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Asymmetric Price Volatility Transmission between U.S. Biofuel, Corn, and Oil Markets

Sayed Saghaian, Mehdi Nemati, Cory Walters, and Bo Chen

Linkages between agricultural commodity and energy prices have become more complex with increased ethanol production. The concern is whether the new corn–ethanol links lead to volatility-spillover transmission between food and energy prices. We investigate asymmetric volatility spillovers between oil, corn, and ethanol prices using a BEKK-multivariate-GARCH approach. Additionally, we use daily, weekly, and monthly futures prices to examine whether the use of different-frequency data leads to inconsistent results. The results support the existence of asymmetric volatility transmission between corn and ethanol prices. Furthermore, the volatility-spillover effects are different for the different-frequency prices, and positive and negative price changes generate inconsistent results.

Key words: asymmetric BEKK-MGARCH modeling, biofuel, corn prices, crude oil prices, ethanol prices

Introduction

The literature points to several factors as sources of increased volatility in agricultural commodity prices in recent years. One of the most-stated causes is the increase in corn-based ethanol production and the new food and ethanol linkages (Serra, 2013; Balcombe, 2011; Wright, 2011; Irwin and Good, 2009). The increased links between energy and agricultural markets raise concerns about whether new corn–ethanol links lead to volatility-spillover effects between prices of energy and agricultural commodities.

Increased food-price volatility and its detrimental effects have profound economic implications, raising concerns among consumers, producers, and policy makers. High price volatility heightens food security concerns for the poor and income stability issues for farmers. It adversely affects poor consumers' incomes and purchasing power, pushing them further into poverty, undernourishment, and hunger. It makes it difficult for farmers to make production plans and investment decisions. The quick and unexpected changes in food prices can interrupt markets, affecting social stability and government policy.[1] Hence, the massive increase in U.S. ethanol production raises the need for a deeper understanding of its effects on price volatility in food crops from which ethanol is produced. de Gorter, Drabik, and Just (2015) argue that studying these effects is important in order to understand changes in the prices of food, such as corn.

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[1] There is plenty of research on the links between food price volatility and political instability (e.g., de Gorter, Drabik, and Just, 2015).

The literature on price links between energy and agricultural commodity markets has grown (Serra, Zilberman, and Gil, 2011), but it mostly focuses on price levels (Serra and Zilberman, 2013). However, some argue food price volatility is a greater danger than high food prices (de Gorter, Drabik, and Just, 2015). In addition, while there is little evidence that food and biofuel price increases have the same effects as price decreases (Serra and Zilberman, 2013), the literature on asymmetric volatility interaction is scarce and mostly ignores the impact of asymmetric transmission. With asymmetric volatility spillovers, the burden and benefits of sudden price changes distribute unevenly across markets and could have welfare implications for producers as well as consumers. We found only two studies that address asymmetric price volatility: one using oil, rapeseed, and biodiesel data from Germany (López Cabrera and Schulz, 2016), and another using biodiesel blend and refined-sunflower oil prices from Spain (Abdelradi and Serra, 2015). We found no study addressing asymmetric price volatility spillovers between U.S. energy (oil and ethanol) and agricultural commodity markets.

In this research, we use an asymmetric multivariate-GARCH (MGARCH) model to assess the volatility-spillover effects between oil, ethanol, and corn prices. We investigate whether U.S. ethanol and corn-price volatility interactions respond differently to price increases and decreases. It is unclear whether ethanol price variation is higher during price increases or whether ethanol price increases have a stronger impact on corn price volatility as price declines. This research contributes to the existing literature by focusing on the asymmetric volatility transmission between oil, ethanol, and corn prices.

Another contribution of this research is to evaluate whether the frequency of price observations influences the estimation results. The question is whether the use of different-frequency data (i.e., daily, weekly, or monthly) leads to different cross-market volatility interactions. Previous studies of energy and commodity prices have used only one particular data frequency, producing mixed results (Elyasiani, Perera, and Puri, 1998; Gardebroek, Hernandez, and Robles, 2016). For example, Du and Lu McPhail (2012); Alom, Ward, and Hu (2011); and Harri and Hudson (2009) used daily datasets and found energy prices transmit volatility to food prices. However, Du, Yu, and Hayes (2011) and Serra and Gil (2012) used weekly frequency data, and Serra and Gil (2013) used a monthly dataset and found energy prices do not transmit volatility to food prices.[2] Hence, the use of different-frequency data could be one of the factors producing mixed results that lead to different conclusions about volatility spillovers across energy and agricultural commodity markets.[3]

We use high-frequency (daily) futures prices and compare the results with weekly and monthly frequencies. In response to positive and negative price changes in oil, ethanol, and corn prices, we find evidence of asymmetric volatility spillovers between corn and ethanol markets. The results also show that for different data frequencies, corn prices respond differently to price changes in oil and ethanol prices. In addition, the results show volatility spillovers between corn and ethanol markets for all data frequencies, but the volatility of ethanol only affects corn-price volatility for the daily-frequency prices, an indication that data frequency influences the results.

Background and Literature Review

The energy and agricultural sectors interlink because energy is an input into farm production, processing, and distribution, and a significant portion of the variable costs of agricultural products is in the form of fuel and fertilizer, which directly depend on energy prices. In the last decade, however, crude oil prices and environmental concerns led U.S. policy makers to adopt alternative biofuel sources (i.e., ethanol from corn) (Vedenov, Duffield, and Wetzstein, 2006).[4]

[2] For a full list of those studies and their inconsistent results, see Serra and Zilberman (2013).

[3] Other reasons for the inconsistent results could be different time periods, different model specifications, different countries, or different combination of prices employed (de Gorter, Drabik, and Just, 2015).

[4] For the theoretical links between corn, ethanol, and crude oil and how U.S. biofuel policies (e.g., mandates and blending wall) may affect corn and ethanol prices and volatility interactions, see de Gorter, Drabik, and Just (2015).

Ethanol, the major liquid biofuel produced in the United States, is made mainly from feedstock such as corn, which comprises more than 90% of domestic ethanol (U.S. Department of Energy, Alternative Fuels Data Center, 2016). U.S. corn utilization from 1999 through 2013 indicates corn used in ethanol production has had the largest increase, from 566 million bushels in 1999 to 5 billion bushels in 2013, a 775% increase (Taylor and Koo, 2013). The amount of corn used for ethanol grew from less than 1.4 billion bushels (about 13% of total use) in 2004 to 5.2 billion bushels (about 38% of total use) in 2014 (Taylor and Koo, 2015). Condon, Klemick, and Wolverton (2015) argue that an increase in ethanol production by one billion gallons increases corn prices by 3%–4%.

A review of agricultural economics literature indicates the importance of energy impacts in determining agricultural commodity prices. The emergence of large-scale ethanol production has further strengthened the links between these two sectors, specifically between corn and ethanol prices (Serra and Zilberman, 2013; Taheripour and Tyner, 2008). The increased price correlation between food and energy markets in recent years (Tyner, 2010) is likely to lead to stronger volatility spillovers between these prices. The literature refers to volatility generally as unexpected price changes (de Gorter, Drabik, and Just, 2015).

Compared to the past, we have experienced higher commodity price variability with wider variation (Irwin and Good, 2009). In the early 2000s, the coefficient of variation for corn ranged from 0.05 to 0.1, but it increased in the mid-2010s, ranging from 0.08 to 0.25 (Trujillo-Barrera, Mallory, and Garcia, 2012). In recent years, grain prices have demonstrated high volatility with negative economic and social consequences (Wright, 2011). Some argue that volatility in the energy markets is likely transmitted to the food sector through the ethanol linkage (e.g., Muhammad and Kebede, 2009).

The linkages between energy and agricultural commodities price levels have been examined extensively with mixed results (e.g., Balcombe and Rapsomanikis, 2008; Saghaian, 2010; Serra and Gil, 2012; Mensi et al., 2014; Myers et al., 2014; Nemati, 2017). Those studies investigated the links between energy and agricultural commodity prices—such as corn, sorghum, soybean, sugar, and wheat—with ethanol, biodiesel, gasoline, and crude oil for different countries like the United States, Brazil, Germany, Spain, etc.[5]

The literature on volatility-spillover effects between the energy and agricultural sectors has also grown quickly, producing mixed results. For example, Gardebroek and Hernandez Gardebroek and Hernandez (2013) used weekly spot prices to test volatility spillovers between crude oil, ethanol, and corn prices in the United States. Their results indicated significant spillovers from corn to ethanol prices but not the reverse. In addition, they did not find major cross-volatility effects from crude oil to corn markets, and their results did not provide any evidence of energy market volatility causing price volatility in the U.S. corn market. Trujillo-Barrera, Mallory, and Garcia (2012) used mid-week closing futures prices of corn, ethanol, and crude oil from 2006–2011 to study volatility-spillover effects and found volatility transmission from corn to the ethanol market.

Serra and Gil (2013) used a monthly dataset for corn and ethanol nominal prices between January 1990 and December 2010 to study U.S. corn stocks in relation to macroeconomic variables such as interest rates. Their results indicated volatility transmission between ethanol and corn markets. Du and Lu McPhail (2012) studied the relation between U.S. ethanol, corn, and crude oil futures using daily data and found no long-run relation between corn and biofuel prices but that crude oil and ethanol prices transmit volatility to corn prices. Looking at Brazilian ethanol and energy markets, Serra, Zilberman, and Gil (2011) showed that crude oil prices not only influence ethanol prices but also price volatility, and this volatility is transmitted, though weakly, to the sugar market. They found strong linkages between energy and food prices in Brazil.

Alom, Ward, and Hu (2011) found that energy price volatility transmits to feedstock prices when studying the relation between world crude prices with Asia and Pacific food price indexes. Zhang et al. (2009) studied volatility spillovers between weekly U.S. ethanol, corn, soybean, gasoline, and

[5] For a comprehensive review of this literature, see Condon, Klemick, and Wolverton (2015); Serra (2013); and Serra and Zilberman (2013).

crude oil prices. Their results showed no spillover effects from ethanol price volatility to corn and soybean prices, but they found volatility transmission from agricultural commodity prices to energy prices. Haixia and Shiping (2013) analyzed the price volatility spillovers among China's crude oil, corn, and fuel ethanol markets and observed a higher interaction among the three markets after September 2008. Their results showed spillover effects from the crude oil market to the corn and ethanol markets. They also found bidirectional spillover effects between corn and ethanol markets.

Some researchers have studied volatility effects only between oil and agricultural commodities, leaving out ethanol. For example, Nazlioglu, Erdem, and Soytas (2013) studied volatility transmission between crude oil and agricultural commodities and found no volatility transmission between crude oil and agricultural commodity markets in the pre-Great Recession period (before 2006) but that oil market volatility spilled over to the agricultural markets in the post-crisis period.

A couple of recent empirical studies are the only literature investigating asymmetry in volatility transmission relations between biofuel and food markets. López Cabrera and Schulz (2016) used oil, rapeseed, and biodiesel data to study volatility linkages between energy and agricultural commodity prices in Germany. Their results indicated that concerns about biodiesel being the cause of high and volatile agricultural commodity prices are unjustified. Abdelradi and Serra (2015) used the asymmetric MGARCH model to study price volatility relations between biodiesel blend and refined sunflower-oil prices in Spain and showed a bidirectional and asymmetric volatility spillover between these two commodity prices.

To our knowledge, nobody has investigated asymmetric volatility transmission in the U.S. energy and agricultural commodity markets. The present research fills that gap, concentrating on asymmetric spillover effects between crude oil, ethanol, and corn prices. We also use recent futures prices with three different time frequencies (i.e., daily, weekly, and monthly) to explore whether the use of different-frequency data can lead to mixed results, which could be one of the reasons for some of the inconsistent results found in the previous literature.

Data Description and Analyses

Daily, weekly, and monthly time series commodity futures data are collected for crude oil, corn, and ethanol prices from January 1, 2007, to November 19, 2015. Crude oil and ethanol prices are in dollars/gallon, and corn prices are in dollars/bushel. We use CMEGroup corn futures, CMEGroup ethanol futures, and NYMEX crude oil prices. We follow Trujillo-Barrera, Mallory, and Garcia (2012) in the way we construct the dataset. To construct price series containing the same maturity date, we use closing prices of the commodity with the fewest contracts, which is corn. To avoid possible contract anomalies that can occur during the delivery month or just before the delivery month, we roll in the month prior on the third business day prior to the twenty-fifth calendar day (Trujillo-Barrera, Mallory, and Garcia, 2012). Commodity price futures data come from Barchart.[6] Following Gardebroek, Hernandez, and Robles (2016), the weekly and monthly price data are the corresponding prices for the last trading day of the week and month, respectively.

The volatility spillovers between crude oil, corn, and ethanol markets may become unclear when using a long-span dataset. However, using a short-span dataset may decrease the size of price changes across markets in a way that is too small to show statistical significance (Gardebroek, Hernandez, and Robles, 2016). We transform the price series into logarithm format for our analyses to convert absolute changes to percentage changes and stabilize the variance of the data. As shown in figure 1, there are close co-movements among corn, crude oil, and ethanol prices during the 2007–2015 period. Figures 2–4 present daily price returns for crude oil, corn, and ethanol, respectively. We define percentage price changes, called returns, as $y_{it} = \log(P_{it}/P_{it-1}) \times 100$, where P_{it} is the price of crude oil, corn, or ethanol at time t. Using returns as a volatility measure is consistent with previous studies such as Trujillo-Barrera, Mallory, and Garcia (2012).

[6] http://www.barchart.com

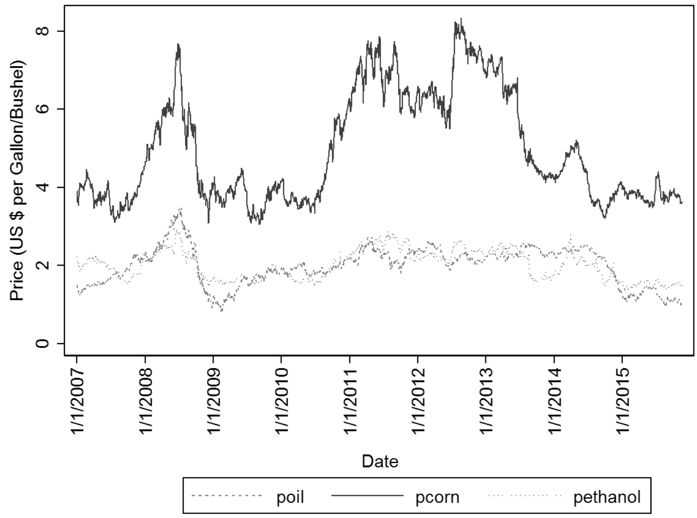

Figure 1. Prices of Crude Oil, Ethanol, and Corn, 1/1/2007–11/19/2015

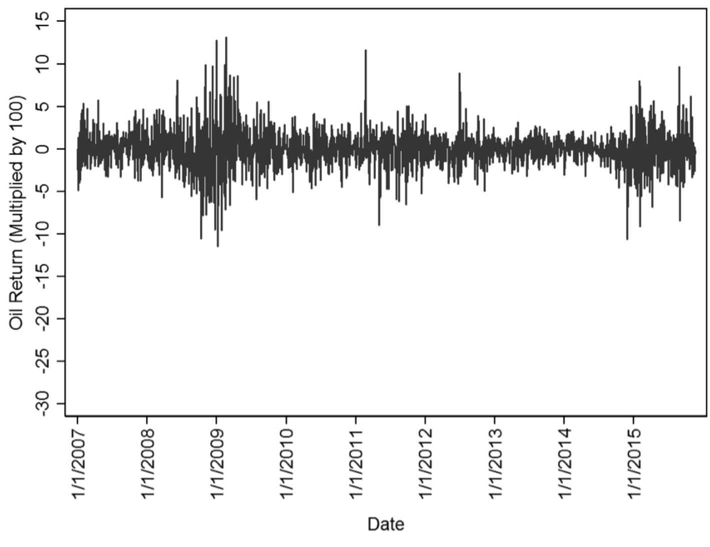

Figure 2. Crude Oil Returns, 1/1/2007–11/19/2015

Table 1 presents descriptive statistics for the price returns for crude oil, corn, and ethanol prices. The Jarque and Bera (1980) test statistics reject the null hypothesis of the normal distribution. The kurtosis in all markets exceeds 3, indicating leptokurtic distribution. We therefore estimate the BEKK model assuming a Student's t-density for the price changes. Ljung-Box (LB) test statistics for up to 45–85 lags in the daily data, 6–12 lags in the weekly data, and 2–4 lags in the monthly data reject the null hypothesis of no autocorrelation in all three markets' returns and squared returns. This autocorrelation in the daily, weekly, and monthly squared returns is an indicator of nonlinear dependency in the returns. The nonlinear relationships are due to the time-varying conditional volatility.

Figures 2–4 present daily price returns for crude oil, corn, and ethanol, respectively. These figures also show that price volatility in the oil, corn, and ethanol markets varies over time. For

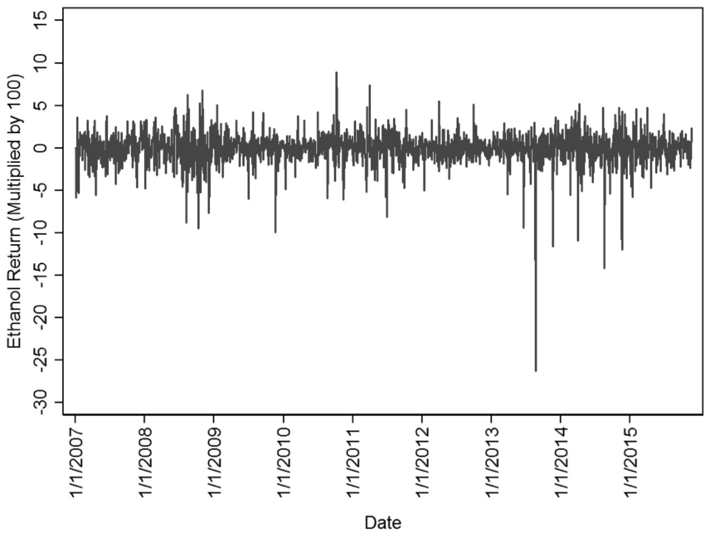

Figure 3. Corn Returns, 1/1/2007–11/19/2015

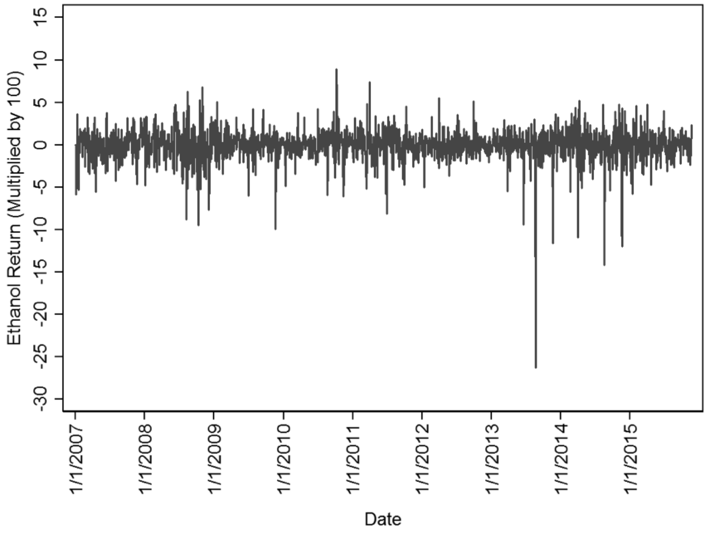

Figure 4. Ethanol Returns, 1/1/2007–11/19/2015

example, the crude oil price series reached historically high returns in late 2008, then plummeted rapidly in early 2009, which coincided with the deepening of the global financial crisis. Even though crude oil and ethanol prices remained relatively stable after 2009, corn prices continued to sway with a large magnitude. The volatility-clustering phenomenon can also be spotted in figures 1–4. These patterns motivate using the MGARCH approach to model interdependencies in the first and second moments of the returns within and between markets.

Table 2 reports the correlation matrix for the three variable returns. The correlation matrices with different-frequency data indicate that the correlation between crude oil and ethanol prices is higher than the correlation between crude oil and corn. Corn and ethanol prices have the highest correlation among the different data frequencies. This is expected since corn is the primary ingredient in the production of ethanol.

Table 1. Summary Statistics for U.S. Crude Oil, Corn and Ethanol Returns, 1/1/2007–11/19/2015

	Daily			Weekly			Monthly		
Statistic	**Oil**	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**
Mean	-0.013	-0.001	-0.010	-0.091	-0.016	-0.076	-0.319	-0.020	-0.290
S.D.	1.916	1.686	1.610	4.730	4.650	4.456	9.832	9.823	9.165
Min	-11.433	-13.139	-26.294	-24.331	-17.901	-25.401	-39.106	-25.879	-23.316
Max	13.136	8.662	8.873	21.417	18.877	14.601	24.328	24.937	22.213
Skewness	0.646	0.001	0.001	0.000	0.127	0.127	0.005	0.325	0.325
Kurtosis	0.000	0.000	0.000	0.000	0.000	0.000	0.009	0.909	0.909
Normality	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.606	0.606
N	2,346	2,346	2,346	468	468	468	107	107	107

Table 2. Crude Oil, Ethanol, and Corn Correlation Coefficients of Returns

	Daily			Weekly			Monthly		
	Oil	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**
Oil	1			1			1		
Corn	0.31***	1		0.30***	1		0.31***	1	
Ethanol	0.32***	0.55***	1	0.32***	0.59***	1	0.39***	0.67***	1

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

Table 3. Unit Root Test Results for the Lagged-Level and Returns of Daily Prices

	Test			
Series	**ADF**	**DF-GLS**	**KPSS**	**Decision**
A. Logged levels				
Oil	−1.17	−0.89	2.01	$I(1)$
Corn	−1.75	−1.57	3.08	$I(1)$
Ethanol	−2.33	−2.34	3.67	$I(1)$
B. Returns				
Oil	−14.69	−18.13	0.07	$I(0)$
Corn	−14.05	−13.81	0.05	$I(0)$
Ethanol	−14.74	−12.47	0.03	$I(0)$

Notes: Critical values at the 1% and 5% significance levels for ADF, DF-GLS, and KPSS tests are (−4.02 and −3.44), (−3.53, −2.99), and (0.216 and 0.146).

The first step in the volatility modeling is testing for the unit roots in each individual series. The unit root and stationary tests are shown in table 3. Panel A of table 3 shows the unit root test results of the natural log of each daily price series. To determine whether the series have a unit root, we used the Augmented Dickey–Fuller (ADF), (Dickey and Fuller, 1981), and the Dickey–Fuller GLS (DF-GLS) tests (Elliott, Rothenberg, and Stock, 1996), assuming both a constant and a trend. Kim and Mark (2017) argue that DF-GLS is more robust than ADF. We also used the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test because unit root tests have low power against trend-stationary alternatives (Kwiatkowski et al., 1992). The optimal lag length was selected using the Bayesian information criterion (BIC). As shown in panel A of table 3, the null hypothesis of the unit root at the level was not rejected by the ADF and DF-GLS test statistics. Moreover, the null hypothesis of the trend stationarity was rejected by the KPSS test. The conclusion is that all three price series are nonstationary, or integrated of order one, I(1). We repeated the unit root and stationarity tests using the first difference of the returns series, shown in panel B of table 3. ADF, DF-GLS, and KPSS test results suggested that the first differences of the series were stationary, or integrated of order zero, I(0). This procedure was also repeated with the weekly and monthly data price series and the results were similar; all three price series have a unit root, I(1), in levels and stationary, I(0), in the first-difference format. Hence, we estimated the univariate and multivariate volatility models with the first difference of the data series of crude oil, ethanol, and corn for daily, weekly, and monthly frequencies.

Methodological Approach and Model Development

Price data series usually demonstrate clustering volatility in which the variance of prices at a given time shows some degree of autocorrelation. Furthermore, price volatility is not limited in one market but can be transmitted across related markets. The autoregressive conditionally heteroskedastic (ARCH) and generalized autoregressive conditionally heteroskedastic (GARCH) models are introduced to study the variance of time series data. Engle (1982) introduced the ARCH model, which allows variance–covariance of the current model errors to be a function of the actual size of the lagged error terms. Later Bollerslev (1986) extended the ARCH model to a generalized form (GARCH) that solves the limitation of the ARCH models in explaining persistent volatility by allowing the variance–covariance matrix to depend on both lagged residuals and its own lags.

By using the multivariate-GARCH models, we can study both volatilities and co-volatilities of several markets (Bauwens, Laurent, and Rombouts, 2006). These models can be specified using different functional forms, but some of these functional forms are more restrictive and do not allow for volatility spillovers across different markets. In this paper, we use the BEKK (Baba, Engle, Kraft, and Kroner) model developed by Engle and Kroner (1995). The BEKK model refers to the specific parameterization of the MGARCH model, and it is a dynamic conditional model having the attractive property that the conditional covariance matrices are positive definite. The BEKK-MGARCH model is also limited in the sense that it is incapable of capturing the asymmetric volatility patterns in time series data. To overcome this limitation, we follow the Kroner and Ng (1998) procedure and use the asymmetric specification of BEKK-MGARCH mode, which allows us to test to see whether price increases and decreases have the same impact on corn and energy prices.

For the conditional mean equation, we use a trivariate vector autoregressive moving average (VARMA) (1,1) specification with the returns of the crude oil, corn, and ethanol prices as the dependent variable. The conditional mean equation takes the following form:

(1)
$$\mathbf{Z_t} = \phi + \psi\mathbf{Z_{t-1}} + \mathbf{\Theta}\sqrt{h_t} + \theta\boldsymbol{\varepsilon}_{\mathbf{t}-1} + \boldsymbol{\varepsilon}_{\mathbf{t}}$$
$$\boldsymbol{\varepsilon}_{\mathbf{t}}|\mathbf{\Omega_{t-1}} \sim (0,\ \mathbf{H_t}),\ \mathbf{H_t} = \begin{bmatrix} \mathbf{h_{oo,t}} & \mathbf{h_{oc,t}} & \mathbf{h_{oe,t}} \\ \mathbf{h_{co,t}} & \mathbf{h_{cc,t}} & \mathbf{h_{ce,t}} \\ \mathbf{h_{eo,t}} & \mathbf{h_{ec,t}} & \mathbf{h_{ee,t}} \end{bmatrix},$$

where $\mathbf{\Omega_{t-1}}$ is the set of information available up to the period $t-1$ and

(2)
$$\mathbf{Z_t} = \begin{bmatrix} \Delta\mathbf{lno_t} \\ \Delta\mathbf{lnc_t} \\ \Delta\mathbf{lne_t} \end{bmatrix};\ \boldsymbol{\varepsilon}_{\mathbf{t}} = \begin{bmatrix} \boldsymbol{\varepsilon}_{\mathbf{o,t}} \\ \boldsymbol{\varepsilon}_{\mathbf{c,t}} \\ \boldsymbol{\varepsilon}_{\mathbf{e,t}} \end{bmatrix};\ \mathbf{h_t} = \begin{bmatrix} \mathbf{h_{oo,t}} \\ \mathbf{h_{cc,t}} \\ \mathbf{h_{ee,t}} \end{bmatrix},$$

(3)
$$\psi = \begin{bmatrix} \psi_{11} & \psi_{12} & \psi_{13} \\ \psi_{21} & \psi_{22} & \psi_{23} \\ \psi_{31} & \psi_{32} & \psi_{33} \end{bmatrix};\ \Theta = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} \end{bmatrix};\ \theta = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix}.$$

For the conditional variance equation, we use the asymmetric form of the BEKK (1,1,1) specification. The model takes the following form:

(4)
$$\mathbf{H_t} = \mathbf{CC'} + \mathbf{A'}\boldsymbol{\varepsilon}_{\mathbf{t}-1}\boldsymbol{\varepsilon}'_{\mathbf{t}-1}\mathbf{A} + \mathbf{B'H_{t-1}B} + \mathbf{D'v_{t-1}v'_{t-1}D},$$

where $\mathbf{H_t}$ is the conditional variance–covariance matrix defined above. **A**, **B**, and **D** are 3×3 matrices of parameters to be estimated and **C** is a 3×3 lower triangular matrix to ensure the positive definite property of **H**. The elements of matrix **A** are the coefficients of the autoregressive conditional heteroskedasticity (ARCH) term, which identify the effect of a price change in own market (diagonal elements) and the spillover effects on the conditional volatility of the markets on each other (off-diagonal elements). The coefficients of the GARCH terms are shown by the elements of matrix **B** and are indicators of the effects of past volatility on the own market and the effects of past volatility spillovers from the other markets on the conditional volatility of each market. It is noteworthy to mention that the ARCH and GARCH terms are indicators of short-term and long-term persistent volatility, respectively.

Furthermore, $v_{t-1} = \varepsilon_{t-1} o I_{\varepsilon<0}(\varepsilon_{t-1})$, where o is the Hadamard product (element-by-element multiplication) of the vectors, and the elements of matrix **D** characterize the potential asymmetric volatility transmission between crude oil, corn, and ethanol. In fact, the diagonal elements are indicators of the significance of the asymmetric effect for own market, and off-diagonal elements are indicators of the significance of asymmetric effects between the markets. Using this specification, we estimate 63 parameters (30 parameters in the mean model and 33 in the conditional variance model). We use Ljung–Box statistics to test for autocorrelation and employ McLeod–Li statistics to test for the ARCH effects, which tests the null hypothesis of no ARCH effect in the model. RATS-9 software was used for the analyses.

Empirical Results

The asymmetric BEKK-MGARCH model is estimated using the quasi-maximum likelihood method, and the results are presented in table 4. Panel A of table 4 presents the conditional mean results and panel B presents the conditional variance results. In the conditional-mean equation, the main diagonal coefficients of the ψ matrix (ψ_{11}, ψ_{22}, and ψ_{33}) capture own-market dependency; for example, the dependence of the daily returns in the crude oil, corn, or ethanol market on its lagged value. Furthermore, the off-diagonal coefficients of this matrix (i.e., ψ_{ij} where $i \neq j$) capture cross-market dependency; for example, the dependence of the daily returns in market i on the lagged values in market j.

The asymmetric volatility-spillover effects are captured using matrices **A** and **D**. The coefficients in the main diagonal of matrix **A** (a_{11}, a_{22}, and a_{33}) capture own-volatility spillovers and off-diagonal coefficients (i.e., a_{ij} where $i \neq j$) capture cross-market volatility spillovers. The main diagonal coefficients of matrix **D** (d_{11}, d_{22}, and d_{33}) test whether negative or positive price changes in oil, corn, or ethanol prices result in more own-volatility spillovers. The off-diagonal coefficients in this matrix (i.e., d_{ij} where $i \neq j$) test whether the effects of lagged negative or positive price changes in market i on the current volatility in market j result in more cross-volatility spillovers.

The results of the asymmetric BEKK-MGARCH model estimation with the daily dataset indicates that the mean returns of oil, corn, and ethanol markets are influenced by their own lagged returns but not by cross-market lagged returns. The estimation results for the volatility spillovers are indicative of strong ARCH effects, with current volatility of oil, corn, and ethanol affected by their own lagged volatility. Specifically, these results show that ethanol returns have the most persistent ARCH effect for daily and monthly data, $\hat{\alpha}_{33} = 0.562$ and $\hat{\alpha}_{33} = 0.724$, respectively, and corn returns have the most persistent ARCH effect for weekly data, $\hat{\alpha}_{22} = 0.349$. Interestingly, only ethanol returns have ARCH effects with strong levels of significance (i.e., they are consistently significant at the 1% level of significance across different time periods). Furthermore, cross-market volatility-spillover results indicate that the lagged volatility in the oil market affects only the current ethanol volatility (i.e., $\hat{\alpha}_{13} = -0.044$ with p-value $= 0.001$), not corn. The lagged volatility in the oil market has no effect on the current corn or ethanol return volatility (neither $\hat{\alpha}_{12}$ nor $\hat{\alpha}_{13}$ is statistically significant) for the weekly data. Finally, the cross-market volatility-spillover results for monthly

Table 4. Estimation Results for Asymetrice BEKK-MGARCH Model for Oil, Corn, and Ethanol (in That Order)

	Daily		Weekly		Monthly	
A. Conditional Mean Equation						
ϕ_{10}	0.011	(0.758)	0.034	(0.834)	0.696	(0.416)
ψ_{11}	-0.038^{*}	(0.042)	0.044^{*}	(0.059)	0.297^{***}	(0.001)
ψ_{12}	0.044	(0.122)	0.049	(0.223)	-0.262^{**}	(0.016)
ψ_{13}	−0.022	(0.236)	0.030	(0.415)	−0.005	(0.965)
ϕ_{20}	−0.013	(0.684)	−0.112	(0.426)	0.286	(0.669)
ψ_{21}	−0.023	(0.115)	0.004	(0.891)	0.046	(0.615)
ψ_{22}	0.066^{**}	(0.001)	-0.094^{***}	(0.006)	-0.350^{***}	(0.004)
ψ_{23}	0.023	(0.161)	0.041	(0.299)	0.229^{**}	(0.043)
ϕ_{30}	−0.037	(0.183)	-0.132^{***}	(0.000)	−0.012	(0.985)
ψ_{31}	−0.013	(0.277)	0.058	(0.526)	0.099	(0.173)
ψ_{32}	−0.010	(0.625)	0.033^{***}	(0.000)	0.069	(0.524)
ψ_{33}	0.087^{***}	(0.000)	-0.069^{***}	(0.000)	-0.282^{**}	(0.026)
B. Conditional Variance Equation						
c_{11}	-0.150^{***}	(0.000)	0.868^{***}	(0.001)	5.753^{***}	(0.005)
c_{21}	0.211^{***}	(0.000)	-0.782^{*}	(0.056)	6.384^{***}	(0.000)
c_{22}	-0.142^{**}	(0.030)	-0.734^{*}	(0.054)	−0.002	(0.999)
c_{31}	0.084	(0.310)	-0.560^{**}	(0.019)	4.806^{***}	(0.000)
c_{32}	-0.287^{***}	(0.000)	−0.246	(0.402)	−0.001	(0.999)
c_{33}	0.000	(0.999)	0.000	(0.999)	0.000	(0.999)
a_{11}	0.121^{***}	(0.000)	0.071^{*}	(0.072)	−0.184	(0.185)
a_{12}	0.019	(0.132)	0.055	(0.158)	-0.709^{***}	(0.000)
a_{13}	-0.044^{***}	(0.001)	0.039	(0.223)	-0.552^{***}	(0.000)
a_{21}	−0.031	(0.193)	−0.137	(0.116)	0.337	(0.119)
a_{22}	0.233^{***}	(0.000)	0.349^{***}	(0.00)	0.305^{*}	(0.087)
a_{23}	-0.286^{***}	(0.000)	0.108^{**}	(0.036)	-0.295^{**}	(0.045)
a_{31}	0.031	(0.122)	0.065	(0.139)	−0.148	(0.241)
a_{32}	-0.089^{***}	(0.001)	−0.042	(0.236)	0.141	(0.340)
a_{33}	0.562^{***}	(0.000)	0.157^{***}	(0.000)	0.724^{***}	(0.000)
b_{11}	0.973^{***}	(0.000)	0.890^{***}	(0.000)	0.332	(0.136)
b_{12}	−0.001	(0.784)	−0.016	(0.496)	−0.338	(0.174)
b_{13}	0.000	(0.996)	−0.009	(0.611)	−0.009	(0.960)
b_{21}	0.018	(0.122)	0.123	(0.152)	0.055	(0.787)
b_{22}	0.957^{***}	(0.000)	0.898^{***}	(0.000)	0.230	(0.183)
b_{23}	0.077^{***}	(0.000)	-0.039^{*}	(0.070)	0.610^{***}	(0.000)
b_{31}	−0.004	(0.551)	0.005	(0.775)	0.323	(0.274)
b_{32}	0.024^{***}	(0.002)	0.024^{*}	(0.065)	-0.329^{*}	(0.099)
b_{33}	0.835^{***}	(0.000)	0.962^{***}	(0.000)	-0.695^{***}	(0.000)
d_{11}	-0.246^{***}	(0.000)	0.341^{***}	(0.000)	0.585^{***}	(0.003)
d_{12}	0.002	(0.917)	0.021	(0.708)	−0.225	(0.344)
d_{13}	-0.068^{***}	(0.003)	−0.072	(0.118)	0.339^{*}	(0.059)
d_{21}	0.007	(0.789)	0.135	(0.134)	0.591	(0.213)
d_{22}	-0.058^{*}	(0.096)	−0.030	(0.680)	0.482^{*}	(0.064)
d_{23}	-0.453^{***}	(0.000)	0.345^{***}	(0.000)	−0.075	(0.732)
d_{31}	0.038^{**}	(0.032)	-0.199^{***}	(0.002)	-0.681^{***}	(0.002)
d_{32}	-0.055^{**}	(0.018)	0.125^{*}	(0.057)	0.043	(0.850)
d_{33}	0.238^{***}	(0.000)	-0.124^{**}	(0.028)	−0.183	(0.483)

Continued on next page...

Table 4. – continued from previous page

	Daily			Weekly			Monthly		
C. Model Diagnoses									
AIC	11.68			16.74			21.61		
SBC	11.81			17.22			22.98		
Log-L	−13,482			−3,805			−1,070		
Obs.	2,317			461			104		
	Oil	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**
D. Residual Diagnostics for Independent Series									
Ljung–Box (20)	10.44	32.68	12.60	17.67	27.31	17.53	26.54	24.02	26.99
Ljung–Box (40)	40.01	60.01	26.43	32.53	56.87	44.94	66.80	53.86	75.26
McLeod–Li (20)	12.41	6.28	5.93	23.37	26.97	19.83	22.35	26.39	26.12
McLeod–Li (40)	34.70	27.06	11.47	41.05	54.40	32.95	60.12	75.94	52.29

Notes: Subscripts 1, 2, and 3 refer to oil, corn, and ethanol, respectively. Parameters in the conditional mean and variance equations are as defined in the model. Numbers in parentheses are indicators of p-values. Single, double, and triple asterisks (*, **, ***) indicate (statistical) significance at the 10%, 5%, and 1% level.

prices shows that the lagged volatility in the oil market affects the current ethanol and corn return volatility ($\hat{\alpha}_{12} = -0.709$ with p-value $= 0.000$ and $\hat{\alpha}_{13} = -0.552$ with p-value $= 0.000$).

The results indicate that the lagged volatility in the corn market affects the current volatility in the ethanol market, but the lagged volatility in the corn market has no significant impact on the oil market, regardless of data frequency. That is, $\hat{\alpha}_{21}$ is not statistically significant, but $\hat{\alpha}_{23}$ is. Also, the results indicate that only the corn market lagged-volatility effect on the current volatility in the ethanol market is strongly significant across all three periods (i.e., significant at the 1% level of significance). Finally, ARCH effect in the ethanol market shows that the lagged volatility in the ethanol market affects the current volatility in the corn market only with daily data (i.e., $\hat{\alpha}_{32} = -0.089$ with p-value $= 0.000$), but it has no significant impact on the oil market, regardless of data frequency, and $\hat{\alpha}_{31}$ is not statistically significant.

Interestingly, these results point to the first sign of an asymmetric relation between the oil, corn, and ethanol markets. We observe a unidirectional volatility-spillover effect from oil to the ethanol market, since $\hat{\alpha}_{31}$ is statistically insignificant for all the datasets, but $\hat{\alpha}_{13}$ is statistically significant for daily and monthly datasets. That is, oil price volatility influences ethanol price variations, but ethanol price variability does not transmit to oil prices. Serra, Zilberman, and Gil (2011) also showed that crude oil price volatility influences ethanol prices in the Brazilian ethanol and energy markets. However, corn and ethanol price volatility influence each other ($\hat{\alpha}_{23}$ and $\hat{\alpha}_{32}$ are both statistically significantly; i.e., bidirectional spillover effects between corn and the ethanol market). Using daily datasets, Du and Lu McPhail (2012); Alom, Ward, and Hu (2011); and Harri and Hudson (2009) only found energy prices transmitting volatility to food prices.

The results for the effects of positive and negative price changes, matrix **D**, are also indicative of asymmetric volatility-spillover transmission. The main diagonal coefficients of matrix **D** show that negative rather than positive price changes in these markets are associated with higher volatility with daily data (all three coefficients, $\hat{d}_{11} = -0.246$, $\hat{d}_{22} = -0.058$, and $\hat{d}_{33} = -0.238$, are statistically significant). We observe asymmetric ARCH effects only in the oil and ethanol markets with weekly data ($\hat{d}_{11} = 0.341$, $\hat{d}_{33} = -0.124$, respectively) and only in the oil and corn markets with monthly data ($\hat{d}_{11} = 0.585$, $\hat{d}_{22} = 0.482$, respectively). Note that we observe strong levels of significance across all three periods only in the oil market (i.e., only $\hat{d}_{11}$ is significant at the 1% level of significance for all three periods). In addition, negative rather than positive price changes in the ethanol market are associated with higher volatility spillover in the corn market. Moreover, negative rather than positive price changes in the crude oil and corn markets are associated with higher volatility spillovers in the ethanol market. Overall, the corn and ethanol markets respond differently to positive and negative price changes in the oil, ethanol, or corn markets, indicating asymmetric

Table 5. Summary of the Volatility-Spillover Effects between Oil, Corn, and Ethanol

	Oil on:			Corn on:			Ethanol on:		
	Oil	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**	**Oil**	**Corn**	**Ethanol**
Daily	YES	NO	YES	NO	YES	YES	NO	YES	YES
Weekly	YES	NO	NO	NO	YES	YES	NO	NO	YES
Monthly	NO	YES	YES	NO	YES	YES	NO	NO	YES

volatility-spillover effects. Hence, price volatility transmits unevenly across these markets, leading to uneven distribution of the effects during sudden price changes, with welfare implications for market agents.

We employed data of three different frequencies to investigate whether the use of different-frequency data influences results and compared and contrasted their impacts on volatility spillovers. Those results are presented in columns 4 and 5 of table 4. The conditional mean results indicate stronger lagged-return effects for the oil market when using the monthly dataset. The corn and ethanol returns were influenced by their own lagged returns for all data frequencies. However, the lagged returns of the oil market only influenced the returns in the corn market when using the monthly dataset, and the lagged returns of the ethanol market only influenced the corn market when using the weekly dataset. In addition, the lagged returns of the corn market only influenced the returns in the ethanol market for the monthly dataset. Table 5 summarizes these results.

Overall, this study finds several interesting results independent of data frequency: (i) lagged corn and ethanol volatility has no significant effect on current oil volatility, (ii) lagged corn volatility affects current ethanol volatility, and (iii) lagged corn and ethanol volatility influences own current volatility. In addition, we found volatility-spillover effects from oil to corn and ethanol markets and ethanol volatility spillovers to corn, depending on data frequency used. Hence, for volatility-spillover analysis in this research, data frequency matters, and the three different-frequency data produce inconsistent results, an important point that other researchers must consider.

Conclusions

The U.S. biofuel industry grew sharply in the last decade as farmers converted land from other uses to increase corn production to produce ethanol. Consequently, a stronger connection was established between the energy and food sectors. The new corn–ethanol links may increase price volatility, exacerbating the instability of agricultural commodity prices.

Energy sector linkages to agriculture are important determinants of farm prices and income, especially in the current corn-based ethanol production environment, oil market volatility, and global economic conditions. These factors are of paramount importance to farmers as well as consumers as agricultural commodity prices have experienced higher price volatility in recent years. There are concerns that the new corn–ethanol links and increased ethanol production raise food price variation, creating a growing interest in measuring these effects and their consequences.

The literature on links between energy and agricultural commodity markets is vast, but it mostly focuses on price levels (Serra, 2013; Serra and Zilberman, 2013) rather than price volatility or asymmetry in price volatility–spillover effects. However, higher commodity-price variation raises more concerns than higher prices. In addition, those results are mixed and inconsistent, possibly due to the use of varying data frequencies, among other factors such as changing demand and supply conditions. In this study, the asymmetric price volatility–spillover effects between agriculture and energy markets were the focus of attention. Relying on three different-frequency commodity futures data, an asymmetric BEKK-MGARCH model incorporated daily, weekly, and monthly corn, ethanol, and crude oil prices. Our primary objective was to identify whether the new oil–corn–ethanol links cause volatility-spillovers and risk and instability transmission between corn and ethanol markets and whether the volatility spillovers are asymmetric, responding differently to price changes.

We used CMEGroup corn futures, CMEGroup ethanol futures, and NYMEX crude oil, over a period sufficient to capture both the birth and realization of a fully functioning ethanol industry. We also used the asymmetric multivariate GARCH model to investigate whether corn price instability could get worse with energy price increases rather than decreases; that is, whether ethanol price increases and declines have varying effects on corn price volatility. Moreover, by using three different-frequency datasets, we investigated whether the results are robust to the frequency of the dataset used. Now that the United States is functioning with a well-established ethanol industry, we can study government biofuel policies and their indirect and unintended effects and consequences.

Our results showed that the use of different data frequencies matters in analyzing volatility spillovers. These findings could at least partially explain the inconsistent results of previous studies. This inconsistency is also evident in our empirical results, as some estimates are statistically significant with one dataset but not with others. The results of this study indicate that to capture statistically significant volatility-spillover effects between U.S. food and biofuel markets, working with higher frequency data (i.e., daily) is recommended. However, we cannot generalize this conclusion based on just one study, and more research is required.

Notably, the results show that the corn market responds differently to price changes in the crude oil and ethanol markets. There was evidence of volatility-spillover effects from corn to the ethanol market regardless of dataset frequency used; however, we found volatility-spillover effects from ethanol to the corn market only using the daily dataset. We found asymmetric volatility-spillover effects between food and biofuel markets; these effects were bidirectional, going both ways from biofuel prices to food prices and vice versa, depending on the data frequency. In addition, the ethanol and corn returns volatility responded differently to positive and negative price changes in the crude oil, ethanol, and corn markets.

Overall, this study shows the corn–ethanol links exist and there are asymmetric volatility-spillover effects between U.S. biofuel and the commodity sectors, but the statistically significant estimated coefficients for the different-frequency data used indicate those effects are very small, and hence, the impact is low. Therefore, while some have emphasized the seriousness of price variation and regard this issue as a policy priority, its main causes lay somewhere beyond biofuel policies and the new corn–ethanol links, like traditional sources such as oil shocks, climate change, theory of competitive storage, and demand and supply shocks, among others. Future studies are required to investigate the factors that drive the varying and conflicting results of food and biofuel volatility links, using alternative model specifications and different time-span datasets for comparison and contrast.

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