

Lihong Lu McPhail (USA)

A structural VAR approach to disentangle RIN prices

Abstract

The Renewable Fuel Standard (RFS) of the Energy Independence and Security Act of 2007 mandated 36 billion gallons of renewable fuel use annually by 2022. Within the RFS, the system of Renewable Identification Numbers (RINs) was created by the Environmental Protection Agency (EPA) to facilitate compliance with the mandate. Understanding the RIN prices can provide key insights regarding the impact of RFS2 on biofuels markets and their resulting impact on energy, agriculture, and welfare. Despite the importance of the RIN market, prior research is limited to using partial equilibrium models to predict RIN supply, demand, and prices. Utilizing a newly available dataset on actual RIN prices, the author applies a structural Vector Auto Regression (VAR) model to examine the dynamics of gasoline, corn, and conventional ethanol RIN prices. The author finds that during the sample period (2009:01–2011:03) conventional ethanol RIN prices are mainly driven by gasoline price shocks instead of corn price shocks. The author also finds that a positive conventional ethanol RIN price shock leads to a statistically significant decline in corn price while its impact on gasoline price is not significant.

Keywords: RINs, biofuel, RFS, structural VAR, energy policy.

JEL Classification: Q10, Q20, Q40, C10.

Introduction

The production of biofuels, particularly ethanol, has grown significantly in the past decade in the US, driven by rising crude oil prices, policies aimed at energy independence, and environmental concerns. An important element of US biofuel policy is the Renewable Fuel Standard (RFS). The RFS originated with the Energy Policy Act of 2005 (EPAct), but the Energy Independence and Security Act (EISA) of 2007 increased the RFS mandate and created sub-mandates for four categories of biofuels, resulting in the current RFS legislation, hereafter referred to as RFS2. Since the origination of the RFS, corn-based ethanol production increased from 3.9 billion gallons in 2005 to 13.2 billion gallons in 2010 in the US (Renewable Fuel Association). Meanwhile, the share of corn used for ethanol increased from less than 15% for the 2005/06 marketing year to about 40% for 2010/2011 (USDA Economic Research Service). If the RFS2 which mandated 36 billion gallons of renewable fuel use annually in 2022 is met, ethanol use will comprise about 25% of gasoline consumption in the coming years. This will have important consequences for agriculture and energy commodity markets.

The system for Renewable Identification Numbers (RINs) was developed by the US Environmental Protection Agency (EPA) to ensure compliance with the RFS mandates. The RINs are used by obligated parties to demonstrate compliance with their pro rata share of a particular year's mandate. The RINs are commonly referred to as the currency of compliance. Understanding the RIN market is critical for understanding the impact of the RFS mandates on agriculture, energy, and welfare.

To date, research on RINs has focused on simulating RIN prices, supply, demand, and stocks. Partial equilibrium simulation models of the US agriculture, biofuel, and RIN markets have been utilized to address this issue including Thompson, Meyer and Westhoff (2008a, 2008b, 2009a, 2009b, 2010), Babcock (2009a, 2009b), and Donahue, Meyer, and Thompson (2010). While these studies shine considerable light on the nature of the RIN market, their results are sensitive to the choice of the model used to conduct the study, specifically, assumptions about elasticities.

More generally, a broader stand of research has applied time series analysis to investigate the complex relationship between agriculture and energy prices. Structural Vector Auto Regression (VAR) models have been increasingly employed to investigate issues confronting energy and agricultural markets. Compared to reduced form VARs, structural VAR models enable us to decompose variables into economic shocks and provide meaningful interpretation of the results. Killian (2009) proposed a structural VAR model of the global crude oil market, and decomposed the real price of crude oil into three components: crude oil supply shocks, shocks to aggregate demand for all industrial commodities, and demand shocks specific to oil. To examine evolution of US retail gasoline prices, Killian (2010) developed a structural VAR model of the global crude oil market and the US retail gasoline market. McPhail (2011) extended Killian (2010) to include the US ethanol market and found that a policy-driven ethanol demand expansion causes a decline in crude oil and US gasoline prices.

For this study, we develop a structural VAR model of US gasoline, corn, and conventional ethanol RIN markets to examine how RIN prices respond to corn and gasoline price shocks and whether corn and gasoline prices respond to conventional ethanol RIN price shocks.

© Lihong Lu McPhail, 2012.

The views expressed are those of the author and should not be attributed to the Economic Research Service or US Department of Agriculture.

We attempt to gain a rigorous empirical understanding of RIN prices by examining the dynamics of gasoline, corn, and conventional ethanol RIN prices. We utilize newly available daily conventional ethanol RIN price data from Hart Energy Ethanol and Biofuels News based on national survey of blenders and brokers.

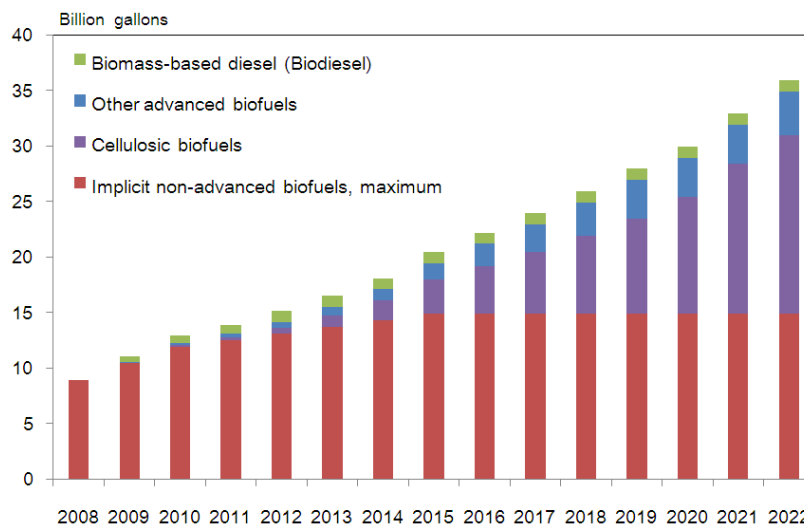
We find that a positive gasoline price shock causes conventional ethanol RIN price to decrease, while a positive corn price shock lowers conventional ethanol RIN price. We also find that during the sample period (2009:01–2011:03) conventional ethanol RIN price variation is mainly driven by gasoline price shocks, while corn price shocks account for very little of RIN price variation. Our results also show that a positive conventional ethanol RIN price shock leads to a statistically significant decline in corn price while its impact on gasoline price is not statistically significant.

The remainder of the paper is organized as follows. The next section provides background information on the RIN market. Section 2 lays out the conceptual framework to understand RIN prices. Section 3

describes the empirical strategy. Section 4 describes the data. Section 5 reports impulse response analysis. Section 6 reports variance decomposition analysis. The last section concludes.

1. Background

The RFS2 of the EISA (2007) created sub-mandates for four types of biofuels: biomass-based diesel (hereafter referred to as biodiesel), cellulosic biofuels, advanced biofuels, and total renewable fuel. The four mandates are defined by eligible feedstock types, production process, and lifecycle greenhouse gas emission reduction targets. The four mandates also have a hierarchy. For example, the total RFS for 2011 is 13.95 billion gallons, of which 12.6 billion gallons are the unrestricted portion of the mandate (indicated by implicit non-advanced biofuels, maximum, in Figure 1) which conventional ethanol is qualified to meet, and the rest has to come from advanced biofuels. For the advanced biofuels RFS, EISA specifies the required volumes for biodiesel and cellulosic biofuels, while the rest can be met by other advanced biofuels that satisfy the feedstock and greenhouse gas reduction requirement.



Source: EISA (2007).

Note: Biodiesel RFS was specified through 2012. Subsequent years “shall not be less than the applicable volume for calendar year 2012.”

Fig. 1. Renewable fuel standard by type

On November 30th of each year, the EPA calculates annual percentage standard by dividing the volume of renewable fuel required by the EISA for the following year by the volume of gasoline and diesel projected to be consumed in that year according to the Energy Information Administration (EIA). In 2011, the percentage standard for cellulosic biofuel is 0.003%, the percentage standard for biodiesel for 2011 is 0.69%, the percentage standard for advanced biofuel is 0.78%, and the percentage standard for renewable fuel is 8.01%¹. Due to four percentage

standards, obligated parties have four renewable volume obligations (RVOs). Each RVO is calculated by each percentage standard times the annual volume of gasoline and diesel is produced or imported.

The obligated parties are any party that produces or imports gasoline and diesel in the 48 states, which also includes blenders that produce gasoline from non-renewable blendstocks². Every year obligated parties are required to meet their RVO through the

¹ <http://www.epa.gov/otaq/fuels/renewablefuels/420f10056.htm>.

² However, there are exceptions for producers and importers who produce or import less than 10,000 gallons per year.

accumulation of RINs. A RIN is a 38-character numeric code that is generated by the producer or importer of renewable fuel representing gallons of renewable fuel produced or imported and assigned to batches of renewable fuel. These RINs must be transferred with renewable fuel as ownership of a volume of renewable fuel is transferred through the distribution system. Once the renewable fuel is ob-

tained by an obligated party or actually blended into a motor vehicle fuel, the RIN can be separated from the volume of renewable fuel and then either used for compliance, held for future compliance, or traded. Figure 2 shows the movements of biofuels and RINs. The system for RINs was developed by the EPA to ensure compliance with the RFS mandates.

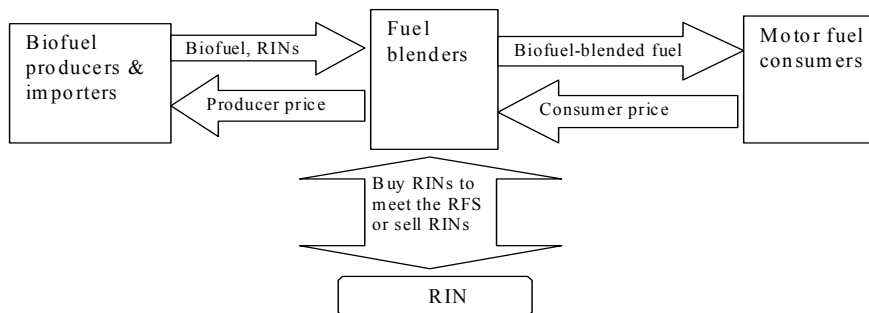


Fig. 2. Movements of biofuels and RINs

If an obligated party has not acquired sufficient RINs to meet its RVOs, then under certain conditions it can carry a deficit into the next year so long as the full deficit and obligation is covered in the next year. If an obligated party acquires more RINs than it needs to meet its RVOs, then it can transfer the excess RINs to another party or retain the excess RINs for compliance with its RVOs in the following year subject to the 20% rollover cap. The rollover cap says that no more than 20 percent of a current year obligation can be satisfied using RINs from previous year. These options reduce their cost of meeting their own RVOs. There are also non-obligated parties who, when registered with the EPA, are also allowed to trade RINs. RINs are valid for compliance purposes for the calendar year in which they are generated, or the following calendar year (within the rollover limit defined above), so a RIN expires if unused after two years.

The RINs are the basic units for compliance for the RFS program, so it is important that parties have confidence when generating and using them. The EPA has developed a new system called the EPA Moderated Transaction System (EMTS) to manage RIN transactions¹. EMTS provides a mechanism for screening RINs and a structured environment for conducting RIN transactions². Parties must first register with EPA. Once registration occurs, parties will have to create an account via EPA's Central Data Exchange (CDX). Once individual accounts are established within EMTS, parties will be able to submit transactions. For example, a renewable fuel producer can electronically submit a volume of re-

newable fuel produced or imported, as well as a number of the RINs generated and assigned. EMTS will automatically screen each batch and either reject the information or allow RINs created in the RIN generator's account. After RINs have entered the system, parties may then trade them. The seller posts a sale of a number of RINs at certain price. Then buyer logs into EMTS and accepts transaction assuming it is correct. Upon acceptance, buyer's RIN account is automatically increased by the number of RINs sold at X price. RIN transactions are required to be verified and certified on a quarterly basis. The RIN price is one of the new information required to be submitted under RFS2³.

As we discussed above, there are at least four types of RINs needed to be generated to meet four RVOs. However, in this paper, we focus on conventional ethanol RINs because of the following. First, the sample on daily biodiesel RIN prices is very short, which limits the validity of our analysis. Second, currently there is no cellulosic biofuel RINs generated⁴. For the 2010 compliance period, the EPA reduced the required volume of cellulosic biofuels from 100 million gallons specified by EISA to 5 million gallons. To compensate for low cellulosic volume, the EPA made cellulosic biofuel waiver credits available to obligated parties for end-of-year compliance at a price of \$1.56 per gallon-RIN⁵. For the 2011 compliance period, the EPA reduced the required volume of cellulosic biofuels from 250 million gallons specified by EISA to 6.6 million gallons. The EPA also made cellulosic biofuel waiver

¹ Under RFS1, parties made various errors in generating and using RINs.
² Starting July 1, 2010, renewable fuel producers and importers, gasoline and diesel refiners, renewable fuel exporters, RIN owners, and any other RFS2 regulated party must use EMTS.

³ Page 14733 of *Federal Register*, Vol. 75, No. 58, Friday, March 26, 2010 / Rules and Regulations.
⁴ <http://www.epa.gov/otaq/fuels/renewablefuels/compliancehelp/rfsdata.htm>.
⁵ "Regulation of Fuels and Fuel Additives: Changes to Renewable Fuel Standard Program; Final Rule", *Federal Register*, Vol. 75, No. 58, Friday, March 26, 2010 / Rules and Regulations.

credits available to obligated parties for end-of-year compliance at a price of \$1.13 per credit¹. These waiver credits are not allowed to be traded or banked for future use, and are only allowed to be used to meet cellulosic biofuel standard for the year that they are offered. Moreover, unlike cellulosic biofuel RINs, waiver credits may not be used to meet either the advanced biofuel standard or the total renewable fuel standard. For more details on the RINs, please refer to McPhail et al. (2012).

2. The conceptual framework

Theoretically, if we assume away rolling over or carrying a deficit, the core value of RIN is the gap between the supply price (P_s) and the demand price (P_d) for biofuel at mandated level of RFS (Figure 3). The supply price is the price needed to allow biofuel producers to cover the cost of producing the mandated quantity indicated by RFS in Figure 3, and the demand price is the price fuel consumers are willing to pay for fuel substitutes. The core value is positive when the mandate is binding (when the RFS mandated level is higher than the quantity Q^* the market would produce and demand), indicated by Figure 3, and zero under non-binding mandate (when the mandated level is lower than or equal to the quantity Q^* market will produce and demand). It is important to note that the supply price (the price producers receive) is equal to the demand price (the price consumers willing to pay) plus the core value of the RIN.

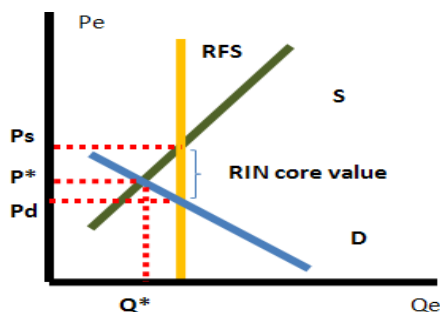


Fig. 3. Biofuels market with a binding mandate

One of the key factors affecting the price of RINs is the price of feedstocks. The price of a feedstock accounts for a large percentage of the biofuel production cost. A surge in feedstock prices will increase the production cost of biofuels and decrease the supply of biofuels. Thus the supply for RINs decreases, and the prices for RINs increase. This case is indicated by upward shift of the supply curve in Figure 4. The opposite is true when feedstock prices decrease. The yield of a feedstock is one of the primary factors affecting the price of the feedstock in the short run. For example, when corn yield is higher than expected,

prices of corn and production cost of conventional ethanol decrease. Thus the supply of both conventional ethanol and associated RINs increases and the prices of conventional ethanol RINs decrease. The opposite is true when corn yields are lower than expected.

The price of gasoline will certainly play a significant role in shaping RIN prices, except in the case that a mandate is completely not binding, the changing gasoline price will not change the prices of associated RINs and the RIN prices will stay near the transaction costs. In most cases, higher gasoline prices lead to a higher willingness to pay for the substitute ethanol (a higher demand price), thus lowering the price for RINs, that is, the gap between the supply price and the demand price. This case is indicated by upward shift of the demand curve in Figure 4. Lower gasoline prices lead to lower willingness to pay for the substitute ethanol, thus increasing the prices for RINs.

Government policies supporting consumption of ethanol also affect RIN prices. The current Volumetric Ethanol Excise Tax Credit (VEETC), 45 cents per gallon tax credits to ethanol blenders, increases blenders' willingness to pay for ethanol, thus lowers the price for RINs. This case is also indicated by upward shift of the demand curve in Figure 4. The VEETC is set to expire on December 31, 2011. Conventional ethanol RIN prices are expected to rise if this tax credit is not renewed.

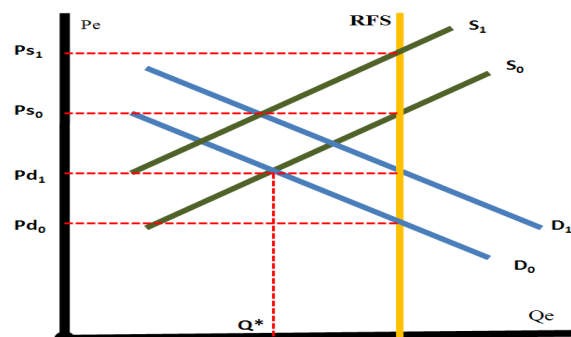


Fig. 4. RIN price change under a binding mandate

It is possible that intermediaries buy biofuels along with RINs from producers and sell RINs to obligated parties. The RIN prices obligated parties pay might be different from the prices producers receive. The difference can be contributed to transaction cost and/or speculative component. Speculators who register with the EPA are allowed to buy and sell RINs. If they anticipate a shortage of RINs next year, they can buy RINs this year and hold and sell them next year. This will potentially reduce the number of RINs available for this year's compliance and increase RIN prices.

3. Empirical strategy

Recent literature suggests that large scale ethanol production has led to greater integration between corn and gasoline markets (Du and McPhail, 2012). There-

¹ "Regulation of Fuels and Fuel Additives: 2011 Renewable Fuel Standards; Final Rule", *Federal Register*, Vol. 75, No. 236, Thursday, December 9, 2010 / Rules and Regulations.

fore, we use a simultaneous-equation system to examine the dynamics of gasoline, corn, and conventional ethanol RIN prices. Based on the conceptual framework discussed above, we develop a three-variable structural VAR of these three markets¹. The three daily variables are defined as a vector $x_t = pg_t, pc_t, prin_t$, where pg_t is the price of gasoline, pc_t is the price of corn, $prin_t$ is the price of conventional ethanol RIN². Our SVAR model provides estimates of the impacts that corn and gasoline market shocks have on the markets of conventional ethanol RINs.

The structural VAR representation is:

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

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

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

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

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

where E is the unconditional expectation operator, and Σ_ε is the covariance matrix for the shocks. As there are 6 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 $e_t = A_0^{-1} \varepsilon_t$:

$$e_t \equiv \begin{pmatrix} e_t^{pg} \\ e_t^{pc} \\ e_t^{prin} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{pg_shock} \\ \varepsilon_t^{pc_shock} \\ \varepsilon_t^{prin_shock} \end{pmatrix}. \tag{4}$$

The recursive structure of the structural VAR model is achieved by assuming that not all variables of interest will respond to shocks contemporaneously. All of these assumptions can be read from the previous equation $e_t = A_0^{-1} \varepsilon_t$. For example, we assume that it takes, at least, one day for gasoline prices to respond shocks in corn and conventional ethanol RIN markets. Similarly, we assume that it takes at least one day for corn prices to respond shocks in conventional ethanol RIN market. Beyond these restrictions on the contemporaneous feedback at daily frequency, the model allows all feedback among all variables.

4. Data

Figure 5 shows the daily prices of current year conventional ethanol RINs, corn, and gasoline. The sample period is from 2009:01 to 2011:03. Corn prices are the daily settlement prices of the nearest to maturity contracts traded in the Chicago Mercantile Exchange (CME), and gasoline prices are the daily settlement prices of the nearest to maturity contracts traded in the New York Mercantile Exchange (NYMEX) for RBOB gasoline. Daily current year conventional ethanol RIN prices are collected from Hart Energy Ethanol and Biofuels News based on national survey of blenders and brokers. The advantage of using level is that the estimates remain consistent whether the prices are integrated or not. Furthermore, standard inference on impulse responses, in levels, will remain asymptotically valid. Inference also is asymptotically valid to the possible presence of cointegration among these prices (see, e.g., Sims, Stock and Watson, 1990; Lütkepohl and Reimers, 1992). However, estimates would be inconsistent if cointegration and/or unit root are falsely imposed.

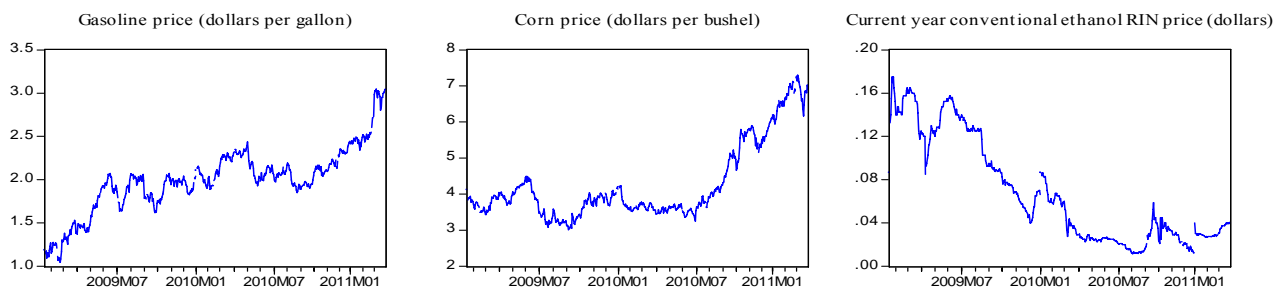


Fig. 5. Daily gasoline, corn, and current year ethanol RIN prices

¹ Because VEETC was in place throughout the sample period, we do not include it in our model.

² EPA permits previous RINs to be rolled over for next year's compliance, so extra RINs from last year could be counted toward meeting current year RFS subject to a 20% cap on the amount of an obligated party's current year RVO that could be met using previous RINs. RIN prices for previous year and current year are available during current year.

Block Exogeneity Wald test, a multivariate generalization of the Granger causality test, was performed to detect whether to incorporate an additional variable into a VAR. In our case, the test is whether lags of one price Granger cause any other

price in the system. Our results reported in Table 1 show that lags of every price Granger cause the other price in the system, except that lags of conventional ethanol price do not Granger cause the gasoline price.

Table 1. Block Exogeneity Wald test results

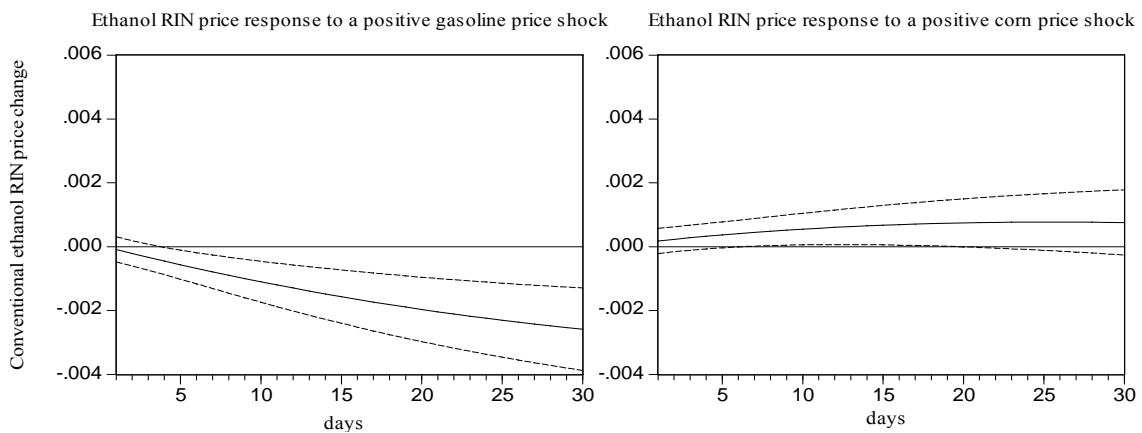
Dependent variable: Gasoline prices		
Excluded	Chi-sq	Prob.
Corn prices	8.417	0.004
Ethanol RIN prices	0.000	0.985
All	8.478	0.014
Dependent variable: Corn prices		
Excluded	Chi-sq	Prob.
Gasoline prices	3.190	0.074
Ethanol RIN prices	6.401	0.011
All	6.444	0.040
Dependent variable: Ethanol RIN prices		
Excluded	Chi-sq	Prob.
Gasoline prices	13.785	0.000
Corn prices	6.156	0.013
All	14.204	0.001

We utilized sequential modified Log Likelihood Ratio test (LR), Akaike Information Criterion (AIC), and Schwartz Information Criterion (SIC) to choose number of lags to include in a SVAR model. Estimation of the model with alternative lags yielded robust and qualitatively similar results. For reporting the results, a 1 day lag specification is 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.

5. Impulse response analysis

To examine distinct dynamic responses of conventional ethanol RIN prices to corn and gasoline price shocks, we use impulse response analysis. Figure 6

presents the responses of conventional ethanol RIN prices to corn and gasoline price shocks from impact to day 30. As expected, a positive gasoline price shock causes conventional ethanol RIN price to decrease, and the negative responses are statistically significant from day 3 to 30. When gasoline price increases, the willingness to pay for ethanol as a gasoline substitute increases. As we discussed before, the price of conventional ethanol RIN is the gap between the supply price and the demand price, the conventional RIN price drops when the demand price for ethanol increases. A positive corn price shock causes conventional ethanol RIN price to increase, and these positive responses are statistically significant from day 5 to 20. Increased corn price led to higher production cost of ethanol, thus increasing conventional ethanol RIN prices.

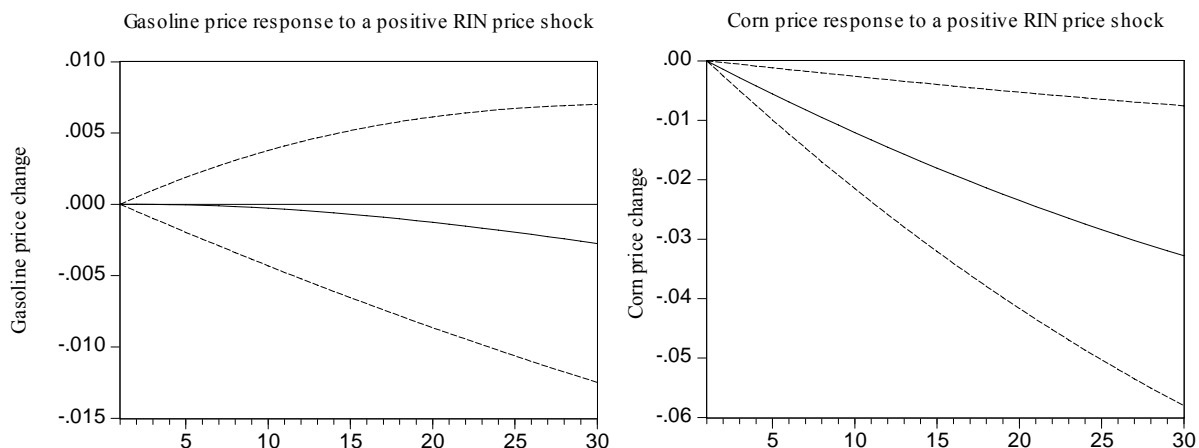


Notes: Solid line represents the mean impact. Dotted lines represent two standard deviation impacts from the mean. Standard errors for the impulse responses are calculated using the Monte Carlo approach of Runkle (1987).

Fig. 6. Conventional ethanol RIN price responses to positive gasoline and corn price shocks

Figure 7 presents the responses of gasoline and corn prices to a positive conventional ethanol RIN price shock from impact to day 30. The response of gasoline prices to a positive RIN price shock is not statistically significant over the horizon. However, a positive conventional ethanol RIN price shock causes corn price to

drop. Our conceptual framework suggests that the ethanol price (the supply price) is equal to the demand price plus the RIN value. Thus high RIN price leads to high ethanol price, which leads to lower demand for ethanol, which leads to lower demand for corn from ethanol, which leads to lower corn price.



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

Fig. 7. Gasoline and corn price responses to a positive conventional ethanol RIN price shock

6. Variance decomposition analysis

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

Table 2 reports the percentage of the variance of the error made in forecasting conventional ethanol RIN prices due to a specific shock at a specific time horizon. These estimates show the relative importance of each shock in explaining the fluctuation of conven-

tional ethanol RIN prices. It is shown that in 30 days gasoline price shocks account for 17.68% of conventional ethanol RIN price variation while corn price shocks account for less than 3%. In 60 days the importance of gasoline price shocks in explaining conventional ethanol RIN price variation increases to about 42% while the importance of corn price shocks stays the same. In 90 days more than 54% of conventional ethanol RIN price variation can be attributed to gasoline price shocks. These results show that during the sample period conventional ethanol RIN price variation is mainly driven by gasoline price shocks, while the corn price shocks account for very little of RIN price variation.

Table 2. Percent contribution of each shock to the variability of conventional ethanol RIN price

Days	Gasoline price shock	Corn price shock	Ethanol RIN price shock
1	0.04	0.15***	99.81***
30	17.68**	2.47	79.85***
60	41.67***	2.27	56.06***
90	54.73***	2.11	43.16***

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. Standard errors for the variance decompositions are calculated using the Monte Carlo approach of Runkle (1987).

Table 3 shows the percentage of the variance of the error made in forecasting gasoline prices due to a specific shock at a specific time horizon. It is shown that conventional ethanol RIN price shocks’ importance in explaining gasoline price variation is not statistically significant. However, in 90 days, corn price shocks explain about more than 28% of gasoline price varia-

tion. This result is consistent with the recent literature on the strengthening relationship between corn and gasoline markets due to large scale biofuel production (Du and McPhail, 2011). The increased use of corn as an ethanol feedstock has exposed corn market to gasoline price shocks based on ethanol’ role as a gasoline substitute.

Table 3. Percent contribution of each shock to the variability of gasoline price

Days	Gasoline price shock	Corn price shock	Ethanol RIN price shock
1	100***	0	0
30	94.47**	5.41*	0.12
60	80.64***	17.86**	1.5
90	66.3***	28.86**	4.84

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. Standard errors for the variance decompositions are calculated using the Monte Carlo approach of Runkle (1987).

Table 4 shows the percentage of the variance of the error made in forecasting corn prices due to a specific shock at a specific time horizon. It is shown that in 90 days, conventional ethanol RIN price shocks explain about 20% of corn price variation.

This suggests that the evolution of corn prices now also depends on conventional ethanol RIN market. This provides empirical evidence that biofuel mandates contribute to agricultural commodity market volatility.

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

Days	Gasoline price shock	Corn price shock	Ethanol RIN price shock
1	7.78***	92.22***	0
30	2.53	92.99***	4.48
60	1.63	85.68***	12.69
90	2.49	77.66	19.85*

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels. Standard errors for the variance decompositions are calculated using the Monte Carlo approach of Runkle (1987).

Conclusions

We apply a structural VAR model to examine the impact of gasoline and corn price shocks on conventional ethanol RIN market, as well as the responses of gasoline and corn prices to a positive conventional ethanol RIN price shock. One key finding is that a positive gasoline price shock leads to a statistically significant decline in conventional ethanol RIN price, while a positive corn price shock leads to a statistically significant increase in conventional ethanol RIN price. We also find that a positive conventional ethanol RIN price shock leads to a statistically significant decline in corn price while its impact on gasoline price is not statistically significant.

Understanding RIN prices is critical to understanding the impact of RFS on commodity markets. Debate on whether biofuel policies contribute to rising

commodity prices might be better informed by a good understanding of how RFS works through RIN system. Our finding that conventional ethanol RIN price shocks play an important role in explaining corn price variation provides empirical evidence that biofuel mandates contribute to agricultural commodity market volatility.

Understanding RIN prices is also critical to understanding the welfare impact of biofuel policy. The total core cost of meeting the RFS is equal to the mandated quantity times the per-unit cost of meeting the RFS. The price of RIN best measures the per-unit cost of meeting the RFS. Therefore a high RIN price indicates high cost of meeting the RFS. Our results also provide empirical evidence that the cost of meeting the RFS increases when corn prices increase or gasoline prices decrease.

References

1. Babcock, B.A. (2009a). "Renewable Identification Numbers and the Renewable Fuels Standard: How They Support Corn and Soybean Prices", *Iowa Ag. Review*, Vol. 15, No. 1.
2. Babcock, B.A. (2009b). "Intricacies of Meeting the Renewable Fuels Standard", *Iowa Ag. Review*, Vol. 15, No. 2.
3. Donahue, D.J., Seth Meyer, and Wyatt Thompson (2010). "RIN Risks: Using Supply and Demand Behavior to Assess Risk in the Markets for Renewable Identification Numbers used for Renewable Fuel Standard Compliance", Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. Available at: <http://www.farmdoc.illinois.edu/nccc134>.
4. Du, X., and L.L. McPhail (2012). Inside the Black Box: Price Linkage and Transmission between Energy and Agricultural Markets, *The Energy Journal*, 33 (2), pp. 171-194.
5. Killian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market, *American Economic Review*, 99 (3), pp. 1053-1069.
6. Killian, L. (2010). Explaining fluctuations in gasoline prices: a joint model of the global crude oil market and the U.S. retail gasoline market, *Energy Journal*, 31 (2), pp. 87-112.

7. Lütkepohl, H., Reimers, H.E. (1992). Impulse Response Analysis of Cointegrated Systems, *Journal of Economic Dynamics and Control*, 16, pp. 53-78.
8. McPhail, L.L. (2011). Assessing the impact of US ethanol on fossil fuel markets: A structural VAR approach, *Energy Economics*, 33 (6), pp. 1177-1185.
9. McPhail, L.L., Westcott, P., and H. Lutman (2011). "The Renewable Identification Number System and U.S. Biofuel Mandates", BIO-03, Economic Research Service, United States Department of Agriculture, Washington, DC.
10. Runkle, D.E. (1987). Vector Autoregressions and Reality, *Journal of Business and Economic Statistics*, pp. 437-42.
11. Sims, C.A., Stock, J.H., Watson, M.W. (1990). Inference in Linear Time Series with Some Unit Roots, *Econometrica*, 58, pp. 113-144.
12. Thompson, W., S. Meyer, and P. Westhoff (2008a). "How does Petroleum Price and Corn Yield Volatility Affect Ethanol Markets with and without an Ethanol Use Mandate?" *Energy Policy*.
13. Thompson, W., S. Meyer, and P. Westhoff (2008b). "Mandate economics applied to US biofuel policies", Paper presented at the Annual Meeting of the International Agricultural Trade Research Consortium held at Scottsdale, Arizona, on December 7-9, 2008.
14. Thompson, W., S. Meyer, and P. Westhoff (2009a). "Renewable Identification Number Markets: Draft Baseline Table". FAPRI-MU Report #07-09.
15. Thompson, W., S. Meyer, and P. Westhoff (2009b). "Renewable Identification Numbers are the Tracking Instrument and Bellwether of U.S. Biofuel Mandates", *EuroChoices*, Vol. 8, Issue 3, pp. 23-50.
16. Thompson, W., S. Meyer, and P. Westhoff (2010). "The New Markets for Renewable Identification Numbers", *Applied Economic Perspectives and Policy*, Advance Access Published on September 29, 2010.