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Volatility Spillovers in the U.S. Crude Oil, Corn, and Ethanol Markets

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Abstract

This paper analyzes volatility spillovers from energy to agricultural markets in the U.S. which have increased due to strong crude oil price volatility and the large growth in ethanol production in the period 2006-2011. Results suggest that spillovers from crude oil to corn and ethanol markets are similar in magnitude over time, and are particularly significant during periods of high turbulence in the crude oil market. Volatility spillovers between corn and ethanol also exist, but primarily from the corn to ethanol market. The findings provide clear evidence of the stronger linkages between corn and ethanol that have been created during the biofuel era.

***Keywords**: volatility spillovers, crude oil, corn, ethanol, futures prices*

Introduction

Agricultural commodity prices have changed considerably during the period 2006-2011, influenced in large part by increasing demand from developing countries, devaluation of the US dollar, supply shocks in key producing regions, strong variability in crude oil prices, and the development of the biofuel industry in the United States. These last two factors have had a considerable impact on the relationships between energy and agricultural markets.

In modern times, agricultural prices have always been linked to energy prices through input costs. However, since at least 2006 the link between energy and agricultural prices has expanded to output prices Balcombe and Rapsomanikis (2008); Campiche, Bryant, Richardson, and Outlaw (2007), largely explained by the tremendous growth of ethanol production as an alternative source of energy.

Corn-based ethanol production is a response to high and volatile crude oil prices. It has been promoted by policies designed to improve U.S. energy security, a search of renewable energy sources, reduction of greenhouse gas emissions, and the development of rural areas. Tax credits, consumption mandates, and high tariffs on foreign ethanol have been implemented as a result.

Figure 1 shows the expansion of the ethanol industry in the U.S. which has been responsible for most of the increase in corn production. In contrast, other uses of corn have remained relatively stable during the last 30 years. Ethanol usage began to increase in the 1990's, expanded dramatically after 2004-2005, and now accounts for 25%-30% of total corn use. Mallory, Hayes, and Irwin (2010) identify that given the current circumstances, if corn is priced at the margin by its value as an input in producing energy, then it should respond to the fundamentals in the energy markets as much as it would respond to fundamentals in the agricultural markets.

To date, most of the studies of the relationship between energy and agricultural commodity prices have focused on two areas, price level transmission (e.g. Serra, Zilberman, Gil, and Goodwin (2010)), and partial or general equilibrium models that examine alternative biofuel policy scenarios (e.g. Yano, Blandford, and Surry (2010); Thompson, Meyer, and Westhoff (2009), less attention has been paid to linkages and spillovers in price volatility.

The stronger linkages between energy and agricultural markets that have been boosted during the biofuel era are creating potential new sources of price uncertainty for market participants and policy makers. Harri, Lanier, and Darren (2009) identify that cross commodity covariances and dynamics have changed in recent years. Volatility spillovers from energy prices also can heighten risk in agricultural markets. Increased price volatility results in greater costs for managing risks, and complicates price discovery and investment choices. In turn, it can potentially influence the cost of food, agricultural and biofuel policies, firm production and business decisions, trade tariffs, hedging, and portfolio strategies. As a consequence, a more complete analysis of volatility can be beneficial to understand the new market dynamics that affect corn and ethanol markets, their interrelationships, and their link to the crude oil market.

The literature on volatility spillover between energy and agricultural markets in the U.S. is scarce. However, previous studies by Wu, Guan, and Myers (2011); Du, Yu, and Hayes (2011); Harri and Darren (2009) find significant volatility linkages between crude oil and corn prices. Although they argue that the relationship is largely explained by ethanol production, ethanol prices are not explicitly included in their analyses. Studies of ethanol price volatility and its relationship with crude oil and corn in the US have been explored by Zhang et al. (2009) . They find little evidence of linkages in either level or volatility among U.S. oil, ethanol, and corn prices before 2007.

There is still much to learn about the nature of volatility transmission from energy to agricultural markets in recent years. We identify the price volatility relationships of ethanol with crude oil and corn in the United States during the period 2006-2011. We provide the effect on an emerging ethanol market which may be useful to ethanol producers and consumers, offering a better understanding of the new linkages that have recently emerged.

To study the volatility linkages we adopt a trivariate model similar to Ng (2000) and Wu, Guan, and Myers (2011). In this model exogenous shocks from the oil market are transmitted to the corn and ethanol markets. Corn and ethanol markets interact, therefore we allow for volatility spillovers between them. The model is sketched in Figure 2. For the estimation we follow a two-stage procedure. In the first stage, a vector error correction model (VECM) of the cointegrated corn and ethanol prices is estimated. In the second stage, we use the residuals from the VECM, to model ethanol and corn volatilities in a Multivariate Generalized Autoregressive Conditional Heteroskedasticy (MGARCH) framework jointly with the exogenous random shock from the crude oil market.

This procedure permits the volatility in crude oil to directly affect the conditional volatility in corn and ethanol. After estimating the spillovers from oil to corn and ethanol, we calculate volatility spillover ratios that give a measure of the relative importance of the crude oil volatility spillover on the overall conditional variance of corn and ethanol. We also explore volatility spillovers between ethanol and corn and the conditional correlation between those commodities.

We begin the analysis in July 2006 and extend the sample through January 2011. We focus our attention on a period of strong price volatility and strong increase in corn based ethanol production in the U.S. We find strong volatility spillovers from crude oil to both corn and ethanol, however the spillover is stronger in the ethanol market. Spillovers between corn and ethanol are also identified, finding significantly larger spillovers from corn to ethanol.

Previous Work

Although volatility spillovers are a relevant economic phenomenon frequently analyzed in the financial markets[1] relatively few studies have examined the volatility transmission between energy and agricultural markets. Due to changing market conditions, growing interest in the research has emerged. Several papers find evidence of volatility linkages from crude oil prices to agricultural commodities during the biofuel era. Wu, Guan, and Myers (2011) identify strong volatility spillovers from crude oil prices to corn cash and futures prices in the U.S. particularly after the introduction of the 2005 Energy Policy Act.

Similarly, Du, Yu, and Hayes (2011) develop a stochastic volatility model to assess the role of various economic factors on oil price variation, finding that speculation, scalping, and petroleum inventories are important components. Further, they detect volatility spillovers among crude oil, corn, and wheat markets, especially after the fall of 2006.

Harri and Darren (2009) evaluate mean and variance dynamics between futures prices of crude oil, corn, and a proxy of exchange rates. They find significant volatility transmission and evidence of crude oil price variance causing variance of corn prices. Although the previous studies assert that the interdependence between corn and energy markets is largely induced by ethanol production, they do not provide direct empirical evidence as ethanol prices are included in the analyses.

Ethanol price volatility and its relationship with corn, soybean, gasoline, and oil in the US are explored by Zhang et al. (2009). They model price volatility by using a GARCH BEKK, splitting their data in two periods: 1989-1999 as the ethanol pre-boom stage, and 2000-2007 as the ethanol boom period. Their results suggest no significant links between oil, ethanol, and corn volatilities in any period. Furthermore, they find no long-run relationships among agricultural and energy price levels in the U.S. which is consistent with other studies for that period.

Serra, Zilberman, and Gil (2010) investigate volatility spillovers between crude oil, ethanol, and sugar prices in Brazil from 2000 to 2008. They provide strong evidence of cointegration between those prices, and use a joint estimation of a vector error correction model and a multivariate GARCH to account for the volatility spillovers. They find that the increased volatility in crude oil markets results in increased volatility in ethanol markets. As well, significant volatility spillovers from Brazilian ethanol to sugar markets exist.

Equilibrium models have also been used to evaluate the ties between energy and agricultural markets. Interesting insights on the effects of price variability and the role of biofuel policies such as tax credit, blending mandate, and consumption mandate have been provided by Yano, Blandford, and Surry (2010), Thompson, Meyer, and Westhoff (2009) and Hertel and Beckman (2011). Their results suggest that high fluctuations in the crude oil price create high variability in the corn price in the absence of mandates. On the other hand, under the mandates, the impact of crude oil prices on corn prices is reduced while the impacts from variations in corn supply on corn prices are increased.

[1] For an excellent survey on volatility transmission literature please consult at Soriano Felipe and Climent Diranzo (2006)

As seen, since the boom in ethanol production, strong linkages between energy and agricultural markets have been identified. However, the results lack an analysis of the relationship of ethanol price volatility with crude oil and corn volatilities under the current policy scenario and market conditions. In the next section we describe our approach to modeling these relationships.

Model

Volatility Spillover Model

To identify and measure volatility spillovers between crude oil (co), corn (c), and ethanol (th) markets (2), we follow an approach similar to the framework used by Ng (2000) and Wu, Guan, and Myers (2011). Here, an external crude oil shock generates spillovers to the corn and ethanol markets, while the corn and ethanol markets interact. The model is specified as:

$$\Delta co_t = e_{co,t} \tag{1}$$

$$\begin{bmatrix} c_t \\ th_t \end{bmatrix} = \begin{bmatrix} \mathrm{E}[c_t|I_{t-1}] \\ \mathrm{E}[th_t|I_{t-1}] \end{bmatrix} + \begin{bmatrix} \varepsilon_{c,t} \\ \varepsilon_{th,t} \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} \varepsilon_{c,t} \\ \varepsilon_{th,t} \end{bmatrix} = \begin{bmatrix} \varphi_t \\ \omega_t \end{bmatrix} e_{co,t} + \begin{bmatrix} e_{c,t} \\ e_{th,t} \end{bmatrix} \tag{3}$$

In Equation (1) the first difference of crude oil log pricesco_t (Δ is is the first difference operator) equals a random shock $e_{co,t}$. This equation is supported by the findings of market efficiency in crude oil markets by Kawamoto and Hamori (2011). Equation (2) defines corn and ethanol prices at time t as the sum of the conditional expectations of prices formed with information at t-1 I_{t-1}, plus random shocks$\varepsilon_{c,t}$, $\varepsilon_{th,t}$. The random shocks of corn and ethanol prices are presented in equation (3). They correspond to the sum of two terms; the first is the product of the exogenous random shock of crude oil by the respective spillover φ_t and ω_t into each market. The second terms are the idiosyncratic errors of corn and ethanol $e_t = [e_{c,t}, e_{th,t}]$. These errors can be mutually correlated but they are uncorrelated to the crude oil innovation.

The volatilities of the model are specified as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e^2_{co_t-1} + \lambda_1 d_{t-1} e^2_{co_t-1} + \alpha_2 \sigma^2_{t-1} \tag{4}$$

$$H_t = C'C + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B \tag{5}$$

In equation (4) crude oil price volatility is modeled as an univariate Threshold Generalized Autoregressive Conditional Heteroskedasticity model (TGARCH). This model allows asymmetry on the random shock, where d_{t-1} is a dummy variable that takes a value of 1 if $e_{co,t} \leq 0$ and 0 otherwise. The volatility of the errors $e_{c,t}$,$e_{th,t}$ is specified using the Baba, Engle, Kraft and Kroner (BEKK) specification of a multivariate GARCH which has two desirable characteristics. It is positive definite by construction and it allows the estimation of the volatility spillovers between corn and ethanol. The BEKK GARCH model is defined in equation (5)[2], where H_t is the BEKK conditional volatility; C is an upper triangular matrix that corresponds to the constant. The squared lagged errors are $e_{t-1}e'_{t-1}$, A is the matrix of ARCH parameters, Ht is the lagged conditional volatility, and B is the matrix of GARCH parameters.

To identify more clearly how the corn and ethanol volatilities interact and to see how corn and ethanol volatilities are influenced by the volatility in the oil market, first consider the bivariate BEKK GARCH from equation (5):

$$\begin{bmatrix} h_{cc,t} & h_{cth,t} \\ h_{thc,t} & h_{thth,t} \end{bmatrix} = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} e^2_{c,t-1} & e_{c,t-1}e_{th,t-1} \\ e_{th,t-1}e_{c,t-1} & e^2_{th,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h^2_{cc,t-1} & h_{cth,t-1} \\ h_{thc,t-1} & h_{thth,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

Matrix multiplication leads to equations (6) and (7), where $h_{cc,t}$, and $h_{thth,t}$ are conditional volatilities of corn (c) and ethanol (th), $h_{cth,t}$ is the conditional covariance, and $e_{ij,t-1}$ (i,j) = c,th are the lagged own squared and cross-market random shocks.

$$\begin{aligned} h_{cc,t} = c^2_{11} + a^2_{11}e^2_{c,t-1} + 2a_{11}a_{21}e_{c,t-1}e_{th,t-1} + a^2_{21}e^2_{th,t-1} + b^2_{11}h_{cc,t-1} + \\ 2b_{11}b_{21}h_{cth,t-1} + b^2_{21}h_{thth,t-1} \end{aligned} \tag{6}$$

$$\begin{aligned} h_{thth,t} = c^2_{12} + c^2_{22} + a^2_{12}e^2_{c,t-1} + 2a_{12}a_{22}e_{c,t-1}e_{th,t-1} + a^2_{22}e^2_{th,t-1} + b^2_{12}h_{cc,t-1} \\ +2b_{12}b_{22}h_{cth,t-1} + b^2_{22}h_{thth,t-1} \end{aligned} \tag{7}$$

Now take the square of equation (3) and under the assumption of no correlation between $e_{co,t}$ and $e_t = [e_{th,t}, e_{c,t}]$ the conditional variances of ethanol and corn are given by:

$$\mathrm{E}(\varepsilon^2_{th,t}|I) = h_{cc,t} + \varphi^2_t\sigma^2_t \tag{8}$$

$$\mathrm{E}(\varepsilon^2_{c,t}|I) = H_{thth,t} + \omega^2_t\sigma^2_t \tag{9}$$

Where the signs and significance of φ and ω determine whether volatility spillovers from crude oil markets exist (Wu, Guan, and Myers, 2011).

Data and Preliminary Analysis

Data are from the Office of Futures and Options Research (OFOR). It consist of nearby daily closing futures log prices of crude oil West Texas Intermediate (CO) from NYMEX, ethanol (TH) from CBOT, and corn (C) from CBOT, for the period July 30, 2006 to January 19, 2011. That

[2]The asymmetry of the GARCH BEKK was tested by a LM test. The null hypothesis of the asymmetric parameters equal to zero cannot be rejected, given that the log likelihood of the restricted and unrestricted models is virtually the same.

corresponds to the period of increased volatility spillovers between crude oil and corn identified in the literature.

It could be argued that U.S. ethanol has not been included in previous volatility spillovers studies because representative market prices are hard to obtain and the futures contract is thinly traded. However, Dahlgran (2010) argues despite an open interest in ethanol futures that is a small fraction of annual U.S. usage, the ethanol futures market is efficient.

Figure 3 shows the prices normalized by their own means and Table 1 presents summary statistics of log prices, and returns. Crude oil and corn prices exhibit a larger range and variance than ethanol during the period. However, the coefficient of variation for ethanol prices and returns is higher than those for crude oil and corn prices and returns, suggesting that ethanol are more volatile per unit of return than the other two commodities. Returns are virtually mean reverting, which is a signal of market efficiency. Skewness results suggest that prices and returns are relatively symmetrically distributed. Finally, kurtosis results suggest that prices are not normally distributed. Returns of crude oil and ethanol are normal while corn returns tend to be platykurtic. As a result we assume that the random shocks of our model follow a t-distribution.

Figure 4 shows the prices and returns dynamics of crude oil, ethanol, and corn from July 2006 to January 2011. Crude oil price has been upward sloping for most of the period except for the steep decrease from summer 2008 until spring 2009. Crude oil price is strongly influenced by monetary and macroeconomic factors such as business cycles and exchange rates, coupled with the increased demand of newly industrialized countries, and a likely diminishment in production as indicated by Hamilton (2011). Returns variability for oil is high and clustered during the price decrease and the recovery.

Corn prices and returns at the bottom of Figure 4 present similar dynamics to crude oil prices in some periods, particularly from fall 2007 to the end of 2008. In November 2008 we see crude oil prices fall and after February 2009 start to increase. Corn prices seem to move within a price band, but in summer 2010 start to escalate. Similar to crude oil returns, corn and ethanol returns exhibited more volatility during the steep price decrease in 2008. After fall 2007, the co-movements between ethanol and corn prices are more consistent.

In Table 1 we see significant and substantial correlations between prices and returns, particularly in prices where all the correlations exceed 0.55. The correlation declines for returns, this could be partly explained by common trends shared by the prices which are likely to be integrated of order (1).

Unit Root and Cointegration Tests

Augmented Dickey Fuller (ADF) and Phillips-Perron unit root test are performed. Results suggest that the prices are non-stationary. Meanwhile, returns reject the null of non-stationarity. (See Table 7 in the appendix). Six lags for the ADF test were chosen by AIC model selection criterion. We also examined the ACF and PACF to ensure the residuals are white noise.

Table 2 shows the results of the Johansen test of cointegration for the three bivariate relationships. The test strongly rejects the null hypothesis of no cointegration between prices of corn and ethanol, therefore a long-run equilibrium relationship between these two variables during the period September 2006 to January 2011 is found. The other two bivariate relationships crude oil price-ethanol price and crude oil price-corn price cannot reject no cointegration at 10% level.

Estimation

For equation (1), the first difference of crude oil log prices, we include 5 own lags to obtain white noise residuals which are used to estimate equation (4). For equation (2), since there is strong evidence of cointegration between corn and ethanol a vector error correction model (VECM) is estimated. Model selection criterion (AIC) is used to determine lags, the VECM is represented as:

$$\Delta c_t = \pi_1 ECT_{1,t-1} + \sum_{i=1}^{5} \beta_i \Delta c_t + \sum_{i=1}^{5} \gamma_i \Delta th_t + \varepsilon_{c_t,t} \tag{10}$$

$$\Delta th_t = \pi_2 ECT_{2,t-1} + \sum_{i=1}^{5} \delta_i \Delta c_t + \sum_{i=1}^{5} \phi_i \Delta th_t + \varepsilon_{th,t} \tag{11}$$

The estimation of equations (10) and (11) generates residuals that are then used to jointly estimate equations (3) and (5) using a quasi-maximum likelihood procedure. This two-stage procedure is commonly used, and although it is consistent it may not be efficient.

We assume error process for equations (4) and (5) to follow a t-distribution, and allow the quasi-maximum likelihood procedure to obtain the shape of the distribution that provides the best fit to the series. Diagnostic tests, including portmanteau test, ARCH-LM, normality, and inspection for stationarity (i.e., modulus of the eigenvalues), suggested no misspecification [3]. For equations (6) and (7) we take the product of the matrix multiplication of equation (5) and compute its standard errors by the delta method. The calculations of equations (8) and (9) follow directly from the estimated results.

Results

Table 3 presents the results of the vector error correction model and Granger causality tests. Results indicate unidirectional Granger causality from corn to ethanol prices. Diagnostic tests of the VECM show no evidence of autocorrelation, however there is evidence of ARCH effects.

The results in Table 5 provide the estimates of the spillovers from crude oil to corn φ and crude oil to ethanol ω jointly with the BEKK coefficients of the idiosyncratic errors of corn and ethanol. Strongly significant spillover coefficients confirm the existence of volatility linkages from crude oil markets, with spillovers to corn being slightly higher than the spillover to ethanol. The TGARCH is used to estimate the conditional volatility of crude oil. Results in Table 4 suggest a strong asymmetry in the ARCH component of the model-negative innovations generate a bigger impact on volatility than positive shocks. The GARCH component indicates a significant and relatively

[3]Diagnostic test can be requested to the authors

long lasting effect of the random shocks. The conditional of the crude oil is plotted in Figure 5. The largest conditional volatility is observed during the financial crisis at the end of 2008 and the recovery period in spring 2009.

Volatility Spillover Ratios

We measure the strength of the volatility transmission from crude oil to corn and ethanol by calculating volatility spillover ratios, which are defined as::

$$\frac{\varphi_t^2 \sigma_t^2}{h_{cc,t} + \varphi_t^2 \sigma_t^2} \in [0, 1] \tag{12}$$

$$\frac{\omega_t^2 \sigma_t^2}{h_{thth,t} + \omega_t^2 \sigma_t^2} \in [0, 1] \tag{13}$$

These ratios measure the share of crude oil markets shocks on the overall volatility in corn and ethanol markets at different points in time, and are plotted in Figure 5.

As expected, the spillover effect from the crude oil to corn and ethanol followed the dynamics of the conditional volatility of crude oil. Volatility spillover ratios were usually smaller than 20% but went as high as 50% during the financial crisis and the recovery period of 2008-2009. Even though the spillover ratios to ethanol and corn seem to be similar in size, ethanol exhibited higher ratios during most of the sample period. It is clear than ethanol and corn volatilities are strongly influenced by crude oil volatility and tend to move together. However, particularly in the later part of the period (February-March 2010 and June 2010) spillovers to ethanol market appear to be considerably larger.

Recall that the corn and ethanol idiosyncratic errors are uncorrelated to crude oil errors, but corn and ethanol errors are allowed to correlate with one another. This allows us to identify volatility spillovers between corn and ethanol. To allow a direct interpretation of the coefficients of the conditional volatilities of corn and ethanol, we calculated the parameters of equations (6) and (7) that are presented in Table 6.

Table 6 is divided in two parts. The top of Table 6 provides the corn conditional variance, $h_{cc,t}$ Most of the volatility in corn is market specific, since the effect of the own lagged squared errors a_{11}^2, and the conditional lagged variance b_{11}^2 are highly significant. Ethanol appears to affect corn volatility only indirectly through the covariance, since the coefficient $2b_{11}b_{21}$ is significant and negative. Meanwhile, the direct effect a_{21}^2 from the ethanol market innovation is not significant, and the indirect effect $2a_{11}a_{21}$ is only significant 10%. The bottom of Table 6 provides the ethanol conditional variance, $h_(thth, t)$. Here, own significant ARCH and GARCH effects also exist. But, with the exception of the effect of the lagged corn volatility b_{12}^2, strong spillovers from corn to ethanol volatility are present.

To further explore the interactions between corn and ethanol, we inspect their conditional correlations obtained from the GARCH BEKK, which is displayed in Figure 6. Although time varying, the correlations suggest a stronger relationship has emerged between corn and ethanol markets particularly after the fall of 2007. This is consistent with the closeness of the volatility spillovers from crude oil and the cointegrating relationships; it is evident that these markets have become more closely related during the biofuel era.

Conclusions

Volatility spillovers from energy to agricultural markets are an economic phenomenon that has gained importance in recent years. Since volatility in the agricultural markets incorporates fluctuations from energy markets, high variability in crude oil prices, and an enhanced connection between these markets, leads to added uncertainty.

Previous literature shows evidence of strong and increasing volatility spillovers between crude oil and corn in the U.S. in particular after the introduction of the Energy Policy Act of 2005. However, little is known of the relationships of ethanol price volatility with crude oil and corn volatilities in the United States. In this paper we fill this gap using a trivariate model that links exogenous crude oil random shocks to corn and ethanol innovations during the 2006-2011 period.

In contrast to Zhang et al. (2009) we find strong volatility spillovers from crude oil market to the corn and ethanol markets. The volatility spillover ratios are rather similar in magnitude over time in both markets, but with a stronger effect in the ethanol market. The effect of crude oil price volatility on corn and ethanol volatilities has usually been below 20%, but during periods of high turbulence in the crude oil market, volatility of corn and ethanol has been higher and more responsive, with volatility spillover ratios as high as 50%.

Volatility spillovers between corn and ethanol also exist, however the corn to ethanol spillovers are significant while spillovers from ethanol to corn are only modest at best. An explanation of this finding is that corn is a larger and more diversified market that has several sources of uncertainty such as exports and feed markets. On the other hand, ethanol is a protected market by high tariffs in the U.S., and blending and consumption mandates may give a reasonable expectation of production. Therefore, ethanol's sources of uncertainty are likely to come mainly from energy and corn price volatility.

The evidence suggests that corn and ethanol are becoming more closely connected as measured by the changes in their conditional correlations, by the cointegrating relationship, and by systematic nature of the volatility spillovers from the crude oil market. The knowledge of these strong systematic linkages may provide useful information to producers and consumer not only in the corn market but particularly in the ethanol market. Understanding volatility transmission from crude oil and corn has important implications to the agents in the ethanol markets, playing a role on investment and hedging decisions, and in the definition of biofuel policies.

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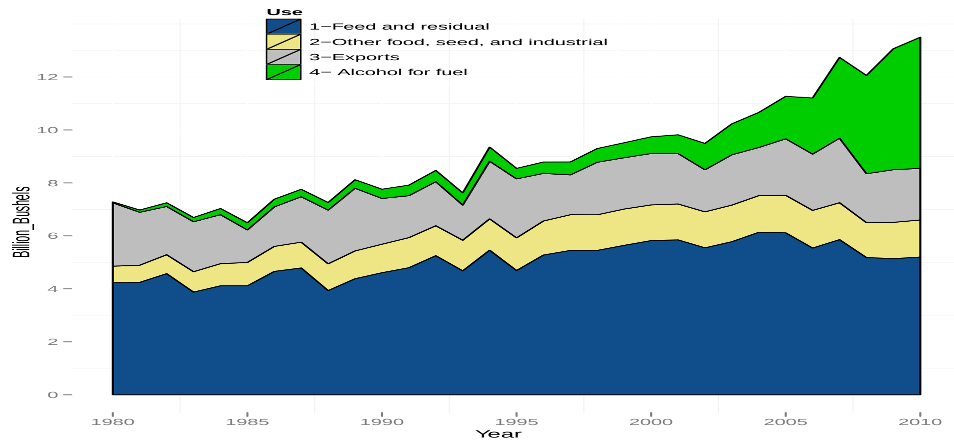
Figures and Tables

Figure 1: US Corn Use



Source:USDA

Figure 2: Volatility Transmission Model

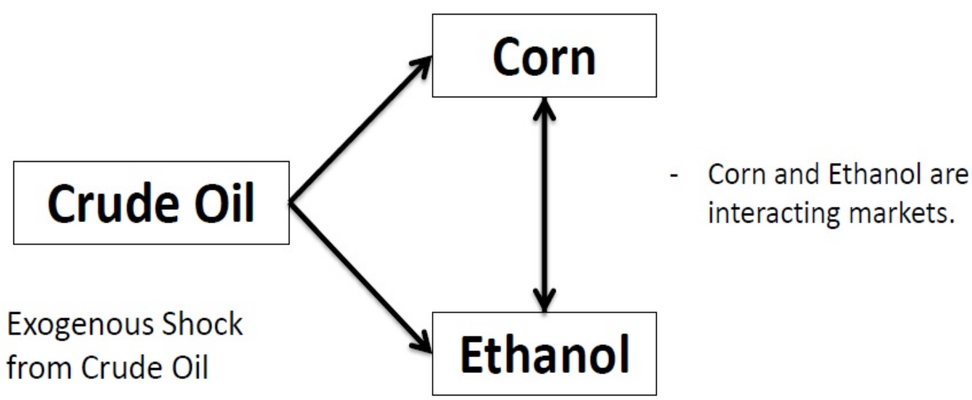


Figure 3: Prices Divided by Mean

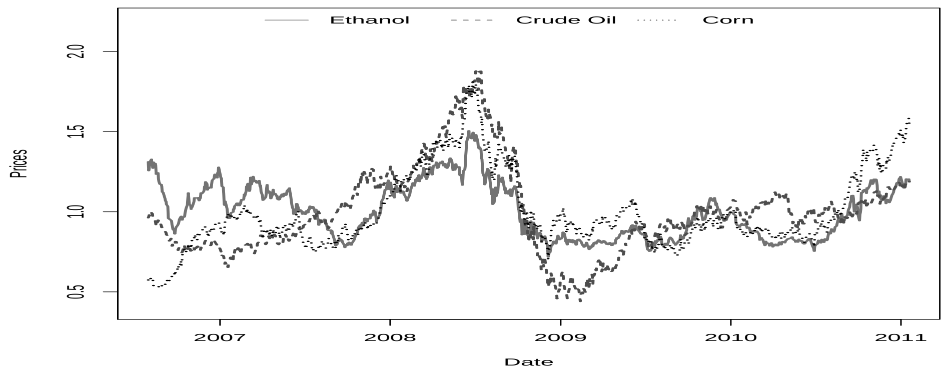


Figure 4: LogPrices, and Returns

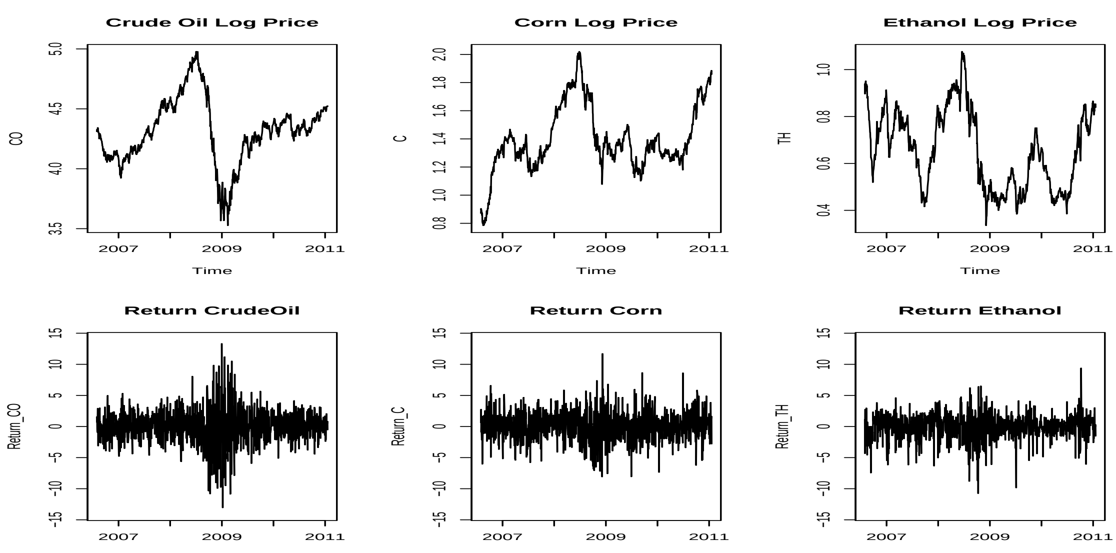


Figure 5: Conditional Standard Error of Crude Oil and Spillover Ratios of Corn and Ethanol

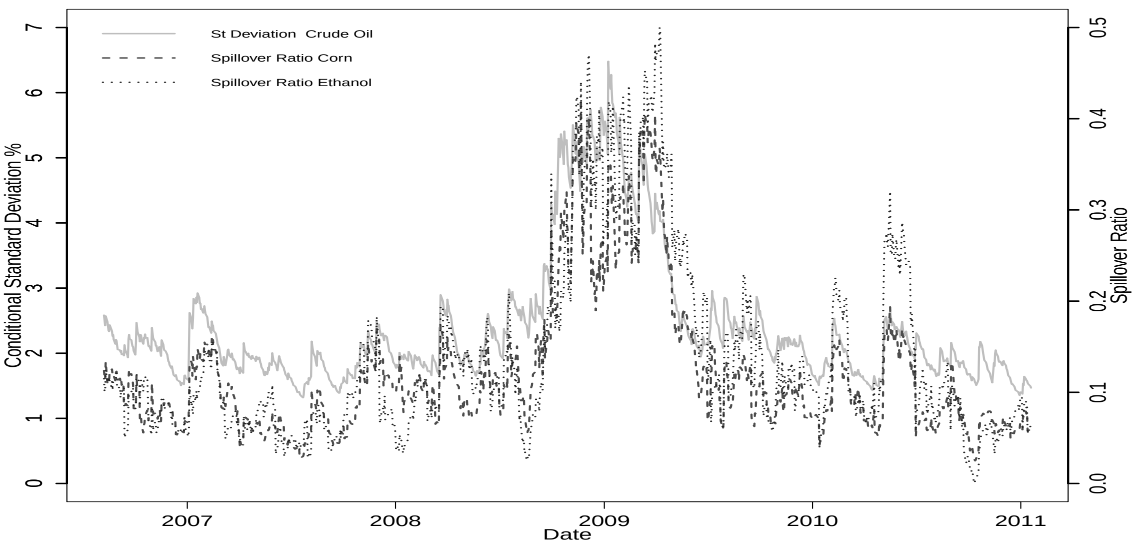


Figure 6: Correlation BEKK

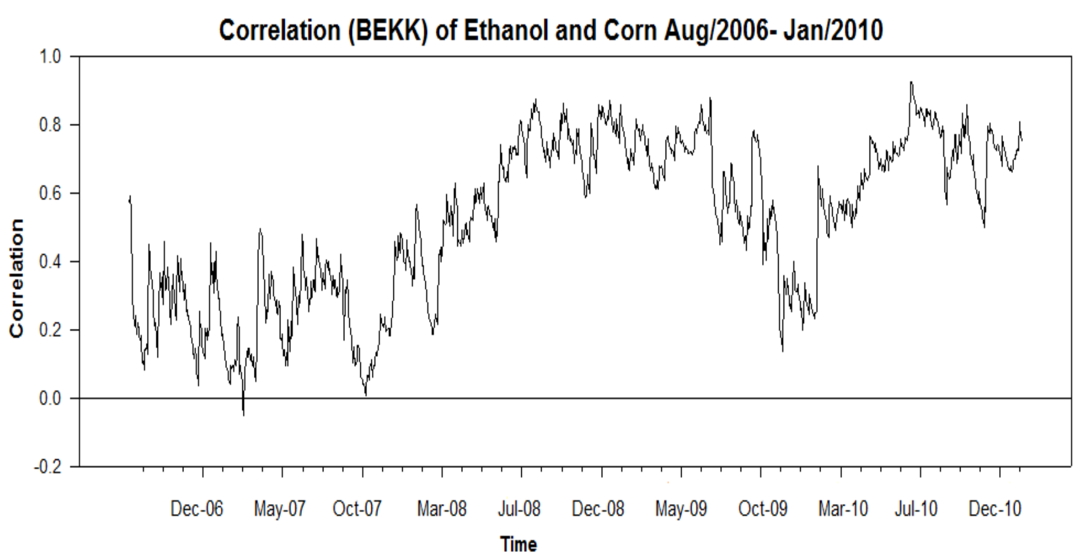


Table 1: Summary Statistics and Correlations

	Crude Oil	Ethanol	Corn	Returns Crude Oil	Returns Ethanol	Returns Corn
nobs	1127	1127	1127	1127	1127	1127
Minimum	3.53	0.34	0.78	-13.07	-10.78	-8.10
Maximum	4.98	1.08	2.02	13.34	9.40	11.72
1. Quartile	4.14	0.49	1.27	-1.41	-0.99	-1.16
3. Quartile	4.46	0.79	1.52	1.48	1.14	1.51
Mean	4.31	0.65	1.40	0.02	-0.01	0.09
Median	4.31	0.65	1.35	0.08	0.11	0.06
SE Mean	0.01	0.00	0.01	0.08	0.06	0.07
LCL Mean	4.30	0.64	1.39	-0.13	-0.12	-0.05
UCL Mean	4.33	0.66	1.41	0.17	0.11	0.22
Variance	0.07	0.03	0.05	6.99	3.75	5.31
Stdev	0.27	0.16	0.23	2.64	1.94	2.30
Skewness	-0.04	0.25	0.32	-0.10	-0.71	-0.02
Kurtosis	0.27	-1.01	0.24	3.05	3.15	1.29
Coef. Variation	0.06	0.25	0.17	1.32	2.43	0.26

Correlations	Crude Oil	Ethanol		Returns Crude Oil	Returns Ethanol
Ethanol	0.575*		Ret Ethanol	0.448*	
Corn	0.612*	0.570*	Ret Corn	0.375*	0.552*

Prices are in logs. Returns are multiplied by 100. * Sign. at 1%

Table 2: Johansen Tests for Cointegration Rank

a) Variables: Corn and Ethanol						Lags: 6	
	Eigen	Trace Stat	95% CV	99% CV	Max Stat	95% CV	99% CV
r0	0.0202	26.68	19.96	24.60	22.89	15.67	20.20
r1	0.0034	3.79	9.24	12.97	3.79	9.24	12.97
b) Variables: CrudeOil and Corn						Lags:2	
	Eigen	Trace Stat	95% CV	99% CV	Max Stat	95% CV	99% CV
r0	0.0083	12.49	19.96	24.60	9.37	15.67	20.20
r1	0.0028	3.12	9.24	12.97	3.12	9.24	12.97
c) Variables: Crude Oil and Ethanol						Lags: 6	
	Eigen	Trace Stat	95% CV	99% CV	Max Stat	95% CV	99% CV
r0	0.0078	10.96	19.96	24.60	8.75	15.67	20.20
r1	0.0020	2.21	9.24	12.97	2.21	9.24	12.97

Table 3: Vector Error Correction for Log Prices of Corn and Ethanol

$$\Delta c_t = \sum_{i=1}^{5} \beta_i \Delta c_t + \sum_{i=1}^{5} \beta_i \Delta th_t + \varepsilon_{c_t,t} + \pi_1 ECT1_{t-1}$$

$$\Delta th_t = \sum_{i=1}^{5} \gamma_i \Delta c_t + \sum_{i=1}^{5} \gamma_i \Delta th_t + \varepsilon_{th,t} + \pi_2 ECT2_{t-1}$$

Dependent Variable Δc_t

Variable	Coeff	Std Error	T-Stat	Signif
$\Delta Ethanol_{t-1}$	-0.0182	0.0434	-0.4182	0.6759
$\Delta Ethanol_{t-2}$	-0.0431	0.0432	-0.9986	0.3182
$\Delta Ethanol_{t-3}$	-0.0070	0.0430	-0.1634	0.8702
$\Delta Ethanol_{t-4}$	-0.0333	0.0431	-0.7737	0.4393
$\Delta Ethanol_{t-5}$	-0.0317	0.0430	-0.7364	0.4616
$\Delta Corn_{t-1}$	0.0295	0.0361	0.8168	0.4142
$\Delta Corn_{t-2}$	0.0169	0.0361	0.4695	0.6388
$\Delta Corn_{t-3}$	0.0326	0.0360	0.9047	0.3658
$\Delta Corn_{t-4}$	0.0467	0.0360	1.2977	0.1946
$\Delta Corn_{t-5}$	-0.0148	0.0360	-0.4127	0.6799
$ECT1_{t-1}$	0.0006	0.0007	0.9115	0.3622

Dependent Variable : Δth_t

Variable	Coeff	Std Error	T-Stat	Signif
$\Delta Ethanol_{t-1}$	-0.0150	0.0359	-0.4181	0.6759
$\Delta Ethanol_{t-2}$	0.0319	0.0357	0.8948	0.3711
$\Delta Ethanol_{t-3}$	0.0585	0.0356	1.6434	0.1006
$\Delta Ethanol_{t-4}$	0.0639	0.0356	1.7947	0.0730
$\Delta Ethanol_{t-5}$	-0.0698	0.0356	-1.9621	0.0500
$\Delta Corn_{t-1}$	0.0256	0.0299	0.8563	0.3920
$\Delta Corn_{t-2}$	-0.0062	0.0298	-0.2078	0.8354
$\Delta Corn_{t-3}$	0.0062	0.0298	0.2082	0.8351
$\Delta Corn_{t-4}$	0.0351	0.0298	1.1783	0.2389
$\Delta Corn_{t-5}$	0.0757	0.0297	2.5448	0.0111
$ECT2_{t-1}$	-0.0019	0.0006	-3.3526	0.0008

Test for Granger-Causality:

H0: Corn do not Granger-cause Ethanol	
Test statistic =	2.1254
pval-F(1; 6, 2210) =	0.0476
H0: Ethanol do not Granger-cause Corn	
Test statistic =	0.6586
pval-F(1; 6, 2210) =	0.6832

Table 4: TGARCH for Crude Oil

Equation 4: $\sigma_t^2 = \alpha_0 + \alpha_1 e_{co_t-1}^2 + \lambda_1 d_{t-1} e_{co_t-1}^2 + \alpha_2 \sigma_{t-1}^2$				
Variable	Coeff	Std Error	T-Stat	Signif
α_0	0.0000	0.0000	2.2897	0.0220
α_1	0.0260	0.0170	1.5304	0.1259
λ_1	0.0757	0.0253	2.9885	0.0028
α_2	0.9219	0.0195	47.1770	0.0000

Table 5: GARCH BEKK

Equation 5: Corn = c, Ethanol=th $H_t = C'C + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B$				
Variable	Coeff	Std Error	T-Stat	Signif
φ	0.0034	0.0002	14.4166	0.0000
ω	0.0029	0.0002	16.0378	0.0000
C(c,c)	0.0046	0.0010	4.7963	0.0000
C(th,c)	0.0033	0.0007	5.0155	0.0000
C(th,th)	0.0000	0.0008	0.0000	0.9996
A(c,c)	0.2257	0.0351	6.4227	0.0000
A(c,th)	0.0578	0.0265	2.1768	0.0295
A(th,c)	0.0929	0.0442	2.1011	0.0356
A(th,th)	0.2614	0.0407	6.4272	0.0000
B(c,c)	0.9578	0.0128	74.9127	0.0000
B(c,th)	-0.0249	0.0093	-2.6629	0.0077
B(th,c)	-0.0329	0.0143	-2.3032	0.0213
B(th,th)	0.9514	0.0129	73.8438	0.0000

Table 6: BEKK Conditional Variances

Equations 6 and 7: (Corn = c, Ethanol = th)

$$h_{cc,t} = c_{11}^2 + a_{11}^2 e_{c,t-1}^2 + 2a_{11}a_{21}e_{c,t-1}e_{th,t-1} + a_{21}^2 e_{th,t-1}^2 + b_{11}^2 h_{cc,t-1} + 2b_{11}b_{21}h_{cth,t-1} + b_{21}^2 h_{thth,t-1}$$

$$h_{thth,t} = c_{12}^2 + c_{22}^2 + a_{12}^2 e_{c,t-1}^2 + 2a_{12}a_{22}e_{c,t-1}e_{th,t-1} + a_{22}^2 e_{th,t-1}^2 + b_{12}^2 h_{cc,t-1} + 2b_{12}b_{22}h_{cth,t-1} + b_{22}^2 h_{thth,t-1}$$

$h_{cc,t}$		c_{11}^2	a_{11}^2	$2a_{11}a_{21}$	a_{21}^2	b_{11}^2	$2b_{11}b_{21}$	b_{21}^2
Value		0.0000	0.0510	0.0261	0.0086	0.9174	-0.0631	0.0011
t-Statistic		2.3982	3.2113	1.7042	1.0505	37.4564	-2.3347	1.1516
S.E.		0.0000	0.0159	0.0153	0.0082	0.0245	0.0270	0.0009
Signif .		0.0165	0.0013	0.0883	0.2935	0.0000	0.0196	0.2495
$h_{thth,t}$	c_{12}^2	c_{22}^2	a_{12}^2	$2a_{11}a_{22}$	a_{22}^2	b_{12}^2	$2b_{12}b_{22}$	b_{22}^2
Value	0.0000	0.0000	0.0578	0.0302	0.2614	0.0006	-0.0473	0.9514
t-Statistic	2.3982	0.0000	2.1768	2.2989	6.4272	1.3314	-2.7026	73.8438
S.E.	0.0000	0.0000	0.0265	0.0131	0.0407	0.0005	0.0175	0.0129
Signif.	0.0165	0.9996	0.0295	0.0215	0.0000	0.1830	0.0069	0.0000

Appendix

Table 7: ADF and Phillips Perron Tests

ADF Test					
Variable.Model	Lags	tValue	1pct	5pct	10pct
Crude Oil.none	5	0.31	-2.58	-1.95	-1.62
Crude Oil.drift	5	-1.94	-3.43	-2.86	-2.57
Crude Oil.trend	5	-1.95	-3.96	-3.41	-3.12
Return Crude Oil.none	4	-5.52	-2.58	-1.95	-1.62
Return Crude Oil.drift	4	-5.53	-3.43	-2.86	-2.57
Ethanol.none	6	-0.05	-2.58	-1.95	-1.62
Ethanol.drift	6	-2.04	-3.43	-2.86	-2.57
Ethanol.trend	6	-2.12	-3.96	-3.41	-3.12
Return Ethanol.none	5	-13.4	-2.58	-1.95	-1.62
Return Ethanol.drift	5	-13.4	-3.43	-2.86	-2.57
Corn.none	1	0.86	-2.58	-1.95	-1.62
Corn.drift	1	-1.93	-3.43	-2.86	-2.57
Corn.trend	1	-1.95	-3.96	-3.41	-3.12
Return Corn.none	1	-23.03	-2.58	-1.95	-1.62
Return Corn.drift	1	-23.06	-3.43	-2.86	-2.57

Phillips Perron Test			
	Lags	Statistic	P-val
Crude Oil Long Lags	21	-1.62	0.74
Crude Oil Short Lags	7	-1.53	0.78
Return Crude Oil Long Lags	21	-34.92	0.01
Return Crude Oil Short Lags	7	-34.97	0.01
Ethanol Long Lags	21	-2.24	0.48
Ethanol Short Lags	7	-2.12	0.53
Return Ethanol Long Lags	21	-33.34	0.01
Return Ethanol Short Lags	7	-33.25	0.01
Corn Long Lags	21	-2.04	0.56
Corn Short Lags	7	-1.94	0.60
Return Corn Long Lags	21	-32.89	0.01
Return Corn Short Lags	7	-32.82	0.01