. The non-causality in variance tests further indicates that only the ethanol market seems to be directly affected by past innovations and variance from the other markets, particularly from the corn market as discussed next.

The estimated parameters of the T-BEKK model further permit us to derive an impulse–response analysis of the conditional return volatilities. This analysis provides additional insights about the cross-volatility dynamics between markets, including the direction of volatility interdependence. The simulation comprises both direct and indirect effects across markets after simulating an initial shock in one of them. Fig. 3 presents the impulse–response functions derived by iterating, for each market variance resulting from Eq. (2), the response to an innovation equivalent to a 1% increase in the conditional volatility of the market where the innovation first occurs. The responses are measured as percentage deviations from the initial conditional volatility in each market. The simulation indicates that a shock originated in the corn market has a relatively higher initial effect on the volatility of returns in the ethanol market than on the own corn market (1.4 times larger). This strong volatility spillover effect from corn to ethanol is due to the importance of corn as major input in US ethanol production. The lack of persistence in the impulse–response functions of the ethanol market is also interesting; the adjustment process in this market is very fast after an own or cross (corn) innovation. This suggests that volatility shocks are processed very fast by traders. As indicated above, separate volatility innovations in oil and ethanol markets do not appear to spill over to other markets. This implies that corn price volatility is not affected by volatility in crude oil via input prices (e.g. via energy and fertilizer prices), nor that additional volatility in corn has arisen due to ethanol.

This result partially resembles the findings of Zhang et al. (2009), who also do not find important spillover effects from energy to agricultural markets. These authors, however, also do not find volatility spillovers from corn to ethanol markets as we do (they only find cross effects from soybeans to ethanol prices). A possible explanation for the different findings is that our analysis includes a more recent sample period, where the interdependencies between corn and ethanol markets (particularly from corn to ethanol prices) seem to have become stronger, as inferred also from our preliminary analysis. Our results also tie with those of Trujillo-Barrera et al. (2012) who work with futures prices. The authors find volatility transmission from corn to the ethanol market in recent years (2006–2011), but not the opposite. Yet, the authors further find volatility spillovers from crude oil to both corn and ethanol markets, which could be explained by the use of futures prices (instead of spot prices) that are also likely driven by speculation, herd behavior and scalping, among other factors. In the next section, we evaluate changes in the dynamics of volatility transmission between energy and corn prices across different periods, after appropriately segmenting our sample based on the presence of structural breaks in the analyzed series.

Table 4 reports the full estimation results of the DCC model. This model allows us to examine whether the level of volatility interdependence between markets has changed across time.[10] As in the T-BEKK model, the number of lags (one lag) corresponds to the optimal number as determined by the Schwarz criterion (equal to 15.7). The reported diagnostic tests for the standardized squared residuals (LB, LM and HM statistics) and the estimated degrees of freedom parameter (5.9) also support the adequacy of the model specification.

The magnitude and direction of the coefficient estimates in the conditional mean equation (top panel) are very similar to the estimates obtained using the T-BEKK model. Again, we do not observe mean spillovers in the returns across energy and corn markets, and both oil and ethanol returns show positive own-market dependence while corn returns exhibit a negative dependence.

Regarding the conditional variance–covariance equation (bottom panel), the Wald test rejects the null hypothesis that the adjustment parameters α and β are jointly equal to zero at a one percent significance level, suggesting that the time-variant conditional correlations between markets assumed in the DCC model are a plausible assumption.

Fig. 4 presents the dynamic conditional correlations for each market pair, which result from the DCC model estimates. The figure also includes constant conditional correlations and one standard deviation confidence bands for comparison, based on Bollerslev (1990) CCC model. Whereas the T-BEKK results indicated volatility spillovers from corn to ethanol for the full sample, the DCC estimates shows an important increase in the level of volatility interdependence between ethanol and corn markets in recent years. The correlation has changed from a small or negative correlation to a positive and increasing relationship beginning on 2007, one year after MTBE was effectively banned in the United States and left ethanol as the alternative oxygenate for gasoline. The interdependence between oil and corn markets also appears to have increased in recent years, although we do not find major volatility spillover effects across these markets when using the T-BEKK model on our full sample.[11]

[10] We also estimated a varying conditional correlation (VCC) model developed by Tse and Tsui (2002), which has a dynamic correlation structure very similar to that of the DCC. The estimation results and correlation patterns obtained with the VCC model are very similar to those of the DCC model. Further details are available upon request from the authors.

[11] We do find some volatility spillovers from oil to corn markets and from oil to ethanol markets when segmenting our sample, which we discuss in the next section.

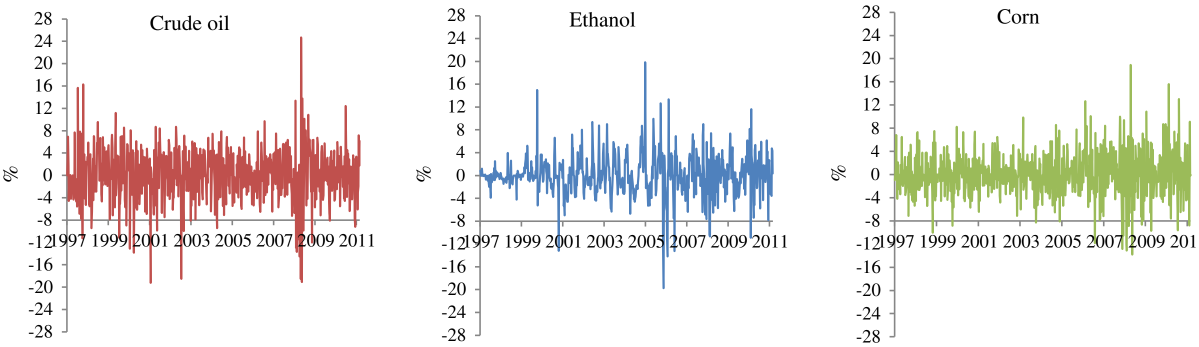

Fig. 2. Oil, ethanol and corn weekly returns, 1997–2011.

The correlation between oil and ethanol markets, in turn, has basically fluctuated across time without a particular trend, but with important peaks both during the first major expansion of ethanol refining in the United States in the beginning of the 2000s and during the recent food crisis of 2007–2008. The other market correlations considered also show peaks during the recent food crisis, suggesting an overall higher interrelation between energy and corn markets during that specific period.

5.2. Volatility interactions across time

We now turn to examine if the conditional volatility interactions between energy and corn markets have changed across time considering the important changes in biofuel policies in the United States in the past decade and the food price crisis of 2007–2008. To perform this task, we first formally test for the presence of structural breaks in the volatility of the return series under analysis. Based on these test results, we then segment our sample accordingly and estimate the T-BEKK model over the different sample periods to evaluate if there have been changes in the dynamics and cross-dynamics of volatility between oil, ethanol and corn markets. This procedure also allows us to account for potential effects (if any) of structural breaks when examining cross-volatility dynamics (see also Van Dijk et al., 2005).

We implement the test for the presence of unknown structural breaks proposed by Lavielle and Moulines (2000), which is suitable for strongly dependent processes such as GARCH processes (Carrasco and Chen, 2002). In particular, this test assumes beta-mixing conditions, which are satisfied by GARCH processes. Similar to Benavides and Capistran (2009) and Hernandez et al. (in press), we apply the test over the squared returns as a proxy for volatility. Fig. A.1 in the Supplementary Appendix shows the results of the test. The identified break dates represent the estimated change-points using the minimum penalized contrast procedure developed by Lavielle and Moulines (2000).[12] We find important shifts in the volatility of all three return series, which can be associated to particular events in these markets. In the case of ethanol, we observe a break in the dynamics of ethanol returns during mid-2006 (July 7), a period when refiners across all states were effectively forced to eliminate MTBE from gasoline and ethanol was left as the sole alternative oxygenate. In the case of oil and corn, we find a break in these series during mid-2008 (June 6 in corn and September 19 in oil), a period when the food crisis was felt most severely. Consequently, we divide our sample in two subperiods: September 19, 1997 through June 30, 2006 and September 26, 2008 through October 28, 2011.

Tables A.2 and A.3 in the Supplementary Appendix present the full results of the T-BEKK model for the corresponding sample periods using the Schwarz criterion to determine the optimal number of lags (one lag). As in our base results, the diagnostic tests for the standardized squared residuals (LB, LM and HM statistics) and the estimated degrees of freedom parameters (5.8 and 10.5) support the adequacy of the model specifications.

A comparison of the conditional mean equations across the two sample periods does not reveal major changes in mean spillovers between energy and corn markets. During both periods, the conditional mean returns in oil, ethanol and corn markets are basically only dependent on their own past returns; oil and ethanol show a positive dependence while corn exhibits a negative dependence. In more recent years, however, corn returns also report mean-spillovers from oil returns, suggesting a stronger role of crude oil as an input in corn production at the mean level. This finding is similar to the results of Du et al. (2011) who also found a higher correlation between crude oil and corn prices after 2006. The dependence of ethanol returns on their lagged returns appears, in turn, to have decreased in recent years.

In the case of the conditional variance dynamics, we observe strong GARCH effects in both periods. Yet, while own-volatility spillovers seem to have decreased in magnitude after 2008 in both ethanol and corn markets, own-volatility persistence has increased in all three markets. This implies that energy and corn markets are now deriving more of their volatility persistence from within their own markets. Regarding cross-volatility effects, the reported Wald tests indicate the presence of cross effects during both periods. While the Wald tests for overall spillover and persistence effects indicate that the cross effects have become weaker after 2008, the non-causality in variance tests point out that the ethanol market has become more directly exposed to past innovations and variance from the other markets (corn) in recent years. Oil and corn markets do not seem to be directly affected by the other markets during both sample periods, at least not at conventional statistical levels. The cross-market dynamics, however, are better illustrated through impulse–response functions, which comprise both direct and indirect effects, and to which we now turn.

Figs. 5 and 6 show the simulated responses in the volatility of energy and corn markets to innovations originating in each market during the two sample periods. The innovations are equivalent to a 1% increase in the conditional volatility of the market where the innovation first occurs, and the responses are measured as percentage deviations from the initial conditional volatility in each market. Similar to our full-sample results, we observe cross-volatility spillovers from corn to ethanol markets during the two periods, but these spillovers have become much stronger after 2008, which is in line with the increasing dynamic correlation between these markets observed with the DCC model. Similarly, an innovation in ethanol does not spill

[12] Lavielle and Moulines' (2000) test searches for multiple breaks over a maximum, pre-defined number of potential segments, and uses a minimum penalized contrast to identify the number of breakpoints. We obtain similar results when allowing for two or three possible segments.

Table 3
T-BEKK model estimation results.

Coefficient	Crude oil ($i = 1$)	Ethanol ($i = 2$)	Corn ($i = 3$)
Conditional mean equation			
γ_0	0.285	−0.047	0.013
	(0.146)	(0.072)	(0.118)
γ_{11i}	0.158	0.021	0.028
	(0.037)	(0.016)	(0.027)
γ_{12i}	−0.017	0.558	0.036
	(0.043)	(0.034)	(0.037)
γ_{13i}	−0.040	−0.006	−0.108
	(0.041)	(0.021)	(0.037)
Conditional variance–covariance equation			
c_{i1}	1.186	−0.545	−0.703
	(0.164)	(0.261)	(0.247)
c_{i2}		1.115	−0.596
		(0.287)	(0.445)
c_{i3}			0.000
			(0.041)
a_{i1}	0.202	0.027	−0.037
	(0.037)	(0.032)	(0.039)
a_{i2}	0.007	0.651	0.288
	(0.031)	(0.087)	(0.087)
a_{i3}	0.005	−0.055	0.241
	(0.026)	(0.034)	(0.046)
g_{i1}	0.936	0.044	0.060
	(0.013)	(0.023)	(0.022)
g_{i2}	0.060	0.622	−0.153
	(0.034)	(0.129)	(0.094)
g_{i3}	0.009	0.050	0.925
	(0.015)	(0.038)	(0.033)
ν			6.409
			(0.861)
Wald joint test for all cross-volatility coefficients (H_0: $a_{ij} = g_{ij} = 0$, $\forall i \neq j$)			
Chi-sq			46.360
p-Value			0.000
Wald test for non-causality in variance on each market (H_0: $a_{ij} = g_{ij} = 0$, $\forall j, i \neq j$)			
Chi-sq	6.581	20.111	4.224
p-Value	0.160	0.000	0.377
Ljung–Box test for autocorrelation (H_0: no autocorrelation in squared residuals)			
LB (6)	7.169	5.230	4.126
p-Value	0.306	0.515	0.660
LB (12)	16.115	6.623	17.910
p-Value	0.186	0.881	0.118
Lagrange multiplier (LM) test for ARCH residuals (H_0: no ARCH effects)			
LM (6)	6.597	5.100	4.025
p-Value	0.360	0.531	0.673
LM (12)	13.000	6.855	16.895
p-Value	0.369	0.867	0.154
Hosking Multivariate Portmanteau test for cross-correlation (H_0: no cross-correlation in squared residuals)			
HM (6)			44.149
p-value			0.165
HM (12)			91.800
p-value			0.427
Log likelihood			−5750.1
SBIC			15.849
# observations			736

Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). ν is the degrees of freedom parameter. LB, LM and HM stand for the corresponding Ljung–Box, Lagrange Multiplier and Hosking test statistics.

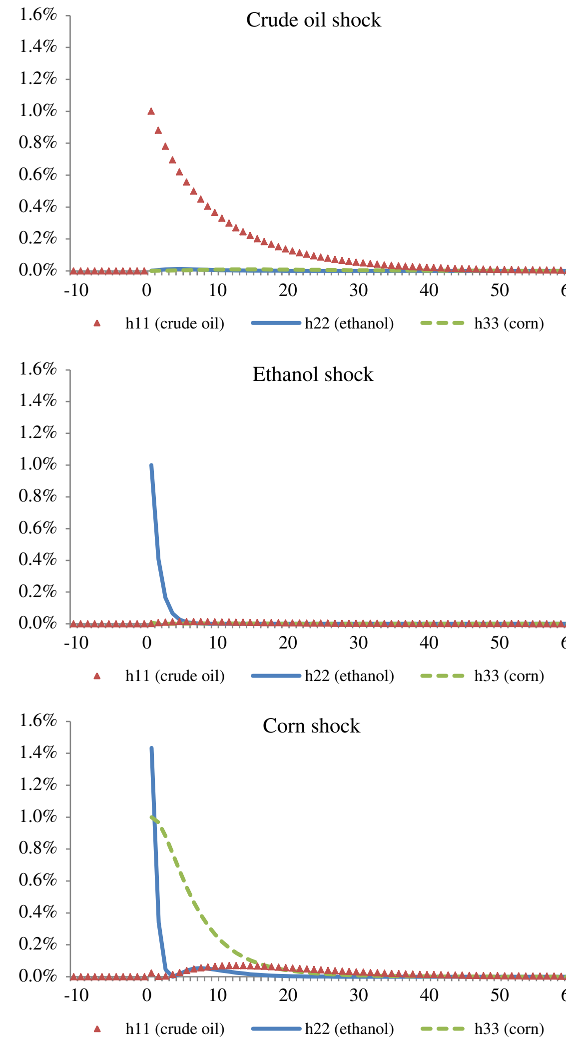

Fig. 3. Impulse–response functions. Note: The responses are the result of an innovation equivalent to a 1% increase in the conditional volatility of the market where the innovation first occurs. The responses are measured as percentage deviations from the initial conditional volatility in each corresponding market. Simulations based on T-BEKK estimation results.

over to other markets in both periods. For the crude oil market this is not surprising at all since the share of ethanol in total fuel demand is still very small. Therefore, ethanol price levels and volatility are not expected to affect crude oil price volatility, regardless of the recent growth in ethanol production. However, when segmenting our sample we do observe volatility spillovers from oil to both ethanol and corn markets, particularly prior to 2006. This latter finding is somewhat surprising and in contrast with the results from the DCC that indicated a stronger correlation between crude oil and corn after 2008. An explanation for these contrasting results could be the positive and significant spillover effect of crude oil return levels on corn return levels after 2008, which may have attenuated conditional volatility spillovers. Another explanation is that the existence of structural breaks in the series could be affecting the identification of volatility spillovers in oil when using the full sample (see also Van Dijk et al., 2005). Still, our results suggest that price volatility in agricultural markets is not necessarily stimulated by stronger links between agricultural and energy markets after the expansion of biofuels in the United States.

6. Concluding remarks

This paper has examined the level of interdependence and volatility transmission between energy and corn markets in the United States using different MGARCH specifications. The main research question is whether price volatility in oil and ethanol markets stimulates price volatility in the corn market. Since corn serves as a major input in US

Table 4
DCC model estimation results.

Coefficient	Crude oil ($i = 1$)	Ethanol ($i = 2$)	Corn ($i = 3$)
Conditional mean equation			
γ_0	0.304	−0.036	0.032
	(0.146)	(0.072)	(0.116)
γ_{11i}	0.151	0.021	0.030
	(0.037)	(0.017)	(0.027)
γ_{12i}	−0.005	0.562	0.038
	(0.042)	(0.036)	(0.037)
γ_{13i}	−0.046	−0.004	−0.115
	(0.041)	(0.022)	(0.037)
Conditional variance–covariance equation			
ω_i	1.246	2.115	1.358
	(0.559)	(0.724)	(0.845)
α_i	0.070	0.471	0.098
	(0.021)	(0.102)	(0.042)
β_i	0.879	0.311	0.812
	(0.036)	(0.138)	(0.089)
α			0.017
			(0.007)
β			0.973
			(0.014)
ν			5.931
			(0.723)
Wald joint test for adjustments coefficients (H_0: $\alpha = \beta = 0$)			
Chi-sq			16658.400
p-Value			0.000
Ljung–Box test for autocorrelation (H_0: no autocorrelation in squared residuals)			
LB (6)	4.222	4.539	3.234
p-Value	0.647	0.604	0.779
LB (12)	7.239	6.040	15.900
p-Value	0.841	0.914	0.196
Lagrange multiplier (LM) test for ARCH residuals (H_0: no ARCH effects)			
LM (6)	3.360	4.551	2.994
p-Value	0.763	0.602	0.810
LM (12)	6.708	6.329	13.764
p-Value	0.876	0.899	0.316
Hosking Multivariate Portmanteau test for cross-correlation (H_0: no cross-correlation in squared residuals)			
HM (6)			41.258
p-Value			0.252
HM (12)			77.854
p-Value			0.816
Log likelihood			−5749.3
SBIC			15.731
# observations			736

Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). v is the degrees of freedom parameter. LB, LM and HM stand for the corresponding Ljung–Box, Lagrange Multiplier and Hosking test statistics.

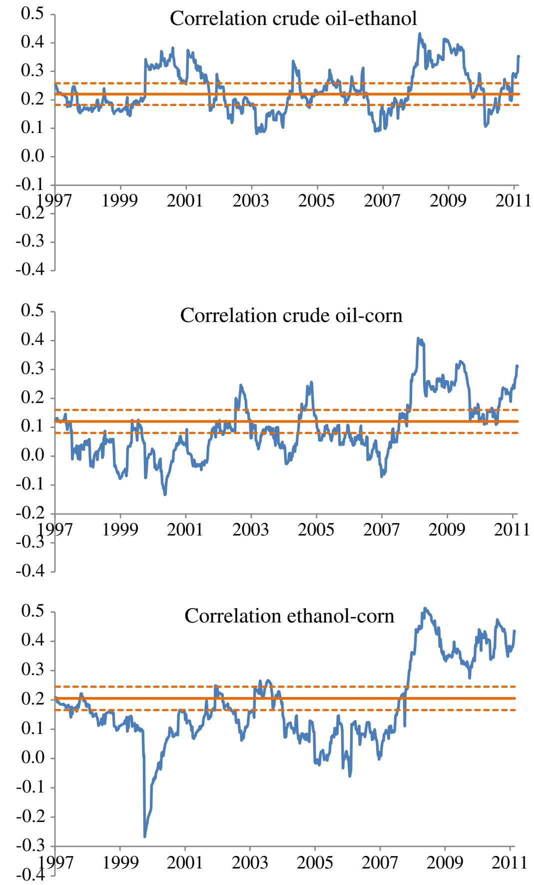

Fig. 4. Dynamic conditional correlations. Note: The dynamic conditional correlations are derived from the DCC model estimation results. The solid line is the estimated constant conditional correlation following Bollerslev (1990), with confidence bands of one standard deviation.

ethanol production, increased demand in ethanol, e.g. due to rising oil prices, may trigger additional demand for corn, leading to additional price volatility in corn prices. This concern has been expressed frequently by policy makers and international organizations (FAO-OECD, 2011). However, in this paper it is recognized that due to different functions of ethanol (viz. as oxygenate and gasoline substitute) and because of the nature of the biofuel sector itself (strong policy involvement and potential blending wall) the strength of these interactions may vary, which may weaken the potential effects of energy price volatility on corn price volatility.

The results of the full sample T-BEKK specification do not provide evidence of mean spillovers in price returns across energy and corn markets. Additionally, these results indicate that there are no volatility spillovers from oil or ethanol to corn. Opposite, a shock in corn price volatility leads to a short-run shock in ethanol price volatility. Apparently, input costs of corn do affect production costs of ethanol, which is reflected in this volatility spillover from corn to ethanol.

When segmenting our sample in two periods, the non-causality in variance tests suggests that the ethanol market has become more directly exposed to past spillovers and persistence from other markets in recent years. The impulse–response analysis, which comprises both direct and indirect cross-effects, further confirm the presence of volatility spillovers from corn to ethanol both prior to 2006 and after 2008. We also observe some spillovers from oil to ethanol and corn when segmenting our sample, especially prior to 2006.

The estimation outcomes of the DCC model, which allows for varying correlations in volatility between commodities, show that the volatility relations are not constant over time. Whereas, the correlation between oil and ethanol price volatility has not changed much over time, the correlation between crude oil and corn and, especially, between ethanol and corn has increased after 2007. The latter can be explained from the effect of corn price volatility on ethanol volatility, whereas the first results may reflect the role of crude oil as an input in corn production.

Overall, we conclude that the often stated concern of increased price volatility in agricultural markets due to biofuels is not supported by our empirical evidence. This implies that modifying US biofuel policies is not effective in reducing agricultural price volatility. The existing price volatility on agricultural markets can better be managed in different ways, such as creating better market monitoring systems or through futures markets, which is also recognized in policy reports (FAO-OECD, 2011).

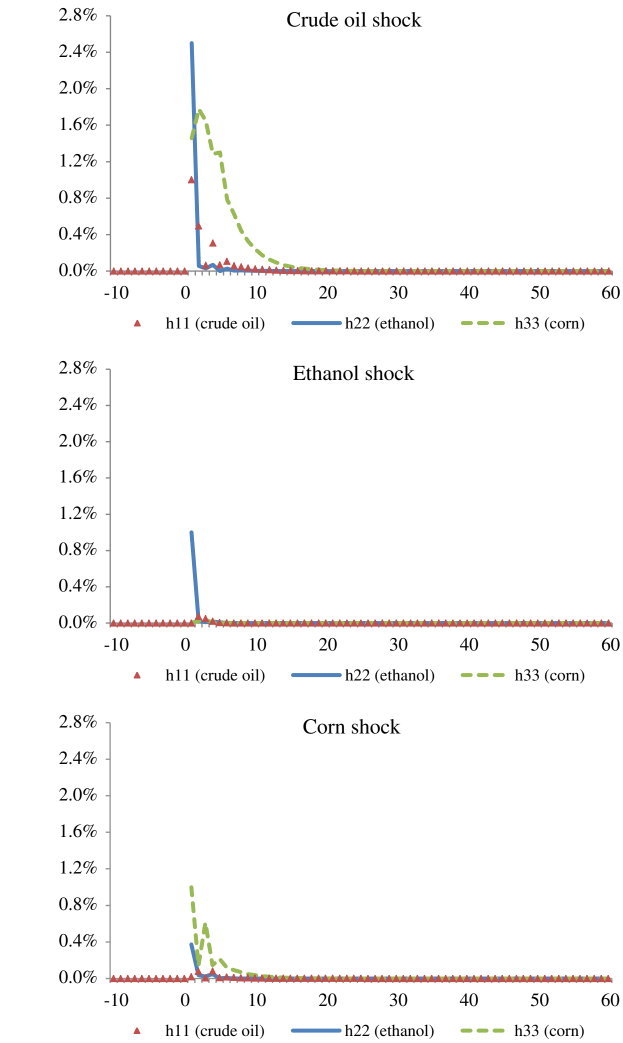

Fig. 5. Impulse–response functions, subperiod 1997–2006. Note: The responses are the result of an innovation equivalent to a 1% increase in the conditional volatility of the market where the innovation first occurs. The responses are measured as percentage deviations from the initial conditional volatility in each corresponding market. Simulations based on T-BEKK estimation results. The sample period corresponds to September 19, 1997 through June 30, 2006.

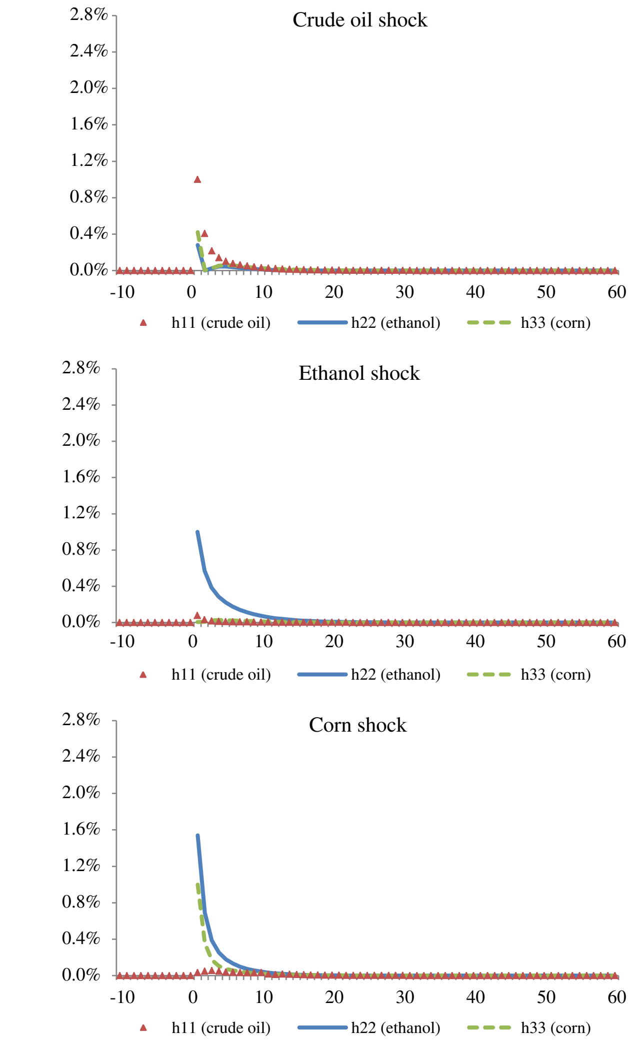

Fig. 6. Impulse–response functions, subperiod 2008–2011. Note: The responses are the result of an innovation equivalent to a 1% increase in the conditional volatility of the market where the innovation first occurs. The responses are measured as percentage deviations from the initial conditional volatility in each corresponding market. Simulations based on T-BEKK estimation results. The sample period corresponds to September 26, 2008 through October 28, 2011.

Although the volatility spillovers from corn to ethanol that were found in this study are not surprising given the fact that US ethanol production is largely corn-based, this does have major implications for the US ethanol industry. Agricultural prices have been very volatile in recent years and may continue to be so in the near future for various reasons (Gilbert and Morgan, 2010). This implies that ethanol prices will continue to exhibit some volatility and might even become more volatile. Major events that disturb US corn production, such as the 2012 drought, will therefore also impact ethanol price volatility in the US. A more diverse portfolio of feedstocks used in biofuel production or a shift towards second-generation biofuels, if technically and economically feasible, could help, in turn, to reduce price volatility in ethanol markets.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2013.06.013.

References

Alghalith, M., 2010. The interaction between food prices and oil prices. Energy Econ. 32, 1520–1522.
Babcock, B.A., 2008. Distributional implications of U.S. ethanol policy. Rev. Agric. Econ. 30, 533–542.
Babcock, B.A., 2011. The impact of US biofuel policies on agricultural price levels and volatility. Issue Paper #35.International Centre for Trade and Sustainable Development (ICTSD).
Babula, R.A., Somwaru, A., 1992. Dynamic impacts of a shock in crude oil price on agricultural chemical and fertilizer prices. Agribusiness 8, 243–252.
Baffes, J., 2011. The energy/non-energy price link: channels, issues and implications. In: Piot-Lepetit, I., M'Barek, R. (Eds.), Methods to Analyse Agricultural Commodity Price Volatility. Springer Science, New York, pp. 31–44.

Balcombe, K., Rapsomanikis, G., 2008. Bayesian estimation and selection of nonlinear vector error correction models: the case of sugar–ethanol oil nexus in Brazil. Am. J. Agr. Econ. 90, 658–668.

Bauwens, L., Laurent, S., Rombouts, J.V.K., 2006. Multivariate GARCH models: a survey. J. Appl. Econ. 21, 79–109.

Benavides, G., Capistran, C., 2009. A note on the volatilities of the interest rate and the exchange rate under different monetary policy instruments: Mexico 1998–2008. Working Paper Series 2009–10. Banco de Mexico.

Bollerslev, T., 1990. Modeling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. Rev. Econ. Stat. 72, 498–505.

Bollerslev, T., Wooldridge, J.M., 1992. Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. Econ. Rev. 11, 143–172.

Byrne, J.P., Fazio, G., Fiess, N., 2011. Primary commodity prices. Co-movements, common factors and fundamentals. World Bank Policy Research Working Paper 5578 (33 pp.).

Carrasco, M., Chen, X., 2002. Mixing and moment properties of various GARCH and stochastic volatility models. Econ. Theory 18, 17–39.

Chaudhuri, K., 2001. Long-run prices of primary commodities and oil prices. Appl. Econ. 33 (4), 531–538.

de Gorter, H., Just, D., 2008. 'Water' in the U.S. ethanol tax credit and mandate: implications for rectangular deadweight costs and the corn–oil price relationship. Rev. Agric. Econ. 30, 397–410.

Du, X., Yu, C.L., Hayes, D., 2011. Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis. Energy Econ. 33, 497–503.

Engle, R., 2002. Dynamic conditional correlation—a simple class of multivariate GARCH models. J. Bus. Econ. Stat. 20, 339–350.

Engle, R., Kroner, F.K., 1995. Multivariate simultaneous generalized ARCH. Econ. Theory 11, 122–150.

FAO-OECD, 2011. Price Volatility in Food and Agricultural Markets: Policy Responses. (June, available at www.worldbank.org/foodcrisis).

Fiorentini, G., Santana, E., Calzolari, G., 2003. Maximum likelihood estimation and inference in multivariate conditionally heteroskedastic dynamic regression models with Student t innovations. J. Bus. Econ. Stat. 21, 532–546.

Gallagher, L., Twomey, C., 1998. Identifying the source of mean and volatility spillovers in Irish equities: a multivariate GARCH analysis. Econ. Soc. Rev. 29, 341–356.

Gilbert, C.L., Morgan, C.W., 2010. Food price volatility. Phil. Trans. R. Soc. B 365, 3023–3034.

Hernandez, M.A., Ibarra, R., Trupkin, D.R., 2013. How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets. Eur. Rev. Agric. Econ. http://dx.doi.org/10.1093/erae/jbt020 (in press).

Karolyi, G.A., 1995. A multivariate GARCH model of international transmissions of stock returns and volatility: the case of the United States and Canada. J. Bus. Econ. Stat. 13, 11–25.

Lavielle, M., Moulines, E., 2000. Least-squares estimation of an unknown number of shifts in a time series. J. Time Series Anal. 21, 33–59.

Long, X., Su, L., Ullah, A., 2011. Estimation and forecasting of dynamic conditional covariance: a semiparametric multivariate model. J. Bus. Econ. Stat. 29, 109–125.

Luchansky, M.S., Monks, J., 2009. Supply and demand elasticities in the U.S. ethanol fuel market. Energy Econ 31, 403–410.

Meyer, S., Thompson, W., 2010. Demand behavior and commodity price volatility under evolving biofuel markets and policies. In: Khanna, M., Scheffran, J., Zilberman, D. (Eds.), Handbook of Bioenergy Economics and Policy. Natural Resource Management and Policy, Vol. 33. Springer Science, New York, pp. 133–148.

Nazlioglu, S., Erdem, C., Soytas, U., 2012. Volatility spillover between oil and agricultural commodity markets. Energy Econ. http://dx.doi.org/10.1016/j.eneco.2012.11.009.

Rajagopal, D., Zilberman, D., 2007. Review of environmental, economics and policy aspects of biofuels. Policy Research Working Paper 4341. The World Bank.

Serra, T., 2011. Volatility spillovers between food and energy markets: a semiparametric approach. Energy Econ. 33, 1155–1164.

Serra, T., Zilberman, D., Gil, J.M., 2011a. Price volatility in ethanol markets. Eur. Rev. Agric. Econ. 38, 259–280.

Serra, T., Zilberman, D., Gil, J.M., Goodwin, B.K., 2011b. Nonlinearities in the US corn–ethanol–oil–gasoline price system. Agric. Econ. 42, 35–45.

Silvennoinen, A., Teräsvirta, T., 2009. Multivariate GARCH models. In: Andersen, T.G., Davis, R.A., Kreiß, J.-P., Mikosch, T. (Eds.), Handbook of Financial Time Series. Springer, Berlin, pp. 201–229.

Sorda, G., Banse, M., Kemfert, C., 2010. An overview of biofuel policies across the world. Energy Pol. 38, 6977–6988.

Trujillo-Barrera, A., Mallory, M., Garcia, P., 2012. Volatility spillovers in the U.S. crude oil, ethanol, and corn futures markets. J. Agric. Res. Econ 73 (2), 247–262.

Tse, Y.K., Tsui, A.K.C., 2002. A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. J. Bus. Econ. Stat. 20, 351–362.

Van Dijk, D., Osborn, D.R., Sensier, M., 2005. Testing for causality in variance in the presence of breaks. Econ. Lett. 89, 193–199.

Worthington, A., Higgs, H., 2004. Transmission of equity returns and volatility in Asian developed and emerging markets: a multivariate GARCH analysis. Int. J. Fin. Econ. 9, 71–80.

Wu, F., Guan, Z., Myers, R.J., 2011. Volatility spillover effects and cross hedging in corn and crude oil futures. J. Futures Markets 31 (11), 1052–1075.

USDA, 2012. Bioenergy — background. http://www.ers.usda.gov/topics/farm-economy/bioenergy/background.aspx (Accessed: August 3, 2012).

Zhang, Z., Lohr, L., Escalante, C., Wetzstein, M., 2009. Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. Energies 2, 320–339.