Considering Macroeconomic Indicators in the Food versus Fuel Issues

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Abstract

In this study, a Structural Vector Autoregression model (SVAR) is employed to decompose how supply/demand structural shocks affect food and fuel prices within fuel and corn markets. Results indicate that the relative importance of each structural shock in explaining the variation of corn prices is different. Our findings support the hypothesis that corn prices increase as a response to those positive demand shocks in the short run, while in the long run, global competitive agricultural commodities markets as well as positive supply shocks respond to commodity price shocks, restoring prices to its long-run trends. In conclusion, fundamental market forces of demand and supply as well as real economic aggregated demand shocks were the main contributors of the 2007-2008 food price spike.

Key Words

food, fuel

1. Introduction

A widely considered view both in policy circles and the domain of public perception is that the dominant underlying driver of the 2007-2008 price spikes was increased use of crops for the production of biofuels (Diao et al., 2008; Abbott et. al, 2008). This shift from fossil fuels to biofuels, which has in large part been fostered through national agriculture and energy policies motivated by increased oil price volatility, energy security ambitions, and environmental concerns, is particularly prominent among many Kyoto Protocol signatory countries (Balcombe and Rapsomanikis, 2008). The rapidly growing market for biofuels has given rise to the perception that rapid biofuel expansion generates upward pressure on global food prices, exacerbating global hunger problems (Runge and Senauer, 2007). These concerns have given rise in some policy circles of calls for agricultural and energy policies be reprioritized where food takes precedence before fuel (in short food before fuel).

In contrast to this perception, evidence is provided countering the hypothesis that a shift from fossil fuel toward biofuels has caused a food versus fuel issue. Instead evidence is presented supporting the hypothesis that global economic activity is theunderlying long-run driver of food and fuel prices. As the global economy expands (contracts), food prices along with fuel prices rise (fall). Increased biofuel production may cause short-run food price increases but not long-run price shifts. There is a time lag in a supply response to a positive food demand shift but once supply responds, any price increases are are mitigated. The long-run effects of food and fuels are driven by global economic activity.

2. Theory

As outlined by Qiu et al.(2011), surges and downturns of ethanol and food prices are not isolated incidents, but economic consequences (Gohin and Chantret,2010 ; Von Braun et al., 2008; Mcphail and Babcock, 2008; Chen el al., 2010; Balcombe and Rapsomanikis, 2008). Kappel et al. (2010) argue that fundamental market forces of demand and supply were the main drivers of the 2007-2008 food price spike. In a supply and demand model, economic theory suggests agriculture will respond to a commodity price increase from a biofuel or other demand shock. As illustrated in Figure1, a demand shock will shift the demand curve outward from Q_D to Q_D'. This results in a short-run increase in the agricultural commodity price, from p_e to p_e', leading to existing firms earning short-run pure profits (total revenue above total costs). The magnitude of this increase in price depends on how responsive supply, in the short run, is to the demand shift (represented as an increase in supply from Qe to Q_S. However, in the long-run, existing firms will expand production and new firms will enter yielding a further increase in supply. Assuming no cost adjustments, this increase in supply will restore the market price to the long-run equilibrium price p_e.

Generally the responses to the demand shifters are rapid, while supply-utilization adjustments are slower. A shift in demand will elicit an immediate price increase response. While the supply response will take a number of months as agriculture gears up to increased production. With this supply and demand model, the issue is how rapid is this supply response and what is its magnitude. If supply is able to rapidly respond to a demand shift, then there is no food versus fuel issue. If not, then there is cause for concern.

In 1979, Vincent et al., (1979) indicated the days of cheap corn are not over. Prices may be more stable as corn production expands to meet ethanol requirements and second generation ethanol, increased buffer stocks, and new technologies emerge (Vincent et al., 1979). This prediction of stable agricultural commodity prices would still hold if supply responses are rapid enough to mitigate demand. However, expanding global economic activity will continue to put upward pressure on both food and fuel prices.

3. Methodology

3.1 Model

In the area of food vs. fuel, Vector Error Correction Model (VECM) and Computable General Equilibrium (CGE) Models are the two dominant methods. However, it is generally difficult to distinguish cotemporaneous supply-demand linkages and isolate impacts from macroeconomic variables in those models. Economic theories and implications under the econometric models are usually obscure as well. Recently, Vector Autoregression (VAR) models are widely used in macroeconomic analysis. Such models are an efficient tool for capturing the dynamic interactions among variables. Early in 1980, Sims employed a VAR model to study the relationship among alternative aggregates. However, a major shortcoming of VAR is failure to combine economic implications under the model (Hamilton, 1994). Thus, structural vector Autoregression (SVAR) models are proposed to mitigate the shortcoming and identify the relevant innovations. With SVAR, unpredictable changes in the prices and demand/supply are decomposed into mutually orthogonal components with economic interpretations.

The literature is limited in SVAR models for the food vs. fuel issue. Kilian (2009) employed a SVAR model to identify dynamic effects of different shocks in the global crude oil market by decomposing those shocks into crude oil supply shocks, specific crude oil demand shocks and aggregate shocks to all industrial commodities. He extended the model by including the gasoline market (Kilian 2010). With Kilian's model as a foundation, Mcphail (2010) analyzed the impacts of expanding U.S. ethanol markets on the global oil markets. This literature identifies cotemporaneous dynamic innovations within the energy market. Limited research has quantified simultaneous structural innovations between the food and fuel markets. Zhang et.al. (2007) employed SVAR models to capture contemporaneous interactions among ethanol, corn, gasoline, and MTBE, but macroeconomic effects are excluded in their work. Almirall et.al. (2010) employed SVAR to analyze how U.S. crop prices responded to shocks in acreage supply, but they only considered ethanol in the fuel markets, i.e., effects from gasoline and crude oil were excluded, and there were no macroeconomic effects impact considered.

We develop our SVAR model based on Kilian (2009, 2010), Maphail (2010), Zhang et. al. (2007) and Almirall et.al.(2010).

Let y_t represent an (n x 1) vector containing n variables at time t. The dynamics of y_t are assumed to be governed by a VAR (p) model,

$$y_t = B_0 + B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_i y_{t-i} + \cdots + B_2 y_{t-p} + e_t \tag{1}$$

With contemporaneous correlations among those innovations considered, the VAR model could be rewritten as a following SVAR model

$$Ay_t = AB_0 + AB_1 y_{t-1} + AB_2 y_{t-2} + \cdots + AB_i y_{t-i} + \cdots + AB_2 y_{t-p} + Ae_t \tag{2}$$

$$= A_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \tag{3}$$

where $A_0 = AB_0$, $A_i, = AB_i$, and $\varepsilon_t = Ae_t$. The error term ε_t is assumed to be the vector of serially uncorrelated structural innovations with variance-covariance matrix defined as a diagonal.

$E(\varepsilon_t) = 0$,

$E(\varepsilon_t{}'\varepsilon_t) = \Omega$,

$E(\varepsilon_t{}'\varepsilon_s) = 0, \quad t \neq s$

Thus, the following reduced form for the VAR model is:

$$y_t = A^{-1} A_0 + \sum_{i=1}^{p} A^{-1} A_i y_{t-i} + e_t \ , \tag{4}$$

Where we assume that A^{-1} is a recursive matrix of A, and $e_t = A^{-1} \varepsilon_t$.

To build the macroeconomic linkage between the food and fuel markets, we define $y_t = (So_t, Real_t, Po_t, Pg_t, Dg_t, Pe_t, Se_t, Pf_t, Sf_t)$, where So is the Crude oil; $Real$ is the real economic activities; Po is the real price of crude oil; Pg is the real price of gasoline; Dg is the gasoline demand; Pe is the real price of ethanol; Se is the Ethanol supply; Pf is the real price of food and Sf is the Food supply.

Based on Kilian (2009) and Mcphail(2010), we obtain the decomposed matrix form of $e_t = A^{-1} \varepsilon_t$ as follows.

$$\begin{pmatrix} e^{So_t} \\ e^{Real_t} \\ e^{Po_t} \\ e^{Pg_t} \\ e^{Dg_t} \\ e^{Pe_t} \\ e^{Se_t} \\ e^{Pf_t} \\ e^{Sf_t} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{21} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{41} & a_{41} & a_{42} & a_{43} & 0 & 0 & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 & 0 & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & 0 & 0 & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} & 0 & 0 \\ a_{81} & a_{82} & a_{83} & a_{84} & a_{85} & a_{86} & a_{87} & a_{88} & 0 \\ a_{91} & a_{92} & a_{93} & a_{94} & a_{95} & a_{96} & a_{97} & a_{98} & a_{99} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{\text{So\_shock}} \\ \varepsilon_t^{\text{Real\_shock}} \\ \varepsilon_t^{\text{Do\_shock}} \\ \varepsilon_t^{\text{Sg\_shock}} \\ \varepsilon_t^{\text{Dg\_shock}} \\ \varepsilon_t^{\text{De\_shock}} \\ \varepsilon_t^{\text{Se\_shock}} \\ \varepsilon_t^{\text{Df\_shock}} \\ \varepsilon_t^{\text{Sf\_shock}} \end{pmatrix} \quad (5)$$

Definitions of shocks

In the fuel and food markets, supply and demand shocks are both included as well as shocks from real economic activities. Oil supply shocks, $\varepsilon_t^{\text{So\_shock}}$, are defined as the unanticipated factors that would shift the supply curve of oil and affect the availability of the crude oil. Those shocks are generally referred to as unexpected political events in oil exporting countries (wars and revolutions such as the Libyan Revolution). Real activity shocks (aggregate demand shocks), $\varepsilon_t^{\text{Real\_shock}}$, are shocks that will affect all the global commodities (including oil). This is based on a globalization perspective, given the price of oil is not an isolated incident of the specific demand and supply influences powers of the crude oil market, but also a consequence of the global business cycle, for example, the recent great recession. Oil demand shocks, $\varepsilon_t^{\text{Do\_shock}}$, are defined as shocks from the precautionary demand, which is an illustration of people's uncertainty of the oil supplies. For example, as summarized by Kilian (2009), the largest negative precautionary demand since March

1974 occurred after the collapse of OPEC, while the largest positive precautionary demand happened after Iraq's invasion of Kuwait. Oil demand shocks are mainly caused by rapid expansion of economic developing countries where with economic growth a greater proportion of oil relative to economic activity is required. Gasoline Supply shocks, $\varepsilon_t^{\text{Sg\_shock}}$, are shocks that shift the supply curve of gasoline. Those shocks usually come from the refining of the gasoline, for example, accidents of refineries such as accidents and weather (hurricanes) that lead to the decrease of gasoline supply. Gasoline demand shocks, $\varepsilon_t^{\text{Dg\_shock}}$, are shocks that change gasoline demands, for example, changes of consumer's preferences, changes of demographic structure and degree of gasoline, and other unobserved shocks that might shift the gasoline demand curve. For example, the rapid increase in demand for automobiles in Asia. Ethanol demand shocks, $\varepsilon_t^{\text{De\_shock}}$, are shocks that change the ethanol demand. Summarized by Mcphail (2010), the U.S. ethanol industry is mainly policy driven than market driven, thus government regulations, mandates and regulations such as phase out of MTBE, relaxation of blend wall are considered as demand shocks. Ethanol supply shocks, $\varepsilon_t^{\text{Se\_shock}}$, are those shocks resulted from input costs (e.g. change of corn price) or yield variations. Food demand shocks, $\varepsilon_t^{\text{Df\_shock}}$, are defined as shocks that shift the food demand curve, and mainly refer to the changes of consumers' preferences and their nutrition acknowledgement. For example, the mark increases in caloric consumption within Asia. Food supply shocks, $\varepsilon_t^{\text{Sf\_shock}}$, are defined as shifts of the supply curve, and are usually referred to those unanticipated weather impacts (such as floods and droughts) , improvement of technologies (such as reduced tillage technology, improved drying and irrigation system, efficient application of fertilizers, and improved crop varieties) and reduced cost of inputs.

Identification of Assumptions

Mcpahil (2010) states that the smaller the fuel market is, the more agile it would be, thus fewer assumptions are imposed. Real economic shocks (aggregate demand shocks) are considered to yield impacts on fuel and food prices, based on findings that macroeconomic activities play a role in food and fuel volatilities.

For the oil market, it is assumed that crude oil supply will respond to the oil supply shocks instantaneously without responding to the oil demand shocks and aggregate shocks contemporaneously. The underlying rational is that even precautionary demand shocks and oil demand shocks exist, they will not affect the oil production in a short-run, due to the costly industry characteristics (i.e., the oil supply is very inelastic). Crude oil supply is mainly controlled by OPEC which has established capacity constraints. Capacity is based on the expected long-run global economic growth and not on short-run demand shocks. Real economic activities relate to the oil supply shocks and aggregate demand shocks, since given globalization, oil is acting as a key factor in various economic activities. We define $\alpha_{23} = 0$ based on the Kilian and Vega (2008) finding that there is no feedback from macroeconomic factors to the oil price within a month. For the crude oil price, we define it as a consequence of interactions of oil demand-supply as well as macro economy shocks. Specifically, the oil demand shocks might result in a price jump of crude oil. It might produce instant and potentially large impacts on the crude oil price, even with the oil supply fixed (Killian, 2009).

For the gasoline market, gasoline production has a relatively sluggish response to gasoline supply shocks than the gasoline price. Given enough gasoline storage, the short-run gasoline supply could be treated as perfectly elastic (Kilian, 2010). Thus, due to the lag of information transmission, gasoline demand shocks could not change the gasoline price instantaneously, while supply shocks, such as refinery fires or cost shocks from the price change of imported oil, will be passed to the gasoline prices within the same month. Gasoline demand changes attributes to shocks from the oil market, macroeconomic activities, and gasoline demand-supply structural innovations.

For the ethanol market, structural shocks from oil market, macroeconomic activities, and gasoline market are assumed to affect the ethanol market contemporaneously, based on the advocates of bioenergy and competition between biofuels and conventional fuels. We assume $\alpha_{67} = 0$ under the assumptions that short-run supply of U.S. ethanol is perfectly elastic. It is assumed ethanol supply shocks cannot be transmitted to the ethanol price instantaneously. For simplicity, we also assume$\alpha_{68} = \alpha_{69} = \alpha_{78} = \alpha_{79} = 0$, based on the rationale that with the current U.S. government incentives and regulations, the food versus fuel choice is tilted toward fuel (Reilly and Paltsev, 2007).

For the food market, we assume that food price and food supply respond to structural shocks from fuel markets and macroeconomic activities based on the following two reasons: First, economic theory indicates that fuels act as key inputs in the agricultural commodity production (i.e., pass-through effects of fuel markets to the food markets); Second, competition between increased crop demand for biofuel refining and providing food. We assume $\alpha_{89} = 0$ since economic theory suggests that agricultural commodity prices will increase from its demand shocks, while in the long-run agricultural will respond to the demand shock by increasing supply. For example, Abbott et al. (2009) have identified three major demand shifters (shocks) which caused the food spike in 2007-2008: increased food demand, low value of dollar and new linkage of energy and agricultural markets.

3.2. Innovation Accounting: Structural Impulse Response Functions (SIRFs)

Impulse response function (IRF) captures the effect of an innovation on future values of the dependent variable within the time series model. Since ε_t is defined as a vector of serially uncorrelated structural innovations whose variance-covariance matrix is diagonal, and A^{-1} is defined as a lower triangular matrix, the SVAR model defined above is just identified. The reduced form e_t, will respond to the vector of orthogonal structural innovations ε_t , and the response coefficient will capture the dynamic consequences of the structural shocks.

In a more straightforward way, given the invertibility of the well-defined SVAR model, we can get mapping from VAR to VMA (Vector Moving Average Models) as follows:

$$y_t = C(L)e_t \quad (6)$$

$$= D(L)\,\varepsilon_t \quad , \tag{7}$$

where $D(L) = A^{-1} C(L)$.

Thus, the dynamic multiplier of the structural impulse response function is defined as follows:

$$SIRF(s, j, t) = \frac{\partial y_{t+s}}{\partial \varepsilon_{jt}} = \frac{\partial y_{t+s}}{\partial e_t^{'}} \frac{\partial e_t}{\partial \varepsilon_{jt}} = \psi_s a^j \tag{8}$$

Here, $SIRF(s, j, t)$ captures the dynamic response of y_{t+s} with respect to the structural innovation ε_{jt}, where ψ_s is the matrix of coefficients for the VMA defined equation (6), and a^j is the *j*th column of A^{-1}.

3.3. Innovation Accounting: Cumulative Impulse Response Functions (CIRFs)

Structural Impulse Response Functions only capture how those dependent variables respond to a one-time acreage shock. However, it fails to describe how the dependent variables respond to repeated structural shocks. Thus, Cumulative Impulse Response Function (CIRF) is proposed, and the function is given as follows:

$$\mathrm{CIRF}(s, t) = \sum_{j=0}^{n} \mathrm{SIRF}(s, j, t) \tag{9}$$

3.4. Innovation Accounting: Structural Forecast Error Variance Decomposition Analysis (SFEVD)

Forecast Error Variance Decomposition Analysis measures the relative importance of each structural shock on food and fuel prices, as well as quantifying the amount of information each structural shock contributes to the fuel and food prices.

The mean square error of the s-period-ahead forecast of y is defined as follows:

$$MSE(\hat{y}_{t+s}|_t) = [E(y_{t+s} - \hat{y}_{t+s}|_t)(y_{t+s} - \hat{y}_{t+s}|_t)'] \quad (10)$$

$$= \Omega + \psi_1 \Omega \psi_1' + \psi_2 \Omega \psi_2' + ... + \psi_{s-1} \Omega \psi_{s-1}'$$

$$= \sum_{j=1}^{n} \left\{ \mathrm{var}(\varepsilon_{jt}) [a_j a_j' + \psi_1 a_j a_j' \psi_1' + \psi_2 a_j a_j' \psi_2' + ... + \psi_{s-1} a_j a_j' \psi_{s-1}'] \right\} \quad (11)$$

Where Ω is the variance-covariance matrix of reduced error term e_t,

$\Omega = E(e_t e_t')$

$$= a_1 a_1' \,\mathrm{var}(\varepsilon_{1t}) + a_2 a_2' \,\mathrm{var}(\varepsilon_{2t}) + ... + a_n a_n' \,\mathrm{var}(\varepsilon_{nt}) \quad (12)$$

Therefore, the contribution of the *j*th orthogonalized structural innovation to the MSE of the s-period-ahead forecast is captured by the Structural Forecast Error Variance Decomposition function (SFEVD) as follows

$$SFEVD_{j,s,t} = \frac{\mathrm{var}(\varepsilon_{jt})(a_j a_j' + \psi_1 a_j a_j' \psi_1' + \psi_2 a_j a_j' \psi_2' + ...\psi_{s-1} a_j a_j' \psi_{s-1}')}{MSE(\hat{y}_{t+s}|_t)} \quad (13)$$

Specifically, if the value for $SFEVD_{j,s,t}$ is greater than 50%, it indicates that the *j*th orthogonal structural innovations is more important compared to the others in driving the process above.

4. Data

Monthly data from January 1994 to October 2010 are used in this study and collected from different data sources. For the fuel markets, world oil supply, U.S. real imported crude oil prices, U.S. ethanol production, and U.S. real regular retail gasoline prices are obtained from the Energy Information Administration (EIA) website. Following Kilian (2009), we treat the U.S. product supply of finished motor gasoline deducting the U.S. oxygenate plant production of fuel ethanol as an approximation of U.S. gasoline consumption, both of which could be obtained from EIA. Nominal monthly ethanol price is obtained from a data inquiry.

For the food market, U.S. real corn price is obtained from the Foreign Agricultural, USDA. The corn supplies are obtained from Economic Research Service (ERS), USDA. However, these supplies are measured on a quarterly scale. To obtain monthly data for corn supplies, we employ cubic spline interpolation which is a widely used nonparametric smoothing technique for economists and statistician to convert time-series data into the time-series data in a smaller frequency (Conover ,1999 ; Habermann & Kindermann, 2007). In this study, plugging in the value of average monthly corn supply (i.e., quarterly corn supply/3) as the original observation values, monthly corn supplies will be simulated.

Consumer price index (CPI) is obtained from Bauru of Labor Statistics, where 1982-1984 is the baseline. In this study, real prices are used, defined as nominal price/CPI*100.

Following Kalian's (2009) study, Baltic Exchange Dry Index (BDI) is used as a measurement of the global real economic activities. As summarized by Kilian(2009), BDI is an ideal indicator of changes in the global demand for raw materials and commodities driven by the global business cycle. In some studies, exchange rate is used as an surrogate of global real economic activities, and in some literatures exchange rate has been proved to influence energy and agricultural commodity markets (for example, Hanson et al.,1979; Gohin and Chantret, 2010; Saghaian,2010; Abbott et.al., 2008). However, exchange rate is a bilateral concept. To measure the real global economic activities, an exchange rate index might be needed, which requires a large number of exchange rates to be collected. Thus here, we use BDI as a proxy of real economy activities due to convenience and availability considerations.

Data Descriptions

To avoid spurious regressions, all the prices and quantities are tested by an Augmented Dickey Fuller (ADF) test with constant and a time trend considered. The test statistics are reported in Table 1. As expected, ADF test statistics of crude oil supply and ethanol supply are not significant at any significant level for their original data form and corresponding logarithm transformations. This is anticipated, since U.S. ethanol supply and world crude oil supply have experienced exponential expansion, even logarithm transformations might fail to capture those corresponding shocks. All the ADF statistics for the first differences of logarithm data show stationary at a significant level of 1%. Thus, for the convenience of explanation, we employ first difference of logarithm transformation for all the prices and quantities in this study, which are percentage changes of prices and quantities.

5. Results

Joint consideration of Akaike Information Criterion/ Schwarz Beysian Criterion/ Hannan and Quinn Criterion suggests a a lag of four to be selected in our SVAR model. Impulse response functions and Forecast error variance decomposition results are presented as follows.

How corn prices respond to structural shocks?

Table 2 and Figure 2.a and Figure 2.b indicate how corn prices respond to structural shocks within different months. As shown by Figure 2.a, a positive corn demand shocks will elicit an immediate price increase of corn prices and this impulse response is the strongest among all those structural impulse response function graphs. Given the relative unresponsiveness of demand and supply for staple food commodities, small shifts in demand can lead to a significant movement in prices. However, though time, such response of corn price with respect to the corn demand shocks will die out in a long run.

By contrast, in spite of the much weaker impulse response compared to that from corn demand shocks in a short run, corn price does not decrease as a response to the positive corn supply shocks until the second month. This negative impulse response just lasts for one month and then becomes positive. In the long run, positive effects will gradually die out, although some few small “jump-up” of corn price happen around month six. The sluggish responses of corn price with response to the supply shocks occur since the agricultural sector take a number of months to respond.

Figure 2.b illustrates CIRFs of structural shocks on the corn prices. A repeated corn demand shock increases the corn prices instantly, and finally stabilizes the impact in a long run. As anticipated, the cumulative effects are much larger than the one-time corn demand shock effects shown in Figure 5.1.a and much wider confident intervals are obtained indicating bigger standard errors. CIRF for the corn supply shocks on the corn price are not significant, implying that repeated corn supply shocks almost yield no cumulative effects of the corn price. However, attention should be

paid since the CIRFs usually fail to capture changes of expectations, which corporate with repeated structural shocks, and they might alter the underlying data-generating process and the true track of impulse response functions (Almirall et.al., 2010).

Table2 shows how each structural shock contributes to the forecast error variance of corn price. As shown, up until month one, the majority of the forecast error comes from the corn demand shocks, which is approximate 94% ; ethanol demand shocks is the second biggest factor contributing to the forecast. In the long run (up to 60 months), although corn demand shocks are still the biggest contributor of the forecast error of the corn price, its relative importance has significantly decreased. By contrast, corn supply shocks explain up to 6.38% of the 60-months ahead forecast error in corn prices, acting as the third contributor. Gasoline supply shocks and crude oil supply shocks contribute to 8.16% and 5.36% of the error respectively; supporting the pass-through effects of the energy input, i.e., a decrease of energy prices would shift the supply curve of agricultural commodities to the right, which subsequently decrease agricultural commodity prices (Chen et al., 2010). Those results are consistent with the hypothesis stated earlier in this paper, that in the short run, positive shocks which shift the demand curve of the agricultural commodity to the right will increase in the agricultural commodity price leading to existing firms earning short-run pure profits (total revenue above total costs). However, in the long run, existing firms will expand production and new firms will enter yielding a further increase in supply, assuming no cost adjustments, which will restore the market price to the long-run equilibrium.

Increased proportion of corn supply shocks in explaining corn price supports the necessity of food stocks and an important role that food supply plays in the price stabilization in the long run. Reduced tillage technology, improved drying and irrigation systems, and efficient application and timing of fertilizer and improvements of technologies will increase the supply of food, which will buffer the short-run price spikes in a long run.

Ethanol demand shocks contribute almost invariant proportion to the SFEVD of the corn price, indicating that ethanol demand shocks yield persistent impacts on the volatility of the corn price. Proportion that ethanol demand shocks accounts for the SFEVD of the corn price is only around 4%, indicating that although for current U.S. government incentives and regulations, the food vs. fuel choice is tilted toward fuel; ethanol demand shocks only contribute a fairly small proportion of the forecast error of the corn price.

How ethanol prices respond to structural shocks?

Table 3, Figure 3 indicate how ethanol prices respond to those structural shocks in different months. A positive ethanol demand shock will elicit an instant peak in the ethanol price, indicating that policy driven demand shocks (such as current blending mandate) are prone to increase ethanol demand, which in turn drives up ethanol prices. The positive impulse response quickly decreases and overshoots at month two. In a long run, impulse response of ethanol price with respect to corn demand shocks gradually die out. Corn supply shocks seem to yield weaker impacts on the ethanol prices in the short run compared to the corn demand shocks. A positive supply shock leads to an instant increase of ethanol prices in month one, but such a positive impulse response just lasts for another three months. Positive gasoline supply shocks elicit significant increase of ethanol price, although in the long run such a SIRF will gradually dies out. This finding supports the statement that ethanol and gasoline are complementary with each other. At a current blend wall cap (no more than 15%), increasing the gasoline supply will lead to an increase in the demand for ethanol, consequently push up the ethanol prices.

Table 3 lists how each structural shock contributes to the forecast error variance of ethanol prices. As shown, up until month one, the biggest contributor is ethanol demand shocks, which accounts for 82.13% of forecast error variance of ethanol prices. As expected, ethanol supply shocks, corn supply shocks and corn demand shocks will not affect ethanol prices in the short run (up until one month), due to the identification of the assumptions. In the long run (up to 60 months), although proportion of ethanol demand shocks explaining the forecast error variance decrease to 62.51%, they are still the biggest contributors of the ethanol price variation, 59.37% more than the proportion explained by ethanol supply shocks, indicating that policy driven factors are more influential than others in explaining ethanol price volatilities.

Crude oil demand shocks and gasoline demand shocks account for around 15% of SFEVD of ethanol prices in the short run, and almost 18% in the long run, signifying that volatility of ethanol price is not only influenced by its own demand shocks, but also a consequence of oil demand shocks and gasoline demand shocks.

Corn demand shocks and corn supply shocks only account for 5.05% of the ethanol price forecast error variance. Although U.S. ethanol mainly comes from corn, shocks from corn market only yield limited effects on the ethanol prices. This is consistent with Reilly and Paltsev's findings (2007): the food vs. fuel choice is tilted toward fuel under current policies and incentives.

How gasoline prices respond to structural shocks?

Table 4, Figure 4 show how gasoline price respond to those structural shocks to different months. As shown by Figure 4, gasoline price peaks immediately with respect to positive demand shocks (around 0.02), which seems unanticipated, while it goes down rapidly and reaches the bottom (approximate -0.018) at month four. This might be because of the sluggish response of gasoline price with respect to supply shocks. In the long run, price response with Gasoline demand shocks yield negative impacts on the gasoline price, although those impulse responses are not significant both in short- and long run.

Positive Ethanol demand shocks will lead to an increase of gasoline price before month 3. As a result, ethanol and gasoline are complements with each other. As discussed in the earlier part, the U.S. ethanol demand is mainly positive driven, such as relaxation of ethanol mandate. The relaxation of blend wall from 10% to 15% will increase the consumption of ethanol demand, while for the gasoline market, how will it impact the gasoline demand consumption is still ambiguous. Results here support our previous research that now an anomaly occurs when the positive expansion effect offsets the negative substitution effects, which imply that a positive ethanol blend wall shift is prone to increase petroleum gasoline demand (Qiu et.al. 2011).

Ethanol supply shocks seem to have insignificant impacts on the gasoline demand both in short and long run. As anticipated, gasoline price increases as a response to positive oil demand shocks, although those impulses die out as time goes by.

Table 4 shows how each structural shock contributes to the forecast error variance of gasoline prices. In month one, gasoline supply shocks, crude oil shocks accounts for 54.36% and 37.19%, respectively, while crude oil supply shocks and real economic activity shocks explain the rest. In the long run, although importance of gasoline supply shocks and crude oil demand shocks decrease, they are still the biggest contributors. Gasoline supply shocks account much more than the gasoline demand shocks, which might be explained by the inelastic property of gasoline demand and supports Kilian’s findings (2010) that fluctuations in the gasoline price are almost determined exclusively by the gasoline supply shocks.

Relative importance of the real shocks increases significantly in the long run (60months), presenting that price volatility is not only consequence of demand and supply shocks from its own market, but also the heating up and cooling off of macroeconomic activity.

Ethanol demand shocks contribute 3.97% in the long run, while ethanol supply shocks only explain 0.91% of the variation of gasoline price. This small proportion of gasoline price variation explained by the ethanol market shocks indicates that although policies to promote the ethanol were implemented, those shocks still yield limited impacts on volatility of error of gasoline price due to the relative market share of ethanol. Structural shocks from corn markets accounts for a low proportion of gasoline price as well.

How crude oil prices respond to structural shocks?

Table 5, Figure 5 show how crude oil prices respond to those structural shocks to different months.Crude oil prices exhibit similar patterns with gasoline prices, as response to the crude oil demand and supply shocks. Similar to those fuel prices and corn prices we've discussed before, crude oil price are mainly driven by the crude oil demand shocks. The overshooting of crude oil price in the first few months support Kilian's (2009) findings that people's precautionary demand of crude oil act immediately to those exogenous political events, which in turn, result in instant and sharp decrease of crude oil price. Structural shocks from ethanol and corn demand shocks yield almost marginal effects on the crude oil prices.

Consistent with Kilian's (2010) results, crude oil demand shocks explain the majority of the volatility of crude oil prices both in short and long run, indicating that precautionary demand plays a more important role than those crude supply shocks mainly from external political events. Structural shocks of gasoline, ethanol and food markets accounts limited proportions in explaining the volatility of crude oil prices. It seems that shocks from real economic activities contribute a much larger proportion in explaining the crude oil volatility compared to the other shocks (expect for the crude oil demand shocks), especially in the long run. This might be explained in a globalization perspective, as a major input for all the economies, crude oil might be not only influenced by its corresponding demand/supply powers, but also driven by the global business cycle.

Compared to gasoline, ethanol, real economic aggregated demand shocks contribute more to the crude oil prices. As a consequence, it seems that the larger the fuel market is, the more important aggregate demand shocks will be explaining fuel volatilities.

5. Conclusions

In this study, a Structural Vector Autoregression model (SVAR) is employed to decompose how supply/demand structural shocks affect food and fuel prices within fuel and corn markets. Results indicate that although corn demand shocks explain the majority of corn prices both in short and long run, the relative importance of each structural shock in explaining the variation of corn prices is different. Our findings support the hypothesis that corn prices increase as a response to those positive demand shocks in the short run, while in the long run, global competitive agricultural commodities markets as well as positive supply shocks respond to commodity price shocks, restoring prices to its long-run trends.

Our results show that although the food versus fuel choice is tilted toward fuel, ethanol demand shocks only contribute a fairly small proportion of the forecast error of corn prices. The proportion of ethanol demand/supply shocks in explaining crude oil and gasoline prices are relatively limited both in short and long runs, indicating that influence of the ethanol market on the other fuel market are still small.

For the price volatility, corn, crude oil and ethanol are mainly governed by their own demand shocks, while gasoline price variation are more influenced by the gasoline supply shocks both in short and long runs. This is consistent with Kappel et al. (2010)'s statement that fundamental market forces of demand and supply were the main drivers of the 2007-2008 food price spike.

For all the markets, real economic aggregated demand shocks contribute more in the long run than in the short run. The real economic aggregated shocks explain more of the forecast error variance of crude oil price than gasoline and ethanol prices, which indicates that the larger the fuel market is, the more important aggregate demand shocks will play in explaining fuel volatilities.

Our results show that agricultural commodity prices might serve as a market signals, the decentralized competitive agricultural commodities markets will respond to the demand shocks instantly, while in a long run, decentralized freely operating markets will mitigate the persistence of these shocks and restore prices to their long-run trends although there is a time lag of the response. Spikes in agricultural commodity prices, whether caused by biofuels, climate, or just human mistakes, cause irreparable harm to the global poor. Therefore, in the short run, it is important to ensure food availability to all, but most importantly to the global poor. In the long-run, markets will adjust. Policies, including agricultural commodity buffers, designed to blunt these short-run price spikes should be reconsidered as a tool to reduce food volatility (Zhang et al., 2010).

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Figure 1 Supply and Demand Short- and Long-run Shifts

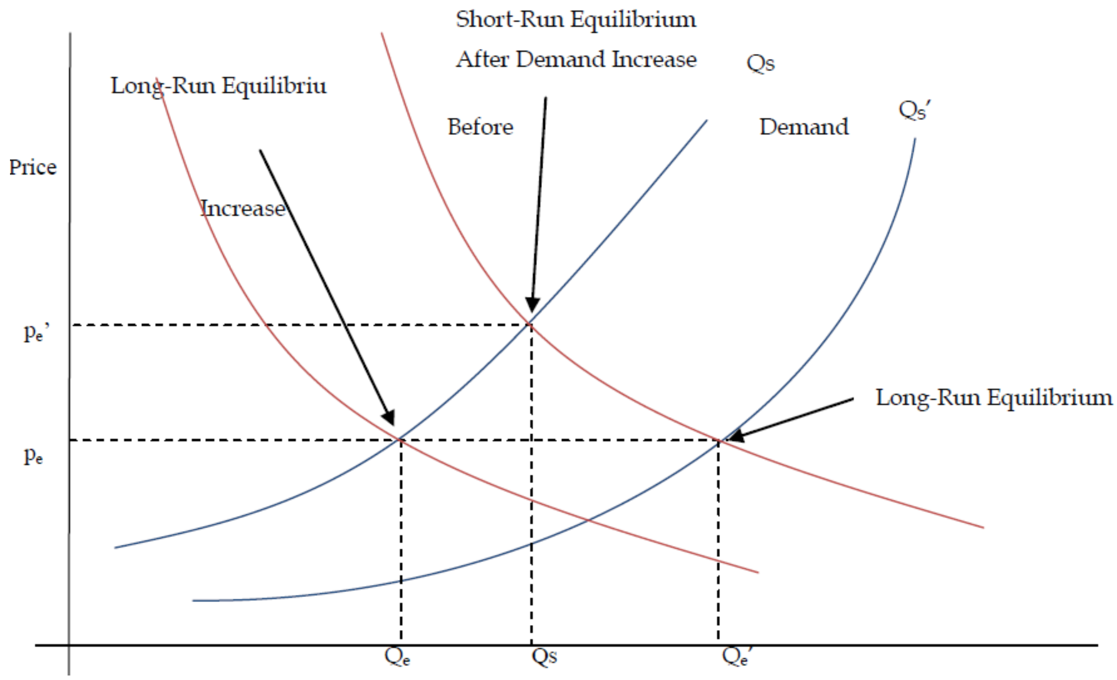

Table 1 Augmented Dickey-Fuller Unit Root Tests Results

Variable	Dickey-Fuller Statistics		
	data	Logarithms data	First Differences of Logarithms data
Supply and Demand			
Crude oil supply	-2.862	-3.164*	-13.921***
Gasoline demand	-5.333***	-4.343*	-14.264***
Ethanol Supply	1.462	-2.243	-11.499***
Corn Supply	-11.952***	-10.591***	-8.804***
Prices			
Crude Oil	-4.147***	-3.382*	-8.020***
Ethanol	-4.675****	-4.348***	-10.317***
Gasoline	-4.704***	-5.510***	-10.253***
Corn	-2.472	-2.417	-7.567***
Real Economic Activities			
Baltic Exchange Dry Index	-3.052**	-3.556**	-9.531***

Note: *** indicates significant at 1% level, ** indicates significant at 5% level, and *indicates significant at 10% level.

Table 2 Forecast Error Variance Decomposition of Corn Price

month	so_shock	real_shock	do_shock	sg_shock	dg_shock	de_shock	se_shock	dc_shock	sc_shock
1	0.16	0.33	0.01	0.00	0.00	4.46	1.07	93.97	0.00
2	3.79	0.26	1.92	3.77	1.27	3.44	2.02	79.66	3.89
4	3.53	0.26	1.89	5.61	1.62	3.15	5.25	74.42	4.27
6	3.86	2.79	1.76	6.96	2.43	3.43	5.60	68.99	4.20
12	5.02	2.62	1.88	8.09	3.80	4.17	5.76	63.18	5.48
18	5.06	2.58	1.98	8.09	3.96	4.22	5.77	62.27	6.07
24	5.22	2.61	2.06	8.16	4.27	4.28	5.74	61.46	6.20
30	5.22	2.61	2.07	8.15	4.30	4.29	5.73	61.31	6.32
36	5.29	2.62	2.09	8.17	4.39	4.29	5.71	61.09	6.34
48	5.33	2.62	2.10	8.16	4.44	4.29	5.71	60.97	6.37
60	5.36	2.63	2.10	8.16	4.46	4.29	5.70	60.92	6.38

Table 3 Forecast Error Variance Decomposition of Ethanol Price

month	so_shock	real_shock	do_shock	sg_shock	dg_shock	de_shock	se_shock	dc_shock	sc_shock
1	2.47	0.01	6.01	9.37	0.01	82.13	0.00	0.00	0.00
2	1.88	1.80	12.89	7.27	0.34	71.04	2.14	2.57	0.07
4	3.19	3.00	12.13	7.79	0.33	66.68	2.74	3.86	0.28
6	4.56	4.42	11.59	7.33	0.38	64.03	2.78	4.40	0.51
12	5.09	4.94	11.44	7.11	0.52	62.98	3.03	4.31	0.58
18	5.08	4.96	11.43	7.17	0.72	62.62	3.04	4.31	0.68
24	5.08	4.95	11.42	7.19	0.73	62.56	3.04	4.32	0.70
30	5.08	4.95	11.42	7.19	0.74	62.53	3.04	4.32	0.72
36	5.08	4.95	11.42	7.19	0.75	62.52	3.04	4.32	0.72
48	5.08	4.95	11.42	7.20	0.75	62.51	3.04	4.32	0.72
60	5.09	4.95	11.42	7.20	0.75	62.51	3.04	4.32	0.72

Table 4 Forecast Error Variance Decomposition of Gasoline Price

month	so_shock	real_shock	do_shock	sg_shock	dg_shock	de_shock	se_shock	dc_shock	sc_shock
1	3.82	4.64	37.19	54.36	0.00	0.00	0.00	0.00	0.00
2	2.60	16.88	40.89	36.68	0.18	0.75	0.23	0.02	1.78
4	11.88	14.58	32.45	35.94	0.90	1.62	0.31	0.42	1.90
6	11.25	13.95	33.20	34.35	0.96	1.84	0.69	0.51	3.25
12	10.66	14.25	29.98	31.67	4.05	3.29	0.85	0.78	4.46
18	10.73	14.01	29.56	30.98	4.18	3.82	0.87	0.87	4.97
24	10.69	13.88	29.32	30.81	4.46	3.91	0.89	0.89	5.15
30	10.67	13.83	29.24	30.73	4.48	3.95	0.90	0.91	5.28
36	10.67	13.81	29.20	30.69	4.54	3.96	0.90	0.91	5.31
48	10.67	13.79	29.18	30.67	4.55	3.97	0.91	0.92	5.34
60	10.67	13.79	29.17	30.66	4.56	3.97	0.91	0.92	5.35

Table 5 Forecast Error Variance Decomposition of Crude Oil Price

month	so_shock	real_shock	do_shock	sg_shock	dg_shock	de_shock	se_shock	dc_shock	sc_shock
1	0.25	8.01	91.74	0.00	0.00	0.00	0.00	0.00	0.00
2	0.86	13.49	82.24	2.79	0.33	0.15	0.05	0.00	0.09
4	8.34	16.03	68.90	3.50	0.46	0.72	1.66	0.24	0.14
6	8.07	15.49	66.68	4.58	0.87	0.93	2.15	0.26	0.97
12	8.44	16.42	62.69	4.89	1.75	1.76	2.19	0.53	1.32
18	8.39	16.37	62.11	4.92	1.91	1.90	2.18	0.59	1.62
24	8.41	16.30	61.83	4.98	2.08	1.95	2.18	0.60	1.68
30	8.42	16.27	61.70	4.99	2.09	1.97	2.18	0.62	1.77
36	8.43	16.25	61.63	5.00	2.14	1.98	2.18	0.62	1.77
48	8.44	16.24	61.57	5.00	2.16	1.98	2.18	0.63	1.80
60	8.45	16.23	61.55	5.00	2.16	1.98	2.18	0.63	1.80

Figure2.a SIRF of Corn Price

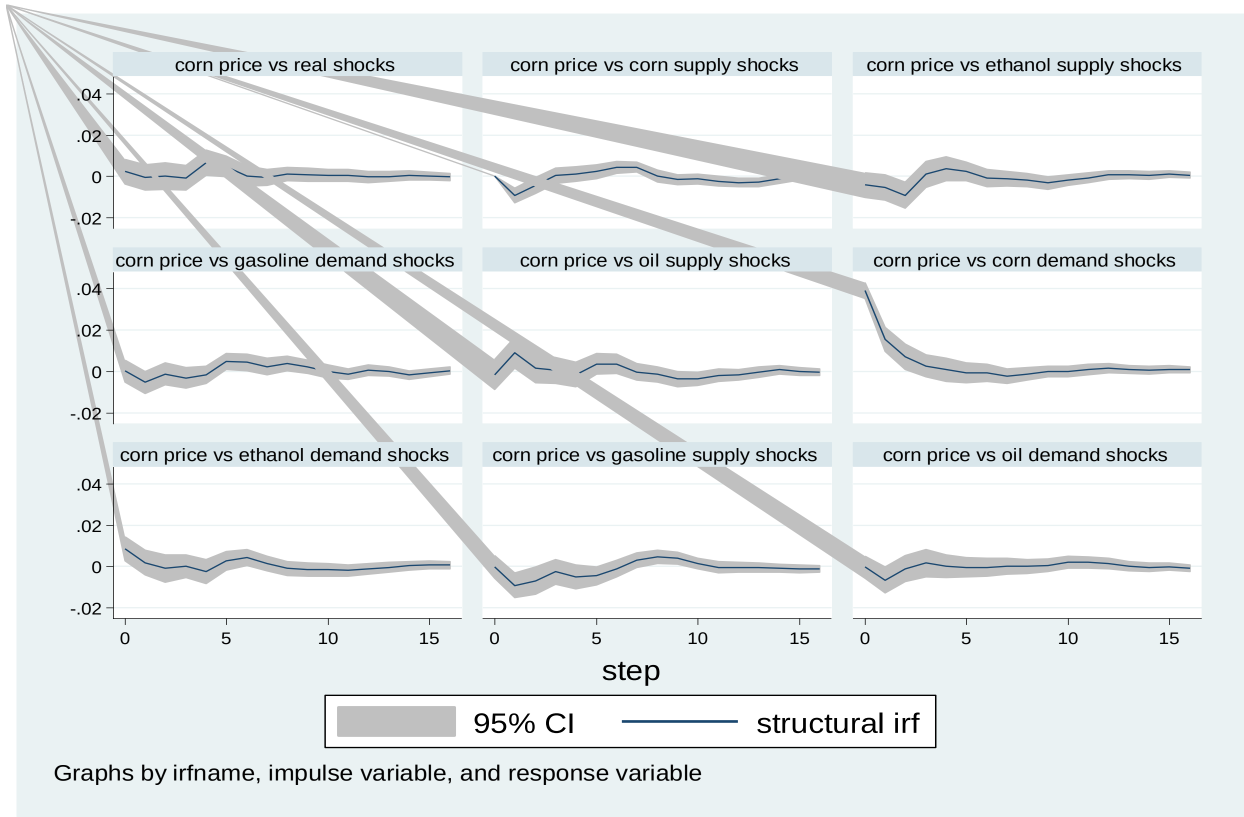

Figure2.b CIRF of Corn Price

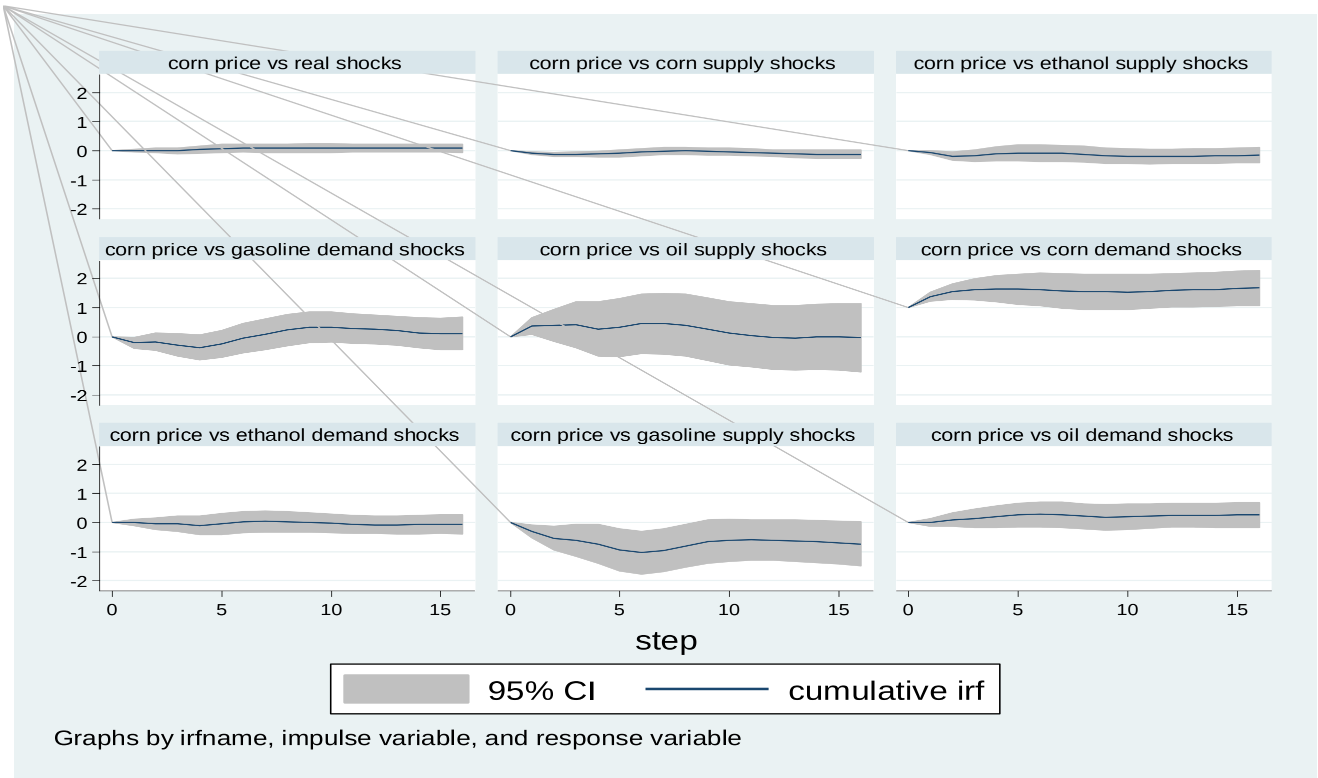

Figure3 SIRF of Ethanol Price

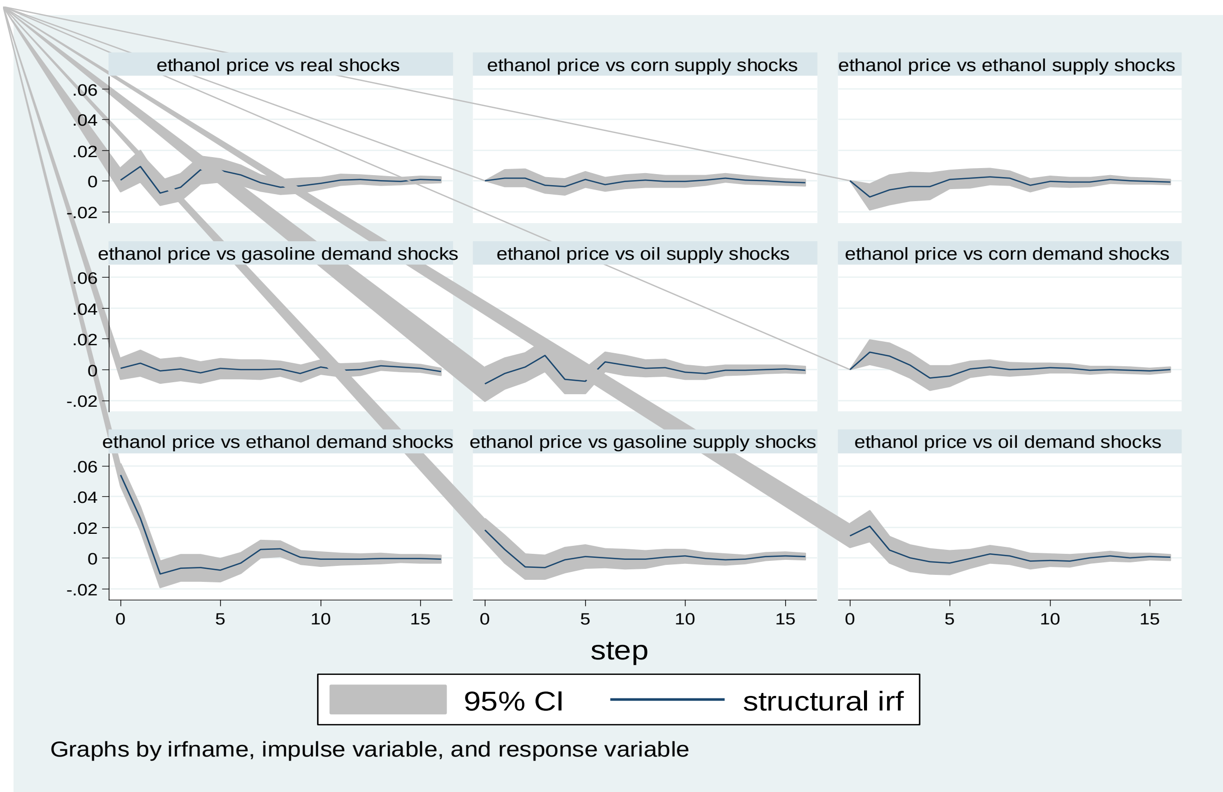

Figure 4 SIRF of Gasoline Price

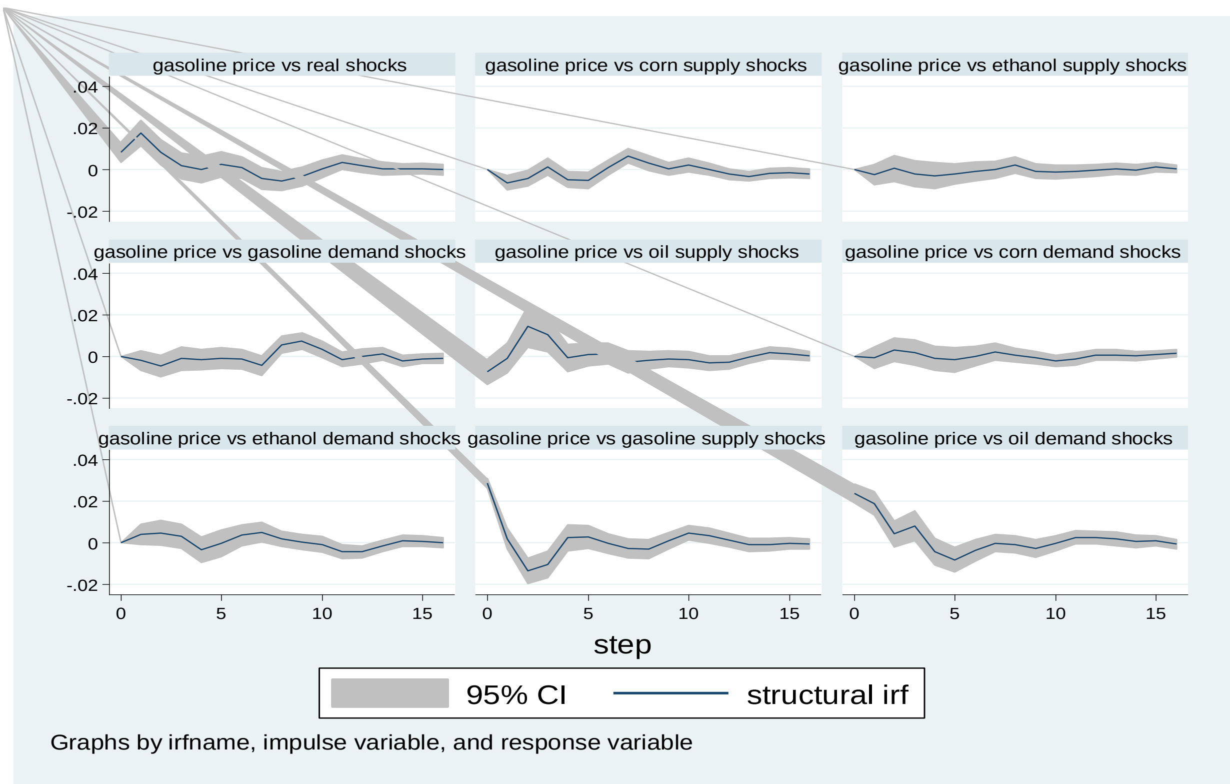

Figure 5 SIRF of Crude Oil Price