Asymmetric Price Volatility Transmission between U.S. Food and Energy Markets

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Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1

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Abstract: Links between agricultural commodity and energy prices have become more complex with increased ethanol production. The concerns are whether the new corn-ethanol links lead to volatility-spillover effects between food and energy prices and different data-frequencies is the reason for previous inconsistent results. We investigate the asymmetric volatility-spillover effects between U.S. feedstock and biofuel prices, using an asymmetric BEKK-multivariate-GARCH approach, with daily, weekly, and monthly futures-price frequencies. The results show asymmetric volatility-spillover effects between corn and ethanol prices, and the volatility of corn and ethanol returns respond differently to positive and negative shocks, demonstrating asymmetric volatility transmission, depending on different data-frequencies.

Key Words: Asymmetry, corn prices, crude oil prices, ethanol prices, volatility, Asymmetric BEKK-MGARCH modeling

JEL Classifications: *E60; Q10; Q19*

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1. Introduction

The energy and agricultural sectors interlink because energy is input into farm production, processing, and distribution, and a significant portion of the variable costs of agricultural products in the form of fuel and fertilizer directly depends on energy prices. In the last decade, however, crude oil prices and environmental concerns led U.S. policymakers to adopt alternative biofuel sources, i.e., ethanol from corn[1] (Vedenov, Duffield, and Wetzstein 2006). The emergence of large-scale ethanol production further strengthens the links between these two sectors, specifically between corn and ethanol prices (Serra and Zilberman 2013, Taheripour and Tyner 2008). Increasing integration of energy and agricultural commodities brings into question the spillover effects of energy price volatility on price volatility of agricultural commodities.

The literature refers to volatility generally as unexpected price changes (De Gorter, Drabik, and Just 2015). Some argue we have experienced dramatic price changes in the agricultural commodities, as well as higher commodity price variability with wider variation compared to the past (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).

[1] 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).

The increases in food price volatility and the detrimental effects of price volatility have profound economic implications, raising the concerns of consumers, producers, as well as policy makers. High price volatility could make it more difficult for farmers to plan, affect food security and substantially impact the world's poor. It could adversely affect incomes and purchasing power of poor consumers, pushing them further into poverty, undernourishment, and hunger. De Gorter, Drabik, and Just (2015) argue that understanding the linkages is important to study the changes in food prices such as corn. The quick and unexpected changes in food prices can interrupt markets and affect social stability[2] and government policy. Hence, the massive increase in ethanol production in the U.S. raises the need for a deeper understanding of its effects on price volatility in food crops from which ethanol is produced.

In this paper, we use an asymmetric multivariate GARCH (AMGARCH) model to assess the effects of energy price volatility on food commodity price volatility by studying the asymmetric price volatility relations between crude oil, ethanol and corn prices in the U.S. Because of the increasing links between energy and agricultural sectors, literature on the price links of these markets is growing (Serra, Zilberman, and Gil 2011). However, most of the studies focus on the price levels (Serra and Zilberman 2013), even though some have argued 'food price volatility as 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 interactions as price decreases (Serra and Zilberman 2013), the literature on asymmetric price volatility interactions between food and biofuel markets is scarce, and previous literature

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

mostly ignores the asymmetric impact. We found only two studies that addressed asymmetric price volatility: Cabrera and Schulz (2016) used oil, rapeseed, and biodiesel data in Germany, and Abdelradi and Serra (2015) used biodiesel blend and refined-sunflower oil prices in Spain.

This research contributes to the existing literature by focusing on the asymmetric volatility-spillover effects in the U.S. biofuel and food markets. We investigate whether U.S. ethanol and corn-price volatility interactions respond differently to price increases than decreases. It is unclear whether ethanol price variability is higher during price increases, or whether ethanol price increases have a stronger impact on corn price volatility than price declines. To our knowledge, nobody has investigated the asymmetric volatility spillover effects between the U.S. energy and agricultural sectors.

Another contribution of this research is the use of recent futures price data to evaluate whether the frequency of the datasets influences the results. The concern is whether using data with different time frequencies lead to different results for the cross-market interactions. Previous studies used only a particular data frequency (e.g., either daily, weekly, or monthly), while different data frequencies could lead to different conclusions about volatility spillovers across markets (Elyasiani, Perera, and Puri 1998, Gardebroek, Hernandez, and Robles 2015).

We used the high-frequency daily dataset and compared the results with the longer span, weekly and monthly datasets. The results showed corn prices respond differently to the shocks from oil and ethanol prices, depending on the data frequency, and asymmetric volatility spillover effects for the corn and ethanol markets. In addition, we found evidence of asymmetric ethanol and corn returns volatility effects in respond to positive and negative shocks in the oil, ethanol, and corn markets. We also found evidence of volatility spillover effects from corn to the ethanol market for all the data frequencies, but the ethanol volatility affected the corn market only when using the daily data.

The organization of the rest of the paper is as follows: in Section 2, we present background and related literature, followed by dataset description in Section 3. Section 4 presents the research methodology, and Section 5 presents and discusses the estimation results. Section 6 provides concluding remarks and implications.

2. Background and Literature Review

Agricultural commodity prices have experienced high price volatility in recent years. The literature points to several factors as the source of this increase in commodity price variability. Among the stated causes in the literature is the increase in corn-based ethanol production and the new food and ethanol linkages (Serra 2013, Balcombe and Prakash 2011, Wright 2011, Irwin and Good 2009). Ethanol is the major liquid biofuel produced in the U.S. mainly from feedstock such as corn, which comprises more than 90% of domestic ethanol (the U.S. Department of Energy [DOE], 2011). The U.S. corn utilization from 1999 through 2013 indicates corn used in ethanol production has had the largest increase. Corn used for ethanol production increased from 566 million bushels in 1999 to 5 billion bushels in 2013, 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 (the U.S. Department of Agriculture [USDA], 2015). Condon, Klemick, and Wolverton (2015) argue an increase in ethanol production by one billion gallons increases corn prices by three to four percent.

A review of agricultural economics literature indicates the importance of energy impacts in the determination of agricultural commodity prices. 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. 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. For example, Balcombe and Rapsomanikis (2008) studied the nexus between sugar, ethanol, and crude oil in Brazil. Their results indicate that in the long run, oil prices affect Brazilian sugar prices. Saghaian (2010) investigated the causal relation between energy and agricultural prices, specifically considering the relation between crude oil, ethanol, corn, wheat and soybean prices in the U.S., using the monthly price series from January 1996 to December 2008. The results showed a strong correlation between energy and agricultural prices, but the evidence on causal links between these two sectors was mixed.

In another related work, Serra and Gil (2012a) studied the relation between crude oil and biodiesel blends and crude oil and diesel prices in Spain. They found that there is an asymmetric dependence between crude oil and biodiesel prices but a symmetric dependence between diesel and crude oil prices. Mensi et al. (2014) used international prices to identify between energy and agricultural commodity prices. The authors found significant linkages between energy and agricultural commodity prices such as corn, wheat, and sorghum. Myers et al. (2014)studied the comovements between feedstock and energy prices and found no comovements between these prices in the long run. Nemati (2016) investigated the relationships among the prices of gasoline, ethanol, and agricultural products that included soybeans and corn, using monthly data from January 1986 to November 2014. The result indicated that there was a relationship between energy and agricultural product prices and this relationship intensified during the last decade. For a comprehensive review of this literature, see Condon, Klemick, and Wolverton (2015), Serra and Zilberman (2013), and Serra (2013).

The literature on volatility spillover effects between the energy and agricultural sectors has also grown quickly with mixed results. Gardebroek and Hernandez (2013) used weekly spot prices to test volatility spillovers between crude oil, ethanol, and corn prices in the U.S. 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 volatility in energy markets causing price volatility in the U.S. corn markets. 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 the corn to the ethanol market.

Serra and Gil (2012b) used a monthly dataset of 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 McPhail (2012) studied the relation between U.S. ethanol, corn, and crude oil futures using daily data. They found there was no long-run relation between corn and biofuel prices but that crude oil and ethanol prices transmit volatility to corn prices. Serra, Zilberman, and Gil (2011) showed crude oil prices not only influence ethanol prices in the Brazilian ethanol and energy markets, 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 the Pacific food price indexes. Zhang et al. (2009) studied volatility spillovers between weekly U.S. ethanol, corn, soybean, gasoline and 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 there was 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 the biofuel and food markets. Cabrera and Schulz (2016) used oil, rapeseed, and biodiesel data in Germany to study volatility linkages between energy and agricultural commodity prices. Their results indicated that concerns about biodiesel being the cause of high and volatile agricultural commodity prices are rather unjustified. Abdelradi and Serra (2015) used the AMGARCH model to study the price volatility relations between biodiesel blend and refined sunflower-oil prices in Spain. Their results showed a bidirectional and asymmetric volatility spillover between these two commodity prices.

The present paper fills the gap in this literature by investigating asymmetric volatility interactions in the U.S. energy and agricultural commodity markets, concentrating on asymmetric spillover effects between crude oil and U.S. corn and ethanol prices. We also use recent futures price datasets with three different time frequencies, i.e., daily, weekly, and monthly, to explore whether the mixed results found in the literature are partially due to the different data frequencies used.

3. Data Description and Analyses

Daily, weekly, and monthly time-series commodity futures data are collected for crude oil, corn, and ethanol prices for 2006:11:22 to 2015:11:19 period. Crude oil and ethanol prices are in dollars/gallon, and corn prices are in dollars/bushel. 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 contract 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 25th calendar day (Trujillo-Barrera, Mallory, and Garcia 2012). Commodity price futures data come from "Barchart.com." Following Gardebroek, Hernandez, and Robles (2015), 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 the shocks across markets in a way that is too small to show statistical significance (Gardebroek, Hernandez, and Robles 2015). We transformed the price series into logarithm format for our analyses. As shown from figure 1, there are close co-movements among corn, crude oil, and ethanol prices during the 2006-2015 period. Figures 2-4 present daily price returns for crude oil, corn, and ethanol, respectively. Daily price returns are defined by $y_{it}=ln(p_{it}/p_{it-1})*100$, where p_{it} is the price of crude oil, corn, or ethanol at time t. Figures 2-4 depict the volatility of the three products varying widely over time between these commodities. For example, the crude oil market is more volatile than the corn and ethanol markets. Crude oil price series reached historical high returns in late 2008 while plummeting rapidly during the early part of 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 swaying with a large magnitude. The volatility-clustering phenomenon can also be spotted from figures 1-4.

Table 1 presents descriptive statistics for log levels (in panel A) and returns (in panel B) for the crude oil, corn, and ethanol prices. The Jarque and Bera (1980) test statistics rejects the null hypothesis of the normal distribution. The kurtosis in all markets exceeds three, indicating leptokurtic distribution. We, therefore, estimate the BEKK model assuming a Student's t-density for the shocks. Ljung-Box (LB) test statistics for up to 45 and 85 lags in the daily data, 6 to 12 lags in the weekly data, and 2 to 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. This non-linear relationship can be due to the time-varying conditional volatility, which is also shown in figures 2-5 for the daily data. These patterns motivate using AMGARCH 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 variables in log-levels (panel A) and returns (panel B). The correlation matrices with different data frequencies indicate that the correlation between crude oil and ethanol prices is higher than 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.

The first step in the volatility modeling is testing for the unit roots in each of 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. We also used the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test because unit root tests have a 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 (panel A of table 3) is that all the 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 the 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.

4. 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 Heteroscedastic (ARCH) and Generalized Autoregressive Conditionally Heteroscedastic (GARCH) models are introduced to study the variance of time series data. Engle (1982) introduced the ARCH model in which it 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). The GARCH model 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 (MGARCH) 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). BEKK 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 to capture 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 model. By using the Asymmetric BEKK-MGARCH model, we can test to see if increases and decreases in energy prices have the same impact on corn 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:

$$Z_t = \phi + \psi Z_{t-1} + \Theta\sqrt{h_t} + \theta\varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \sim (0, H_t), H_t = \begin{bmatrix} h_{oo,t} & h_{oc,t} & h_{oe,t} \\ h_{co,t} & h_{cc,t} & h_{ce,t} \\ h_{eo,t} & h_{ec,t} & h_{ee,t} \end{bmatrix} \qquad (1)$$

where Ω_{t-1} is the set of information available up to the period *t-1* and

$$Z_t = \begin{bmatrix} \Delta lno_t \\ \Delta lnc_t \\ \Delta lne_t \end{bmatrix}; \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{o,t} \\ \varepsilon_{c,t} \\ \varepsilon_{e,t} \end{bmatrix}; \quad h_t = \begin{bmatrix} h_{oo,t} \\ h_{cc,t} \\ h_{ee,t} \end{bmatrix} \quad (2);$$

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

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

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

where 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 Heteroscedasticity (ARCH) term, which identifies the effect of a shock 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 the 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 the Ljung-Box statistics to test for autocorrelation. We also employ the 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.

5. Empirical Results

The asymmetric BEKK-MGARCH model is estimated using the Quasi-Maximum Likelihood method and the results are presented in table 4. Panel I of table 4 presents the conditional mean results and panel II presents the conditional variance results. In the conditional-mean equation, the main diagonal coefficients of the ψ matrix ($\psi_{11}, \psi_{22}, and\ \psi_{33}$) captures own-market dependency; for example, the dependence of the daily returns in the crude oil, corn and ethanol market on its lagged value. Furthermore, the off-diagonal coefficients of this matrix ($i.e.\ \psi_{ij}\ where\ i \neq j$) captures 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 shocks to oil, corn, and ethanol prices result in more own-volatility spillovers than positive shocks. The off-diagonal coefficients in this matrix ($i.e. d_{ij}\ where\ i \neq j$) test whether the effects of lag negative shocks in market *i* on the current volatility in market *j* result in more cross-volatility spillovers than positive shocks.

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 lag returns, but not by the cross-market lag 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 lag volatility. Furthermore, cross-market volatility-spillover estimation results indicate that the lag volatility in the oil market affects only the current ethanol volatility, not corn. Moreover, the lag volatility in the corn (ethanol) market affects the current volatility in the ethanol (corn) market, but the lag volatility in the corn or ethanol markets has no significant impact on the oil market. Interestingly, the results point to the first sign of asymmetric relation between the oil, corn, and ethanol markets. That is, we observe unidirectional volatility-spillover effect from oil to the ethanol market, but bidirectional spillover effects between corn and the ethanol market.

The results for the effects of positive and negative shocks, matrix D, are also indicative of asymmetric volatility-spillover transmission. That is negative shocks to these markets are associated with higher volatility than positive shocks. In addition, negative shocks to the ethanol market are associated with higher volatility spillover in the corn market than positive shocks. Moreover, negative shocks in the crude oil and corn markets are associated with higher volatility spillovers in the ethanol market than positive shocks. Overall, the corn and ethanol markets respond differently to positive and negative shocks in the oil, ethanol, or corn markets, indicating asymmetric volatility-spillover effects.

We employed three different data frequencies, i.e., daily, weekly, and monthly, to compare and contrast their impacts on volatility spillovers. Those results are presented in columns 4 and 5 of table 4, respectively. The conditional mean results indicate stronger lagged-return effects for the oil market when using 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 those results for the three different data frequencies, indicating using different data frequencies influence the volatility spillover results. Hence in volatility spillover analysis, data frequency matters

6. Conclusions

U.S. biofuel production increased 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 due to the growth in the biofuel industry. The new biofuel and agricultural links may increase price volatility, exacerbating agricultural commodity markets instability.

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. Agricultural commodity prices have experienced higher price volatility in recent years. There are concerns that the new ethanol-corn links and the increased ethanol production raise food price variation. Moreover, there is a growing interest in measuring these effects and their consequences.

The literature on links between feedstock and biofuel markets is vast, but they have mostly focused on price levels (Serra 2013, Serra and Zilberman 2013), rather than price volatility or asymmetry in price-volatility spillover effects. In addition, those results are mixed and inconsistent, possibly due to the use of varying data frequencies, among other reasons 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 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 transfer risk and instability to commodity markets from energy markets because of volatility spillovers between corn and ethanol markets, and whether the volatility-spillovers are asymmetric.

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 time-series model to investigate whether biofuel price increases and declines have different impacts on feedstock price-volatility, and whether food price instability could get worse with energy price increases rather than decreases. Moreover, by using three different data frequencies, we investigated whether the results are robust to the frequency of the dataset used. Now the U.S. is functioning with a well-established ethanol industry. We can explore whether government biofuel policies have indirect and unintended consequences.

The results show in analyzing volatility spillovers, data frequency matters. These findings could explain the inconsistent results of the studies that have used different data frequencies[3]. For example, Du and 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, Cindy, and Hayes (2011) and Serra and Gil (2012a) used weekly datasets, and Serra and Gil (2012b) used a monthly dataset; these studies found energy prices do not transmit volatility to food prices[4].This inconsistency is also evident in our empirical results as some estimates are statistically significant with one dataset, but not with other datasets. One possible explanation for this inconsistency could be the fact that weekly or monthly datasets are averages of daily prices with the loss of some information due to the averaging. 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 the corn market responds differently to the shocks from crude oil and ethanol markets. There was evidence of volatility-spillover effects from corn to the ethanol market regardless of dataset frequency used, however, only when the daily dataset was used, we found volatility-spillover effects from ethanol to the corn market. We found asymmetric volatility-spillover effects between food and biofuel markets and the effects were

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

[4] For a full list of those studies and their time-spans used, see Serra and Zilberman (2013).

bidirectional, going both ways from biofuel prices to food prices and vice-versa, depending on the data frequency used. In addition, the ethanol and corn-returns volatility responded differently to positive and negative shocks 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 commodity sectors, but the statistically significant estimated coefficients for all three data frequencies 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, the theory of competitive storage and demand and supply shocks, among others. Future studies are required to investigate the factors that derive the varying and conflicting results of food and biofuel volatility links, using alternative model specifications and different time-span data frequencies for comparison and contrast.

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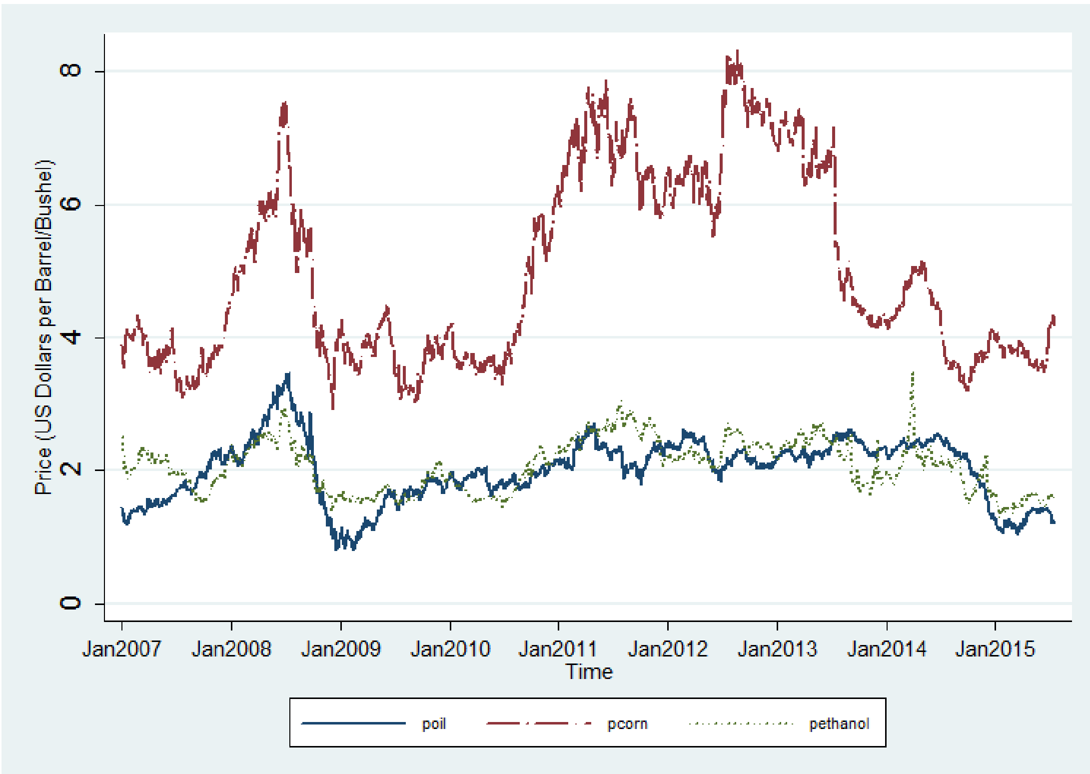

Figure 1: Prices of Corn, Ethanol and Crude Oil from 2007:01:01 to 2015: 11:19.

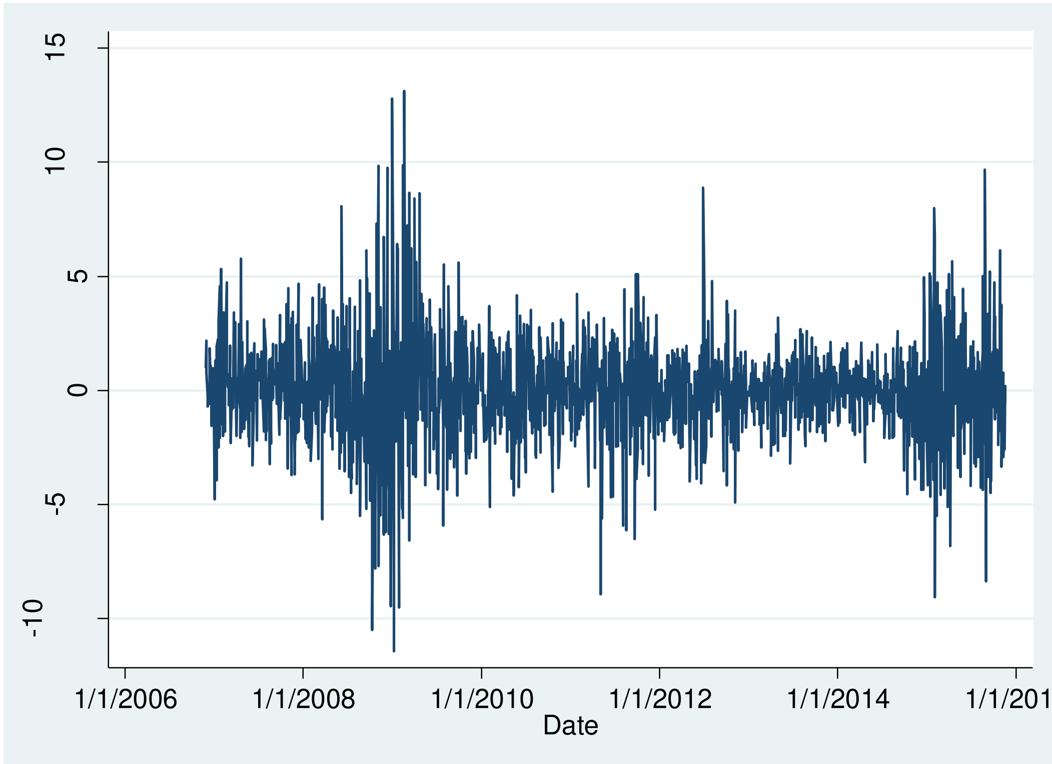

Figure 2: Crude Oil Returns from 2007:01:01 to 2015:11:19.

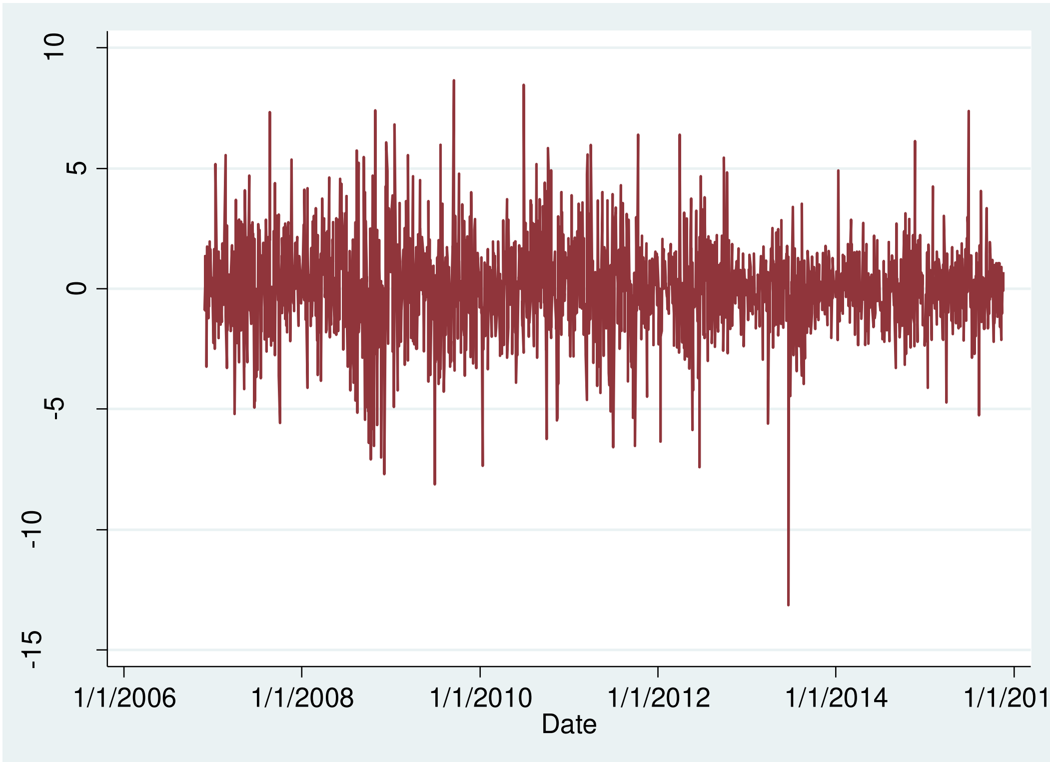

Figure 3: Corn Returns from 2007:01:01 to 2015:11:19.

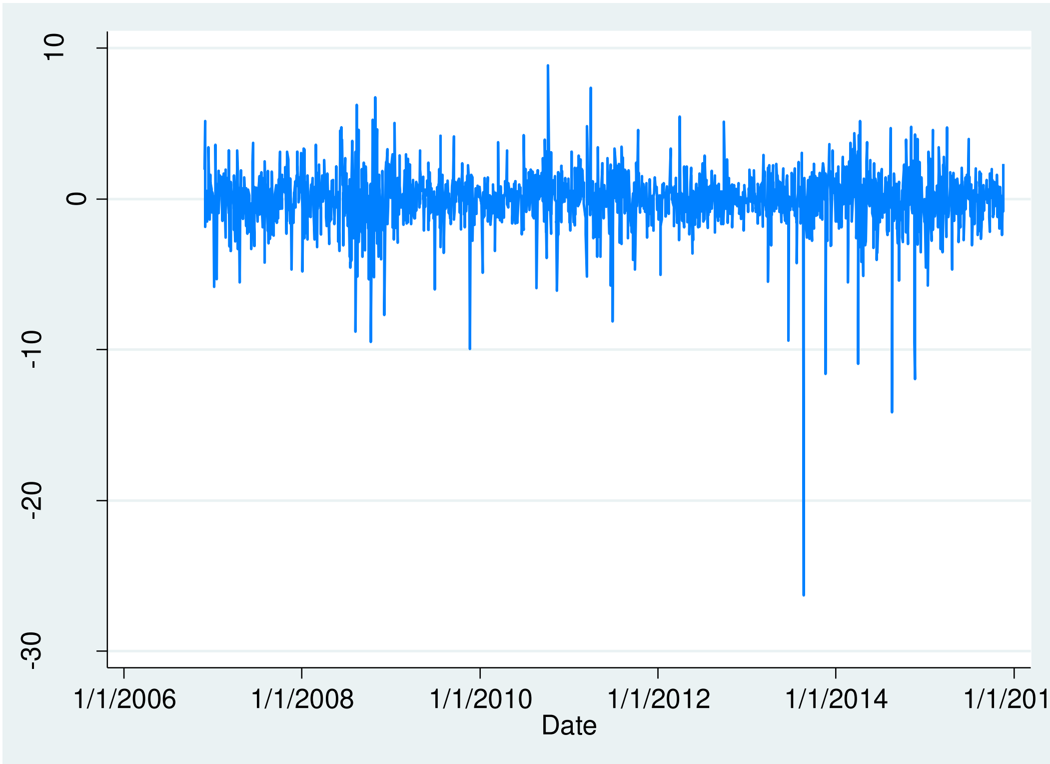

Figure 4: Ethanol Returns from 2007:01:01 to 2015:11:19.

Table 1: Summary Statistics of the U.S. Crude Oil, Corn and Ethanol Prices: 2007:01:01 to 2015:07:18

	Daily			**Weekly**			**Monthly**		
Statistic	Oil	Corn	Ethanol	Oil	Corn	Ethanol	Oil	Corn	Ethanol
A. Log Variable									
Mean	0.649	1.561	0.681	0.650	1.561	0.681	0.658	1.564	0.681
S.D.	0.272	0.271	0.191	0.271	0.272	0.191	0.262	0.271	0.190
Min	-0.212	1.119	0.282	-0.113	1.119	0.313	-0.008	1.165	0.326
Max	1.245	2.122	1.077	1.245	2.110	1.077	1.208	2.088	1.041
Skewness	0.000	0.000	0.906	0.000	0.001	1.000	0.005	0.074	0.995
Kurtosis	4.20	4.80	5.63	4.23	5.63	6.36	5.60	6.52	7.85
Jarque–Bera	185.32	98.23	321.20	223.25	102.32	423.21	322.20	231.02	523.23
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.024	0.000	0.000
# Observations	2,347	2,347	2,347	469	469	469	108	108	108
B. Returns	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	-11.43	-13.13	-26.29	-24.33	-17.90	-25.40	-39.10	-25.87	-23.31
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
# Observations	2,346	2,346	2,346	468	468	468	107	107	107

Table 2: Crude Oil, Ethanol, and Corn Correlation Coefficients

	Daily			**Weekly**			**Monthly**		
	Oil	Corn	Ethanol	Oil	Corn	Ethanol	Oil	Corn	Ethanol
A. Log Variable									
Oil	1			1			1		
Corn	0.61*	1		0.60*	1		0.61*	1	
Ethanol	0.69*	0.85*	1	0.69*	0.86*	1	0.69*	0.85*	1
B. Returns	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

Note: * indicates 1% statistical significance level.

Table 3: Unit Root Test Results for the Lagged-level and First-differenced Lagged-level (returns) of Daily Prices

Series	Test			Decision
	ADF	DF-GLS	KPSS	
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).

Table 4: Estimation Results for VARMA-BEKK-AGARCH (oil-corn-ethanol)

	Daily		Weekly		Monthly	
I. 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)
II. 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)
III. Model diagnoses						
AIC	11.68		16.74		21.61	
SBC	11.81		17.22		22.98	
Log-L	-13482		-3805		-1070	
Obs.	2,317		461		104	

IV. Residual diagnostics for independent series	oil	corn	ethanol	oil	corn	ethanol	oil	corn	ethanol
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: parameters in the conditional mean and variance equations are as defined in the model. Numbers in parenthesis are indicators of *p-values*. Also, *, **, and *** represent the levels of significance at 10%, 5%, and 1% respectively.

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