U.S. Energy Price Volatility Spillover in Global Corn Markets

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Abstract

This paper examines the impact of energy price shocks within the U.S. to the corn market prices both in the U.S. and in the world. It allows for structural breaks and identifies the price volatility in the corn markets before and after energy policy changes within the U.S. in 2005 and 2007. In particular, this paper develops structural VAR model and a structural VECM model respectively for the series before and after policy change. Results indicate that there is a substantial difference in the dynamic response of corn prices to an ethanol price shock after the policy change. Findings also suggest that an ethanol price shock is more important and persistent than a gasoline price shock while explaining the corn price volatility in corn markets.

Key Words: SVAR, SVECM, Energy Policy, Energy Price, Corn Price

1 INTRODUCTION

The food versus fuel debate has been occurring more prominently after the major policy changes within the U.S.; Energy Policy Act of 2005 and Energy Independence and Security Act of 2007. Senauer (2008) argues that fluctuations in crop-based biofuel use due to the change in the oil price directly impacts the demand of agricultural products' and their prices. Specifically for U.S. corn based ethanol, it increases the price of corn. According to Senauer (2008), the acreage response of corn for its higher demand pulls away the land under soybean production and results in a soybean price increase. Additionally, any adverse shock in the energy market also results in the decline of agricultural productivity and increases agricultural product prices (Hochman et al., 2010; Wang and McPhail, 2014). However, some studies also suggest that the significance of the dynamic relationship between energy price and food prices shouldn't be generalized. Zilberman et al. (2012) argued that the impact of a biofuel price change on the food commodity price movements depends on the crops and locations. They found that the biofuel price change in general has a minimal impact on food price. A recent study by Zhang and Qu (2015) in China also found that the effects of oil price shocks varies across the agricultural commodities; cash crops are more vulnerable than food crops. Although Zilberman et al. (2012) didn't fully study the impact of fuel prices, they suggest that the corn based ethanol production has a significant impact on food commodity prices.

Some of the recent research focused on identifying the linkage between corn price, energy price and energy policies within U.S. Du et al. (2012) studied relationship of gasoline, ethanol and corn prices within U.S. using the data from March 2005 to March 2011. They found that the shocks in the ethanol market has the largest impact on the corn price. McPhail and Babcock (2012) looked at the impact on the corn and gasoline price due to ethanol policies shocks. In particular, their study focused on the Renewable Fuel Standard (RFS) of the Energy Independence and Security Act (EISA) 2007 and the blend wall. The RFS represents the ethanol amount mandate for each type of biofuel for each year and the blend wall is the maximum amount of ethanol that can be blended into gasoline. McPhail and

Babcock (2012) hypothesized that supply shocks due to these two policies can shape both the demand and the scale of price variability of corn and gasoline. Using three-stage least squares and a stochastic partial equilibrium model, they found that ethanol policies increase both the corn and gasoline price volatility. Carter et al. (2012) argued that the U.S. 2007 biofuel legislation has increased the use of corn significantly in the ethanol production. They estimated that without the ethanol mandate corn price could have been 40% lower in 2012. (Gardebroek and Hernandez, 2013) also studied the volatility spillovers to and from energy and corn markets in the U.S. They found the correlation between corn and ethanol price has increased after 2007; however, they argued that modifying biofuel policies may not be effective in reducing agricultural price volatility. Condon et al. (2015) reviewed the published articles to understand the diverse estimates related to impact of ethanol policy on corn prices (0% to 80%). After performing meta-analysis, they concluded that a one-billion-gallon expansion of the U.S. corn ethanol mandate in 2015 could lead to a 3 to 4% increase in corn prices in the same year.

This study also looks at the relationship of corn, ethanol and gasoline prices but it is not limited to the corn market within U.S. Therefore, the subtle difference between this research work and past studies is that it has included the response of global corn price to the U.S. energy market shocks. Although the total corn export from the U.S. accounts for a relatively small share of U.S. corn demand (nearly 15 percent), it represents an average of 60 percent of world corn exports[1]. Therefore, U.S. corn production and prices not only determines the U.S. corn price but also largely dominates the world corn market. Hence, it is crucial to study the response of U.S. energy prices shocks on the corn prices within the U.S. and at the global level. Gasoline price are included in this study for two reasons. First, higher gasoline prices may cause ethanol production to be more profitable that can increase the corn demand. This potential demand shock to the corn market is expected to raise the price of corn both within and outside U.S. Secondly, the higher price of the gasoline (which is a key input of corn production) can result the supply shock in the corn production. This supply shock may increase the price of corn within the U.S. and its spill-over to the

[1] USDA ERS-Trade

global market. Following Avalos (2013), this study also tests for a structural break and identifies two appropriate econometric models to study the impact of energy market shocks in U.S. corn price and the volatility spill over to the global corn market before and after U.S. biofuel promotion policies. In particular, Structural Vector Auto Regressive (SVAR) and Structural Vector Error Correction (SVEC) models are used for the four-time series dataset (US gasoline price, US ethanol price, US corn price and global corn price) respectively for before and after the major energy policies change.

2 DATA

This study use monthly ethanol price (dollar per gallon), gasoline price (dollar per gallon) and corn price (dollar per bushel) within the U.S. from the USDA[2]. Monthly world corn price (dollar per bushel) is obtained from Federal Reserve Economic Data (FRED)[3]. After merging these two datasets there are four time series varaiables from Jan 1982 to Feb 2016. Plotting these four monthly series indicates some potential structural break after the year 2005 (Figure 1). While conducting similar research work using the corn, oil and soybean prices, Avalos (2013) found a structural break point in May 2006. A chow test is performed in this study at the same point (May 2006) using world corn price as a dependent variable and remaining three-time series as independent variables. The Chow test failed to reject no breaks at the specified breakpoints. Hence, the original dataset is divided into two datasets. Within the first ranging from January 1982 to April 2006 (293 data points) and the second from May 2006 to February 2016 (117 data points). This research is conducted separately for two different scenarios; "Before" the energy policy (January 1982 to April 2006) and "After" the energy policy (May 2006 to February 2016). The R-software package as described in Pfaff et al. (2008) is used for estimation of the unit root test, cointegration test (if necessary), model estimation, impulse response identification and forecast error variance decomposition for both scenarios.

[2]U.S. Bioenergy Statistics
[3]FRED Economic Data

3 BEFORE

3.1 Unit Root Test

An augmented Dickey-Fuller model is used to test for the presence of unit root for each variable. Results of the unit root test is presented in the Table 1. There are three different ADF test models for each of these four time series variables. The first model doesn't have any intercept and trend, the second model includes an intercept, a trend and a drift variable is included in the third model. If unit root is rejected in one of the models then there is no need to apply any transformation in the series. The test failed to reject the null hypothesis of unit root for gas_b (gasoline price before fuel policy) at the 5% level of statistical significance. Thus, the first differenced gasoline price series is constructed (gas_b1).

The unit root is rejected at least in one of the three ADF models for the ethanol price (eth_b), the U.S. corn price (usa_b) and the global corn price (world_b) at the 5% level of statistical significance. There is no need to apply any difference in these data series. Since gasoline price was the only non-stationary variable, no cointegration test is performed in this data series. The Structural Vector Autoregressive (SVAR) model is estimated with first differenced gasoline prices and the level of ethanol, U.S. corn price and world corn price.

3.2 Structural Vector Autoregressive (SVAR) Model

Structural Vector Auto Regressive (SVAR) models are used to relate the U.S. and global corn prices to price shocks in the U.S. ethanol and gasoline market. The SVAR model is estimated with monthly data for the four time series before the energy policy change. The VAR (p) is of the following form:

$$x_t \;=\; A_1\, x_{t-1} \;+ \ldots +\; A_p\, x_{t-p} + u_t \qquad (1.1)$$

where, x_t is the vector of four annual time series price variables and P is the lag order. A Structural VAR model has the following form:

$$A_0 x_t \;=\; A_1^*\, x_{t-1} \;+ \ldots +\; A_p^*\, x_{t-p} + B\varepsilon_t \qquad (1.2)$$

where, A_0 and A_1^* are the parameters to be estimated. Multiplying the both side of equation 1.2 by A_0^{-1} results in a reduced form VAR:

$$x_t = A_0^{-1} A_1^* x_{t-1} + \ldots + A_0^{-1} A_p^* x_{t-p} + u_t \tag{1.3}$$

where, u_t is the vector of residuals in the reduced form and can be expressed as: $u_t = A_0^{-1} B \varepsilon_t$. Because an A-type SVAR model is estimated, the B Matrix is set to I_K. Theoretical restrictions are imposed to the recursive system on A_0^{-1} based on the economic theory. It is assumed that the variables won't respond to the contemporaneous shocks from variables other than those being allowed to respond. In this study, the reduced form residual term u_t can be expressed in the following way:

$$u_t \equiv \begin{bmatrix} u_t^{gas} \\ u_t^{eth} \\ u_t^{usa} \\ u_t^{world} \end{bmatrix} \equiv \begin{bmatrix} \theta_{11} & 0 & 0 & 0 \\ \theta_{21} & \theta_{22} & 0 & 0 \\ \theta_{31} & \theta_{32} & \theta_{33} & 0 \\ \theta_{41} & \theta_{42} & \theta_{43} & \theta_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{gasoline\ price\ shock} \\ \varepsilon_t^{ethanol\ price\ shock} \\ \varepsilon_t^{usa\ corn\ price\ shock} \\ \varepsilon_t^{world\ corn\ price\ shock} \end{bmatrix} \tag{1.4}$$

In this SVAR model, shocks enters the equations recursively so that the additional shock of later equation doesn't affect the variables in the equations that precedes it in the same period. Therefore, the gasoline shock enter in the first equation; gasoline and ethanol shocks enter the second equation; gasoline, ethanol and the U.S. corn price shocks enter the third equation; and finally gasoline, ethanol, U.S. corn price and global corn price shocks enter the fourth equation. This study assumes that the gasoline price shock is not affected by any other contemporaneous shock from any variables in the identified system. The US corn price is allowed to respond to shocks from ethanol and gasoline prices. Also, the global corn price is allowed to respond to shocks from ethanol, gasoline and U.S. corn prices. After estimating SVAR, the impulse response analysis is conducted to identify the dynamic response of corn price variables to the energy price shock. Additionally, the forecast error variance decomposition is performed to identify the contribution and the importance of the energy shocks to the corn prices. The Impulse Response Function (IRF) is used to analyze the short run dynamic response of the U.S. and global corn price to the structural shock in the energy price shock during the Jan 1982 to April 2006 period. The forecast error variance decomposition is estimated to understand the importance of each shocks explaining U.S. and World Corn price fluctuations.

3.3 Impulse Response of Corn Prices

Figure 4 and 5 indicates that the there is not a statistically significant response of U.S. corn prices to energy price shocks before the major policy change. Figure 6 shows that the U.S. corn price is affected substantially by the U.S. corn market shocks.

In case of world corn prices figure 7 and figure 8, there is no statistically significant response of world corn price to a shock in the U.S. energy prices before the change in major energy policies. Figure 9 shows that world corn price responds positively and significantly to U.S. corn price shocks. The effect becomes less significant after ten months. Figure 10 shows that the response of world corn prices to specific corn market shocks are stronger and persistent for more than a year.

3.4 Forecast Error Variance Decomposition of Corn Prices

Table 2 shows that in the short run (year 1), a gasoline price shock explains about 0.1% of the U.S. corn price fluctuation. Ethanol prices explain 0.4% of U.S. corn price volatility. In the long run (after 5 years), gasoline and ethanol prices shock respectively contribute 0.3% and 0.2% in the U.S. corn price volatility. A shock in the global corn market doesn't contribute to the U.S. corn price volatility in short run (year 1); but, it becomes high (50.6%) in the long run (10 year).

Table 3 illustrates that a gasoline price shock doesn't contribute to the world corn price fluctuation for almost two years. Whearas, the contribution from ethanol price shock is 0.4% in the year 1. In the long run (year 10) both of these shock contribute almost same percentage (ethanol slightly higher) in the fluctuation in the world corn prices (0.2%).

Almost 62.8% of fluctuations in the world corn price is contributed by a shock in the U.S. corn price in the short run (year 1). This effect is persistent over the longer time horizon as it contributes 36.6% of world corn price fluctuation in year 10.

4 AFTER

4.1 Unit Root Test

Table 4 shows the three different cases of ADF test for each of these four time-series variables from May 2006 to February 2016. First model doesn't have any intercept and trend, the second model includes an intercept, and the third model includes both a trend and drift variables. If the unit root is rejected in one of the models, then there is no need to transform the variable. In the dataset after fuel policy change, the test failed to reject the null hypothesis of unit root for gasoline price (gas_a), U.S. corn price (usa_a) and world corn price (world_a) at the 5% level of statistical significance. Hence, these three non-stationary time series variables are first differenced. The unit root is rejected at least in one of the above three ADF models for ethanol price at 5% level of statistical significance. So, there is no need to difference this series. Since there are three non-stationary variables, a cointegration test was estimated. Table 5 shows the results of Johansen's cointegration test. The maximal eigenvalue test is used to determine the number of cointegrating relationships. The results show that the null hypothesis of two cointegrating relationships is rejected for the VAR model.

Additionally, a VEC model is estimated with restriction of one cointegration relationship for further investigation by allowing the normalization of the long-run relationship with respect to gasoline prices. The coefficients of the CI vector and loading parameters are presented in the Table 6. It shows that a temporary shock is caused mainly by the gasoline prices. This information is helpful when imposing the identification restrictions on the SVEC model. Finally, the dataset using three first differenced variable along with the stationary ethanol price variable is estimated with the SVEC model.

4.2 Structural Vector Error Correction Model

The SVEC model is chosen based on the results of the cointegration test to investigate the impulse response behavior and perform a forecast error decomposition between the energy and corn prices. In this study, the SVEC B model is estimated by setting the A matrix to an identity. Then the equation is represented as the following SVEC model:

$$\Delta x_t \; = \; \propto \beta^T \; x_{t-1} \; + \ldots \; + \Gamma_1 \;\; \Delta x_{t-p} + B\varepsilon_t \qquad (2.1)$$

where $u_t = \; B\varepsilon_t$ and $\varepsilon_t \sim$ N $(0, \, I_K)$.

Identification of SVEC type B model results in six linear independent restrictions. Since the CI relationship is interpreted as the stationary gasoline price setting relationship, the four entries in the gasoline price column of the long run matrix are zero. Furthermore, the U.S. ethanol price and U.S. corn price are assumed not to be driven by global corn prices. Therefore, the elements in the second and third row of world corn price column in the long run matrix is imposed with zero coefficients. A restriction in the short run matrix is also imposed assuming that U.S. ethanol price does not exert immediate impact on the global corn price. Therefore, the last element of the ethanol price is imposed with a zero coefficient. Coefficient estimates of the short-run and long-run matrix are presented in the Table 7 and Table 8. Using the SVEC model, impulse response function analysis and forecast error decomposition are esimated. Impulse Response Function (IRF) is used to analyze the short run dynamic response of the U.S. and global corn prices to the structural shock in the energy price. Additionally, the forecast error variance decomposition helps to understand the importance of each shock while explaining the US and world Corn price fluctuations.

4.3 Impulse Response of Corn Prices

Figure 11 illustrates that U.S. corn price does not have a statistically significance response to a gasoline prices shock. However, figure 12 indicates that a shock in the ethanol prices has a significantly negative impact on the U.S. corn price in the short run (third month). Also, the response of U.S. corn price to a corn market specific shock is positive and statistically significant (Figure 13). The shock lasts for a longer period of time.

Figure 14 shows that response of world corn prices to a gasoline price shock is statistically insignificant. However, there is highly negative and statistically significant response of world corn prices to a ethanol price shock (Figure 15). The magnitude is very high and also the impacts last for long time period. Similarly, the word corn prices response to a U.S. corn price shock is positive and statistically significant (Figure 16). This response is also high during the initial month after shock and lasts for a period of time. Furthermore, there is a significant and positive response of world corn price to the world corn market specific shocks in the first month and then the response becomes statistically insignificant (Figure 17).

4.4 Forecast Error Variance Decomposition of Corn Prices

Table 9 indicates that an ethanol price shock contributed 0.9% in the fluctuation in U.S. corn price in the short run (year 1) and the contribution from gasoline price shock is 11.8%. In the long run (year 10), the ethanol price shock still has a high percentage contribution (5.6%) in the US corn prices compared to a gasoline price shock (2.3%). More than 87% of the variation in the US corn prices is attributed to the U.S. corn market specific shocks both run and 92% in the year 10.

Table 10 indicates that nearly 7.5% variation in the world corn price fluctuation is attributed to a shock in the U.S. gasoline prices in the year 1. Because of our restrictions on the contemporaneous matrix; there is no contribution from ethanol price shock in the short run. However, in the long run (year 10), about 8.2% of the world corn price fluctuation can be attributed to the shock in the ethanol market whereas the contribution from the gasoline shock in the longer horizon is almost insignificant (2%). Additionally, the most of the fluctuation in the world corn prices is attributed to the shock in the US corn prices (more than 88%) both during the short run and long run. However, the world corn market specific shock contributes a very small fluctuation (0.3% in the year 1 and 0.1% in the year 10) to the global corn price.

5 BEFORE AND AFTER COMPARISION

Impulse response function analysis indicated that both the U.S. and world corn prices didn't significantly respond to the ethanol and gasoline price shocks before the policy change. However, both prices significantly and negatively responded to ethanol market price shocks after the policy change. The impact to global corn price is more persistent. Since the policy focused on the greater energy independence by producing more biofuels, it is likely that any shock in the ethanol market within the U.S. after policy change signicantly contributed to the corn price fluctuation within and outside U.S.

Based on the variance decomposition analysis, ethanol price shock is more important than a gasoline price shock for corn price variation both before and after the policy in the longer time horizon. Findings suggest that the ethanol price shock on both U.S. and world corn price becomes more important after the policy change. Most importantly, after year 2, the contribution of the ethanol shock to world corn price is higher than the U.S. corn price fluctuation in both the policy change scenarios. Furthermore, immediate U.S. corn price shock to the world corn price is much higher after the policy change (92.2%) than before the change (62.8%).

6 CONCLUSION

The United States is the largest producer and exporter of the corn in the world. Although only 20% of U.S. corn produce is exported to the world market, it accounts for nearly 60% of world corn exports. Any little change in U.S. corn exports can results in large change in the global corn market price. This research work is focused on the impact of U.S. energy price shocks before and after the two major energy policy changes (the Energy Policy Act of 2005 and the Energy Independence and Security Act (EISA) of 2007) on the U.S. and world corn prices. SVAR and SVEC models are estimated respectively for the dataset before and after the policy change. After these estimations, impulse response function predicted the short run dynamic response of corn prices to the US gasoline and ethanol price shocks and forecast error variance decomposition estimated the importance of these shocks.

Results suggest that biofuel production related policies within the U.S. impacts the world price of corn. In addition, the demand led price change may last for a longer period of time. Therefore, any policy change that leads to a demand shock in the corn market should be complemented by the policies that improve its supply dynamics. Further research needs to be completed to know whether and to what extent these policy changes impact other food sectors within U.S. as well as to the global food prices.

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Table 1: Augmented Dickey-Fuller Test Before Policy Change

Variables	Model 1 (None) Test Statistics Value	Model 2 (Drift) Test Statistics Value		Model 3 (Drift and Trend) Test statistics Value		
	Constant (tau1)	Constant (tau2)	Drift (phi1)	Constant (tau3)	Drift (phi 2)	Trend (phi3)
Gasoline price	0.614	-0.36	0.38	-1.15	1.9	2.46
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)
Ethanol Price	-0.31	-3.14**	4.99	-3.13	3.74	5.54
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)
U.S. Corn Price	-0.85	-4.14**	8.61	-4.29**	6.14**	9.21**
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)
Global Corn Price	-0.68	-3.56**	6.33**	-3.60**	4.32	6.48**
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)

Note: ** denotes statistical significance at 5% level. Critical value at 5% level is in the parentheses.

Table 2: FEVD of US Corn Prices Before Policy Change

Period (year)	Gasoline Price	Ethanol Price	U.S. Corn Price	Global Corn Price
1	0.001	0.004	0.995	0.000
2	0.000	0.002	0.936	0.062
3	0.003	0.003	0.856	0.138
4	0.004	0.004	0.779	0.213
5	0.004	0.003	0.710	0.283
6	0.004	0.003	0.649	0.344
7	0.004	0.002	0.597	0.397
8	0.003	0.002	0.554	0.441
9	0.003	0.002	0.518	0.477
10	0.003	0.002	0.488	0.506

Table 3: FEVD of World Corn Prices Before Policy Change

Period (year)	Gasoline Price	Ethanol Price	U.S. Corn Price	Global Corn Price
1	0.000	0.004	0.628	0.369
2	0.000	0.001	0.628	0.370
3	0.002	0.001	0.591	0.406
4	0.003	0.001	0.547	0.450
5	0.003	0.001	0.505	0.492
6	0.003	0.001	0.467	0.529
7	0.003	0.001	0.435	0.562
8	0.002	0.001	0.407	0.589
9	0.002	0.001	0.385	0.612
10	0.002	0.002	0.366	0.630

Table 4: Augmented Dickey-Fuller Test After Policy Change

Variables	Model 1 (None) Test Statistics Value	Model 2 (Drift) Test Statistics Value		Model 3 (Drift and Trend) Test statistics Value		
	Constant (tau1)	Constant (tau2)	Drift (phi1)	Constant (tau3)	Drift (phi 2)	Trend (phi3)
Gasoline Price	-0.9	-2.372	2.9	-2.23	1.97	2.87
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)
Ethanol Price	-1.51	-4.03**	8.48**	-4.01**	5.68**	8.14**
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)
U.S. Corn Price	-0.23	-1.96	1.98	-1.53	1.57	2.30
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)
Global Corn Price	-0.31	-2.05	2.13	-1.74	1.62	2.40
	(-1.95)	(-2.87)	(-4.61)	(-3.42)	(-4.71)	(-6.30)

Note: ** denotes statistical significance at 5% level. Critical value at 5% level is in the parentheses.

Table 5: Johansen 's Cointegration Test After Policy Change

Null Hypothesis	Test statistics (λ_{max})
$r <= 2$	33.09**
	(-12.25)
$r <= 1$	35.51**
	(-18.96)
$r = 0$	70.98**
	(-23.11)

Note: ** denotes statistical significance at 5% level. Critical value at 5% level is in the parentheses.

Table 6: VECM with one Cointegration Relationship After Policy Change

Vector	Gasoline Price	U.S. Corn Price	Global Corn Price	Trend
$\hat{\beta}^T$	1	7.22	-7.122	0.001
$\hat{\alpha}^T$	-0.001	-0.086	0.101	-0.001

Table 7: Estimated Contemporaneous Impact Matrix After Policy Change

	Gasoline Price	Ethanol Price	U.S. Corn Price	Global Corn Price
Gasoline Price	0.015	0.054	0.045	0.210
	(0.018)	(0.021)	(0.024)	(0.197)
Ethanol Price	0.019	0.199	0.035	-0.023
	(0.023)	(0.022)	(0.022)	(0.024)
U.S. Corn Price	0.098	-0.028	0.267	-0.007
	(0.097)	(0.024)	(0.035)	(0.022)
Global Corn Price	-0.098	0.000	0.342	0.018
	(0.106)	(0.000)	(0.037)	(0.015)

Note: Standard errors in the parentheses.

Table 8: Estimated Long Run Impact Matrix After Policy Change

	Gasoline Price	Ethanol Price	U.S. Corn Price	Global Corn Price
Gasoline Price	0.000	-0.028	0.034	0.149
	(0.000)	(0.024)	(0.019)	(0.142)
Ethanol Price	0.000	0.233	0.058	0.000
	(0.000)	(0.033)	(0.031)	(0.000)
U.S. Corn Price	0.000	-0.054	0.199	0.000
	(0.000)	(0.021)	(0.023)	(0.000)
Global Corn Price	0.000	-0.067	0.204	0.023
	(0.000)	(0.023)	(0.024)	(0.022)

Note: Standard errors in the parentheses.

Table 9: FEVD of U.S. Corn Price After Policy Change

Period (year)	Gasoline Price	Ethanol price	U.S. Corn Price	Global Corn Price
1	0.118	0.009	0.872	0.001
2	0.093	0.020	0.886	0.001
3	0.065	0.033	0.901	0.001
4	0.053	0.042	0.905	0.001
5	0.043	0.046	0.910	0.001
6	0.037	0.049	0.913	0.000
7	0.032	0.052	0.915	0.000
8	0.029	0.054	0.917	0.000
9	0.026	0.055	0.919	0.000
10	0.023	0.056	0.920	0.000

Table 10: FEVD of World Corn Price After Policy Change

Period (year)	Gasoline Price	Ethanol Price	U.S. Corn Price	Global Corn Price
1	0.075	0.000	0.922	0.003
2	0.059	0.047	0.881	0.013
3	0.048	0.063	0.878	0.010
4	0.040	0.066	0.883	0.011
5	0.034	0.071	0.884	0.011
6	0.030	0.075	0.885	0.011
7	0.026	0.077	0.886	0.011
8	0.023	0.079	0.886	0.011
9	0.021	0.081	0.887	0.011
10	0.019	0.082	0.887	0.011

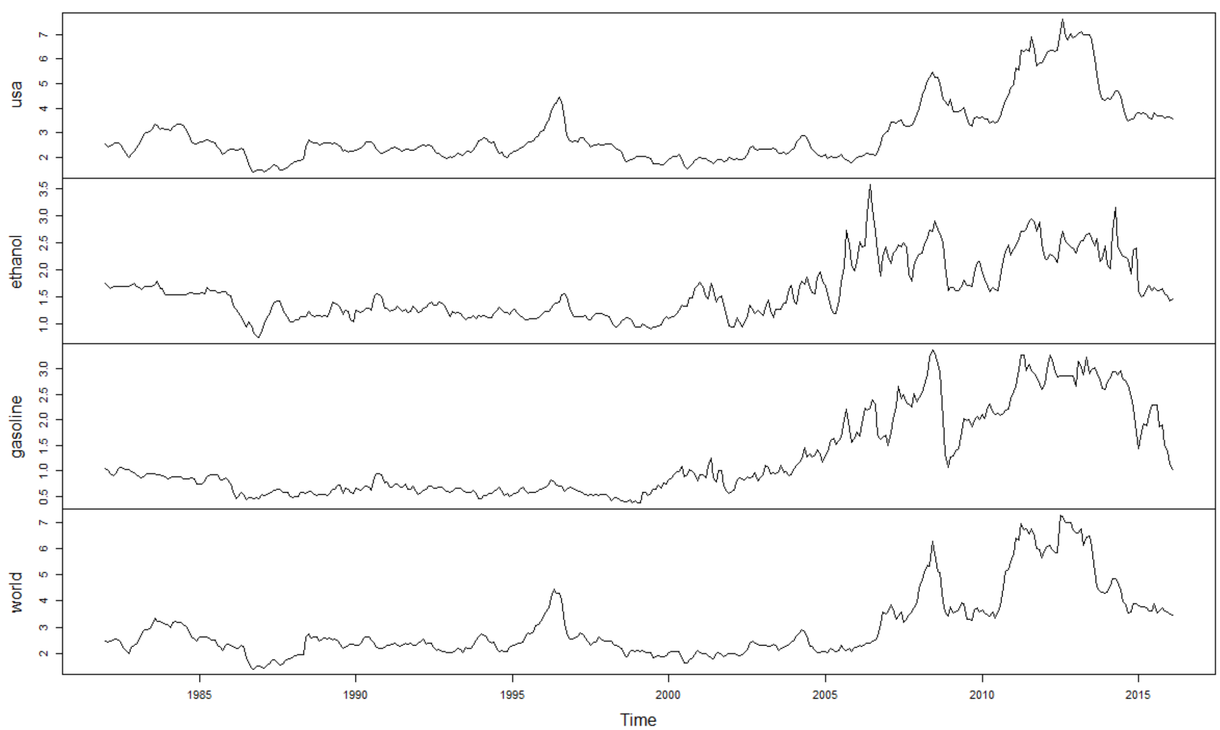

Figure 1: Corn,Ethanol and Gasoline Price Trend(Jan 1982 to Feb 2016)

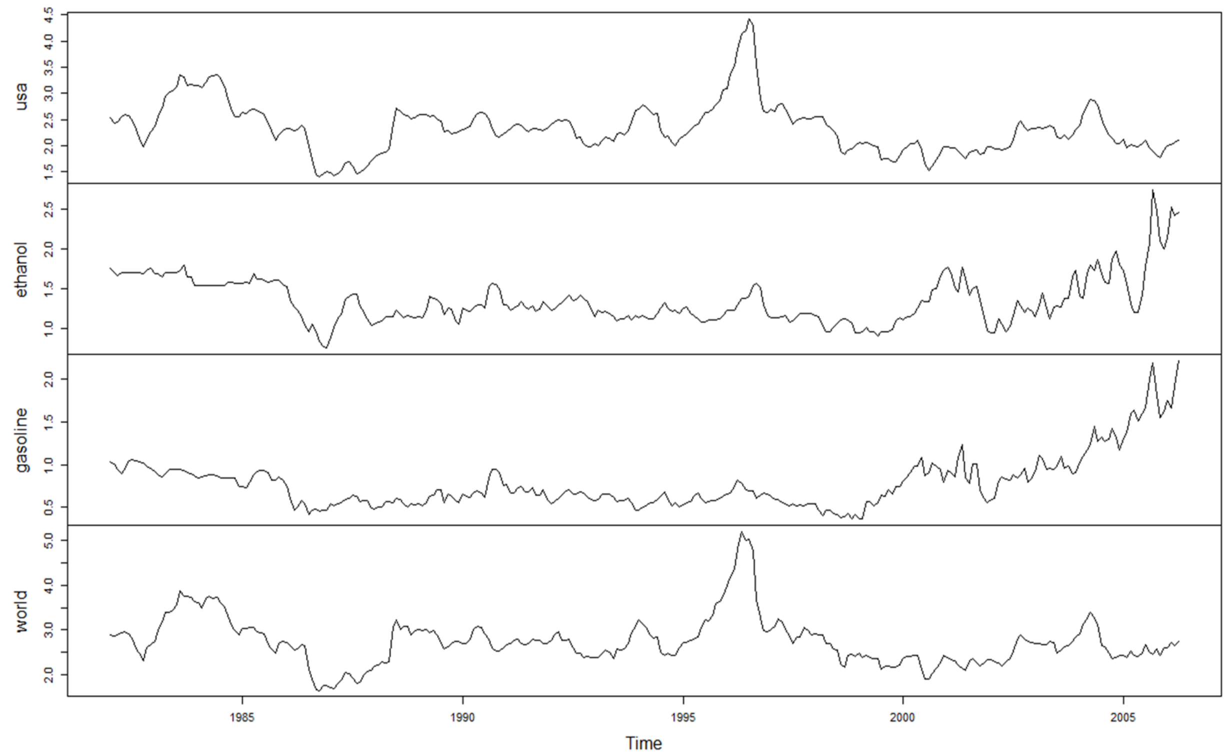

Figure 2: Corn,Ethanol and Gasoline Price Trend (Jan 1982 to April 2006)

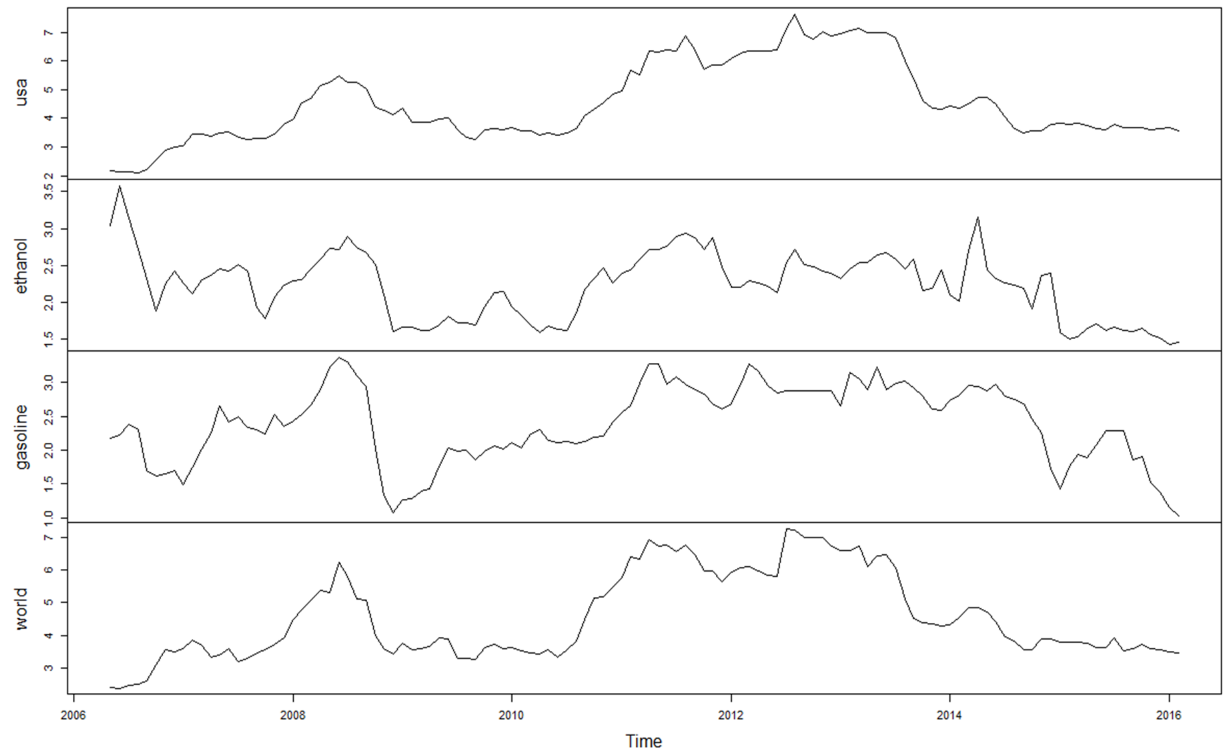

Figure 3: Corn,Ethanol and Gasoline Price Trend(May 2006 to Feb 2016)

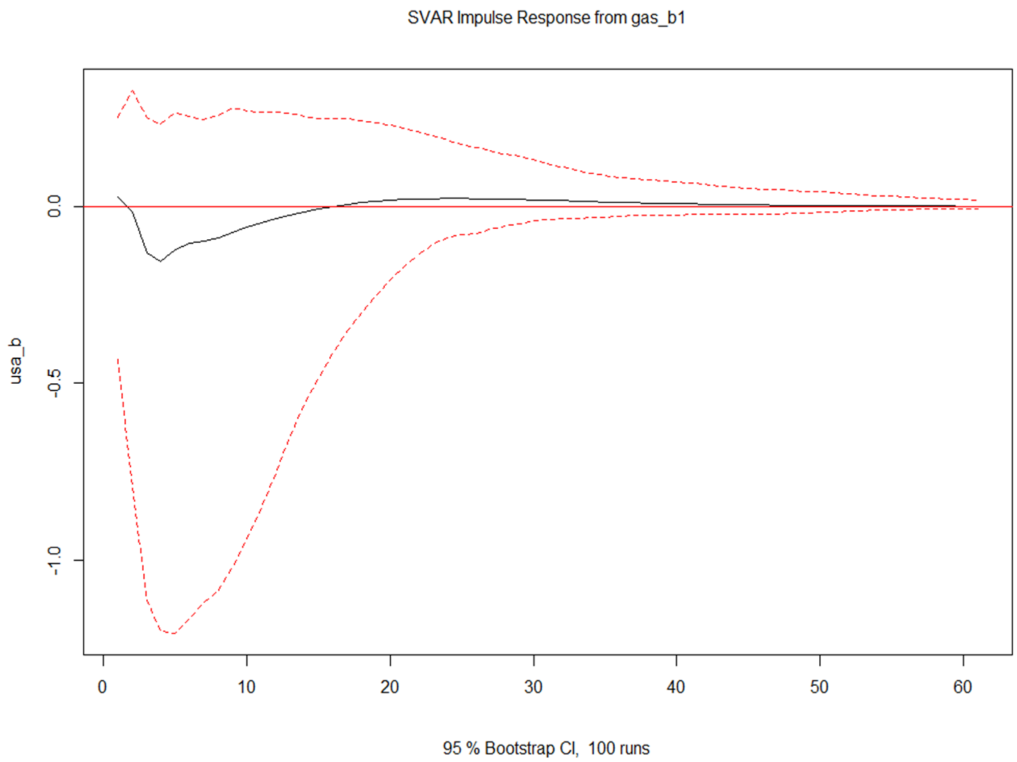

Figure 4: U.S. Corn Price Response → Impulse from Gasoline Price Shock

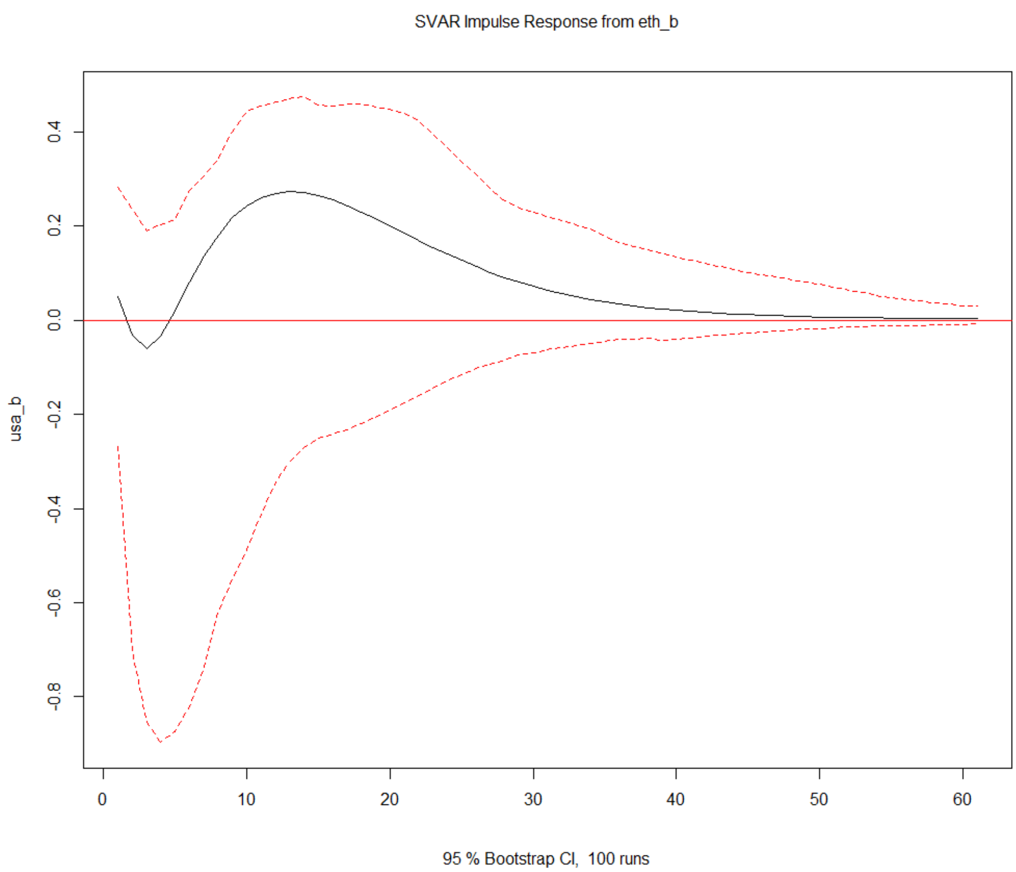

Figure 5: U.S. Corn Price Response→ Ethanol Price Shock

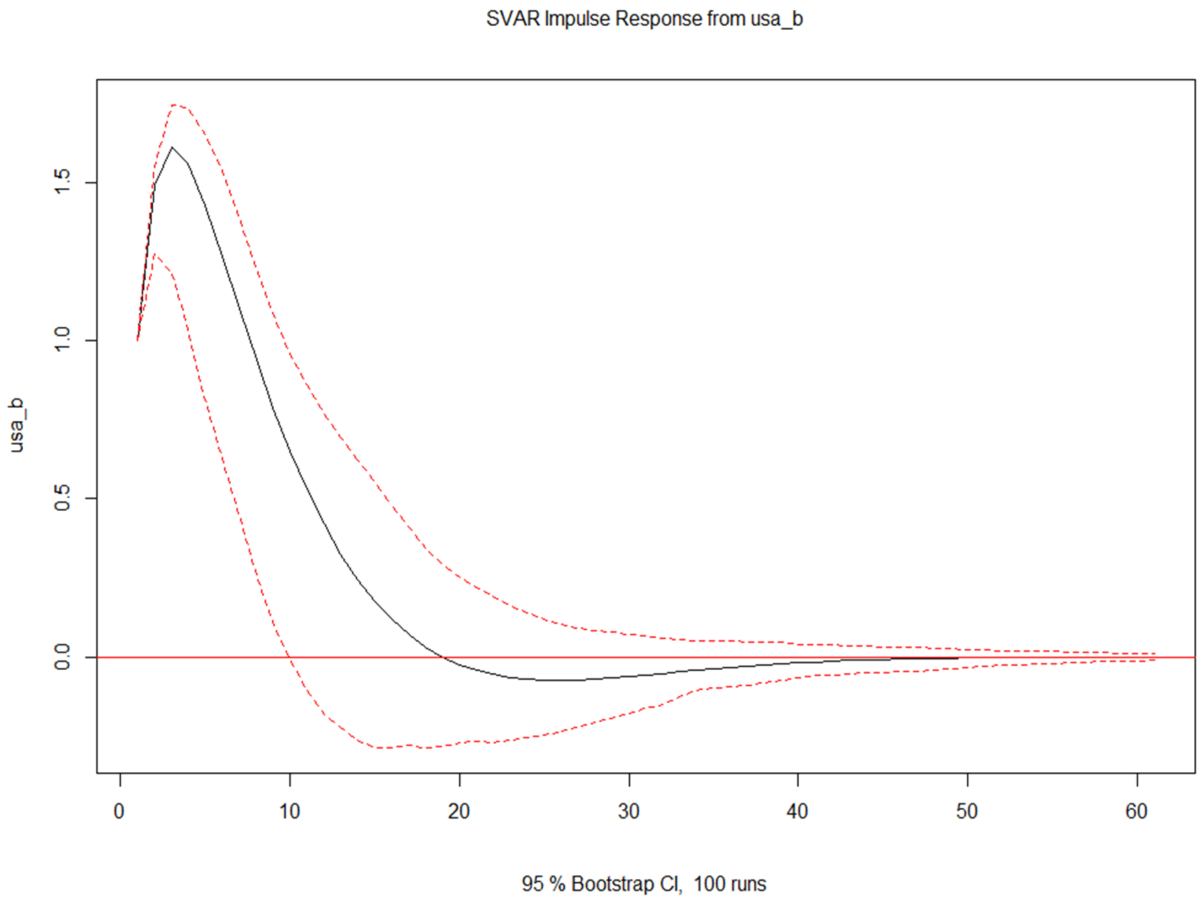

Figure 6: US Corn Price Response→ U.S. Corn Price Shock

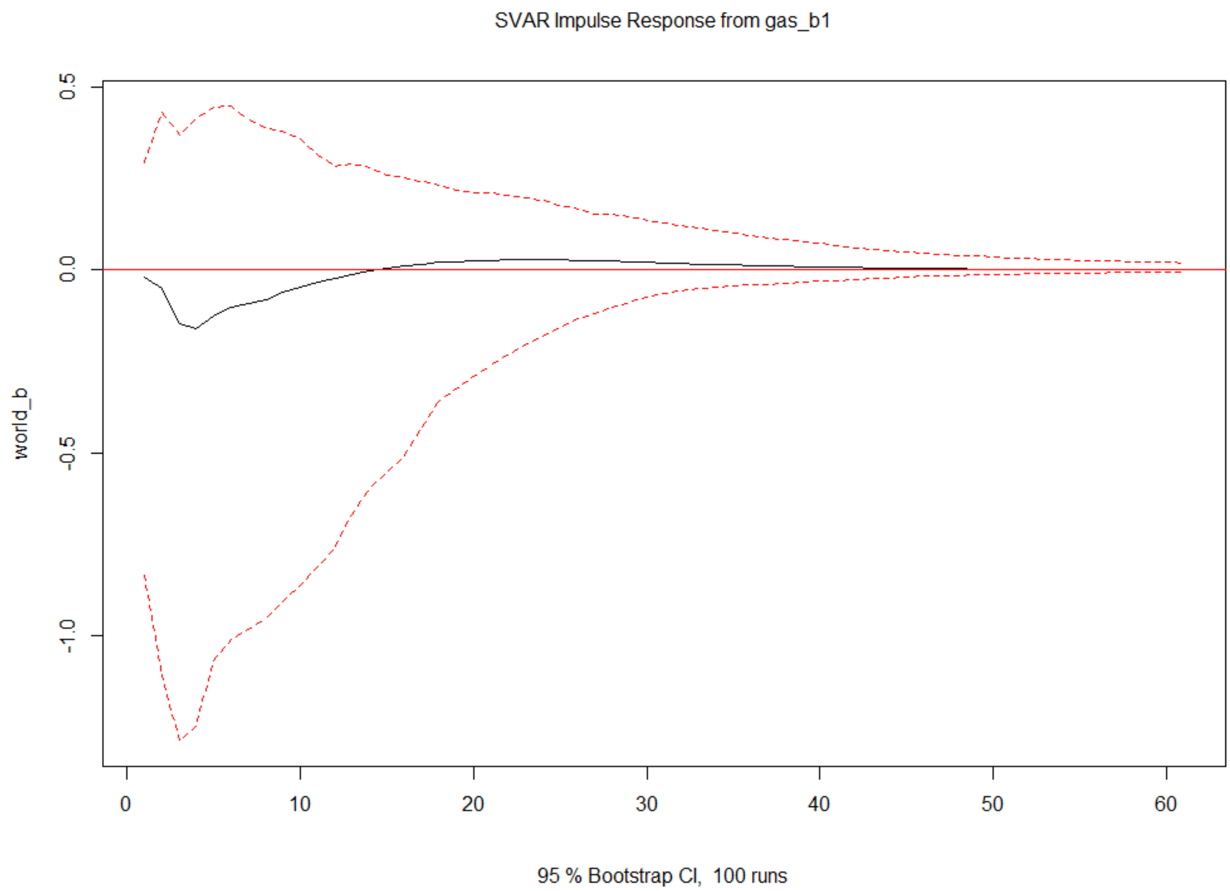

Figure 7: World Corn Price Response→ Impulse from Gasoline Price Shock

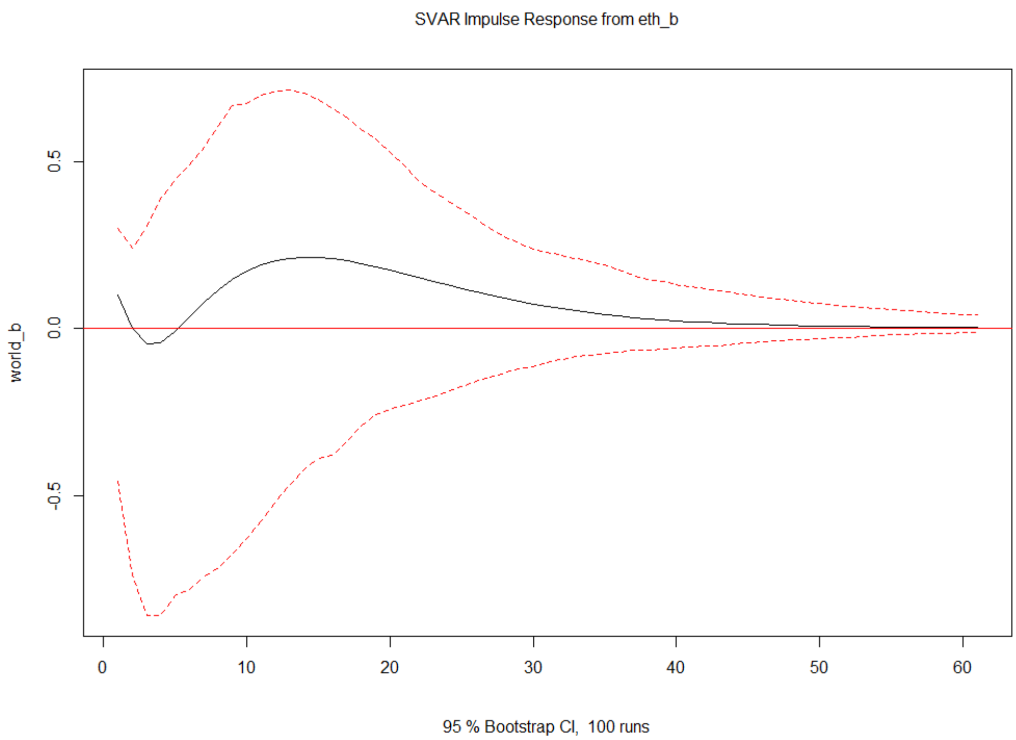

Figure 8: World Corn Price Response → Ethanol Price Shock

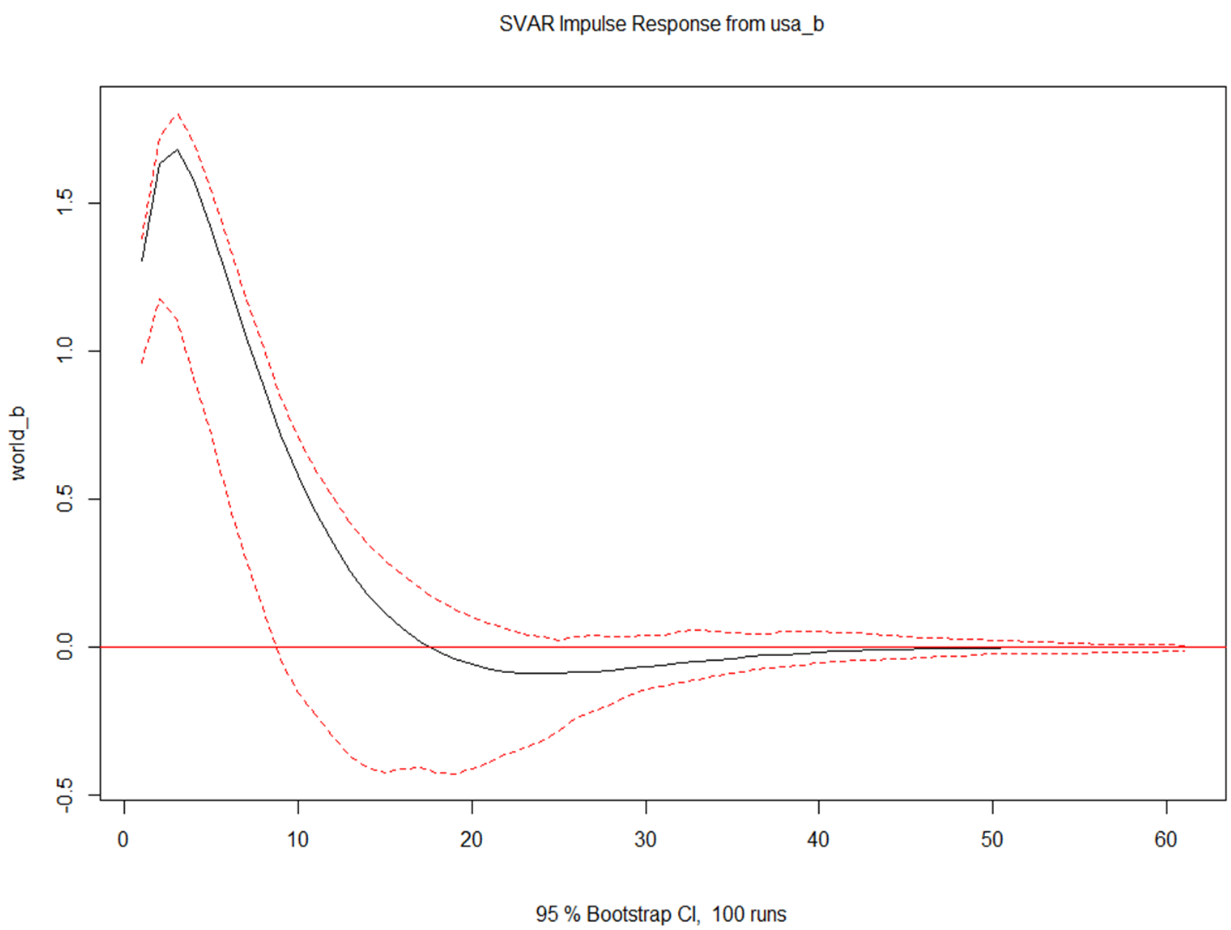

Figure 9: World Corn Price Response → U.S. Corn Price Shock

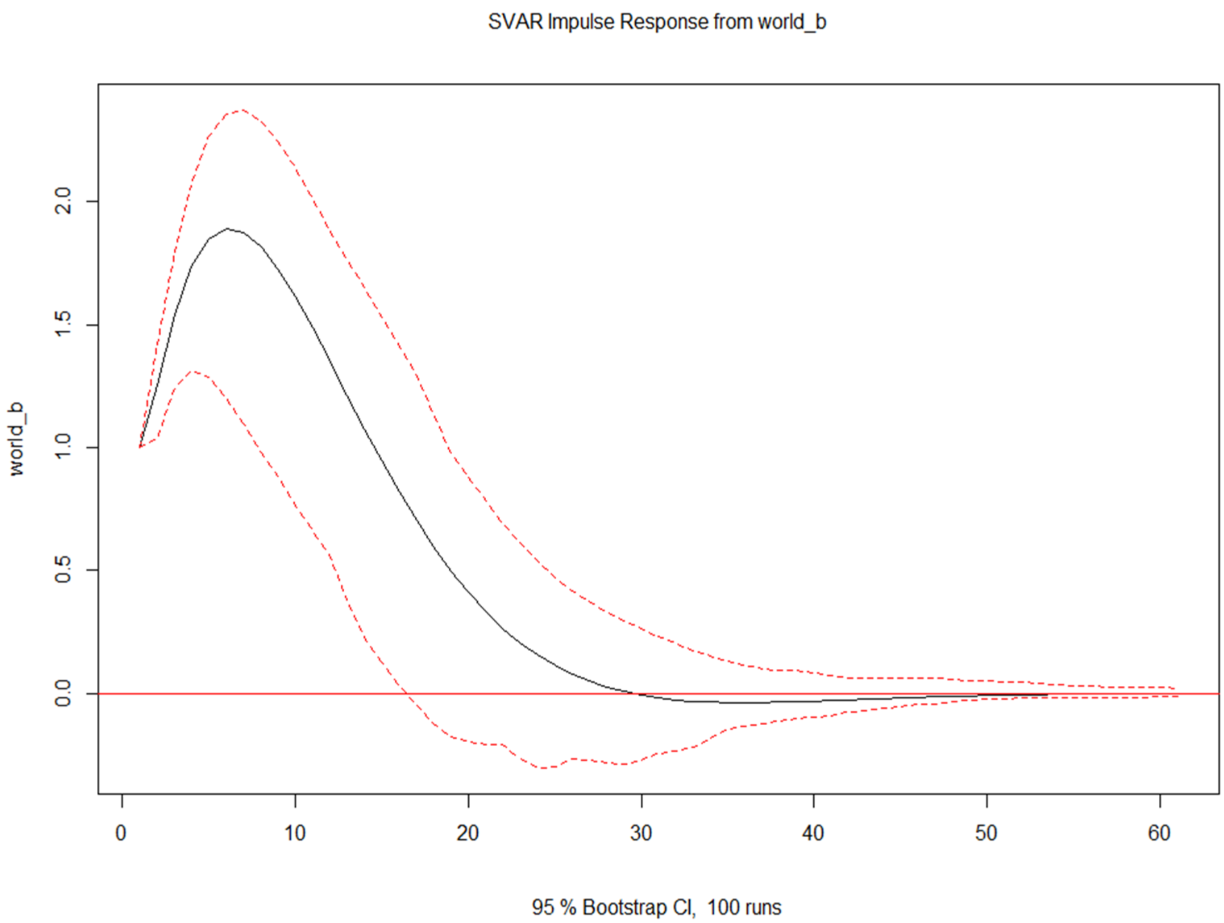

Figure 10: World Corn Price Response → World Corn Price Shock

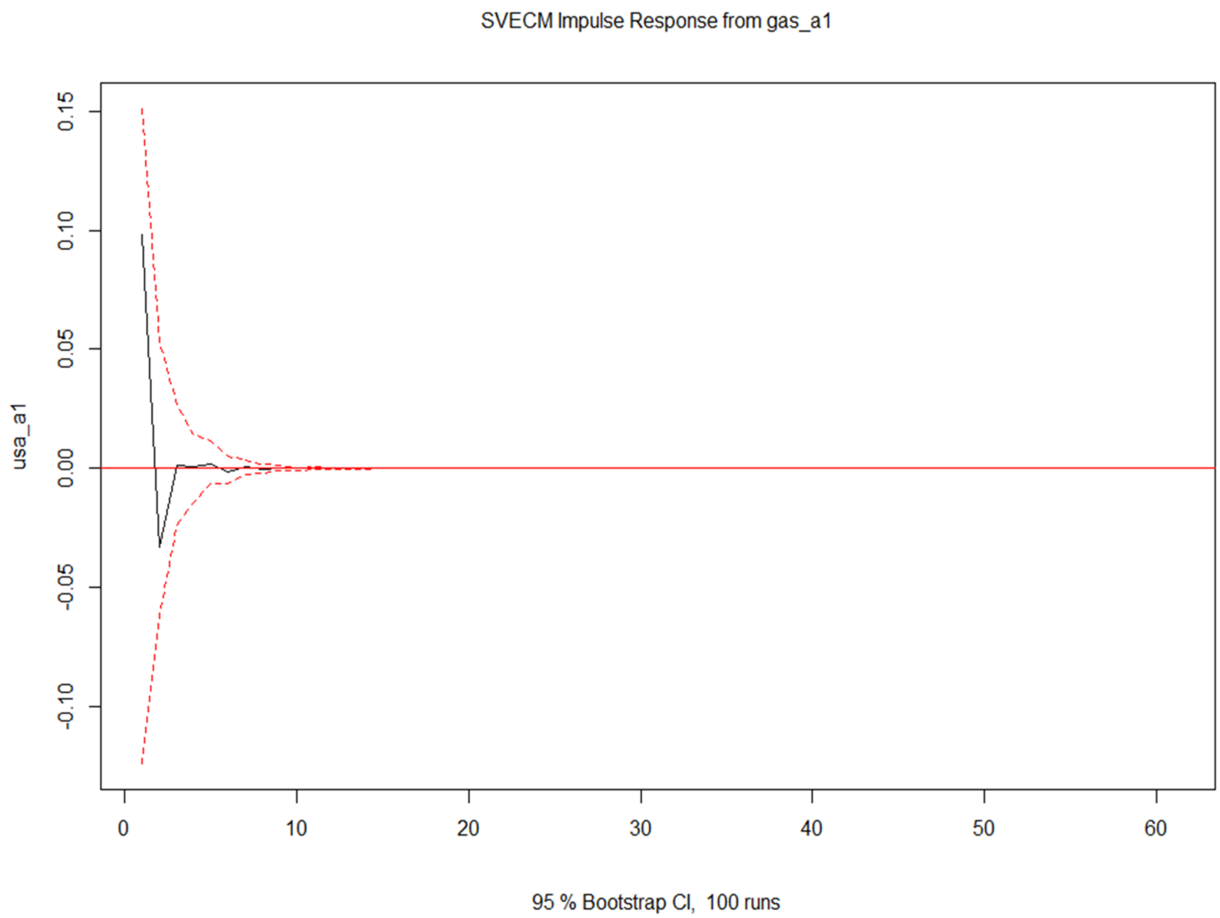

Figure 11: U.S. Corn Price Response → Impulse from Gasoline Price Shock

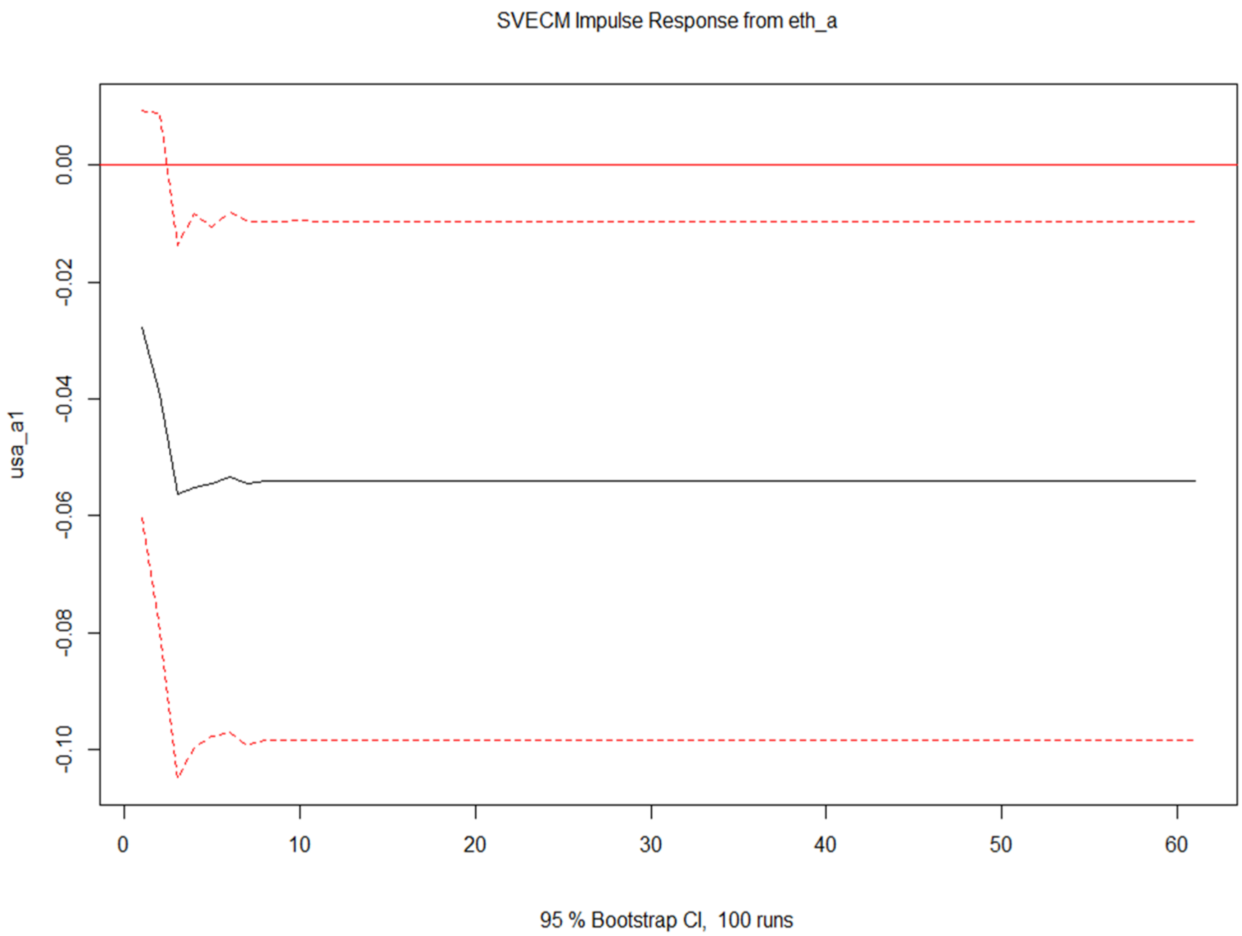

Figure 12: U.S. Corn Price Response → Ethanol Price Shock

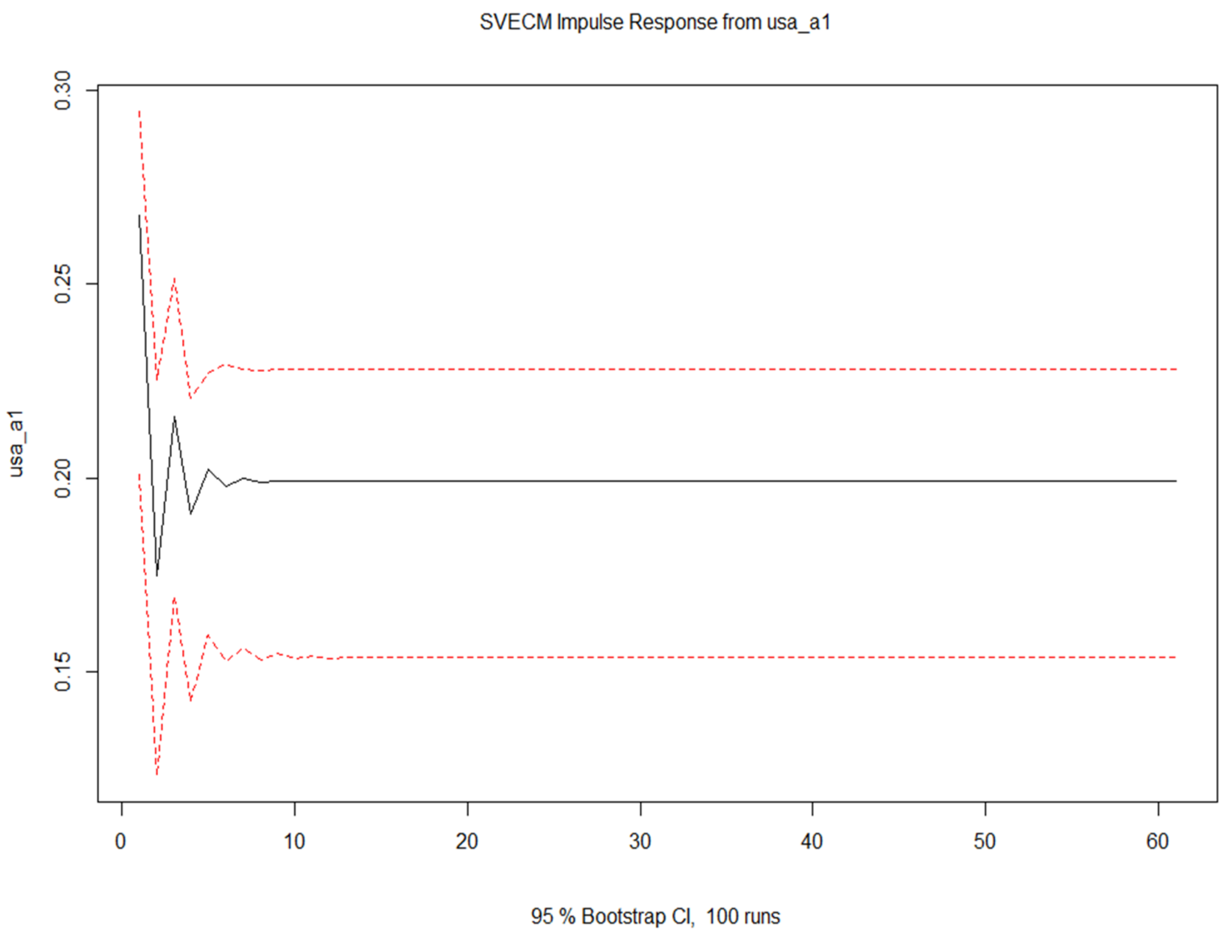

Figure 13: U.S. Corn Price Response → US Corn Price Shock

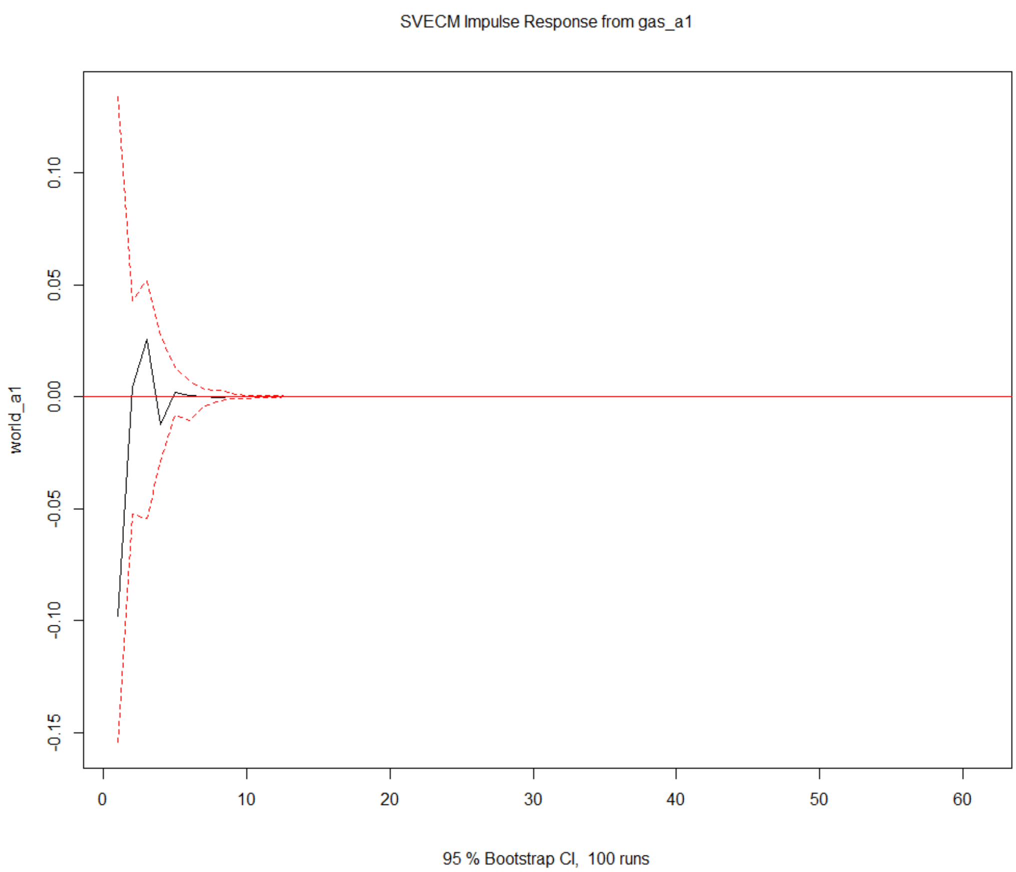

Figure 14: World Corn Price Response → Impulse from Gasoline Price Shock

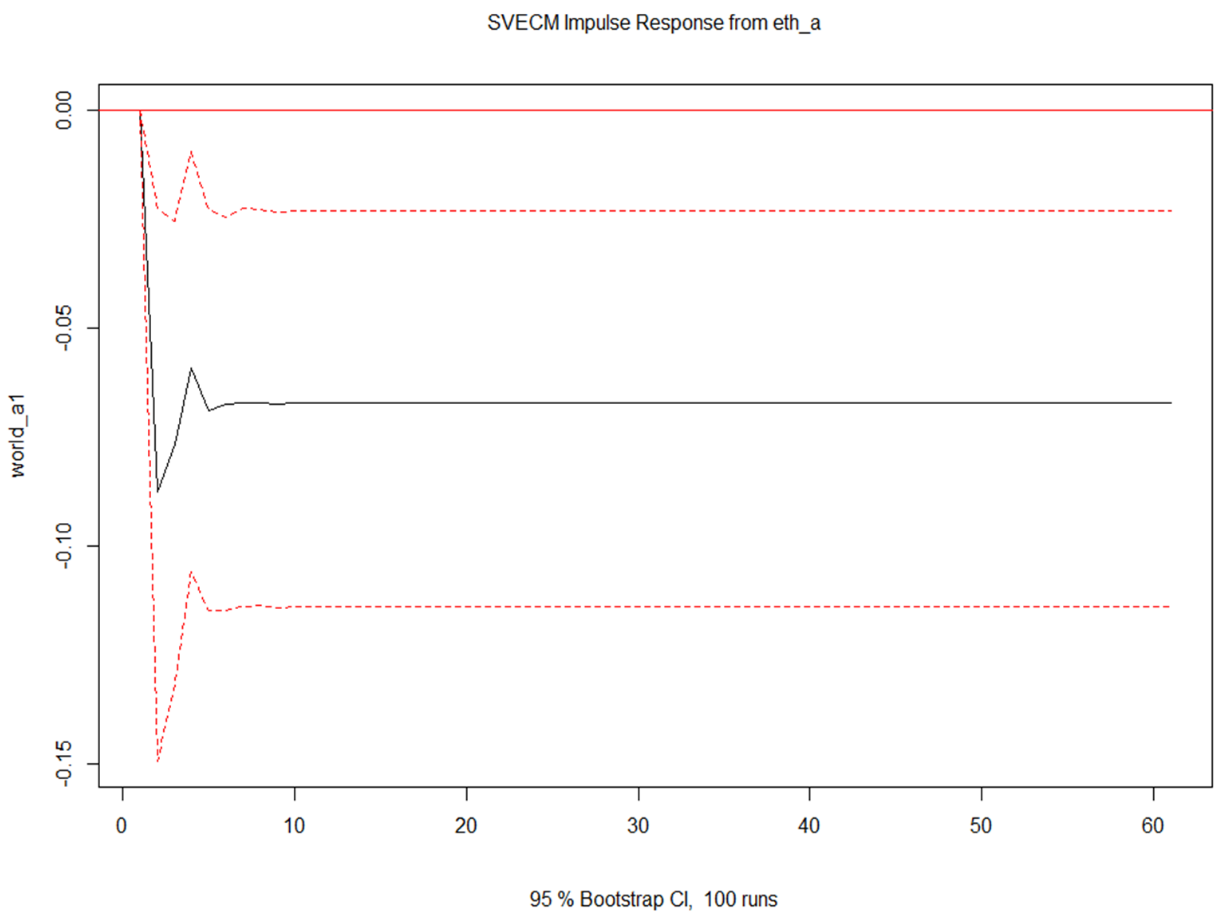

Figure 15: World Corn Price Response → Ethanol Price Shock

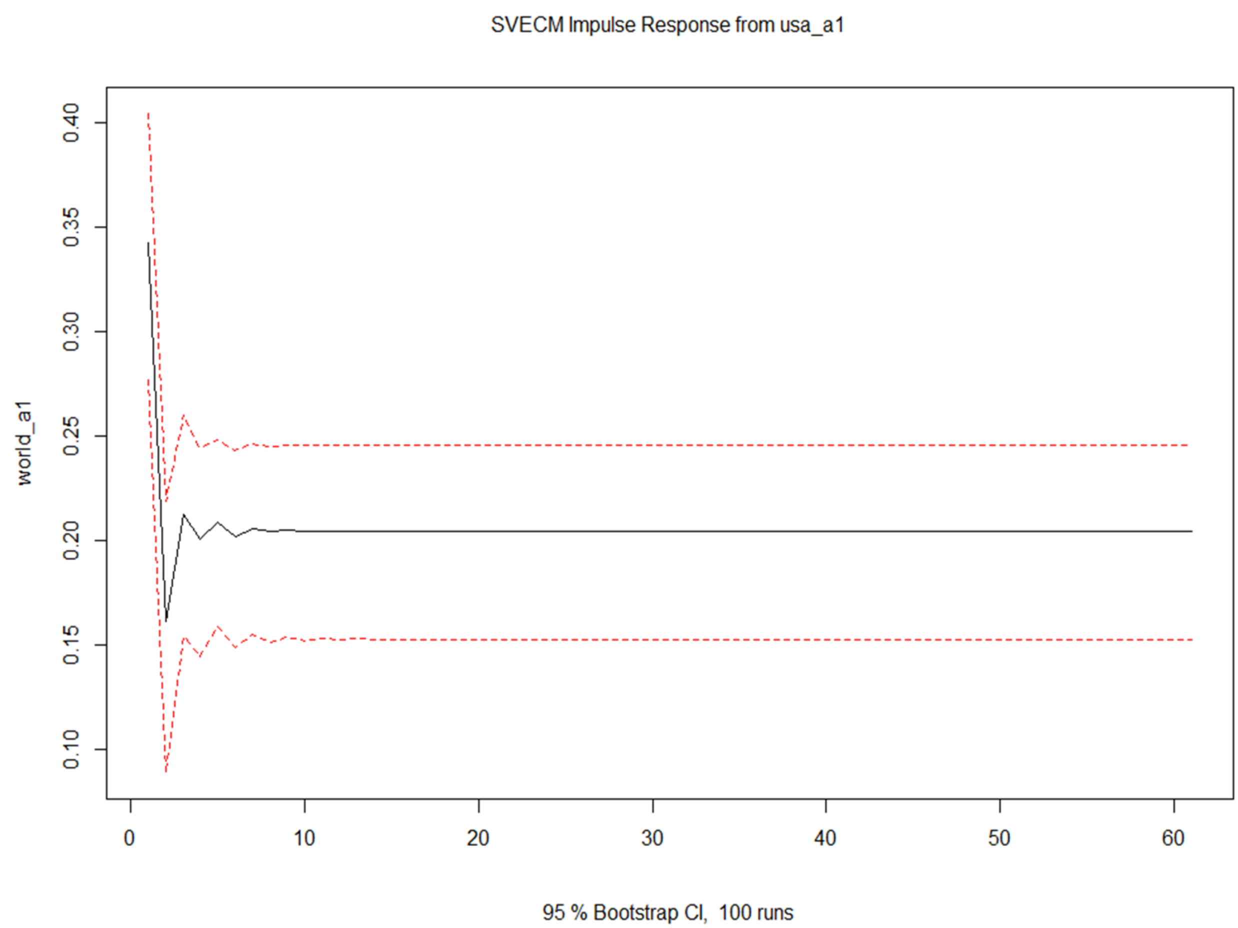

Figure 16: World Corn Price Response → U.S. Corn Price Shock

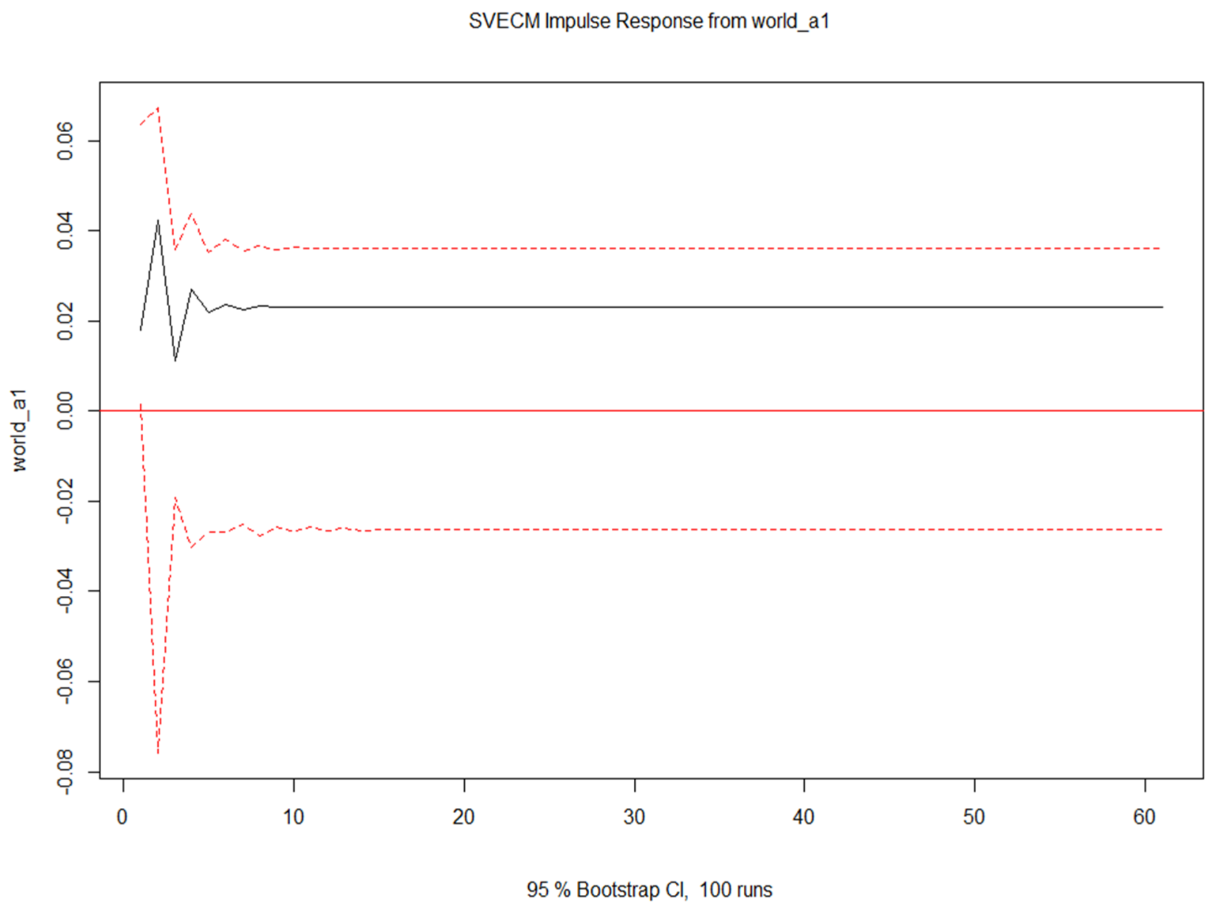

Figure 17: World Corn Price Response → World Corn Price Shock