



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

Paper prepared for the 123rd EAAE Seminar

PRICE VOLATILITY AND FARM INCOME STABILISATION

Modelling Outcomes and Assessing Market and Policy Based Responses

Dublin, February 23-24, 2012



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

Gardebroek, C.¹ and Hernandez, M.A.²

1 Agricultural Economics and Rural Policy Group, Wageningen University, Wageningen, The Netherlands

2 Markets, Trade and Institutions Division, International Food Policy Research Institute, Washington DC, USA

koos.gardebroek@wur.nl

Do energy prices stimulate food price volatility?

Examining volatility transmission between US oil, ethanol and corn markets

Gardebroek, C. and Hernandez, M.A.

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. Preliminary results indicate a higher interaction between ethanol and corn markets in recent years, particularly after 2006. 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 classification: 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 have 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

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

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 further 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.

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 and subsidies 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), modelling volatility spillovers provides better insight into the dynamic price relationship between markets, but

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.

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 period covers both the pre- and ethanol boom periods with important changes in energy policies promoting the use of biofuels and significant improvements in bioenergy technologies; it also covers the recent food price crisis of 2007-2008, a period of particular interest with unprecedented price variations.

Preliminary 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 presents the empirical approach used to examine volatility transmission between energy and corn markets. Section 3 describes the data. Section 4 presents and discusses the estimation results. Section 5 concludes.

2. 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 US. 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,

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.

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

$$r_t = \gamma_0 + \sum_{j=1}^p \gamma_j r_{t-j} + \varepsilon_t, \quad (1)$$

$$\varepsilon_t | I_{t-1} \sim (0, H_t),$$

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, $\gamma_j, j=1, \dots, p$, 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 $\gamma_j, j=1, \dots, p$, 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

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

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 $R_t = (\rho_{ij,t})$, $i, j = 1, \dots, 3$, the conditional variance-covariance matrix H_t is defined as

$$H_t = D_t R_t D_t \quad (3)$$

where

$$D_t = \text{diag}(h_{11,t}^{1/2} \dots h_{33,t}^{1/2}), \quad (4)$$

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

$$R_t = \text{diag}(q_{11,t}^{-1/2}) Q_t \text{diag}(q_{33,t}^{-1/2}) \quad (5)$$

with the 3x3 symmetric positive-definite matrix $Q_t = (q_{ij,t})$, $i, j = 1, \dots, 3$, given by

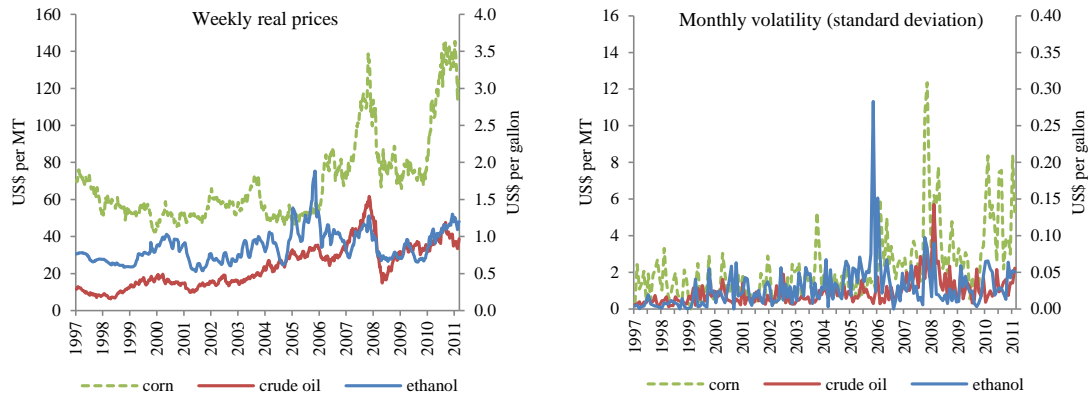
$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}, \quad (6)$$

and $u_{it} = \varepsilon_{it} / \sqrt{h_{iit}}$. \bar{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.

3. 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. 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 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 the

⁶ We also identified average ethanol rack prices in Nebraska, starting on July 2003, from the state's Ethanol Board; Nebraska 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.

past year. The price hike 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 rise and fall 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 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 As in Zhang et al. (2009), the subsample periods roughly represent the pre-ethanol boom (prior to 2000) and ethanol boom years; we further subdivide the boom period in 2000-2005 and 2006-2011, considering the ban in the use of MTBE in 2006. A comparison across periods indicates that energy and corn markets have become more interconnected in the past years. We find a statistically significant positive correlation in the returns of all markets for 2006 onwards; the correlation between corn and ethanol markets is also stronger than the correlation between the other markets. 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, especially in more recent years. Yet establishing sources of interdependence, particularly on price volatility transmission, requires further analysis as discussed below.

Table 1: Correlation of weekly returns, 1997-2011

Commodity	1997-1999			2000-2005			2006-2011			Total sample		
	Oil	Ethanol	Corn	Oil	Ethanol	Corn	Oil	Ethanol	Corn	Oil	Ethanol	Corn
Oil	1.000	0.083	-0.065	1.000	0.191*	0.014	1.000	0.267*	0.278*	1.000	0.217*	0.143*
Ethanol		1.000	0.070		1.000	0.024		1.000	0.381*		1.000	0.240*
Corn			1.000			1.000			1.000			1.000
# observations			120			313			304			737

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

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. Corn returns are also the most volatile.

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 also exceeds three, pointing to a leptokurtic

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.

Dublin – 123rd EAAE Seminar

Price Volatility and Farm Income Stabilisation

Modelling Outcomes and Assessing Market and Policy Based Responses

distribution. We estimate, then, both the BEKK and DCC models assuming a Student-t density for the innovations.⁸

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*

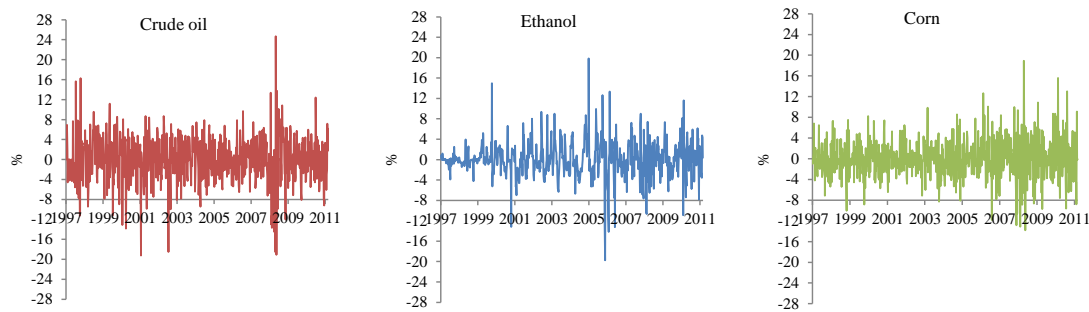
Note: The symbol (*) denotes rejection of the null hypothesis at the 5% significance level. AC is the autocorrelation coefficient.

Finally, 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 series, probably due to time varying conditional volatility, as observed also 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.

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 using this method can result in consistent parameter estimates regardless that the log-likelihood function assumes a normal distribution while the series are skewed and leptokurtic.

*Price Volatility and Farm Income Stabilisation
Modelling Outcomes and Assessing Market and Policy Based Responses*

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



4. RESULTS

This section presents the estimation results of the T-BEKK and DCC models used to examine the dynamics of volatility transmission between energy and agricultural prices in the United States. We omit presenting the first moment estimated equations to save space.

Table 3 reports the coefficient estimates for the conditional variance-covariance matrix of the T-BEKK model. This model allows for own- and cross-volatility spillovers and persistence between markets. The a_{ii} coefficients, $i = 1, \dots, 3$, 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 at the bottom of 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 residual diagnostic test 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 T-BEKK model.

*Price Volatility and Farm Income Stabilisation
Modelling Outcomes and Assessing Market and Policy Based Responses*

Table 3: T-BEKK model estimation results

Coefficient	Crude oil (<i>i</i> =1)	Ethanol (<i>i</i> =2)	Corn (<i>i</i> =3)
c_{i1}	1.186 (0.164)	-0.545 (0.261)	-0.703 (0.247)
c_{i2}		1.115 (0.287)	-0.596 (0.445)
c_{i3}			0.000 (0.041)
a_{i1}	0.202 (0.037)	0.027 (0.032)	-0.037 (0.039)
a_{i2}	0.007 (0.031)	0.651 (0.087)	0.288 (0.087)
a_{i3}	0.005 (0.026)	-0.055 (0.034)	0.241 (0.046)
g_{i1}	0.936 (0.013)	0.044 (0.023)	0.060 (0.022)
g_{i2}	0.060 (0.034)	0.622 (0.129)	-0.153 (0.094)
g_{i3}	0.009 (0.015)	0.050 (0.038)	0.925 (0.033)
Wald joint test for cross-correlation coefficients			
$H_0: a_{ij}=g_{ij}=0, \forall i \neq j$			
Chi-sq			46.360
<i>p</i> -value			0.000
Test for standardized squared residuals (H_0 : no autocorrelation)			
LB(6)	7.169	5.230	4.126
<i>p</i> -value	0.306	0.515	0.660
LB(12)	16.115	6.623	17.910
<i>p</i> -value	0.186	0.881	0.118
Log likelihood			5750.1
# observations			736

Note: Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.

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 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.

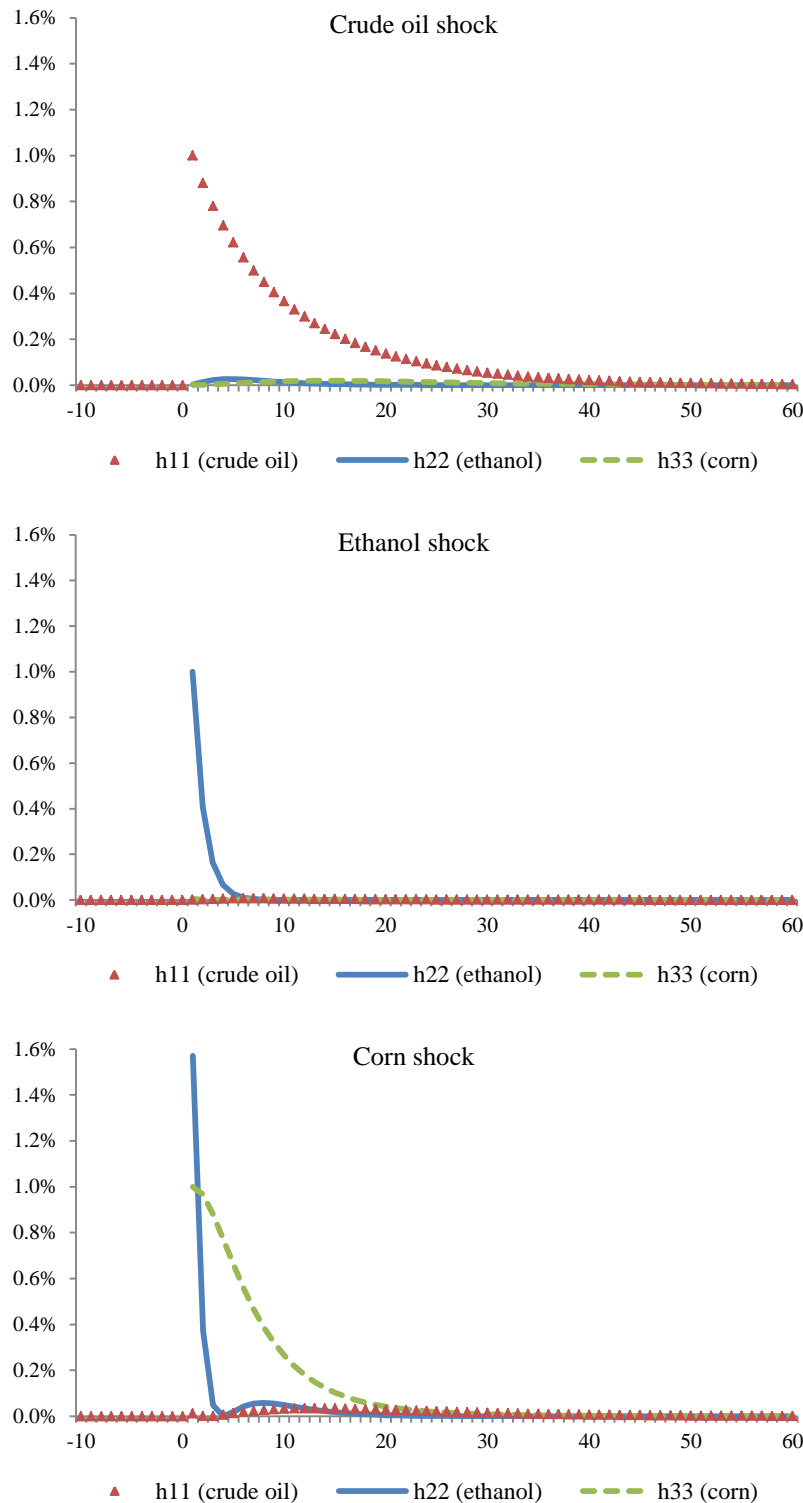
An impulse-response analysis helps to better illustrate volatility spillovers by simulating the response of a market, in terms of its conditional return volatility, to innovations separately originating in each market. Figure 3 presents impulse-response functions derived by iterating, for each market variance resulting from expression (2), the response to an innovation equivalent to a 1% increase in the own 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 (1.6 times larger). As indicated above, separate innovations in oil and ethanol markets do not appear to spill over 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.

Overall, the results 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. Further evaluation of changes in the dynamics of volatility transmission between energy and corn prices across different sample periods is pending.

Turning to the DCC model, Table A.2 reports the full estimation results. This model is not useful to identify the sources of volatility transmission but allows us to examine whether the level of interdependence between markets has changed across time. The Wald test reported at the bottom of the table rejects the null hypothesis that the adjustment parameters α and β are jointly equal to zero at one percent significance level, suggesting that the time-variant conditional correlations 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. The reported diagnostic tests for the standardized squared residuals (LB statistics) also support the adequacy of the model specification.

Figure 4 presents the dynamic conditional correlations for each market pair, based on the DCC model estimates. In line with our previous results, the figure shows an important increase in the level of interdependence between ethanol and corn markets. The correlation has in fact changed from a negative 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 spillover effects across these markets.

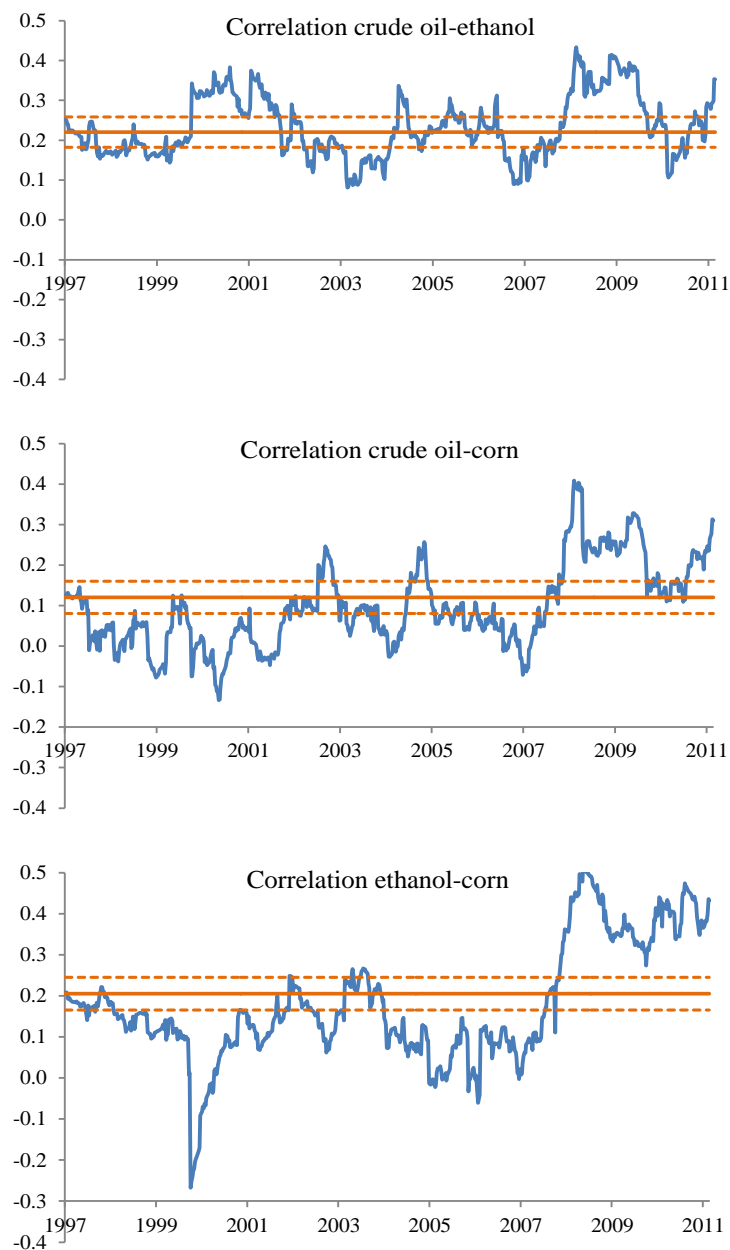
Figure 3. Impulse-response functions of T-BEKK model



Note: The responses are the result of an innovation equivalent to a 1% increase in the own 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 correlation between oil and ethanol markets, in turn, has basically fluctuated across time without a particular trend. All correlations also exhibit peaks during the recent food crisis of 2007-2008, suggesting a high interrelation between energy and corn markets during that specific period.

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.

5. 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 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, shows that these relations are not constant however. Whereas, the correlation between oil and ethanol price volatility has not changes 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 detailed overview of the US biofuel policies affecting these markets. Accounting for structural breaks in the returns series using appropriate tests for strongly dependent processes (e.g., Lavielle and Moulines, 2000) is also pending. 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 Rapsomanikis, G. (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., Laurent, S. and Rombouts, J.V.K. (2006). Multivariate GARCH Models: A Survey. *Journal of Applied Econometrics* 21: 79-109.
- 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.
- Bollerslev, T. and Wooldridge, J. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances. *Econometric Reviews* 11:143-172.
- de Gorter, H. and Just, D. (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 Kroner, F.K. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory* 11: 122-150.

*Price Volatility and Farm Income Stabilisation
Modelling Outcomes and Assessing Market and Policy Based Responses*

- Fiorentini, G., Santana, E. and Calzolari, G. (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 Twomey, C. (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., Ibarra, R. and Trupkin, D.R. (2011). How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets. Discussion Paper 1109, International Food Policy Research Institute (IFPRI). Washington DC: IFPRI.
- 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 Moulines, E. (2000). Least-squares estimation of an unknown number of shifts in a time series. *Journal of Time Series Analysis* 21: 33-59.
- Long, X., Su, L. and Ullah, A. (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 Monks, J. (2009). Supply and demand elasticities in the U.S. ethanol fuel market. *Energy Economics* 31: 403-410.
- Rajagopal, D. and Zilberman, D. (2007). Review of environmental, economics and policy aspects of biofuels. Policy Research Working Paper 4341, The World Bank. Washington DC: The World Bank.
- Serra, T. (2011). Volatility spillovers between food and energy markets: A semiparametric approach. *Energy Economics*, forthcoming.
- Serra, T., Zilberman, D. and Gil, J.M. (2010). Price volatility in ethanol markets. *European Review of Agricultural Economics* 38: 259-280.
- Serra, T., Zilberman, D., Gil, J.M. and Goodwin, B.K. (2011). Nonlinearities in the US corn-ethanol-oil-gasoline price system. *Agricultural Economics* 42: 35-45.
- Worthington, A. and Higgs, H. (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., Lohr, L., Escalante, C. and Wetzstein, M. (2009). Ethanol, Corn, and Soybean Price Relations in a Volatile Vehicle-Fuels Market. *Energies* 2: 320-339.

Dublin – 123rd EAAE Seminar

Price Volatility and Farm Income Stabilisation

Modelling Outcomes and Assessing Market and Policy Based Responses

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: DCC model estimation results

Coefficient	Crude oil ($i=1$)	Ethanol ($i=2$)	Corn ($i=3$)
ω_i	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
α_i	0.070 (0.021)	0.471 (0.102)	0.098 (0.042)
β_i	0.879 (0.036)	0.311 (0.138)	0.812 (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			4419.0
# observations			736

Note: Standard errors reported in parentheses. LB stands for the Ljung-Box statistic.