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Impacts of renewable fuel regulation and production on agriculture, energy, and welfare

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Impacts of renewable fuel regulation and production on agriculture, energy, and welfare

by

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DEDICATION

I dedicate this work to my husband Joseph Eugene McPhail, my daughter Sumay Lu McPhail, my mother Jianying Zhou, and my father Yaping Lu.

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ABSTRACT

The purpose of this dissertation is to study the impact of U.S. federal renewable fuel regulations on energy and agriculture commodity markets and welfare. We consider two federal ethanol policies: the Renewable Fuel Standard (RFS) contained in the Energy Security and Independence Act of 2007 and tax credits to ethanol blenders contained in the Food, Conservation, and Energy Act of 2008. My first essay estimates the distribution of short-run impacts of changing federal ethanol policies on U.S. energy prices, agricultural commodity prices, and welfare through a stochastic partial equilibrium model of U.S. corn, ethanol, and gasoline markets. My second essay focuses on studying the price behavior of the renewable fuel credit (RFC) market, which is the mechanism developed by the Environmental Protection Agency (EPA) to meet the RFS. RFCs are a tradable, bankable, and borrowable accounting mechanism to ensure that all obligated parties use a mandated level of renewable fuel. I first develop a conceptual framework to understand how the market works and then apply stochastic dynamic programming to simulate prices for RFCs, examine the sensitivity of prices to relevant shocks, and estimate RFC option premiums. My third essay assesses the impact of policy led U.S. ethanol on the markets of global crude oil and U.S. gasoline using a structural Vector Auto Regression model of global crude oil, U.S. gasoline and ethanol markets.

CHAPTER 1. INTRODUCTION

The Renewable Fuel Standard that is contained in the Energy Security and Independence Act (2007) mandates 36 billion gallons of renewable fuel use by 2022. Responding to previous mandates and high energy prices, U.S. corn-based-ethanol production increased from 4 billion gallons in 2005 to 9 billion gallons in 2008 substituting 6.25% of our gasoline consumption. Ethanol production in the 2008 marketing year used 3.667 billion bushels of corn accounting for 26.7% of total corn production. The government-supported ethanol market has linked U.S. corn and gasoline markets together, fundamentally changing the determination of agriculture commodity prices both in the United States and abroad.

The link between agriculture and energy through renewable fuel raises many important questions. My first essay examines the short-run impact of changing ethanol policies including the RFS and the blenders' tax credits by addressing the following two questions: What would happen to the markets of corn, ethanol, and gasoline, if U.S. ethanol policies change tomorrow? Who would win and who would lose? The second essay focuses on the RFS and the renewable fuel credits market, also known as the Renewable Identification Number (RIN) market developed by the EPA to facilitate compliance with the RFS. This new market for RINs leaves many unanswered questions including: what is the price behavior of RINs, and how sensitive are these prices to relevant shocks? My third essay measures the impact of policy-led ethanol market shocks on U.S. gasoline and global crude oil markets using a structural vector auto-regression model.

The first essay "Impacts of Changing Ethanol Policies on the Distribution of Prices and Welfare" presents a stochastic, short-run structural model of U.S. corn, ethanol, and gasoline markets to estimate the distribution of price and welfare impacts associated from changing federal ethanol policies on producers and consumers of corn, ethanol, and gasoline. We consider changes to two policies: the Renewable Fuel Standard and the current blenders' tax credit. We introduce five stochastic variables to capture the primary sources of price uncertainty in these commodity markets including corn yield and global crude oil price. The model is calibrated to expected market conditions in February 2010 for the 2010 corn marketing year. We show that in the short run, elimination of both policies would decrease average corn prices by a total of 9.6%. Thus, a complete elimination of federal support for corn based ethanol would not bring corn prices back down to pre-ethanol levels in the short run. This might be surprising because the existence of corn ethanol industry is largely due to these supports. The reason why removal of these same policies has only a modest effect on corn price is because existing U.S. ethanol plants will only shut down if their variable cost of production is not covered. We also find that elimination of both programs would reduce corn price volatility by about 43% and this reduction in price volatility would also reduce option prices and directly affect revenue insurance premiums in the U.S. crop insurance program. Changes in ethanol policies would, however, have large distributional impacts. Corn growers, ethanol producers, and fuel consumers have an incentive to maintain high ethanol consumption, while gasoline and livestock producers have an incentive to reduce ethanol production.

The second essay "Pricing Renewable Fuel Credits Under Uncertainty" develops a conceptual framework and a stochastic dynamic programming model to understand the prices of renewable fuel credit market, also called the Renewable Identification Number (RIN) market, which was developed by the EPA to facilitate compliance with the Renewable Fuel Standard set by the Energy Independence and Security Act of 2007. The creation of the RIN market poses a number of questions including how the RIN market functions, how RIN prices are formed, and which factors affect price levels and price volatility. Current analyses by Thompson, Meyer and Westhoff (2008a, 2008b, 2009) addressing these questions ignore the banking and borrowing provisions and the formation of markets for options on future RIN prices. We consider these provisions to be crucial to the study of current and future RIN prices and address them directly. We consider an agent's optimal use of renewable fuels and optimal investment in RINs over the regulated periods to meet their obligation under the Renewable Fuels Standard. An agent's first-order conditions from the multiperiod problem can be interpreted as temporal arbitrage conditions for RIN prices. We solve a stochastic dynamic programming problem to study the distribution of future RIN prices, to estimate the potential cost of options on RIN futures, and explore the current and future price impacts from relevant shocks. We estimate that the expected 2010 RIN price is \$0.10 with a \$0.08 standard deviation. We also find that from 2010 to 2014, banking and borrowing provisions will save oil companies \$5.56 billion, and eliminating tax credits will cost oil companies \$17.6 billion but save tax payers \$29.7 billion.

The third essay “Assessing the Impact of U.S. Ethanol Market Shocks on Global Crude Oil and U.S. Gasoline: A Structural VAR Approach” develops a joint structural vector auto regression (SVAR) model of the global crude oil market, U.S. gasoline and ethanol markets to examine how shocks in each market affect the other two. We observe that despite growing crude oil demand from emerging countries, global oil production has stagnated since 2005. We hypothesize that at least part of this lack of response is due to the ever increasing government support for renewable fuels such as ethanol. We also examine responses of global crude oil price, U.S. gasoline price and U.S. gasoline consumption to ethanol demand and supply shocks. We find statistically significant responses of global oil production to ethanol demand shocks. Shocks to ethanol demand are mainly driven by government policies suggesting that oil producers may respond to the U.S. government support for renewable fuel. We do not find a statistically significant impact of shocks to ethanol markets on crude oil prices, suggesting that ethanol is not yet a big enough player in the transportation fuel market for its impact on crude oil to be measured empirically. Our results also show that ethanol demand and supply increases cause statistically significant drops in real gasoline prices, but do not affect the growth rate of gasoline consumption significantly. Unanticipated shifts in demand and supply for all three markets are evaluated to determine their impacts on real prices of crude oil, U.S. gasoline and U.S. ethanol.

CHAPTER 2. IMPACTS OF CHANGING ETHANOL POLICIES ON THE DISTRIBUTION OF PRICES AND WELFARE

Introduction

Before corn ethanol, energy prices affected crop prices mainly through their impact on production costs. Federal support for corn ethanol has fundamentally changed this relationship. The new role of energy prices and U.S. ethanol policies in determining food and fuel prices has renewed the importance of understanding the fundamental determinants of commodity prices. Elobeid et al. (2006) and Tokgoz et al. (2007) estimate the long-run impacts of ethanol on agriculture using a zero-profit condition on the ethanol sector to determine the long-run price of corn. Gardner (2007), and de Gorter and Just (2009a,b) use supply and demand curves to determine the welfare impacts of ethanol policies that affect the price of corn. The policies examined include stylized mandates, and tax credits. These studies have increased our understanding of the relationship between crude oil prices (or gasoline prices) and the long-run price of corn. But corn consumers, policymakers, and farmers are also interested in how crude oil prices and biofuels policies affect the price of corn in the short run. The short-run link between crude and corn is complicated by uncertain corn supplies, the time it takes to add ethanol capacity, and the existence of federal mandates.

Figure 1 illustrates how variations in crude oil prices affect corn prices in the short run. Corn supply in excess of non-ethanol corn demand is depicted by XC. The equilibrium corn price is found by the intersection of this excess supply curve and the derived demand for corn from the ethanol industry, shown initially by the demand D0. At any time there is a maximum amount of corn that can be processed into ethanol because of industry capacity constraints. This is denoted as the vertical line labeled CAP. Federal mandates, in the form of the Renewable Fuels Standard (denoted by RFS[1]), place a lower limit on ethanol demand and domestic ethanol production. In figure 1, industry capacity exceeds RFS, which has been the case so far.

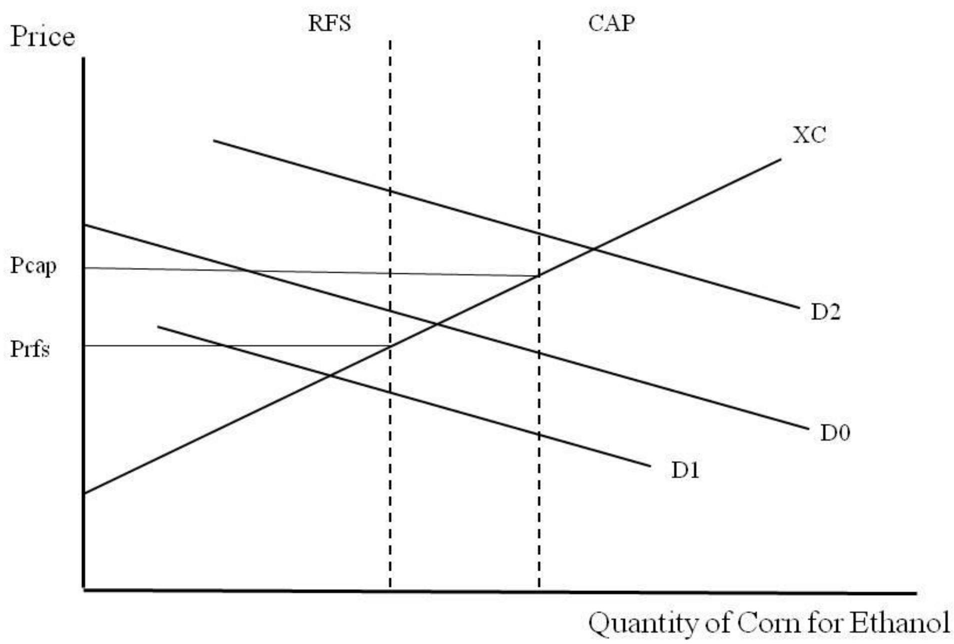

Figure 1 Impact of a crude oil price shock on the price of corn

A change in crude oil prices will shift the derived demand for corn because ethanol is

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[1] The RFS originated from the Energy Policy Act 2005, and was expanded by the Energy Independence and Security Act 2007. The new RFS mandates 36 billion gallons of renewable fuel use by 2022 and breaks into four specific mandates: corn ethanol, cellulosic ethanol, bio-based diesel, and other advanced biofuels. Here we specifically look at the corn ethanol mandates.

a substitute for gasoline. As long as the equilibrium quantity in the ethanol market falls between RFS and CAP price, changes in crude oil prices directly affect corn prices. However, when the equilibrium quantity falls below RFS, as it does with demand D1, then drops in crude oil prices have no impact on corn prices, because RFS places a floor on the demand of corn from ethanol. Prfs in figure 1 denotes the price of corn when the ethanol production is equal to RFS. For crude oil prices that result in equilibrium quantities greater than CAP, as is the case with demand D2, hikes in crude oil prices have no impact on corn prices, because industry capacity places a ceiling on the demand of corn from ethanol, at least until additional capacity can be added.

Analysis of ethanol policy is complicated by these floors and ceilings. The U.S. Environmental Protection Agency (EPA) was required to analyze a 2008 request by Governor Perry of Texas to reduce the ethanol mandate. To conduct such an analysis requires consideration of the probability distribution of crude oil prices. If the equilibrium quantity of ethanol exceeds RFS for all possible crude oil prices, then there is no impact of a reduction in the mandate. If there is some range of crude oil prices that makes the mandate binding, then policy impacts must be calculated with reference to the distribution of crude oil prices.

Estimation of the impact of crude oil prices on the volatility of corn prices is also complicated by the floor and ceiling. Crude oil price volatility will be directly reflected in the volatility of corn prices for equilibrium prices between RFS and CAP in figure 1, but not for corn quantities above and below. Thus, the pricing of put and call options for corn will be impacted by the floor and ceiling demand of corn from ethanol. The magnitude of the impact will depend on the probability that the ethanol industry operates at capacity and that the mandate binds.

Variations in corn supply complicate the analysis further, as shown in figure 2. To simplify, figure 2 assumes that the demand for corn consists of feed demand and ethanol demand. The total demand for corn (CABD in figure 2) is simply the horizontal summation of the two. Total demand is a parallel shift of feed demand for quantities of corn in excess of feed demand plus the capacity constraint, and for quantities less than feed demand plus the RFS. The price of corn is determined by the location of the supply curve. For corn supplies between points A and B, the price of corn is driven primarily by variations in demand from the ethanol industry. For corn supplies to the left of A and to the right of B, the marginal buyer of corn is the livestock industry and the short-run elasticity of demand for livestock feed will determine how high the price will go in short-crop years and how low the price will go in bumper-crop years. The kinks in demand and the role of uncertain supply show the need for careful modeling of corn demand and supply volatility for short run analysis.

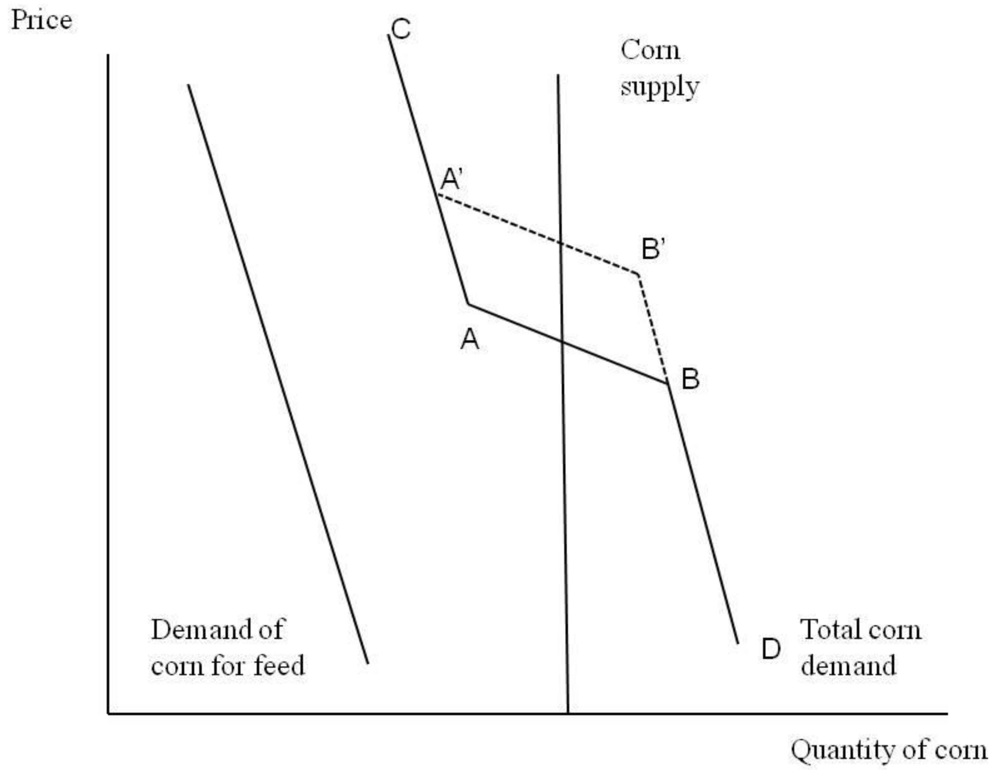

Figure 2 Impact of a corn supply shock on the price of corn

The contribution of this essay is the analysis of the price and welfare impacts of alternative ethanol policies in the short run. The analysis is conducted with a stochastic partial equilibrium model that explicitly accounts for important sources of volatility in the corn market as well as the existence of maximum and minimum effects of crude oil prices on the price of corn. The model follows the simplified models shown in figures 1 and 2 taking into account the important factors that determine the price of corn, including stochastic corn supply, crude oil prices, natural gas prices and capacity of the ethanol industry. The model is calibrated to expected market conditions in February of 2010 for the 2010 corn marketing year. The distribution of prices and welfare impacts from changing U.S. ethanol mandates and tax credits are calculated using the calibrated model. The results provide useful insights about the short-run impacts of federal ethanol policies on welfare, price volatility, and the inherent trade-offs involved when a food crop is used to produce biofuels.

A Stochastic Model of the Markets of U.S. Corn, Ethanol, and Gasoline

To understand fully the relationship between crude oil and corn prices and the impact of policies on this relationship, we develop short run demand and supply curves for gasoline, ethanol, and corn, include the impact of policy variables on these curves, and introduce five stochastic variables to the model. The demand and supply curves are calibrated to the latest Food and Agricultural Policy Research Institute (FAPRI) baseline report, the Energy Information Administration (EIA)'s Short-Term Energy Outlook, and available market information before the model is run. We solve for three market clearing prices conditional on realizations of the stochastic states of the world. Expected prices and estimates of the price volatility of corn, ethanol, and gasoline are obtained by solving the model for multiple draws of the random variables and then taking averages and standard deviations of prices across all draws. The distributions of prices are conditional on available information at the date the model is run.

We capture the main uncertainty of three markets by introducing the following stochastic variables: planted acres, corn yield[2], ethanol industry capacity, the price of crude oil, and the price of natural gas. The marginal distributions of these variables and the

[2] The corn supply curve is vertical as in figure 1, but the quantity of the fixed supply is a random variable at the time the model is solved because harvested acres and yield are not known.

correlation among these variables are discussed in detail below. This stochastic model is flexible and has been continuously updated to recognize new market conditions. As changes in the distributions of stochastic variables and parameter estimates available, new versions of the model are simulated.

The supply and demand of each market are specified to include two policy variables. First, the blenders' tax credit ($0.45-per-gallon Volumetric Ethanol Exercise Tax Credit) included in the Food, Conservation, and Energy Act of 2008 is a direct subsidy given to ethanol blenders, which increases the willingness of blenders to buy ethanol. Hence the blenders' tax credit effectively shifts out the derived demand for corn from ethanol. The second policy variable is the RFS contained in the Energy Security and Independence Act of 2007 ensures that ethanol consumption is at least equal to the mandated level. If the mandate binds, the price of ethanol must increase to induce ethanol plants to produce the mandated level. Table 1 lists the four specifics of renewable fuel standards. Please note that mandates are for the overall biofuels and for the advanced and cellulosic levels. However, FAPRI projects that cellulosic biofuels, advanced biofuels, biodiesel production will not exceed mandated level, meeting the overall mandate necessarily requires enough corn ethanol to be produced. For this reason, we include a conventional biofuels mandate in Table 1. More than 99% of US ethanol imports were Brazilian sugarcane ethanol, which is qualified for meeting advanced mandate specified by the EPA. Because of the high probability of advanced mandate binding[3], we argue that imported sugarcane ethanol RINs will be used to meet

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[3] The advanced biofuels mandate increases to 1 billion gallon for 2014, but FAPRI's projection of US ethanol imports is less than 500 million gallons for 2014. So it makes economic sense for blenders to save their extra advanced biofuel RINs when they anticipate in the future years that the mandate has a high probability of binding.

current advanced mandate or be rolled over to meet future advanced mandate. For this reason we do not include import tariff for our baseline.[4] Under this specification we then simulate prices under different policy scenarios. The model specification and results reported below are based on the information of February 2010.

Year	Conventional Biofuel (billion gallons)	Cellulosic Biofuel (billion gallons)	Biodiesel (billion gallons)	Other Advanced Biofuel (billion gallons)	Total RFS (billion gallons)
2008	9	0	0	0	9
2009	10.5	0	0.5	0.1	11.1
2010	12	0.1	0.65	0.2	12.95
2011	12.6	0.25	0.8	0.3	13.95
2012	13.2	0.5	1	0.5	15.2
2013	13.8	1	1	0.75	16.55
2014	14.4	1.75	1	1	18.15
2015	15	3	1	1.5	20.5
2016	15	4.25	1	2	22.25
2017	15	5.5	1	2.5	24
2018	15	7	1	3	26
2019	15	8.5	1	3.5	28
2020	15	10.5	1	3.5	30
2021	15	13.5	1	3.5	33
2022	15	16	1	4	36

Table 1 Renewable Fuel Standard of the Energy Independence and Security Act 2007[5]

Corn Supply

The corn supply equals corn production plus the beginning stock of corn. Corn

[4] The next chapter will explain RFS and RINs in a greater detail.
[5] Source: http://www.ethanolrfa.org/resource/standard/

production equals the product of harvested acreage and yield per harvested acre. Harvested acreage equals planted acreage times the percentage of acres harvested. Corn production is thus defined by $Q_c^S = (A_c * h_c) * y_c$ where Q_c^S denotes the corn production, A_c is planted acreage of corn, h_c is the percentage of acres harvested, and y_c is yield per harvested acre.

U.S. yields from 1957 to 2009 reported by the National Agricultural Statistics Service (NASS) are used to estimate a beta distribution of yield per harvested acre to represent uncertainty about 2010 corn yields. These yields are first de-trended using a linear trend and constant coefficient of variation.[6] The average percent deviation multiplied by the 2010 trend yield from FAPRI is used to estimate the standard deviation, maximum, and minimum of 2010 yield. The estimated marginal distribution for 2010 corn yield:

$$p(y_c) = \frac{\Gamma(p_y + q_y)(y_c - \underline{y_c})^{p_y - 1}(\overline{y_c} - y_c)}{\Gamma(p_y)\Gamma(q_y)(\overline{y_c} - \underline{y_c})^{p_y + q_y - 1}} \tag{1}$$

where $\overline{y_c} = 187$, $\underline{y_c} = 119$, $p_y = 2.6$ and $q_y = 1.7$. Because yield is mainly affected by weather, we assume it is independent from other stochastic variables; that is, we assume that harvested yield is independent of planted acreage, ethanol industry capacity, crude oil price, and natural gas price.

We use the difference between prospective planted acreages from USDA's annual report that is released in March and the actual planted corn acreage from 1965 to 2007 to obtain a distribution of stochastic planted acreage subject to the March report. Because USDA's "Prospective Planting" report won't be released until the end of March, we use FAPRI 2010

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[6] More sophisticated trend models were fit to the yield model, but the 2010 projected trend yield and the estimated percent deviations from trend over the time series differed little from those obtained from a simple linear trend.

baseline prediction of 89.6 million planted acres of corn in 2010 to be the mean planted acreage. The standard deviation of these historical differences between the predicted acres and the actual acres is 2.155 million acres. There was no discernable increase over time in the accuracy of this report. Therefore we assume the marginal distribution of farmers' intended planted acreage in 2010 (in million acres) $A_c \sim N(89.6, 2.215)$. FAPRI predicts that U.S. farmers will harvest 91.8% of planted acres, so we set $h_c = 0.918$.

It is reasonable to expect a positive correlation between planted acres and crude oil prices, because a high crude oil price shifts up the demand for ethanol and therefore the demand of corn from ethanol and the price of corn. An anticipated high price for corn will lead farmers to plant more corn. To estimate the correlation between planted acres and corn prices, we look at the change of December corn futures prices from March 1st to April 30th for each year from 1990 to 2008 and the difference between the predicted acreage of USDA March prospective plantings report and the actual planted acreage for each year from 1990 to 2008. Figure 3 plots the acreage difference and price difference for each year and indicates no strong positive correlation. For all years except 1997, 2000, and 2004, the two differences indicate either no correlation or negative correlation. For example, in 2007, the December corn futures prices dropped but the actual planted acres were 3 million more than the predicted indicated by March prospective planting report. In 2008, the actual planted acres were almost the same as the predicted acres, while the futures price of corn went up from \$5.7 to \$6.3 per bushel. Therefore we assume that after farmers make their planting decisions in March, they will not plant more if a high corn price is observed before May, that is, the marginal distribution of planted acreage is independent from corn prices. Because crude oil prices affect planted acres through corn prices, we assume the marginal distribution of planted acreage is independent from the distribution of crude oil prices. We do not assume that the farmers' planting decision is independent from crude oil price, but only assume that the fluctuation of crude oil prices from March to May will not change their planting decision made in March. If a positive correlation does exist, high crude oil price leads to more acres and lower corn price and lower cost of producing ethanol, and then more supply for ethanol, thus lowers the probability of mandate binding. We also assume that planted acreage is independent from other random variables including ethanol industry capacity and natural gas prices.

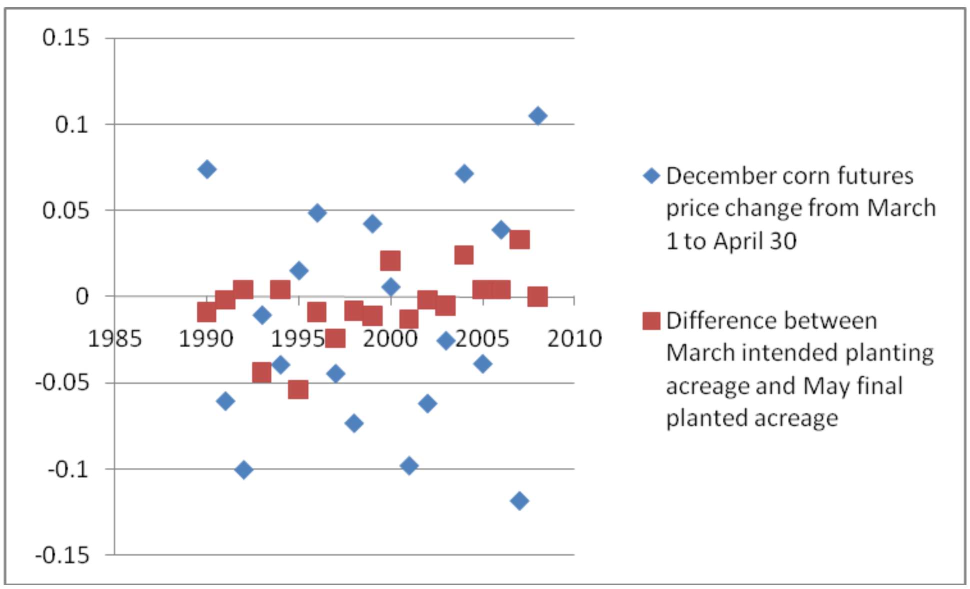

Figure 3 Scatter plot of changes of December corn futures price and planting acreage from March 1st to April 30th (1990-2008)

Corn Demand

Non-ethanol demand for corn equals the sum of four demands: food (food and seed and HFCS), feed (feed and residual), stocks, and exports. All four demands are modeled as linear in the average price \$3.71 per bushel received by farmers in 2010 as reported by FAPRI. Parameters for these demand curves are obtained by using short-run own-price elasticity of demands[7] from FAPRI and calibrating to FAPRI baseline projection which will be released in March 2010. FAPRI projected that food, feed and export demand would be 1.297 billion, 5.274 billion, and 2.017 billion bushels, and ending stocks would be 1.6 billion bushels for the 2010 marketing year. The resulting four demand curves are $Q_{c,2010}^{D,\text{food}} = 1388 - 24.5 * P_{c,2010}$;

$Q_{c,2010}^{D,\text{feed}} = 6271 - 170 * P_{c,2010}$; $Q_{c,2010}^{D,storage} = \max(1000, 5603.5 - 1078.8 * P_{c,2010})$; and

$Q_{c,2010}^{D,\text{export}} = 3933 - 516.5 * P_{c,2010}$. We assume there exists a floor demand of 1 billion bushels for corn storage demand, which is estimated by the lowest storage to use ratio from 1990 to 2008. [8]

The demand of corn from the ethanol industry is determined by ethanol production capacity *E*, the percentage of capacity that is in operation λ, and the number of bushels of corn required to produce a gallon of ethanol θ: $Q_c^{D,e} = E * \lambda * \theta$.

Ethanol industry capacity for the 2010 marketing year was unknown in February of 2010. Thus it is treated as a random variable. Lists of plants on-line and under construction are tallied by the Renewable Fuels Association.[9] It suggests that industry capacity on January 19th, 2010 was around 13 billion gallons and capacity under construction was around 1.432 billion gallons. We assume that the maximum capacity for the 2010 marketing year is 14.5 billion gallons, the minimum capacity is 13 billion gallons, and the expected capacity is 13.5 billion gallons. A beta

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[7] Short-run price elasticity of feed demand is -0.19; price elasticity of food demand is -0.07; price elasticity of export demand is -0.95; and price elasticity of storage demand is -2.5.

[8] It takes time for corn to go from where it is stored to where it is used. Thus there is always a minimum amount of corn that is in the pipeline. This is called pipeline storage. We will never run out of corn because of pipeline storage.

[9] Renewable Fuel Association (RFA): http://www.ethanolrfa.org/industry/locations/

distribution with shape parameters 1.3 and 2.5 is used to capture uncertainty. It is reasonable to assume that ethanol capacity is somewhat dependent on crude oil prices because the level of ethanol operating margins may affect the completion rates of plants that are under construction. There is no reliable data to estimate the correlation between capacity in 2010 and crude oil prices so a reasonable value of correlation of 0.3 is used. Because as we show later crude oil prices and natural gas prices are strongly correlated, capacity and natural gas prices are also positively correlated. A value of correlation between capacity and natural gas prices of 0.1 is used for simulation. A sensitivity analysis indicates that overall results are robust to changes in this correlation. Ethanol capacity is assumed to be independent from corn yield and planted acres, as we argued above. Correlated draws of ethanol industry capacity, natural gas, and crude oil prices were obtained by first drawing independently from their marginal distributions, and then using the Iman and Conover (1982) procedure to impose the desired amount of correlation.

Negative processing margins will cause ethanol plants to shut down and reduce the percentage of capacity that operates. Because all plants pay about the same price for corn, those plants that produce the least ethanol per bushel of corn processed will tend to shut down first. Denote gallons of ethanol produced per bushel of corn as γ. The distribution of γ across the industry determines the proportion of existing capacity that will operate given input and output prices. The production technology of current (as of February 2010) ethanol production capacity has a mean of 2.75 gallons per bushel. The maximum efficiency is assumed to be 2.85 gallons per bushel and a minimum efficiency of 2.5 gallons per bushel. There are no reliable data on which to base plant heterogeneity. A reasonable amount of heterogeneity is represented by fixing the variance equal to 0.005. Using a beta distribution again, the resulting shape parameters are 2.85 and 1.14.

The operating margin per bushel of corn processed for a dry mill ethanol plant is $\pi_E = [\gamma * P_e + D * P_{distillers}] - (P_c + \gamma * OPC + N * P_{ng})$ where π_E is the operating profit margin per bushel, P_e is the ethanol price per gallon, $P_{distillers}$ is the distillers grains price per ton (1 ton equals 2,000 pounds), P_{ng} is the natural gas price per mmBtu, D is tons of distillers grains per bushel, OPC is other operating cost per gallon, and N is the units of natural gas required to process one bushel of corn. The other operating cost for a dry mill ethanol plant in the U.S. is \$0.32 per gallon (F.O. Lichts and Agra CEAS consulting 2007).[10] Every bushel of corn processed returns 17 pounds of DDGS, and 72.8 thousand British thermal units of natural gas are used to process one bushel of corn (CARD).[11]

The marginal distribution of average price of natural gas in 2010 is assumed to be lognormally distributed. The mean of the distribution is estimated by the average NYMEX natural gas futures price of each month from September 2010 to August 2011 on February 5, 2010. The estimated mean was \$6.18 per mmBtu. Price volatility is obtained from the annualized implied volatilities for at-the-money call options of each month from September 2010 to August 2011 on February 5, 2010. The annualized implied volatilities are multiplied by the square root of time to estimate the standard deviation of prices for each month from Sep. 2010 to Aug. 2011. Because the model is annual, the monthly means and standard deviations are converted to an annual mean and standard deviation of natural gas prices using standard formulas. For any set of random variables $X_1, \cdots, X_n$, let $Y = (1/n)\sum_{i=1}^{n} X_i$. Then $Var(Y) = (1/n)^2 \sum_{i=1}^{n} Var(X_i) + 2(1/n)^2 \sum_{i=1}^{n} \sum_{j>i} \rho_{i,j} \sqrt{Var(X_i)}\sqrt{Var(X_j)}$ where $\rho_{i,j}$ is the

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[10] F.O. Lichts, online database, Licht Interactive Data: http://www.agra-net.com/portal/.
[11] Center for Agricultural and Rural Development: http://www.card.iastate.edu/research/bio/tools/.

correlation between X_i and X_j. Thus, the correlation matrix for monthly prices is needed to estimate the volatility of the average price of natural gas for 2010. Historical monthly prices of natural gas from September 1976 to August 2008 are used to estimate the correlation matrix. Table 2 reports the correlation matrix of monthly natural gas prices. The estimated standard deviation for the distribution is 2.06.

Natural gas	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Sep	1	0.95	0.9	0.82	0.82	0.65	0.74	0.7	0.64	0.61	0.84	0.62
Oct	0.95	1	0.97	0.85	0.91	0.76	0.87	0.85	0.79	0.75	0.93	0.74
Nov	0.9	0.97	1	0.91	0.94	0.77	0.89	0.86	0.79	0.74	0.91	0.71
Dec	0.82	0.85	0.91	1	0.9	0.76	0.86	0.82	0.74	0.7	0.81	0.63
Jan	0.82	0.91	0.94	0.9	1	0.92	0.95	0.94	0.9	0.85	0.93	0.75
Feb	0.65	0.76	0.77	0.76	0.92	1	0.89	0.89	0.89	0.84	0.84	0.72
Mar	0.74	0.87	0.89	0.86	0.95	0.89	1	0.99	0.96	0.94	0.96	0.84
Apr	0.7	0.85	0.86	0.82	0.94	0.89	0.99	1	0.98	0.96	0.95	0.83
May	0.64	0.79	0.79	0.74	0.9	0.89	0.96	0.98	1	0.98	0.93	0.82
Jun	0.61	0.75	0.74	0.7	0.85	0.84	0.94	0.96	0.98	1	0.92	0.84
Jul	0.84	0.93	0.91	0.81	0.93	0.84	0.96	0.95	0.93	0.92	1	0.88
Aug	0.62	0.74	0.71	0.63	0.75	0.72	0.84	0.83	0.82	0.84	0.88	1

Table 2 Correlation matrix of monthly prices for natural gas

Distillers grains are valued off of corn prices. The average price ratio of distillers grains to corn from January 2008 to January 2009 was 0.82. Therefore we assume $P_{distillers,t} / 2000 = 0.82 * P_{c,t} / 56$. There is a break-even efficiency level $\widehat{\gamma}$ for each realization of ethanol price, corn price, and natural gas price, $\pi_{E,t}\,|_{\gamma=\widehat{\gamma}} = 0$. Plants with efficiencies greater than this value will operate. Those with lower efficiencies will shut down. Therefore, $\lambda(P_c, P_e, P_{ng}, \gamma) = \Pr(\gamma \geq \widehat{\gamma})$ where λ is the percentage of the ethanol capacity with a nonnegative operating margin. The last component that defines the demand for corn from the ethanol industry is the average bushels of corn required to produce a gallon of ethanol for ethanol plants that are operating $\theta = 1/E(\gamma \mid \gamma \geq \widehat{\gamma})$.

Ethanol Domestic Supply

The analysis above specifies the domestic supply of ethanol for the 2010 marketing year: $Q_e^{DS} = E * \lambda(P_c, P_e, P_{ng}, \gamma)$ where Q_e^{DS} is the domestic ethanol supply.

Ethanol Demand

Ethanol demand is modeled as a segmented demand curve as follows. Demand by gasoline blenders up to 4 billion gallons is quite inelastic because ethanol's use is mandated for some regions of the country that must meet clean air standards and because ethanol is the most economical source of octane in gasoline blends. Fuel blenders are assumed to use one gallon of ethanol to replace one gallon of gasoline and could continue to do so up to about 14 billion gallons, at which level all of the U.S. gasoline supply would consist of 10% blends. But ethanol distribution bottlenecks create a lower willingness to pay for ethanol below its intrinsic value in a fuel blend. Thus, the second segment of demand begins at 4 billion gallons and ends at 10 billion gallons. At 10 billion gallons, ethanol is assumed priced at its energy value. Tax credits increase gasoline blenders' willingness to pay for ethanol by the amount of the subsidy. The Food, Conservation, and Energy Act of 2008 reduced the blenders' tax credit for corn ethanol from \$0.51 to \$0.45 per gallon starting January 2009. Therefore the demand curves of ethanol (in billion gallons) in the 2010/11 marketing year are[12]

$$(2)\quad \begin{aligned} &(d1)\ Q_{e,t}^{D} = 4.22 - 0.2 * (\frac{P_{e,t} - tc_e}{P_{g,t}})\ \forall Q_{e,t}^{D} < 4\ \&\ \frac{P_{e,t} - tc_e}{P_{g,t}} > 1.1 \\ &(d2)\ Q_{e,t}^{D} = 19.64 - 14.22 * (\frac{P_{e,t} - tc_e}{P_{g,t}}) \\ &\qquad \forall Q_{e,t}^{D} \in [4,10)\ \&\ \frac{P_{e,t} - tc_e}{P_{g,t}} \in (0.6781, 1.1] \\ &(d3)\ Q_{e,t}^{D} = Q_{e,t}^{S}\ \&\ \frac{P_{e,t} - tc_e}{P_{g,t}} = 0.6781 \forall Q_{e,t}^{D} \geq 10 \end{aligned}$$

where $Q_{e,t}^{D}$ is the demand of ethanol, tc_e is the $0.45 per gallon tax credit to the ethanol blenders, and $Q_{g,t}^{D}$ is the demand of gasoline. As we indicated above, to meet the overall RFS blenders will need to use 12 billion gallons of conventional ethanol for 2010 and 12.6 billion gallons of conventional ethanol for 2011. As there are 4 months in 2010 and 8 months in 2011 for the 2010/2011 marketing year, the mandate for corn ethanol for the 2010 marketing year is 12.4 billion gallons.

Blended Fuel Demand

Because ethanol is a substitute for gasoline, increases in ethanol consumption will reduce the demand for gasoline. However, a lower ethanol price will decrease the price of ethanol-blended gasoline, thus increasing the demand for ethanol-blended-gasoline and the demand for gasoline. So the net effect of ethanol on the demand and price of gasoline is ambiguous. The demand for ethanol-blended gasoline, Q_f^D, is made a linear function of the ethanol-blended-

[12] These curves are intended to capture fuel blenders' willingness to pay for ethanol.

gasoline price, P_f , which is an average price of ethanol and gasoline weighted by the market share of ethanol: $P_f = \alpha * (P_e - tc_e) + (1-\alpha) * P_g$ where $\alpha = Q_e^* / (Q_e^* + Q_g^*)$. Here we assume that ethanol blenders pass the benefit of tax credit to final fuel users. Adjusting for the energy value of ethanol yields the total quantity of fuel: $Q_f^D = 0.678 * Q_e^D + Q_g^D$. Here we model demand for mileage, which can come from either gasoline or ethanol.

The blended fuel demand curve is calibrated to the Energy Information Administration (EIA)'s short-term energy outlook (February 2010). The demand for motor gasoline for the 2010 marketing year is 140.2 billion gallons and the demand for ethanol is 12.6 billion gallons. Adjusting for the energy value of ethanol, the total demand is equivalent to 148.7 billion gallons of motor gasoline. The price of gasoline from the EIA short-term energy outlook of $2.29 per gallon and price of ethanol from the futures market of $1.72 are used to calculate a weighted average price of composite fuel of $2.26 per gallon. With a short-run price elasticity of gasoline demand of -0.34 (Brons et al. 2008), the fuel demand curve (in billion gallons) for the 2010 marketing year is $Q_f^D = 199.26 - 22.37 * P_f$ and the gasoline demand (in billion gallons) for the 2010 marketing year is $Q_g^D = Q_f^D - 0.6781 * Q_e^D$.

Gasoline Supply

In the long run, the growth in biofuels affects both the mix and volume of new refinery capacity that is needed. However, in the short run, U.S. refinery capacity is fixed. Thus, increased ethanol supply will only affect the mix of refinery products. Assume that U.S. refineries take output prices and input prices as given and attempt to adjust the optimal mix of outputs to maximize profits. The profit-maximizing gasoline supply is a function of the price of gasoline relative to distillate fuels and the price of gasoline relative to crude oil. As the focus of this model is the gasoline market, the domestic gasoline supply is made a function of the price of gasoline relative to crude oil (Dahl 1981) with a short-run price elasticity of supply 0.77 (Tsurumi 1980). The gasoline supply curve is calibrated to the EIA's short-term energy outlook. The domestic gasoline supply is 127 billion gallons, the average RBOB gasoline price is $2.29 per gallon, and the average crude oil price is $82.25 per barrel for the 2010 marketing year. Thus, the U.S. gasoline supply curve (in billion gallons) for the 2010 year is $Q_g^{DS} = 124.46 + 97*(P_g / P_{crude})$.

The average price of crude oil is assumed to follow a lognormal distribution. The method used to estimate the distribution of crude oil prices follows the method used to estimate the distribution of natural gas prices. Monthly prices of Oklahoma WTI crude oil from September 1986 to July 2008 were used to estimate the correlation matrix of monthly crude oil prices.[13] Table 3 reports the historical correlation matrix of monthly crude oil prices. The estimated mean for the average crude oil price for 2010 is $76.06 per barrel and the estimated standard deviation is 26.56.

[13] http://www.eia.doe.gov .

Crude oil	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug
Sep	1	0.99	0.98	0.97	0.96	0.96	0.95	0.95	0.94	0.93	0.94	0.9
Oct	0.99	1	0.99	0.98	0.97	0.96	0.96	0.96	0.95	0.95	0.95	0.91
Nov	0.98	0.99	1	0.99	0.98	0.98	0.97	0.97	0.97	0.97	0.97	0.91
Dec	0.97	0.98	0.99	1	0.99	0.99	0.98	0.98	0.98	0.98	0.98	0.93
Jan	0.96	0.97	0.98	0.99	1	0.99	0.98	0.98	0.98	0.98	0.98	0.95
Feb	0.96	0.96	0.98	0.99	0.99	1	1	0.99	0.99	0.99	0.99	0.96
Mar	0.95	0.96	0.97	0.98	0.98	1	1	0.99	0.99	0.99	0.99	0.98
Apr	0.95	0.96	0.97	0.98	0.98	0.99	0.99	1	0.99	0.99	0.99	0.98
May	0.94	0.95	0.97	0.98	0.98	0.99	0.99	0.99	1	1	1	0.98
Jun	0.93	0.95	0.97	0.98	0.98	0.99	0.99	0.99	1	1	1	0.98
Jul	0.94	0.95	0.97	0.98	0.98	0.99	0.99	0.99	1	1	1	0.99
Aug	0.9	0.91	0.91	0.93	0.95	0.96	0.98	0.98	0.98	0.98	0.99	1

Table 3 Correlation matrix of monthly prices for crude oil

The correlation (0.918) between Oklahoma WTI crude oil annual prices and the U.S. natural gas wellhead prices was estimated using annual prices from 1986 to 2007.

U.S. gasoline imports depend on the price difference between U.S. gasoline and foreign gasoline, transportation costs, trade policies and other factors. We use global crude oil price to approximate for the price of foreign gasoline and assume that US gasoline imports are a function of the price ratio of U.S. gasoline and global oil. There are no available data on the price elasticity of gasoline import supply, so monthly data from January 2005 to June 2008 were used to estimate the elasticity of gasoline import supply to the price ratio of U.S. gasoline to crude. As there is no trend indicated in the monthly data for this period, we control for hurricanes and the summer driving season, and estimate the following regression equation

$$(3) \qquad \ln(Q_g^{IS}) = 10.33 + 0.44 * \ln\left(\frac{P_g}{P_{crude}/42}\right) + 0.19 * D_{hurricane} + 0.13 * D_{summer}$$

where Q_g^{IS} is gasoline import supply (the monthly finished gasoline import), $D_{hurricane}$ is the hurricane dummy, and D_{summer} is the summer dummy. All of the estimated coefficients are statistically significant at 5% significance level and the adjusted R-square is 0.4881.

The estimated elasticity of gasoline import supply to the relative per gallon price of gasoline to crude β_1^{gIS} is 0.44. EIA predicts the gasoline import supply to be 12.1 billion gallons for the 2010 marketing year in the January 2010 Short-Term Energy Outlook. Using the estimated elasticity, we calibrate the gasoline import supply curve to the EIA Short-Term Energy Outlook. Thus, the gasoline import supply Q_g^{IS} (in billion gallons) is

$Q_g^{IS} = 6.7176 + 193.3215 * (p_g / P_{crude})$ and the total gasoline supply Q_g^S is $Q_g^S = Q_g^{DS} + Q_g^{IS}$.

Equilibrium in the Corn, Ethanol, and Fuel Markets

For each realization of yield, acreage, ethanol production capacity, natural gas price and crude oil prices, the equilibrium prices of corn, ethanol and gasoline are solved when three markets clear:

$$Q_{c,t}^{S} + Q_{c,t-1}^{D,storage} = Q_{c,t}^{D,feed} + Q_{c,t}^{D,food} + Q_{c,t}^{D,storage} + Q_{c,t}^{D,\text{export}} + Q_{c,t}^{D,ethanol} \tag{4}$$

where $Q_{c,t-1}^{D,\text{storage}}$ is the beginning stock of corn at time t.

$$Q_{e,t}^{D} = Q_{e,t}^{DS} + Q_{e,t}^{IS} \tag{5}$$

We assume no borrowing is allowed, the demand for ethanol $Q_{e,t}^{D}$ should be equal or greater than 12.4 billion gallons. If the mandate binds, then we solve for the price of ethanol that induces enough plants to produce 12.4 billion gallons.

(6) $$Q_{g,t}^{D} = Q_{g,t}^{DS} + Q_{g,t}^{IS}$$

Results

The price and welfare impacts of changing U.S. ethanol policy varies significantly with the level of crude oil prices, as shown in figure 1, and with the realization of other important random variables, including corn supply. Thus, it is important not only to simulate equilibrium market prices with respect to the distributions of exogenous random variables but also to report the distribution of results. Thus, results are generated for 1,000 sets of draws of all random variables in the model. The sample moments across the 1,000 solutions represent the distribution of production, price, and welfare impacts of alternative U.S. biofuels policies. The same set of 1,000 draws is used for all scenarios to avoid confounding the effects of variations in draws with the effects of the alternative policies.

The model is run using information available in February 2010. Results for four alternative policy scenarios are generated. These four are (1) a baseline set of policies that maintain the EISA mandate and the blenders' tax credit; (2) removal of the mandate, continuation of the tax credit; (3) removal of the tax credit, continuation of the mandate; and (4) removal of both policies.

The EPA is responsible for promulgating regulations to ensure that gasoline sold in the U.S. contains the mandated volume of renewable fuel specified by the RFS. The obligated parties of the RFS are refiners, importers, and certain blenders of gasoline. To enable universal compliance, the EPA developed a renewable fuel credit trading program called Renewable Identification Number (RIN) Exchange. A RIN is a gallon of ethanol. The system requires a RIN to be issued with each shipment of biofuels. Blenders can use the RIN for their own compliance or they can sell excess RINs to others through the RIN Exchange.[14] The market price of RIN is the difference between the demand and supply prices of ethanol. RIN price is positive when the mandate is binding.

Welfare impacts on market participants are calculated as follows. The change in consumer surplus for domestic feeders, corn importers, food users, ethanol blenders,[15] and fuel users[16] is estimated using the demand curves. The change in producer surplus for gasoline producers and gasoline exporters is estimated using their supply curves. The change in producer surplus for ethanol producers are approximated by the change in the quasi-rent to ethanol producers because 2010 production capacity is not modeled as a function of the price of ethanol. The quasi-rent to ethanol producers is equal to

$(P_e - 0.32) * Q_e^{DS} - Q_c^{D,e} * [P_c - (17/2000) * P_{distillers} + (72.8/1000) * P_{ng}]$. If the capacity is not fixed, ethanol producer surplus would be larger under certain baseline scenarios when the industry runs at full capacity. Because of this, eliminate either policy would overestimate the loss for ethanol producers. The change in producer surplus of corn growers is approximated by the change in corn revenue, because the production decision and costs are assumed to be the same across the scenarios. We do not model corn supply response because the planted acreage is assumed to be fixed, thus we overestimate the loss of corn producers from elimination of ethanol support policies. Welfare estimates demonstrate magnitudes of transfers among consumers and

[14] Blenders are also given the option to bank RINs for future compliance or borrow RINs under special circumstance. For our simulation, we assume away banking and borrowing provisions and that mandates have to be met each year.

[15] The consumer surplus of ethanol blenders (the area under the blenders' ethanol demand curve) measures the net benefit of blending ethanol to meet performance requirements and clean air standards. The obligated parties who blend ethanol are gasoline producers and importers.

[16] The consumer surplus of using ethanol as a substitute for fuel is captured by the fuel demand curve.

producers of corn, ethanol, and gasoline.

Values of policy parameters that vary by calendar year are transformed to the model's 2010 marketing year (September 1, 2010 to August 31, 2011). The tax credit is set at $0.45 per gallon based on the Food, Conservation, and Energy Act of 2008. To meet the total RFS, 12 billion gallons of corn-based ethanol are needed in 2010 and 12.6 billion gallons are needed in 2011. With two-thirds of the 2010 marketing year in 2011, this translates into a requirement of 12.4 billion gallons for the marketing year. The mandate does not reflect the possibility of a credit for exceeding the RFS in previous and future years.

Baseline Results

The first row of results in Table 4 reports the mean of the 1,000 equilibrium solutions under the baseline set of policies. For the 2010 marketing year, our baseline corn price distribution has a mean (the expected price) of $4.04 per bushel[17] and a price volatility of 21.4%, which is lower than the implied volatility 34% for the at-the-money corn call option on February 18th, 2010 at the Chicago Board of Trade (CBOT). Our estimated price volatility is lower, because our model only captures the major uncertainty in the market. The mean for ethanol producer prices, RBOB gasoline prices, and blended fuel prices are $1.998, $2.266, and $2.204 per gallon. On average, 99.1% of ethanol domestic production capacity is operating and average domestic ethanol production is 13.37 billion. The high ethanol production level is due to the high operating margin, about 40 cents per gallon, for an average efficient ethanol plant under the

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[17] The average corn price of baseline scenario is above FAPRI's prediction $3.71 per bushel. Even though the demand of corn from food, feed, export, and storage are assumed to be linear in price and similar to the FAPRI model, demand of corn from ethanol is nonlinear in price. The beta distribution of efficiency index along with short-run shut down condition determines the percentage of ethanol plants operating. Our projection about demand of corn from ethanol is higher, because our model predicts higher ethanol price and higher ethanol industry capacity utilization and production.

average market condition. The probability that the mandate binds is 7%. This probability implies that removing the mandate will have a relative small price and welfare impact because removal of the mandate will have no impact on 93% of the model solutions. RIN prices are positive for 7% of scenarios when the mandate is binding and RIN prices are zero for 93% of scenarios when the mandate is not binding. The average 2010 RIN price is 1.15 cents.

Policy Scenario	Corn price ($/bu)	Ethanol producer price ($/gal)	Gasoline price ($/gal)	Fuel price ($/gal)	Ethanol production (million gal)	Ethanol industry capacity utilization	Gasoline production (million gal)	Gasoline imports (million gal)	Probability mandate binds
Mandate, Tax cedit	4.039	1.998	2.266	2.204	13371	99.1%	127578	13312	7%
Tax credit	4.010	1.988	2.268	2.205	13304	98.6%	127582	13319	
Mandate	3.896	1.652	2.271	2.219	12859	95.3%	127584	13324	48%
No Programs	3.649	1.570	2.296	2.238	12041	89.2%	127620	13400	
	Percentage change from baseline scenario								
Tax credit	-0.7%	-0.5%	0.1%	0.1%	-0.5%	-0.5%	0.00%	0.1%	
Mandate	-3.5%	-17.3%	0.2%	0.7%	-3.8%	-3.8%	0.00%	0.1%	
No Programs	-9.6%	-21.4%	1.3%	1.6%	-9.9%	-9.9%	0.03%	0.7%	

Table 4 Average price and production impacts from changing ethanol policies in 2010

Mandate Elimination

The second row of Table 4 shows the average price and production under the scenario with only tax credit and the first row of the second set results of Table 4 shows the average price and production impact from removing mandate. The welfare impacts (mean, standard deviation, median, minimum, and maximum) of removing the mandate are presented in the first set of results shown in Table 5. For 93% of the solutions, removing the mandate has zero impact, because the blenders’ tax credit, high crude oil prices, and modest corn prices lead to a higher demand than the mandated level. When mandate is binding, removing the mandate would lead to less ethanol demand, lower ethanol price and production, therefore less demand for corn from ethanol and lower corn prices. Average corn price across all draws would drop by 0.7%, the producer price of ethanol would drop by 0.5%, and ethanol production would drop by 0.5%. Note that the relatively small impact of removing the mandate is largely a result of the mandate only binding 7% of the time. When the mandate is binding, removing the mandate would increase the demand for gasoline and the price of gasoline. Average ethanol-blended-gasoline price would increases by 0.1%.

The welfare impacts of eliminating the mandate equal zero in 93% of model solutions in which the mandate does not bind. Thus, the median welfare impact is zero. Ethanol blenders would win, because in 7% of the cases blenders would not need to incur extra cost to use more than the profit maximizing level when the mandate is removed. On average, corn growers would lose about $300 million and this loss occurs when enforcement of the mandate maintains ethanol production even when corn prices would otherwise dictate that ethanol plants would shut down. Ethanol producers and fuel consumers would also lose $29 million and $233 million from mandate elimination. Overall, eliminating the mandate transfers wealth from corn growers to corn users and from fuel users to gasoline producers. Note that the magnitude of welfare transfers among consumers and producers is sensitive to the assumed price elasticity of supply and demand.

Policy Scenario		PS of Corn Growers	CS of Domestic Feeders	CS of Food users	CS of corn Importers	CS of ethanol blenders	PS of Ethanol Producers	Government Revenue	CS of Fuel users	PS of gasoline producers	PS of gasoline importers
Tax credit	Mean	-299	135	36	27	993	-29	30	-233	283	31
	Stdev	1374	627	167	117	3665	131	141	1080	1315	148
	Median	0	0	0	0	0	0	0	0	0	0
	Maximum	0	6090	1646	992	16440	0	1406	0	12715	1614
	Minimum	-12964	0	0	0	0	-1160	0	-10277	0	0
Mandate	Mean	-1736	724	182	237	-1322	-4193	6017	-2203	566	58
	Stdev	1970	833	211	258	1850	2221	170	2011	1943	204
	Median	-1139	452	111	172	-197	-5274	6041	-1780	309	33
	Maximum	0	3437	879	1062	0	0	6371	0	4701	637
	Minimum	-8158	0	0	0	-5580	-6371	5580	-6585	-4839	-480
No Programs	Mean	-4,527	1,964	497	617	-257	-4,442	6,017	-5,151	3,759	397
	Stdev	5131	2290	586	665	347	1893	170	5033	3,708	401
	Median	-2373	943	233	357	-168	-5274	6041	-3824	2,787	289
	Maximum	0	9363	2498	2111	1897	-751	6371	0	15,613	2,016
	Minimum	-19538	0	0	0	-1601	-6371	5580	-16279	0	0

Table 5 Distribution of welfare changes from alternative ethanol policies ($ millions)

Tax Credit Elimination

Our baseline results show that the probability of mandate binding is 7%. The impacts of eliminating tax credits from baseline are different based on whether the mandate is binding or not. If the mandate is binding for the baseline scenario, eliminating tax credits would not change the demand, supply, or producer price of ethanol, nor would it change the demand of corn from ethanol or the price of corn. But elimination of tax credits would increase the consumer price of ethanol, which would allow the blended fuel price to increase. The increased blended fuel price would lead to a lower demand for blended fuel, and thus a lower demand for gasoline because demand for ethanol stays the same equal to the mandate. A lower demand for gasoline would reduce the gasoline price. Therefore, removing tax credits when the mandate is binding would hurt fuel users, gasoline producers, and gasoline importers. For the non-binding-mandate baseline scenario, eliminating tax credits would decrease demand, supply, and producer price of ethanol, and also decrease the demand of corn from ethanol and the price of corn. Meanwhile, a decreased demand for ethanol might lead to an increased demand for gasoline, which would lead to a higher gasoline price. Removal of the tax credit when the mandate is not binding would hurt corn growers, ethanol blenders, ethanol producers and fuel users. It would increase government revenue and benefit domestic feeders, food users, corn importers, and gasoline producers. However, the impact would be modest because the mandate would keep ethanol demand and production high. Because the mandates only bind for 7% of the baseline cases, the average impact reflects the effect of tax credit elimination from the non-binding-mandate baseline scenarios.

Corn prices would drop by an average of 3.5% from the baseline level. Expected ethanol production would drop by about 3.8% and the expected ethanol producer price would drop by 17.3%. Even though ethanol producer prices would drop, ethanol prices for fuel users would increase because of the removal of ethanol tax credits. The drop in ethanol demand would allow gasoline consumption and prices to increase. Therefore, blended fuel prices would actually increase 0.7%. On average, 95.3% of ethanol domestic production capacity would be operating. The probability that the mandate is binding would be 48%. This high probability demonstrates that tax credits and mandate both work to increase demand for ethanol. Average RIN prices will increase to 11.25 cents. For 7% baseline scenarios when the mandate is binding, eliminating tax credits increases RIN prices by about 45 cents; for 41% scenarios when the mandate is not binding in the baseline but becomes binding after eliminating tax credit, RIN prices are positive and increase by less than 45 cents; for the rest 52% scenarios when mandate is not binding even after eliminating tax credit, RIN prices are zero.

On average, such a policy change would increase expected government revenue by about

$6 billion. Domestic feeders, food users, and corn importers from the U.S. would gain about $724 million, $182 million, and $237 million. Gasoline producers and importers would gain $566 million and $58 million. Corn growers, ethanol blenders, ethanol producers, and fuel users would lose $1.74 billion, $1.3 billion, $4.2 billion, and $2.2 billion.

Both Programs Eliminated

A rollback of both ethanol incentives would have the largest impacts. The expected price of corn would drop by almost 9.6% from the baseline level, to about $3.65 per bushel. The loss of tax credits would cause the producer price of ethanol to drop by 21.4% but the expected fuel price would increase by 1.6% because of an increase in the price of gasoline and consumer price of ethanol. Domestic ethanol production would drop by 9.9% and domestic gasoline supply would increase by 0.03%. On average, 89.2% of ethanol plants would be operating. The average loss to fuel consumers, corn growers, ethanol producers, and ethanol blenders would be $5.15 billion, $4.5 billion, $4.44 billion, and $ 257 million. Ethanol blenders' loss is relatively small because the benefits of tax credits are mainly passed onto the fuel users. The average gain to gasoline producers, domestic livestock feeders, corn importers, food users, and gasoline importers would be $3.76 billion, $1.96 billion, $617 million, $497 million, and $397 million. Tax payers would gain by more than $6 billion. Note that the magnitude of welfare transfers among consumers and producers is very sensitive to the assumed price elasticity of supply and demand. For example, if we assume more elastic gasoline supply, domestic livestock feeder might become the biggest winner from elimination of both programs instead of gasoline producers.

Impacts of a Short Crop

Generating a set of 1,000 solutions not only provides estimates of the distribution of price and welfare impacts but also provides a deeper understanding of the fundamental relationships among ethanol policy, crude oil prices, and the price of corn. For example, elimination of the mandate would have its greatest impact when either corn yields are low or crude oil prices are low because either event increases the probability that the mandate binds. If one examines the baseline results for the lowest 20% of corn yields, one can determine the likely impacts of a short crop, which is defined here as a one-in-five-year low corn yield. Table 6 reports the price and production impacts of changing ethanol policies under a short corn crop scenario. For these low yields, there is a 35% probability that the mandate binds. Elimination of both ethanol policies in these short-crop years would reduce the average corn price by 20.9%, from $5.26 to $4.16 per bushel. In these years, livestock feeders and food users would gain about $6.88 billion from relief from the high corn prices. Although corn farmers would lose $12.3 billion on average from elimination of the programs, their average revenue from the corn crop at $47 billion in these short-crop years is only 8.6% lower than they would receive on average in the other four years out of five with both programs in place. That is, elimination of the programs in short-crop years would leave corn farmers largely unscathed while helping non-ethanol corn users by driving down the price of corn. Fuel users would be hurt by elimination of the programs in short-crop years. The price of gasoline would increase by 3% because of the decrease in ethanol production, and the ethanol producer price would drop by 19.5%. However, the elimination of tax credits would increase the price consumers pay for ethanol, so the overall impact is a 3.6% increase in blended fuel prices.

Policy Scenario	Corn price ($/bu)	Ethanol producer price ($/gal)	Gasoline price ($/gal)	Fuel price ($/gal)	Ethanol production (million gal)	Ethanol industry capacity utilization	Gasoline production (million gal)	Gasoline imports (million gal)	Probability mandate binds
Mandate, tax credit	5.262	2.039	2.270	2.212	12971	95.9%	127606	13370	35%
Tax credit	5.136	1.997	2.279	2.219	12678	93.8%	127621	13402	
Mandate	5.026	1.924	2.259	2.232	12400	91.7%	127589	13334	100%
No Programs	4.160	1.641	2.339	2.293	9864	73.0%	127704	13576	
	Percentage change from baseline scenario								
Tax credit	-2.4%	-2.1%	0.4%	0.3%	-2.3%	-2.3%	0.0%	0.2%	
Mandate	-4.5%	-5.6%	-0.5%	0.9%	-4.4%	-4.4%	0.0%	-0.3%	
No Programs	-20.9%	-19.5%	3.0%	3.6%	-24.0%	-24.0%	0.1%	1.5%	

Table 6 Price and production impacts of changing ethanol policies in 2010 under a short corn crop scenario

Impacts on Price Volatility and Option Prices

The impact of federal ethanol policies on the volatility of corn prices can be measured by comparing the variability of corn prices in the baseline relative to the variability of equilibrium prices when either or both policies are eliminated. Mandate makes the top segment of corn demand curve (AC) in figure 2 more inelastic, and thus increases the price volatility of corn. Therefore, elimination of mandate would reduce price volatility. Tax credits reduces the top segment of less elastic corn demand (from AC to A’C in figure 2), shifts up the middle segment (from AB to A’B’), and increases the bottom segment of less elastic corn demand (from BD to B’D). Elimination of tax credits would also reduce price volatility because the probability of corn demand equal to the CAP (ethanol industry capacity running at full capacity) is more than 50%. Elimination of both programs would reduce price volatility by about 43% to 12%. Because the price of options is positively correlated to the level of price variability, elimination of both policies would reduce option prices. To illustrate, the average value of an at-the-money call option across the 1,000 equilibrium baseline prices is $0.349 per bushel. The value of an at-the-money option on corn prices across the 1,000 equilibrium prices with no programs is $0.174 per bushel, a reduction of 50%. This reduction in price volatility would also directly affect revenue insurance premiums in the U.S. crop insurance program.

Conclusions

Estimation of the distribution of short-run price and welfare impacts of changes in U.S. ethanol policies requires a detailed understanding of the stochastic relationships between energy prices, operating margins of ethanol plants, corn supply, and ethanol policies. A model that captures these relationships is used to estimate the price and welfare impacts of a change in U.S. ethanol policy for the 2010 marketing year. Policy changes are estimated relative to a baseline policy that includes EISA ethanol mandates and the current blenders' tax credit. Impacts on the average market prices of corn, ethanol, and gasoline from partial and complete removal of these policy instruments are estimated, and changes in average producer surplus, consumer surplus, and government revenue are estimated.

Our results show that in the short run, a change in U.S. policy would not have a large, immediate impact on corn prices, because ethanol plants will keep operating as long as their revenue covers their operating cost. A rollback of both incentives would decrease the expected corn price by 9.6%. A change in ethanol policies would also affect the price that consumers pay for transportation fuel. Elimination of both programs would increase the expected blended fuel price by 1.6%. On average, this would reduce fuel users' consumer surplus by $5.15 billion. Because both the blenders' tax credit and the mandate increase the demand for ethanol, elimination of one of these would not have a large impact on domestic ethanol production. Removing both would decrease domestic ethanol production by 9.9%.

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CHAPTER 3. PRICING RENEWABLE FUEL CREDITS UNDER UNCERTAINTY

Introduction

The Renewable Fuels Standard (RFS) is a provision of the Energy Policy Act 2005 which mandated 7.5 billion gallons of renewable fuel by 2012. The Energy Independence and Security Act (EISA) 2007 expanded the mandate for biofuels to 36 billion gallons by 2022. The Environmental Protection Agency (EPA) is responsible for promulgating regulations to ensure that gasoline sold in the United States contains the required volume of renewable fuel on an annual average basis. To facilitate compliance with the RFS of EISA 2007, EPA developed a renewable fuel credit trading program. Gasoline producers and importers (obligated parties) are required to blend certain percentage of renewable fuel into their gasoline. For each gallon of renewable fuel blended, they get one renewable fuel credit, which has a 38 unit code called Renewable Identification Number (RIN). Therefore renewable fuel credits are also called RINs for short. Each obligated party must give EPA a specified number of RINs to remain in compliance with the RFS.

Firms that generate RINs in excess of their obligations can sell their excess RINs to obligated parties that do not have sufficient RINs to meet their mandate. Obligated parties can bank RINs from the previous year to meet up to 20% of their annual mandate. Obligated parties are also allowed to fall short of their blending requirement in a year, if there are special circumstances. That is, they can borrow RINs from their future obligation as long as they meet their full obligation in the next year plus the deficit from the previous year.

Furthermore, EPA permits non-stakeholders to buy and sell RINs. Therefore, RINs function as an environmental currency and the RFS and RINs together act as a system of floor and trade.

The RIN market poses a number of new questions, including how the RIN market functions, how RIN prices are formed, and which factors affect price levels and price volatility. Existing papers that attempt to address these questions include Thompson, Meyer and Westhoff (2008a, 2008b, 2009). They use the FAPRI-Missouri biofuels model to predict RIN prices in the medium term. Their papers do not provide a conceptual framework for the RIN market and they ignore banking and borrowing provisions.

Our approach begins by considering an agent's optimal use of renewable fuels and optimal investment in RINs over the mandated period to meet the environmental regulation. The mandate is finite so we use dynamic backward induction to solve an agent's multiperiod production and investment choice problem. This approach provides a microeconomic foundation for an agent's optimal production and investment strategies. The agent's first-order conditions from the multiperiod problem can be interpreted as temporal arbitrage conditions for RIN prices. At each period, firms equate the expected marginal cost of blending an additional gallon with the expected price of RIN. Expected RIN prices must increase at the interest rate.

This microeconomic model of an individual firm's behavior is used to construct an aggregate model where all firms collectively behave like a central planner. This model's parameters are calibrated in order to simulate RIN price behavior under a number of scenarios. This model is stochastic so actual RIN prices may differ significantly from their expected path. When a shock occurs, the path from that moment on has to be recomputed, taking into account the number of RINs that have been banked. For example, when a positive feedstock supply shock that decreases the cost of producing and blending biofuels occurs, the price path drops. The cost decrease will lead to higher blending levels when the shock is realized and less demand for RINs in the future. The impact of a crude oil price shock on the price paths is also analyzed.

We measure the distribution of future RIN prices and measure the magnitude of the impact from shocks, by solving a stochastic dynamic programming problem to find optimal decisions in the RIN market by forward-looking agents. We include the two most relevant stochastic variables to capture the primary sources of uncertainty in the market: feedstock yields and crude oil prices. Guassian quadrature is used to generate draws with associated probabilities defining the states of the world. Given states of the world, we use backward induction to solve the optimal blending decisions at each state and for each period. This approach allows us to estimate RIN options in addition to the relevant shocks' impact on RIN values.

Conceptual Model

This model considers an expected-cost-minimizing agent's optimal use of biofuels and optimal investment in RINs over a finite horizon to meet Renewable Fuel Standard. [18] Solving an agent's multiperiod production and investment choice problem provides a theoretical framework for an agent's optimal production and investment strategy. The agent/firm is a representative gasoline producer/importer required to blend a certain

[18] We choose finite horizon instead of infinite horizon model because the RFS ends in 2022. Without RFS in place, RIN prices will be zero.

percentage of biofuels into their gasoline pool.

Setup

Consider a firm, i, that has two control variables: e_{it}, the quantity of biofuels blended each period, and y_{it}, the quantity of RINs bought ($y_{it} > 0$) or sold ($y_{it} < 0$) at price p_t, which will be determined by the equilibrium conditions of all firms in the RIN market over T periods. The level of RINs that are in the bank, $S_i(t)$, is a state variable.

Following Rubin (1996), Cronshaw and Kruse (1996) and Kling and Rubin (1997), the cost function for firm i, $c_{it}(\cdot)$, is the minimum cost of blending $e_{it} - \varepsilon_{it}$ by firm i. It is assumed that c_{it} is twice continuously differentiable: $c_{it}' > 0$ and $c_{it}'' > 0$. e_{it} is firm i's actual blending level at t with RFS requirement. ε_{it} is firm i's optimal voluntary biofuels blending level at t without RFS requirement[19].

The problem facing a single agent (ethanol blender)

We assume that the agent is a price-taker in the RIN market. In addition, it is assumed that there are no transaction costs or taxes when buying or selling RINs. In the presence of uncertainty, the agent will seek to minimize the sum of the expected discounted cost to meet blending obligations under the RFS:

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[19]Firms choose the optimal amount of renewable fuel blending to maximize net benefits, that is, $\max_{\varepsilon_{it}} B_{it}(\varepsilon_{it}) - C_{it}(\varepsilon_{it})$ where $B_{it}(\cdot)$ and $C_{it}(\cdot)$ are the benefit and cost functions of blending biofuels for firm i at time t. Thus, $B_{it}'(\varepsilon_{it}^*) = C_{it}'(\varepsilon_{it}^*)$: at the optimal voluntary blending level, the net marginal benefit of blending an additional gallon of renewable fuel equals zero for each firm at each period without the Renewable Fuel Standard.

(7) $$\min_{\{e_{it},\, y_{it}\}} \left\{ E_0 \left[\sum_{t=0}^{T} \beta^t [c_{it}(e_{it} - \varepsilon_{it}) + p_t y_{it}] \right] \right\}$$

subject to

(8) $$\begin{aligned} S_{it} &= (e_{it} + y_{it} - e_{it}^m) + S_{it-1} \\ S_{i0} &= 0, S_{iT} = 0 \\ e_{it} &> 0 \end{aligned}$$

where β is the discount factor, equal to $1/(1+r)$ where r is the interest rate; S_{it} is the number of RINs in the bank at time t. $S_{iT} = 0$ implies that RINs will be used up before the end of the regulation. This is true as long as RIN prices are positive. Only when RIN prices are zero, the number of RINs might be positive at the end of regulation. We assume unlimited banking and borrowing of RINs for the model[20].

The information and decision variables available to the agent at each period are explained as follows. At each date t, the agent knows the number of RINs in her bank account S $_{it-1}$. Conditional on information at date t, denoted by I_t, she also knows the distributions of future one-period RIN prices $F_{p_t} \mid I_t$ and costs $F_{c_t} \mid I_t$, for dates $\tau = t+1, \cdots, T-1.$ Date t information, I_t, includes all realizations of the number of RINs in the bank and optimal blending level without regulation for all dates up until and including date t. I_t also includes the optimal blending level with regulation and optimal investment in

[20]The EPA only allows banking for up to 20% of the annual mandate and borrowing in special circumstances. The EPA never allows borrowing for two consecutive periods. However, the EPA did not define special circumstances and limits on production capacity in the ethanol industry ensure that aggregate banking will not exceed 20% of the annual mandate. Therefore, it is reasonable to assume full accounting of banking and borrowing.

RINs for all dates up until and including date t-1. Moreover, I_t could include any other state variables known at date t that affect the distributions of future RIN prices and cost structure of blending. Based on this information, the individual's date t decision variable are blending level e_{it} and optimal investment in RINs y_{it}.

Following Pennacchi (2007), let $J(S_{it-1}, I_t, t)$ denote the derived minimum cost function. It is defined as follows:

$$J(S_{it-1}, I_t, t) = \min_{e_{is}, y_{is}, \forall i, s} \left\{ E_t \left[\sum_{s=t}^{T} \beta^{T-s} [c_{is}(e_{is} - \varepsilon_{is}) + p_s y_{is}] \right] \right\} \tag{9}$$

We will solve e_{it} and y_{it} using backward induction.

$$J(S_{iT-1}, T) = \min_{e_{iT}, y_{iT}} E_T[c_{iT}(e_{iT} - \varepsilon_{iT}) + p_T y_{iT}] = \min_{e_{iT}, y_{iT}} c_{iT}(e_{iT} - \varepsilon_{iT}) + p_T y_{iT} \tag{10}$$

subject to

$$S_{iT} = e_{iT} + y_{iT} - e_{iT}^m + S_{iT-1} = 0 \tag{11}$$

which is equivalent to

$$J(S_{iT-1}, T) = \min_{e_{iT}, y_{iT}} c_{iT}(e_{iT} - \varepsilon_{iT}) + p_T(e_{iT}^m - S_{iT-1} - e_{iT}) \tag{12}$$

We differentiate the above equation with respect to the choice variable e_{iT}.

$$\begin{aligned} c_{iT}'(e_{iT}^* - \varepsilon_{iT}) &= p_T \\ y_{iT}^* &= e_{iT}^m - S_{iT-1} - e_{iT}^* \end{aligned} \tag{13}$$

The top equation of (13) says that at the last period each agent equates her marginal cost of blending an extra gallon to meet the regulation to the RIN price. In the last period, the firm will use up all banked RINs and blend enough to meet the last year's obligation.

Now working backwards, consider the agent's optimization problem at date T-1. She has a single period left in her planning horizon.

$$J(S_{iT-2}, T-1) = \min_{e_{iT-1}, y_{iT-1}} c_{iT-1}(e_{iT-1} - \varepsilon_{iT-1}) + p_{T-1}(y_{iT-1}) + \beta E_{T-1}[J(S_{iT-1}, T)] \tag{14}$$

subject to

$$S_{iT-1} = e_{iT-1} + y_{iT-1} - e^{m}_{iT-1} + S_{iT-2} \tag{15}$$

That is,

$$\begin{aligned} J(S_{iT-2}, T-1) = \min_{e_{iT-1}, y_{iT-1}} & c_{iT-1}(e_{iT-1} - \varepsilon_{iT-1}) + p_{T-1}(y_{iT-1}) \\ & + \beta E_{T-1}[J(e_{iT-1} + y_{iT-1} - e^{m}_{iT-1} + S_{iT-2}, T)] \end{aligned} \tag{16}$$

To solve it, we differentiate with respect to e_{iT-1} and y_{iT-1} :

$$\begin{aligned} c'_{iT-1}(e^{*}_{iT-1} - \varepsilon_{iT-1}) &= \beta E_{T-1}[J_S(e_{iT-1} + y_{iT-1} - e^{m}_{iT-1} + S_{iT-2}, T)] \\ p_{T-1} &= \beta E_{T-1}[J_S(e_{iT-1} + y_{iT-1} - e^{m}_{iT-1} + S_{iT-2}, T)] \end{aligned} \tag{17}$$

The top equation of (17) says that the agent's optimal blending level equates her marginal cost of blending an additional gallon in this period to her discounted marginal cost of an additional RIN in the bank account next period. The bottom equation of (17) says that the price of RIN this period equals the discounted marginal cost of increasing an additional RIN in the bank account next period. Therefore, the marginal cost of increasing an additional RIN in the bank at T is equal to RIN price at T p_T , thus $p_{T-1} = \beta E_{T-1}[p_T]$. Both equations together also imply $c'_{iT-1}(e^{*}_{iT-1} - \varepsilon_{iT-1}) = p_{T-1}$; which says that at date T-1, the agent equates her marginal cost of blending to the RIN price.

Now working backwards more, we obtain the following:

$$\begin{aligned} c'_{it}(e^{*}_{it} - \varepsilon_{it}) &= p_t \forall i, t \\ p_t &= \beta^{s-t} E_t[p_s] \ \forall s > t = 0, \cdots, T. \end{aligned} \tag{18}$$

$c'_{it}(e^{*}_{it} - \varepsilon_{it}) = p_t \forall i, t$ says that at each period, each firm blends the optimal amount of ethanol to equate their marginal cost of blending to the RIN price. Firms with low marginal cost that blend more than the required quantity by the RFS supply RINs. Firms with high marginal cost that blend less than the required quantity by the RFS demand RINs. The aggregate demand and supply of RINs determines the price of RINs at each period. In equilibrium, total RINs sold or bought of all firms of all periods is equal to zero. Assume there are N firms,

$$\sum_{i=1}^{N}\sum_{t=0}^{T} y_{it}^{*} = 0 \tag{19}$$

Banking and borrowing provisions lead to temporal non-arbitrage conditions. This expected price path is the defining characteristic of an active futures market. If expected RIN prices increase at a rate greater than the interest rate, we expect that firms will bank RINs. This will lead to higher demand for RINs this period and a higher RIN price for this period. Firms will continue banking until the expected RIN price increases at the interest rate. If expected RIN prices increase at a rate lower than the interest rate, we expect firms to borrow from the future. This will lead to less demand for RINs and lower RIN prices for this period. Firms will continue borrowing until expected RIN prices increase at the interest rate. [21]

Rubin (1996) proves that when allowed to trade with one another, units will collectively behave like a central planner who efficiently blend biofuels to minimize total costs. Thus, the expected RIN price is equal to the expected aggregate marginal cost of blending an additional gallon of biofuels:

$$E_0[p_t] = E_0[c_t^{'}(e_t^{*} - \varepsilon_t)] \tag{20}$$

where $c_t^{'}(\cdot)$ is the aggregate marginal cost of blending, $e_t^{*} = \sum_{i=1}^{N} e_{it}^{*}$ is the aggregate optimal

[21] Non-obligated parties' participation will facilitate to achieve the equilibrium non-arbitrage conditions.

blending level at t and ε_t is the aggregate optimal voluntary biofuels blending level at t with the RFS requirement. The above equation gives us the following insight: firms with marginal cost of blending that is greater than the aggregate marginal cost of blending demand RINs. Firms with marginal cost of blending that is lower than the aggregate marginal cost supply RINs. In equilibrium, RIN prices clear the market.

The problem facing all agents (ethanol blenders)

Now we are ready to look at how blenders act in aggregate. Suppose the central planner chooses the amount of biofuels to blend each period to maximize the total discounted expected net benefits of blending renewable fuel under the constraint of meeting the RFS.

(21) $$\max_{\{e_t\}_0^T} E_0\left[\sum_{t=0}^{T}\beta^t * (b_t(e_t,\varphi_t) - c_t(e_t,\theta_t))\right]$$

subject to

(22) $$\sum_{t=0}^{T} e_t^m \le \sum_{t=0}^{T} e_t$$ $$\{e_t\}_0^T > 0$$

where $b_t(\cdot)$ are the aggregate benefit functions of blending renewable fuel at period t, and φ_t is a vector of stochastic variables which affect the benefit of blending renewable fuel at period t; $c_t(\cdot)$ are the aggregate cost functions of blending renewable fuel at period t and $\widehat{\theta}_t$ is a vector of stochastic variables which affect the cost of blending renewable fuel at period t; β is the discount factor; e_t are the quantities of renewable fuel blended at period t; e_t^m are the minimum amount of renewable fuel required to be blended at period t. Equation (22) says that the central planner blends enough biofuels to meet the mandate over the regulation period[22] and ethanol blending is positive for each period.

Then the Lagrangian is

(23) $$\pounds = E_0\left[\sum_{t=0}^{T}\beta^t(b_t(e_t,\varphi_t)-c_t(e_t,\theta_t))\right]+\lambda\left[\sum_{t=0}^{T}e_t-\sum_{t=0}^{T}e_t^m\right]$$

This problem yields the following necessary conditions:

(24) $$\begin{aligned}\beta^t E_0[b_t^{'}(e_t^*,\varphi_t)-c_t^{'}(e_t^*,\theta_t)]+\lambda=0;\forall t=1,\cdots,T\\ \sum_{t=0}^{T}e_t^m\le\sum_{t=0}^{T}e_t^*\end{aligned}$$

The first necessary condition yields the following:

(25) $$b_t^{'}(e_t^*,\varphi_t)-c_t^{'}(e_t^*,\theta_t)=\beta^{s-t}E_t[b_s^{'}(e_s^*,\varphi_s)-c_t^{'}(e_s^*,\theta_s)]$$

Equation (25) says that when the central planner blends the optimal level at each period, the expected net marginal benefit of blending an additional gallon increases at the interest rate. The second necessary condition says that the total optimal blending for all periods is equal to and greater than the total mandate.

For this aggregate model, the extra cost of meeting the regulation is specified at the difference between the cost of producing the renewable fuel and the benefit of using the renewable fuel. To reconcile with the results from the single blender's problem, we have $E_0[c_t^{'}(e_t^*,\varphi_t)-b_t^{'}(e_t^*,\widehat{\theta}_t)]=E_0[c_t^{'}(e_t^*-\varepsilon_t)]$. This translates into the following: $E_0(p_t)=E_0[c_t^{'}(e_t^*,\varphi_t)-b_t^{'}(e_t^*,\widehat{\theta}_t)]$; which says that the expected RIN price are the expected difference between the aggregate marginal cost of producing the optimal amount of renewable fuel and the aggregate marginal benefit of blending the optimal amount of

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[22] For the case when the total ethanol blending is greater than the total mandates, the benefit of blending more than total mandates is higher than the cost; which means, the total mandates are not binding.

renewable fuel. We also obtain that expected RIN prices increase at the interest rate:

$$p_t = \beta^{s-t} E_t[p_s] \ \forall s > t = 0, \cdots, T. \tag{26}$$

Impact of shocks on expected RIN prices

Actual RIN prices may be quite different from their expected price path. Let us consider what would happen with a positive feedstock supply shock and a subsequent drop in the cost of producing and blending biofuels occurs. The initial impact is an increase in blending and a decrease in the demand for RINs both in the current year and in the future. This drops the expected path of future RIN prices. The path of expected RINs prices will increase with a negative feedstock supply shock and an increase in the cost of producing and blending biofuels. The cost increase will lead to less biofuels production when the shock is realized and more demand for RINs in the future.

Now consider what happens when an unexpected increase in crude oil prices occurs. Higher crude oil prices lead to a higher gasoline prices, which in turn leads to a higher willingness to pay for the substitute biofuels. Thus the marginal benefit of blending biofuels increases. This causes the price path for RINs to drop. The increased demand will lead to a higher blending level when the shock is realized and less demand for RINs in the future. The opposite will hold when an unexpected decrease in crude oil prices occurs.

Simulation Model

We calibrate the values and distributions of the aggregate model's parameters to reflect the corn ethanol RIN market conditions of December 2009 to simulate RIN price behavior under six scenarios. The RFS includes individual mandates for conventional biofuels, cellulosic biofuels, other advanced biofuels, and biodiesel. We simulate RIN prices for corn ethanol as an example. Our simulation model can be modified to estimate RIN prices for cellulosic biofuels and biodiesel.

Calibration

Time is discrete and indexed by $t = 0,1,\ldots,T < \infty$. T is set to be 4.[23] The RFS sets the conventional biofuels mandate for 2010 at 12 billion gallons $e_0^m = 12$, 2011 at 12.6 billion gallons $e_1^m = 12.6$, 2012 at 13.2 billion gallons $e_2^m = 13.2$, 2013 at 13.8 billion gallons $e_3^m = 13.8$ and 2014 at 14.4 billion gallons $e_4^m = 14.4$. Table 1 lists the specific mandates for conventional biofuel, cellulosic biofuel, biodiesel, other advanced biofuel and total RFS from 2008 to 2022. We assume the number of carryover RINs from 2009 is zero. By setting T=4, we assume that the mandates from 2010 to 2014 have to be met in 2014. For an interest rate we use the annualized 3-month LIBOR rate of July 2009 1.5%[24], which is traditionally used as an approximate of a risk-free rate. The discount rate for the theoretical model $\beta = 1/(1+1.5\%)$ [25].

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[23] The choices of time periods, the number of Gaussian Quadrature nodes, the finite grid for the number of RINs in the bank at T are made together to make computational costs feasible. The computational cost increases exponentially when we increase any of these three choices.

[24] http://www.wsjprimerate.us/libor/libor_rates_history.htm

[25] We also simulate the results with a 2.5% interest rate. RIN prices from 2010-2014 under this scenario are almost the same as those under the baseline scenario. Compared to the baseline results, the 2010 RIN price is about 0.2 cents lower, the 2011 RIN price is about 0.1 cents lower, the 2011 RIN price is the same, the 2012 RIN price is about 0.1 cents higher, and the 2013 RIN price is about 0.2 cents higher.

Cost and benefit functions of blending ethanol

Our theoretical model shows $p_t = c_t'(e_t, \varphi_t) - b_t'(e_t, \widehat{\theta}_t)$; that is, the price of RIN is equal to the difference between marginal benefit and marginal cost of blending ethanol. The price p_t reflects the difference between the price that is needed to allow biofuels producers to cover the costs of producing the required amount of biofuels and the market value of biofuels to meet fuel demand (Babcock 2009).

Feedstock costs are the largest determinant of production cost. The feedstock for conventional ethanol is corn. The most relevant stochastic variables φ_t affecting corn prices are crude oil prices p_{ot} and corn yields c_{st}. When yield is high, corn prices are low, all else equal. The higher the corn price, the higher the marginal cost of producing ethanol. We also assume decreasing return to scale production because of the following:

First, increased ethanol production increases demand for corn from ethanol and also increases corn price. Therefore the cost of producing ethanol increases. Second, excess capacity of ethanol industry also implied that more ethanol production means less efficient plants turning on and higher cost of producing ethanol. A change in crude oil prices will shift the derived demand for corn from ethanol, because ethanol is a substitute for gasoline. Therefore, the marginal cost curve is also a function of crude oil price. Following Thompson, Meyer and Westoff (2008b), we calibrate the marginal cost curve to the simulated data for 2009 from the integrated model of McPhail and Babcock.[26] The specific cost function used is

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[26] The model includes the U.S. markets for corn, ethanol, gasoline, soybean, soybean meal, soybean oil, biodiesel and diesel. The supply and demand functions for each market include the following policy variables when applicable: the RFS for ethanol and biodiesel, and the blenders' tax credit to ethanol and biodiesel. The partially stochastic simulation is a defining characteristic of the model. Instead of point values for exogenous variables for future year

$c_t^{'}(e_t,\varphi_t)=2.20+0.00124*p_{ot}-0.01241*c_{yt}+0.00009*e_t$ where the intercept includes all the other factors affecting the cost of blending ethanol, p_{ot} is in dollars per barrel, c_{yt} is in bushels per acre, and e_t is in million gallons.[27] Biofuels substitute for petroleum-based fuels, therefore the price of crude is the single most important factor determining marginal benefits of blending biofuels. Thus the most relevant stochastic variable $\widehat{\theta}_t$ affecting marginal benefit $b_t^{'}(e_t,\widehat{\theta}_t)$ is the crude oil price p_{ot}. Another important factor affecting the benefit is tax credits to ethanol blenders tc_t, because tax credits to ethanol blenders increase their willingness to pay for ethanol. Following Elobeid et. al. 2007, we assume a perfectly elastic demand and a linear marginal benefit function. The parameters of the benefit function are also calibrated to historical data of annual crude oil price and gasoline price from 1980 to 2008 from the Energy Information Administration. The specific benefit function used is $b_t^{'}(e_t,\widehat{\theta}_t)=0.6781*(0.1842+0.0249*p_{ot})+tc_t$, where $tc_t=\$0.45$ per gallon. By letting $tc_t=\$0.45$, we assume the current tax credit 45 cents per gallon will continue to 2014. The benefit function says that the marginal benefit of blending ethanol is equal to the energy value of ethanol plus tax credits to ethanol blenders.

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simulations, exogenous variables are drawn randomly from distributions based on past variances and covariance. Crude oil and natural gas prices and corn and soybean yields are among the exogenous factors determined randomly. This model develops an acreage supply response under expected profit maximization to investigate the net effect of the federal biofuels policies and energy prices on the equilibrium allocation of U.S. corn and soybean acreages.

[27] If farmers harvest 10 more bushels per acre on average, the estimated marginal cost implies that RIN price will decrease by about 10 cents. A bushel of corn produces 2.75 gallons of ethanol on average, so corn price will decrease by about 28 cents per bushel.

The stochastic nature of the world

The stochastic nature of the world is captured by draws from the distributions of the stochastic crude oil prices p_{ot} and corn yields c_{yt}. Corn yields are independent of crude oil prices because yield is mainly dependent on summer growing conditions in the United States Corn Belt.

Corn yields are assumed independent over time in the sense that a bumper crop in 2009 does not affect the probability of a bumper crop in 2010. The mean of corn yield is assumed to follow a linear upward trend. U.S. corn yields from 1980 to 2008 reported by the National Agricultural Statistics Service (NASS) are used to estimate the linear trend. The variation of corn yield each period is captured by a beta distribution. The same data are used to estimate the marginal beta distribution of corn yield to represent variation about 2010-2014 corn yields. These yields are first de-trended using a linear trend. The average percent deviation multiplied by the trend yield is used to estimate the standard deviation of 2010 yield. The marginal distributions of the 2010-2014 corn yields (in bushels per acre) are (Table 7 lists estimated parameters for each year):

$$(27) \qquad p(c_{yt}) \propto \frac{\Gamma(p_{c_{yt}} + q_{c_{yt}})(c_{yt} - \underline{c_{yt}})^{p_{c_{yt}}-1}(\overline{c_{yt}} - c_{yt})}{\Gamma(p_{c_{yt}})\Gamma(q_{c_{yt}})(\overline{c_{yt}} - \underline{c_{yt}})^{p_{c_{yt}}+q_{c_{yt}}-1}}$$

	Minimum	Maximum	p	q
2010	119	181	2.1777	1.3554
2011	120	181	1.7352	0.959
2012	122	184	1.7352	0.959
2013	124	186	1.7352	0.959
2014	125	188	1.7352	0.959

Table 7 Estimated parameters for corn yield beta distribution

Guassian quadrature is used to generate points and weights to discretize the beta distribution. The Matlab code by Miranda and Fackler is used to generate three possible corn yield points and associated probabilities for each year to approximate the beta distribution.[28] Guassian quadrature is one method used to approximate a definite integral of a function. It is usually stated as a weighted sum of function values at specified points within the domain of integration. Gaussian quadrature generates points and weights to exactly match the moment-generating conditions. Guassian quadrature is used because it is the best way we can think of to estimate the expectation and variance of RIN prices. 2010 corn yield uncertainty is approximated by the following: $\Pr(c_{y0} = 132) = 0.1631$; $\Pr(c_{y0} = 154) = 0.5001$; $\Pr(c_{y0} = 174) = 0.3369$.

Crude oil prices in each year are assumed to follow a lognormal distribution. The mean of the distribution is estimated by the average NYMEX crude oil futures prices of each month for which a futures price is quoted. Price volatility is obtained from annualized implied volatilities for at-the-money call options of each month[29]. The annualized implied volatilities are multiplied by the square root of time to estimate the standard deviation of prices for each month. Because the model is annual, the monthly means and standard deviations are converted to an annual mean and standard deviation of crude oil prices using standard formulas. For any set of random variables $X_1, \cdots, X_n$, let $Y = (1/n)\sum_{i=1}^{n} X_i$. Then

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[28] The choices of time periods, Gaussian quadrature nodes, the finite grid for the number of RINs in the bank at T are made together to make the computational cost under control (curse of dimensionality). It is a compromise between computational cost and accuracy.

[29] The futures prices and implied volatilities are obtained on Dec 7, 2009.

$Var(Y) = (1/n)^2 \sum_{i=1}^{n} Var(X_i) + 2(1/n)^2 \sum_{i=1}^{n} \sum_{j>i} \rho_{i,j} \sqrt{Var(X_i)} \sqrt{Var(X_j)}$ where $\rho_{i,j}$ is the correlation between X_i and X_j. To estimate the variance for the annual mean price, the correlation matrix of monthly crude oil prices is needed to estimate the volatility of the average price of crude oil for any year. Monthly prices of Oklahoma WTI crude oil from September 1986 to July 2008 were used to estimate the correlation matrix. The estimated mean for the 2010 average crude oil price distribution is $75 per gallon and the annualized implied volatility is 40%. Guassian quadrature is used again to generate 3 prices and associated probabilities to approximate the lognormal distribution: $\Pr(p_{o0} = 31) = 0.1667$; $\Pr(p_{o0} = 60) = 0.6667$; $\Pr(p_{o0} = 118) = 0.1667$.

Following Gibson and Schwartz (1990), crude oil prices over time are assumed to follow a random walk with a drift. For example, if the realized 2010 average crude oil price is $36 per barrel, then the expected 2011 average crude oil price is $\$36 \times (1 + yield)$. According to Hull (2009), *yield* measures the difference between futures price and spot price, which includes the cost of carry and convenience yield. The cost of carry measures the storage cost plus the interest rate. The convenience yield measures the benefit of holding the physical asset. We estimate the convenience yield by the NYMEX futures prices on December 7, 2009. For example, the yield implied by the NYMEX futures price is 8%. The volatilities for 2010 average crude oil price is approximately equal to 40%. Gaussian quadrature is applied again to generate three points and associated probabilities to approximate each lognormal distribution for average crude oil price. The evolution of crude oil prices from 2010 to 2012 is shown in Figure 4. The first price is the mean of the average annual prices of 2010. The second column presents 3 possible prices in 2010. The third column presents 9 possible prices in 2011. The last column presents 27 possible prices in 2012.

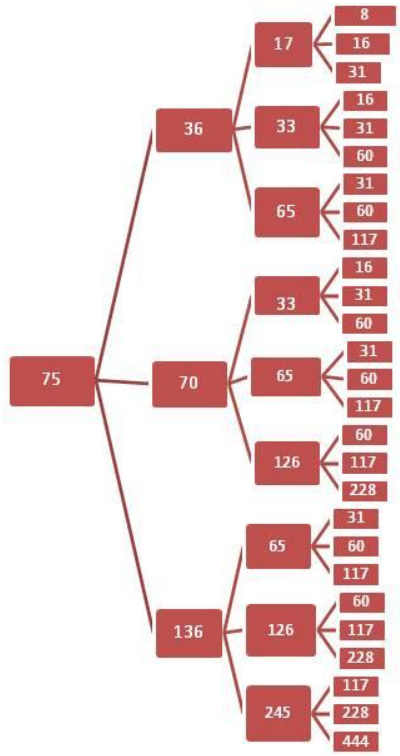

Figure 4 Evolution of crude oil prices ($ per barrel) from 2010 to 2012

The probability transition from each state in 2010 to each state in 2011 is as follows. There are 9 states in 2010 and 27 possible states in 2011. However, there are 81 instead of $27 \times 9 = 243$ possible states for both 2010 and 2011.[30] Following the same approach, we

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[30] Given 3 possible crude oil prices $(p_{o0}^1, p_{o0}^2, p_{o0}^3)$ with probabilities $(w_{o0}^1, w_{o0}^2, w_{o0}^3)$ and 3 possible corn yields $(c_{y0}^1, c_{y0}^2, C_{y0}^3)$ with $(w_{y0}^1, w_{y0}^2, w_{y0}^3)$, there are 9 states in 2010 with associated probabilities

generate crude oil price and corn supply for 2012, 2013, and 2014 and obtain states for all five years ahead.

Stochastic backward induction

Now we will use backward induction to solve ethanol blending levels for each state and for each period.

We first define a finite grid for the number of RINs in the bank at T.[31] The agent chooses the optimal ethanol blending level at T to minimize the cost of meeting the regulation at T, given the available information set at T. The optimal ethanol blending level has to be no less than the mandated level at T minus the number of RINs in the bank at T. At T, the agent knows the number of RINs in her bank account, the marginal cost and benefit of blending ethanol in year T, and optimal blending level for all dates up until year T. The agent

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$\Pr(p_{o0}^{i}, c_{y0}^{j}) = w_{o0}^{i} \times w_{y0}^{j} \forall i = 1,2,3; j = 1,2,3$. For each crude oil price in 2010, there is a crude oil price distribution in 2011. If crude oil price is p_{o0}^{1} in 2010, crude oil price in 2011 has a mean $p_{o0}^{1} * (1 + yield)$ and volatility $40\% \times \sqrt{13/12}$. We apply Gaussian quadrature again to generate 3 prices $(p_{o1}^{1}, p_{o1}^{2}, p_{o1}^{3})$ and associated probabilities $(w_{o1}^{1}, w_{o1}^{2}, w_{o1}^{3})$ from this distribution. Following the same approach, $(p_{o1}^{4}, p_{o1}^{5}, p_{o1}^{6})$ with probabilities $(w_{o1}^{4}, w_{o1}^{5}, w_{o1}^{6})$ are generated from the 2011 price distribution if the 2010 price is p_{o0}^{2} and $(p_{o1}^{7}, p_{o1}^{8}, p_{o1}^{9})$ with probabilities $(w_{o1}^{7}, w_{o1}^{8}, w_{o1}^{9})$ are generated from 2011 price distribution if the 2010 price is p_{o0}^{3}. There are 9 possible crude oil prices in 2010. We also get three corn yields points $(c_{y1}^{1}, c_{y1}^{2}, c_{y1}^{3})$ with probabilities $(w_{s1}^{1}, w_{s1}^{2}, w_{s1}^{3})$ from the 2011 corn yield beta distribution. There are 27 possible states in 2010. However, there are 81 instead of 27*9=243 possible states for both 2010 and 2011 because
$\Pr(p_{o0}^{i}, c_{y0}^{j}, p_{o1}^{h}, c_{y1}^{k}) = \Pr(p_{o1}^{h} \mid p_{o0}^{i}) \times \Pr(p_{o0}^{i}) \times \Pr(c_{y0}^{j}) \times \Pr(c_{y1}^{k})$ where
$\Pr(p_{o1}^{h} \mid p_{o0}^{1}) = w_{o1}^{h} \forall h = 1,2,3; \Pr(p_{o1}^{h} \mid p_{o0}^{1}) = 0 \forall h = 4,\cdots,9;$
$\Pr(p_{o1}^{h} \mid p_{o0}^{2}) = 0 \forall h = 1,2,3,7,8,9; \Pr(p_{o1}^{h} \mid p_{o0}^{2}) = w_{o1}^{h} \forall h = 4,5,6;$
$\Pr(p_{o1}^{h} \mid p_{o0}^{3}) = 0 \forall h = 1,\cdots,6; \Pr(p_{o1}^{h} \mid p_{o0}^{3}) = w_{o1}^{h} \forall h = 7,8,9.$

[31] For simulation, we set the maximum number of RINs banked to be 2 billion, the maximum number of RINs borrowed to be 2 billion, and the space between each point on the grid to be 100 million RINs. The choices of time periods, the number of Gaussian Quadrature nodes, the finite grid for the number of RINs in the bank at T are made together to make the computational costs feasible (curse of dimensionality).

also knows all the realizations of crude oil price and feedstock supply.

For each realized pair of crude oil price and feedstock supplies at T-1, there are 9 possible pairs of crude oil price and feedstock supply at T. Given the minimum costs for each of the 9 states at T, we obtain the expected minimum cost at T, and then solve for the quantity of ethanol blending under the specific state for T-1 which minimize the sum of the cost of meeting regulation at T-1 and the discounted expected minimum cost at T. We repeat this for each possible state at T-1 and obtain the ethanol blending level for each possible state at T-1. This exercise will be repeated from period T-2 until the first period.

We will choose the optimal number of RINs in the bank which minimizes the sum of the discounted expected costs of meeting the total mandates over the 5 periods. Given the optimal blending level, we obtain the RIN prices for each state and for each period.

European call option price simulation

Given the simulated prices and associated probabilities, we use risk-neutral option pricing (Harrison and Kreps 1979) to estimate the European call option premium as follows

$$c = E[e^{-rT} \times \max(p_T - K, 0)] = e^{-rT} \times \sum_i w_i \times \max(p_{iT} - K, 0) \tag{28}$$

where r is the risk-free interest rate, $p_{i\bar{T}}$ is the simulated i th RIN price at maturity, w_i is the probability associated with i th price, K is the strike price, and $\bar{T}$ is the time to maturity.

Simulation Results

We simulate the aggregate model by substituting values for model parameters and giving distributions to corn yields and crude oil prices. These values and distributions are chosen to reflect the corn ethanol RIN market conditions of Dec. 2009. We first set up a baseline scenario before looking at the effects of five shocks to study the response of RIN prices to shocks as well as RIN option prices, which provides useful information for market players attempting to hedge RIN price risk. For this reason we also simulate European at-the-money call option prices for each year from 2010 to 2014. All the parameters for this scenario are listed in the calibration section. Table 8 summarizes RIN price distribution statistics for baseline scenarios including the expectation, standard deviation, price volatility, and European at-the-money call option premium. Our baseline results show that the average 2010 RIN price will be $0.10 with a price volatility of 80%. The uncertainty of RIN price comes from both the uncertainty of the cost of producing ethanol and the uncertainty of the cost of producing gasoline, which is the uncertainty of the benefit of using ethanol. The uncertainty of the cost of producing ethanol comes from both corn yield and crude oil price and the uncertainty of the benefit of blending ethanol comes from crude oil price. Without the RFS, ethanol blenders use the optimal amount of ethanol to maximize its profits. With the RFS in place, when the mandate is binding, ethanol blenders need to use more than the optimal amount of ethanol, and thus lose money for each gallon of ethanol used. The price of RINs measures the extra cost per gallon ethanol blenders need to incur to comply with the RFS. We simply multiply the average RIN prices by the mandated amount of ethanol for each period and estimate that the average cost of meeting RFS for gasoline producers is $6.74 billion. If banking and borrowing are not allowed, the expected RIN prices from 2010 to 2014 are $0.0411, $0.1026, $0.1595, $0.2074, and $0.3857. We simply multiply the average RIN prices by the mandated amount and estimate the average cost of meeting the RFS without banking and borrowing is $12.301 billion. Thus the banking and borrowing provisions will save gasoline producers and importers $5.561 billion. Banking and borrowing provision achieves a 45% cost reduction for gasoline producers to meet the RFS.

RIN Prices	2010	2011	2012	2013	2014
			Baseline		
Expectations	$0.0991	$0.1005	$0.1021	$0.1036	$0.1051
Standard Deviation	$0.09	$0.11	$0.13	$0.14	$0.17
Price Volatility	89%	113%	124%	139%	161%
Option premiums	$0.04	$0.06	$0.07	$0.08	$0.09

Table 8 Baseline results for RIN prices (2010-2014)

Next we introduce the five most relevant shocks to the ethanol market: a shock originating from a crude oil price drop; a negative ethanol demand shock originated from a change in the blenders tax credit; a shock originating from a crude oil price increase; a negative supply shock originating from a short crop for the feedstock of producing ethanol; and a positive supply shock originating from a bumper crop for the feedstock. We simulate RIN price distributions for each year under these five scenarios.

It must be emphasized that our model is based on estimated marginal costs for ethanol blenders and on forward-looking well-informed expectations. That is, our model simulates a well functioning market at equilibrium. Early results from the actual operations of the market during the years 2009 indicate that the market is not yet at equilibrium. The 2008 RIN prices are much cheaper than 2009 RIN prices after considering the time value of money, and ethanol blenders could benefit from banking 2008 RINs for their compliance with RFS for 2009. One possible explanation for the persistent large price gap between 2008 RINs and 2009 RINs is that obligated parties have not utilized their banking options.

Crude oil price shocks

We first simulate what would happen if crude oil price drops. When crude oil price drops, gasoline prices decrease and the quantity demanded for gasoline increases. As a consequence, the willingness to pay for ethanol as a substitute for gasoline decreases and the demand for ethanol decreases. When the demand for ethanol decreases, the demand for corn decreases as well, therefore the price of corn decreases if the supply is fixed[32]. Thus, crude oil price drop also reduces the cost of producing ethanol. Taking into account the effect on both benefit and cost, the net effect of a crude oil price drop on the RIN price is positive. That is, the impact on the demand for ethanol is greater than the impact on the supply curve of ethanol, so the RIN prices increase with a drop in crude oil prices. The opposite holds true when crude oil price increases.

We specifically simulate what would happen if crude oil price drops to $36 per barrel in 2010. Table 9 lists the expectation, standard deviation, price volatility of RIN prices for each year under this scenario. This drop in 2010 will lower the expected crude oil prices from 2011 to 2014 because of the random walk assumption for crude oil prices. The low crude oil price reduces the benefit of blending ethanol as a substitute for petroleum, which leads to a higher expected RIN prices assuming the cost of blending ethanol stays the same. Compared to the baseline, expected RIN prices from 2010 to 2014 increase by about $0.18 (up 180%).

[32] The supply of corn is determined by planted acreage and yield per acre. Farmers make decisions about acreage based on the expectation. So when the crude oil price drop is realized, the planting decision is already made.

RIN Prices	2010	2011	2012	2013	2014
	Results under crude oil price drop				
Expectations	$0.2834	$0.2876	$0.2920	$0.2963	$0.3008
Standard Deviation	$0.03	$0.10	$0.13	$0.17	$0.21
Price Volatility	12%	36%	44%	56%	71%

Table 9 RIN prices under crude oil price drop scenario

We also simulate what would happen if crude oil price increases to $136 per barrel. Table 10 lists the expectation, standard deviation, and price volatility of RIN prices for each year under this scenario. An increase in the crude oil price will increase the marginal benefit of blending ethanol and shift down the path of expected RIN prices greatly. Our results show that expected RIN price drops to almost zero. The standard deviation for the RIN price distribution each period drops to almost zero as well. However, RINs still have value in this scenario because the probability of the mandate binding is positive. If the positive crude oil price shock was accompanied by elimination of the tax credit, then expected future RIN prices would be higher.

RIN Prices	2010	2011	2012	2013	2014
	Results under crude oil price hike				
Expectations	$0.0034	$0.0035	$0.0035	$0.0036	$0.0036
Standard Deviation	$0.00	$0.01	$0.01	$0.02	$0.03
Price Volatility	21%	194%	351%	456%	822%

Table 10 RIN prices under crude oil price hike scenario

Policy shocks

A negative demand shock can originate from a change in policy, such as elimination of the tax credits to blenders. If the federal government removes the current tax credits to blenders, blenders' willingness to pay for ethanol will decrease. Elimination of tax credits to blenders decreases the benefit of blending ethanol and increases RIN prices. Table 11 lists the expectation, standard deviation, and price volatility of RIN prices for each year under this scenario. Under this policy shock expected RIN prices from 2010 to 2014 increases by about \$0.26. This estimate is much lower than the \$0.45 estimated by De Gorter and Just (2008) and Elobeid et.al. (2007). The reason is as follows: only under scenarios illustrated by Figure 5 when the supply price of ethanol Ps (the cost of producing a gallon of ethanol) is higher than the demand price of ethanol (which is equal to the tax credit plus the cost of producing 0.68 gallons of gasoline), elimination of the \$0.45 tax credit will increase RIN prices by \$0.45. Figure 6 shows that when the supply price of ethanol Ps is lower than the demand price of ethanol Pd, specifically, the gap between the cost of producing a gallon of ethanol and the cost of producing 0.68 gallons of gasoline is less than \$0.45 per gallon, in which case, RIN price will increase by less than \$0.45 after elimination of the tax credit. Figure 7 shows that in some cases, the supply price of ethanol Ps is still lower than the demand price of ethanol Pd after eliminating tax credits, RIN price still will be zero. We estimate that eliminating tax credits will cost gasoline producers and importers \$17.6 billion, but save tax payers \$29.7 billion.

RIN Prices	2010	2011	2012	2013	2014
	Results under tax credits elimination				
Expectations	$0.3578	$0.3631	$0.3686	$0.3741	$0.3797
Standard Deviation	$0.18	$0.23	$0.26	$0.28	$0.32
Price Volatility	50%	63%	69%	75%	85%

Table 11 RIN prices under tax credit elimination scenario

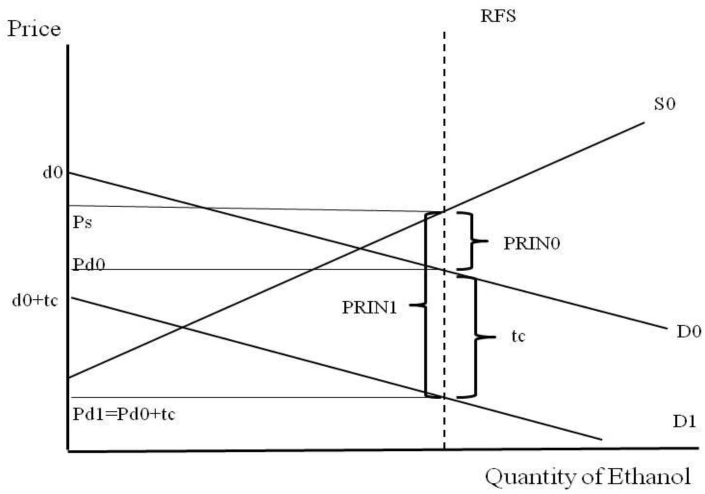

Figure 5 The impact of eliminating tax credit on RIN prices (1)

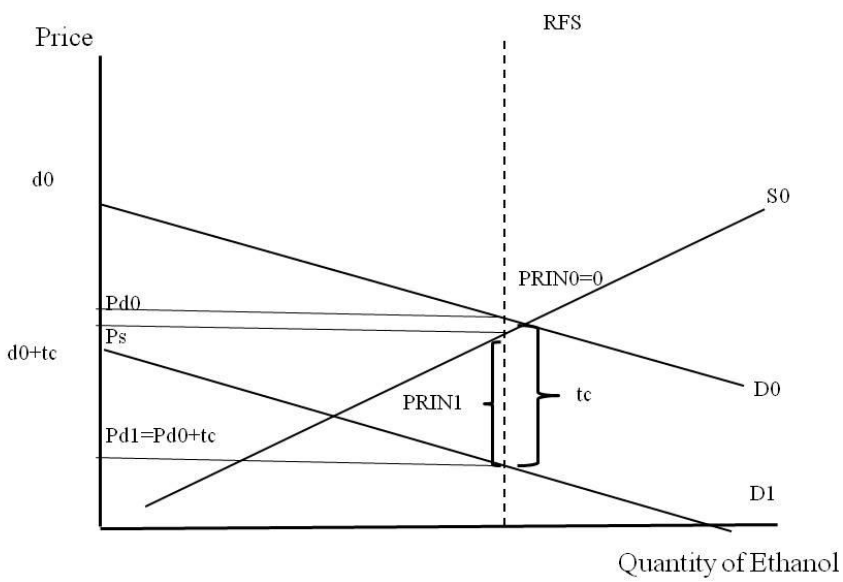

Figure 6 The impact of eliminating tax credits on RIN prices (2)

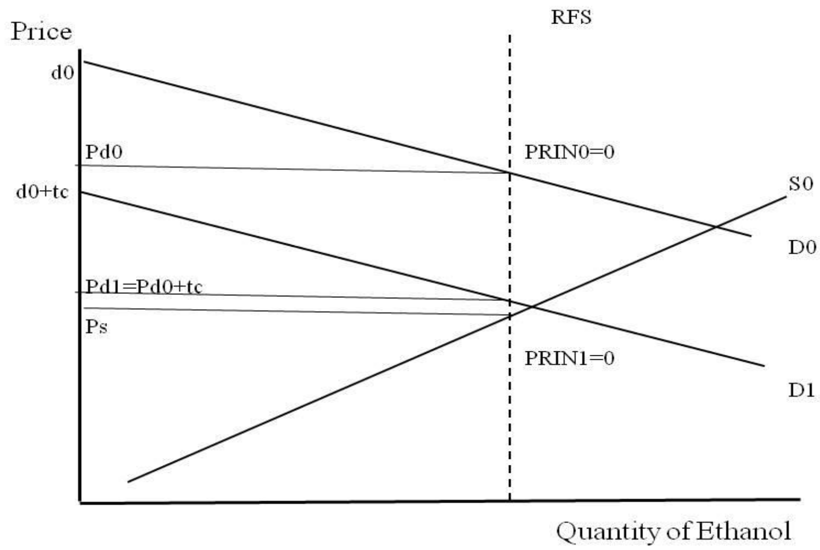

Figure 7 The impact of eliminating tax credits on RIN prices (3)

Negative supply shocks

A negative supply shock for ethanol can originate from a feedstock supply shortage. A short corn crop will increase corn prices, and thus increase the cost of producing ethanol. The increased cost of producing ethanol will increase RIN prices, all else equal. We characterize our negative supply shock as a realized corn yield of 132 bushels per acre in 2010. Table 12 lists the expectation, standard deviation, and price volatility of RIN prices for each year under this scenario.

RIN Prices	2010	2011	2012	2013	2014
	Results under a short corn crop				
Expectations	$0.1175	$0.1193	$0.1210	$0.1229	$0.1247
Standard Deviation	$0.10	$0.13	$0.14	$0.16	$0.18
Price Volatility	84%	105%	116%	129%	147%

Table 12 RIN prices under a short corn crop scenario

Compared to the baseline, expected RIN prices increase by about $0.02 (up 20%). However, if we assume away the banking and borrowing provisions, expected 2010 RIN prices will increase by $0.31(up 310%). Banking and borrowing provisions greatly smooth out the effects of a negative supply shock in 2010 and reduce the volatility of RIN prices.

Positive supply shocks

A positive supply shock can happen with a bumper crop which decreases corn prices, and subsequently decrease the feedstock cost for ethanol production which results in increased ethanol production. The decreased cost of blending ethanol decreases expected RIN prices. We characterize our positive supply shock as a bumper crop in 2010 of 174 bushels per acre. Table 13 lists the expectation, standard deviation, and price volatility of RIN prices for each year under this scenario.

RIN Prices	2010	2011	2012	2013	2014
	Results under a bumper corn crop				
Expectations	$0.0811	$0.0823	$0.0836	$0.0848	$0.0861
Standard Deviation	$0.08	$0.10	$0.11	$0.13	$0.15
Price Volatility	93%	120%	133%	150%	177%

Table 13 RIN prices under a bumper corn crop scenario

If U.S. corn farmers harvest about 174 bushels per acre on average, the expected RIN prices drop by about $0.02 (down 20%) compared to the baseline. The standard deviation of each RIN price distribution drops as well. If we do not allow for banking and borrowing, expected RIN prices for 2010 will drop to zero because the mandate is now easy to meet. Banking and borrowing provision again greatly smooth out the positive effects and reduce the RIN price volatility.

Conclusions

Tradable credit/permit programs are becoming the preferred implementation method when governments issue binding aggregate restrictions on the outcomes of private decisions. From fisheries quotas to greenhouse gas reduction, tradable permit programs are being implemented as the least cost method of achieving desired outcomes. Because it is so new, the market for tradable Renewable Fuel Credits is not well understood by either market participants or by other affected parties. But new Renewable Fuel Credits markets will be created for conventional biofuels, biodiesel, advanced biofuels, and cellulosic-based biofuels over the next few years. In this paper we provide a conceptual framework for how these markets will operate. We show how the banking and borrowing provisions give structure to how RIN prices will vary over time. We estimate that RIN price volatility will be quite high. This likely will increase the demand for greater ability to hedge future RIN price risk. We estimate call option prices for futures Renewable Fuel Credits which would provide buyers of the call option a hedge against rising RIN prices in the future.

One extension of this research should include an accounting for the probability that EPA will provide a waiver for firms' RFS obligations. EPA denied just such a request by

Governor Perry of Texas in 2008. But similar requests by the U.S. livestock industry and by ethanol blenders will occur if low crude oil prices or low corn yields lead to sharp increases in the price of RINs. Any waiver would decrease the volatility of RIN prices, thereby lowering the cost of call options on future RIN prices.

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CHAPTER 4. ASSESSING THE IMPACT OF US ETHANOL MARKET SHOCKS ON GLOBAL CRUDE OIL AND US GASOLINE: A STRUCTURAL VAR APPROACH

Introduction

In 2005, Cambridge Economic Research Associates (CERA) representatives told the U.S. House of Representatives that world crude oil production capacity "has the potential to rise from 87 million barrels per day (mbd) in 2005 to as much as 108 mbd by 2015, with further growth in capacity continuing after that point we see no evidence to suggest a peak before 2020, nor do we see a transparent and technically sound analysis from another source that justifies belief in an imminent peak." Couple this expanding abundance of crude oil with the world's increasing demand for transportation fuels from 2005 to 2008 and one would expect to see an increase in crude oil supply. However, crude oil supply was stagnant from 2005 to 2008 (Figure 8).

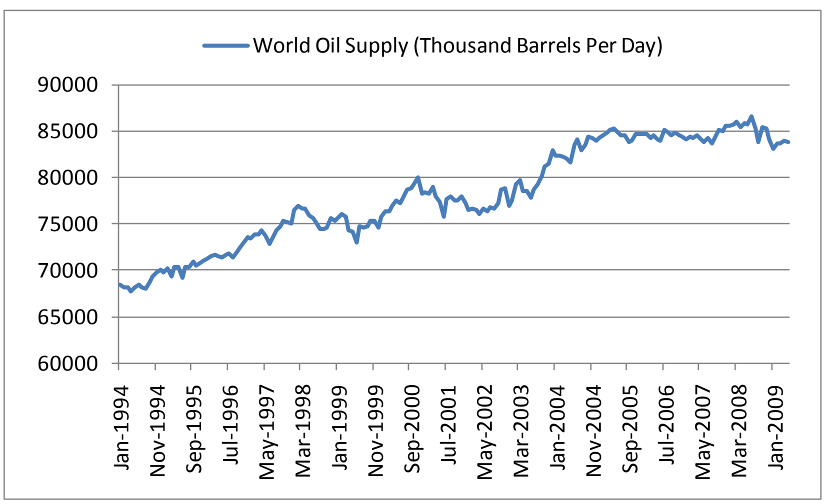

Figure 8 Monthly global oil supply

This three-year period of stagnation in world crude oil supply cannot be explained by the global financial crisis. Over the same period, real global GDP grew by 10.83%.[33] The GDP of the United States did shrink during the second half of 2008, but not enough to offset the previous 2.5 years of strong growth. In total, the real US GDP still grew 5.33% over the three year period.[34]

Hamilton (2009) argues that the stagnation of crude oil supply can be attributed to political instability that disrupted the flow of oil, slower than expected addition of new fields, and declining production from existing mature fields. However, this explanation does not take into account how much more transportation fuel is being used each day. For example, according to the Washington Post, China alone is adding more than 1,000 cars to their streets each day.[35] People from other emerging countries are driving more as well.[36] Killian (2010) argues that the stagnation is due to a lack of exploration and drilling. This explanation, however, is a contradiction to the testimony given by CERA. These arguments may have some explanatory power, but the gap between oil supply and growing demand suggests to us an alternative reasoning.

We hypothesize that the ever increasing support for alternative fuels is at least one of the contributing factors to the stagnant oil supply in the presence of an increasing world demand for transportation fuel. Responding to the previous mandate and high energy prices, U.S. ethanol production increased from 4 billion gallons in 2005 (3% of US gasoline

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[33] Real global GDP is calculated by nominal GDP divided by GDP deflator. World GDP and GDP deflator data are from World Bank's World Development Indicators.

[34] http://www.bea.gov/national/index.htm#gdp

[35] "Creating a car culture in China" by Maureen Fan, Washington Post Foreign Service, Jan21, 2008. http://www.washingtonpost.com/wp-dyn/content/article/2008/01/20/AR2008012002388.html

[36] "Mass car ownership in the emerging market giants" by Marcos Chamon, Paolo Mauro, and Yohei Okawa, Economic Policy, Issue 54, April 2008.

consumption) to 9 billion gallons in 2008 (6.25% of US gasoline consumption) (Figure 9). Meanwhile, global biofuels production increased from 618.8 thousand barrels per day in 2005 to 1055.8 thousand barrels per day in 2008, accounting for about 1.25% of global fuel production. The purpose of the paper is to thoroughly examine the possible impact of ethanol market shocks on traditional fossil fuel markets. Du and Hayes (2009) measure the impact of U.S. ethanol production on gasoline price and profitability of U.S. oil refiners, while treating global oil prices fully exogenous. However, the literature (e.g., Barsky and Killian 2002, 2004) suggests that energy prices must be treated as fully endogenous. This implies that Du and Hayes (2009)'s findings that ethanol significantly reduces the price consumers pay for gasoline might not be robust to relaxing this assumption. To fully examine the impact of policy led ethanol production, we develop a joint model of the global crude oil market, the U.S. gasoline market and the U.S. ethanol market. This approach allows us to view all market impacts on one another as endogenous.

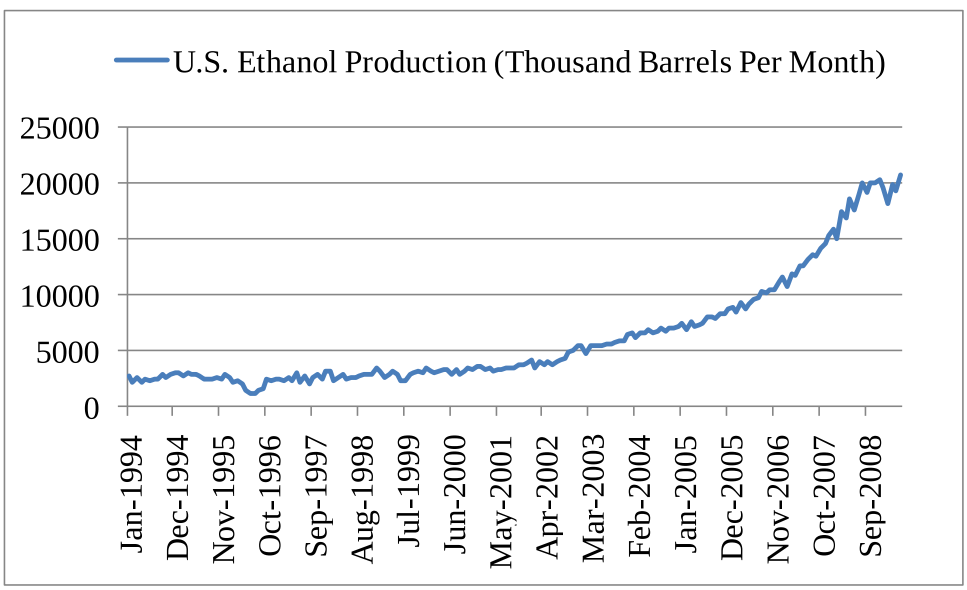

Figure 9 Monthly U.S. ethanol production

Our joint model builds on a recently proposed structural vector autoregression (SVAR) model of the global market for crude oil and the U.S. market for motor gasoline by Killian (2009, 2010). A VAR approach consists of regressing each current variable in the model on all the model variables lagged a specified number of times. VAR is a reduced-form approach, so economic interpretation of the results is difficult unless the reduced form is linked to an economic model. SVARs impose an economic model on the contemporaneous movements of the variables.[37] 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 economic time series (prices or quantities) into demand and supply shocks. Killian (2009, 2010) argues that it is essential to understand the origins of a given price shock, when assessing the responses of prices and quantities, because each demand and supply shock is associated with responses of a different magnitude, pattern and persistence. We therefore identify the underlying demand and supply shocks in these three markets and assess the responses of prices and quantities of each market to unanticipated shifts in demand and supply. Estimates of this joint model suggest that each demand and supply shock has its own distinct dynamic effect on the production and real price of imported crude oil. We also evaluate the overall importance of each shock for the determination of the real prices of crude oil, U.S. gasoline and ethanol.

Our results show that the responses of the rate of global oil production to an unanticipated ethanol demand expansion, largely driven by U.S. government policy, is

[37] The origins of the Structural VAR approach come from the seminal contributions of Sims (1986), Bernanke (1986), and Blanchard and Watson (1986), who employed economic theory to recover the structure of disturbances. Structural VAR models are now a major tool in macroeconomic analysis of monetary, fiscal, and technology shocks (Enders, 2004).

statistically significant. This response would not be picked up through a conventional regression model because its effect is not one directional, but instead sends a shockwave with two peaks and two troughs within a 12 month period. We also find statistically significant negative responses of gasoline price to ethanol demand and supply expansions, consistent with the results of Du and Hayes (2009). However, we do not find statistically significant effect of U.S. ethanol demand or supply expansion on the real price of crude oil or the growth rate of U.S. gasoline consumption.

The remainder of the paper is organized as follows. Section 2 describes the structural VAR model, Section 3 describes the data for estimation, Section 4 summarizes the results from impulse response analysis, Section 5 explains the results of variance decomposition, and Section 6 concludes with a brief summary of the paper.

The Structural VAR (SVAR) Model

To examine the impact of ethanol on global crude oil and U.S. gasoline markets, a seven-variable SVAR of these three markets is developed. The seven monthly variables are $x_t = (\Delta prodo_t, rea_t, rpo_t, rpg_t, \Delta consg_t, rpe_t, \Delta prode_t)'$, where $\Delta prodo_t$ is percentage change in global crude oil production, 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 U.S. RBOB gasoline[38], $\Delta consg_t$ is percentage change in U.S. gasoline consumption, rpe_t is the real price of ethanol, and

[38] "Reformulated gasoline blendstock for oxygenate blending" (RBOB) is motor gasoline blending components intended for blending with oxygenates to produce finished reformulated gasoline. The price of RBOB gasoline excludes the cost of ethanol, which is a type of oxygenate.

$\Delta prode_t$ is level change in U.S. ethanol production[39]. Our SVAR model provides estimates of the impacts that ethanol demand and supply shocks have on the markets of global crude oil and U.S. gasoline. We propose that the following seven variables are driven by seven structural shocks: (1) oil supply shocks; (2) aggregate demand shocks; (3) oil-market specific demand shocks; (4) gasoline supply shocks; (5) gasoline demand shocks; (6) ethanol demand shocks and; (7) ethanol supply 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 because of an exogenous political event, such as the civil unrest in Venezuela (December 2002) or the Iraq war (March 2003). Aggregate demand shocks are defined as unanticipated shifts of the demand curve for all industrial commodities in global markets. One example of aggregate demand shocks is the shift in the demand for industrial commodities caused by the emergence of industrial economies in Asia. Oil specific demand shocks are defined as unanticipated shifts of the demand curve for crude oil. An example of an oil specific demand shock is higher precautionary demand associated with fears about future oil supply. One historical example is the increase of the demand for oil right before the Iraq war (March 2003). Gasoline supply shocks are defined as unanticipated shifts of gasoline supply curve. Examples of gasoline supply shocks include refinery fires that shut down the operation of U.S. refiners and reduce the domestic supply of gasoline or changes in regulations that restrict refinery output. Ethanol demand shocks are defined as unanticipated shifts of ethanol

[39] US ethanol is an infant industry and the size of ethanol industry is growing exponentially. Given the different size of the industry in 1994 and 2008, a 5 percent change in production in 1994 is very different from a 5 percent change in 2008. Therefore, we do not use percentage change, instead use level changes to measure changes in U.S. ethanol production.

demand curves. Examples of ethanol demand shocks include changes in regulations that support ethanol, such as the phase out of MTBE[40], the reduction of tax credits to ethanol blenders, and the introduction of Renewable Fuel Standard. Ethanol supply shocks are defined as unanticipated shifts of the ethanol supply curve. Examples of ethanol supply shocks include unanticipated feedstock price increases led by feedstock supply shortage resulting from a bad crop.

The effects of these seven shocks on our seven 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:

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

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:

(30) $$x_t = A_0^{-1}\alpha + \sum_{i=1}^{p} A_0^{-1} A_i x_{t-i} + e_t$$

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

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

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

$$\Sigma_e = E(e_t e_t^{'}) = A_0^{-1} E(\varepsilon_t \varepsilon_t^{'}) A_0^{'-1} = A_0^{-1} \Sigma_\varepsilon A_0^{'-1} \tag{31}$$

where E is the unconditional expectation operator, and Σ_ε is the covariance matrix for the shocks. As there are 21 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 $e_t = A_0^{-1}\varepsilon_t$:

$$e_t \equiv \begin{pmatrix} e_t^{\Delta prodo} \\ e_t^{rea} \\ e_t^{rpo} \\ e_t^{rpg} \\ e_t^{\Delta consg_t} \\ e_t^{rpe} \\ e_t^{\Delta prode} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{\text{oil supply shock}} \\ \varepsilon_t^{\text{aggregate demand shock}} \\ \varepsilon_t^{\text{oil specific-demand shock}} \\ \varepsilon_t^{\text{gasoline supply shock}} \\ \varepsilon_t^{\text{gasoline demand shock}} \\ \varepsilon_t^{\text{ethanol demand shock}} \\ \varepsilon_t^{\text{ethanol supply shock}} \end{pmatrix} \tag{32}$$

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}.[41] 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

[41] 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.

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 $\Delta consg_t$ to respond to contemporaneous shocks to global shocks 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 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 (see, e.g. Barsky and Killian 2002, 2004).

A contemporaneous response restriction is equivalent to assuming that a demand (or supply) curve is perfectly elastic (or inelastic) 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 of demand are difficult to detect at high frequency. This view is consistent with evidence from interviews of Saudi officials in the early 1980s (see Daniel Yergin 1992).[42] Second, restricting α_{47} to be zero is equivalent to assuming a perfectly elastic short-

[42] The use of a vertical short-run oil supply assumption is convenient, but is not necessary. It can be shown that similar results could be obtained by relaxing the exclusion restrictions on the impact multiplier matrix and

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 at the current retail price, which is assumed to be effectively set by U.S. 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 a perfectly elastic short-run (within a month) demand for US ethanol. Because ethanol substitutes gasoline, we assume that consumers will use up all the ethanol supplied within a month, when ethanol is priced to reflect its energy value based on gasoline price.

Data

The sample period of 1994:01-2009:02 begins with the availability of monthly ethanol production data from the US Department of Energy. We collect monthly data for world oil supply[43], imported crude oil prices[44], New York harbor RBOB gasoline prices[45], U.S. product supplied of finished motor gasoline[46], and U.S. oxygenate plant production of fuel ethanol[47] from the Energy Information Administration. Nominal ethanol prices data are

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replacing them with sign restrictions in conjunction with bounds on the implied impact oil supply elasticity (Killian and Murphy 2009).

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

[44] http://www.eia.doe.gov/emeu/steo/pub/fsheets/real_prices.html

[45] http://tonto.eia.doe.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBOB-NYH&f=M

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

[47] http://tonto.eia.doe.gov/dnav/pet/pet_pnp_oxy_dc_nus_mbbl_m.htm

obtained from the official Nebraska government website[48]. Following Killian, nominal prices and indexes are deflated using the US CPI. Specifically, real prices and real Baltic Exchange Dry Indexes are computed by dividing the nominal prices in a given month by the ratio of the Consumer Price Index (CPI) in that month to the CPI in September of 2009. Figure 10 depicts the monthly real prices of crude oil, US gasoline, and US ethanol. Because finished motor gasoline includes all ethanol blended gasoline, U.S. gasoline consumption in Figure 11 is approximated by U.S. product supplied of finished motor gasoline minus U.S. oxygenate plant production of fuel ethanol.

Following Killian (2009, 2010), the real economic activity index is proxied by the real average close prices of Baltic Exchange Dry Index (Figure 12). A series of Killian's paper 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 demand shocks we need an index that capture shifts in the demand for industrial commodities driven by the global business cycle. Killian proposes to use the dry cargo single voyage ocean freight rates, such as Baltic Exchange Dry Index. The reasoning for using the freight rate to capture the shifts in the demand for industrial commodities are explained by Killian (2009) as following. Even though the supply curve of shipping is relatively flat at low levels of freight volumes in the short and intermediate run (Stopford 1997), as idle ships may be reactivated or active ships may simply cut short layovers and run faster; the slope of the supply curve becomes increasingly steep and freight rates increase, as the demand schedule for shipping services shifts due to increased economic activity. At full capacity the supply curve becomes

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[48] http://www.neo.ne.gov/statshtml/66.html

effectively vertical, as all available ships are operational and running at full speed. Only in the long run will additional shipbuilding lower freight rates, often a time when the initial high levels of economic activity have already subsided. Following a global business cycle upswing there is likely to be a rather drawn-out trough period in the shipping market, as new ships are still being launched, long after the business cycle peak has passed, and excess capacity of shipping prevails. Only gradually will the scrapping of older ships and rising demand due to the business cycle offset this depression in the shipping market.

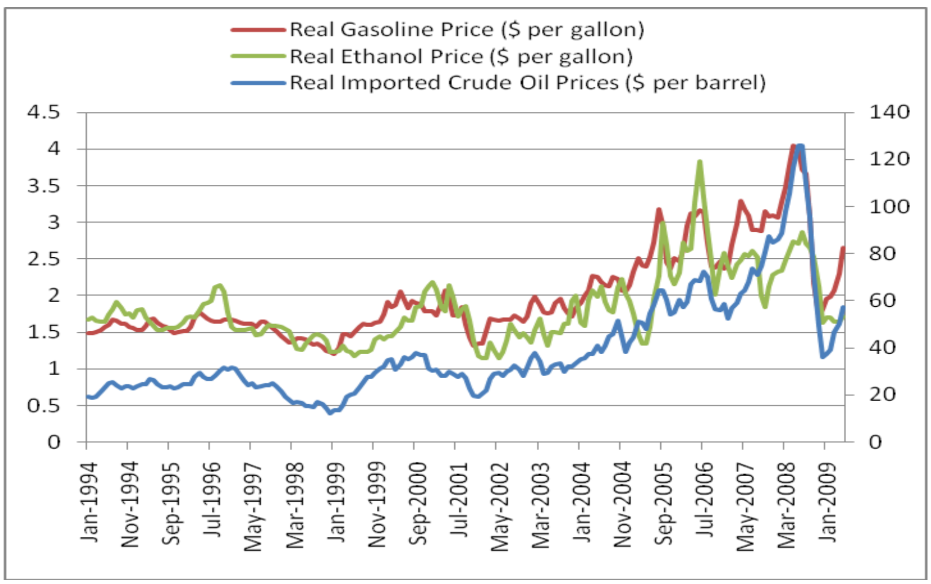

Figure 10 Monthly real prices of crude oil, US gasoline and ethanol

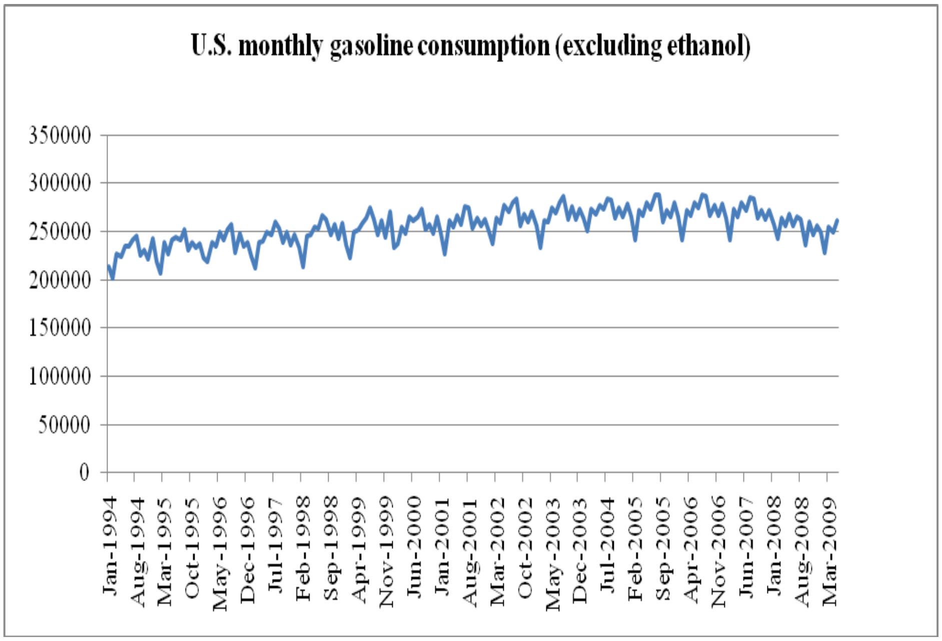

Figure 11 Monthly U.S. gasoline consumption excluding ethanol (thousand barrels)

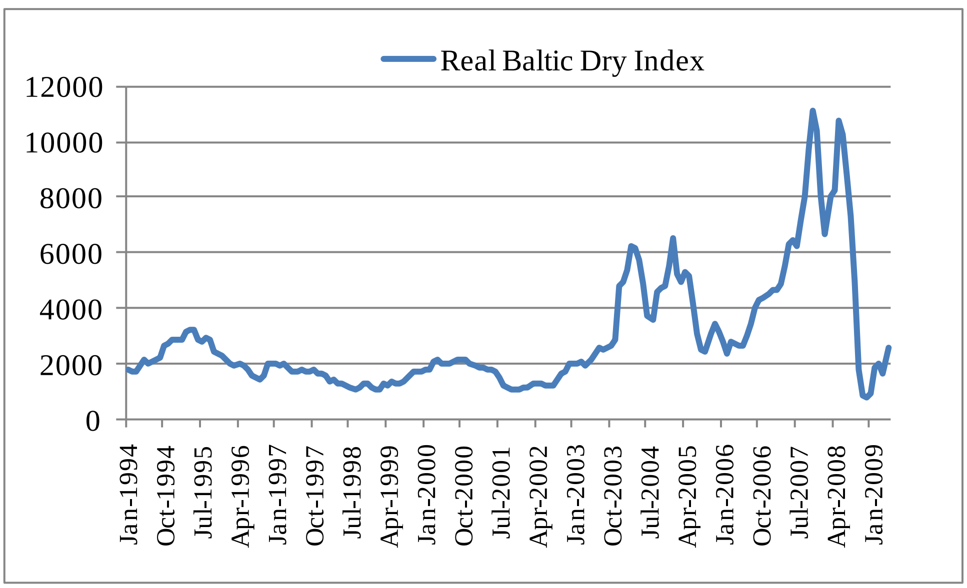

Figure 12 Monthly real Baltic Dry Index

Following Killian (2009,2010), we transform the data of monthly global oil supply to the growth rate of global oil supply; and remove seasonal variation from the data of monthly U.S. gasoline consumption and then transform them to a monthly growth rate of U.S. gasoline consumption. Real prices in levels are used[49], and real global economic activity indexes are detrended[50].

All transformed variables are tested for a unit root using the augmented Dickey-Fuller test with an intercept and trend shown in the equation below; where y is the time-series variable and $\gamma_0, \gamma_1, v, \beta_1, \cdots, \beta_p$ are parameters.

$$\Delta y_t = \gamma_0 + \gamma_1 t + v y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{33}$$

We can reject the hypothesis of existence of a unit root at 10% significance level for all variables.[51]

All transformed variables are evaluated for seasonality. The existence of a trend and seasonality with monthly frequency is tested by estimating the model:

$$y_t = \alpha_0 + wt + \sum_{i=1}^{11} \alpha_i MD_i + \varepsilon_t \tag{34}$$

where y is the time-series variable; $MD_i = 1$ if month i, 0 otherwise; and $\alpha_0, w, \alpha_1, \cdots, \alpha_{11}$ are parameters. We reject the joint hypothesis of no monthly seasonality for monthly real

[49] Economic theory suggests a link between cyclical fluctuations in global real activity and real prices of oil, thus real price of gasoline and ethanol.

[50] Real Baltic Dry indexes seem to have an upward trend if viewed over the sample period. However, over a longer sample period, Killian shows there exists a secular decline in shipping rate. For analysis, we use the transformed data of the index for the real global economic activity in industrial commodity markets provided by Killian at the following website http://www-personal.umich.edu/~lkilian/reaupdate.txt.

[51] The advantage of level specification is that the VAR estimates remain consistent whether the real prices are integrated or not. Moreover, standard inference on impulse responses based on VAR(p) models, p>1, in levels, will remain asymptotically valid. Inference also is asymptotically unvarying to the possible presence of cointegration among these real price series (see, e.g., Sims, Stock and Watson 1990; Lütkepohl and Reimers 1992). Estimates would be inconsistent if we falsely impose cointegration and/or unit root.

gasoline prices with 5% significance, so the seasonal variation of monthly real gasoline prices is removed. We cannot reject the joint hypothesis of no seasonality with monthly frequency at 5% significance for real crude oil prices and real ethanol prices. We reject the hypothesis of a linear trend in real crude oil prices over the period 1970-2009.[52] After making these transformations we test again for unit roots and reject the null hypothesis of existence of a unit root at 10% significance level for all seven transformed data series.[53]

At the 1% significance level, employing a variance ratio test, prices exhibited higher volatility since 2003. A common practice is to use a logarithmic or Box-Cox transformation if the variance does not appear to be constant (Enders, 2004). Therefore, we also run the SVAR model with logarithmic forms of prices to check the robustness of our results. Moreover, we run the SVAR model with a smaller sample from 2003 to 2009 and obtain qualitatively similar results.[54]

We utilized four methods for determining how many lags to include in a SVAR model including log likelihood, Akaike, Schwarz, and Hannan-Quinn. The log likelihood and Akaike indicated a lag length of 14, but Schwarz and Hannan-Quinn criteria indicate shorter lags. Estimation of the model in a SVAR framework at lag lengths of 5 and 10 yielded robust

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[52] Real crude oil prices seem to have an upward trend if viewed only over the sample period. However, over a longer horizon including the 1970s, a period of significant instability in the Middle East, the test indicates that recent increases in real crude price are not a trend. This is consistent with Killian (2009).

[53] Monte Carlo simulations have shown that the power of the various Dicker-Fuller and Phillips-Perron tests is very low and unit root tests do not have the power to distinguish between a unit root and near unit root process. Thus, these tests will too often indicate that a series contains a unit root. Moreover, they have little power to distinguish between trend stationary and drifting processes. In finite samples, any trend stationary process can be arbitrarily well approximated by a unit root process, and a unit root process can be arbitrarily well approximated by a trend stationary process (Enders, 2004).

[54] Qualitatively similar results include the following. First, the responses of the rate of global oil production to an unanticipated ethanol demand expansion, largely driven by U.S. government policy, is statistically significant. Second, we find statistically significant negative responses of gasoline price to ethanol demand and supply expansions. Third, we do not find statistically significant effect of U.S. ethanol demand or supply expansion on the real price of crude oil or U.S. gasoline consumption.

and qualitatively similar results. For reporting the results, a 14 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.

Demand and supply shocks since May of 1995

We compute the historical structural shock vector, ε_t, by multiplying the identification matrix, A_0, by the estimated residuals from the VAR model, e_t, such that $\varepsilon_t = A_0 e_t$. Figure 13 plots the time path of the structural shocks calculated by the model. Observations start in 1995.05, fourteen months after the first period in our sample 1994.01 reflecting the lags used in estimating the VAR model. Table 14 lists the statistics of estimated structural shocks. The second row lists the standard deviation of estimated structural 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. The third row lists the probability of the historical occurrences of a positive shock from May of 1995, and the fourth row lists the probability of the historical occurrences of a negative shock.

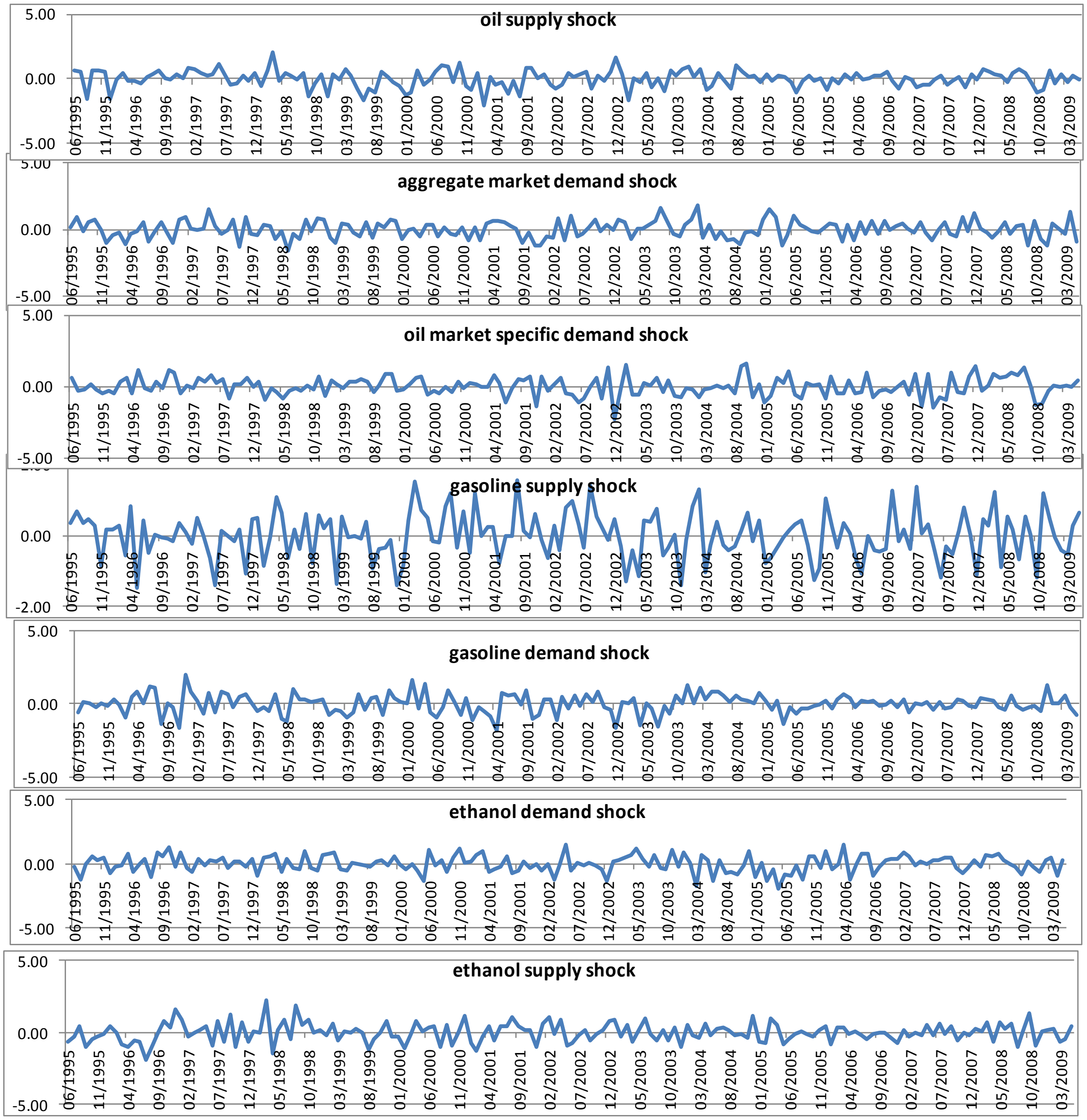

Figure 13 History of demand and supply shocks from SVAR model

	Oil supply shock	Aggregate market demand shock	Oil market specific demand shock	Gasoline supply shock	Gasoline demand shock	Ethanol supply shock	Ethanol demand shock
Standard deviations	0.66	0.64	0.66	0.65	0.65	0.65	0.65
Prob(realized shock> s.d)	0.15	0.17	0.16	0.13	0.15	0.15	0.14
Prob(realized shock <- s.d.)	0.14	0.19	0.14	0.15	0.14	0.15	0.17

Table 14 Descriptive statistics for structural shocks

Impulse Response Analysis

We are interested in understanding how prices and quantities in the global crude oil, US gasoline, and US ethanol markets respond to each of the seven shocks constructed using the SVAR model. To do this we use impulse response analysis. The reduced-form VAR can be written as the following Vector Moving Average (VMA) representation (Sims 1980):

(35) $$x_t = \varphi(B)e_t$$

Insert $e_t = A^{-1}\varepsilon_t$ into this last equation to get:

(36) $$x_t = \varphi(B)A^{-1}\varepsilon_t = \theta(L)\varepsilon_t$$

where $\theta(L) = \sum_{i=0}^{\infty}\theta_i L^i$ and each θ_i is a $7*7$ matrix of parameters from the structural model. The above equation implies that the response of x_{t+i} to ε_t is θ_i. Hence, the sequence of θ_i from $i = 0,1,2,\ldots,$ illustrates the dynamic response of the variable to each of the seven shocks. Standard errors for the impulse responses are calculated using the Monte Carlo approach of Runkle (1987).

Responses for each of the five variables of interest[55] to the seven one-standard deviation structural innovations (or shocks) are summarized in Figures 14 through 18. The blue line represents the mean impact. Red lines show two standard deviations from the mean giving the reader a visual reference of significance at the 5% level. The following five sections address each of these figures in turn. Presenting both negative and positive shocks would be redundant because they are mirrors of each other. Note that all the seven "shocks" are presented as a one standard deviation increase except the gasoline supply shock which is interpreted as a decrease. Gasoline supply shocks represent gasoline supply disruptions. The contemporaneous impulse response is shown along with the 12 months following the shock.

Any interpretation of results from an SVAR model is subjective to some degree. Our comments should therefore be understood as possible explanations, not comprehensive final interpretations.

Figure 14: How crude oil production responds to demand and supply shocks

Three of the seven shocks suggest at least some marginal impact on the growth rate in global crude oil production $\Delta prodo_t$ including shocks to oil supply, aggregate (global) demand and ethanol demand. The most obvious of these is the positive shock on crude oil supply. As expected, the shock increases $\Delta prodo_t$ in the first period.[56]

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55 These are global oil production, real oil price, real U.S. gasoline price, U.S. gasoline consumption, and real ethanol price. Aggregate demand and ethanol supply responses to shocks are not discussed as they are not of interest here.

[56] This is expected because they are one in the same. If we didn't see this result then we would have reason to believe our model is mis-specified.

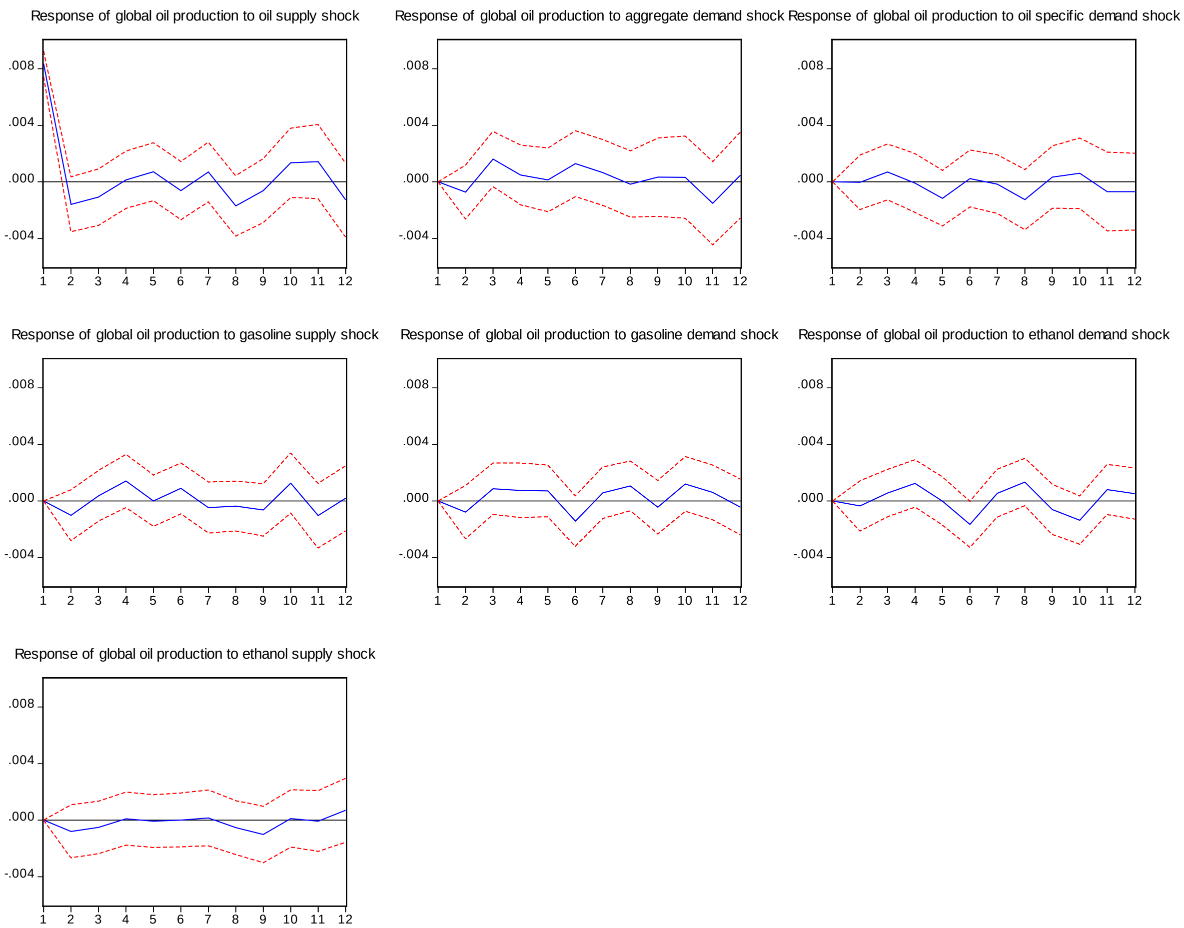

Figure 14 Global oil production response to one standard deviation shocks

A positive aggregate (global) demand shock has a nearly significant[57] positive impact on $\Delta prodo_t$ after two months. However, the lack of a persistent response suggests that crude oil producers do not expect shocks in aggregate demand to be persistent enough to change production levels.[58]

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[57] Significance is defined here as within two standard deviations of the mean effect. This level of significance is indicated in figures 14-18 by the dashed red lines above and below the mean effect given in blue.

[58] 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

Shocks to ethanol demand also appear to have an impact on $\Delta prodo_t$, although the direction and interpretation of this result is not obvious. The shock appears to be followed by a wave with two peaks and two troughs. This result could be mistaken for noise except for two facts: 1) At the 10% level all peaks and troughs are significant, and 2) The impact of an ethanol supply shock shows nothing close to a significant impact on $\Delta prodo_t$. The contrast between the significant (albeit inconsistent) impact of an ethanol demand shock and the complete lack of any response from an ethanol supply shock begs for an explanation. Our hypothesis starts with the understanding that ethanol demand is almost entirely driven by legislation. The ethanol market in the United States would only be a small fraction of what it is today without support in the form of tariffs, tax credits, and mandates,[59] therefore, any shock to ethanol demand is actually a reflection of the change in government support for ethanol. Any positive shock to ethanol demand is a signal of government support for alternative fuel. On the other hand, ethanol supply shocks are largely driven by weather conditions. Our hypothesis is that crude oil producers are going to pay more attention to government legislation than the passing weather. The wave like shape of the impact from an ethanol demand shock is harder to explain. One explanation is that OPEC may react to government support for ethanol by temporarily increasing crude oil supply thereby lowering price in an attempt to erode support for alternative fuels.

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the trend growth of demand are difficult to detect at high frequency. This view is consistent with evidence from interviews of Saudi officials in early 1980s (see Daniel Yergin 1992).

[59] U.S. trade policy on ethanol includes an ad valorem tariff of 2.5% as well as an import duty of $0.54 per gallon. The Food, Conservation, and Energy Act of 2008 includes a $0.45-per-gallon Volumetric Ethanol Exercise Tax Credit for ethanol blenders. The Energy Security and Independence Act of 2008 mandated 36 billion gallons of renewable fuel use in United State by 2022, of which 15 billion gallons could come from corn ethanol.

Figure 15: How crude oil prices respond to demand and supply shocks

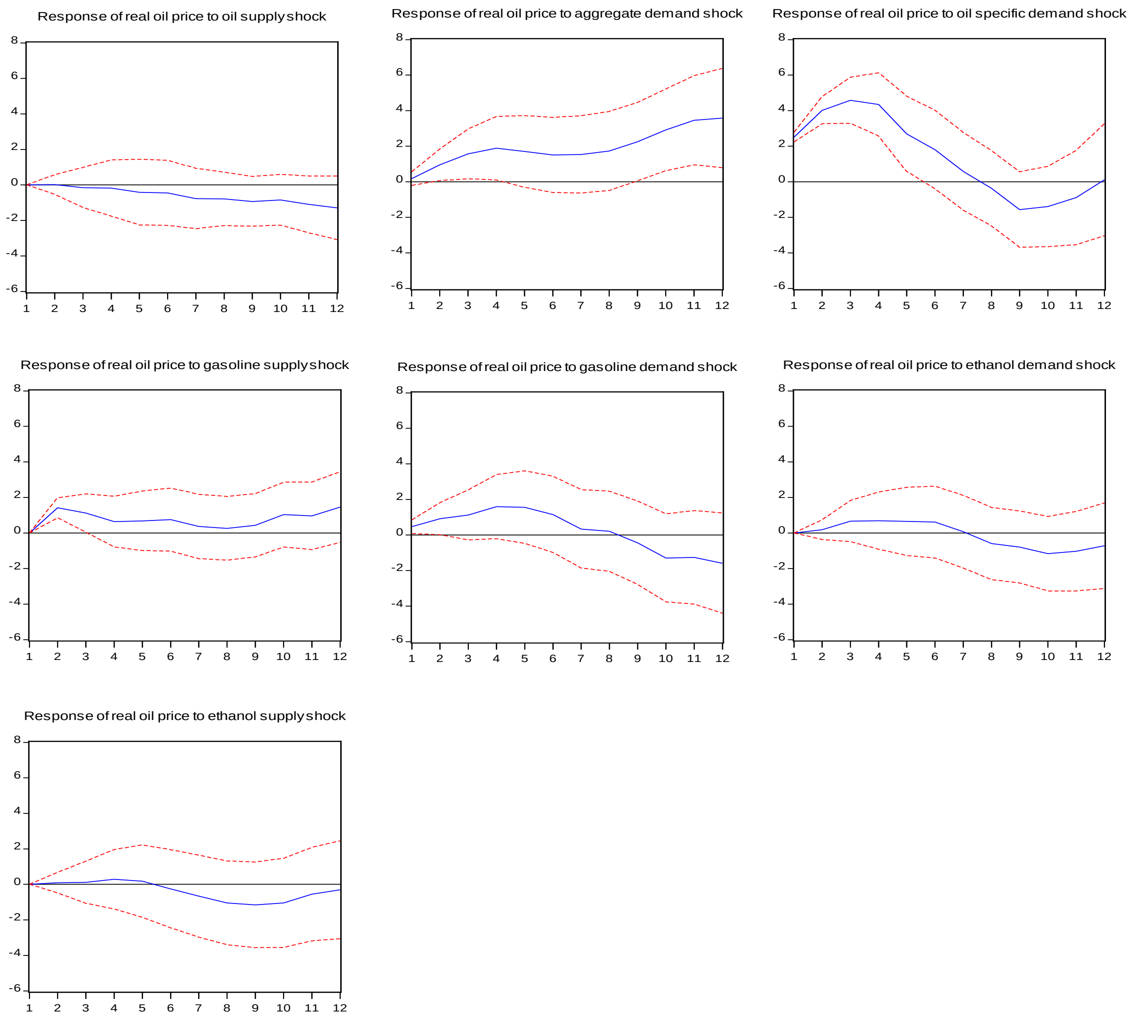

Figure 15 Real oil price response to one standard deviation shocks

Notice first that the impact of shocks on real oil prices rpo_t appear to be much smoother than shocks on the growth rate of oil production $\Delta prodo_t$. This is largely because the oil prices are not presented as a growth rate. For example, recall from the discussion of Figure 14 that a positive oil supply shock will permanently increase $\Delta prodo_t$. Looking at figure 15 we see the effect of the permanent change in $\Delta prodo_t$ is a steady decrease in real oil prices. This is what we would expect to see in any market that experiences a permanent increase in the growth rate of production.

Real oil price rpo_t appears to be more sensitive to shocks than the growth rate of oil production $\Delta prodo_t$. An aggregate demand shock causes a persistent increase in rpo_t. Responses are highly statistically significant for months 2 to 4 and months 9 to 12.[60] An unanticipated increase in oil market specific demand causes an immediate, sharp increase in rpo_t followed by a nearly identical drop in oil price. This result is consistent with the well-documented inelastic short-run demand for oil.[61] Political or environmental events may cause hording of oil (and gas) in the short-run, but this hording will likely be followed by a subsequent drop in demand as consumers use up their reserves. This would lower prices. These results are consistent with Killian (2009, 2010)'s findings, that is, the crude oil price responds more to demand than supply.

The oil price has a significant positive response to U.S. gasoline supply disruptions in month 2. One possible explanation for this is that gasoline supply disruptions will cause commercial inventory to decrease (because of the inelastic gasoline consumption) leading to a higher oil price. This contradicts Killian 2010 who finds that U.S. gasoline supply

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[60] If all data series are stationary, the responses to shocks will finally die out. Here we observe a permanent increase of oil price responding to aggregate demand increase, which indicates that the transformed data we use are not all stationary. The issue of whether the variables in a VAR need to be stationary exists. Sims (1980) and others, such as Doan (1992), recommend against differencing even if the variables contain a unit root. They argue the goal of VAR analysis is to determine the interrelationships among the variables, not the parameter estimates. The main argument against differencing is that it throws away information concerning the comovements in the data. Similarly, it is argued that the data need not be detrended. In a VAR, a trending variable will be well approximated by a unit root plus drift.

[61] See James Hamilton, 2009, “Understanding crude oil prices”.

disruptions reduce the demand for oil and thus reduces the price of oil. The positive oil price response to negative U.S. gasoline supply in month 2 remains even when we used lags of 5 and 10. 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. The gasoline demand shock effect on rpo_t follows a similar pattern as that of the oil specific demand shock, which we assume is for the same reason.

An unanticipated U.S. ethanol demand expansion causes real oil price to increase initially and then decrease after 6 months, but the responses are statistically insignificant over all horizons. A U.S. ethanol supply expansion may have a small negative impact on real oil price after six months. The negative sign is probable because ethanol and gasoline are substitutes.

Figure 16: How U.S. gasoline prices respond to demand and supply shocks

Real gasoline and crude oil price responses to oil market shocks are nearly identical. This is because the gasoline price is largely determined by oil prices. Both gasoline supply disruptions and gasoline demand increases appear to cause gasoline prices to increase.

Ethanol shocks' effects on gasoline prices are consistent and significant. The negative responses of real gasoline price to an unanticipated ethanol demand expansion are statistically significant from month 8 to 10. Negative responses of real gasoline price to ethanol supply shocks are statistically significant for month 8 and 9. Ethanol is a substitute for gasoline; therefore, ethanol either reduces the demand for gasoline or increases the supply of total motor fuel.[62] All else equal, a drop in demand or an increase in supply will bring down the price for gasoline. These results are consistent with the findings of Du and Hayes (2009).

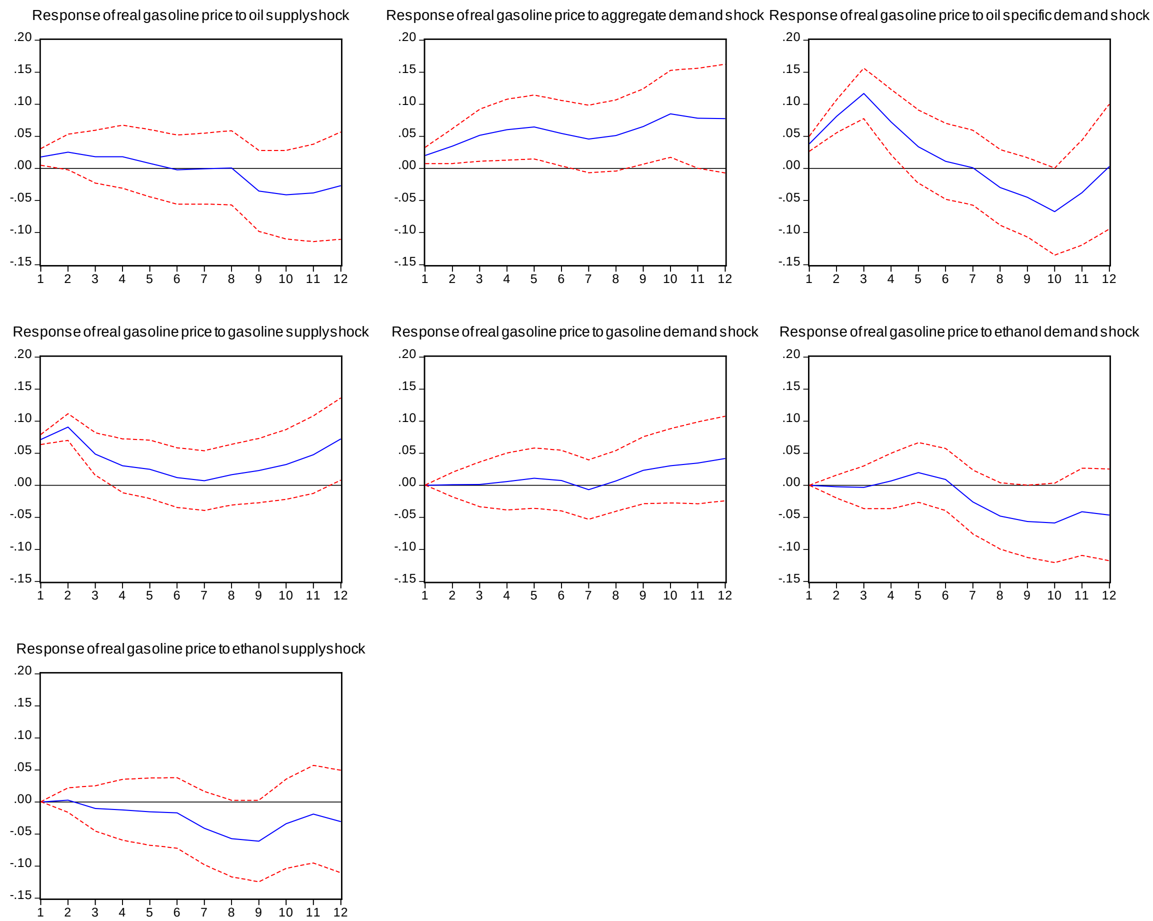

Figure 16 Real gasoline price response to one standard deviation shocks

[62] Only around 35% of the fuel derived from crude oil is used for gasoline. The rest is used for other fuels that do not compete for ethanol such as diesel and jet fuel. The proportion is not flexible making it difficult for gasoline producers to reduce the supply of gasoline without also reducing the supply of other refined products of crude oil.

Figure 17: How U.S. gasoline consumption responds to demand and supply shocks

Notice first how the smooth and flowing responses to shocks in Figures 15 and 16 contrast with the zigzag patterns in Figures 14 and 17. This is largely because of the choice of transformation for the variables of interest. Both crude oil production $\Delta prodo_t$ in Figure 14 and U.S. gasoline consumption $\Delta consg_t$ in Figure 17 are measured as a growth rate. Real oil and gasoline price presented in Figures 15 and 16 are given as a level.

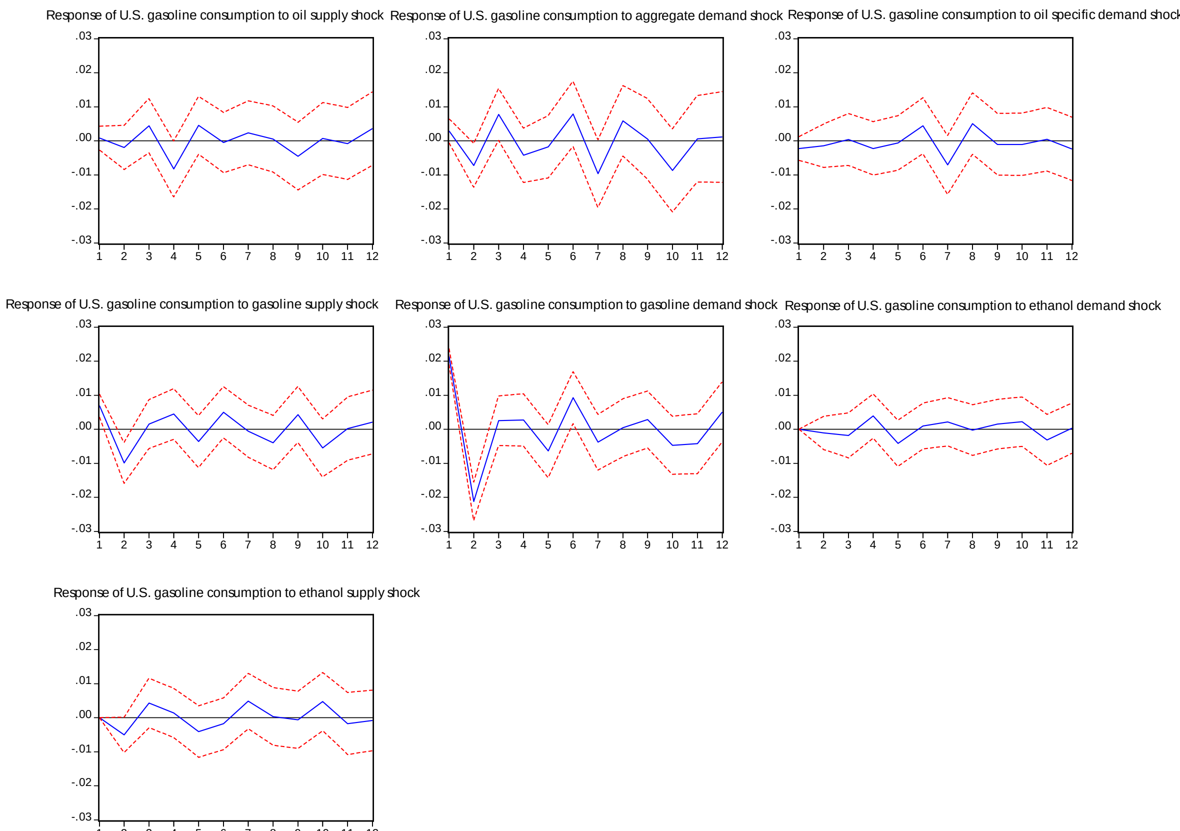

Figure 17 U.S. gasoline consumption response to one standard deviation shocks

Also notice that the aggregate impact of all shocks on the rate of U.S. gasoline consumption over the 12 month period is near zero.[63] This result is consistent with the well-documented short-run inelastic demand for U.S. gasoline.[64] Any decrease (increase) in the rate of consumption is almost always immediately followed by an opposite response the following month. For example, the response of $\Delta consg_t$ to an oil supply shock shows an obvious but modest increase, followed by a large drop significant at the 10% level, followed by another moderate increase, the net effect on $\Delta consg_t$ being at or near zero.

The gasoline supply disruption shows an immediate significant increase in gasoline consumption followed by a significant drop. These responses are consistent with what happened after Hurricane Katrina in 2005. Fuel users ran to the gas station to fill up their tanks right away, which lead to more contemporaneous demand for gasoline and less demand the following month. We also observe a statistically significant instantaneous increase and a statistically significant subsequent drop in gasoline consumption responding to a gasoline demand shock.

We hypothesize in the discussion of Figure 14 that oil production responds to ethanol demand because ethanol demand is driven almost entirely by government legislation. The growth rate of U.S. gasoline consumption, however, does not appear to respond to ethanol demand shocks. This is possibly because the mixed effect of an ethanol demand increase on gasoline consumption. On one hand, as a substitute, ethanol reduces the gasoline demand; on the other hand, ethanol also brings down U.S. gasoline price and thus increases the demand for gasoline.

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[63] The sum of the mean effect (blue line) is always near zero for each of the seven shocks. In other words, the rate of gasoline consumption is rarely (if ever) permanently affected by any of the seven shocks.

[64] See James Hamilton (2009), “Understanding crude oil prices”.

Figure 18: How ethanol prices respond to demand and supply shocks

The real price of ethanol rpe_t does not seem to respond to global crude oil production shocks. Shocks to aggregate demand do have a statistically significant impact on ethanol price but only after 10 months. An unanticipated increase in aggregate demand causes rpe_t to increase with a delay of 6 months, but the responses are statistically significant for months 10 and 11. Real ethanol price is negatively affected by a positive oil specific demand shock. This response is statistically significant for months 1, 10 and 11.

Not surprisingly, a gasoline supply disruption increases real ethanol price. The subsequent increase in the price of gasoline caused by the shock makes ethanol a more attractive substitute. Positive shocks to gasoline demand do not impact ethanol price. As expected, both a positive ethanol demand shock and a negative ethanol supply shock will increase ethanol price.

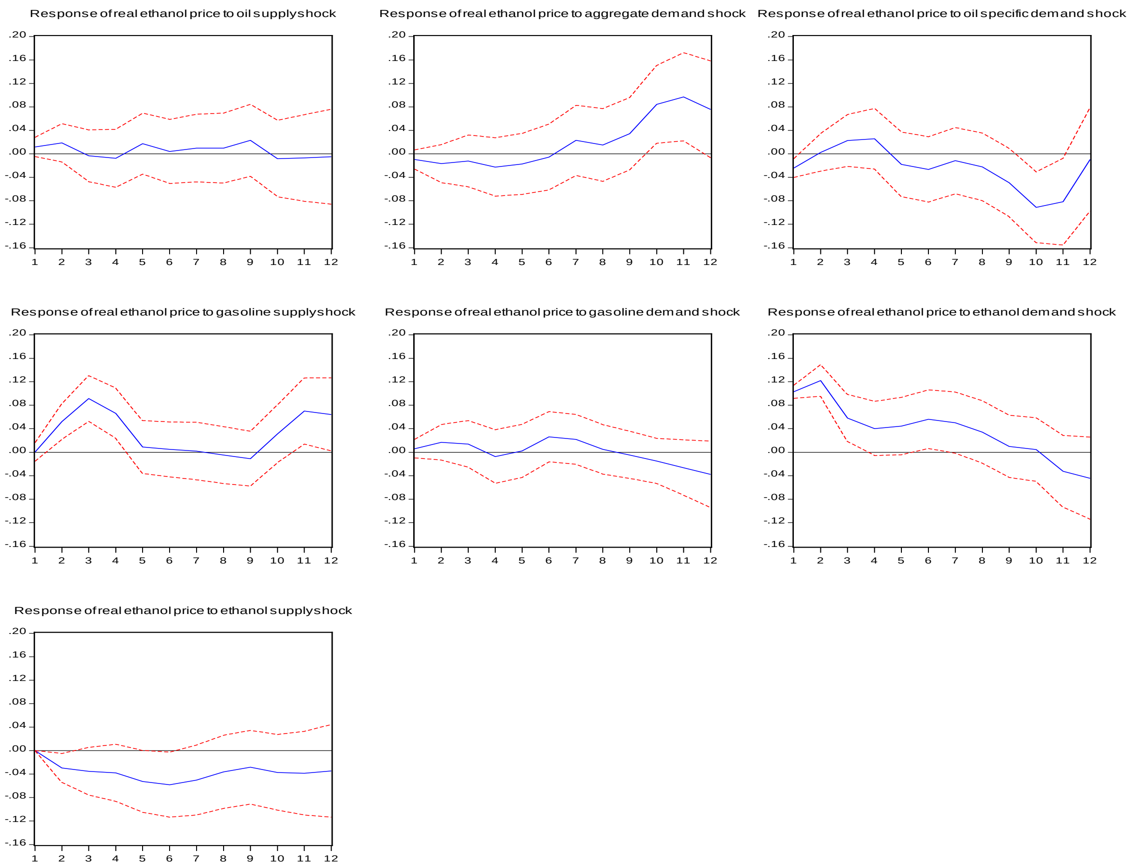

Figure 18 Real ethanol price response to one standard deviation shocks

Variance Decomposition Analysis

A natural concern is how much of the variation of prices and quantities can be attributed to each demand and supply shock. This question can be answered by computing forecast error variance decomposition based on the estimated VAR model. Variance decompositions allocate each variable's forecast error variance to the individual shocks. These statistics measure the quantitative effect that the shocks have on the variables. Following Sims (1980), if $E_{t-j}x_t$ is the expected value of x_t based on all information available at time $t-j$, the forecast error is $x_t - E_{t-j}x_t = \sum_{i=0}^{j-1}\theta_i\varepsilon_{t-i}$. Since the information at time $t-j$ includes all ε occurring at or before time $t-j$ and the conditional expectation of future ε is zero because the shocks are serially uncorrelated. The forecast error variances for the individual series are the diagonal elements in the following matrix:

$$E(x_t - E_{t-j}x_t)(x_t - E_{t-j}x_t)' = \sum_{i=0}^{j-1}\theta_i\Sigma_\varepsilon\theta_i' \tag{37}$$

If θ_{ivs} is (v,s) element in θ_i, and σ_s is the standard deviation for disturbance s (s=1,…,n) , the j-steps-ahead forecast variance of the vth variable is calculated as follows:

$$E(x_{vt} - E_{t-j}x_{vt})^2 = \sum_{i=0}^{j-1}\sum_{s=1}^{n}\theta_{ivs}^2\sigma_s^2 \quad v = 1,2,\ldots,n \tag{38}$$

The variance decomposition function (VDF) writes the j-steps-ahead percentage of forecast error variance for variable v attributable to the kth shock:

$$VDF(v,k,j) = \frac{\sum_{i=0}^{j-1}\theta_{ivk}^2\sigma_k^2}{\sum_{i=0}^{j-1}\sum_{s=1}^{n}\theta_{ivs}^2\sigma_s^2} * 100 \tag{39}$$

Standard errors for the variance decompositions are calculated using the Monte Carlo approach of Runkle (1987).

Explaining the variation of real global crude oil price[65]

Table 15 reports the average contribution of each shock to the overall variation in the

[65] These estimates are based on historical averages for the period since 1994. In practice, the relative importance of each shock may be quite different from one historical episode to the next.

real global oil price in percentage terms. The standard errors of average contributions of structural shocks are reported in parentheses. On impact, 94% of the variation in real crude oil price is accounted for by oil-market specific demand shocks with oil supply shocks and aggregate demand shocks accounting for the rest. Gasoline and ethanol market shocks (and disruptions) do not affect real crude oil price within a month, because of our identifying assumptions. In the long run (5 years) the variation explained by oil-market specific demand shocks drop. Our results suggest that fluctuations in crude oil price are mainly driven by demand, instead of supply. This result is consistent with Killian (2009). Our results also show that in the long run, with about a 90% confidence level the importance of ethanol demand shocks in explaining for the fluctuation of global oil prices are positive.

Horizon	Oil Supply Shock	Aggregate Demand Shock	Oil-Specific Demand Shock	Gasoline Supply Shock	Gasoline Demand Shock	Ethanol Demand Shock	Ethanol Supply Shock
1	5.34	0.32	94.34	0	0	0	0
	(3.53)	(1.10)	(3.56)	0.00	0.00	0.00	0.00
2	5.88	3.43	82.54	7.98	0.04	0.14	0
	(4.66)	(3.15)	(5.88)	(2.88)	(0.39)	(0.47)	(0.34)
3	5.67	6.39	80.31	6.97	0.04	0.61	0.01
	(5.48)	(4.81)	(7.64)	(3.61)	(0.79)	(1.55)	(0.86)
6	8.71	11.49	73.53	5.38	0.09	0.63	0.18
	(8.42)	(8.57)	(12.73)	(5.23)	(2.57)	(4.07)	(3.18)
12	9.95	22.86	47.78	5.93	0.44	8.06	4.99
	(7.81)	(11.75)	(11.74)	(5.61)	(3.88)	(7.13)	(7.45)
60	15.83	15	28.54	12.61	11.71	13.23	3.09
	(8.34)	(10.66)	(16.27)	(6.16)	(9.05)	(6.76)	(10.17)

Table 15 Percent contribution of each shock to the variability of real crude oil price

Explaining the variation of real U.S. retail gasoline price

Table 16 reports the average contribution of each shock to the overall variation in the real U.S. retail gasoline price in percentage terms. On impact, 70% of the variation in real U.S. retail gasoline price is accounted for by gasoline supply shocks exemplified by refinery shocks. Oil-market specific demand shocks account for an additional 20%, aggregate demand shocks account for 5.6%, and oil supply shocks account for 4.4%. In the long run, the importance of gasoline supply shock drops to 16% while the importance of other shocks increases. Again, our results show that demand shocks from the oil market play the most important role in explaining variation in gasoline price. Long run ethanol demand shocks account for 13% of the variation in gasoline prices. The variation explained by ethanol demand shocks is statistically significant from zero.

Horizon	Oil Supply Shock	Aggregate Demand Shock	Oil-Specific Demand Shock	Gasoline Supply Shock	Gasoline Demand Shock	Ethanol Demand Shock	Ethanol Supply Shock
1	4.4	5.59	20.17	69.84	0	0	0
	(2.97)	(3.14)	(5.42)	(5.81)	0.00	0.00	0.00
2	4.05	6.74	33.55	55.6	0	0.02	0.03
	(3.81)	(4.15)	(7.16)	(7.11)	(0.61)	(0.65)	(0.44)
3	3.02	9.94	50.32	36.42	0	0.04	0.26
	(4.00)	(5.92)	(8.78)	(7.82)	(1.09)	(1.51)	(1.26)
6	2.66	23.59	44.16	27.19	0.32	0.83	1.24
	(5.45)	(11.38)	(11.10)	(8.23)	(2.56)	(4.39)	(3.88)
12	4.71	29.98	25.62	18.44	3.24	9.73	8.29
	(5.92)	(11.77)	(9.20)	(6.25)	(4.57)	(6.96)	(7.07)
60	13.31	15.29	23.04	16.44	12.94	14.59	4.39
	(8.15)	(10.76)	(16.74)	(6.21)	(9.52)	(6.48)	(10.20)

Table 16 Percent contribution of each shock to the variability of real gasoline price

Explaining the variation of real U.S. ethanol price

Table 17 shows the average contribution of each shock to the total variation in the real price of ethanol in percentage terms. On impact, that variation is dominated by ethanol demand shocks which account for 87.5% and oil- specific demand shocks which account for 8.4%. In the long run, oil supply shocks account for 10% of the fluctuation of real ethanol price, aggregate demand shocks account for 11.7%, oil-specific demand shocks account for 28%, gasoline supply shocks account for 11%, gasoline demand shocks account for 14.3%, ethanol demand shocks account for 16%, and ethanol supply shocks account for 9%. However, variation in ethanol price explained by oil supply shocks, aggregate demand shocks, gasoline supply shocks and ethanol supply shocks are not statistically significant. These results show that in the long run, the price of ethanol is mainly determined by oil market supply and demand shocks.[66]

[66] This empirical result must also be coupled with the fact that the ethanol industry would not exist without support from government legislation. As long as government support continues, the primary determinant of ethanol price has been fluctuations in the oil market.

Horizon	Oil Supply Shock	Aggregate Demand Shock	Oil-Specific Demand Shock	Gasoline Supply Shock	Gasoline Demand Shock	Ethanol Demand Shock	Ethanol Supply Shock
1	1.5	0.61	8.36	0.25	1.82	87.47	0
	(1.93)	(1.19)	(3.97)	(0.92)	(1.81)	(4.49)	0.00
2	2.4	1.18	3.35	5.56	2.58	84.01	0.91
	(3.21)	(2.64)	(2.20)	(3.90)	(3.43)	(6.01)	(1.49)
3	1.71	1.06	3.35	19.24	4.15	68.66	1.82
	(3.01)	(2.98)	(3.12)	(7.67)	(4.71)	(8.67)	(3.19)
6	1.62	1.01	3.82	18.03	8.28	48.99	18.25
	(4.19)	(3.85)	(4.09)	(7.44)	(6.28)	(8.91)	(8.61)
12	1.32	13.81	12.38	17.26	5.71	30.99	18.54
	(4.41)	(10.02)	(5.74)	(6.34)	(4.99)	(6.41)	(9.51)
60	9.92	11.74	28.01	10.98	14.29	15.65	9.42
	(7.91)	(10.62)	(16.63)	(6.47)	(9.22)	(7.32)	(9.30)

Table 17 Percent contribution of each shock to the variability of real ethanol price

Conclusions

The purpose of this paper is to examine whether ethanol has begun to have an impact on either the global crude oil market or U.S. gasoline market. To do so we develop a structural VAR model of these three markets to examine their interrelationships. We find statistically significant responses of global oil production to ethanol demand shocks. Shocks to ethanol demand are mainly driven by government policies; therefore this result suggests that oil producers respond to the government support for renewable fuel. However, the impact is not one direction but instead produces a shock wave with significant peaks and troughs at the 10% level.[67] We do not find statistically significant impact of shocks to ethanol

[67] Discussed in detail in the results section.

market on crude oil price, which might suggest that ethanol is not yet a big enough player in the transportation fuel market to have a statistically significant impact on crude oil price. Our results also show that ethanol demand and supply increases cause statistically significant drops in real gasoline price, but do not affect the growth rate of U.S. gasoline consumption significantly.

As renewable fuel production keeps on growing worldwide, it would be very interesting to reexamine the interrelationships among these markets after a few years. Renewable fuel production has linked agriculture and energy markets together. An interesting extension of the paper is to include U.S. corn market to examine the interrelationships among global oil, gasoline and corn markets. Because corn production data is only available annually, we do not directly model U.S. corn market for this essay, instead capture the impact of corn market through ethanol supply shock originated from a change of corn price.

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