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 grain markets.

Keywords: Volatility transmission, biofuels, corn, MGARCH

JEL code: Q42, Q11, C32

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 (Renewable Fuels Association). While, traditionally, agricultural prices have been affected by energy (oil) prices through production and transportation costs, the increased demand for agricultural produce in the 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 food price volatility.[1] In addition, the unprecedented spikes of agricultural prices during the 2007-2008 food crisis and the prevailing high price volatility in agricultural commodities have reinforced global fears about energy prices stimulating food price volatility and their potential impact on the poor. Volatile food prices stimulated by changes in energy prices may increase the risk exposure of smallholders, altering hedging and investment decisions and promoting speculative activity in agricultural production. Moreover, the increased demand for biofuels may also result in land-use shifts with important environmental and economic implications for renewable and non-renewable resources.

Economic theory based on market fundamentals and arbitrage activities suggests that oil, ethanol and corn (sugar) prices are interrelated (see, e.g., 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 food 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.

[1] Ethanol production is dominated by the United States and Brazil with 54 and 34 percentage of the market share.

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 estimate a BEKK model using a t-student density (T-BEKK) and a Dynamic Conditional Correlation (DCC) model.[2] We evaluate the magnitude and source of interrelation (whether direct or indirect) between markets and, in particular, whether price volatility in energy markets stimulate price volatility in grain markets. 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 suitable tests for structural breaks in volatility for strongly dependent processes.

The contribution to the literature is twofold. First, 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 Raposomanikis, 2008; Serra et al., 2011). Few exceptions include Zhang et al. (2009), Serra et al. (2010) and Serra (2011) who examine price volatility interactions between energy and agricultural markets in the United States or Brazil following particular parametric and semiparametric multivariate GARCH models.[3] We implement different MGARCH specifications to provide an in-depth analysis of the dynamics and cross-dynamics of price volatility across energy and agricultural markets in the United States. As shown by Gallagher and Twomey (1998), modeling

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[2] The BEKK specification is based on the Engle and Kroner (1995) model; the use of a t-student density is to account for the leptokurtic distribution of the series we work with. For further details on MGARCH modelling with a Student-t density see Fiorentini et al. (2003). The DCC model is the Engle (2002) model, which is also estimated assuming a Student t distribution for the errors.

[3] Of special interest is Zhang et al. (2009), who examine price volatility interactions between US energy and food markets between 1989 and 2007 using a standard BEKK model. Serra et al. (2010) and Serra (2011) focus on the Brazilian market.

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-market dynamics in the conditional volatilities of the markets.[4]

Second, 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 biofuel industry in the United States. 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 unprecedented price variations.

The estimation results indicate a higher interrelation between ethanol and corn markets in recent years, particularly after 2006 when Methyl Tertiary Butyl Ether (MTBE) was effectively banned in the United States and left ethanol as the alternative oxygenate for gasoline. We only find, however, significant volatility spillover effects from corn to ethanol markets but not the converse. We also do not observe major cross-volatility spillovers from oil to corn markets. The results do not provide evidence of volatility in energy prices stimulating volatility in agricultural (corn) prices.

The remainder of the paper is organized as follows. Section 2 provides an overview of biofuel policies in the United States and their implications on the interrelationship between energy and corn markets. 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.

[4] 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 Karolyi (1995) and Worthington and Higgs (2004) studies on volatility transmission in stock markets and Hernandez et al. (2011) study on volatility spillovers in agricultural futures markets.

2 Interrelationships between energy and corn markets and US biofuel policies

The relation between crude oil, ethanol and corn prices is not constant. Meyer and Thompson (2010) discuss various regimes for ethanol demand depending on the price and nature of ethanol demand. One source of ethanol demand stems from addition of ethanol as an 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 gasoline 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, tax credits and other policies. 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 total US corn demand in 2005/2006 (Meyer and Thompson, 2010).

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 has changed across time.[5]

Consider the following model,

$$\begin{aligned} r_t &= \gamma_0 + \sum_{j=1}^{p} \gamma_j r_{t-j} + \varepsilon_t, \\ \varepsilon_t \mid I_{t-1} &\sim (0, H_t), \end{aligned} \qquad (1)$$

where r_t is a 3x1 vector of price returns for oil, ethanol and corn, γ_0 is a 3x1 vector of long-term drifts, γ_j, *j*=1,..,*p*, are 3x3 matrices of parameters, and ε_t is a 3x1 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

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + G'H_{t-1}G, \qquad (2)$$

[5] For a detailed survey of MGARCH models see Bauwens et al. (2006).

where C is a 3x3 upper triangular matrix of constants c_{ij}, A is a 3x3 matrix containing elements a_{ij} that measure the degree of innovation from market i to market j, and the elements g_{ij} of the 3x3 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.

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

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

where

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

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

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

with the 3x3 symmetric positive-definite matrix $Q_t = (q_{ij,t})$, $i, j = 1,...,3$, 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 3x3 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 process (ARMA) type process which captures short-term deviations in the correlation around its long-run level.

4 Data

The data used for the analysis are weekly prices series 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).[6] Corn prices are No.2 yellow corn FOB Gulf prices reported by the Food and Agriculture Organization. Table A.1 in the Appendix provides further details on the sources of information used.

Figure 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. The correlation across markets is further corroborated when comparing the volatility in prices (measured using the standard deviation). Price volatility in the three markets generally evolves in a similar manner.

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

[6] 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.

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.[7] 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.[8] 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, then, 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 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-t density for the innovations.[9] Finally, while the Ljung-Box (LB) statistics for up to 6 and 12 lags

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[7] 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.

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

[9] 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.

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 Figure 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.

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 estimations 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 the dynamics and cross-dynamics of volatility 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 crises of 2007-2008 and 2011.

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 (SBIC). The residual diagnostic test reported at the end of the table also supports the adequacy of the model specification; the LB statistics for up to 6 and 12 lags show no evidence of autocorrelation in the standardized squared residuals of the estimated model.

In the conditional mean equation, the γ_{1ii} coefficients, $i = 1,...,3$, 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 is not 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 addition, while energy markets (specially ethanol) exhibit strong and positive own-mean spillovers, corn markets show negative spillovers. In sum, energy and agricultural markets do not seem to be interrelated at the mean level.[10]

Turning to the conditional variance-covariance equation, the a_{ii} coefficients, $i = 1,...,3$, capture own-volatility spillovers, i.e. the effect of lagged innovations on the current conditional return volatility in market *i*, and the g_{ii} coefficients capture own-volatility persistence, i.e. the dependence of volatility in market *i* on its own past volatility. The off-diagonal coefficients a_{ij} measure, in turn, the effects of lagged innovations originating in market *i* on the current conditional volatility in market *j*, while the off diagonal coefficients g_{ij} measure the dependence of volatility in market *j* on that of market *i*. The Wald test reported in the table 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 results reveal significantly large own-volatility effects in the three markets, indicating the presence of strong GARCH effects. Own-volatility spillovers are higher in ethanol than in crude oil and

[10] 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.

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. In terms of cross-volatility effects, we do not find important spillover effects from both oil and ethanol markets to corn markets, as well as between oil and ethanol. In contrast, we observe that information shocks originating in corn markets have a considerable effect on the (next period) volatility of ethanol returns. In addition, the observed volatility in ethanol returns exhibit a strong dependence on the past volatility in corn markets.

An impulse-response analysis helps to better illustrate volatility spillovers by simulating the response of a market, in terms of its conditional return volatility, to innovations separately originating in each market. Figure 3 presents impulse-response functions derived by iterating, for each market variance resulting from expression (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 effect on the volatility of returns in the ethanol market than on the own corn market (1.4 times larger). As indicated above, separate innovations in oil and ethanol markets do not appear to spillover to other markets. 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.

The resulting conditional volatility dynamics partially resemble the findings of Zhang et al. (2010), 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 difference in 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. In the next section, we evaluate changes in the dynamics of volatility transmission between energy and corn prices across different sample periods.

Table 4 reports the full estimation results of the DCC model. This model is not useful to analyze volatility dynamics but allows us to examine whether the level of volatility interdependence between markets has changed across time. As in the T-BEKK model, the number of lags (one lag) corresponds to the optimal number as determined by the Schwarz criterion. The reported diagnostic tests for the standardized squared residuals (LB statistics) 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. 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. In particular, parameters α and β can be interpreted as the "news" and "decay" parameters capturing the effect of innovations on the conditional correlations over time and their persistence.

Figure 4 presents the dynamic conditional correlations for each market pair, which result from the DCC model estimates. In line with our previous results, the figure shows an important increase in the level of volatility interdependence between ethanol and corn markets. 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 our full sample.[11]

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 dynamics across time

We now turn to examine if the conditional volatility dynamics between energy and corn markets has 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 structural breaks proposed by Lavielle and Moulines (2000), which is more suitable than other tests for strongly dependent processes such as GARCH processes (Carrasco and Chen, 2002). Similar to Benavides and Capistran (2009) and Hernandez et al. (2011), we apply the test over the squared returns as a proxy for volatility. We find important shifts in the

[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.

volatility of all three return series, which can be associated to particular events in these markets.[12] In the case of ethanol, we observe a break in the dynamics of ethanol returns during mid-2006 (July 7), period where 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), period where the food crisis of 2007-2008 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 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 statistics) support the adequacy of the model specifications.

A comparison of the estimation results 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. 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 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

[12] Lavielle and Moulines' 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 break points. We obtain similar results when allowing for two or three possible segments.

cross-volatility effects, the reported Wald tests indicate the presence of cross effects during both periods. These cross-market dynamics are better illustrated through impulse-response functions to which we now turn.

Figures 5 and 6 show the simulated responses in 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 spillover to other markets in both periods. However, when segmenting our sample we do observe volatility spillovers from oil to both ethanol and corn markets, particularly prior to 2006. A plausible explanation for the differences between these results for crude oil and the full-sample results 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. 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 two 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 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.

The results do not provide evidence of mean spillovers in the returns across energy and corn markets. In terms of the conditional volatility dynamics, the results of the T-BEKK specification indicate that shocks in oil or ethanol prices do not lead to shocks in corn prices. In other words, the often stated concern that due to biofuels price volatility in agricultural markets increased due to stronger links with energy markets is not supported by our empirical evidence. However, a shock in corn prices does lead to short-run shock in ethanol prices. Apparently, input costs of corn do affect production costs of ethanol. The results of the T-BEKK model are for the whole sample period. The estimation outcomes of the DCC model, which allows for changing relations in volatility of two commodities, show that these relations are not constant however. Whereas the correlation between oil and ethanol price volatility has not changed much over time, the correlation between crude oil and corn and between ethanol and corn had increased after 2007. The latter can of course 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.

Future work involves formally modelling the potential interrelationships between oil, ethanol and corn prices and providing a more detailed overview of the US biofuel policies affecting these markets. The study aims to further evaluate potential changes in the nature of the dynamic interrelationships between energy and agricultural prices across time.

References

Babcock, B.A. (2008), Distributional implications of U.S. ethanol policy, *Review of Agricultural Economics* 30, 533-542.

Balcombe, K., and G. Rapsomanikis (2008), Bayesian estimation and selection of nonlinear vector error correction models: the case of sugar-ethanol oil nexus in Brazil, *American Journal of Agricultural Economics* 90, 658-668.

Bauwens, L., S. Laurent, and J.V.K. Rombouts (2006), Multivariate GARCH Models: A Survey, *Journal of Applied Econometrics* 21, 79-109.

Benavides, G., and C. Capistran (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, *The Review of Economics and Statistics* 72, 498-505.

Carrasco, M., and X. Chen (2002), Mixing and moment properties of various GARCH and stochastic volatility models, *Econometric Theory* 18, 17-39.

de Gorter, H., and D. Just (2008), 'Water' in the U.S. ethanol tax credit and mandate: implications for rectangular deadweight costs and the corn-oil price relationship, *Review of Agricultural Economics* 30, 397-410.

Engle, R. (2002), Dynamic conditional correlation--a simple class of multivariate GARCH models, *Journal of Business and Economic Statistics* 20, 339-350.

Engle, R., and F.K. Kroner (1995), Multivariate simultaneous generalized ARCH, *Econometric Theory* 11, 122-150.

Fiorentini, G., E. Santana, and G. Calzolari (2003), Maximum likelihood estimation and inference in multivariate conditionally heteroskedastic dynamic regression models with Student t innovations, *Journal of Business and Economic Statistics* 21, 532-546.

Gallagher, L., and C. Twomey (1998), Identifying the source of mean and volatility spillovers in Irish equities: a multivariate GARCH analysis, *Economic and Social Review* 29, 341-356.

Hernandez, M.A., R. Ibarra, and D.R. Trupkin (2011), How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets, IFPRI Discussion Paper #1109.

Karolyi, G.A. (1995), A multivariate GARCH model of international transmissions of stock returns and volatility: the case of the United States and Canada, *Journal of Business and Economic Statistics* 13, 11-25.

Lavielle, M., and E. Moulines (2000), Least-squares estimation of an unknown number of shifts in a time series, *Journal of Time Series Analysis* 21, 33-59.

Long, X., L. Su, and A. Ullah (2011), Estimation and forecasting of dynamic conditional covariance: a semiparametric multivariate model, *Journal of Business and Economic Statistics* 29, 109-125.

Luchansky, M.S., and J. Monks (2009), Supply and demand elasticities in the U.S. ethanol fuel market, *Energy Economics* 31, 403-410.

Meyer, S. and Thompson, W. (2010), Demand behavior and commodity price volatility under evolving biofuel markets and policies. Ch 9 in: Khanna, M., Scheffran, J. and Zilberman, D. (eds.). *Handbook of Bioenergy Economics and Policy*, *Natural Resource Management and Policy* Vol 33, Springer Science, p 133-148.

Rajagopal, D., and D. Zilberman (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 Economics*, forthcoming.

Serra, T., D. Zilberman, and J.M. Gil (2010), Price volatility in ethanol markets, *European Review of Agricultural Economics* 38, 259-280.

Serra, T., D. Zilberman, J.M. Gil, and B.K. Goodwin (2011), Nonlinearities in the US corn-ethanol-oil-gasoline price system, *Agricultural Economics* 42, 35-45.

van Dijk, D., D.R. Osborn, and M. Sensier (2005), Testing for causality in variance in the presence of breaks, *Economics Letters* 89, 193-199.

Worthington, A., and H. Higgs (2004), Transmission of Equity Returns and Volatility in Asian Developed and Emerging Markets: A Multivariate Garch Analysis, *International Journal of Finance and Economics* 9, 71-80.

Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein (2009), Ethanol, Corn, and Soybean Price Relations in a Volatile Vehicle-Fuels Market, *Energies* 2, 320-339.

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.

Table 2. Summary statistics for weekly returns

Statistic	Crude oil	Ethanol	Corn
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*

Note: The symbol (*) denotes rejection of the null hypothesis at the 5% significance level. AC is the autocorrelation coefficient.

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)
Wald joint test for cross-correlation coefficients			
H_0: $a_{ij}=g_{ij}=0, \forall\ i \neq j$			
Chi-sq			46.360
p-value			0.000
Test for standardized squared residuals (H_0: no autocorrelation)			
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
Log likelihood			-5750.1
# observations			736

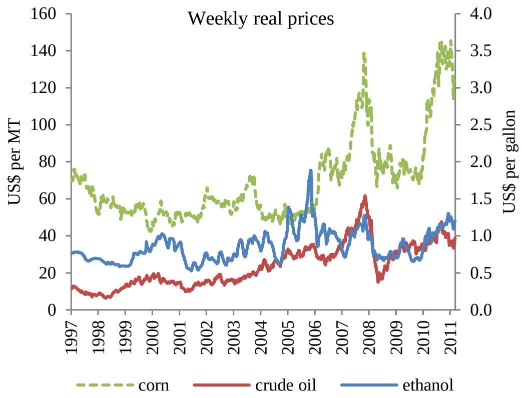
Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). LB stands for the Ljung-Box statistic.

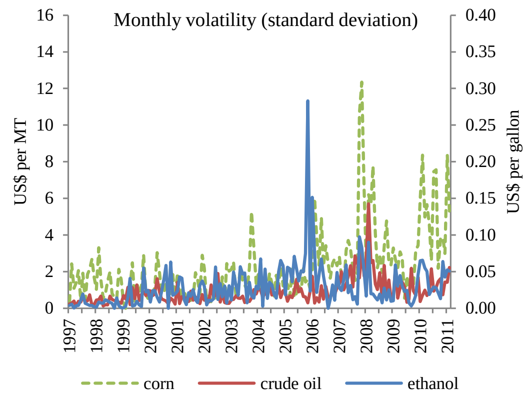
Table 4. DCC model estimation results

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)
Wald joint test for adjustments coefficients (H_0: $\alpha=\beta=0$)			
Chi-sq			16658.400
p-value			0.000
Test for standardized squared residuals (H_0: no autocorrelation)			
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
Log likelihood			-5749.3
# observations			736

Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). LB stands for the Ljung-Box statistic.

Figure 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.

Figure 2. Oil, ethanol and corn weekly returns, 1997-2011

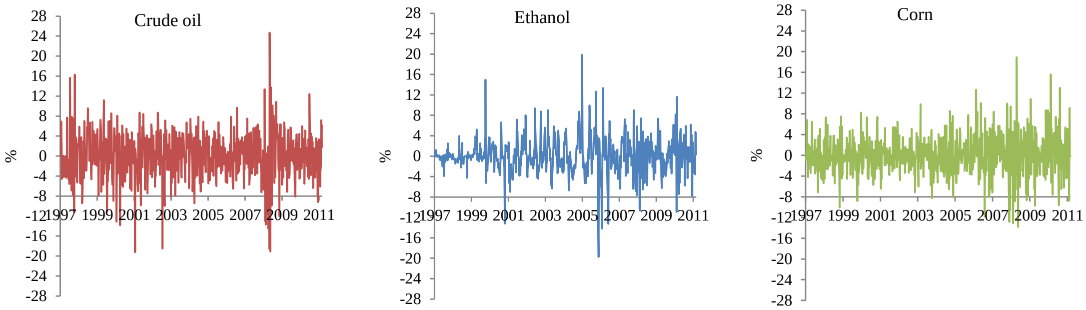
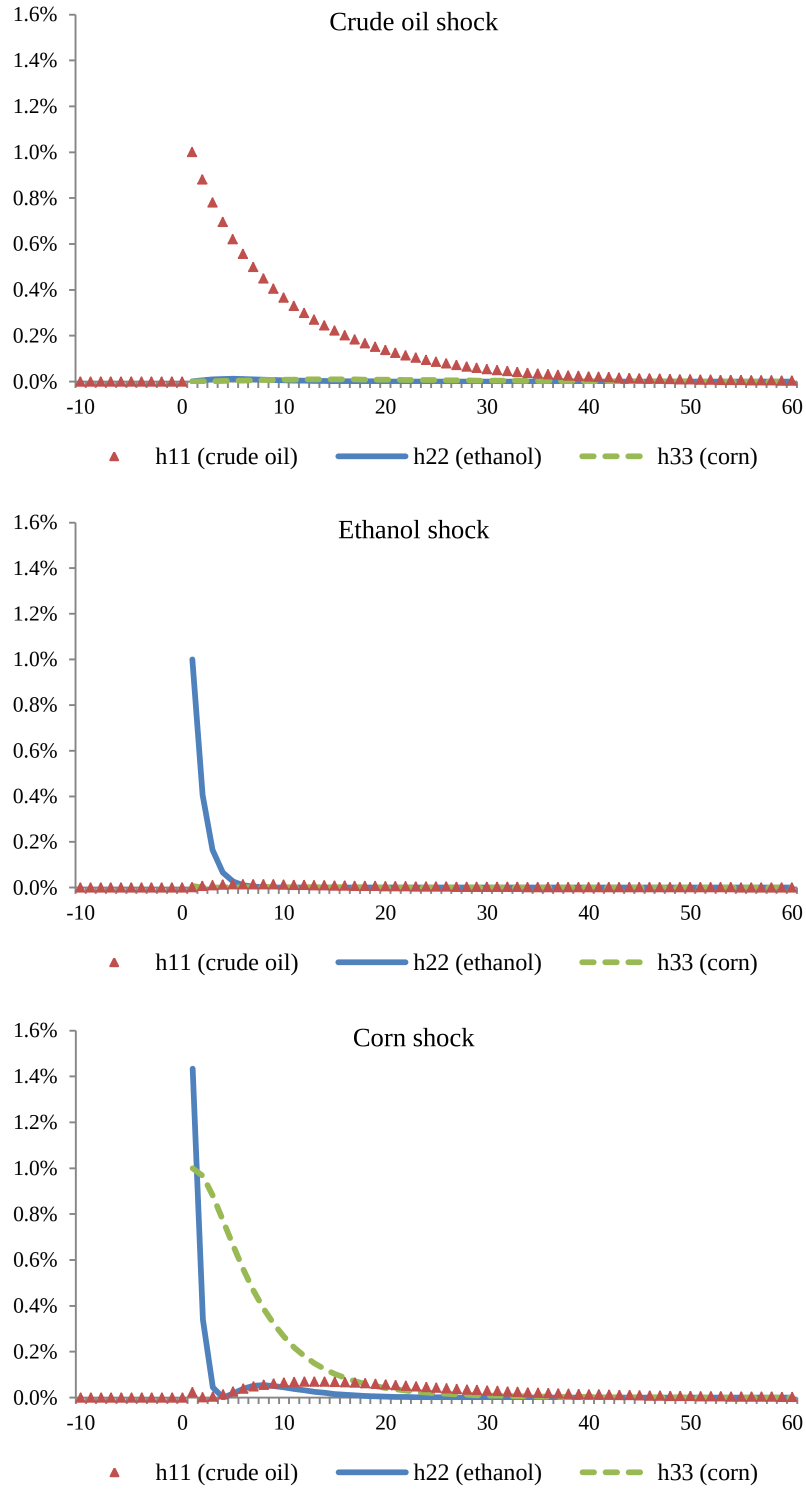
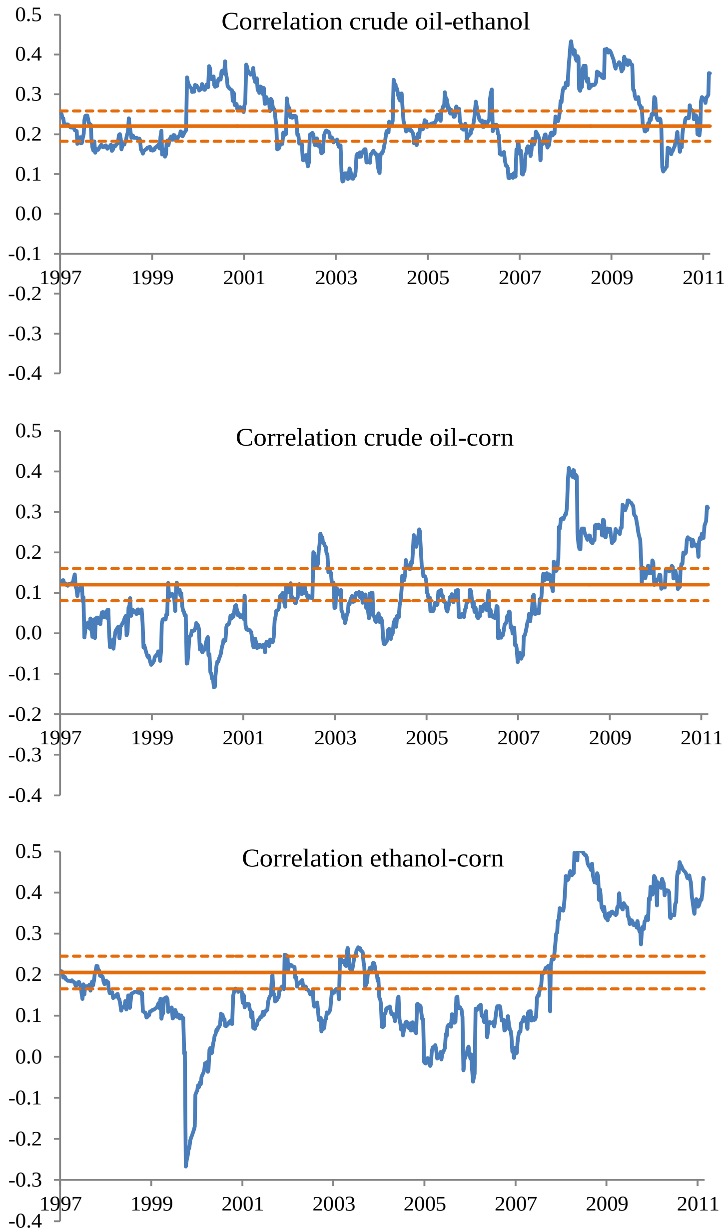


Figure 3. Impulse-response functions



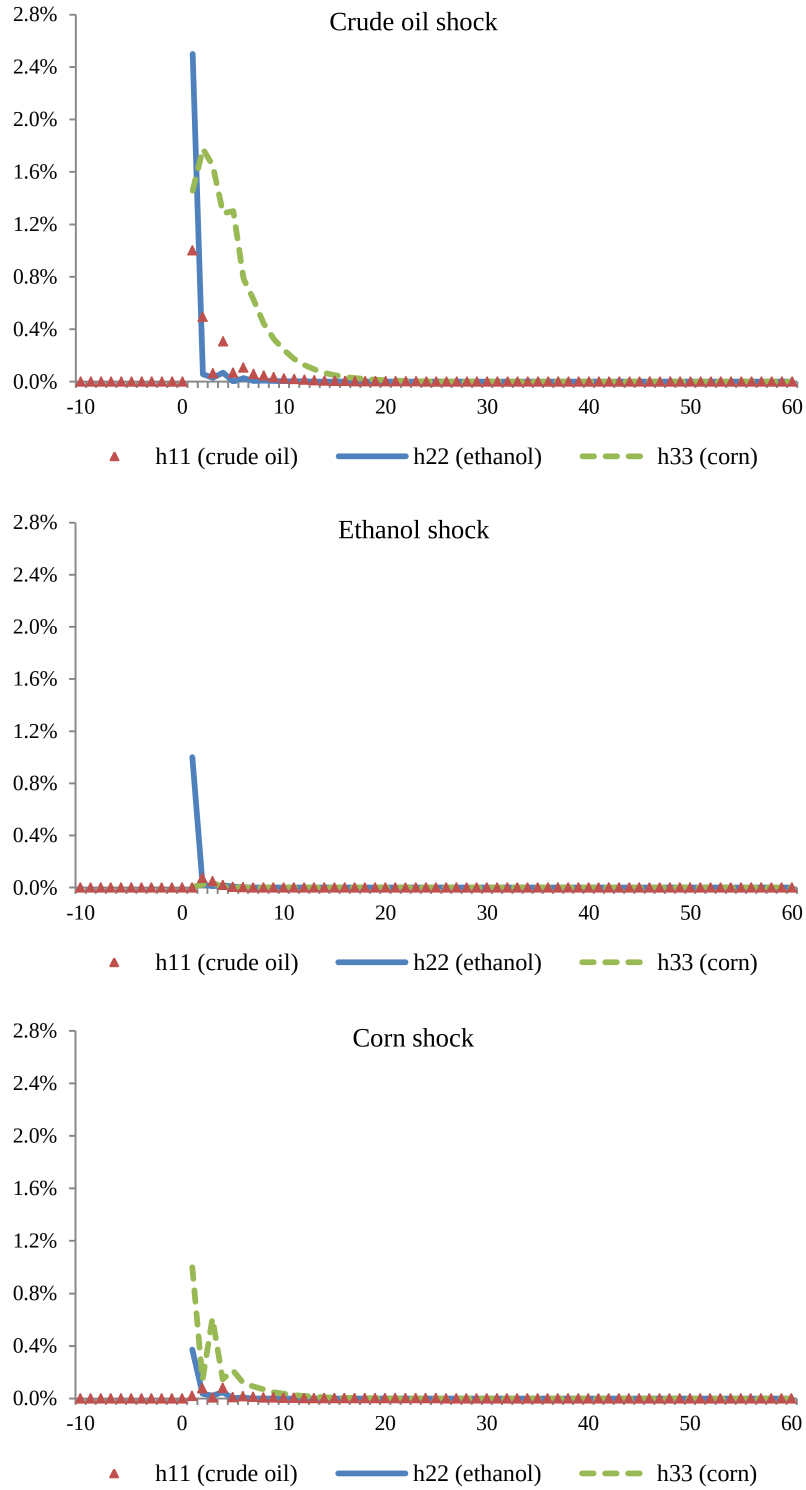
Note: The responses are the result of an innovation equivalent to a 1% increase in the conditional volatility of the market where the innovation first occurs. The responses are measured as percentage deviations from the initial conditional volatility in each corresponding market. Simulations based on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

Figure 4. Dynamic conditional correlations



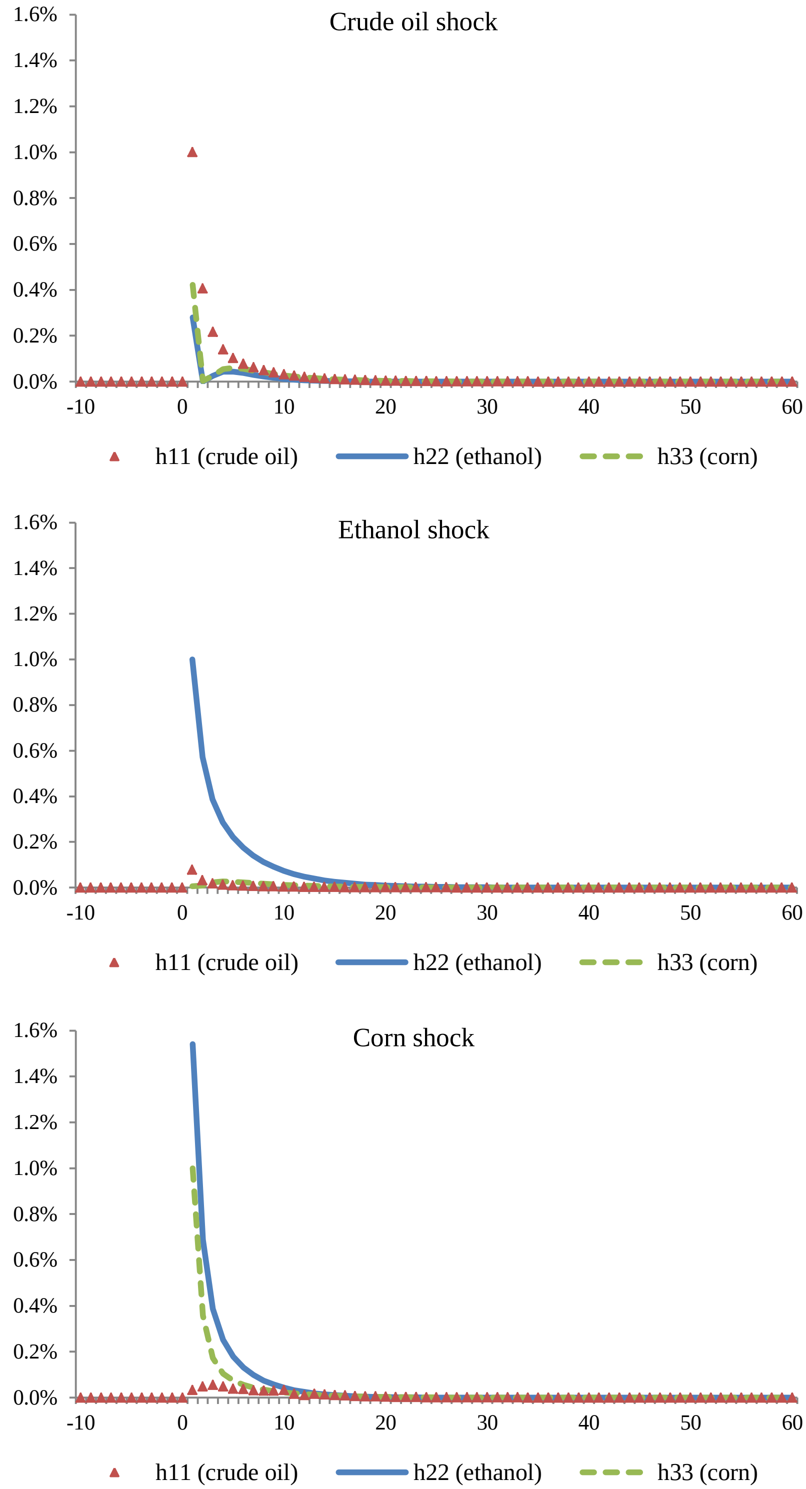
Note: The dynamic conditional correlations are derived from the DCC model estimation results. The solid line is the estimated constant conditional correlation following Bollerslev (1990), with confidence bands of one standard deviation.

Figure 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.

Figure 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.

Appendix

Table A.1. Sources of Data

Price series	Description	Source
Oil	West Texas Intermediate – Cushing, Oklahoma crude oil FOB spot prices	Energy Information Administration (EIA) website www.eia.gov/dnav/pet/pet_pri_spt_s1_w.htm
Ethanol	Denatured fuel ethanol ASTM D4806 spot prices from the Chicago Board of Trade (CBOT)	Commodity Research Bureau (CRB) Infotech CD
Corn	No.2 yellow corn FOB Gulf prices	Food and Agriculture Organization (FAO) International Commodity Prices Database

Table A.2. T-BEKK model estimation results, subperiod 1997 – 2006

Coefficient	Crude oil (i=1)	Ethanol (i=2)	Corn (i=3)
	Conditional mean equation		
γ_0	0.323	-0.050	-0.098
	(0.192)	(0.077)	(0.131)
γ_{11i}	0.126	0.029	0.014
	(0.047)	(0.019)	(0.031)
γ_{12i}	-0.018	0.684	0.029
	(0.063)	(0.037)	(0.047)
γ_{13i}	-0.003	-0.017	-0.080
	(0.064)	(0.026)	(0.049)
	Conditional variance-covariance equation		
c_{i1}	2.748	-0.667	0.765
	(6.306)	(2.412)	(1.827)
c_{i2}		0.671	-1.559
		(1.676)	(0.863)
c_{i3}			0.075
			(0.269)
a_{i1}	0.029	0.009	0.032
	(0.189)	(0.077)	(0.092)
a_{i2}	-0.054	0.601	0.150
	(0.118)	(0.118)	(0.110)
a_{i3}	-0.045	-0.048	0.246
	(0.041)	(0.089)	(0.098)
g_{i1}	-0.438	-0.294	-0.376
	(0.696)	(0.321)	(0.679)
g_{i2}	0.341	-0.136	0.229
	(0.258)	(0.143)	(0.325)
g_{i3}	-0.961	-0.091	0.558
	(1.288)	(0.182)	(0.714)
Wald joint test for cross-correlation coefficients			
H_0: $a_{ij}=g_{ij}=0, \forall\ i \neq j$			
Chi-sq			187.332
p-value			0.000
Test for standardized squared residuals (H_0: no autocorrelation)			
LB(6)	1.928	1.755	2.105
p-value	0.926	0.941	0.910
LB(12)	10.354	2.939	9.712
p-value	0.585	0.996	0.641
Log likelihood			-3417.1
# observations			458

Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). LB stands for the Ljung-Box statistic. The sample period corresponds to September 19, 1997 through June 30, 2006.

Table A.3. T-BEKK model estimation results, subperiod 2008 – 2011

Coefficient	Crude oil (i=1)	Ethanol (i=2)	Corn (i=3)
Conditional mean equation			
γ_0	0.332	0.243	0.163
	(0.319)	(0.231)	(0.352)
γ_{11i}	0.235	0.039	0.139
	(0.084)	(0.047)	(0.077)
γ_{12i}	-0.032	0.211	-0.092
	(0.114)	(0.099)	(0.130)
γ_{13i}	-0.135	0.076	-0.209
	(0.088)	(0.064)	(0.094)
Conditional variance-covariance equation			
c_{i1}	0.890	0.157	-2.609
	(1.429)	(0.889)	(2.248)
c_{i2}		-1.020	-0.492
		(0.312)	(4.384)
c_{i3}			0.001
			(0.082)
a_{i1}	0.545	0.088	-0.027
	(0.234)	(0.180)	(0.181)
a_{i2}	0.288	0.313	0.180
	(0.171)	(0.082)	(0.413)
a_{i3}	-0.354	-0.025	-0.145
	(0.187)	(0.140)	(0.216)
g_{i1}	0.746	-0.019	0.152
	(0.181)	(0.198)	(0.225)
g_{i2}	-0.252	0.849	0.269
	(0.317)	(0.400)	(0.419)
g_{i3}	0.307	0.053	0.608
	(0.245)	(0.497)	(0.424)
Wald joint test for cross-correlation coefficients			
H_0: $a_{ij}=g_{ij}=0, \forall\ i \neq j$			
Chi-sq			45.319
p-value			0.000
Test for standardized squared residuals (H_0: no autocorrelation)			
LB(6)	5.321	3.869	1.899
p-value	0.503	0.694	0.929
LB(12)	15.245	11.766	10.926
p-value	0.228	0.465	0.535
Log likelihood			-1341.5
# observations			161

Note: Standard errors reported in parentheses. Number of lags determined according to Schwarz's Bayesian information criterion (SBIC). LB stands for the Ljung-Box statistic. The sample period corresponds to September 26, 2008 through October 28, 2011.