# Food before Biodiesel Fuel?

**Na Hao**
**University of Georgia**
**Department of Ag & Applied Economics**
**306 Conner Hall, Athens GA 30602**
haona@uga.edu

**Gregory Colson**
**University of Georgia**
**Department of Ag & Applied Economics**
**314-A Conner Hall, Athens GA 30602**
gcolson@uga.edu

**Berna Karali**
**University of Georgia**
**Department of Ag & Applied Economics**
**315 Conner Hall, Athens GA 30602**
bkarali@uga.edu

**Michael Wetzstein**
**University of Georgia**
**Department of Ag & Applied Economics**
**315 Conner Hall, Athens GA 30602**
mwetz@uga.edu

***Selected Paper prepared for presentation at the Southern Agricultural Economics Association (SAEA) Annual Meeting, Orlando, Florida, 3-5 February 2013***

# Food before Biodiesel Fuel?


## Abstract

Biodiesel has recently drawn attention because of its potential to make an important contribution to national energy security and the environment. However, the rapid growth of biodiesel has raised concerns about biodiesel's impact on the price level and volatility of agricultural commodities. To address these concerns this research investigates the short- and long-run relationships between agricultural commodity and fuel markets, and finds interdependencies between the two. The causal linkage between biodiesel and soybean prices is very weak, indicating little likelihood of biodiesel triggering another food crisis. In contrast, oil price shocks have major influence on both fuel and agricultural commodity prices.


Key Words: Biodiesel, Corn, Soybean, Vector error correction model(VECM)

## Food before Biodiesel Fuel?

Biodiesel is a vegetable oil- or animal fat-based diesel fuel used in standard diesel engines. It is distinct from vegetable and waste oils used to fuel converted diesel engines. Biodiesel is typically blended with petrodiesel as a commercially viable, renewable, low carbon pure petrodiesel replacement fuel. With its continued annual growth rate of over 20% globally and 15% in the United States over the past decade, biodiesel has the potential to make an important contribution to national energy security and the environment (Biodiesel, 2012; EIA, 2012). It not only increases energy security and reduces harmful air emissions, but also improves public health and provides safety benefits (AFDC, 2012). With the potential for biodiesel to displace imported oil and improve local and global environmental conditions, the federal government has provided incentives for biodiesel production (tax credits, project grants, and loan guarantees) resulting in a rapid rise in production (DOE, 2013). Within the United States, over 860 million gallons of biodiesel were produced in 2011 compared to 13,900 million gallons of ethanol (RFA, 2012). Although biodiesel production is less than 10% of ethanol, biodiesel production did double from 2010 to 2011 (EIA, 2012).

While biodiesel presents a commercially viable opportunity to reduce dependence on imported fossil fuels, the biomass employed to produce it is also used for agricultural commodities (food, animal feed, and fiber) and functionally (cycling back into the ecosystem). The rapid growth of biodiesel has raised concerns about biodiesel's impact on the price level and volatility of these agricultural commodities, especially soybeans, which is the main feedstock for biodiesel (Haines and Gerpen, 2012).In 2011, approximately 7% of the oil from the U.S. soybean crop was diverted from agricultural commodities to biodiesel production (ERS, 2013). Haines and Gerpen (2012) indicate one approach to gauge the effect of biodiesel on commodities is to compare the changes in food prices with the price of oilseed crops. When oilseed prices peaked in 2008 so did food prices for consumers. However, after the peak when the price of oil seeds fell, food prices did not decline as much. On the other side Haines and Gerpen (2012) note the petroleum oil prices have a potentially significant impact on commodity prices through oil as an input in production and transportation. Biodiesel is also made from animal feed by-products. Biodiesel production uses only the soybean oil, which is normally extracted from the beans before feeding the soy meal to livestock. Thus, use of soybean oil for biodiesel does not prevent animals from eating the soy meal left after the oil is extracted. However, soybean oil prices reached record highs in the summer of 2012 and biodiesel mandates have had a particular impact on the global price of vegetable oil and oilseeds. This drives up the retail price of cooking oil in importing countries such as Haiti and exporting countries such as Indonesia, European Union's (EU) main source of biodiesel. EU's biofuels are 80% biodiesel (Oxfam, 2012). In the U.S., soybean oil used in biodiesel has basically offset the amount lost in food uses due to trans-fat labeling requirements (ASA, 2008).

Understanding and predicting price relationships among petroleum oil, diesel, biodiesel, and soybeans will lead to better policy. Thus, an investigation is warranted determining the effects of fuel markets on the agricultural sector, specifically on soybean production. In this spirit, the aim is to investigate both the short- and long-run relationships between biodiesel and agricultural commodity prices by employing time-series price data on biodiesel, petroleum diesel, crude oil, corn, and soybeans. Thus, the effect on the agricultural sector, specifically corn and soybean production, from energy markets will be investigated.

The underlying hypothesis is the potential agricultural commodity price effects from the biodiesel market are fundamentally different than the effects from the ethanol market. An increase in the price of ethanol stimulates an ethanol supply response with an associated increase in the demand for corn. With approximately 40% of U.S.2011 corn crop going into ethanol production, a percentage change in ethanol production has a marked influence on corn prices (Capehart, 2012; Qiu, Colson, and Wetzstein, 2011). In the short run, this may increase the price of corn. However, in the long run, decentralized competitive agricultural markets will respond to this price rise and increase corn production. This will yield no long-run relation between ethanol and corn prices (Zhang et al., 2010b). In contrast, increased biodiesel production stimulated by a price rise will require more soybean oil with a resulting increase in soybean meal as a byproduct. However, the percentage of soybeans used for biodiesel is small compared to corn for ethanol, so there is unlikely to be much of a short- or long-run price response. This small biodiesel market for soybeans may result in an input price effect. An increase in soybean prices could be funneled into higher biodiesel prices. This may indicate a long-run relationship between biodiesel and soybean prices. The objective is to test the hypothesis that contrary to ethanol a long-run price relation does exist between biodiesel and soybean prices. In the long run, soybean prices influence biodiesel prices.

**Literature**

In support of this hypothesis, expanding the literature on biofuel markets offers a sound foundation. In terms of the domestic and global food before fuel debate, the bulk of the literature is on ethanol's influence on agricultural commodity prices (Qiu, Colson, and Wetzstein, 2011). Recent literature employing a Vector Error Correction Model (VECM) or Vector Autoregressive (VAR) models conclude that energy markets have a short-run impact on the food market, but no long-run impact exists (Qiu et al., 2012; McPhail, 2011,2012).

In contrast to extensive literature on ethanol-market effects on agricultural commodity prices, emergent biodiesel markets have not been as widely investigated. Barros, Alves, and Osaki (2010) consider biofuels (ethanol and biodiesel) and food as possible production outputs. Budgets are developed for each of the possible outputs to determine the subsidy required for adoption. In terms of biodiesel, they conclude it becomes less viable as the demand for vegetable oil raises. Hassouneh et al. (2012) and Busse, Bernhard, and Ihle (2012) investigate the biodiesel market in Spain and Germany, respectively, using a VECM. The results by Hassouneh et al. (2012) indicate a positive correlation among biodiesel, sunflower, and crude oil prices. Multivariate local regressions indicate the speed of biodiesel adjustment toward the long-run equilibrium is faster when biodiesel is cheaper. Busse, Bernhard, and Ihle (2012) investigate changing linkages between diesel and biodiesel prices and between rapeseed oil and soybean. They determine before 2005 and after late 2007, there is a strong relation between biodiesel and diesel prices. Within the 2005 to 2007 interval, biodiesel and rapeseed prices are interdependent. They find a long-run relation between biodiesel and diesel prices and among biodiesel, rapeseed, and soybean oil prices. Kristoufek, Janda, and Zilberman (2012) employ a taxonomy perspective to investigate the relation among prices of petroleum oil, gasoline, biodiesel, ethanol, and agricultural commodities (wheat, sugar cane, soybeans, and sugar beets). Their results indicate in the short-term biodiesel and ethanol are weakly connected with commodities. In contrast, in the medium-term, fuels and commodity prices are not connected. Biodiesel tends to the fuel branch and ethanol to the food branch.

As indicated by Hochman et al. (2012) and Kristoufek et al. (2012), the relation among the prices of fuels and agricultural commodities depends on location, the prices considered, modeling specification, and data intervals (weekly, monthly, or yearly). Ciaian and Kancs (2011) and Zilberman et al. (2013) also indicate theoretically the impact biofuels have on agricultural commodities is ambiguous. Such ambiguity can be resolved with a set of independent empirical investigations addressing the issue from different directions (geographic locations, commodities, data intervals, and empirical methods). Only then is it possible for clear relations to emerge. However, theory suggests that both fuel and agricultural commodity prices are endogenous. As outlined by Ciaian and Kancs (2011), in standard regression models by placing endogenous variables on the right-hand side violates the exogeneity assumption. This problem is resolved by vector autoregressive models. Variables can be tested for exogeneity and then restricted to be exogenous.

**Data**

While investigating short- and long-run linkages between biodiesel and soybean prices, impacts of other fuel and commodity prices should be considered. Thus, along with biodiesel and soybean prices, petroleum oil, diesel, and corn prices are considered as well. Weekly price series are employed spanning the weeks from January 2006 to December 2011. For the fuel markets, U.S. real crude oil and diesel prices are obtained from the Energy Information Administration (EIA). Nominal biodiesel, corn, and soybean prices are acquired from USDA. Nominal prices are adjusted by the Bureau of Labor Statistics Consumer Price Index, with 1982-1984 as the baseline year.

Table 1 lists the summary statistics for the real price series. All the prices have similar coefficient of variations ranging from 0.17 to 0.25 and are all skewed to the left with soybeans relatively closer to being normally distributed. As measured by the kurtosis, oil prices appear to have more of its variance resulting from infrequent extreme deviations relative to the other prices. The Augmented Dickey Fuller tests for all the price series indicate the inability to reject the presence of a unit root at a high confidence level. This suggests that price series are non-stationary.

**Cointegration Estimation**

As discussed by Engle and Granger (1987), a linear combination of two or more non-stationary series that share the same order of integration may be stationary. If such a stationary linear combination exists, the series are said to be cointegrated and long-run equilibrium relationships exist. Although there may be short-run developments that can cause series to deviate, there is a long-run equilibrium relation represented as a linear combination, which ties the individual price series together.

Zilberman et al. (2013) note a potential weakness of past time-series food before fuel studies is estimating the marginal effect, while the total biofuel price effects on food prices may be more appropriate. In this spirit, level data are employed instead of first differences. Employing prices in levels, a lag length of two periods (weeks) was selected based on the likelihood ratio test, with model estimation for alternative lag lengths yielding robust results and nearly identical estimated coefficients.

Employing the Johansen trace test for determining the presence of cointegration among the price series indicates only one cointegration relation involving all five price variables.

$$\begin{aligned} Po = & -30.74 - 72.13Pd + 83.78Pb - 0.10Ps - 0.17Pc \\ & \;\;(10.13) \;\;\; (8.92) \;\;\;\;\; (12.68) \;\;\; (0.02) \;\;\; (0.05) \end{aligned}$$

where Po, Pd, Pb, Ps, and Pc are the price levels of crude oil, diesel, biodiesel, soybean, and corn, respectively. Standard errors in the parentheses indicate all the coefficients are significant at the 1% level, implying a long-run price relation between fuel and agricultural commodity markets. This result is in contrast to recent literature. Zhang et al. (2010a) employing a VECM in examining the relation between fuel prices (ethanol, gasoline, and oil) and agricultural commodity prices (corn, rice, soybeans, sugar, and wheat) indicate commodity prices in the long run are neutral to fuel price changes. Thus, the cointegration result supports the hypothesis that contrary to ethanol a long-run price relation does exist between biodiesel and soybean prices. However, for investigating the underlying reasons, the short- and long-run casual relations between biodiesel and soybean prices should be investigated. A vector error corrections models will allow for such an investigation.

**Vector Error Corrections Model (VECM)**

The existence of cointegration among the price series indicates a long-run causality in at least one direction among the series, but it does not indicate the direction of the causality. Such causality direction can be determined with a VECM, which specifies the short-run dynamics of each price in a framework that anchors the dynamics to the long-run equilibrium relationship (cointegrate). The actual time period of the short-run depends on the nature of the dynamics among the prices. Calculating the impulse response functions provides an indication of the short-run length.

VECM results are presented in Table 2 with associated Granger causality statistics listed in Table 3. Short-run granger causality indicates three causality relations with the price of corn serving as the main driving force:

Pc →Po,

Pc → Pd,

Pc → Ps.

The most striking result is diesel and soybean prices are driven by corn, and between diesel and soybean prices there are no direct short-run causal linkages. Corn prices appear, at least in the short-run, to be serving as an indicator for economic activity. Strong positive economic activity generally simulates expanding agricultural commodity demand with associated rising prices. With the corn price as an economic indicator, oil, diesel, and soybean prices have short-run positive responses to its shock.

This causal linkage between corn prices with oil and diesel prices is expended into the long run as indicated by the Granger long-run causality tests (Table 3). In the long run, corn prices are also influencing biodiesel prices, but not soybean prices. Further, soybean prices are influencing the fuel prices (oil, diesel, and biodiesel) in the long run. Again, economic activity manifested through agricultural commodity prices may explain this linkage. No one-directional causation is detected among the fuel prices. Results indicate simultaneous influence among these fuel prices.

Of particular interest are the short- and long-run relations between the biodiesel and soybean markets. As indicated in Table 3, a biodiesel price change does not precipitate a short- or long-run price effect on soybeans. In contrast, the price of soybeans does influence the long-run price of biodiesel. This one-way long-run price response underlies the long-run relation of biodiesel and soybean prices.

However, Granger causality reported in Table 3 does not indicate the magnitudes of these causal linkages. For such determination, variance-decomposition, listed in Table 4, provides information on the relative magnitude of the causation influence of one price series on another. Specifically, decomposition reflects the percentage of the variance associated with each price in the VECM caused by shocks to the other prices. As indicated in Table 4, the variability of oil prices contributes 70%, 34%, and 25% of the variance for diesel, biodiesel, and soybean prices, respectively. In contrast, the magnitude of the influence corn prices have on fuel prices is relatively small. The variability of corn prices only contributes 4%, 5%, and 10% of the variance for oil, diesel, and biodiesel prices, respectively. However, not surprisingly the contribution is highest for biodiesel. Similar results hold for soybean prices with the exception of it contributing 23% of the variance for corn prices. Thus, although corn and soybean prices are influencing the fuel prices, their degree of influence is relatively small. Oil price shocks are exerting the major price volatilities in the other commodities. This reinforces the idea that the economy is very much oil driven.

Impulse response functions measure the effect of a one standard-deviation shock of a given price on the other price series. Figures 1 and 2 present the response functions for a corn and oil price shock, respectively. As indicated in Figure 1, corn price shocks have limited influence on the other prices. In contrast, an oil price shock does appear to impact other prices, but less so for diesel prices, with the shock dissipating around week 30. This reinforces the greater impact of oil prices on the economy than corn prices.

**Conclusion**

The results confirm the theoretical hypothesis that alternative biofuel markets are different and thus their impact on short- and long-run price relations may vary. In contrast to ethanol, biodiesel prices do appear to have a long-run relation with soybean prices. For policy analysis, results indicate that not all alternative biofuels should be treated the same. One overarching biofuel policy and program may not be effective in promoting alternative energies efficiently. Specifically, if there are no long-run causations between ethanol and agricultural commodities, then long-run policies addressing the food before ethanol issues may not be required. In contrast, for biodiesel, if there is a long-run relation, then some type of long-run policies may be required. With the results indicating soybean price increases being passed onto biodiesel prices, policies directed toward creating a sustainable biodiesel industry should consider this price movement. Such policies may want to consider the short- and long-run potential reduction in fuel-price volatility by the blending of biodiesel with petrodiesel. This portfolio effect would then have the potential to reduce fuel-price volatility. An oil shock or an agricultural commodity shock would have less of a direct effect on blended biodiesel relative to neat biodiesel or unblended petrodiesel.

**References**

AFDC, 2012. "Biodiesel Benefits and Considerations," Alternative Fuels Data Center, Energy Efficiency and Renewable Energy, U.S. Department of Energy, 2012. http://www.afdc.energy.gov/fuels/biodiesel_benefits.html

ASA, 2008. "Myths and Realities Behind Rising Food Prices," American Soybean Association, July 2008. http://www.soygrowers.com/publications/MythsRealhtml/MythsRealities.htm

Barros, G., L Alves, and M. Osaki, 2010. "Biofuels, Food Security and Compensatory Subsidies," *China Agricultural Economic Review* 2: 433-455.

Biodiesel, 2012 "US Biofuel Consumption, Leading Firms, Forecasts, Revenue," *Biodiesel*, July 9, 2012.

Busse, S., B. Brummer, and R. Ihle, 2012. "Price Formation in the German Biodiesel Supply Chain: A Markov-Switching Vector Error-Correction Modeling Approach", *Agricultural Economics* 43:545-559.

Capehart, T. 2012. "Corn," Economic Research Service, USDA, 2012. http://www.ers.usda.gov/topics/crops/corn/background.aspx

Ciaian, P. and D. Kancs, 2011. "Interdependencies in the Energy-Bioenergy-Food Price Systems: A Cointegration Analysis," *Resource and Energy Economics* 33:326-348.

DOE, 2013. "Federal Laws and Incentives for Biodiesel," Alternative Fuels Data Center, Energy Efficiency and Renewable Energy, U.S. Department of Energy, 2013. http://www.afdc.energy.gov/laws/laws/US/tech/3251

EIA, 2012. "Today in Energy," Independent Statistics and Analysis, U.S. Energy Information Administration, U.S. Department of Energy, November 27, 2012. http://www.eia.gov/

Engle, R. and C. Granger, 1987. "Cointegration and Error Correction Representation, Estimation and Testing," *Econometrica* 55: 251-276.

ERS, 2013. Oil Crops Yearbook, USDA, Economic Research Service, 2013. http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1290

Hassouneh, I., T. Serra, and J. Gil, 2012. "Non-parametric and Parametric modeling of Biodiesel-Sunflower Oil-Crude Oil Price Relationships," *Energy Economics* 34: 1507-1513.

Haines, D. and J. Van Gerpen, 2012. "Biodiesel and the Food vs. Fuel Debate," *Farm Energy Home*, June, 2012. http://www.extension.org/pages/27136/biodiesel-and-the-food-vs-fuel-debate

Hochman, G., S. Kaplan, D. Rajagopal, and D. Zilberman, 2012. "Biofuel and Food-Commodity Prices," *Agriculture* 2(3): 272-281.

Kristoufek, L. K. Janda, and D. Zilberman, 2012. "Correlations Between Biofuels and Related Commodities Before and During the Food Crisis: A Taxonomy Perspective," *Energy Economics* 34(5):1380-1391.

McPhail, L.L., 2011. "Assessing the Impact of US Ethanol on Fossil Fuel Markets: A Structural VAR Approach*," Energy Economics* 33(6): 1177-1185.

McPhail, L., X. Du, and A. Muhammad, 2012. "Disentangling Corn Price Volatility: The Role of Global Demand, Speculation, and Energy. *Journal of Agricultural and Applied Economics*. 44:401-410.

Qiu, C., G. Colson, C. Escalante, M. Wetzstein, 2012. "Considering Macroeconomic Indicators in the Food before Fuel Nexus," *Energy Economics* 34:2023-2028.

Qiu, C., G. Colson, and M.E. Wetzstein, 2011. "The Post 2008 Food before Fuel Crisis: Theory, Literature, and Policies," *Biofuel/Book 1*, editer by M. Bernardes, InTech.

Oxfam, 2012. "Europe's Thirst for Biofuels Spells Hunger for Millions, as Food Prices Shoot Up," Oxfam International, September 2012. http://www.oxfam.org/en/grow/pressroom/pressrelease/2012-09-17/europes-thirst-biofuels-spells-hunger-millions-food-prices-shoot-up

RFA, 2012. Statistics, Renewable Fuels Association, Washington, DC, 2012 http://www.ethanolrfa.org/pages/statistics

Zhang, Z., Lohr, L., Escalante, C., Wetzstein, M., 2010a. "Food versus fuel: What do prices tell us?" *Energy Policy* 38(1): 445-451.

Zhang, Z., C. Qiu, and M. Wetzstein., 2010b. "Blend-Wall Economics: Relaxing U.S. Ethanol Regulations Can Lead to Increased Use of Fossil Fuels," *Energy Policy* 38(7): 3426-3430.

Zilberman, D., G. Hochman, D. Rajagopal, S. Sexton, and G. Timilsina, 2013. "The Impact of Biofuels on Commodity Food Prices: Assessment of Findings," *American Journal of Agricultural Economics*, 95(2): 275-281.

**Table 1.**Summary Statistics

| Price | Mean | Standard Deviation | Skewness | Kurtosis | Minimum | Maximum | ADF[a] Test |
|---|---|---|---|---|---|---|---|
| Oil ($/barrel) | 37.66 | 9.36 | 0.52 | 3.41 | 17.29 | 66.05 | 0.42 |
| Diesel ($/gallon) | 1.10 | 0.28 | 0.56 | 2.92 | 0.57 | 1.90 | 0.56 |
| Biodiesel ($/gallon) | 1.85 | 0.31 | 0.64 | 1.95 | 1.47 | 2.50 | 0.98 |
| Soybeans (Cents/bushel) | 493.94 | 95.78 | 0.12 | 2.07 | 315.93 | 735.80 | 0.17 |
| Corn (Cents/bushel) | 216.30 | 56.56 | 0.79 | 2.24 | 147.24 | 350.87 | 0.46 |

[a] ADF test is the Augmented Dickey Fuller test with the values representing MacKinnon approximate p-values.

**Table 2.** VECM Results[a]

| | Oil | Diesel | Biodiesel | Soybean | Corn |
|---|---|---|---|---|---|
| Error Correction Term | | | | | |
| α | −0.037* | −0.001** | −0.001* | 0.008 | 0.026 |
| | (0.057) | (0.000) | (0.000) | (0.161) | (0.088) |
| Lag | | | | | |
| Oil | 0.057 | 0.002 | 0.002 | 2.050 | 0.576 |
| | (0.127) | (0.003) | (0.001) | (1.460) | (0.801) |
| Diesel | −4.224 | −0.144 | 0.060 | −58.895 | −21.198 |
| | (4.886) | (0.129) | (0.054) | (55.930) | (30.698) |
| Biodiesel | −5.115 | −0.731 | 0.105*** | −33.284 | −16.524 |
| | (5.235) | (0.138) | (0.058) | (59.923) | (32.890) |
| Soybean | −0.104 | −0.000 | 0.000 | −0.090 | −0.014 |
| | (0.008) | (0.000) | (0.000) | (0.090) | (0.050) |
| Corn | 0.027** | 0.001* | −0.000 | 0.300** | 0.023 |
| | (0.013) | (0.000) | (0.000) | (0.152) | (0.084) |

Note: *, **, and *** denote significance at the 1%, 5% and 10% level, respectively.
[a] Standard errors are in the parentheses.

**Table 3.** Granger Causality Tests

| Direction of Causality | Short-Run ($\chi 2$ statistics) | Long-Run ($\chi 2$ statistics) |
|---|---|---|
| Corn and Oil | | |
| Pc → Po | 4.04* | 6.99* |
| Po → Pc | 0.52 | 0.08 |
| Corn and Diesel | | |
| Pc → Pd | 7.51* | 4.67** |
| Pd → Pc | 0.48 | 0.08 |
| Corn and biodiesel | | |
| Pc → Pb | 0.53 | 42.57* |
| Pb → Pc | 0.25 | 0.08 |
| Corn and Soybean | | |
| Pc → Ps | 3.87* | 0.00 |
| Ps → Pc | 0.08 | 0.08 |
| Soybean and Oil | | |
| Ps → Po | 1.74 | 6.99* |
| Po → Ps | 1.97 | 0.00 |
| Soybean and Diesel | | |
| Ps → Pd | 0.25 | 4.67** |
| Pd → Ps | 1.11 | 0.00 |
| Soybean and Biodiesel | | |
| Ps → Pb | 1.22 | 42.57* |
| Pb → Ps | 0.31 | 0.00 |
| Biodiesel and Oil | | |
| Pb → Po | 0.95 | 6.99* |
| Po → Pb | 1.38 | 42.57* |
| Biodiesel and Diesel | | |
| Pb → Pd | 0.28 | 4.67** |
| Pd → Pb | 1.21 | 42.57* |
| Diesel and Oil | | |
| Po → Pd | 0.30 | 4.67** |
| Pd → Po | 0.75 | 6.99* |

Note: * and ** denote significance at the 1%, and 5% level, respectively.

**Table 4.**Forecast error variance decomposition after ten periods (weeks)

| Forecast Error Variance for Prices | Contributions of the shocks in Price of | | | | |
|---|---|---|---|---|---|
| | Oil | Diesel | Biodiesel | Soybean | Corn |
| Oil | 0.910 | 0.001 | 0.024 | 0.021 | 0.044 |
| Diesel | 0.704 | 0.194 | 0.014 | 0.035 | 0.053 |
| Biodiesel | 0.336 | 0.146 | 0.182 | 0.231 | 0.105 |
| Soybean | 0.246 | 0.003 | 0.009 | 0.732 | 0.011 |
| Corn | 0.120 | 0.001 | 0.001 | 0.230 | 0.648 |

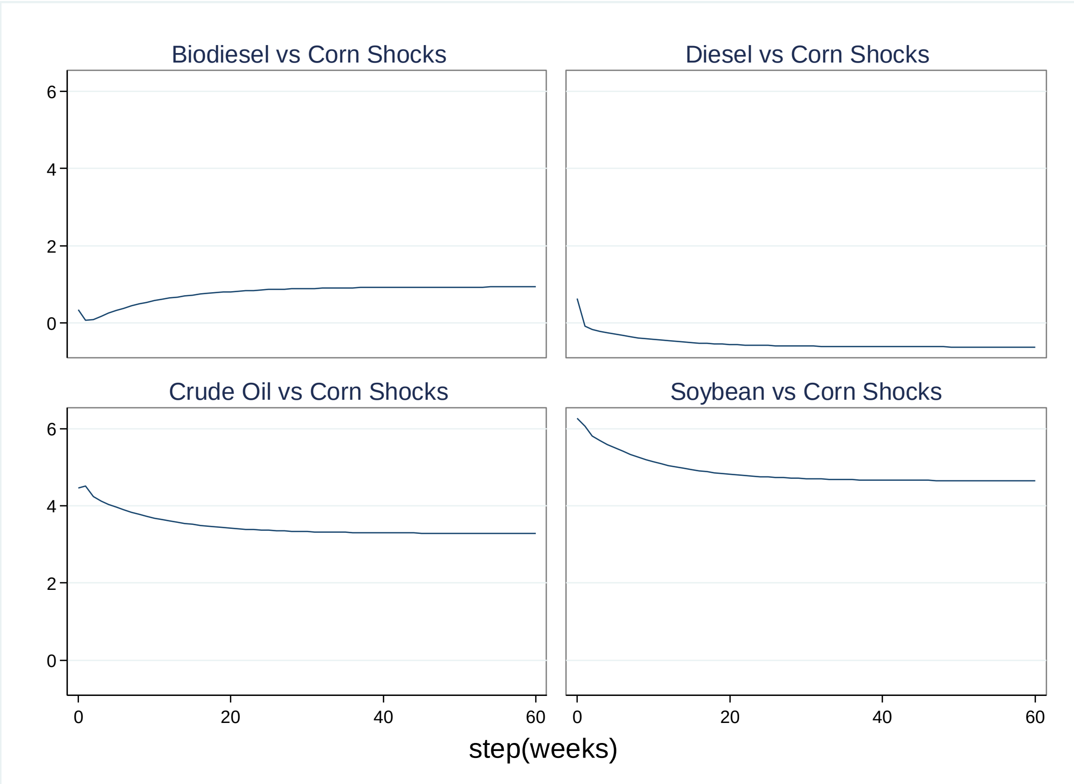


**Figure 1.** Impulse response functions for a corn price shock

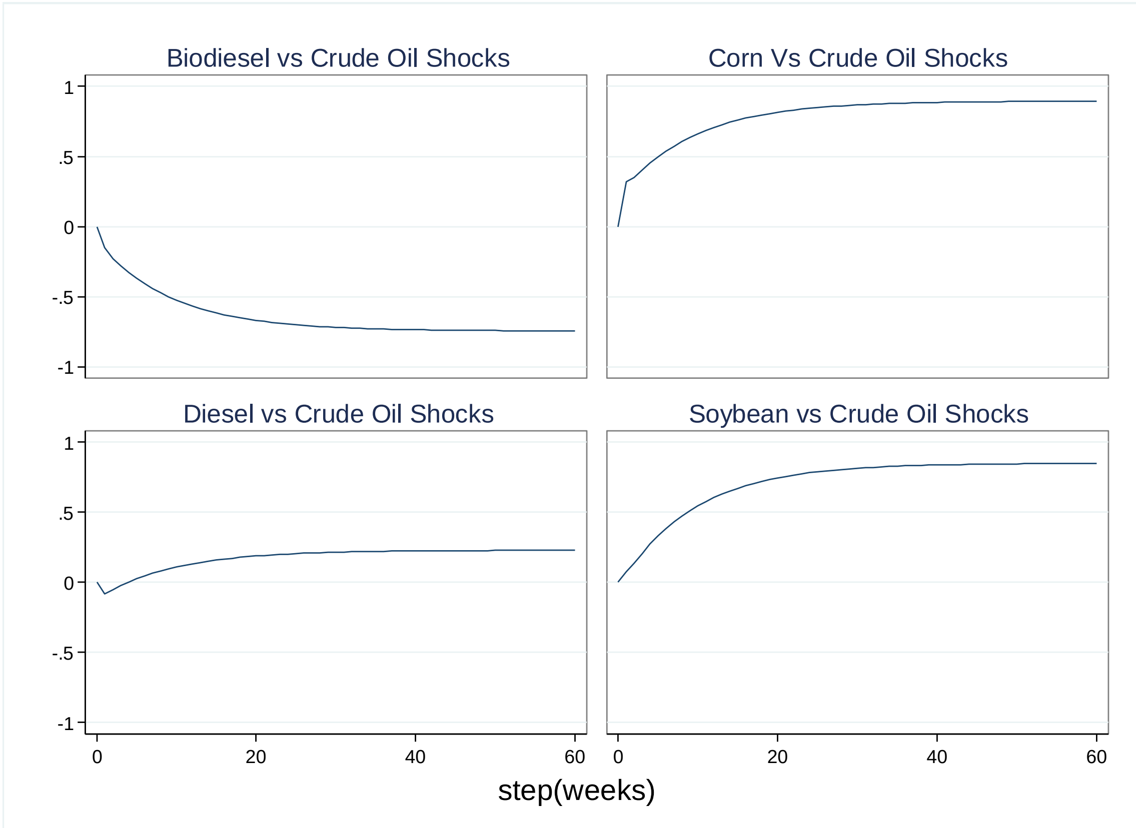


**Figure 2.**Impulse response functions for an oil price shock