Are Price Transmissions between U.S. Energy and Corn Markets Asymmetric?

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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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1 Introduction

In industrialized economies, particularly in the United States, the link between energy and agricultural commodity prices has strengthened in recent years. Part of this effect is attributed to the implementation of the Renewable Fuel Standard (RFS) program under the Energy Policy Act of 2005 (Mallory, Irwin and Hayes, 2012). Concerns about greenhouse gas emissions, high crude oil prices, and the growing dependency on foreign oil supplies provided incentives for the creation of this program to pursue alternative fuel sources such as ethanol and biodiesel. The RFS imposes strict mandates requiring U.S. fuel production to include a minimum amount of renewable fuel, with an increasing target each year. Ethanol produced from corn is the most prominent biofuel in the U.S. Currently, blends of petroleum-based gasoline with 10% ethanol, commonly referred to as E10, account for more than 95% of the fuel consumed in motor vehicles with gasoline engines (U.S. Energy Information Administration, 2016).

The creation of the RFS program has had extensive implications for the ethanol market, and indirectly for the corn market (Baumeister, Ellwanger and Killian, 2016). In 2007, the U.S. Congress passed a legislation that increased by 1.3 billion bushels, over a third of the U.S. corn crop, the total amount of corn required to be processed annually into ethanol for motor-fuel use (Carter, Rausser and Smith, 2016). Given the potential impact of corn price changes on related feed and food markets, it is important to understand how corn prices are affected by unexpected fluctuations in crude oil and ethanol markets. Following the early work of Borenstein, Cameron and Gilbert (1997), a question that emerges is whether the "rockets and feathers" phenomenon affecting the fuel industry is also extended to the ethanol, and consequently corn markets. Although still debated, there is an established perception that oil price increases are followed by immediate increases in fuel prices, while oil price decreases are transmitted to fuel prices only with a delay (Baumeister and Killian, 2014). However, only few studies have analyzed whether the pass-through from energy prices to agricultural prices, and vice versa, is asymmetric.

In the literature, several potential explanations have been offered for asymmetric price behavior: market power and concentration (Azzam, 1999; Peltzman, 2000; Xia, 2009), menu costs (Bailey and Brorsen, 1989; Levy et al., 1997); inventory adjustment practices (Blinder, 1982; Miller and Hayenga, 2001); government intervention (Kinnucan and Forker, 1987; Mohanty, Peterson and Kruse, 1995); and consumption inertia (Xia and Li, 2010). Because the production of biofuels is not commercially viable as costs are higher relative to the costs of fossil fuels extraction, government intervention is essential in providing incentives that ensure adequate biofuel production and consumption (Balcombe and Rapsomanikis, 2009). Therefore, market dynamics in the ethanol industry, mostly influenced by government interventions in the form of mandates, bans, subsidies and import tariffs, as well as production/inventory adjustment costs, and market power are likely to cause nonlinear price adjustments (Serra et al., 2011).

The objective of this study is to evaluate and quantify asymmetric price transmissions among U.S. crude oil, ethanol and corn markets. We focus on two possible directions of asymmetry, from energy to corn and from corn to energy markets, with potentially large welfare implications if responses to price increases and decreases are not symmetric.
We estimate a nonlinear structural vector error correction (VEC) model that allows for asymmetric responses of crude oil, ethanol and corn prices to shocks to any of these series in both long run and short run. The contemporaneous effects in the nonlinear structural VEC model are properly identified using the approach proposed by Rigobon (2003), which is based

on the heteroskedasticity of structural shocks. To systematically test for asymmetric price transmissions and calculate the degree of asymmetry, we use a novel approach proposed by Kilian and Vigfusson (2011), which is based on the estimation of nonlinear impulse responses using Monte Carlo simulation methods.

Results from this study reveal that ethanol prices react asymmetrically to unexpected changes in crude oil prices. This asymmetry is positive, indicating that ethanol prices are more responsive to crude oil price increases than decreases. Moreover, corn prices also react asymmetrically to unexpected changes in ethanol prices. In this case, corn prices are more responsive to ethanol price decreases than increases. These results have important implications for the U.S. ethanol industry, particularly relevant in the current political climate where biofuels policy changes are expected. The impact of government interventions targeting the sustainability of ethanol production and consumption may have unexpected welfare and income distribution effects on both agricultural crop farmers and consumers because of the presence of asymmetry in the pass-through between energy and agricultural commodity prices.

2 Methods

The underlying adjustment dynamics of crude oil, ethanol and corn prices in response to a one-time positive and negative unexpected change in any of these series are captured using a nonlinear vector error correction (VEC) model. Let O_t, E_t and C_t be the crude oil, ethanol and corn prices at time t, respectively. The structural form of the nonlinear VEC model can be written as:

$$
\begin{aligned}
\Delta O_t = a_{10} + I_t b_{11}^{+} ECT_{t-1} + \sum_{k=1}^{p} c_{12,k}^{+} \Delta O_{t-k} + \sum_{k=0}^{p} c_{13,k}^{+} \Delta E_{t-k} + \sum_{k=0}^{p} c_{14,k}^{+} \Delta C_{t-k} \\
+ (1 - I_t) b_{11}^{-} ECT_{t-1} + \sum_{k=1}^{p} c_{12,k}^{-} \Delta O_{t-k} + \sum_{k=0}^{p} c_{13,k}^{-} \Delta E_{t-k} + \sum_{k=0}^{p} c_{14,k}^{+} \Delta C_{t-k} + e_{O,t}
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
\Delta E_t = a_{20} + I_t b_{21}^{+} ECT_{t-1} + \sum_{k=0}^{p} c_{22,k}^{+} \Delta O_{t-k} + \sum_{k=1}^{p} c_{23,k}^{+} \Delta E_{t-k} + \sum_{k=0}^{p} c_{24,k}^{+} \Delta C_{t-k} \\
+ (1 - I_t) b_{21}^{-} ECT_{t-1} + \sum_{k=0}^{p} c_{22,k}^{-} \Delta O_{t-k} + \sum_{k=1}^{p} c_{23,k}^{-} \Delta E_{t-k} + \sum_{k=0}^{p} c_{24,k}^{+} \Delta C_{t-k} + e_{E,t}
\end{aligned}
\tag{2}
$$

$$
\begin{aligned}
\Delta C_t = a_{30} + I_t b_{31}^{+} ECT_{t-1} + \sum_{k=0}^{p} c_{32,k}^{+} \Delta O_{t-k} + \sum_{k=0}^{p} c_{33,k}^{+} \Delta E_{t-k} + \sum_{k=1}^{p} c_{34,k}^{+} \Delta C_{t-k} + \\
(1 - I_t) b_{31}^{-} ECT_{t-1} + \sum_{k=0}^{p} c_{32,k}^{-} \Delta O_{t-k} + \sum_{k=0}^{p} c_{33,k}^{-} \Delta E_{t-k} + \sum_{k=1}^{p} c_{34,k}^{+} \Delta C_{t-k} + e_{C,t}
\end{aligned}
\tag{3}
$$

where Δ is the difference operator; $ECT_{t-1} = O_{t-1} - \gamma_0 - \gamma_1 E_{t-1} - \gamma_2 C_{t-1}$ is the one-period lagged error correction term; and $e_{O,t}$, $e_{E,t}$ and $e_{C,t}$ are uncorrelated structural shocks to the crude oil, ethanol and corn markets, respectively.

This structural nonlinear VEC model distinguishes between long-run and short-run price adjustments. The short-run adjustment is determined by $c_{ij,k}^{+}$ and $c_{ij,k}^{-}$, for equation $i = 1, 2, 3$, variable $j = 2, 3, 4$ and all $k = 0, \ldots, p$, where p is the chosen lag length of the linear VEC model. $c_{ij,k}^{+}$ applies when the corresponding variable is larger than a pre-determined threshold value, while $c_{ij,k}^{-}$ applies when the corresponding variable is less than or equal to such value. In this model, the threshold value for the short-run adjustment is zero. The long-run adjustment is determined by b_{i1}^{+} and b_{i1}^{-}. Here, the indicator function I_t, is restricted as follows:

$$I_t = \begin{cases} 1 \text{ if } ECT_{t-1} > \tau \\ 0 \text{ if } ECT_{t-1} \leq \tau \end{cases} \tag{4}$$

where τ represents the threshold value, which is selected by minimizing the sum of squared errors, with a minimum of 15 percent of the observations in each regime.

To test for cointegration when the long-run price adjustment is suspected of being asymmetric, we employ the Enders and Siklos (2001) test. Here, the cointegration relationship between the three price series, each assumed to be integrated of order one, takes the form:

$$O_t = \gamma_0 + \gamma_1 E_t + \gamma_2 C_t + \varepsilon_t, \tag{5}$$

where ε_t measures the deviation from the equilibrium relationship between O_t, E_t and C_t. To allow for asymmetric adjustment dynamics, deviations from equilibrium are allowed to follow a threshold autoregressive process:

$$\Delta\varepsilon_t = I_{\varepsilon,t}\rho_1\varepsilon_{t-1} + (1 - I_{\varepsilon,t})\,\rho_2\varepsilon_{t-1} + \sum_{k=1}^{P} \delta_k \Delta\varepsilon_{t-k} + \mu_t, \tag{6}$$

where ρ_1 and ρ_2 are the speed of adjustment of $\Delta\varepsilon_t$, and the indicator function $I_{\varepsilon,t}$ has a similar specification as equation (4). To determine whether cointegration exists, we use the t_{Max} and Φ tests. The t_{Max} statistic is the largest t-statistic associated with the estimated coefficients ρ_1 and ρ_2, and the Φ test is an F-test of the joint hypothesis $\rho_1 = \rho_2 = 0$. Simulated critical values for both test are found in Enders and Siklos (2001).

2.1 *Model Identification*

To identify the contemporaneous effects in system (1)-(3), we apply the method proposed by Rigobon (2003), which is based on the heteroskedasticity of structural shocks. This method measures the contemporaneous relationship among 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)-(3) 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, which can be estimated by the generalized method of moments (GMM). Standard errors and confidence intervals can be computed using a fixed-design wild bootstrap (Goncalves and Kilian, 2004).

There are two assumptions that lead to the identification of system (1) - (3): i) parameters in structural equations 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.

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.

2.2 *Testing for Asymmetry*

To test whether price responses to unexpected changes in any of the variables in system (1)-(3) are asymmetric, we apply an impulse response- based test. Under the null hypothesis of symmetry, the vector of impulse responses to a positive price shock should be opposite in sign but of the same magnitude as the vector of impulse responses to a negative price shock of the same size. Therefore, the null hypothesis implies that all elements in the vector calculated as the sum of these two sets of impulse responses are zero. Following Kilian and Vigfusson (2011), impulse response functions are computed using Monte Carlo simulation techniques. For example, the algorithm used to estimate the response of the corn price to a one-time crude oil price shock is:

1. Randomly draw a block of p consecutive values of ΔO_t, ΔE_t and ΔC_t, where p is the lag length of the structural nonlinear VEC model. This defines a history Ω^i.

2. Define e_0 to be the shock to the price that is of interest (in this case the shock to ΔO_t).

3. Define $e_{1,H}$ and $e_{2,H}$ to be vectors holding a draw of $H + 1$ values of the identified shocks to ΔE and ΔC, respectively, where H is the longest horizon for which impulse response functions are calculated.

4. Define $e_{3,H}$ to be a vector holding a draw of H values of the identified shocks to ΔO_t.

5. Predict the values of ΔO_{t+h}, ΔE_{t+h} and ΔC_{t+h} for periods $h = 0, \ldots, H$, conditional on Ω^i, e_{1H}, e_{2H} and $(e_0, e_{3H})'$, where e_0 is defined to be either a positive or negative one standard deviation shock to ΔO_t.

6. Predict the values of ΔO_{t+h}, ΔE_{t+h} and ΔC_{t+h} for periods $h = 0, \ldots, H$, conditional on Ω^i, e_{1H}, e_{2H}, and $(e_0, e_{3,H})'$, where $e_0 = 0$.

7. Calculate the difference in predicted values of the two variables from steps 5 and 6. This difference is the impulse response of corn price to an oil price shock of size e_0,

conditional on Ω^i.

8. Steps 1-7 are repeated 1,000 times. The unconditional impulse response function is the average of the output from step 7 across the 1,000 simulations.

9. Perform a fixed-design wild bootstrap (Goncalves and Kilian, 2004) with 500 replications to calculate confidence intervals.[1] We use the Rademacher pick distribution as suggested by Godfrey (2009).

3 Data

The data use in this analysis corresponds to weekly prices covering the period after the implementation of the Energy Policy Act - May 2006 to December 2016 (558 observations). Although the Act was not passed until 2005, this period is considered because the U.S. policy toward ethanol did not change until May 2006 (Baumeister and Kilian, 2014; Avalos, 2014). Cushing, Oklahoma West Texas Intermediate (WTI) crude oil spot prices FOB (dollars per barrel) were obtained from the U.S. Energy Information Administration (EIA). Omaha, Nebraska #2 yellow corn cash prices paid to farmers (dollars per bushel) were obtained from the Livestock Marketing Information Center. Iowa ethanol cash prices (dollars per gallon) were obtained from the Commodity Research Bureau (CRB). Moreover, to estimate historical volatilities that are used to determine high and low volatility regimes, daily cash price data for WTI crude oil, corn and ethanol were collected from (CRB).

Table 1 presents results from the analysis of univariate time series properties of the data, as well as standard and threshold cointegration test. To test for the presence of a unit root in individual price series, we applied the Augmented Dickey-Fuller (ADF) test.
Results of this test indicate that all price series are nonstationary.
Furthermore, we tested for standard cointegration among price variables using both specifi-

[1]The wild bootstrap accounts for possible conditional heteroskedasticity of the error term.

cations of the Johansen procedure (i.e., maximum eigenvalue and trace statistic). Results indicate that variables are cointegrated with one cointegrating relationship. This result confirms the appropriateness of estimating a structural VEC model.

Table 1 also reports the results from applying the Enders and Siklos's (2001) t_{Max} and Φ tests for threshold cointegration to account for possible asymmetric adjustments to deviations from the long-run equilibrium. This test was performed by estimating equation (6) using the residuals from equation (5) and the specification in equation (4), where the value of τ was set equal to zero ($TC1$) and different from zero ($TC2$). Following Chan (1993), the threshold value in $TC2$ was estimated using the grid search method. Looking at these results, we reject the null hypothesis of no cointegration at the 0.05 significance level in both cases. These results indicate that there is a long-run equilibrium relationship characterized by asymmetric adjustment, which provides justification for estimating a nonlinear structural VEC model.

4 Results and Discussion

Before proceeding with the estimation of the nonlinear structural VEC model, as specified in system (1)-(3), it is necessary to identify the contemporaneous effects. These effects are identified using the heteroskedasticity of structural shocks as proposed by Rigobon (2003). To identify high and low volatility regimes, the Bai and Perron (2003) structural break test was applied to weekly average historical price volatilities of crude oil, corn and ethanol. We allowed up to 5 breaks and used a trimming of at least 0.15, so each segment has a minimum of 15 percent of the observations in the sample. The best number of breaks was selected based on the Bayesian Information Criterion (BIC). Results from this test indicate the presence of one high volatility regime from April 11, 2008 to February 26, 2010, which coincides with the financial market crisis of 2008. All other observations are defined as the low volatility regime.

Table 2 presents the results from the contemporaneous coefficients and structural variances estimation, along with corresponding p-values. Focusing on the contemporaneous coefficients, we find that crude oil and corn prices affect each other at time t. Because this is a bi-directional effect, system (1)-(3) cannot be estimated without further assumptions. Therefore, we assume that the contemporaneous effects of crude oil and corn prices on each other are symmetric by imposing the estimated values delivered by GMM, so that $c^+_{14,0} = c^-_{14,0} = -0.23$ and $c^+_{32,0} = c^-_{32,0} = 0.50$. As identification requires heteroskedasticity of the structural shocks, we also report the ratio of the estimated variances from system (1)-(3). To verify we have achieved identification, at least one of these ratios should be greater than 1. Results indicate that the variance of structural shocks for both crude oil and corn prices is larger in regime 1 (high volatility) compared to regime 2 (low volatility). Therefore, the selected high volatility regime is sufficient to achieve identification.

The nonlinear structural VEC model is estimated using the natural logarithms of weekly crude oil, ethanol and corn prices in first differences. Based on AIC and the evaluation of autocorrelation patterns, system (1)-(3) was estimated using three lags. The cointegration vector parameters were estimated using the Engle and Granger (1987) method to maintain consistency with the Enders and Siklos test. Results from the estimation of this model are not presented since the main objective of this study is to test for asymmetric price transmissions among energy and corn markets. Therefore, we proceed with the analysis of results from the impulse response-based test.

Results from the asymmetry test conducted using computed cumulative nonlinear impulse response functions are presented in figure 1. Each row corresponds to one of the three equations in the nonlinear structural VEC model. To facilitate the interpretation of results, we first focus on the top right plot. In this plot, the solid line "*diff-IRF*" shows the net response of the corn price to a one-time positive and negative oil price shock. The magnitude of the response is measured in percentages (%) and is depicted on the vertical axis, while the number of weeks after the shock is on the horizontal axis. The size of the shock is one standard deviation. The reason we use cumulative impulse responses is to account for the fact that variables are in log-differences. Accumulating over time makes the interpretation of price reactions in percentages, which is the same as tracing a shock to the variables in levels. The 90% confidence intervals are computed using the fixed-design wild bootstrap estimates, and are represented by the dashed blue lines. The null hypothesis of symmetry is rejected if confidence intervals of "*diff-IRF*" do not contain 0. Therefore, our impulse response based test is based on the statistical significance of the solid black line depicted in each plot.

Focusing on price responses following unexpected changes in oil prices, we reject the null hypothesis of symmetry at the 0.05 significance level in one case. This case shows a positive asymmetric response in ethanol prices during the first 3 weeks after a shock to oil prices (first row, second plot). That is, after a 4% positive and negative shock to crude oil price, the net result is an increase of 0.9% in ethanol prices, three weeks after the shock. This finding suggests that prices received by ethanol producers adjust more fully to crude oil price increases than decreases. Economically, the magnitude of asymmetry is significant compared to the size of the oil price shock. That is, the net effect of a dollar increase and decrease in the price of crude oil is a 22.5 cents increase in the price of ethanol. A possible explanation for this finding is related to the ethanol market structure which is heavily influenced by government interventions. As producers of gasoline are required to blend certain amount ethanol to meet RFS, if the price of oil increases, the cost of producing gasoline increases and ethanol becomes an inexpensive alternative to add octane into gasoline. Therefore, an increase in the price of oil drives up the demand for ethanol and subsequently, ethanol prices increase. Conversely, as oil prices decrease, gasoline may become less expensive than ethanol. However, because of the RFS mandate, ethanol must be still blended into gasoline which causes the price of ethanol to decrease slower or at a smaller magnitude than gasoline prices.

Looking at price responses following unexpected changes in the price of ethanol, we reject the null hypothesis of symmetry at the 0.10 significance level in one case. Corn prices react asymmetrically to ethanol price shocks (second raw, third plot). Following a

3.4% increase and decrease in the price of ethanol, the net result is a 0.6% decrease in the price of corn, one week after the shock. This finding suggest that ethanol price decreases are transmitted more fully to corn producers than ethanol price increases. Economically, the net effect of a dollar increase and decrease in the price of ethanol translates roughly into an 18 cents decrease in the price of corn. This finding has important welfare implications for corn producers, suggesting that RFS mandates may potentially provide ethanol producers with a certain degree of market power. However, a more profound assessment is needed to determine whether asymmetry in this case is driven by market power. Lastly, when analyzing price responses to unexpected changes in corn prices, we fail to reject the null hypothesis of symmetry in all cases. This finding indicates that corn price increases and decreases cause the same effect (but in opposite sign) in both ethanol and crude oil prices.

5 Conclusions

Following the increased reliance of biofuels production in the U.S., the pass-through between energy and agricultural commodity prices has been a topic of main concern, particularly because of its potential implications in the food versus fuel debate.
Of particular interest in this study is to evaluate whether the "rockets and feathers" phenomenon affecting the fuel industry is also extended to the ethanol, and consequently corn markets. In our empirical analysis, we estimate price transmissions between crude oil, ethanol and corn markets using a nonlinear structural VEC model, which allows for asymmetric responses in both the long-run and the short-run. Moreover, model identification is achieved via heteroskedasticity of structural shocks. An important contribution of this study is the use of a novel approach to test for asymmetric price transmissions, which is based on the simulation of nonlinear impulse response functions.

Results from this study reveal that ethanol prices react asymmetrically to unexpected changes in crude oil prices. This asymmetry is positive, indicating that ethanol prices are more responsive to crude oil price increases than decreases. This finding is explained by both the substitution relationship between gasoline and ethanol and government interventions. That is, if the price of oil increases, the cost of producing gasoline increases and ethanol becomes an inexpensive alternative to add octane into gasoline. This drives up the demand for ethanol and subsequently, ethanol prices increase. Conversely, as oil prices decrease and gasoline becomes less expensive, the demand for ethanol may not be significantly affected. This is consistent with a binding blending mandate which creates an inelastic demand for ethanol (Babcock, 2013).

Corn prices react asymmetrically to unexpected changes in ethanol prices. However, in this case, corn prices are more responsive to ethanol price decreases than increases. This finding has direct welfare implications for corn producers, suggesting that RFS mandates may potentially provide ethanol producers with a certain degree of market power. However, a more detailed analysis is necessary to test whether market power drives this result. Therefore, it remains a topic of future research. Overall, our results have important implications for the U.S. ethanol industry, particularly relevant in the current political climate where biofuels policy changes are expected. The impact of government interventions targeting the sustainability of ethanol production and consumption may have unexpected welfare and income distribution effects on both agricultural crop farmers and consumers because of the presence of asymmetry in the pass-through between energy and agricultural commodity prices.

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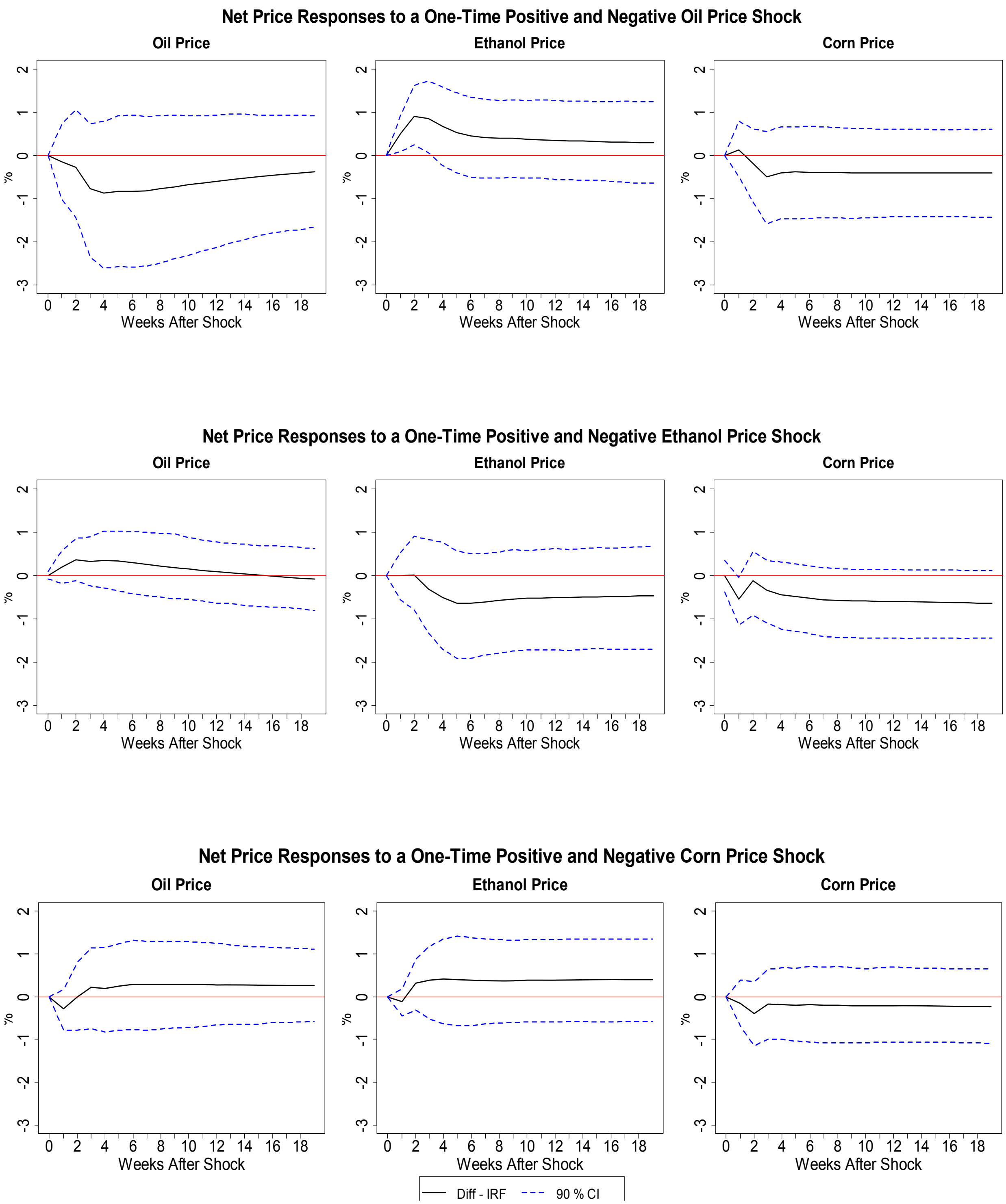

Figure 1. Results from the Impulse Response-Based test of Symmetry

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

Test	**Test-Statistics**		
Augmented DF	*None*	*Constant*	*Trend*
Oil	-0.28	-2.60	-2.95
Ethanol	-1.15	-2.71	-2.94
Corn	-0.40	-1.60	-1.68
Johansen Cointegration	*Max. Eigen.*	*Trace*	
$r = 0$	44.21**	54.92**	
$r \leq 1$	8.13	10.71	
$r \leq 2$	2.58	2.58	
Threshold Cointegration	$tMax$	Φ	*threshold*
TC 1	-2.21**	6.92**	0
TC 2	-2.07**	8.04**	-21.33

Notes: AIC was used to determine the appropriate lag lengths for the ADF test, with a maximum of 52 lags allowed. The null hypothesis under the ADF test is nonstationary. The critical values are -1.95, -2.87 and -3.42 for the 0.05 significance level, corresponding to the specifications using no deterministic terms, a constant (but not trend) and a trend, respectively. The null hypothesis under the Johansen Cointegration test is the number of cointegration vectors (r). The null hypothesis under the Threshold Cointegration test is no cointegration. Approximate critical values for the $tMax$ and Φ tests are tabulated by Enders and Siklos (2001). ** indicates the rejection of the null hypothesis at the 0.05 significance level.

Table 2. Contemporaneous Parameter Estimates

Parameter	**Estimates**	
	Coefficient	*p-Value*^{a}
$c_{13,0}$ (Ethanol $\rightarrow$ Oil)	-0.01	0.77
$c_{14,0}$ (Corn $\rightarrow$ Oil)	-0.23	0.00
$c_{22,0}$ (Oil $\rightarrow$ Ethanol)	0.05	0.06
$c_{24,0}$ (Corn $\rightarrow$ Ethanol)	-0.04	0.69
$c_{32,0}$ (Oil $\rightarrow$ Corn)	0.50	0.00
$c_{33,0}$ (Ethanol $\rightarrow$ Corn)	0.14	0.12
$var(e_O^1)$	40.08	0.00
$var(e_E^1)$	7.85	0.00
$var(e_C^1)$	22.27	0.00
$var(e_O^2)$	11.90	0.00
$var(e_E^2)$	12.29	0.00
$var(e_C^2)$	14.59	0.00
		p-Value^b
$var(e_O^1)/var(e_O^2)$	3.37	0.00
$var(e_E^1)/var(e_E^2)$	0.64	0.00
$var(e_C^1)/var(e_C^2)$	1.53	0.00

Notes: *p-Value* (a) corresponds to the test of the null hypothesis: $H_0 : c_{ij,0} = 0$ for equation $i = 1, 2, 3$, and variable $j = 2, 3, 4$. *p-Value* (b) corresponds to the test of the null hypothesis $H_0 : var(e_g^1)/var(e_g^2) \leq 1$, for market $g = Oil, Ethanol, Corn$.