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

Andrés Trujillo-Barrera, Mindy Mallory, and Philip Garcia

This article analyzes recent volatility spillovers in the United States from crude oil using futures prices. Crude oil spillovers to both corn and ethanol markets are somewhat similar in timing and magnitude, but moderately stronger to the ethanol market. The shares of corn and ethanol price variability directly attributed to volatility in the crude oil market are generally between 10%-20%, but reached nearly 45% during the financial crisis, when world demand for oil changed dramatically. Volatility transmission is also found from the corn to the ethanol market, but not the opposite. The findings provide insights into the extent of volatility linkages among energy and agricultural markets in a period characterized by strong price variability and significant production of corn-based ethanol.

Key words: biofuels, corn, crude oil, energy-agricultural co-movements, ethanol, multivariate GARCH, volatility spillovers

Introduction

Recently, agricultural commodity prices have exhibited considerable variability. Sumner (2009) argues that the percentage price increases for grains from 2006 through mid-2008 were among the largest in history. Then in the summer of 2008 prices fell sharply but recovered swiftly, and have exhibited unusually large and sustained volatility to the present (Wright, 2011). As seen in figure 1, from 1980 to 2005 historical corn volatility—measured as the annualized standard deviation of daily percentage price changes—was usually below 25%, but since 2006 it has increased, reaching levels above 40%. Prakash (2011) corroborates this volatility for corn as well as for other agricultural commodities using the implied volatility from options.

The current literature offers multiple possible reasons for strong recent fluctuations in agricultural commodity prices (Baffes, 2011; Wright, 2011; Gilbert and Morgan, 2010; Irwin and Good, 2009). Researchers have identified rapid economic growth in developing countries, underinvestment in agriculture, low inventory levels, supply shocks in key producing regions, fiscal expansion and lax monetary policy in many countries, the depreciation of the U.S. dollar, high energy prices, and the diversion of food crops into the production of biofuels as contributing to increased volatility. A focal point for understanding the increased price variability is the change in the relationship among energy and agricultural markets influenced by policies to stimulate ethanol production (Hertel and Beckman, 2011; Tyner, 2010; Muhammad and Kebede, 2009).

Energy costs have traditionally influenced agricultural markets, but with the growth in corn-based ethanol production as an energy source (figure 2), the relationships among these markets appear to have strengthened. Since ethanol is a substitute for petroleum-based motor fuel and corn

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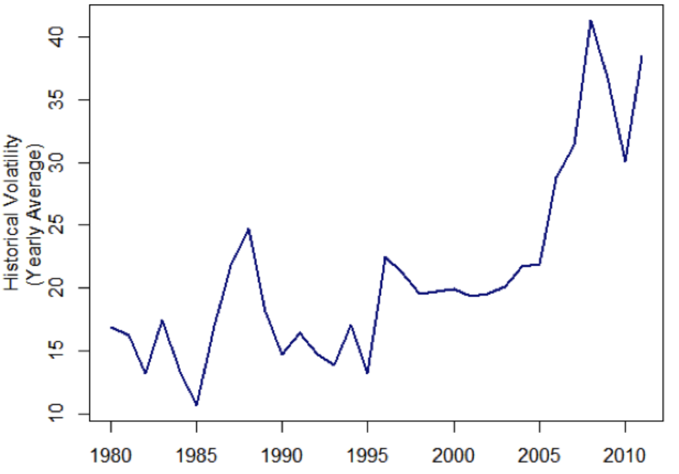

Figure 1: Annual Corn Volatility, 1980-2011

Notes: Historical volatility is the standard deviation of the daily percentage price change using nearby futures settlement prices (CME).

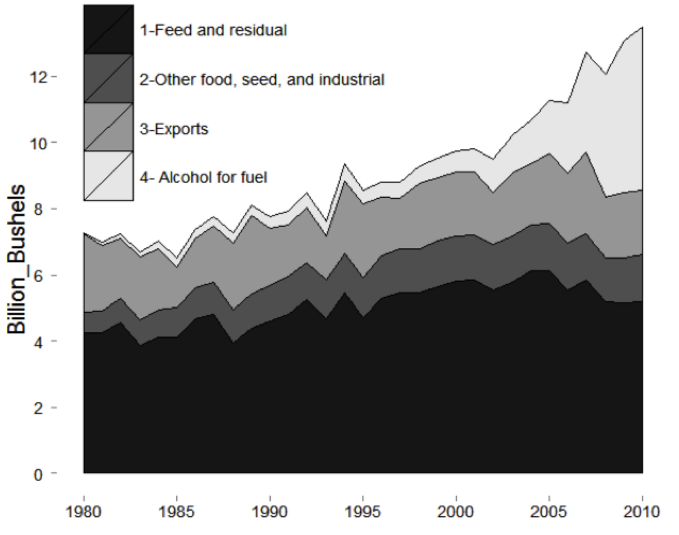

Figure 2: U.S. Corn Use, 1980-2010

is an input in ethanol production, general equilibrium economic models predict that equilibrium petroleum-based energy prices, ethanol, and corn can be viewed as jointly determined (Cui et al., 2011). However, petroleum-based energy markets are much larger than the ethanol and corn markets, suggesting in practice that the direction of causality should run from crude oil to the corn and ethanol markets. Indeed, considerable applied research has explored this hypothesis in domestic and foreign markets (Campiche et al., 2007; Balcombe and Rapsomanikis, 2008). Most studies focused on price level transmission (Serra et al., 2010) and on equilibrium analysis of alternative biofuel policy scenarios (Yano, Blandford, and Surry, 2010; Thompson, Meyer, and Westhoff, 2009).

Less attention has been paid to understanding price volatility (i.e., the conditional variance of price changes, which is viewed as risk), its transmission among these markets, and the degree to which volatility in the energy complex contributed to the recent variability in agricultural commodity prices. Volatility spillover occurs when price volatility in one market affects price volatility in others. We investigate volatility spillover from crude oil to corn and ethanol in U.S. markets in order to identify the degree to which systematic variability in oil prices has contributed to variability in corn and ethanol prices.

Zhang et al. (2009) find little evidence of linkages in either price-level or volatility among U.S. oil, ethanol, and corn prices for the period 1989-2007. In contrast, Wu, Guan, and Myers (2011), Du, Yu, and Hayes (2011), and Harri and Darren (2009) find significant volatility linkages between crude oil and corn prices in more recent years. However, these researchers do not incorporate ethanol prices despite arguing that the relationship is largely explained by ethanol production. We complement this work by evaluating volatility spillovers to the ethanol market and identifying the direction and strength of the spillovers between corn and ethanol. Additionally, we extend the previous literature by examining these relationships during and after the 2009 financial crisis.

Using a trivariate model (Ng, 2000; Wu, Guan, and Myers, 2011), we find volatility linkages from crude oil market to corn and ethanol markets during 2006-2011, during which corn-based ethanol production accounted for 25-35% of total corn use. The volatility spillovers are particularly strong when the oil market price plummeted during the financial crisis, with higher impact in the ethanol market than in the corn market. Significant spillovers also existed from the corn to ethanol market. The strong linkages among these markets, mixed with high price volatility, create new sources of uncertainty for market participants and policy makers. High volatility results in greater costs for managing risks in productive activities, complicates price discovery and investment choice, and ultimately may affect the cost of food in domestic and world markets.

Background and Previous Work

Studies by Tothova (2011) and Hertel and Beckman (2011) illustrate that crude oil and agricultural commodity prices exhibited relatively low or even negative correlation prior to 2006. However, the combination of high oil prices and ethanol policies has fueled the growth of the ethanol industry, which currently consumes nearly one third of corn produced in the United States. Ethanol production in the United States increased from 3.4 billion gallons in 2004 to 13.8 billion gallons in 2011, while the price of corn doubled. Virtually all ethanol produced is blended into gasoline, contributing 13.19 billion gallons to the 138.50 billion gallons of gasoline consumed in the United States in 2010 (U.S. Energy Information Administration, 2012).

Policy has played a crucial role in stimulating ethanol production growth. Import tariffs and blenders fuel tax credits (per gallon tax credit was \$.51 per gallon before 2009 and \$.45 per gallon after 2009) made added output attractive to refiners. Legislation to improve energy security and to reduce air pollution was key to ethanol market expansion (Muhammad and Kebede, 2009). The Energy Policy Act in 2005 established the Renewable Fuel Standard (RFS) program, which mandated that a minimum of 7.5 billion gallons of renewable fuels be incorporated into gasoline supply by 2012. In December 2007, a new RFS was passed under the Energy Independence and Security Act, mandating renewable fuels production of 12 billion gallons by 2012 and 36 billion gallons by 2022.

Ethanol production also has been spurred by the need for an oxygenate to replace Methyl Tertiary Butyl Ether (MTBE) in gasoline blends. MTBE, a petroleum-based oxygenate, was blended with gasoline as a substitute for lead to prevent pre-ignition pinging and to reduce pollution. However, MTBE was banned by many states because of suspected links between cancer and groundwater contamination caused by fuel spills. The elimination of MTBE and its replacement by ethanol were accelerated by the 2005 Energy Policy Act, which made refiners continuing to use MTBE liable for claims (Serra et al., 2011). In the presence of these links among energy and agricultural markets, we expect volatility in crude oil prices to spill over into the corn and ethanol markets, creating volatility there as well.

Zhang et al. (2009) explore ethanol price volatility and its relationship with corn, soybean, gasoline, and oil in the United States by employing a multivariate GARCH framework and using weekly wholesale prices between 1989 and 2007. They split 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 among oil, ethanol, and corn volatilities in either period. Furthermore, they find no long-run relationships among agricultural and energy price levels.

Du, Yu, and Hayes (2011) investigate the spillover of crude oil prices to agricultural commodity prices using stochastic volatility models and weekly crude oil, corn, and wheat futures prices between November 1998 and January 2009. Consistent with Zhang et al. (2009), they find no evidence of spillover for the earlier portion of their sample (through October 2006). However, between October 2006 and January 2009 the results indicate significant volatility spillover from the crude oil market to the corn market, which they explain by tightened interdependence between these markets induced by ethanol production. Despite identifying the statistical link between these markets, the extent of the relationship was not clearly determined.

Wu, Guan, and Myers (2011) draw conclusions similar to those of Du, Yu, and Hayes (2011) using weekly data from January 1992 to June 2009. Using a model in which exogenous oil market shocks influence the corn market, they provide a metric to quantify the strength of the volatility spillovers and find evidence of significant spillovers from crude oil prices to U.S. corn spot and futures prices, particularly after the introduction of the Energy Policy Act of 2005. Harri and Darren (2009) also provide insights to the mean and variance dynamics among futures prices of crude oil, corn, and a proxy for exchange rates with daily observations from April 2003 until March 2009. They find significant volatility transmission and evidence of crude oil price variance causing variance of corn prices.

Equilibrium models and simulations have also been used to evaluate the ties among energy and agricultural markets. Many researchers have offered insights on the effects of price variability and the role of biofuel policies such as tax credits and mandates (e.g., Thompson, Meyer, and Westhoff, 2009; Yano, Blandford, and Surry, 2010; Hertel and Beckman, 2011). Researchers have identified strong linkages among energy and agricultural markets, but their results do not analyze the relationship of ethanol price volatility to crude oil and corn volatilities under recent policy scenarios and market conditions.

Volatility Spillover Model

To identify and measure volatility spillovers between crude oil (co), corn (c), and ethanol (th) markets, we use an approach similar to 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:

$$\Delta co_t = E[\Delta co_t \mid I_{t-1}] + e_{co,t}, \tag{1}$$

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

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

In equation (1) the change of crude oil prices (Δ is the first difference operator), co_t, equals a conditional expected change in crude oil prices formed with information at $t-1$, I_{t-1}, plus random shock, $e_{co,t}$. 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 $\varepsilon_{c,t}$, $\varepsilon_{th,t}$. Equation

(3) defines the random shocks of corn and ethanol prices, which correspond to the sum of two terms; the first is the product of the exogenous random shock of crude oil, $e_{co,t}$, and the respective spillover coefficient, ϕ and ω, for each market. The second terms are the idiosyncratic errors of corn and ethanol $\boldsymbol{e}_t = [e_{c,t}, e_{th,t}]$, which can be mutually correlated but are uncorrelated to the crude oil innovation. Hence, the overall behavior of price shocks in the corn and ethanol markets, $\begin{bmatrix} \varepsilon_{c,t} \\ \varepsilon_{th,t} \end{bmatrix}$, is affected by shocks in the crude oil market and in their own markets, which are not independent of each other but do not affect the crude oil market.[1]

To identify the overall effect, we need to specify the structure of the conditional variance of crude oil (i.e., $e_{co,t}$) and the relationship between the conditional variances in the corn and ethanol markets (i.e., $\boldsymbol{e}_t = [e_{c,t}, e_{th,t}]$) over time. We specify these as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{co,t-1}^2 + \lambda_1 d_{t-1} e_{co,t-1}^2 + \alpha_2 \sigma_{t-1}^2, \tag{4}$$

$$\boldsymbol{H}_t = \boldsymbol{C}'\boldsymbol{C} + \boldsymbol{A}'\boldsymbol{e}_{t-1}\boldsymbol{e}_{t-1}'\boldsymbol{A} + \boldsymbol{B}'\boldsymbol{H}_{t-1}\boldsymbol{B}, \tag{5}$$

where $\boldsymbol{H}_t$ is the BEKK conditional volatility, $\boldsymbol{C}$ is an upper triangular matrix that corresponds to the constant, $\boldsymbol{e}_{t-1}\boldsymbol{e}_{t-1}'$ are the squared lagged errors, $\boldsymbol{A}$ is the matrix of ARCH parameters, $\boldsymbol{H}_{t-1}$ is the lagged conditional volatility, and $\boldsymbol{B}$ is the matrix of GARCH parameters.[2] Equation (4) models crude oil price volatility as a univariate Asymmetric Generalized Autoregressive Conditional Heteroskedasticity model (GJR-GARCH) introduced to the literature by Glosten, Jagannathan, and Runkle (1993). This model allows asymmetry on the random shock, where d_{t-1} is a dummy variable that takes a value of 1 if $e_{co,t-1} \leq 0$, and 0 otherwise. The volatility of the errors $e_{c,t}$ and $e_{th,t}$ 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. Equation (5) defines The BEKK GARCH model.

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

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

Matrix multiplication leads to:

$$\begin{aligned}
h_{cc,t} = {} & c_{11}^2 + a_{11}^2 e_{c,t-1}^2 + 2a_{11}a_{21}e_{c,t-1}e_{th,t-1} + a_{21}^2 e_{th,t-1}^2 + b_{11}^2 h_{cc,t-1} + \\
& 2b_{12}b_{22}h_{cth,t-1} + b_{22}^2 h_{thth,t-1},
\end{aligned} \tag{6}$$

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

[1] This reflects the notion that an OPEC announcement can impact corn and ethanol markets, and that weather information for the growing period in South America may affect U.S. corn and ethanol markets, but South American weather is highly unlikely to affect the oil market.

[2] Asymmetry of the GARCH BEKK was not supported using a LM test.

where $h_{cc,t}$ and $h_{thth,t}$ are conditional idiosyncratic volatilities of corn (c) and ethanol (th), $h_{cth,t}$ is the conditional covariance, and $e_{ij,t}(i,j) = c, th$ are the lagged own squared and cross-market random shocks. Taking the square of equation (3) and under the assumption of no correlation between $e_{co,t}$ and e_t the conditional variances of ethanol and corn are given by:

$$E(\varepsilon_{c,t}^2 \mid I_{t-1}) = h_{cc,t} = \phi^2 \sigma_t^2, \tag{8}$$

$$E(\varepsilon_{th,t}^2 \mid I_{t-1}) = h_{thth,t} = \omega^2 \sigma_t^2, \tag{9}$$

where the significance of ϕ^2 and ω^2 determine whether volatility spillovers from crude oil markets exist. Volatility spillovers between corn and ethanol are determined by the signs and significance of the terms in equations (6) and (7).

Data and Preliminary Analysis

Data are the nearby mid-week closing futures (Wednesday) 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 November 9, 2011.[3] This corresponds to a period of strong demand for corn-based ethanol production and sharp and substantial changes in oil prices.

Crude oil, corn, and ethanol prices are available for differing contract months. To develop a conformable and continuous price series, we use the closing prices of the contract months for the commodity with the fewest contracts, which is corn. The corn market has five contracts maturing in December, March, May, July, and September. As the contract comes to maturity, the series is rolled forward to the price of the next closest contract. We do this on the third business day prior to the 25th calendar day of the month preceding the delivery month to avoid price anomalies that can sometimes occur in the delivery month. Since a portion of the analysis requires differenced data which are useful to examine, we define weekly percentage price changes, called returns, as $R_t = \log P_t - \log P_{t-1}$. These are computed by using the closing prices of futures contracts.[4]

Figure 3 shows the prices divided by their own means, which allows us to graph the price series on the same scale. Table 1 presents summary statistics of log prices and returns. The coefficients of variation of ethanol prices and returns are higher than those for crude oil and corn, suggesting that ethanol exhibits higher volatility. The means of the returns are virtually zero, and skewness results suggest that prices and returns are relatively symmetrically distributed. Excess kurtosis indicates that prices are not normally distributed.

Figure 4 illustrates the prices and returns dynamics of crude oil, ethanol, and corn. Crude oil displayed a positive trend in prices beginning at the end of 2006 until summer 2008, followed by a steep decrease lasting until spring 2009. The financial crisis that dampened worldwide demand for oil was one of the main causes of the sharp decline. However, crude oil prices rebounded and by fall 2009 were back to 2006 observed levels. Since that point, crude oil prices have exhibited considerable variability. Returns variability for crude oil is high and clustered during the price decline and recovery.

Corn and ethanol prices and their returns exhibit similar dynamics to crude oil, particularly from fall 2007 to the end of 2008. Corn prices fell sharply in fall 2008, similar to crude oil prices, until spring 2009. During 2009 and part of 2010 prices appeared to move within a band, but in summer 2010 they escalated again. By 2011 prices were near the same levels observed prior to the financial crisis. Ethanol prices follow a similar patterns, but exhibit more price variability during 2009 and 2010. Despite the difference in variability, more co-movement between ethanol and corn

[3] Dahlgran (2010) argues that despite an open interest that is a small fraction of annual U.S. usage, the ethanol futures contract is reflective of market conditions. In our analysis, we explored the robustness of our findings looking at daily, weekly, and weekly average data to assess the potential effects of limited liquidity in the ethanol market. Results are very similar.

[4] The term "returns" is used in the literature to refer to the percentage change in value of holding an asset for a period of time, and here is synonymous with the weekly percentage price change.

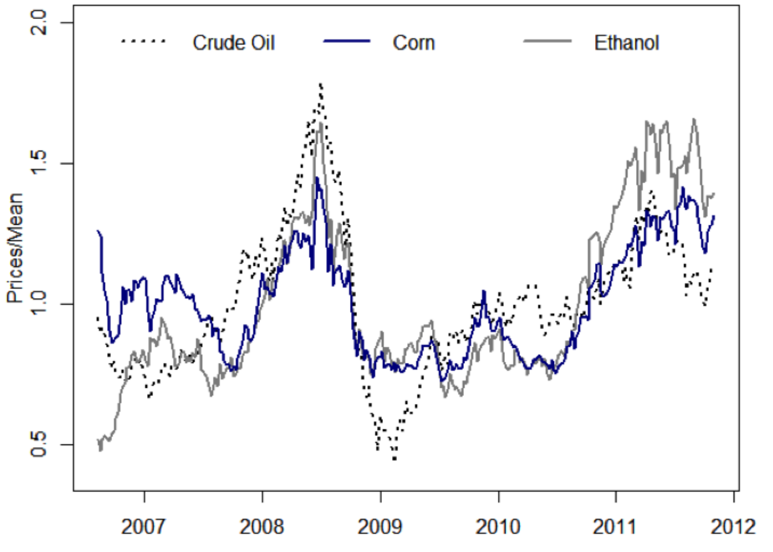

Figure 3: Prices Divided by Own Mean

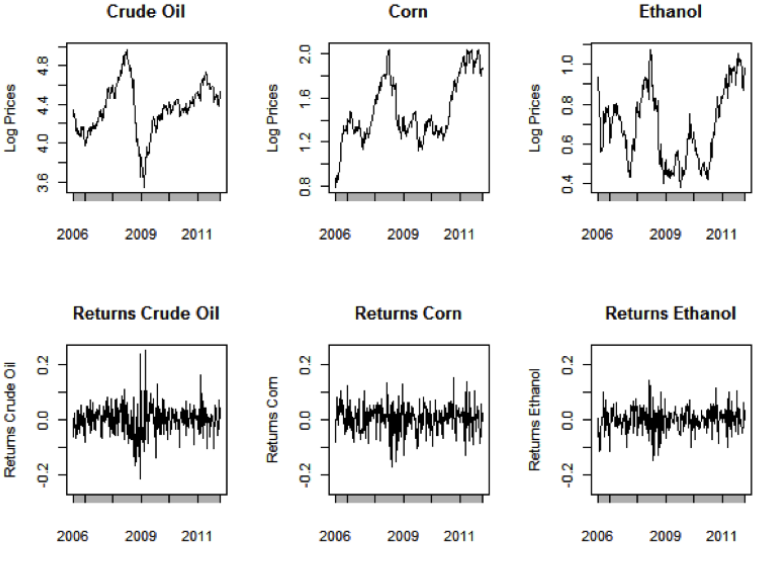

Figure 4: Log Price and Returns

prices appears to exist starting in fall 2007. Similar to crude oil returns, corn and ethanol returns exhibited more volatility during the steep decline in prices. Table 1 shows significant and substantial correlations between prices and returns, in particular a strong correlation between corn and ethanol.

We perform Augmented Dickey Fuller (ADF) and Phillips-Perron unit root tests. Results suggest that the prices are nonstationary, but returns are stationary.[5] Lags for the ADF test were chosen by AIC model selection criterion, and the ACFs and PACFs also were examined to ensure the residuals were white noise.

[5] Test results are available from the authors on request.

Table 1: Summary Statistics and Correlations (N = 274)

				Returns		
Statistics	**Crude Oil**	**Ethanol**	**Corn**	**Crude Oil**	**Ethanol**	**Corn**
Minimum	3.54	0.38	0.80	−21.23	−14.74	−16.89
Maximum	4.97	1.08	2.04	25.46	14.16	15.30
1st Quartile	4.18	0.51	1.29	−3.23	−2.43	−2.67
3rd Quartile	4.52	0.83	1.75	3.50	2.70	3.49
Mean	4.35	0.69	1.49	0.07	0.02	0.35
Median	4.36	0.67	1.39	0.46	0.04	0.75
Variance	0.07	0.03	0.08	0.30	0.19	0.26
SD	0.26	0.18	0.28	5.44	4.37	5.12
Skewness	−0.27	0.20	0.33	0.21	−0.18	−0.27
Excess kurtosis	0.18	−1.19	−0.75	3.28	0.98	0.66
Coeff. Variation	0.06	0.27	0.19	74.79	232.60	14.65

	Correlations		**Returns**	
	Crude Oil	**Ethanol**	**Crude Oil**	**Ethanol**
Ethanol	0.64***		0.44***	
Corn	0.66***	0.78***	0.36***	0.60***

Notes: Crude oil, ethanol, and corn prices are in logs, and the returns are multiplied by 100. Triple asterisks (***) represent significance at the 1% level.

Table 2: Johansen Cointegration Tests

	(a) Corn and Ethanol						
		Trace	**Critical Value**		**Max**	**Critical Value**	
Cointegration Rank	**Eigen**	**Statistic**	**95%**	**99%**	**Statistic**	**95%**	**99%**
None	0.098	32.09***	19.96	24.60	28.09***	15.67	20.20
At most 1	0.015	3.99	9.24	12.97	3.99	9.24	12.97
	(b) Crude Oil and Corn						
		Trace	**Critical Value**		**Max**	**Critical Value**	
Cointegration Rank	**Eigen**	**Statistic**	**95%**	**99%**	**Statistic**	**95%**	**99%**
None	0.039	16.08	19.96	24.60	10.55	15.67	20.20
At most 1	0.002	5.53	9.24	12.97	5.53	9.24	12.97
	(c) Crude Oil and Ethanol						
		Trace	**Critical Value**		**Max**	**Critical Value**	
Cointegration Rank	**Eigen**	**Statistic**	**95%**	**99%**	**Statistic**	**95%**	**99%**
None	0.008	8.95	19.96	24.60	6.39	15.67	20.20
At most 1	0.002	2.56	9.24	12.97	2.56	9.24	12.97

Notes: Triple asterisks (***) represent significance at the 1% level. Lag length was selected based on AIC.

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 corn and ethanol prices, supporting the presence of a long-run equilibrium relationship between these two markets. We cannot reject the null hypothesis of no cointegration at the 10% level for the other two bivariate relationships: crude oil-ethanol and crude oil-corn.

Estimation

For equation (1), the first difference of crude oil log prices, we include three own lags to obtain white noise residuals, which are used to estimate equation (4). For equation (2), a vector error correction model (VECM) is estimated since there is strong evidence of cointegration between corn and ethanol. Findings from (Mallory, Irwin, and Hayes, forthcoming 2012) also support a long-run equilibrium relationship between ethanol and corn. Model selection criterion (AIC) is used to determine lags; the VECM is represented as:

$$\Delta c_t = \pi_1 ECT_{t-1} + \sum_{i=1}^{2} \beta_i \Delta c_{t-1} + \sum_{i=1}^{2} \gamma_i \Delta th_{t-i} + \varepsilon_{ct,t}, \tag{10}$$

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

where ECT_{t-1} denotes the error correction term. Estimating equations (10) and (11) generates residuals that are the estimates of the corn and ethanol shocks presented in equation (3). These are used to jointly estimate equations (3) and (5) using a quasi maximum likelihood procedure. While not efficient, this two-stage procedure is asymptotically consistent and is commonly used because it avoids convergence and local maxima problems Silvennoinen and Terasvirta (2009).

For equations (10), (11), and (for consistency) (1), we used the continuous price series described earlier. The procedure used to generate the series can create artificial jumps in the data that correspond to the rollover dates, which could potentially affect the results. As identified by Carchano and Pardo (2009), there is no established method to account for the rollover effect when creating a continuous price level series. Here we follow Bessler and Covey (1991) and Franken, Parcell, and Tonsor (2011) to assess the potential effects. To test whether the jumps at contract rollover affect our results, we include dummy variables for the rollover dates in the cointegration tests, the corresponding vector error correction model, and in the GJR-GARCH and BEKK estimations. We find the dummy variables to be insignificant in general and to have no effect on the results of the analysis.

Based on the characteristics of the series, we assume the error process for equations (4) and (5) 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.[6] For equations (6) and (7), we take the product of the matrix multiplication of equation (5) and compute its standard errors using the delta method. The calculations of equations (8) and (9) follow directly from the estimated results.

Estimation Results

The GJR-GARCH is used to estimate the conditional volatility of crude oil. Results in table 3 suggest asymmetry in the ARCH component of the model. Negative innovations generate a bigger impact on volatility than positive shocks; in this case, λ_1 is not only larger than α_1, but λ_1 is highly statistically significant, while α_1 is not. The GARCH component indicates that the random shocks have a significant and relatively long-lasting effect. The conditional standard errors of the crude oil market are 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. Table 4 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, but there is evidence of ARCH effects.

[6] Diagnostic tests are available from the authors on request.

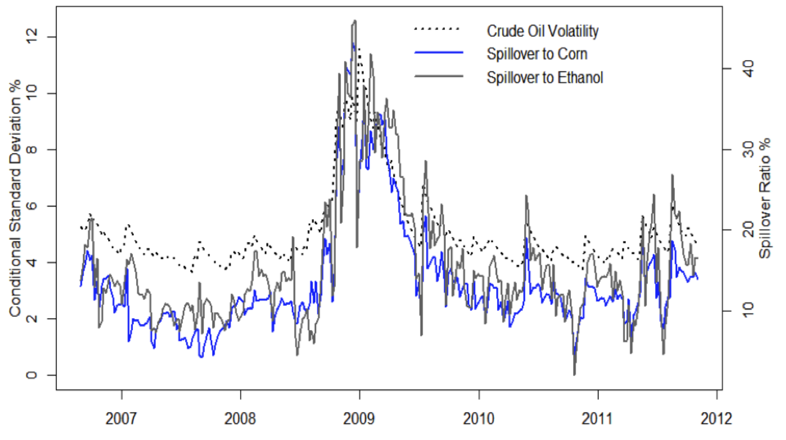

Figure 5: Conditional Standard Error of Crude Oil and Corn and Ethanol Spillover Ratios

Table 3: GJR-GARCH for Crude Oil

Variable	Coeffcient	t-Statistic
α_0	0.00	1.77
α_1	0.00	0.43
λ_1	0.14**	2.11
α_2	0.88**	15.78

Notes: Double asterisks (**) represent significance at the 5% level.

The results in table 5 provide the estimates of the price shocks spillovers from crude oil to corn, ϕ, and crude oil to ethanol, ω, with the BEKK coefficients of the idiosyncratic errors of corn and ethanol. Strongly significant spillover coefficients confirm the existence of volatility linkages from the crude oil market, with spillovers to corn being higher than the spillover to ethanol.

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:

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

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

Figure 5 plots these ratios, which measure the portion of the conditional variability in corn and ethanol prices attributable to crude oil price shocks at different points in time. The spillover effect from the crude oil to corn and ethanol follows the dynamics of the conditional volatility of crude oil. During the period of analysis, volatility spillover ratios from crude oil averaged 14% for corn and 16% for ethanol, displaying a large range between 4% and 44%. However, the histograms (figure 6) and summary statistics of the spillover ratios (table 6)—in particular their interquartile ranges—suggest that during the period 2006-2011 crude oil shocks have consistently been responsible for 10% to 20% of the conditional volatility of corn and ethanol.

Further, figure 5 shows that particularly after the 2009 financial crisis period, volatility spikes in crude oil seem to be closely linked to the peaks in spillover ratios, occasionally reaching more than

Table 4: Vector Error Correction for Corn and Ethanol Prices

	Dependent Variable: Δc_t	
Variables	**Coefficients**	**t-Statistic**
ΔCorn_{t-1}	0.09	1.17
ΔCorn_{t-2}	0.02	0.23
$\Delta \text{Ethanol}_{t-1}$	−0.17	−1.92
$\Delta \text{Ethanol}_{t-2}$	0.15	1.69
ECT_{t-1}	0.01	1.32
	Dependent Variable: Δth_t	
Variables	**Coefficients**	**t-Statistic**
ΔCorn_{t-1}	0.17***	2.63
ΔCorn_{t-2}	0.05	0.73
$\Delta \text{Ethanol}_{t-1}$	−0.11	−1.50
$\Delta \text{Ethanol}_{t-2}$	−0.00	−0.05
ECT_{t-1}	−0.01***	−3.07
Test for Granger-causality:		
H_0: Corn does not Granger-cause Ethanol		
Test statistic	3.67	
p-value	0.01	
H_0: Ethanol does not Granger-cause Corn		
Test statistic	2.47	
p-value	0.06	

Notes: Triple asterisks (***) represent significance at the 1% level.

Table 5: BEKK GARCH

Variable	**Coefficients**	**t-Statistic**
ϕ	0.36***	6.85
ω	0.30***	7.31
C(c,c)	0.03***	4.75
C(th,c)	0.02***	4.71
C(th,th)	0.00	0.00
A(c,c)	0.45***	4.32
A(c,th)	0.22***	2.34
A(th,c)	−0.12	−1.16
A(th,th)	0.24***	2.63
B(c,c)	0.78***	9.53
B(c,th)	−0.17***	−2.51
B(th,c)	−0.14	−1.18
B(th,th)	0.77***	6.58
ϕ^2	0.13***	3.42
ω^2	0.09***	3.65

Notes: Triple asterisks (***) represent significance at the 1% level.

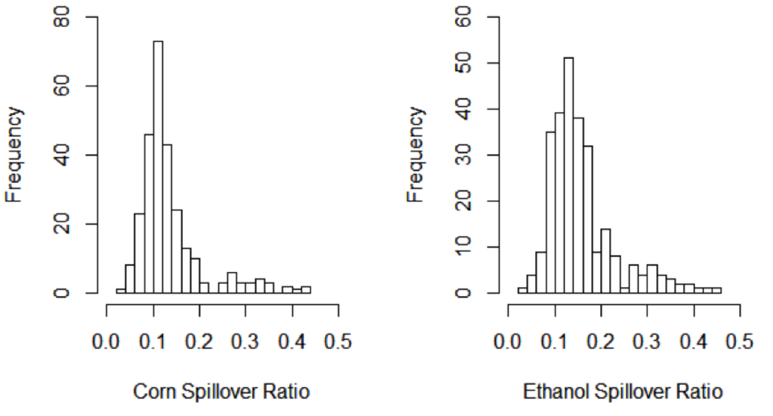

Figure 6: Histograms of Ethanol and Corn Spillover Ratios, 2006-2011

Table 6: Summary Statistics of Volatility Spillover Ratios (N = 271)

	Estimated Corn Spillover Ratio	**Estimated Ethanol Spillover Ratio**
Minimum	0.04	0.05
Maximum	0.43	0.44
1st Quartile	0.10	0.11
3rd Quartile	0.15	0.18
Mean	0.14	0.16
Median	0.12	0.14
SD	0.07	0.07
Skewness	2.01	1.55
Excess kurtosis	4.18	2.42

20%. Virtually all the spillover ratios higher than 20% took place after the sharp decline of oil prices in 2008. This is more noticeable for ethanol, where its interquartile range shows that spillover ratios higher than 18% took place in 25% of the occurrences. It is clear that ethanol and corn volatilities are strongly influenced by crude oil volatility and tend to move together. Although the spillover ratios to ethanol and corn seem similar in size, ethanol exhibited higher ratios during most of the sample period.

To investigate the volatility spillovers between the corn and ethanol markets, we calculate the parameters of equations (6) and (7). The top of table 7 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 does not affect corn volatility since coefficients a_{21}^2, $2a_{11}a_{21}$, $2b_{11}b_{21}$, and b_{21}^2 are not significant. The bottom of table 7 provides the ethanol conditional variance, $h_{thth,t}$. Here, own significant GARCH effects exist. The coefficients $2a_{12}a_{22}$ and $2b_{12}b_{22}$ show strong spillovers from corn to ethanol volatility.

To further investigate the interactions between corn and ethanol, we provide their conditional correlations obtained from the GARCH BEKK (figure 7). Although time varying, the correlations suggest a stronger relationship between corn and ethanol markets, particularly starting in 2008. This is consistent with the observed similarity in spillovers from crude oil to the two markets and the cointegrating relationship estimated; it is evident that these markets have been closely related in recent years. Finally, to identify the economic magnitude of the increased risk associated with the volatility spillovers for participants in corn and ethanol markets, consider their impact on the price of a corn option (table 8). Begin with the price of an at the money call option on a corn futures contract

Figure 7: BEKK Correlation between Ethanol and Corn

Table 7: BEKK Conditional Variances

				Conditional Variance of Corn				
$h_{cc,t}$		c_{11}^2	a_{11}^2	$2a_{11}a_{21}$	a_{21}^2	b_{11}^2	$2b_{11}b_{21}$	b_{21}^2
Coefficients		0.00***	0.20***	0.20	0.01	0.62***	−0.22	0.02
t-Statistics		2.38	2.16	1.58	0.58	4.76	−1.24	0.59
				Conditional Variance of Ethanol				
$h_{thth,t}$	c_{12}^2	c_{22}^2	a_{12}^2	$2a_{12}a_{22}$	a_{22}^2	b_{12}^2	$2b_{12}b_{22}$	b_{22}^2
Coefficients	0.00***	0.00***	0.06	0.11***	0.06	0.03	−0.27***	0.60***
t-Statistics	2.37	0.00	1.17	2.50	1.31	1.25	−2.82	3.29

Notes: Triple asterisks (***) represent significance at the 1% level.

Table 8: Economic Magnitude of the Volatility Spillovers in the Corn Market

No Spillover from Oil		**With 15% Spillover from Oil**		**With 45% Spillover from Oil**	
Corn Volatility	**B-S Call Price**	**Corn Volatility**	**B-S Call Price**	**Corn Volatility**	**B-S Call Price**
25%	\$0.34/bushel	28%	\$0.39/bushel	34%	\$0.47/bushel
	\$1,700/contract		\$1,950/contract		\$2,350/contract

Notes: Risk free interest rate = 5%, corn futures price = \$5.00, and strike price = \$5.00 for 6 months to maturity. Annualized corn conditional volatility = $\sqrt{h_{cc,t} + \phi^2\sigma_t^2}\sqrt{52}$.

six months from maturity that is trading at \$5.00 per bushel. In the absence of volatility spillover from the oil market and annualized volatility in the corn market of 25%, the Black-Scholes price of the option is \$0.34 per bushel. Here, we estimated that a typical spillover during the period 2006-2011 from oil to corn was approximately 15%. This translates into an annualized corn volatility of 28% with the option price increasing from \$0.34 to \$0.39 per bushel. Therefore, a typical spillover represents an increase on cost of the option of 14% from the baseline, which is equivalent to \$250 per contract. During the height of the volatility, we estimated that spillovers from the oil to the corn market were nearly 45%. In this case the at the money call option price increases from \$0.34 to \$0.47 per bushel, which represents an increase of 38% in the cost of the option. This translates into a \$650 per contract increase in the cost of the option due to volatility spillover from the oil market during the financial crisis.

Conclusions and Remarks

Using a trivariate model, we identify volatility spillovers from the crude oil futures market to ethanol and corn futures markets during 2006-2011, a period when corn-based ethanol production reached

25-35% of total corn use and the oil market experienced dramatic changes. We find strong and varying volatility transmission from crude oil to the corn and ethanol markets, with moderately more intense effects emerging in the ethanol market. The effect of crude oil price volatility on corn and ethanol averaged almost 15%, but reached 45% during periods of high variability in the crude oil market. At the maximum, the added volatility as a result of the spillover would have resulted in a 38% cost increase to users of corn options. Spillovers also existed from the corn to ethanol market, but there was no evidence of spillovers from ethanol to corn. This transmission is consistent with causality tests performed on the level data and with the idea that the corn market is able to absorb short-run shocks in demand from the energy sector more readily than the ethanol market, because grain can be reallocated from other uses such as exports, feed, food, and stocks. Evidence from the cointegrating relationship, the changes in conditional correlations (particularly after mid-2008), and the systematic nature of the spillovers from the crude oil market indicate that the corn and ethanol markets have been closely connected during the period.

In light of the increased variability, risk management strategies become more important to decision makers. For private decision makers there is evidence that instruments such as the futures market still can offer hedging opportunities (Wu, Guan, and Myers, 2011), but it is clear that the changing nature of the volatilities places a high value on the use of time-vary hedging strategies. Options strategies can also be powerful tools in an environment of high price volatility. For instance, a long straddle position that involves the simultaneous purchase of an at the money call option and a put option can be profitable when prices are rapidly changing. Recently, new risk management instruments such as Volatility Index Futures (VIX) for crude oil and corn also have been introduced at the Chicago Mercantile Exchange. VIX contracts are designed to manage short-term volatility, and their payoffs are determined by changes in volatility. Wang, Fausti, and Qasmi (2012) argue that the Corn VIX will improve volatility forecasting and enhance market participants' ability to more accurately gauge price risk in the corn market. Over-the-counter variance swaps allow users to trade future realized volatility against current implied volatility. It remains to be seen if the liquidity and performance of these instruments will be sufficient for managing this added market risk.

Developing an understanding of magnitude and timing of market shocks is an important dimension of risk management. Clearly, the effect of crude oil price and biofuel policies on corn and ethanol price volatility is highly dependent on the market context. The main biofuels policy instruments during the period were the blender's tax credit, the Renewable Fuel Standard, and the import tariffs. The subsidy increased demand for ethanol, which in turn increased ethanol and corn prices. The import tariff limited competition with Brazilian ethanol and reduced the market's ability to handle potential unexpected supply disruptions. However, the tariff likely had only a small impact on price volatility during 2006-2011 (Babcock, 2011). In a forward context, the blender tax credit and the import tariffs were eliminated by the end of 2011. Under the mandate, a minimum quantity of ethanol must be consumed, regardless of fuel, corn, and ethanol prices. As processors respond to the changes in the oil market, increases in required ethanol production over time may support the added volatility identified here. However, when the mandate is binding, corn feedstock demand sensitivity to ethanol and energy price shocks will be reduced (Yano, Blandford, and Surry, 2010).

Developing a sense of timing for risk management purposes may be more problematic, since it is difficult to anticipate shocks and their more lasting effects. Government policies to promote market transparency by improving information and surveillance systems (e.g., IFPRI's Early Warning System) may enable better monitoring of market situations and permit quick response. In addition, since conditional volatility tends to cluster, the information of crude oil volatility combined with volatility spillover ratios to corn and ethanol can be seen as a step towards monitoring and anticipating volatility shocks and their transmission.

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