# Identification in Structural Models Linking Energy and Corn Cash Markets

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## Introduction

Following the increased reliance on biofuels in industrialized economies, particularly in the United States after the passage of the Energy Policy Act of 2005, the question of how changes affecting oil and ethanol markets are transmitted to agricultural commodities markets has been a subject of major concern in the literature (Sierra and Zilberman, 2013). To answer this question, researchers have typically applied reduce-form vector autoregressive (VAR) or vector error correction (VEC) models to time series data to establish causal links between these markets. However, according to Baumeister and Kilian (2014), most part of this literature is based on atheoretical models that are incapable of establishing such links in the data. That is, they lack of any economic interpretation because reduced-form errors are mutually correlated (Kilian and Vigfusson, 2011). Therefore, claims about how changes in energy markets impact grain commodity markets, and vice versa, are not well founded.

To deal with this problem, researchers have turned to structural VAR and VEC models. The estimation of these models requires additional identifying assumptions that must be motivated based on economic theory. The assumptions most commonly employed for identification are imposed by using exclusion, sign, short-run, long-run, and covariance restrictions. However, in the case of agricultural markets, such restrictions are hard to justify a priori.

The objective of this study is to determine causal links between energy and corn commodity markets using structural VAR and VEC models. More specifically, to quantify how shocks to crude oil and ethanol markets are transmitted to corn cash prices, and vice versa. Here, the identification problem is solved by implementing a novel approach proposed by Rigobon (2003), which is based on the heteroskedasticity of structural shocks. An advantage of using this approach is that it does not rely on a specific ordering of variables in the model. Identification is achieved by recognizing regimes of high and low volatility. Thus, this method estimates, rather than imposes, the pattern of contemporaneous correlations between price variables used in this analysis. This study adds to the literature by illustrating the use of this approach where regimes of high and low volatility are identified using information obtained from historical price volatility data.

Understanding the links between oil, ethanol and corn cash markets is critical not only for producers and processors as they make production, marketing, and risk management decisions, but also for policy makers as they design policies that may be intended to support the ethanol industry.

Since corn is used for human consumption, to feed farm animals, as a raw material in the production of ethanol, and also competes with other agricultural commodities for fertilizer, and scarce water and land resources, market effects of such policies could be much broader than anticipated.

**The Identification Problem**

Structural VAR models were first proposed by Sims (1980) as an alternative to traditional large-scale dynamic simultaneous equations models. According to Kilian (2013), structural VAR models have four main applications. First, they are used to study the expected response of model variables to a given one-time structural shock. Second, they are used to forecast error variance decompositions that quantify the average contribution of a given structural shock to the variability of the data. Third, they provide a framework to measure the cumulative contribution of each structural shock to the evolution of each variable over time, known as historical decompositions. Finally, these models allow the construction of forecast scenarios conditional on hypothetical sequences of future structural shocks. Structural inference in VAR models require differencing between correlation and causation. The generation of such interpretation is known as *identification* of a model (Sims, 1986). The identification problem cannot be typically solved using statistical tools. Instead, identification assumptions must be motivated based on economic theory.

To illustrate the identification problem, consider the following bivariate one lag system:

$$Y_t = a_0 + a_1 X_t + a_2 Y_{t-1} + a_3 X_{t-1} + \varepsilon_{Y_t}$$
$$X_t = b_0 + b_1 Y_t + b_2 Y_{t-1} + b_3 X_{t-1} + \varepsilon_{X_t}$$

where, the time path of variable $Y_t$ is affected by current and past realizations of variable $X_t$, and vice versa. $\varepsilon_{Y_t}$ and $\varepsilon_{X_t}$ are uncorrelated white-noise disturbances with standard deviations of $\sigma_Y$ and $\sigma_X$, respectively. The structure of this system incorporates feedback because $Y_t$ and $X_t$ are allowed to affect each other. Thus, it cannot be consistently estimated without further information. Using matrix algebra, one can write the previous system in the compact form:

$$\begin{bmatrix} 1 & -a_1 \\ -b_1 & 1 \end{bmatrix} \begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} a_2 & a_3 \\ b_2 & b_3 \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Y_t} \\ \varepsilon_{X_t} \end{bmatrix}$$

which is equivalently to:

$$AZ_t = \Gamma_0 + \Gamma_1 Z_{t-1} + \varepsilon_t$$

where,

$$A = \begin{bmatrix} 1 & -a_1 \\ -b_1 & 1 \end{bmatrix},\ Z_t = \begin{bmatrix} Y_t \\ X_t \end{bmatrix},\ \Gamma_0 = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix},\ \Gamma_1 = \begin{bmatrix} a_2 & a_3 \\ b_2 & b_3 \end{bmatrix},\ Z_{t-1} = \begin{bmatrix} Y_{t-1} \\ X_{t-1} \end{bmatrix},\ \varepsilon_t = \begin{bmatrix} \varepsilon_{Y_t} \\ \varepsilon_{X_t} \end{bmatrix}$$

The VAR model in reduced form is obtained by pre-multiplying the previous expression by $A^{-1}$:

$$Z_t = A^{-1}\Gamma_0 + A^{-1}\Gamma_1 Z_{t-1} + A^{-1}\varepsilon_t$$

The same model can be represented as:

$$Z_t = \mathrm{D}_0 + \mathrm{D}_1 Z_{t-1} + e_t$$

where the system contains only lagged variables and no contemporaneous effects. Note that the reduced form error term $e_t$ is a composite of the two structural shocks $\varepsilon_{Y_t}$ and $\varepsilon_{X_t}$:

$$e_t = A^{-1}\varepsilon_t$$

equivalently to:

$$\begin{bmatrix} e_{Y_t} \\ e_{X_t} \end{bmatrix} = \frac{1}{(1 - a_1 b_1)} \begin{bmatrix} 1 & a_1 \\ b_1 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{Y_t} \\ \varepsilon_{X_t} \end{bmatrix}$$

Because reduced form shocks $e_t$ are correlated, studying the response of vector $Z_t$ to these shocks does not provide any information about the response of $Z_t$ to the structural shocks $\varepsilon_{Y_t}$ and $\varepsilon_{X_t}$. This latter response is of main interest if one wants to learn about the structure of the markets under study (Kilian, 2013). To reconstruct $\varepsilon_{Y_t}$ and $\varepsilon_{X_t}$ it is necessary to recover the elements of $A^{-1}$ from consistent estimates of the reduced-form parameters. To do so, one needs to impose identification assumptions or restrictions based on economic theory. Such restrictions may take the form of exclusion restrictions, sign restrictions, or recursive restrictions (i.e., Cholesky decomposition). However, in some cases, such as in the analysis of price dynamics between agricultural and related markets, it is not possible to justify these restrictions a priori. In such cases, researchers have to implement more complex identification techniques.

**Empirical Methods**

The main goal of this study is to estimate and compare the average response of all price variables included in the *Oil-Corn* model to a given one-time structural shock before and after the passage of the Energy Policy Act of 2005. Our baseline structural bivariate VAR model, accounting for nonstationary price variables, is:

$$\Delta Oil_t = a_{10} + \sum_{k=1}^{p} a_{2,k}\Delta Oil_{t-k} + \sum_{k=0}^{p} a_{3,k}\Delta Corn_{t-k} + \varepsilon_{Oil,t} \quad (1)$$

$$\Delta Corn_t = b_{10} + \sum_{k=0}^{p} b_{2,k}\Delta Oil_{t-k} + \sum_{k=1}^{p} b_{3,k}\Delta Corn_{t-k} + \varepsilon_{Corn,t} \quad (2)$$

where, $\Delta$ is the difference operator, $Oil_t$ and $Corn_t$ represent the natural logarithm of crude oil and corn in period $t$, respectively (multiplied by 100). $\varepsilon_{Oil,t}$ and $\varepsilon_{Corn,t}$ are uncorrelated structural shocks to crude oil and corn, respectively. The lag length $p$ is chosen by minimizing the Akaike information criterion (AIC).

The presence of time $t$ variables as regressors in the system (1) – (2) represents the identification problem. That is, price variables are allowed to affect each other. Thus, it cannot be consistently estimated without further information. One way to achieve identification would be to assume $a_{3,0} = 0$. This would be equivalent to identifying the system by Cholesky decomposition on the reduced form residual covariance matrix. However, there is no evidence supporting the direction of contemporaneous causality between these markets, where crude oil prices affect corn prices contemporaneously, but not vice versa. Therefore, to solve the identification problem, we implement the method of identification through heteroskedasticity proposed by Rigobon (2003).

*Identification through heteroskedasticity*

This method, based on the heteroskedasticity of the structural shocks, measures the contemporaneous relationship between price variables by recognizing two regimes, one of high volatility and other of low volatility. Under a simple assumption of homoscedasticity, the system that represents the variance-covariance matrix of the reduced form residuals derived from (1) – (2) contains more unknowns than equations. The recognition of two regimes allows us to specify a system that has the same number of equations and unknowns (just identified system), which can be estimated by the generalized method of moments (GMM). There are two assumptions that lead to the identification of system (1) – (2): i) parameters are stable across the heteroskedasticity regimes, and ii) structural shocks are not correlated (Rigobon, 2003). The first one is the usual assumption imposed on ARCH or GARCH type models, and the second assumption is standard in the literature (Ehrmann, Fratzscher and Rigobon, 2011).

To illustrate the implementation of this identification approach, system (1) – (2) can be rewritten in its reduced form:

$$\Delta Oil_t = \alpha_{10} + \sum_{k=1}^{p} \alpha_{2,k} \Delta Oil_{t-k} + \sum_{k=1}^{p} \alpha_{3,k} \Delta Corn_{t-k} + e_{Oil,t} \quad (3)$$

$$\Delta Corn_t = \beta_{10} + \sum_{k=1}^{p} \beta_{2,k} \Delta LC_{t-k} + \sum_{k=1}^{p} \beta_{3,k} \Delta C_{t-k} + e_{Corn,t} \quad (4)$$

In this system, the reduced form residuals are composites of the three structural shocks $\varepsilon_{Oil,t}$ and $\varepsilon_{Corn,t}$. This relationship can be stablished as:

$$\begin{bmatrix} e_{Oil,t} \\ e_{corn,t} \end{bmatrix} = A^{-1} \begin{bmatrix} \varepsilon_{Oil,t} \\ \varepsilon_{Corn,t} \end{bmatrix}$$

For simplicity, the $B^{-1}$ matrix is defined as:[1]

$$A^{-1} = \begin{bmatrix} 1 & \delta_1 \\ \delta_2 & 1 \end{bmatrix}$$

Then, reduced form residuals can be specified as:

$$e_{Oil,t} = \varepsilon_{Oil,t} + \delta_1\, \varepsilon_{Corn,t}$$
$$e_{Corn,t} = \delta_2\, \varepsilon_{Oil,t} + \varepsilon_{Corn,t}$$

which shows how reduced form residuals are correlated. Thus, a one-time shock to any of the variables included in a reduced form model will not tell us anything about the structure of their underlying markets. To reconstruct $\varepsilon_{Oil,t}$ and $\varepsilon_{Corn,t}$ it is necessary to recover the elements of $A^{-1}$ from consistent estimates of the reduced-form parameters. Under the assumptions of homoscedasticity of the structural shocks, we have:

$$var(e_{Oil}) = var(\varepsilon_{Oil}) + \delta_1^2 var(\varepsilon_{Corn})$$
$$cov(e_{Oil}, e_{Corn}) = \delta_2 var(\varepsilon_{Oil}) + \delta_1 var(\varepsilon_{Corn})$$
$$var(e_{Corn}) = \delta_2^2 var(\varepsilon_{Oil}) + var(\varepsilon_{Corn})$$

This is a system of three equations and four unknowns, so it is not possible to estimate $A^{-1}$ without additional restrictions. Rigobon (2003) built on the logic that by recognizing two or more regimes in the variances of the structural shocks, it is possible to identify the system with no further restrictions. Letting the subscript $i = 1, 2$ denote the regime, the following moment conditions can be specified:

$$\begin{aligned} var(e_{Oil}^i) &= var(\varepsilon_{Oil}^i) + \delta_1^2 var(\varepsilon_{Corn}^i) \\ cov(e_{Oil}^i, e_{Corn}^i) &= \delta_2 var(\varepsilon_{Oil}^i) + \delta_1 var(\varepsilon_{Corn}^i) \\ var(e_{Corn}^i) &= \delta_2^2 var(\varepsilon_{Oil}^i) + var(\varepsilon_{Corn}^i) \end{aligned} \tag{5}$$

[1] It does not make a difference to divide each element of the matrix to the determinant of $A$ because it is a constant.

Here, there are six equations, and six unknowns: $\delta_1$, $\delta_2$, $var(\varepsilon_{Oil}^1)$, $var(\varepsilon_{Corn}^1)$, $var(\varepsilon_{Oil}^2)$ and $var(\varepsilon_{Corn}^2)$, indicating that the identification problem can be solved. The variance-covariance matrix of the reduced form residuals can be computed for both regimes after estimating the reduced form system (3) – (4).[2] The coefficients in $A^{-1}$ can be estimated by GMM using system (5) as moment conditions, and standard errors can be obtained using the fixed-design wild bootstrap (Goncalves and Kilian, 2004) with the Rademacher distribution as the pick distribution (Godfrey, 2009).

Before conducting the estimation procedure, the key question is how to identify regimes in which the relative variances of the crude oil and corn market structural shocks changed over time. Recent events affecting energy and corn markets represent a natural framework for regime identification. This is because these events are associated with large and, in some cases, persistent increases in volatility. In this study, regimes are identified by looking at the behavior of historical volatilities. In this procedure, structural break tests are conducted in each historical volatility series to find significant breaks. Thus, allowing us to define the regime windows systematically. Because we are interested in finding all possible volatility regimes, we use the Bai and Perron (2003) test to find multiple breaks.

## Results and Discussion

In this study, three different models were estimated: two bivariate SVAR using crude oil and corn prices for periods pre- and post-Energy Policy Act of 2005, and one trivariate SVEC model using crude oil, corn and ethanol prices corresponding to the period after the implementation of the Act. The data used for estimating these models are weekly Cushing, Oklahoma West Texas Intermediate (WTI) crude oil spot prices FOB (dollars per barrel) and weekly Omaha, Nebraska #2 yellow corn cash prices (dollars per bushel) from September 1997 to November 2015 (947 observations). The U.S. Energy Information Administration (EIA) is the source for WTI crude oil cash price data and the Livestock Marketing Information Center for U.S. corn cash prices paid to farmers. Weekly Iowa ethanol cash prices (dollars per gallon), from May 2006 to November 2015 (494 observations), were obtained from the Commodity Research Bureau (CRB). Moreover, to

[2] The reduced form system (3) – (4) can be estimated by ordinary least squares (OLS).

estimate historical volatilities, daily cash price data for WTI crude oil, corn and ethanol were collected from (CRB).

Following Baumeister and Kilian (2014), we split our sample in May 2006, when U.S. policy toward ethanol changed with the implementation of the Energy Policy Act of 2005, establishing a closer link between oil prices and corn prices. Therefore, model 1 (*Oil-Corn*) is estimated using observations from September, 1997 to April, 2006; whereas models 2 (*Oil-Corn*) and 3 (*Oil-Ethanol-Corn*) are estimated using observations from May 2006 to November 2015.

Table 1 presents results from the analysis of univariate time series properties, as well as cointegration relationships among price variables in each model. To test for the presence of a unit root in individual price series, we applied Augmented Dickey-Fuller (DF) tests. Results indicate that all price series are nonstationary in every period.[3] Furthermore, we tested for cointegration among price variables using both specifications of the Johansen procedure (i.e., maximal eigenvalue and trace statistic). Variables in the two bivariate models are not cointegrated. Conversely, variables in the trivariate model are cointegrated with one cointegration relationship. Thus confirming the appropriateness of estimating a SVEC model.

*Measuring the Contemporaneous Relationship across Energy and Corn Prices*

To identify contemporaneous coefficients in SVAR and SVEC models using the heteroskedasticity of structural shocks, the first step is to identify high and low volatility regimes. This task was performed by applying the Bai and Perron (2003) structural break test to weekly average historical price volatilities of crude oil, corn and ethanol.[4] This test allows to identify multiple breaks. We allowed up to 5 breaks and used a trimming of at least 0.15, so each segment has a minimum of 15 observations. The best number of breaks was selected based on the Bayesian Information Criterion (BIC). Results are depicted in figures 1 and 2, corresponding to the pre- and post-Energy Policy Act periods, respectively. The dotted lines in each plot indicates the break date, and the red horizontal lines represent confidence bands for each break. In both figures, the price volatility in the crude oil market presents larger variations than the price volatility in the corn market.

[3] AIC was used to determine appropriate lag lengths for the Augmented DF test.

[4] Daily historical volatilities (20-day) for each variable were first calculated using daily prices, and then averaged over the corresponding weekdays to obtain weekly historical volatilities. Daily historical volatilities were calculated following the procedure indicated by CRB. For more information on this procedure visit: http://www.crbtrader.com/support/options.asp

Looking at figure 1, the high volatility regime in the crude oil market ranges from 2000-09-22 to 2008-03-08. This is not the case, however, for the corn market where the high volatility regime is in period: 1997-09-18 – 1999-09-10. Conversely, the high volatility regimes for crude oil and corn coincide in the post-Energy Policy Act period, as depicted in figure 2. Here, the high volatility regime corresponds to period 2008-04-11 – 2010-02-26, which coincides with the market recession in 2008. Moreover, the high volatility regime for the ethanol market (not depicted) ranges from 2013-08-30 to 2015-11-05. Since it is not necessary to specify all the different heteroskedasticity regimes to achieve identification, we define period 2000-09-22 to 2008-03-08 as the high volatility regime (regime 1), and all other observations as low volatility regime (regime 2), for the pre-Energy Policy Act period. Similarly, for the post-Energy Policy Act period, we define period 2008-04-11 – 2010-02-26 as the high volatility regime (regime 1), and all other observations as low volatility regime (regime 2).[5]

As the identification strategy delivers estimates of the variances of $\varepsilon_{Oil}$ and $\varepsilon_{Corn}$ in models 1 and 2, and also $\varepsilon_{Ethanol}$ in model 3, for both high and low volatility regimes, we can formally verify that this choice of regimes is appropriate by comparing the magnitudes of the structural shock variance estimates. That is, we can test whether the magnitudes of the variances in the high volatility regime are systematically larger than the corresponding variances in the low volatility regime, as discussed further below. The next step is the estimation procedure.

In the estimation procedure of models 1 and 2 (*Oil-Corn*), we follow four steps. First, the reduced form VAR model is estimated as described in system (3) – (4).[6] Based on AIC, these models are estimated using 3 lags. Second, model residuals are used to construct the variance-covariance matrix for each regime. Third, these variance-covariance matrices are used to create the moment conditions that enter in the GMM estimation of the contemporaneous coefficients and structural shocks variances, as described in system (5). Fourth, standard errors are computed using a fixed-design wild bootstrap (500 replications). In the case of model 3 (*Oil-Ethanol-Corn*), we follow the same steps with the only difference than instead of estimating a reduced form VAR we

[5] Identification only requires that there are differences in the variances across the regimes we have selected. Therefore, it is not necessary that all variances in high volatility regimes are larger than those in low volatility regimes (Rigobon, 2003).

[6] Results from the estimation of the reduced form VAR and VEC models are not presented but are available upon request. AIC was used to select the best number of lags.

estimate a reduced form VEC with 3 lags. Because model 3 includes ethanol as a third variable, the relationship between reduced form and structural residuals is now established as:

$$\begin{bmatrix} e_{Oil,t} \\ e_{Etha,t} \\ e_{Corn,t} \end{bmatrix} = \tilde{A}^{-1} \begin{bmatrix} \varepsilon_{Oil,t} \\ \varepsilon_{Etha,t} \\ \varepsilon_{Corn,t} \end{bmatrix}$$

where,[7]

$$\tilde{A}^{-1} = \begin{bmatrix} 1 & \delta_{12} & \delta_{13} \\ \delta_{21} & 1 & \delta_{23} \\ \delta_{31} & \delta_{32} & 1 \end{bmatrix}$$

Then, we derive (6) system following the same steps used to obtain system (5). Letting the subscript $i = 1, 2$ denote the regime, system (6) is specified as follows:

$$\begin{aligned} var(e_{Oil}^i) &= var(\varepsilon_{Oil}^i) + \delta_{12}^2 var(\varepsilon_{Etha}^i) + \delta_{13}^2 var(\varepsilon_{Corn}^i) \\ cov(e_{Oil}^i, e_{Etha}^i) &= \delta_{21} var(\varepsilon_{Oil}^i) + \delta_{12} var(\varepsilon_{Etha}^i) + \delta_{13}\delta_{23} var(\varepsilon_{Corn}^i) \\ cov(e_{Oil}^i, e_{Corn}^i) &= \delta_{31} var(\varepsilon_{Oil}^i) + \delta_{12}\delta_{32} var(\varepsilon_{Etha}^i) + \delta_{13} var(\varepsilon_{Corn}^i) \\ var(e_{Etha}^i) &= \delta_{21}^2 var(\varepsilon_{Oil}^i) + var(\varepsilon_{Etha}^i) + \delta_{23}^2 var(\varepsilon_{Corn}^i) \\ cov(e_{Etha}^i, e_{Corn}^i) &= \delta_{21}\delta_{31} var(\varepsilon_{Oil}^i) + \delta_{32} var(\varepsilon_{Etha}^i) + var(\varepsilon_{Corn}^i) \\ var(e_{Corn}^i) &= \delta_{31}^2 var(\varepsilon_{Oil}^i) + \delta_{32}^2 var(\varepsilon_{Etha}^i) + var(\varepsilon_{Corn}^i) \end{aligned} \tag{6}$$

In this case, system (6) has twelve equations and twelve unknowns, from which the moment conditions are derived. This system is solved using the same regimes of high and low volatility identified for the post-Energy Policy Act period.

Results are presented in table 2. P-values for the tests of statistical significance of contemporaneous coefficients $H_0: \delta_j = 0$ are reported. As identification requires heteroskedasticity of the structural shocks, we also report the ratio of the estimated variances of structural shocks from systems (5) for models 1 and 2 and system (6) for model 3. To verify we achieved identification, at least one of these ratios should be greater than 1. Corresponding p-

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[7] The structural shocks have been normalized so that each one of them has a one unit effect on its corresponding variable.

values for the tests of the null hypotheses $H_0: var(\varepsilon_g^1)/var(\varepsilon_g^2) \leq 1$, for market $g = Oil, Etha$ and $Corn$, are also included.

Results from the test of the ratios of variances of structural shocks in table 2 are used to verify whether or not we were able to identify the systems. In all three models, the variance of structural shocks for crude oil is larger in regime 1 compared to regime 2. For example, in model 2, the variance of the crude oil structural shock in regime 1 is almost 4 times larger than in regime 2 (40.8 vs. 10.7). Moreover, in model 1, the variance of the corn structural shock is smaller in regime 1 than in regime 2. This is consistent with the expectations since high volatility regimes did not coincide for both variables in model 1, and only the one for crude oil was selected. The opposite occurs in model 2, since the periods of high volatility did coincide. Results from model 3 are similar to those in model 2. However, because the period of high volatility did not coincide for ethanol, the variance of its structural shock is larger in regime 2 (7.6 vs. 12.7). The bootstrapped p-values of the null hypotheses $H_0: var(\varepsilon_g^1)/var(\varepsilon_g^2) \leq 1$ are 0 in all cases, except when the high volatility regime corresponded to regime 2 (e.g., corn in model 1 and ethanol in model 3). These results indicate that the large increase in the variances of the structural shocks in the selected high volatility regimes is sufficient to achieve identification.

Continuing with table 2, we now focus on parameters estimates of contemporaneous coefficients $\delta_j$ (corresponding to matrices $A^{-1}$ for models 1 and 2, and matrix $\tilde{A}^{-1}$ for model 3). Comparing the contemporaneous effects of oil prices in corn prices ($\delta_2$) between models 1 and 2, this effect changes from being close to 0 on the period pre-Energy Policy Act, to 0.50 the period after. Moreover, the contemporaneous effect of corn prices on crude oil prices ($\delta_1$) changes from 0.10 to -0.18 between both periods. Thus, suggesting that the causal links between these two markets have changed after the passage of the Energy Policy Act. However, it does not necessarily indicate that the passage of this Act is the sole reason for the observed change.

Focusing on the contemporaneous coefficients in model 3 (table 2), we can observe a similar pattern as the one in model 2. For example, a 1 percent increase in the price of crude oil leads to a 0.43 percent increase in the price of corn on the same week after the shock ($\delta_{31}$). Interestingly, the contemporaneous effect of corn prices on ethanol prices is 0. That is, the estimate of $\delta_{23}$ is both economically and statistically insignificant. Although statistically significant, the instantaneous effect of ethanol prices on crude oil prices, and vice versa are economically insignificant – ($\delta_{12}$) and ($\delta_{21}$), respectively. Finally, the instantaneous effect of ethanol prices on corn prices is positive and statistically significant ($\delta_{32}$).

*Analysis of Impulse Response Functions*

After identifying the contemporaneous effects in both systems, we are interested in evaluating the total effect, contemporaneous and lagged, of a shock to each market on itself and on the other variables included in the system. To do this, we focus on the calculation of cumulative impulse response functions.

Cumulative impulse response functions calculated over the periods pre- and post-Energy Policy Act are presented in figures 3 and 4, respectively. Each figure contains two plots representing the percentage response of crude oil to a one percent shock to the price of corn, and vice versa, during a 25-week period. The solid line represents the impulse response, and the inner and outer dotted lines represent the 68% and 95% bootstrapped confidence intervals, respectively. Comparing crude oil price responses between the two periods, we observe that before May 2006, a shock to the price of corn had no statistically significant effect on the price of crude oil, except on the week when the shock hit the crude oil market (figure 3). After May 2006, the price of crude oil reacts slightly negatively to a one percent corn price shock. However, this effect is short-lived and dies out one week after the shock (figure 4).

Focusing on corn price responses to shocks on the price of crude oil, it is evident that corn prices became more responsive to crude oil price changes after the passage of the Energy Policy Act. That is, before May 2006 corn price responses following shocks in the crude oil market are close to zero and insignificant (figure 3). However, after May 2006, they become positive and statistically significant (figure 4). Thus confirming that price dynamics between these two markets have strengthened after the passage of the Act.

Finally, figure 5 shows the percentage responses of crude oil, ethanol and corn prices following a one percent shock to each price series. On-diagonal plots represent cumulative impulse responses of each price variable on itself. As expected, these responses are positive and statistically significant in every case. Shocks to the price of oil impact both ethanol and corn positively. However, this effect is more pronounced and persistent in the ethanol market. That is, corn prices are affected by the oil price shock during a short period of time, which is not consistent with our findings from model 2. A possible explanation for this finding relies on the reaction of crude oil and corn prices to ethanol price shocks. Here, we observe that both price series show a positive and statistically significant response. However, this response is larger in the corn market. Consistent with previous literature, this result confirms that ethanol is an important link between crude oil and corn markets. This is because once ethanol prices are introduced into the system, corn price responses to crude oil shocks are substantially reduced. Moreover, corn price shocks have no effect on oil and ethanol markets.

**Conclusions**

Causal and dynamic relationships between energy and agricultural markets have been a topic of interest in the literature. This study supplements existing work by addressing the identification problem encountered during the estimation of structural models which are typically used to explore links between these markets. We use the method proposed by Rigobon (2003), which is based on the heteroskedasticity of structural shocks. By identifying regimes of high volatility and low volatility, we are able to estimate contemporaneous effects between variables without imposing any additional or ad hoc restrictions in structural models. We implement this identifying method because there is no strong a priori reason to support a specific set of contemporaneous exclusion restrictions, and there is no reason to think that one exists, particularly in the study of agricultural markets. This is a key component of this study since the reliability of the estimates reported, more specifically in the analysis of the impulse responses, depends on the validity of the identifying assumptions that have been imposed.

Using weekly average cash prices from September 1997 to November 2015, we estimate two SVAR corresponding to the periods pre- and post-passage of the Energy Policy Act of 2005 to capture price dynamics between crude oil and corn prices. Then, we also estimate one SVEC model that accounts for the cointegration relationship established when ethanol prices enter into the system in the latter period. We find evidence of both unidirectional and bidirectional price transmission between crude oil, ethanol and corn markets in the post-Act period. More specifically, ethanol and corn prices positively react to a shock in the price of crude oil. Also, crude oil prices have a positive response to ethanol price shocks, but fail to react following a corn price shock. Corn prices are positively affected by ethanol price shocks indicating that the ethanol market is the main link between energy and corn markets.

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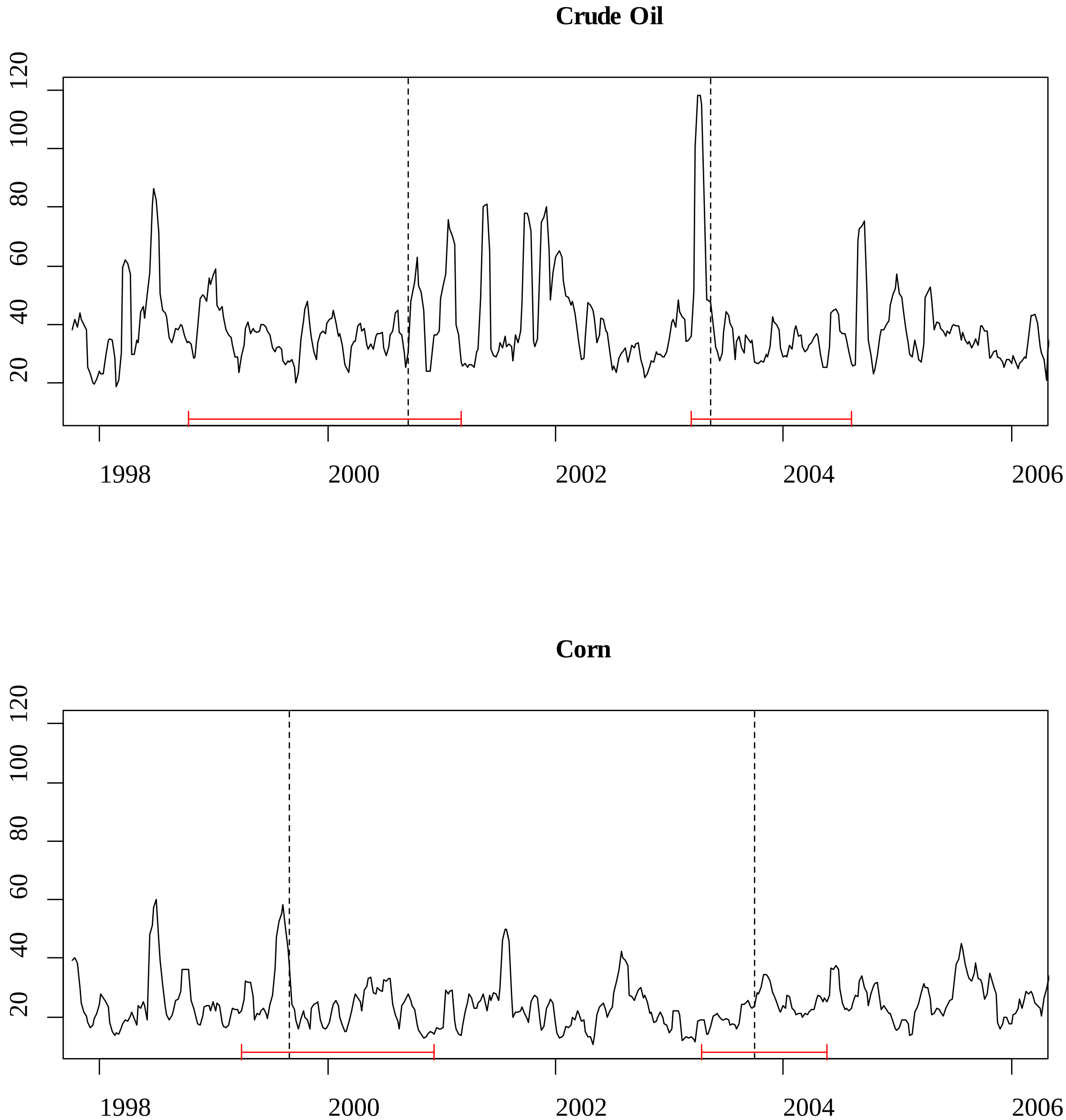


Figure 1. Weekly Average Historical Price Volatilities for Crude Oil and Corn & Identified Regimes (Sep 1997 – Apr 2006)

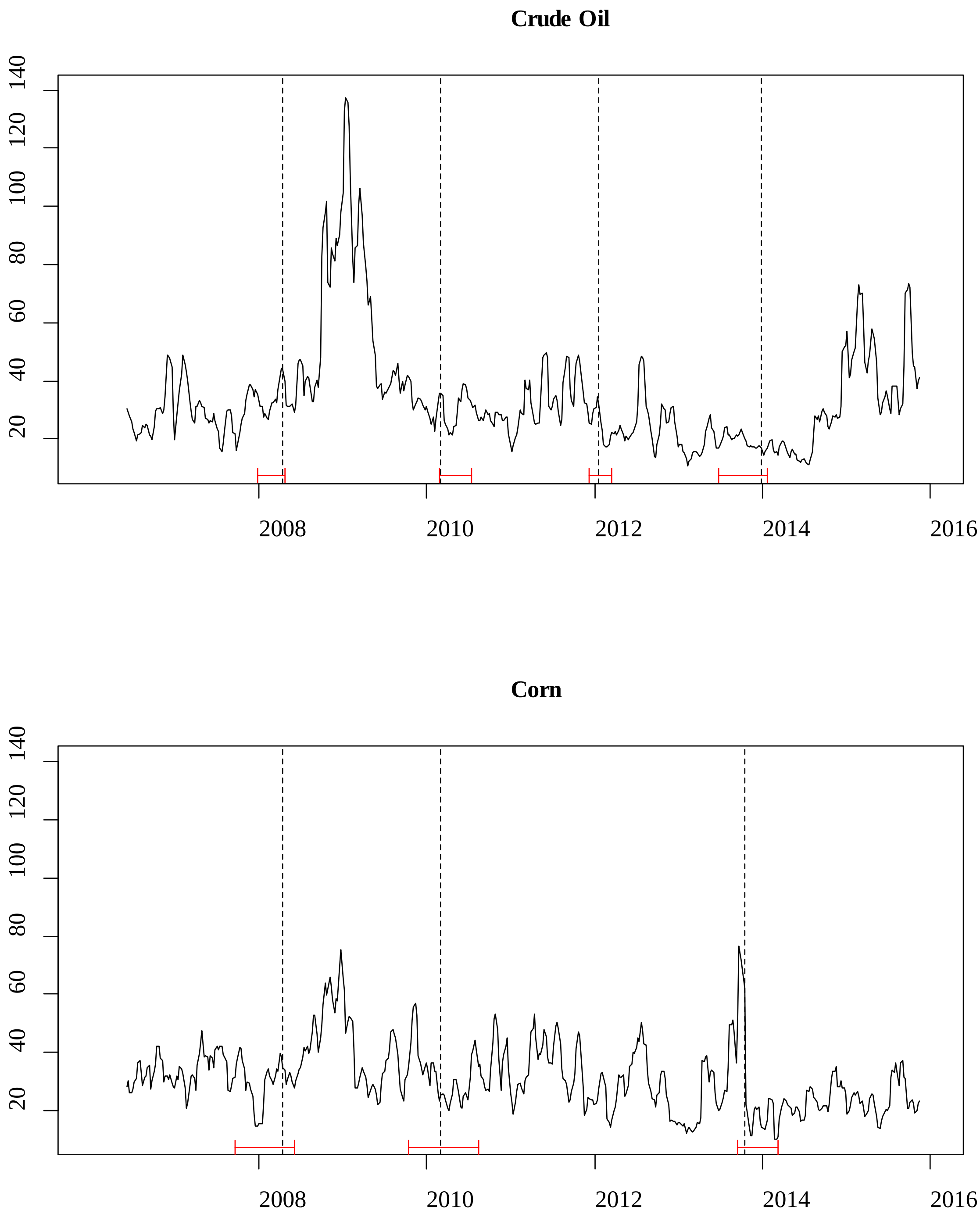


Figure 2. Weekly Average Historical Price Volatilities for Crude Oil and Corn & Identified Regimes (May 2006 – Nov 2015)

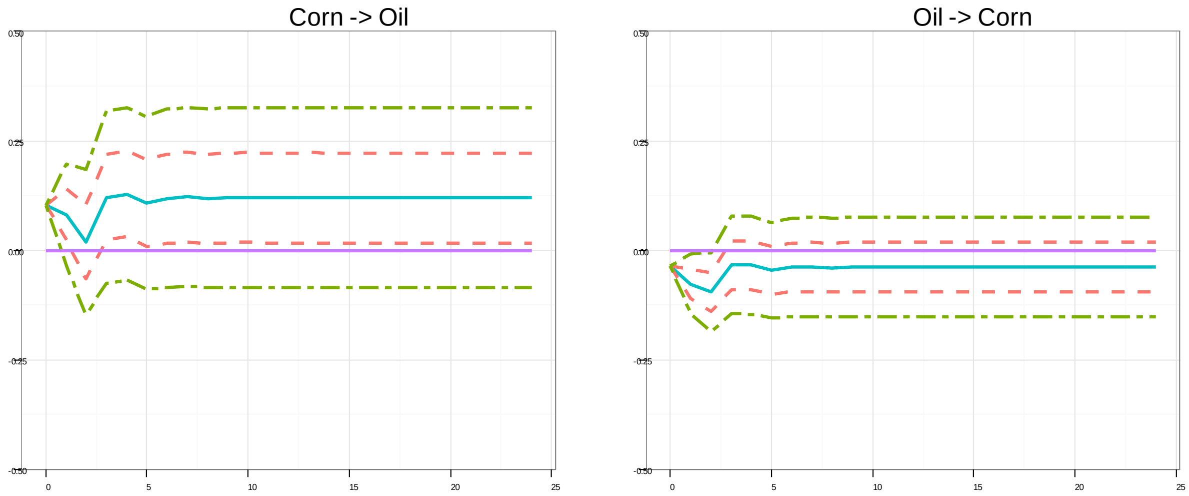


Figure 3. Response to a 1% Corn and Crude Oil price shock, respectively – Pre-Energy Policy Act (Sep 1997 – Apr 2006)

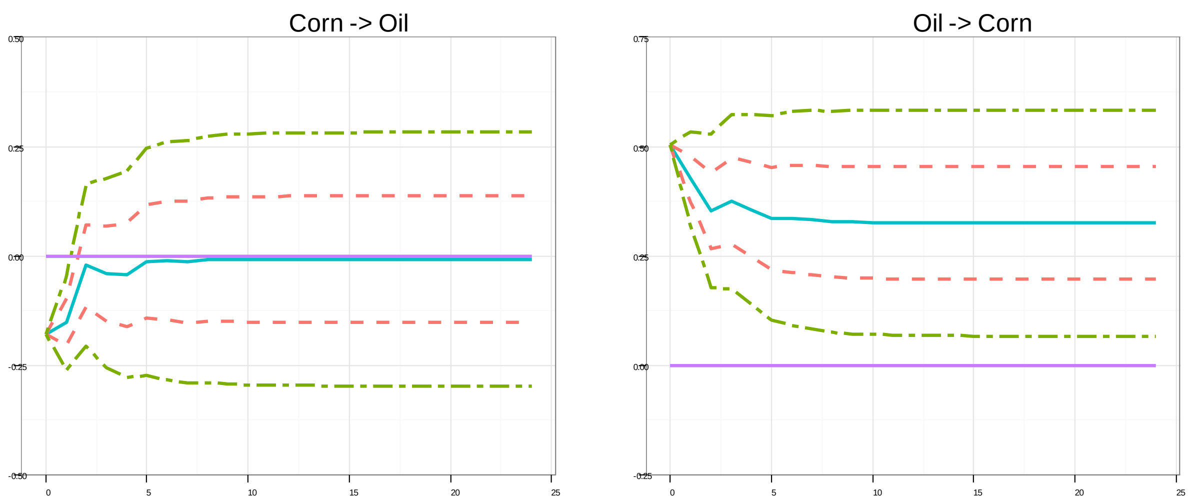


Figure 4. Response to a 1% Corn and Crude Oil price shock, respectively – Post-Energy Policy Act (May 1997 – Nov 2015)

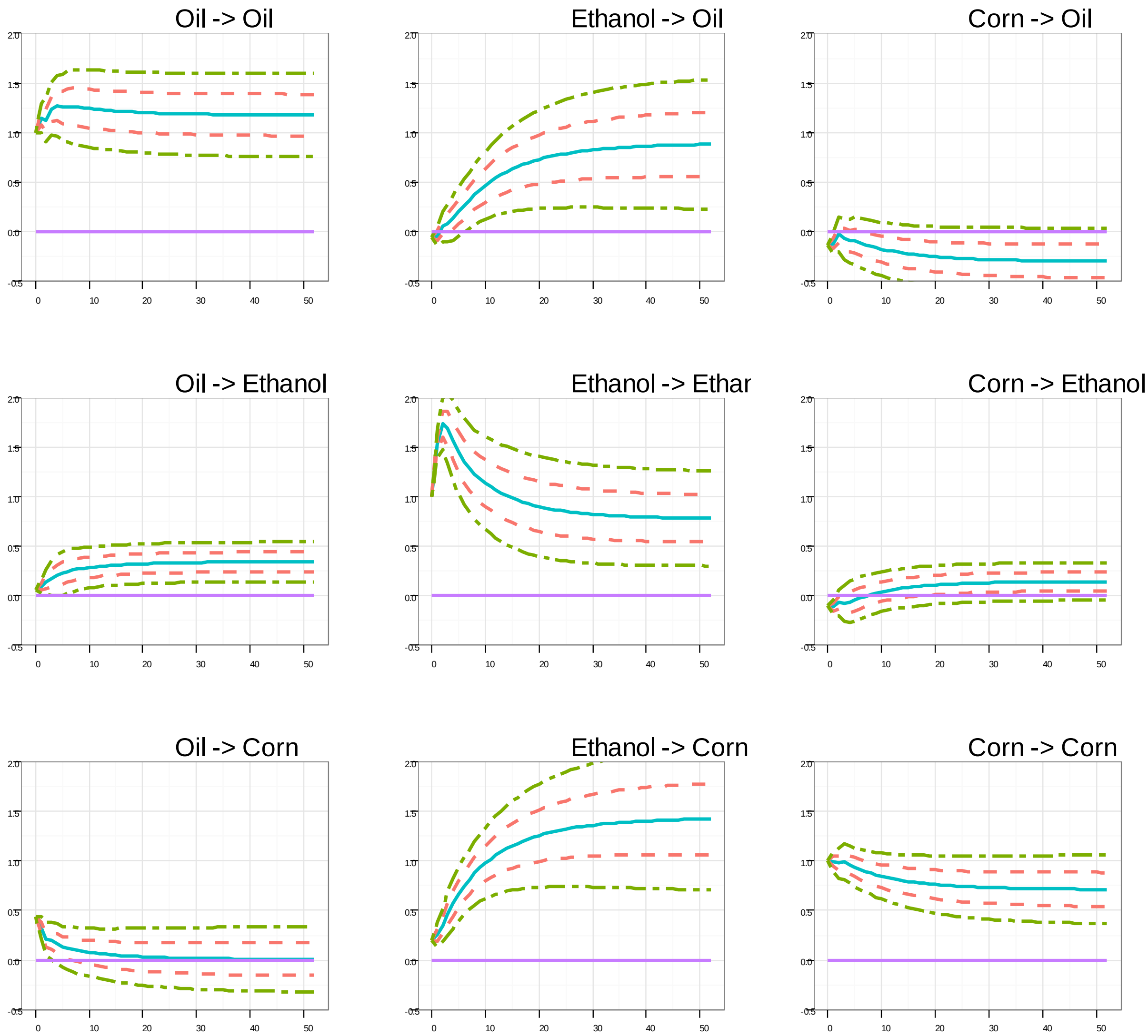


Figure 5. Response to a 1% Oil, Ethanol and Crude Oil price shock, respectively – Post-Energy Policy Act (May 1997 – Nov 2015)

Table 1. Unit Root and Cointegration Tests Results for Weekly Average Oil, Corn and Ethanol cash prices

| Test | Test-statistics | | | |
|---|---|---|---|---|
| | Sep 1997 – Apr 2006 | | May 2006 – Nov 2015 | |
| **Augmented DF** | *Constant* | *Trend* | *Constant* | *Trend* |
| *Oil* | -0.70 | -1.98 | -1.93 | -2.99 |
| *Corn* | -2.60 | -2.63 | -1.99 | -1.49 |
| *Ethanol* | | | -2.79 | -2.83 |
| **Johansen Cointegration** | *Max. Eigen.* | *Trace* | *Max. Eigen.* | *Trace* |
| Model Oil–Corn | | | | |
| $r = 0$ | 6.60 | 8.29 | 8.31 | 11.92 |
| $r \leq 1$ | 1.68 | 1.68 | 3.61 | 3.61 |
| Model Oil–Ethanol–Corn | | | | |
| $r = 0$ | | | 38.22** | 50.44** |
| $r \leq 1$ | | | 9.24 | 12.22 |
| $r \leq 2$ | | | 2.98 | 2.98 |

Notes: AIC was used to determine appropriate lag lengths for the ADF test. The null hypothesis under the ADF test is nonstationary. The critical values are -2.87 and -3.42 for the 0.05 significance level, corresponding to the specifications using a constant (but not trend) and a trend, respectively. The null hypothesis under the Johansen cointegration test is the number of cointegration vectors (*r*). ** indicates rejection of the null hypothesis at the 0.05 significance level.

Table 2. Contemporaneous Parameter Estimates

| Parameter | Estimates | | | |
|---|---|---|---|---|
| | Sep 1997 – Apr 2006 | | May 2006 – Nov 2015 | |
| **Model Oil – Corn** | | | | |
| | *Coefficient* | *p-value* [a] | *Coefficient* | *p-value* [a] |
| $\delta_1$ | 0.103 | 0.001 | -0.180 | 0.000 |
| $\delta_2$ | -0.036 | 0.083 | 0.504 | 0.000 |
| $var(\varepsilon_{Oil}^1)$ | 22.109 | 0.000 | 40.834 | 0.000 |
| $var(\varepsilon_{Corn}^1)$ | 7.345 | 0.000 | 23.756 | 0.000 |
| $var(\varepsilon_{Oil}^2)$ | 17.344 | 0.000 | 10.705 | 0.000 |
| $var(\varepsilon_{Corn}^2)$ | 13.157 | 0.000 | 16.153 | 0.000 |
| | | *p-value* [b] | | *p-value* [b] |
| $var(\varepsilon_{Oil}^1)/var(\varepsilon_{Oil}^2)$ | 1.274 | 0.000 | 3.814 | 0.000 |
| $var(\varepsilon_{Corn}^1)/var(\varepsilon_{Corn}^2)$ | 0.558 | 1.000 | 1.471 | 0.000 |
| **Model Oil–Ethanol–Corn** | | | | |
| | | | | *p-value* [a] |
| $\delta_{12}$ | | | -0.062 | 0.003 |
| $\delta_{13}$ | | | -0.139 | 0.000 |
| $\delta_{21}$ | | | 0.056 | 0.002 |
| $\delta_{23}$ | | | -0.095 | 0.071 |
| $\delta_{31}$ | | | 0.435 | 0.000 |
| $\delta_{32}$ | | | 0.199 | 0.000 |
| $var(\varepsilon_{Oil}^1)$ | | | 40.616 | 0.000 |
| $var(\varepsilon_{Etha}^1)$ | | | 7.625 | 0.000 |
| $var(\varepsilon_{Corn}^1)$ | | | 23.368 | 0.000 |
| $var(\varepsilon_{Oil}^2)$ | | | 10.818 | 0.000 |
| $var(\varepsilon_{Etha}^2)$ | | | 12.712 | 0.000 |
| $var(\varepsilon_{Corn}^2)$ | | | 15.753 | 0.000 |
| | | | | *p-value* [b] |
| $var(\varepsilon_{Oil}^1)/var(\varepsilon_{Oil}^2)$ | | | 3.754 | 0.000 |
| $var(\varepsilon_{Etha}^1)/var(\varepsilon_{Etha}^2)$ | | | 0.599 | 1.000 |
| $var(\varepsilon_{Corn}^1)/var(\varepsilon_{Corn}^2)$ | | | 1.483 | 0.000 |

Notes: *p-value (a)* corresponds to the test of the null hypothesis $H_0$: $\delta_j = 0$. *p-value (b)* corresponds to the test of the null hypothesis $H_0$: $var(\varepsilon_g^1)/var(\varepsilon_g^2) \leq 1$, for market $g$.