AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

On the Dynamics of Price Discovery: Energy and Agricultural Markets with and without the Renewable Fuels Mandate

Layla Shiva, David A. Bessler, Bruce A. McCarl[1]

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's

2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Copyright 2014 by Layla Shiva, David Bessler, Bruce McCarl. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

[1] Layla Shiva is a PhD student, David A. Bessler is regent professor, and Bruce A. McCarl is regent professor, all in department of Agricultural Economics, Texas A&M University. Correspondence can be directed to: laylashiva@tamu.edu.

On the Dynamics of Price Discovery: Energy and Agricultural Markets with and without the Renewable Fuels Mandate

We model the energy–agriculture linkage through structural vector autoregression (VAR) model. This model quantifies the relative importance of various contributing factors in driving prices in both markets. The LiNGAM algorithm from the machine learning literature is used to help identify structural parameters in contemporaneous time. We perform conditional forecasting, taking into account the renewable fuel standards policies, and compare the forecasted path of prices with and without the renewable fuels mandates.

Key Words: ethanol, vector autoregression, renewable fuel standard, graph theory

Introduction

Enhancing energy security and GHG emission reduction are important reasons to promote renewable energy sources such as biofuels. To encourage biofuels, US government has implemented ethanol subsidies and renewable fuel standards on the amount of ethanol to be blended to transportation fuel. Ethanol is a gasoline additive. Since it contains higher octane than gasoline, it burns cleaner. The feedstock for grain ethanol (or first generation of biofuels) is mainly corn. The increase in corn demand as a biofeedstocks, especially after 2006 ethanol boom, and limited land resources causes a competition for land between food and fuel. Accordingly, a strong link between crude oil, gasoline and corn prices has been formed. The evolving interdependency between energy and agriculture markets in US is the subject of this study.

Subsidization of ethanol in the United States began with the Energy Policy Act of 1978. Since then, the subsidy has ranged between 40¢ per gallon and 60¢ per gallon of ethanol, and until it was discontinued on December 31, 2011 was 45¢ per gallon (Abbott, Hurt and Tyner 2011). Throughout the last three decades of ethanol production, the subsidy has been a fixed amount, invariant with oil or corn prices (Tyner and Taheripour 2008). In 1990, the Clean Air Act was passed, which required vendors of gasoline to have a minimum oxygen percentage in their product because adding oxygen enables the fuel to burn cleaner. Therefore a cleaner environment became another important reason for ethanol subsidies.

For the oil industry to meet the oxygen percentage standard requirements, there were two options: 1) use ethanol that contains a high percentage of oxygen by weight, or 2) use methyl tertiary butyl ether (MTBE). MTBE was generally a cheaper alternative than ethanol, so it was the favored way of meeting the oxygen requirements throughout the 1990s. However MTBE showed negative environmental consequences infiltrating water supplies and it was viewed as highly toxic. Consequently, MTBE was gradually banned on a state-by-state basis (Birur, Hertel and Tyner 2009).

The 2006 Ban of MTBE, combined with high crude oil price (which climbed to over $100/bbl in 2004) and the ethanol tax credit raised the profitability of ethanol industry particularly beginning in 2004 and 2005. High profit margins from ethanol production in 2004–2007 encouraged a rapid investment in ethanol industry in these years (Tyner et al.

2008). Between 2006 and 2008, the correlation between crude oil and corn prices was strong, in part because ethanol was needed to supply the oxygenate market. After 2008 the oxygenate market was largely saturated, ethanol prices ceased their rapid rise (and corn prices rose significantly), making ethanol production unprofitable in many cases. In 2008-09 and afterward, we see a high correlation (about 0.84 in 2008) between ethanol and corn prices, since the profitability of ethanol production depends on corn price (Abbott, Hurt and Tyner 2011).

On December, 2007, the Energy Independence and Security Act of 2007 (H.R. 6) was signed into law. This comprehensive energy legislation amends the Renewable Fuels Standard (RFS) signed into law in 2005. RFS sets forth a phase-in for renewable fuel volumes beginning with 9 billion gallons in 2008 and ending at 36 billion gallons in 2022. By doing so, the legislation seizes on the potential that renewable fuels offer an opportunity to reduce foreign oil dependence and greenhouse gas emissions and provide meaningful economic opportunity across this country; putting America firmly on a path toward greater energy stability and sustainability (Renewable Fuel Association).

Growth of the ethanol industry in last few years makes corn an energy crop, as well as the world’s most important source of grain for production of livestock, poultry, and dairy products. This transition established a relationship between ethanol and corn price and also the products from corn. Production of biofuels affects the agriculture market in that diversion of land to produce biofeedstocks may reduce the supply of other products and as a result there is a likely rise in prices. Since ethanol is oxygen enhancing additive and a replacement for gasoline, its price has a relationship with gasoline and also crude oil.

The ranges of fluctuation in these relationships have been different during past years (Wisner 2009).

Figure 1 shows the indices of corn, crude oil, ethanol, and gasoline prices since 2000 based on data from energy information administration (EIA) and USDA. The main point of this graph is commodity prices have moved together for the most part. As we can see before 2007 corn price and crude oil price show small responses to each other's movement, but after this time they show a stronger relationship. The same is true for corn and gasoline. Gasoline's price has not increased as much as crude oil's price since 2007, the reason could be that crude oil is not the only cost factor in gasoline production.

In recent years, drop in gasoline usage in US and market limitations to future growth in the blending of biofuel have resulted in fall of ethanol consumption (Westcott and McPhail 2013). This fall even leads to unsatisfaction of RFS requirements and that cause some uncertainty on EPA implementation of RFS for 2014 and beyond and penalties to parties who are not able to encounter the requirements (Westcott and McPhail 2013).

Brief literature review

Birur, Hertel and Tyner (2009) examined the effect of the ethanol boom on the price of other agricultural commodities. They indicated that the rapid growth of corn price in 2006-07 affected the price of soybeans as well, since there were substantial shifts of soybeans acreage to corn. Corn is used primarily as an animal feed. Poultry, meat and eggs faced largest shock as two-thirds of poultry feed consists of corn. As a consequence, the total cost of producing poultry meat and eggs has increased by about 15 percent over this period. Alexander and Hurt (2007) suggest that in the long run, food will be able to compete successfully with the use of crops for fuel, but probably with somewhat higher food prices and greater costs of food to consumers.

The literature does address the interactions of ethanol production and the energy market. For instance, Du and Hayes (2009) calculated the average impact of ethanol production on the gasoline price. Estimation results indicate that, on average, over the whole sample period (2000-2010) the growth in ethanol production reduced wholesale gasoline prices by $0.25/gallon. Also changes in the price of crude oil were found to have effects on the biofuel's production and prices. The FAO 2010 explains when crude oil prices increase; two main factors affect agricultural commodity markets. First, the production costs for the crop increase so this leads to a reduction in supply and therefore raises commodity prices. Second, the increase in oil-based fuel prices provides an incentive to biofuel producers to expand production, which in turn expands demand for agricultural feedstock crops causing prices to increase more. The expansion in biofuel supply may also decreases because of the rise in commodity prices. The net impact on commodity markets will depend on the degree of increase in biofuel prices relative to the increase in total crop production cost.

Bryant and Outlaw (2006) also studied the effect of absence, existence and different combinations of government policies (RFS and exemption of tax credits) on ethanol production and price by 2012. They conclude that due to powerful market-based incentives the increases in levels of ethanol production would be likely in coming years, even in the absence of government programs. Carter, Rausser and Smith (2012) also estimate that corn prices were about 30 percent greater, on average, between 2006 and

2010 than they would have been if ethanol production had remained at 2005 levels with no RFS. Tyner (2010) studied links between agriculture and energy markets and found strong correlation between crude oil and corn prices in 2006-2008 and little link between ethanol and corn prices. But in 2009, when there was ethanol surplus in the market the link between ethanol and corn price was strongest.

Empirical methods

Vector Autoregression model

In this study, we use Vector autoregression (VAR) model for our analysis. Considering regularities of world without imposing any prior restriction is an advantage of VAR (Greene 2003). A VAR can be expressed as:

$$X_t = \sum_{i=1}^{k} \mathrm{B}_i X_{t-i} + CZ_t + u_t$$

Where X_t a (mx1) vector of variables and m is is the number of series. Z_t is a (qx1) vector of strictly exogenous variables. B_i and C are appropriately dimensioned matrices of coefficients. The integers k and t are the number of lags and time indexes, respectively. u_t is the innovation term and it is assumed to be white noise, means E (u_t) = 0.. The innovations u_t and u_s are independent for s≠t. Although serially uncorrelated, contemporaneous correlation among the elements of u_t is possible, $\sum = \mathrm{E}(u_t u_t{}')$ is an (mxm) positive definite matrix.

Contemporaneously correlated innovations could mislead the information one gleans from the vector autoregression (by confounding innovation accounting results). A Choleski factorization is one way to address this issue. In this method, we need to pre multiply the system by lower triangular matrix P^{-1}, such that $P^{-1} \sum P^{-1'} = I$. The problem with this method is that it imposes an ordering through Choleski factorization. Our theory is sometimes not rich enough to suggest which series are exogenous. A Bernanke factorization is another option which allows more general causal flows. Following (Bernanke 1986) one can write the innovations as a linear function of orthogonal innovations:

$$e_t = Au_t$$

Multiplying matrix A to non-orthogonal innovations, gives orthogonal innovations provides the identified structural VAR. The transformed VAR will thus look as follows:

$$AX_t = \sum_{i=1}^{k} \mathrm{AB}_i X_{t-i} + ACZ_t + Au_t$$

If $AX_t = Y_t$ and $AC = B$, then we can also write the equation in moving average form as follows:

$$Y_t = BZ_t + \sum_{s=0}^{\infty} \Psi_s e_{t-s}$$

There exist some rules in the literature on number of free parameters to maintain identification (Doan 1993). Compare to Choleski decomposition which imposed a just identified structure, Bernanke allows more flexible identification method based on theory. In this study we will use algorithms of inductive causation (Pearl 2000) with acyclic graphical representations to hold identifying restrictions on matrix A (Awokuse and Bessler 2003).

Directed Acyclic Graphs

The graphical approach to recognize the causal ordering among the variables is directed acyclic graphs which is based on graph theory. This method pictures the causal flow among the variables by using arrows and vertices (Pearl 2000) and statistically inferred information about the probability distribution of the estimated residuals. In another word, it consists of a set of variables and the directed or undirected edges between some of the variables (Pearl 1995). A causal model such as A → B is a directed graph, which means A causes B. It means one can change the value of B by changing the value of A. A directed acyclic graph is a directed graph that contains no directed cyclic paths (Spirtes, Glymour and Scheines 2000). For instance A→B→C→A is a cyclic graph, since we return to the same variable as we start with.

Directed acyclic graphs show the conditional independencies as implied by the recursive product decomposition (Awokuse and Bessler 2003):

$$\Pr(x_1, x_2, x_3, \dots, x_n) = \prod_{i=1}^{n} \Pr(x_i | pa_i)$$

Here Pr is the probability of the variables $x_1, x_2, x_3, \dots, x_n$ and pa_i is the minimum subset of variables that comes before x_i in causal sense.

Pearl (1995) also suggests the concept of D-separation as a method in DAGS to verify the causal ordering. A variable d-separates two variable when it blocks the information flow between them. One basic pattern of causal relationship is the causal chain (A→B→C). In this chain A and C are dependent unless we condition on B. The other pattern is causal fork (A← B→C), in which A and C are dependent until we condition on B. Also the last pattern is a causal collider (A→B←C), in this case A and C are independent but are dependent when we condition on B. DAGs realize the causal direction first by testing the correlation between the variables and then by conditional correlation on the third variables and following the above rules of causal ordering.

Figure 2 depicted the Lingam (Linear Non-Gaussian Acyclic Model) algorithm (Shimizu et al. 2006) which is used in this study to figure out the causal ordering among the variables. This method is appropriate when at most one of the variable's noises may be Gaussian. Spirtes et al. (2010) explain this method as a system such as:

1) $X = \varepsilon_x$
2) $Y = aX + \varepsilon_y$
3) $Z = bX + \varepsilon_z$

Where a, b and c are the coefficients and ε_x , ε_y , ε_z are independent noises. If we write these equations in reduced forms, we will have:

4) $X = \varepsilon_x$
5) $Y = a\varepsilon_x + \varepsilon_y$
6) $Z = b\varepsilon_x + ac\varepsilon_x + c\varepsilon_y + \varepsilon_z$

LiNGAM algorithm can find the correct matching of coefficients in the Independent Component Analysis (ICA) matrix (Hyvärinen and Oja 2000) and prune away any insignificant coefficients using statistical criteria (Spirtes et al. 2010). A unique DAG will be constructed, since the coefficients are determined for each variable. The required assumptions are: 1) no unmeasured common causes; 2) dependent variable could be explained by a linear equation; 3) relation among variables are not deterministic; 4) i.i.d sampling; 5) Markov condition, which is probability distribution explain one variable is only condition on the variables of direct cause (Spirtes et al. 2010).

Forecasting and conditional forecasting

In the literature, using conditional forecasting is an approach to evaluate a policy. It is of interest sometimes to consider the forecast of some variables in the system conditional on some knowledge of the future path of other variables in the system. (Sims, Goldfeld and Sachs (1982) address important issues on how to conduct a formal policy analysis.

We can use Vector Autoregression to do policy analysis. Assuming a policy instrument is exogenous; one can view a VAR model's forecasts conditional on different hypothetical values of instrument as capturing the effect of alternative instrument settings on the endogenous variables (Cooley and LeRoy 1985). If we force some values on future path of one variable, this will result in restrictions on the other variables of the system as well. In general forecasting our best guess of future disturbances could be zero, but in conditional forecasting by forcing a value on some variables we cannot assume zero disturbances on other variables. The disturbance is not zero to adapt real values to the required (policy) values.

If we wish to forecast one period ahead conditional on a specific policy, we know the future of policy variable and also the model at the current time. Here is the setup:

$$y_{t+1} = \Psi_0\, e_{t+1} + \Psi_1\, e_t + \Psi_2\, e_{t-1} + \cdots$$

This equation is shows at time t we are predicting for t+1. Since we know the current and past states (history), so we will have:

$$y_{t+1} = \Psi_0\, e_{t+1} + Known$$

Identification of this system depends on the structure imbedded in the matrix Ψ_0. This structure on Ψ_0, will communicate the implied path on other variables, in addition to the policy variable whoes future values the governmental authority sets. Therefore for this model to be identified, we need sufficient restrictions on Ψ_0 matrix. For VAR in N variables if we leave more than N(N-1)/2 parameters free (to be estimated) the model is not identified. The restrictions on Ψ_0, come from theory or inductive causation. We can use the algorithms of inductive causation (communicated through the DAG structure) on the VAR innovations derive the restriction on Ψ in contemporaneous time.

Data

The data of this study are monthly data, starting from January 2000 to April 2013 for total observations of 160. We decide to choose data generated after 2000, since most ethanol production increases over the post 2000 period. Our data includes corn price, ethanol price (ethp), ethanol production (eprod) and also soybean price, cattle price and hog price (soyp, cattp, hogp) are representatives to show the effects on agricultural market. In addition we study the Crack ratio (crkr), to show effects of energy market following Du and Hayes (2009) and Knittel and Smith (2012). The crack ratio is a measure of the refining margin. Du and Hayes (2009) define it as the price of gasoline divided by the price of oil. The gasoline price variable is the "total gasoline wholesale/resale price by refiners", which excludes taxes and reflects primarily gasoline prior to blending with ethanol. The crude oil price is the "national average refiner acquisition cost of crude oil". These data and also Ethanol production are obtained from the U.S. Energy Information Administration (EIA) website. The agricultural products prices are from the USDA website. The ethanol price data source is Hart's Oxy-Fuel News. The Data are deflated by the consumer price index (CPI). To get the real prices, each price is divided by, CPI in each month/CPI in April 2013. CPI index is from U.S. Bureau of Labor Statistics website. Plots of the price series for each market are provided in Figure 3.

Empirical results

Stationarity

We have performed two test of stationarity of the variables, Dickey–Fuller (DF) and Augmented Dickey–Fuller (ADF). DF and ADF test results are given in Table 1. DF results show that at both critical value ethanol price, crack ratio and hog price are stationary and the rest of variables are non-stationary. The ADF test also presents that the crack ratio and hog price variables with 2 and 1 lag respectively, are stationary at 5% critical value and at 10% critical value, ethanol price with 2 lags is also stationary. The rest of variables are showing non stationary.

Optimal lag length

We use Schwarz loss, Akaike loss, Hannan and Quinn's phi measures to determine the optimal length of lags for the VAR model (Table 2). To find the optimal lag we tried these tests for different set of regressions with seasonality, break and lags. We implement the Bai-Parron break test and we choose ethanol production's break at 2009:02. The optimal lag length results shows smaller numbers with only seasonality and lags and not break included. As one can see in this table, Schwarz loss, Hannan and Quinn's phi measures and Akaike loss are minimized at 1, 2 and 10 lags respectively. Smaller lag length seems to be more reasonable for our study, so we need to choose between Schwarz loss or Hannan and Quinn's phi measures. We will use a two-lag VAR model suggested by Hannan and Quinn's phi measure since the Schwarz loss metric may have a tendency to over-penalize additional regressors compared to the other metrics (Geweke and Meese 1981).

Estimation results of two-lag VAR

The p-values of F-test associated with the null hypothesis of both coefficients of one and two-lagged prices jointly equal to zero at 10% level of statistical significance are given in Table 3. As one can see in the table, all the variables have at least one other significant coefficient in their equation, except for hog equation. Corn price coefficient is significant in both ethanol price and ethanol production. Also corn price and ethanol production are significant in crack ratio along with soybeans price coefficient. Soybeans, Cattle and hog price coefficients are significant in five equations out of total of seven. Ethanol price is only significant in ethanol production equation.

Identifying contemporaneous structure

We use LiNGAM algorithm to identify the causal structure of the variables in the model. This algorithm is appropriate to use when at most one variable is Gaussian. Therefore, the Normality test has been applied before using LiNGAM in this study. A Jarque- Bera test has been applied to the data to determine whether they follow the skewness and kurtosis matching a normal distribution or not. The test statistic is as follows:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

Where n is the number of observation, S is the sample skewness, and K is the sample kurtosis. The results of the normality test are that we reject the null hypothesis of normality for all the variables except for ethanol price.

Using TETRAD (Scheines and Spirtes 1994) we implement LiNGAM algorithm with prune factor 0.7 to figure out the contemporaneous structure among the seven variables. Figure 4 represents causal structure among the variables of our model. As one can see in this figure, energy and agriculture markets are connected through the edges between corn price and ethanol price. The information flow is Corn price causes soybeans price and also ethanol price.

Forecast error variance decomposition

The results of forecast error variance decomposition are reported in table 4. The time horizon of decompositions is zero (contemporaneous time), 1 month (short horizon), 6 months, 1 year and 3 years ahead (long term). The forecast error variance decomposition suggests that that in contemporaneous time agriculture market prices are all exogenous, except for soybeans which its variation is explained by innovations from corn (39.72%).

Variation of corn price in long horizon is explained mainly by ethanol production and cattle price (11% and 13.3% respectively) and together with other variables they explain 50% of variation in corn price. In short run, the variations in cattle and hog prices are accounted only by corn and soybeans price innovations and soybeans share is higher than corn. But then in long term ethanol price and production and also crack ratio play role in explaining cattle and hog prices. For instance, crack ratio and ethanol production explain around 11% and 3.4% of cattle price respectively.

In energy market, crack ratio is showing exogeneity in contemporaneous time and the variations in ethanol price are explained by itself mainly and also by corn price (4.7%).In 6 months horizon, Variations in ethanol price are explained by crack ratio for about 10%, but this amount decreases in long run (3 years) to about 8.7%. we can see overall, share of crack ratio in explaining ethanol price is higher than corn price in the longer term. And the immediate effect of corn price on ethanol price is higher than crack ratio.

Moreover, although in short run the variables of the model only explain about 9% of the variation in ethanol production but in long term (3years) this number increases to about 75%. The main variables which describe ethanol production variation in long term are crack ratio, cattle and hog prices.

Innovation Accounting

We present impulse response functions to analyze the effects of a one-time only shock of one of the series on the other series. One can see impulse response functions represented in graph 5. Horizontal axes on the sub-graphs represent the horizon or number of months after shock, which is 36 months in our study. Vertical axes show the standardized response to the one time shock in each market. The variable's names are labeled at top of the columns.

As one can see in the graph 5, a shock in ethanol production transferred as a positive and long lasting impulse to almost all of the agriculture market commodities' prices (corn, soybeans and cattle). Also in the energy market, a shock in ethanol production has a negative influence on crack ratio, which dampens to zero in the long run. This means increase in ethanol production decrease the gasoline refining margin and so gasoline price relative to crude oil price. Also a shock in ethanol price will lead to a negative short term impulse in crack ratio, which dampens to zero in longer term. Moreover the effects of a shock to crack ratio on ethanol price is the same. The reason could be explained as when the price of ethanol increases, demand of blended fuel will decrease and so do demand and price of gasoline. Therefore ethanol price and gasoline price in short run are acting as complementary goods. This also explains a negative response of corn price to one time shock in crack ratio in short run. Increase in blended fuel price will lead to decrease in demand of ethanol and also decrees in ethanol price and therefore corn price. Also as one can see in the graph, the ethanol production will respond negatively to a shock in crack ratio, which persists over the long term.

A positive shock of ethanol price also leads to a positive short impulse in hog price. Part of this raise might be due to the long lasting increase of corn price, when ethanol price shock happens. When ethanol price increases there might be more incentives to allocate land to biofeedstocks instead of other crops which could be used as food for livestock. This concept can also be seen as an increase in soybeans price after a shock to ethanol production.

We note also a one-time shock in corn price will lead to short positive impulse to ethanol price, since the ethanol production cost will increase. Also a shock to corn price will lead to positive response of soybeans price. Since soybeans is an important grain for animal feed, it could be a good substitute when price of corn increase. This excess demand will affect the soybeans price to increase, and it gradually dampens to zero.

Forecasting and conditional forecasting

Forecasting exercises for prices has been performed by the year 2022. In our forecasting we took in to account the Renewable Fuel Standards (RFS2) annual amount of ethanol content in blended fuel with gasoline. RFS2 sets forth 13.8 and 14 billion gallons of corn ethanol by 2013 and 2014 respectively. This amount will be fixed at 15 billion gallons from 2015 to 2022 to promote advanced biofuels, such as cellulosic ethanol from switchgrass. The required amount of ethanol blended into fuel is declared yearly, so we have calculated the required monthly amount by calculating the monthly weights of ethanol production. Taking this mandatory amount of ethanol from RFS2 in our model, we construct a conditional forecasting.

Comparing conditional and unconditional forecasts, one can see that all agricultural commodities prices and ethanol price will be higher when we take into account for RFS requirements in our model, except for hog prices and crack ratio. One can see the forecasting results in the **Error! Reference source not found.**6. The solid line after Jan 2013 to the end of 2022 is the unconditional forecast and the dotted line is the forecast conditional on RFS policies. Conditional forecasting gives us a corn price which is 15% higher than unconditional forecast for the price average of 2022. This difference is 5% for ethanol price and also 14% and 3.5% for soybeans and cattle prices. By contrast, the conditional forecasts regarding RFS requirements leads to almost 6% lower gasoline price than when there are no RFS requirements in the model.

In 2013, the blend wall limits ethanol consumption in E10 (motor gasoline contains 10%ethanol) to about 13.3 billion gallons (April 2013 short term Energy Outlook). For this reason and also constant gasoline consumption of 138 billion gallons as in predictions, ethanol falling short of required amount in the mandate (Coyle 2013; Westcott and McPhail 2013). This extra amount of RFS was substituted by blending advanced biofuels in excess of advanced RFS or by using accumulated credits (RINs) (Irwin and Good 2013a). There are two ways to meet EPA requirement and expand the blend wall: 1) increase in domestic gasoline consumption, 2) consumption of E15 or E85 instead of E10 (Irwin and Good 2013b). For this last one to happen we need a lower ethanol price compare to gasoline price since a same amount of ethanol contains 25% less energy (Irwin and Good 2013a). At May 7th 2014, Energy Information Administration had released a projection on (Irwin and Good 2013b)(Irwin and Good 2013b)(Irwin and Good 2013b)(Irwin and Good 2013b)the amount of ethanol accredited to RFS (Annual energy outlook 2014). One can compare the projection amount with RFS requirement in table 5. We performed conditional forecasting on prices regarding EIA projection of ethanol amount as well.

The average ethanol price for the year 2022 shows 4.8, 0.8, 2.8 percent decrease in corn, ethanol and cattle price compare to the forecast conditional on RFS requirements. This number is also showing 1% increase for crack ratio which together with ethanol price decrease could make E85 more economically feasible.

Discussion

This study shows a significant linkage between agriculture and energy market through corn. The results of directed acyclic graphs suggest that at contemporaneous time corn causes soybeans price and ethanol price. Renewable fuel standards requirements and rise in ethanol for demand affect the agriculture market.

Diversion of land to produce biofeedstocks and reduction in supply of other products are some other issues regarding biofuels policies. Innovation accounting methods are employed to summarize the integration between agriculture and energy markets.

Forecast error variance decomposition suggests that ethanol production explains about 10% of corn and soybeans prices in our model in longer term. These products count as a feed for livestock as well, so their price rise has effects on livestock prices as well. Corn price and soybeans price together count for about 12 and 18 percent of change in cattle and hog prices.

Moreover crack ratio explains about 8.7% of ethanol price changes. Immediately after a given positive shock to ethanol production the crack ratio will decrease. This could be explained by the higher demand for ethanol. A rise in ethanol price will lead to higher blended fuel price. The rise in blended fuel price then will lead to decrease in its demand. This will also cause gasoline price to decrease. Impulse response results confirm that a positive shock to ethanol price will decrease the crack ratio right after the shock, though it dampens to zero, shortly after the pulse in ethanol price.

Finally we study conditional price forecasts taking RFS policies into account. Results are showing higher prices for almost all the model's commodities, and a lower crack ratio, compare to no RFS restrictions forecasts by 2022.

Today Corn ethanol covers 10% of finished motor gasoline in US (E10). E85 (with 70-85% ethanol content) is consumed in limited volumes, and the infrastructure is not prepared to increase this volume. One concern of today's ethanol industry is that we have reached a blending limit known as blending wall. That means reaching the RFS targets for corn ethanol by 2022 will require raising the E10 blend standard for regular vehicles. We have also performed a forecasting exercise regarding EIA projection of ethanol accredited for RFS by 2022. The results indicate a smaller increase in ethanol price and a larger decrease in gasoline price (both around 1%) compare to the forecasts conditioning on RFS requirements.

References

Abbott, P.C., C. Hurt, and W.E. Tyner "What's driving food prices in 2011?" (2011):

Alexander, C., and C. Hurt *Biofuels and their impact on food prices*Purdue University Cooperative Extension Service, 2007.

Awokuse, T.O., and D.A. Bessler "VECTOR AUTOREGRESSIONS, POLICY ANALYSIS, AND DIRECTED ACYCLIC GRAPHS: AN APPLICATION TO THE US ECONOMY." *Journal of Applied Economics* 6 (2003):

Bernanke, B. "Alternative explanations of the money-income correlation." Carnegie-Rochester Conference Series on Public Policy no. 25, North-Holland, Amsterdam (1986):

Birur, D.K., T.W. Hertel, and W.E. Tyner "The biofuels boom: implications for world food markets." *The Food Economy Global Issues and Challenges.Wageningen: Wageningen Academic Publishers* (2009):61-75.

———"The biofuels boom: implications for world food markets." *The Food Economy Global Issues and Challenges.Wageningen: Wageningen Academic Publishers* (2009):61-75.

Bryant, H., and J. Outlaw "US Ethanol Production and Use Under Alternative Policy Scenarios ." AFPC Research Report 06-1 (2006):

Carter, C., G. Rausser, and A. Smith "The effect of the US ethanol mandate on corn prices." *Unpublished manuscript* (2012):

Cooley, T.F., and S.F. LeRoy "Atheoretical macroeconometrics: a critique." *Journal of Monetary Economics* 16 (1985):283-308.

Coyle, W.T. "USDA Economic Research Service-Next-Generation Biofuels: Near-Term Challenges and Implications for Agriculture." (2013):

Du, X., and D.J. Hayes "The impact of ethanol production on US and regional gasoline markets." *Energy Policy* 37 (2009):3227-34.

Geweke, J., and R. Meese "Estimating regression models of finite but unknown order." *Journal of Econometrics* 16 (1981):162.

Greene, W.H. *Econometric analysis*Pearson Education India, 2003.

Hyvärinen, A., and E. Oja "Independent component analysis: algorithms and applications." *Neural Networks* 13 (2000):411-30.

Irwin, S., and D. Good "The Ethanol Blend Wall, Biodiesel Production Capacity, and the RFS...Something Has to Give." (2013a):

———"Expanding the Ethanol Blend Wall - a Role for E85?" (2013b):

Knittel, C., and A. Smith, "Ethanol production and gasoline prices: a spurious correlation." (2012):

Pearl, J. "Causal diagrams for empirical research." *Biometrika* 82 (1995):669-88.

———*Causality: models, reasoning and inference*Cambridge Univ Press, 2000.

Renewable Fuel Association "Renewable Fuel Standard." http://www.ethanolrfa.org/pages/renewable-fuel-standard

Scheines, R., and P. Spirtes *Tetrad II: Tools for Causal Modeling: User's Manual and Software*Lawrence Erlbaum Ass, 1994.

Shimizu, S., P.O. Hoyer, A. Hyvärinen, and A. Kerminen "A linear non-Gaussian acyclic model for causal discovery." *The Journal of Machine Learning Research* 7 (2006):2003-30.

Sims, C.A., S.M. Goldfeld, and J.D. Sachs "Policy analysis with econometric models." *Brookings Papers on Economic Activity* (1982):107-64.

Spirtes, P., C.N. Glymour, and R. Scheines *Causation, prediction, and search*MIT press, 2000.

Spirtes, P., C. Glymour, R. Scheines, and R. Tillman "Automated search for causal relations: Theory and practice." (2010):

Tyner, W., F. Dooley, C. Hurt, and J. Quear "Ethanol pricing issues for 2008." *Industrial Fuels and Power* 1 (2008):50-7.

Tyner, W.E. "The integration of energy and agricultural markets." *Agricultural Economics* 41 (2010):193-201.

Tyner, W., and F. Taheripour "Biofuels, policy options, and their implications: Analyses using partial and general equilibrium approaches." *Journal of Agricultural & Food Industrial Organization* 6 (2008):

Westcott, P., and L. McPhail "USDA Economic Research Service-High RIN Prices Suggest Market Factors Likely To Constrain Future US Ethanol Expansion." (2013):

———"USDA Economic Research Service-High RIN Prices Suggest Market Factors Likely To Constrain Future US Ethanol Expansion." (2013):

Wisner, R. "*Corn, ethanol and crude oil relationships implication for biofuels industry*." AgMRC Renewable Energy Newsletter (2009):

Table 1.Dickey–Fuller (DF) and Augmented Dickey–Fuller (ADF) for non-stationary of variables.

Variables	Dickey-Fuller		Augmented Dickey-Fuller		
	Test	Q	Test	K	Q
Corn Price	-0.29	62.23	-0.32	1	60.99
		(0.00)			(0.00)
Ethanol Price	-4.31	45.71	-2.84	2	31.18
		(0.12)			(0.69)
Crack Ratio	-5.15	70.42	-2.99	2	61.52
		(0.00)			(0.00)
Ethanol Production	0.13	667.99	-0.08	1	249.14
		(0.00)			(0.00)
Soybeans Price	-1.43	70.78	-1.28	1	38.30
		(0.00)			(0.36)
Cattle Price	-2.46	302.88	-2.33	1	81.43
		(0.00)			(0.00)
Hog Price	-3.51	76.56	-3.30	1	71.05
		(0.00)			(0.00)

The DF test is implemented through an ordinary least squares regression of the first differences of prices on a constant and one lag of the levels of prices (Greene 2003). In ADF test, k lags of dependent variable are included in the regression. The null hypothesis for the test statistic of both tests is the data is non stationary in levels. The null hypothesis is rejected when the observed t-statistics are less than this critical value. The 5% and 10% critical values are (-2.89, -2.58) (Fuller, 1976). ADF regression runs with 12 lags and the chosen lag number (K) is the minimized Schwarz loss metric. Also the Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value with respect to each Q-statistics is given in the parenthesis.

Table 2.VAR optimal lag length determination

Number of lags	Schwarz Information Criterion (SIC)	Hannan and Quinn Information Criterion (HQIC)	Akaike Information Criterion (AIC)
1	14.0694*	12.4485	10.4536
2	14.5285	12.3103*	10.2122
3	15.6201	12.8047	10.6032
4	16.9162	13.5036	10.1988
5	18.0327	14.0229	10.6147
6	19.1616	14.5546	11.0430
7	19.9150	14.7108	10.0959
8	20.8277	15.0263	10.3080
9	21.8751	15.4765	10.6549
10	22.8041	15.8082	10.8833
11	23.4828	15.8898	9.8615
12	23.9342	15.7439	9.6123*

Note: * indicates the most appropriate lag order for the considered model.

The information criteria used to identify the optimal lag length (p) of a VAR process are $AIC = \ln\left(det\widehat{\Omega}_p\right) + p\left(\frac{2n}{T}\right)$,$SIC = \ln\left(det\widehat{\Omega}_p\right) + p\left(\frac{nlnT}{T}\right)$, and $HQIC = \ln\left(det\widehat{\Omega}_p\right) + p\left(\frac{2nln(lnT)}{T}\right)$, where $\widehat{\Omega}_p$ is the maximum likelihood estimate of variance-covariance matrix of Ω, p is the proposed lag length, n is the number of variables, and T is the sample size.

Table 3. p-values associated with F-tests for the null hypothesis of the coefficients on one- and two-lagged prices on each of 7 variables are equal to zero in the two-lagged VAR(2) model estimation results.

dependent variable	CORP	ETHP	CRKR	EPROD	SOYP	CATTP	HOGP
CORP	0.000*	0.388	0.075*	0.182	0.621	0.232	0.301
ETHP	0.967	0.000*	0.260	0.013*	0.447	0.829	0.278
CRKR	0.124	0.025*	0.000*	0.379	0.415	0.012*	0.828
EPROD	0.134	0.393	0.033*	0.000*	0.094*	0.317	0.977
SOYP	0.091*	0.861	0.060*	0.046*	0.000*	0.011*	0.209
CATTP	0.005*	0.028*	0.843	0.006*	0.064*	0.000*	0.175
HOGP	0.011*	0.025*	0.223	0.183	0.056*	0.098*	0.000*

* Indicates the p-values below 10% significance level.

Table 4. Forecast error variance decompositions from two-lag VAR.

Step		CORP	ETHP	CRKR	EPROD	SOYP	CATTP	HOGP
CORP	1	100.00	0.00	0.00	0.00	0.00	0.00	0.00
	2	97.19	0.01	1.34	0.46	0.45	0.26	0.24
	7	79.14	0.48	3.48	1.14	1.00	7.83	6.90
	13	69.30	0.74	2.40	2.58	0.83	13.32	10.80
	37	54.78	3.80	3.09	11.07	1.42	13.32	12.49
ETHP	1	4.71	95.28	0.00	0.00	0.00	0.00	0.00
	2	5.29	92.37	0.00	0.45	0.06	0.47	1.33
	7	2.79	79.96	9.42	0.37	2.08	2.57	2.79
	13	3.43	71.91	9.05	0.36	6.64	5.14	3.43
	37	5.01	66.43	8.79	1.10	8.67	6.49	3.47
CRKR	1	0.00	0.00	100.00	0.00	0.00	0.00	0.00
	2	0.30	0.03	96.77	0.35	1.33	0.03	1.15
	7	0.29	1.99	85.75	0.70	8.12	1.37	1.75
	13	0.41	2.07	81.74	1.37	9.57	2.14	2.67
	37	1.09	1.75	69.35	3.68	8.52	10.88	4.70
EPROD	1	0.00	0.00	0.00	100.00	0.00	0.00	0.00
	2	0.56	1.72	0.98	92.24	1.69	0.93	1.85
	7	0.73	6.62	2.96	69.19	4.79	10.97	4.70
	13	0.39	6.30	6.59	51.03	5.55	19.31	10.79
	37	2.62	2.30	9.91	25.15	2.37	42.79	14.82
SOYP	1	39.72	0.00	0.00	0.00	60.27	0.00	0.00
	2	38.39	0.05	0.55	0.07	60.82	0.00	0.09
	7	34.14	1.43	1.12	0.85	50.08	2.92	9.42
	13	34.50	2.99	1.03	2.68	40.25	4.44	14.09
	37	29.45	3.89	2.97	9.97	30.20	6.75	16.74
CATTP	1	0.00	0.00	0.00	0.00	0.00	100.00	0.00
	2	0.00	0.01	0.07	0.00	2.49	97.16	0.23
	7	0.43	0.04	9.02	0.02	7.45	76.59	6.42
	13	0.90	0.03	11.75	0.19	7.82	69.95	9.33
	37	2.04	0.24	11.36	3.40	10.12	63.84	8.97
HOGP	1	0.00	0.00	0.00	0.00	0.00	0.00	100.00
	2	1.61	0.00	0.09	0.00	0.34	0.11	97.82
	7	2.15	2.30	1.53	0.10	2.22	2.68	88.97
	13	1.72	3.05	1.72	0.12	10.49	7.82	75.05
	37	1.58	2.84	3.32	0.91	16.17	11.20	63.95

Table 5. Ethanol requirement in RFS and EIA projection of credits earned from ethanol.

	RFS requirements	EIA projection
2013	13.8	13.31
2014	14.5	12.73
2015	15	13.59
2016	15	13.65
2017	15	13.84
2018	15	13.91
2019	15	13.95
2020	15	14.06
2021	15	14.12
2022	15	14.37

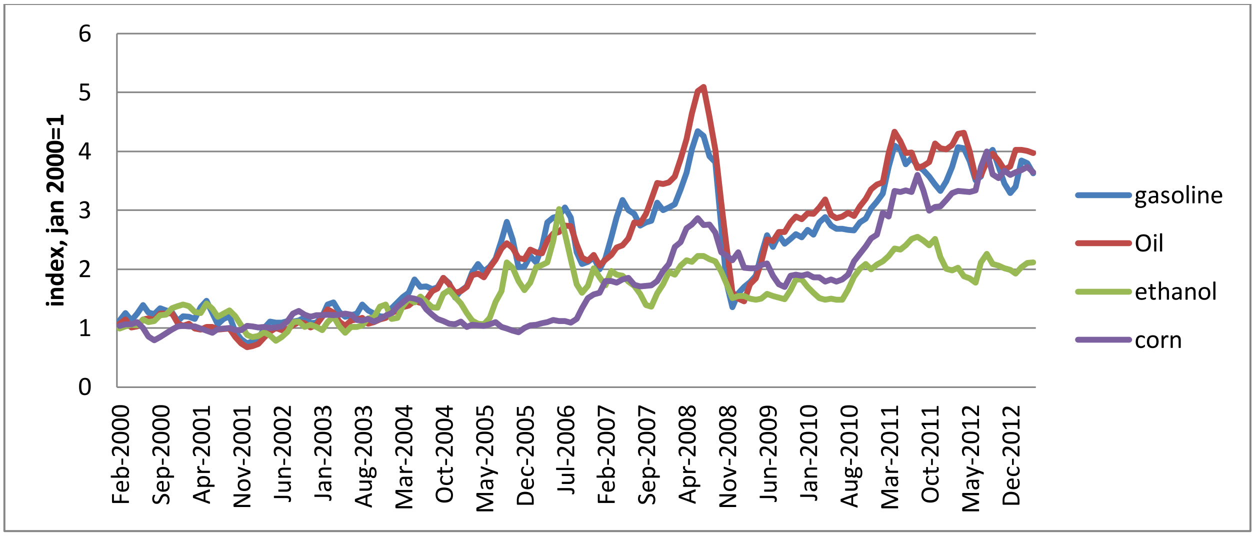


Figure 1: Price index of agriculture and energy commodities.

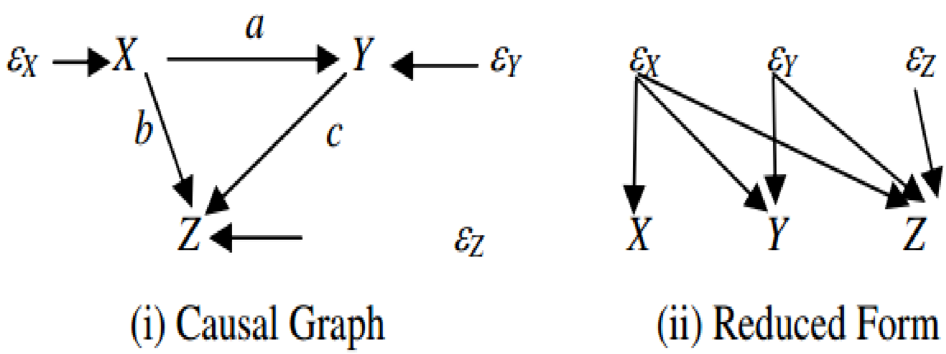


Figure 2: Causal graph and reduced form- taken from Spirtes et al. 2010

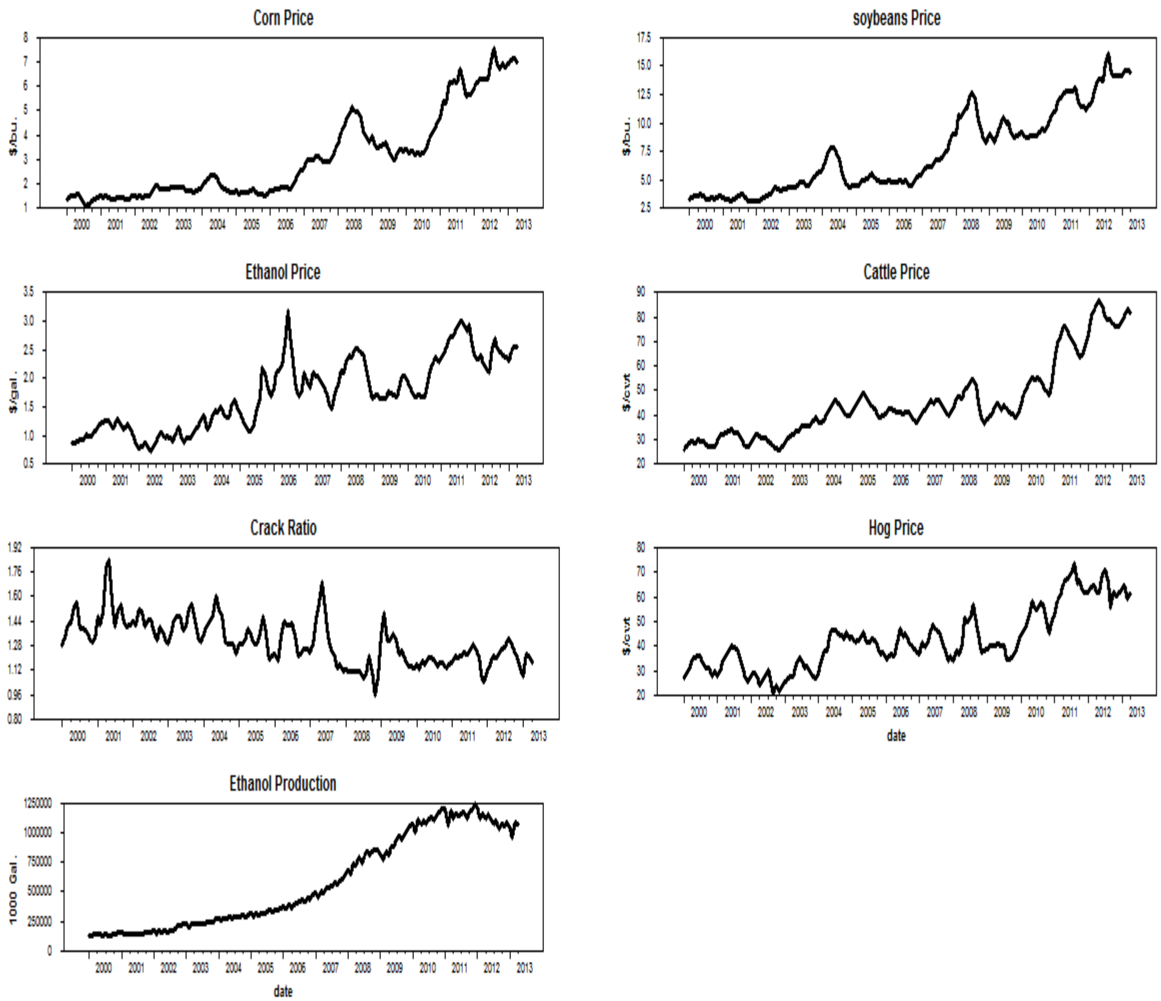


Figure 3: Monthly time series plot (January2000- April 2013)

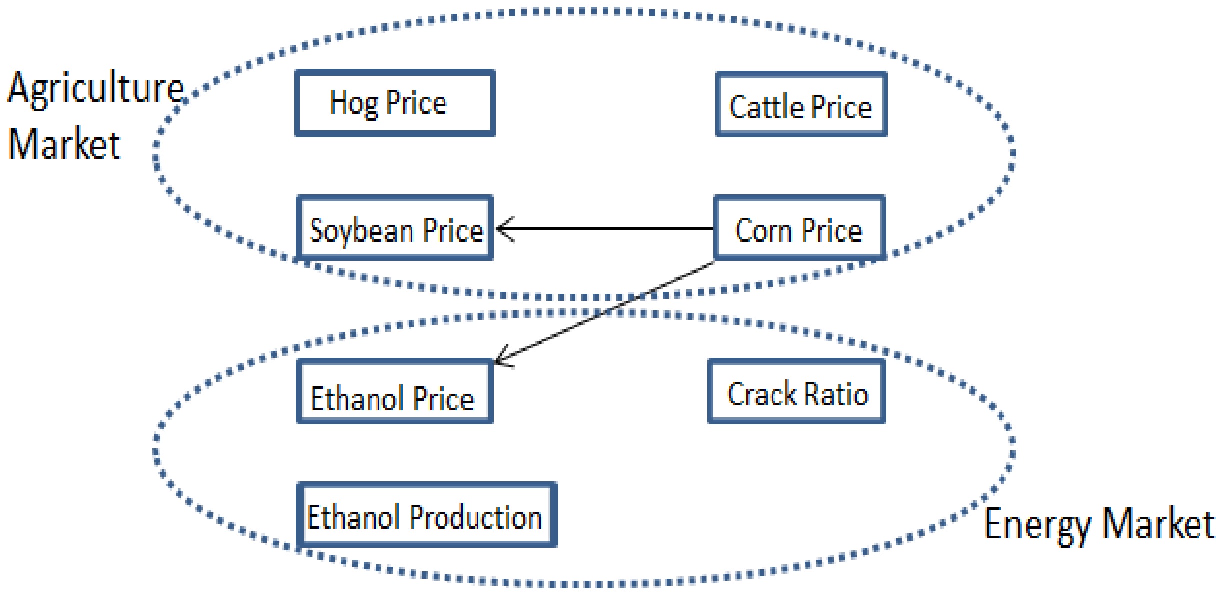


Figure 4: Directed acyclic graphs at 0.7 prune factor using LiNGAM.

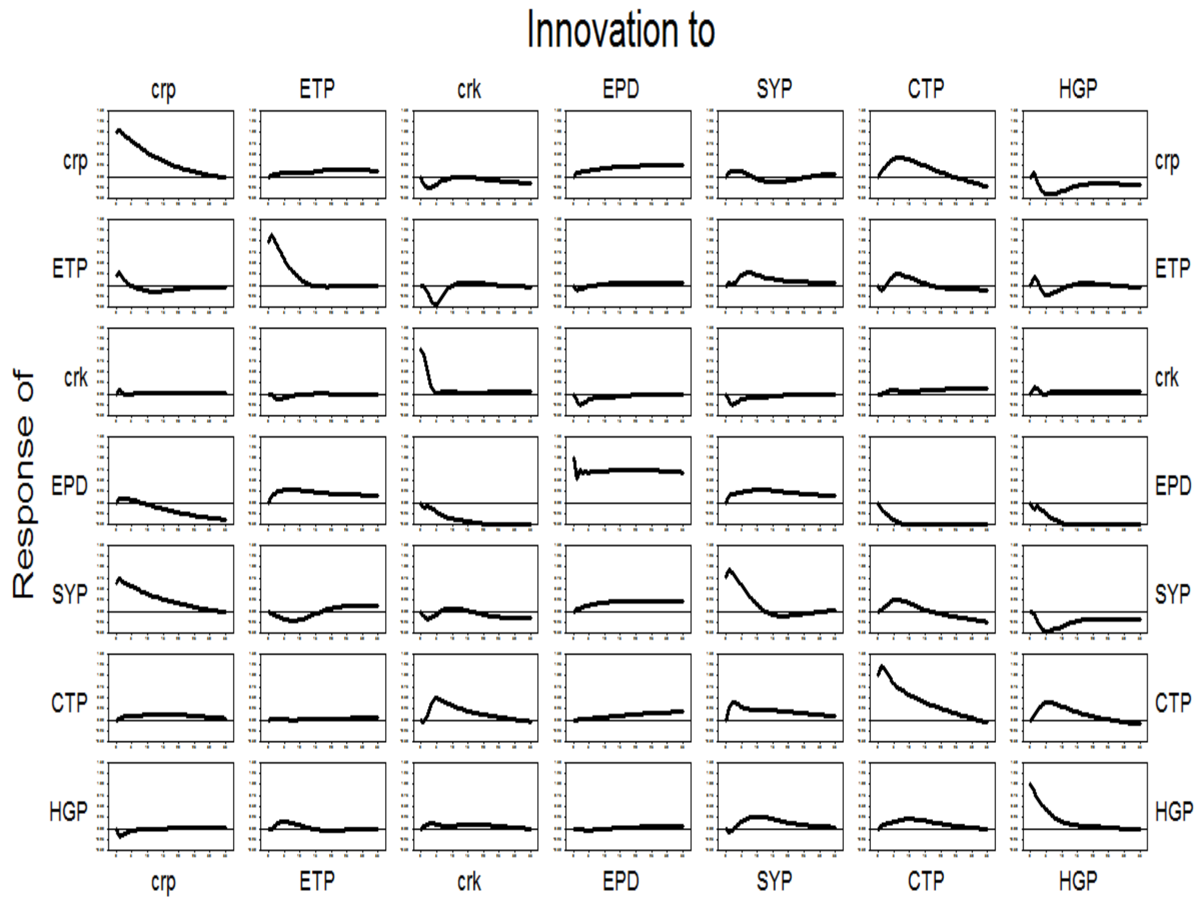
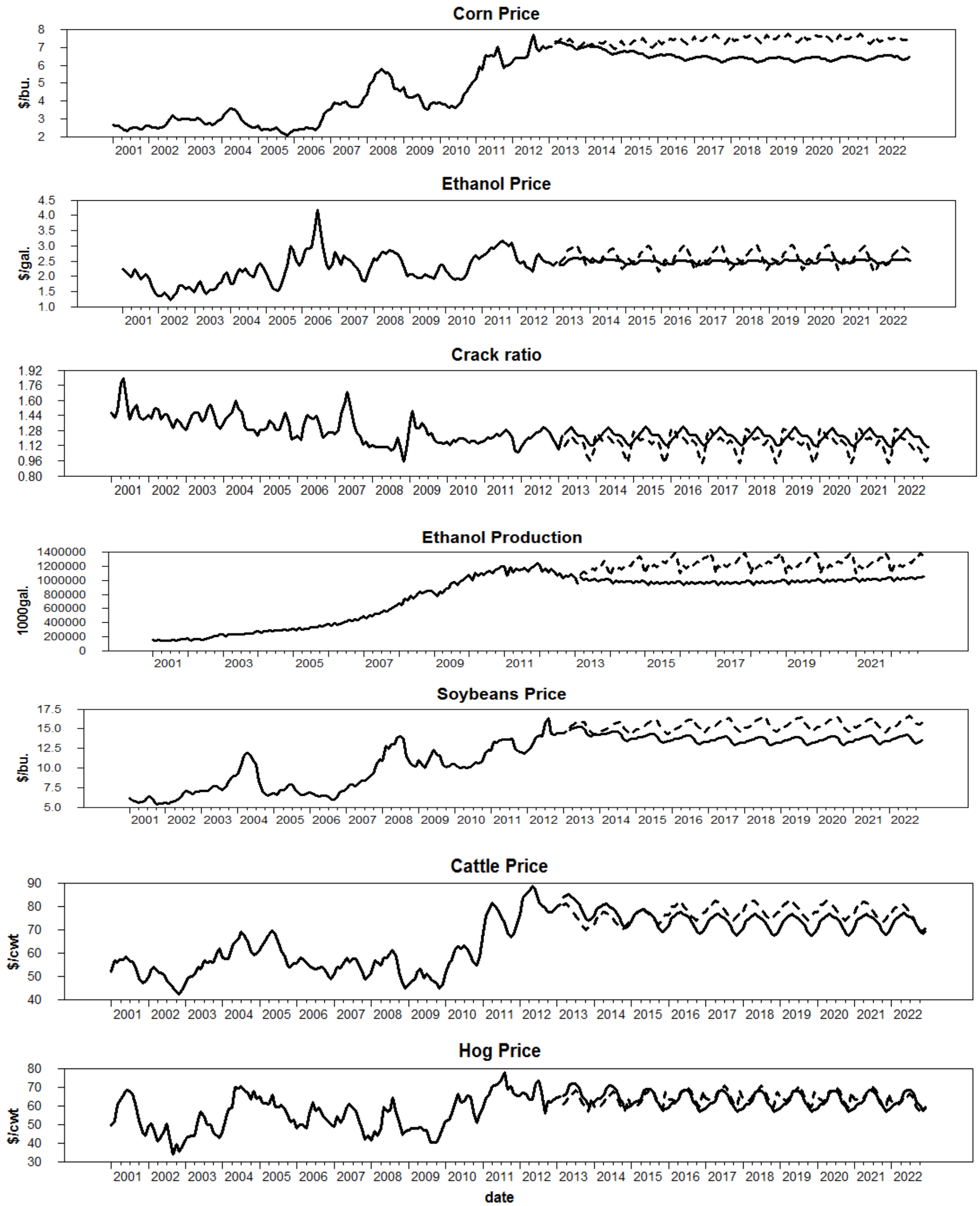


Figure 5: Impulse response functions from innovation of two-lag VAR.



----- Conditional Forecasts ——— Unconditional Forecasts

Figure 6.Conditional and unconditional forecasts by the year 2022.