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Assessing the impact of US ethanol on fossil fuel markets: A structural VAR approach☆

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ABSTRACT

Despite the growing importance of biofuels, the effect of biofuels on fossil fuel markets is not fully understood. We develop a joint structural Vector Auto Regression (VAR) model of the global crude oil, US gasoline, and US ethanol markets to examine whether the US ethanol market has had any impact on global oil markets. The structural VAR approach provides a unique method for decomposing price and quantity data into demand and supply shocks, allowing us to estimate the distinct dynamic effects of ethanol demand and supply shocks on the real prices of crude oil and US gasoline. Ethanol demand in the US is driven mainly by government support in the form of tax credits and blending mandates. Shocks to ethanol demand therefore reflect changes in policy more than any other factor. In contrast, ethanol supply shocks are driven by changes in feedstock prices. A principle finding is that a policy-driven ethanol demand expansion causes a statistically significant decline in real crude oil prices, while an ethanol supply expansion does not have a statistically significant impact on real oil prices. This suggests that even though US ethanol market is small, the influence of US biofuels policy on the crude oil market is pervasive. We also show that ethanol demand shocks are more important than ethanol supply shocks in explaining the fluctuation of real prices of crude oil and US gasoline.

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1. Introduction

The effect of biofuels on fossil fuel markets has attracted growing interest in the biofuel literature. Several studies have addressed the impact on gasoline prices (Du and Hayes, 2009;McPhail and Babcock, 2008; Rajagopal, et al., 2007; Sexton et al., 2008), but the impact on crude oil markets has been limited to analytical presentations (de Gorter and Just, 2009; Hochman, et al., 2010; Lapan and Moschini, 2009) and computational general equilibrium models (Gehlhar et al., 2010). Meanwhile, applications of time series analysis on price data have shown oil prices to Granger-cause ethanol prices (Balcombe and Rapsomanikis, 2008; Saghaian, 2010; Zhang et al., 2009, 2010). Nevertheless, the evidence on the causal link from ethanol to oil is mixed (Saghaian, 2010). Recently, structural VAR models,[2] a major tool in macroeconomic analysis of monetary, fiscal, and technology shocks, have been applied to the study of biofuels (Cha and Bae, 2011; Zhang, et al., 2007). Yet, to date, the structural VAR approach has not been used to explore the impact of ethanol on global oil markets.

To examine the impact of ethanol on fossil fuel markets, we differentiate between the impact of an ethanol demand shock and the impact of an ethanol supply shock. This distinction is necessary because the driving forces for ethanol demand and supply shocks are different. US ethanol demand is mainly driven by policies in the form of tax credits and blending mandates, and therefore demand shocks mainly result from changes in policy. In contrast, shocks to ethanol supply are mainly driven by changes in feedstock (e.g., corn) prices,[3] caused by yield variations and other factors. Killian (2010) argues that it is essential to differentiate between demand and supply shocks, because each demand and supply shock is associated with responses of a different magnitude, pattern and persistence. Our main hypothesis is that a policy-driven ethanol demand shock affects fossil fuel markets, while a shock to ethanol supply driven by feedstock price variation does not affect fossil fuel markets.

This paper utilizes a joint structural VAR model of the global crude oil market, the US gasoline market and the US ethanol market. The model builds on a recently proposed structural VAR model of the global market

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[2] The structural VAR approach origins from the seminal contributions of Sims (1986), Bernanke (1986), and Blanchard and Watson (1986), who used economic theory to uncover the structure of disturbances. Currently, structural VARs are an important tool in analysis of monetary, fiscal, and technology shocks (Enders, 2004).

[3] While ethanol can be produced from a variety of feedstocks, corn has served as the predominant feedstock for US ethanol production. Conversion of corn-based ethanol is a proven technology, and a production and distribution system has already evolved to serve the US corn market.

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for crude oil and the US market for motor gasoline by Killian (2010). This approach allows us to view all market impacts as endogenous. VAR is a reduced-form method, so it is difficult to interpret the results unless the reduced form is linked to an economic model. Structural VARs impose an economic model on the contemporaneous movements of the variables. As such, they allow for the identification of the parameters of the economic model and the structural shocks. This technique provides a unique decomposition of prices and quantities into demand and supply shocks. We therefore identify the underlying demand and supply shocks in these three markets and assess the responses of prices of each market to unanticipated shifts in demand and supply by impulse response analysis. Additionally we employ variance decomposition analysis to evaluate the overall importance of each shock in the determination of the real prices of crude oil, US gasoline and ethanol.

Our key result indicates that ethanol demand expansion leads to a statistically significant decline in real crude oil prices, while there is no statistically significant effect of ethanol supply expansion on real crude oil prices. This suggests that even though the US ethanol market is small and accounts for less than 1% of global fuel market, the influence of US ethanol policy on the global fossil fuel markets is pervasive.

2. The US ethanol and gasoline markets

In the transportation sector, ethanol is the world's most widely used liquid biofuel (US Energy Information Administration). The US ranks first in ethanol production, accounting for more than 50% of global ethanol production in 2009. In the US, blenders added about 11 billion gallons of ethanol to gasoline in 2009 accounting for about 8% of gasoline consumption by volume. About 99% of ethanol consumed in the US is added into gasoline in volume mixtures up to 10% ethanol and 90% gasoline (E10), which can be used by all cars and light trucks. But only specific types of vehicles can use mixtures greater than 10% ethanol. In October 2010, the US Environmental Protection Agency (EPA) ruled that E15 can be used in cars and light trucks of model year 2007 and newer. Later in January 2011, the EPA approved E15 for 2001–06 cars and light trucks. E85 containing up to 85% ethanol can be used by Flexible Fuel Vehicles (FFVs). However, most FFVs on the road are fueled with gasoline or E10 rather than E85.

Policy makers have introduced different policies to support biofuels. The Energy Security Act of 1979 created a Federal ethanol tax incentive to reduce dependence on foreign oil. Gasoline marketers were permitted to claim this Federal ethanol tax incentive. Demand for ethanol received a boost in 1990 with the passage of the Clean Air Act Amendments (CAAA) which established reformulated gasoline (RFG) and oxygenated fuel additive requirement in specific regions of the US during the winter months to reduce carbon monoxide. The two most common fuel additives were methyl tertiary butyl ether (MTBE) and ethanol. Environmental concerns about MTBE led many states to ban its use, and ethanol thus became the oxygenate of choice for the RFG program.

The Energy Policy Act (EPAct) of 2005 was one of the critical factors driving the surge in ethanol. This act maintained RFG air quality standards, thereby continuing the need for reformulated gasoline. Furthermore, the act held oil companies liable for MTBE spills, thus reducing use of MTBE and stimulating ethanol demand. This act also originated the RFS program (RFS1), which mandated 7.5 billion gallons of renewable fuel to be blended into gasoline by 2012. The scope of the RFS (RFS2) was expanded by the Energy Independence and Security Act (EISA) of 2007, which mandated 36 billion gallons of renewable fuel use annually by the year 2022. If the RFS2 is met, ethanol use will comprise about 25% of gasoline consumption in the coming years. As the US is the world's largest petroleum consumer, and gasoline is one of the major fuels in the US refined from crude oil, an examination of US ethanol's impact on global oil markets is warranted.

3. The structural VAR (SVAR) model

To examine the impact of ethanol on global crude oil and US gasoline markets, we develop a seven-variable SVAR of these three markets, based on a recently proposed model of global crude oil and US gasoline by Killian (2010). The seven monthly variables[4] are defined as a vector $x_t = (os_t, rea_t, rpo_t, rpg_t, gd_t, rpe_t, es_t)'$, where os_t is growth rate in global crude oil production[5], rea_t is real global economic activity used in Killian (2009), rpo_t is the real price of crude oil, rpg_t is the real price of US gasoline, gd_t is growth rate in US gasoline consumption[6], rpe_t is the real price of ethanol, and es_t is level change or first difference in US ethanol production[7]. Our SVAR model provides estimates of the impacts that ethanol demand and supply shocks have on the markets of global crude oil and US gasoline. We propose that the seven variables are driven by the following seven structural shocks: (1) oil supply shocks (os_shocks); (2) aggregate demand shocks (ad_shocks); (3) oil-market specific demand shocks (od_shocks); (4) gasoline supply shocks (gs_shocks); (5) gasoline demand shocks (gd_shocks); (6) ethanol demand shocks (ed_shocks) and; (7) ethanol supply shocks (es_shocks).

Shocks are conceptually defined here as demand or supply curve shifts that are not anticipated by the SVAR model. For example, oil supply shocks are defined as unanticipated shifts to the oil supply curve. This may occur due to an exogenous political event, such as the civil unrest in Venezuela in December 2002 or the Iraq war in March 2003. Shocks to aggregate demand are designed to capture shifts of the demand for all industrial commodities (including crude oil) in global markets driven by the global business cycle such as the emergence of industrial economies in Asia. Oil specific demand shocks are designed to capture shifts of the precautionary demand for crude oil such as the increase of the demand for oil with fears about future oil supply right before the Iraq war in March 2003. Gasoline supply shocks may occur because of refinery fires that shut down the operation of US refiners and reduce the domestic supply of gasoline or changes in regulations that restrict refinery output. Gasoline demand shocks are designed to capture shifts in gasoline demand, which might be caused by changes in consumer preferences, changes in demographic structure and the degree of urbanization. Ethanol demand shocks are defined as unanticipated shifts of ethanol demand curves and usually occur due to changes in regulations that support ethanol, such as the phase out of MTBE[8], the introduction and reduction of tax credits to ethanol blenders, and the introduction and expansion of Renewable Fuel Standard. Ethanol supply shocks are usually caused by changes in feedstock prices, which might result from yield variations or changing input costs.

[4] It is reasonable to expect that a dollar-denominated asset like oil is affected by the value of the dollar. Although many studies highlight the effect of changing crude oil prices on exchange rate, the direct empirical evidence of this hypothesis is scant. For example, studies (Chen and Chen 2007; Coudert et al., 2007) examine the link between oil prices and the U.S. exchange rate and find that the causality runs from oil prices to the exchange rate but not vice versa. Because the main focus of our paper is to examine the impact of ethanol on oil, we do not include the value of dollar into our SVAR model.

[5] Following Killian (2009), global oil production data are transformed to the growth rates of global oil production which are stationary, as shown later in the paper.

[6] Following Killian (2010), monthly US gasoline consumption data are transformed to the growth rates of US gasoline consumption which are stationary, as shown later.

[7] US ethanol production data are measured in first difference, instead of growth rate. The reason for this is that US ethanol production grew exponentially over this period, the same growth rate for different years implies very different magnitude of change in the ethanol production, thus using growth rates will not help us identify the supply shocks we are interested in. As shown later, first difference in US ethanol production is stationary.

[8] MTBE (methyl tertiary butyl ether) has been a popular gasoline additive used as an oxygenator to raise octane levels until it was discovered to cause groundwater contamination. Many US states banned MTBE, thus fuel blenders were led to other alternatives, like ethanol. (Zhang, et al., 2007)

The effects of these seven shocks on our variables of interest are evaluated to determine which are statistically significant, when they become significant and how long they remain significant. The structural VAR representation is:

$$A_0 x_t = \alpha + \sum_{i=1}^{p} A_i x_{t-i} + \varepsilon_t \tag{1}$$

where p is the lag order, and ε_t denotes the vector of serially and mutually uncorrelated structural innovations. The reduced-form VAR representation is:

$$x_t = A_0^{-1}\alpha + \sum_{i=1}^{p} A_0^{-1} A_i x_{t-i} + e_t. \tag{2}$$

If A_0^{-1} is known, the dynamic structure represented by structural VAR could be calculated from the reduced-form VAR coefficients, and the structural shocks ε_t can be derived from estimated residuals $\varepsilon_t = A_0 e_t$. Coefficients in A_0^{-1} are unknown, so identification of structural parameters is achieved by imposing theoretical restrictions to reduce the number of unknown structural parameters to be less than or equal to the number of estimated parameters in the VAR residual variance–covariance matrix. Specifically, the covariance matrix for the residuals, Σ_e, is

$$\Sigma_e = E\left(e_t e_t^{'}\right) = A_0^{-1} E\left(\varepsilon_t \varepsilon_t^{'}\right) A_0^{'-1} = A_0^{-1} \Sigma_\varepsilon A_0^{'-1} \tag{3}$$

where E is the unconditional expectation operator, and Σ_ε is the covariance matrix for the shocks. As there are 28 unique elements in Σ_e, we impose the following recursive structure on A_0^{-1} such that the reduced-form errors e_t can be decomposed according to $e_t = A_0^{-1}\varepsilon_t$:

$$e_t \equiv \begin{pmatrix} e_t^{os} \\ e_t^{rea} \\ e_t^{rpo} \\ e_t^{rpg} \\ e_t^{gd} \\ e_t^{rpe} \\ e_t^{es} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{os\_shock} \\ \varepsilon_t^{ad\_shock} \\ \varepsilon_t^{od\_shock} \\ \varepsilon_t^{gs\_shock} \\ \varepsilon_t^{gd\_shock} \\ \varepsilon_t^{ed\_shock} \\ \varepsilon_t^{es\_shock} \end{pmatrix}. \tag{4}$$

The recursive structure of the structural VAR model is achieved by assuming that not all variables of interest will respond to shocks contemporaneously. All of these assumptions can be read from the previous equation $e_t = A_0^{-1}\varepsilon_t$. For example, we assume that global crude oil producers take at least one month to respond to all shocks except for those on crude oil supply. We impose this restriction by making all values on the top row of the A_0^{-1} matrix zero except for α_{11}.[9] Fewer contemporaneous response restrictions are placed on more localized variables of interest to reflect the smaller (more agile) nature of these markets. A multi-national industry so dependent on large amounts of capital investment, such as the global crude oil market, takes time to respond to changes in the global economy. Allowing contemporaneous responses to shocks would only be appropriate for smaller and thus more agile industries. For this reason we allow the US gasoline market variables rpg_t and gd_t to respond to contemporaneous shocks to global oil market such as those on oil supply and aggregate demand, but not contemporaneous shocks to the much smaller ethanol market. Following this logic, even fewer restrictions are placed on the much smaller (more agile) ethanol market than the US gasoline market. Beyond these restrictions on the contemporaneous feedback at monthly frequency, the model allows all feedback among all variables within and across blocks, consistent with the well-established notion that energy prices must be treated as fully endogenous (Barsky and Killian 2002, 2004).

A contemporaneous response restriction is equivalent to putting restrictions on a demand (or supply) curve in the short run. First, allowing only α_{11} in the first row of A_0^{-1} to be non-zero is equivalent to assuming a perfectly inelastic short-run (within a month) supply curve of crude oil (conditional on all lagged variables). The rationale for this assumption is that changing oil production is costly. Oil producers set production based on expected trend growth in demand. They do not revise the production level in response to unpredictable high-frequency variation in the demand for oil, since changes in the trend growth in demand are difficult to detect at high frequency. Second, restricting α_{45} to be zero is equivalent to assuming a perfectly elastic short-run (within a month) supply curve of US gasoline. Following Killian (2010), we assume that gasoline distributors have enough gasoline stored to supply the required quantities of gasoline (within a month) at the current retail price, which is assumed to be effectively set by US refiners. Domestic refiners set retail prices by adding a markup to the price of imported crude oil, and are price takers in the global crude oil market. Increases in the price of imported crude oil are being passed on by refiners to the retail price of gasoline within the same month. Third, restricting α_{67} to be zero is equivalent to assuming that demand for ethanol within a month is only a function of gasoline price. It is important to note that this holds no matter if ethanol is a substitute or complement to gasoline.[10]

4. Data

Fig. 1 shows the monthly data for seven key variables. The sample period of 1994:01–2010:02 begins with the availability of monthly ethanol production data from the US Department of Energy. We collect monthly data for world oil supply,[11] imported crude oil prices,[12] regular gasoline retail prices,[13] US product supplied of finished motor gasoline,[14] and US oxygenate plant production of fuel ethanol[15] from the Energy Information Administration. Nominal ethanol rack prices data are obtained from the Nebraska energy office website.[16] Nominal prices and indexes are deflated using the US Consumer Price Index (CPI). Specifically, real prices and real Baltic Exchange Dry Index (BDI) are computed by dividing the nominal prices in a given month by the ratio of the CPI in that month to the CPI in March of 2010. Because finished motor gasoline includes all ethanol blended gasoline, US gasoline consumption is approximated by US product supplied of finished motor gasoline minus US oxygenate plant production of fuel ethanol. Following Killian (2009), the real economic activity index is proxied by the real average close prices of BDI. A series of papers by Killian show that oil supply shock measures alone do not explain the bulk of oil price fluctuations and thus demand shocks play an important role. To quantify these

9 We must allow contemporaneous response in crude oil production to crude oil supply because crude oil producers are the cause of crude oil supply shocks.

10 Ethanol is a complement to gasoline when it is used as a fuel additive. However, in the case when consumers use E10, E15, and E85 voluntarily, high gasoline price will lead to more use of ethanol (Thompson et al. 2008). Ethanol has about two-thirds of the energy value of gasoline which implies lower miles traveled per gallon of ethanol. Many consumers would buy ethanol only if its price (on a volume basis) is at an offsetting discount with respect to the price of gasoline. Because the current RFS2 mandates are applied to fuel blenders, consumers are free to choose which fuel they buy. Blenders must price ethanol low enough that consumers buy at least the mandated quantity. In this case ethanol is a substitute to gasoline.

11 http://tonto.eia.doe.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=50&pid=53&aid=1.

12 http://www.eia.doe.gov/emeu/steo/pub/fsheets/real_prices.html.

13 http://www.eia.doe.gov/emeu/steo/realprices/index.cfm.

14 http://tonto.eia.doe.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MGFUPUS1&f=M.

15 http://tonto.eia.doe.gov/dnav/pet/pet_pnp_oxy_dc_nus_mbbl_m.htm.

16 http://www.neo.ne.gov/statshtml/66.html.

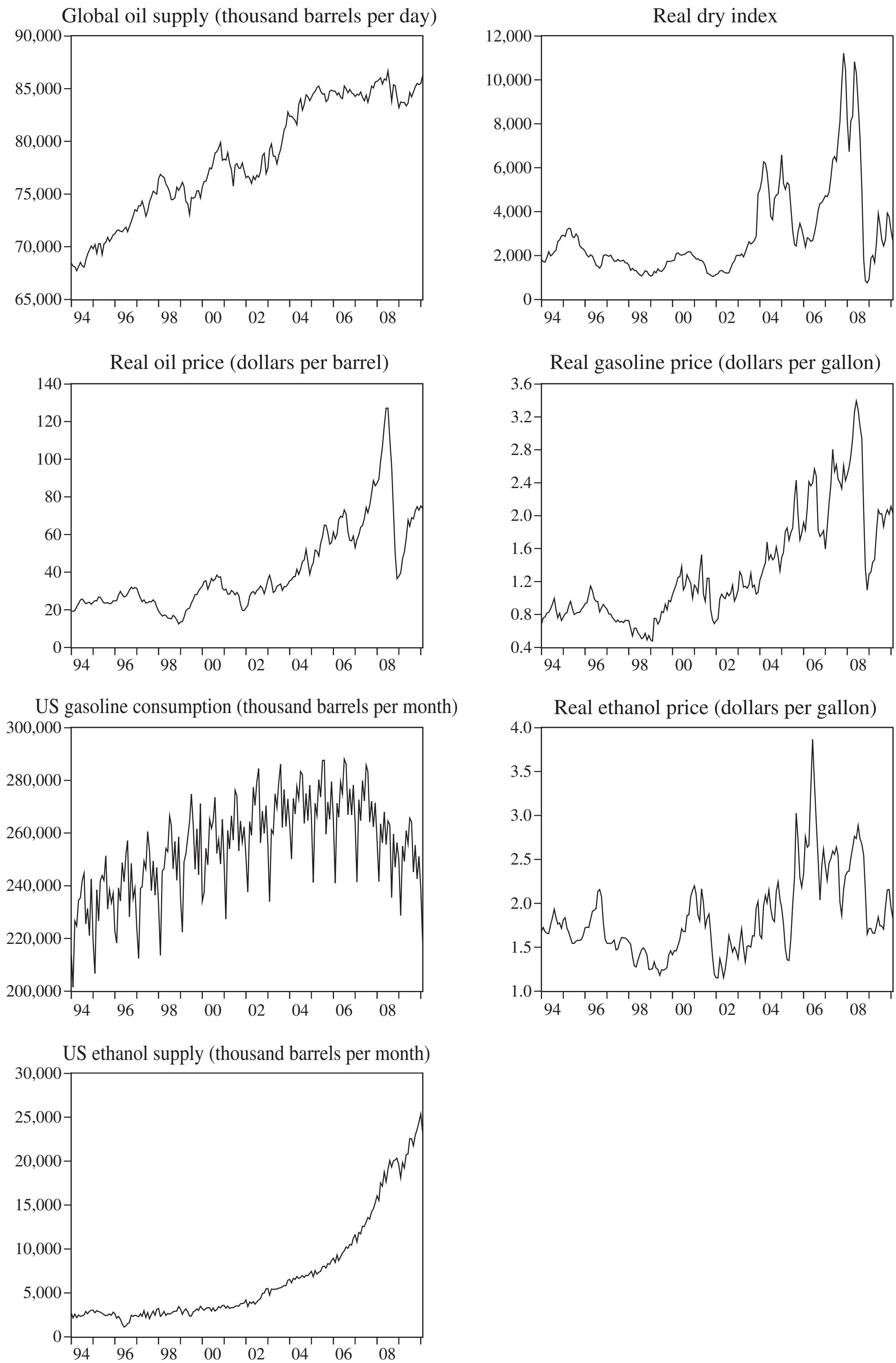


Fig. 1. Data plots for key variables.

Table 1
ADF test results.

Variables	Augmented Dickey Fuller test statistics (with constant and trend)
os	−12.24 (1)***
rea	−3.84 (1)**
rpo	−4.15 (1)***
rpg	−3.62 (2)**
gd	−3.62 (1)**
rpe	−3.18(2)*
es	−3.73 (1)**

The numbers in the parentheses indicate the number of lags chosen for the ADF test based on the Schwarz Info Criterion. Critical values for level with constant and trend are 1% = −4.01, 5% = −3.43, 10% = −3.14.
*** Denotes statistical significance at 1% level.
** Denotes statistical significance at 5% level.
* Denotes statistical significance at 10% level.

demand shocks the BDI is used to capture shifts in the demand for industrial commodities driven by the global business cycle.

Following Killian (2009), the monthly data of global oil production are transformed to a monthly growth rate. The monthly data of US gasoline consumption are seasonally adjusted by the Census X12 method with multiplicative adjustment[17] and then transformed into a monthly growth rate of US gasoline consumption. The monthly data of real US gasoline prices are also seasonally adjusted by the Census X12 method with multiplicative adjustment. The monthly data of US ethanol production are first differenced instead of transformed to the growth rate. The size of ethanol industry is growing exponentially, so the growth rate of ethanol production is not appropriate to be used to capture ethanol supply shocks. To make this point clear, the magnitude of an ethanol supply shock measured by a 5% growth in ethanol production in 1994 is much smaller than an ethanol supply shock measured by a 5% growth in 2008. Therefore, we use level changes to measure changes in US ethanol production.

These transformed data series are tested for a unit root using the augmented Dickey–Fuller test (Table 1)with a trend and constant shown in the equation below; where y is the time-series variable and γ_0, γ_1, v, β_1, ⋯, β_p are parameters. We reject the hypothesis of existence of a unit root at 10% significance level for all variables of interest.[18]

$$\Delta y_t = \gamma_0 + \gamma_1 t + v y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{5}$$

At the 1% significance level, employing a variance ratio test, three prices exhibited higher volatility since 2003. A common practice is to use a logarithmic transformation if the variance does not appear to be constant (Enders, 2004). Therefore, we also run the SVAR model with logarithmic forms and the main results are found to be robust to this permutation. To incorporate possible structural change, we divided the sample into two periods: 1994.01–2005.12 and 2006.01–2010.02, based on the general conclusion argued by previous studies (Campiche, et al., 2007; Frank and Garcia, 2010; Harri, et al., 2009). These studies argue that the emergence of higher oil prices and increased biofuel production beginning around 2006 has caused a closer relationship between energy prices and agricultural (including biofuels) prices than had been experienced prior to 2006. If there is a structural change in SVAR model, we expect that ethanol supply shocks might have a significant impact on crude oil prices for the later period. However, the results from two different samples are similar and consistent with our main conclusions from the baseline specification.

Table 2
Granger causality test results.

Null hypotheses	F-Statistic	Decision
Real ethanol price does not Granger Cause real oil price	2.34(12)	Reject***
Real oil price does not Granger Cause real ethanol price	3.50(12)	Reject***
US ethanol production increase does not Granger Cause real oil price	1.34(12)	Do not reject
Real oil price does not Granger Cause US ethanol production increase	4.29(12)	Reject***

The numbers in () indicate the number of lags chosen for the test.
*** Denotes statistical significance at 1% level.

Granger causality tests are performed to examine the causality between oil and ethanol. Our results (Table 2) confirm the typical results in the literature: oil prices granger cause ethanol prices. However, we find that real ethanol prices granger cause real oil prices. We also find that real oil price granger causes US ethanol production increase, but not vice versa.

We utilized sequential modified Log Likelihood Ratio test (LR) and Akaike Information Criterion (AIC) to choose number of lags to include in a SVAR model. Estimation of the model with alternative lags yielded robust and qualitatively similar results. For reporting the results, a 12 month lag specification was selected. The model is estimated by the method of least squares, because all the regression equations have the same right-hand-side variables, thus negating the need for a Seemingly Unrelated Regression (SUR) approach.

Before impulse response and variance decomposition analysis, we compute historical demand and supply shocks, ε_t, by multiplying the identification matrix, A_0, by the estimated residuals from the VAR model, e_t, such that $\varepsilon_t = A_0 e_t$. Estimated historical demand and supply shocks presented in Fig. 2 can help understand the magnitude of the shocks. A positive shock is defined as one standard deviation above the mean, while a negative shock is defined as one standard deviation below the mean.

5. Impulse response analysis

To examine distinct dynamic responses of real prices of global crude oil and US gasoline to ethanol demand and supply shocks, we use impulse response analysis. Fig. 3 presents the responses of real crude oil prices to ethanol demand and supply shocks from impact to month 12.[19] US ethanol demand expansion causes real oil price to decrease, and the negative responses are statistically significant from month 8 to 12. However, a US ethanol supply expansion does not have a statistically significant impact on real oil prices in the short run. In the long run, responses of real crude oil prices to shocks will finally die out due to the stationarity of data series. These distinct short run responses are due to the different driving forces for ethanol demand and supply shocks. The US ethanol demand is mainly driven by

[17] http://www.census.gov/srd/www/x12a/index.html.

[18] The advantage of using level is that the estimates remain consistent whether the real prices are integrated or not. Furthermore, standard inference on impulse responses, in levels, will remain asymptotically valid. Inference also is asymptotically same to the possible presence of cointegration among these prices (see, e.g., Lütkepohl and Reimers 1992; Sims et al., 1990). However, estimates would be inconsistent if cointegration and/or unit root are falsely imposed. Nevertheless, we followed Killian's approach of using growth rate in global oil production and growth rate in US gasoline consumption; because we believe that a change in the growth rate of oil production can better capture an oil supply shock than a change in the level as global oil production follows a trend. The same is true for US gasoline consumption.

[19] Our findings about the impact of shocks in crude oil and gasoline markets on crude oil prices are consistent with Killian's except one. We find that real oil price responds positively to US gasoline supply disruptions with statistical significance. This contradicts Killian 2010 who finds that US gasoline supply disruptions reduce the demand for oil and thus reduces the price of oil, but is consistent with the occurrence after Hurricane Katrina and Rita. The positive oil price response to negative US gasoline supply remains even when we use alternative lags. Killian (2010) used a much larger sample and chose a lag that allowed his estimated structural shocks to be more consistent with historical events. Our results suggest that Killian's results might not be robust to different lags or a change in sample size.

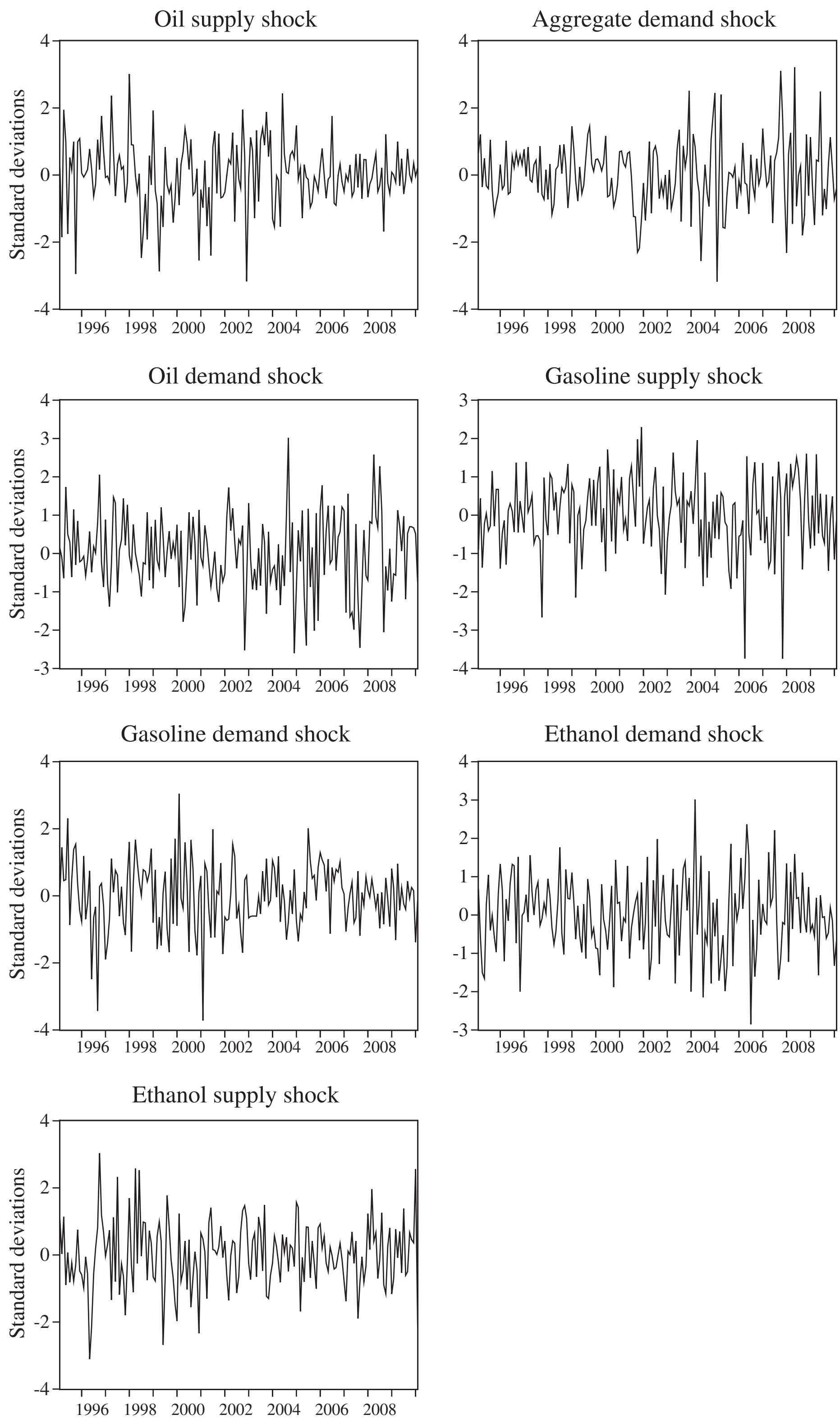
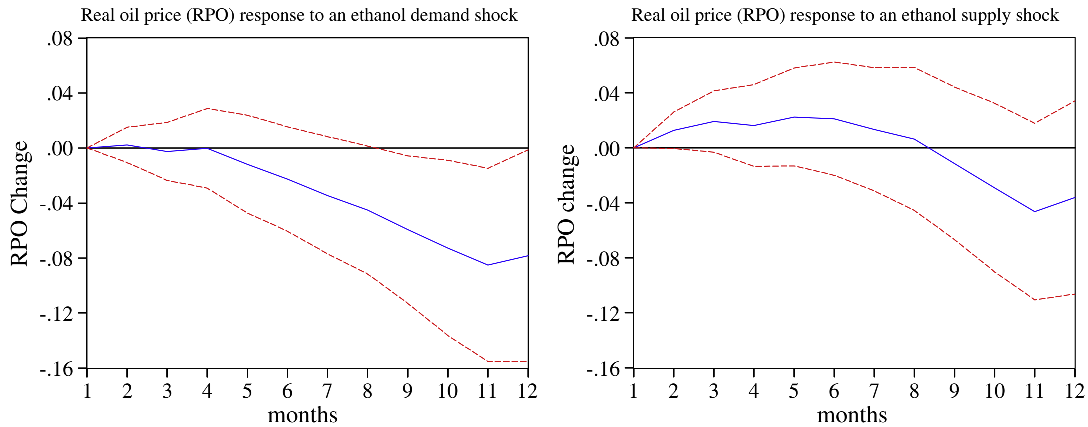


Fig. 2. Estimated historical structural shocks.

government support in the form of tax credits and blending mandate. Shocks to ethanol demand therefore reflect changes in policy more than any other factor. An ethanol demand expansion indicates stronger support for biofuels and more competition for crude oil demand; which leads to a decrease in oil prices. Unlike ethanol demand, ethanol supply shocks are mainly driven by changes in corn prices, for example, drought leads to less corn supply and higher ethanol production cost. An ethanol supply expansion therefore indicates lower production costs which might result from a lower corn price. As ethanol only accounts for less than 1% of global fuel supply, the impact of corn price variation on oil prices is not important. These results suggest that even though the US ethanol



Solid line represents the mean impact. Dotted lines represent two standard deviation impacts from the mean.
Standard errors for the impulse responses are calculated using the Monte Carlo approach of Runkle (1987).

Fig. 3. Real oil price responses to one standard deviation shocks from impact to month 12.

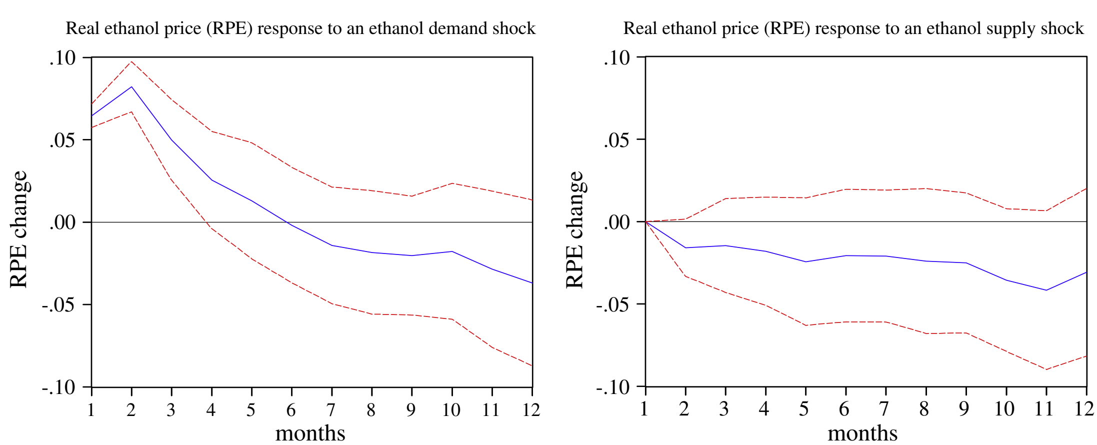
market is small in relation to the global fossil fuel market and the impact of an ethanol supply expansion on crude oil prices is negligible, the impact of US biofuel policy on crude oil prices is important.

The response of real US gasoline price to ethanol demand and supply shocks are similar to that of the real oil price. Real gasoline price decreases with statistical significance to an ethanol demand expansion, but the negative responses of real gasoline price to an ethanol supply expansion are statistically insignificant over all horizons. Again different responses are due to different causes for these two shocks. Specifically, an ethanol demand expansion reflects stronger government support for ethanol use which leads to reduced use for unblended gasoline and lower price of gasoline. Contrarily, an ethanol supply expansion reflects lower corn prices whose impact on real gasoline prices is not yet significant. Fig. 4 presents responses of real US ethanol prices to ethanol demand and supply shocks. As expected, a positive ethanol demand shock increases real ethanol prices while a positive ethanol supply shock causes real ethanol prices to decrease.

6. Variance decomposition analysis

We are interested in how important of each demand and supply shock in explaining the fluctuation of these prices. These questions can be addressed by computing forecast error variance decomposition based on the estimated structural VAR model. Variance decomposition analysis allocates each variable's forecast error variance to the individual shocks. These statistics measure the quantitative effect that the shocks have on the variables.

Table 3 reports the percentage of the variance of the error made in forecasting real crude oil prices due to a specific shock at a specific time horizon. These estimates show the relative importance of each shock in explaining the fluctuation of real crude oil prices. Please note that these estimates are based on historical averages for the period since 1994, but the relative importance of each shock may be quite different from one historical episode to the next. It is shown that on impact 98% of variation in real crude oil prices is accounted for by oil-market specific demand shocks with aggregate demand shocks and oil supply shocks accounting for the rest. Gasoline and ethanol market shocks do not affect real crude oil price within a month due to the identifying assumptions. Our results suggest that in the long run (5 years) oil demand shocks are relatively more important than oil supply shocks in explaining oil price fluctuation since 1994. As oil producers set production level based on their prediction about future demand, surges in oil prices are due to demand outstripping supply while drops in oil prices are due to sluggish demand. This is consistent with Killian's findings. It is also shown that gasoline supply shocks are more important than gasoline demand shocks in explaining oil price fluctuation. This is intuitive because US gasoline demand is less volatile than US gasoline supply due to the very inelastic nature of US



Solid line represents the mean impact. Dotted lines represent two standard deviation impacts from the mean.
Standard errors for the impulse responses are calculated using the Monte Carlo approach of Runkle (1987).

Fig. 4. Real ethanol price response to one standard deviation shocks.

Table 3
Percent contribution of each shock to the variability of real crude oil price.

Months	Oil supply shock	Aggregate demand shock	Oil specific demand shock	Gasoline supply shock	Gasoline demand shock	Ethanol demand shock	Ethanol supply shock
1	0.1	2.4	97.6***	0.0	0.0	0.0	0.0
	(1)	(2)	(2)	0	0	0	0
6	0.1	35.1***	45.3***	13.6**	0.4	1.5	3.9
	(3)	(11)	(11)	(6)	(1)	(4)	(5)
12	0.3	27.3**	22.6***	27.9***	0.7	17.0*	4.2
	(4)	(12)	(9)	(11)	(2)	(10)	(4)
24	3.3	20.3**	22.1**	32.8***	1.8	15.2*	4.4
	(7)	(10)	(11)	(11)	(3)	(9)	(7)
36	3.6	15.2*	16.8*	37.3***	1.9	21.5**	3.8
	(8)	(9)	(9)	(10)	(3)	(11)	(7)
60	6.8	11.6	13.3	35.9***	1.6	27.7**	3.0
	(9)	(8)	(10)	(11)	(4)	(10)	(8)

The numbers in () indicate standard errors. Standard errors for the variance decompositions are calculated using the Monte Carlo approach of Runkle (1987).
*** Denotes statistical significance at 1% level.
** Denotes statistical significance at 5% level.
* Denotes statistical significance at 10% level.

gasoline demand. We also find that ethanol demand shocks are relatively more important than ethanol supply shocks in explaining crude oil price fluctuation. As we already discussed, ethanol demand shocks are mainly due to changes in policy while shocks to ethanol supply are mainly due to changes in feedstock prices. This result suggests that ethanol policies are more important than feedstock prices in explaining the variation in oil prices. The variance decomposition results further support our hypothesis by indicating the importance of ethanol demand shocks in explaining global oil prices. We find similar results for explaining the variation in gasoline prices.

Predicting crude oil prices is an impossible task even for the short run due to the difficulty of predicting the future evolution of determinants. Our results show that the evolution of crude oil prices now also depends on biofuel market, especially, biofuel demand. Biofuel demand is driven mainly by biofuel policy besides the developments in crude oil and gasoline markets. Hence biofuel policy risk contributes to crude oil price risk. One implication of our results is that the development of global biofuel market makes the impossible task of predicting crude oil prices even more difficult.

Table 4 shows the percentage of the variance of the error made in forecasting real ethanol prices due to a specific shock at a specific time horizon. On impact, ethanol demand shocks account for 78% of the variation, gasoline supply shocks account for 12.5%, and oil-specific demand shocks account for 7.9%. In the long run, oil supply shocks account for 4.8% of the fluctuation of real ethanol price, aggregate demand shocks account for 4.7%, oil-specific demand shocks account for 10.3%, gasoline supply shocks account for 36.6%, gasoline demand shocks account for 4.9%, ethanol demand shocks account for 28.4%, and ethanol supply shocks account for 10.2%. The future evolution of US ethanol prices is likely to depend heavily on the development in global oil and US gasoline markets. As we discussed above that the change in crude oil prices is impossible to predict, given the close relationship between crude oil prices and US ethanol prices, it is very likely that predicting US ethanol prices will be extremely difficult.

Table 4
Percent contribution of each shock to the variability of real ethanol price.

Months	Oil supply shock	Aggregate demand shock	Oil specific demand shock	Gasoline supply shock	Gasoline demand shock	Ethanol demand shock	Ethanol supply shock
1	0.5	0.6	7.9**	12.5***	0.5	78.0**	0.0
	(1)	(1)	(4)	(4)	(1)	(5)	0
6	4.0	1.2	8.5	28.1***	9.0	43.6***	5.6
	(4)	(3)	(6)	(9)	(6)	(9)	(6)
12	2.2	5.1	9.3*	39.0***	6.1	27.0***	11.3
	(5)	(6)	(6)	(10)	(4)	(7)	(6)
24	2.4	4.9	11.2	38.5***	53	26.4***	11.3
	(8)	(6)	(8)	(10)	(3)	(8)	(7)
36	2.8	5.0	11.2	37.3***	5.3	27.4***	11.1
	(9)	(8)	(8)	(9)	(3)	(7)	(7)
60	4.8	4.7	10.3	36.6***	4.9	28.4***	10.2
	(10)	(8)	(9)	(10)	(3)	(9)	(9)

The numbers in () indicate standard errors.
*** Denotes statistical significance at 1% level.
** Denotes statistical significance at 5% level.
* Denotes statistical significance at 10% level.

7. Conclusions

We develop a structural VAR model of global crude oil, US gasoline and US ethanol markets to examine whether US ethanol has begun to have an impact on fossil fuel markets. The structural VAR approach allows us to decompose price and quantity data into demand and supply shocks, and to study the impact of ethanol demand and supply shocks on variables of interest by impulse response and variance decomposition analysis. One key result is that ethanol demand expansion leads to a statistically significant decline in real prices of crude oil and gasoline, while there is no statistically significant effect of ethanol supply expansion on these prices. US ethanol demand is mainly driven by US ethanol policy. Shocks to ethanol demand reflect changes in ethanol policy more than any other factor. In contrast, shocks to ethanol supply are mainly driven by changes in feedstock prices. This suggests that even though the US ethanol market is small, the influence of US ethanol policy on fossil fuel market is important, but the impact of feedstock price variation on fossil fuel market is negligible.

This article begins to empirically examine the impact of US ethanol on fossil fuel markets and has important implication for biofuel policy evaluation. We demonstrate that biofuels' effect on crude oil markets is important and therefore should not be ignored when examining the welfare impact of biofuel policy. The global biofuel industry is at its cross road. Many countries have started to reconsider their biofuel policies because of apprehension due to global food crisis and ambiguity regarding environmental benefits of biofuels (Timilsina and Shrestha, 2010). Specifically, for US, the 45-cents-per-gallon tax credits for ethanol blenders are set to expire on Dec. 31st, 2011 and their future are under debate. Furthermore, the EISA of 2007 allows for waivers and modifications to the RFS2 if the US Environmental Protection Agency determines there is an inadequate domestic supply to meet the RFS or if the RFS would severely harm the economy.

Biofuel policies designed to reduce dependence on foreign energy have ramification that reaches far beyond the energy sector. Our results provide empirical evidence that biofuel outcomes can ripple across the entire economy through crude oil prices. Crude oil plays key roles in global consumption, production, and trade. Oil prices appear to have made a material contribution to most economic recessions for the US (Hamilton, 2009a,b). Understanding these impacts has potential implications for national security and economic growth.

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