The Price Shock Transmission during the 2007-2008 Commodity Bull Cycle: A Structural Vector Auto-Regression Approach to the "Chicken-or-Egg" Problem

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2009 AAEA & ACCI Joint Annual Meeting, Milwaukee, WI, July 26-28, 2009

Introduction

Commodity and energy prices exhibited an unprecedented increase between October 2006 and July 2008, only to fall sharply during the last months of 2008 (see **figures 3 to 12**). There is no shortage of economic factors to potentially explain this phenomenon, including a steadily increasing then suddenly dropping demand from China and India, large mandated increases in ethanol production, droughts in some key agricultural producer countries, production plateaus in some major oil-producing countries, refinery capacity limits, demand pressure from the derivatives market owing to the diversification properties of commodities, etc. Clearly, agricultural input, output, and energy products are closely related economically. In addition to biofuels, the connection points include nitrogen-based solution liquid fertilizers, fossil fuels used in agricultural production, limited acreage available for field crops, and so on. For example, the primary input used to produce anhydrous ammonia is natural gas, which represents 80-90% of the cost of production.

While prices of major agricultural crops and energy products have fallen dramatically in late 2008, input costs (e.g. fertilizer) approximately doubled during 2008 and remained high for a few months after the end of the commodity bull cycle. Likewise, prices of agricultural commodities have remained relatively high compared with historical levels, even though the supply- and demand-side pressure has lessened. Despite an evident close connection, it is not entirely clear how exogenous price shocks are transmitted through the system, and whether particular commodities drive up the prices of other commodities. The proposed paper attempts to address this "chicken-or-egg" problem by applying the Structural Vector Autoregression (SVAR) framework to the analysis of a wide range of commodity prices.

The purpose of this paper is to model and estimate an SVAR model of multiple commodity prices in order to: Investigate the transmission mechanism of the price shocks associated with the commodity boom of 2006-2008 and subsequent bust and identify changes (if any) relative to earlier time periods (e.g. 2004-2006) Evaluate the possibly asymmetrical relationship between different commodity and energy price variables Test hypotheses of causality in a time series definition (Granger and graph-theoretic) The SVAR approach while relatively uncommon in agricultural economics is widely used in empirical macroeconomics. Exceptions include notably Orden and Fackler (1989) on the money-agriculture relationship as well as more recently, Babula, Bessler, Reeder, and Somwaru (2004) on the soybean complex, Babula, Bessler and Payne (2001) on wheat and wheat-based products, and Zhang, Vedenov and Wetzstein (2007)on the competitiveness of ethanol as an alternative fuel.

The main contribution of this paper is to provide a tentative answer to the question of how agricultural input, output and energy product prices are related and whether this relationship has changed in recent years

Procedures and Data

The dataset consists of weekly observations for nominal prices of principal agricultural outputs (grains, oilseeds, meats), agricultural inputs (fertilizer, urea), and energy products (crude oil, gasoline, diesel, natural gas, electricity). Structural assumptions are derived from economic theory. The methodology consists of defining and estimating a structural

VAR model, studying impulse response functions and the variance decomposition, and testing for the direction of causality. Given that a longstanding problem is the sensitivity of the results to identifying assumptions, graph analysis is used here as it is a promising approach to identify the structure of the variance-covariance matrix and therefore overcome the observational equivalence of various reduced-form models implied by different identification approaches (e.g. Swanson and Granger, 1997; Demiralp and Hoover, 2003).

In the present study we use futures contract settlement prices, with the exception of fertilizer prices, as explained below. Indeed, for actively-traded contracts, the futures price provides price discovery and an unbiased estimate of the spot price at a future date (adjusting for cost-of-carry for storable commodities). For most of the agricultural and energy products we consider, futures price data are available. Two exceptions are ethanol, which only started trading in 3/2005, and fertilizer, e.g. diammonium phosphate, urea ammonium nitrate, and urea (nitrogen), which only traded during the period 2004-2007 and then only in very low volumes. For ethanol, we use all available observations, from 3/2005 to 3/2009. For fertilizer prices, the futures data is not sufficient. Instead, we use the Index of Prices Paid (Fertilizer Prices) from the USDA-NASS over the time period 1/2000-3/2009. These data have a monthly frequency, therefore to match the data with the rest of our weekly data, we use a low-order quadratic spline to interpolate observations.

Since reliable ethanol price data is only available beginning in 2005, we estimate two models: first, a model excluding ethanol, using all observations from 2001 to 2009, and second, a model that includes ethanol but covers only the period 2005-2009. Effectively, we are imposing a structural break associated with the growth of the ethanol industry and we are looking for evidence of a change in the relationships between these commodities.

Vector Autoregression Model

The first step is to consider an "agnostic" or reduced-form joint model of all commodity price time series. All prices are specified in natural logs to facilitate the interpretation of the coefficients. A simple Vector Autoregression (VAR) is appropriate if the data are stationary, i.e. I(0). If however the data are nonstationary, I(1), then an Error Correction Model (ECM) is more appropriate.

To determine whether the data are stationary or not, we use Autocorrelation Functions (with confidence intervals), Augmented Dickey-Fuller (ADF) tests, and KPSS tests. The ADF test has a null of a unit root (nonstationarity), but is known to have low power. We find that we can reject the null of a unit root for some but not all commodity price series.

However, the ACF suggests that serial correlation in all commodity price series is not persistent: correlation declines quickly and dissipates after about 60 business days (one quarter). Therefore, the low power of the unit root test is most likely the reason for our inability to reject the null in the case of some commodities. Moreover, Wang and Tomek (2007) find that once structural breaks are accounted for, commodity prices clearly do not contain a unit root. Lastly, using KPSS tests for all commodities we are unable to reject the null of no unit root.

Overall, the evidence suggests that all commodity price series are stationary and can be safely modeled using a VAR. We consider both classical and Bayesian VAR models, and for the latter we estimate models using the so-called "Minnesota prior" of Doan, Litterman and Sims (1984). However, the results are not significantly different and the number of available observations is adequate for the estimation of a low-order VAR, therefore we proceed to use the classical rather than the Bayesian model.

A common approach is to use Likelihood Ratio tests to determine the optimal VAR model lag length, by comparing a larger (unrestricted) model with a smaller (restricted) model. We find that the 5-lag VAR model is preferred.

Evidence from Granger-causality tests

Once the VAR model is estimated, we can test for Granger-causality between each pair in the ten-commodity system. This provides a baseline approach to establish the causal chain among commodities. We may claim that a lagged regressor X(t-1) Granger-causes a present time regressand Y(t) if Y(t) is better predicted by using X(t-1) as well as all other information available before t, instead of using only the latter. The null in each case is that the lagged regressor X(t-1) does not Granger-cause (explain) the present time regressand Y(t). The results are presented in **table 1.**

The results, using the 5% level of significance, establish the following relationships:

- Corn price Granger-causes soybean and wheat prices
- Soybean price Granger-causes corn and wheat prices
- Wheat price Granger-causes corn, crude oil, fertilizer, heating oil, live cattle, and soybean prices
- Crude oil price Granger-causes corn, fertilizer and soybean prices
- Fertilizer price (index) Granger-causes corn, crude oil, heating oil and live cattle prices

- Heating oil price Granger-causes fertilizer price
- Natural gas price Granger-causes heating oil price

Evidence from Directed Acyclic Graphs

A different and more recent approach to causality, due to Pearl (1995) and to Spirtes, Glymour and Scheines (1993) and introduced to agricultural economics by Bessler and Akelman (1998), is the application of Directed Acyclic Graphs (DAGs). For a description of DAGs, we refer the reader to Haigh and Bessler (2004).

The computational implementation is accomplished using the PC algorithm in the Tetrad IV software (Spirtes, Glymour, Scheines and Ramsey, 2009). The results, at the 10% level of significance, from an application of DAGs to the residuals from the above-defined VAR suggest the following causal ordering:

- Corn price is a direct cause of soybean price
- Wheat price is a direct cause of soybean price
- Corn and wheat prices are causally related but the direction is indeterminate
- Live cattle price is a direct cause of lean hogs price
- Heating oil price is a direct cause of natural gas price
- Crude oil and heating oil prices are causally related but the direction is indeterminate
- Fertilizer price is a direct cause of natural gas price

The DAG results are quite different from the Granger-causality results. Notably, there are three groups grains/oilseeds, meats, and energy. According to this analysis, there is no direct causality running between any commodity from one group to another from a different group. Note again that DAGs reveal contemporaneous causation, while Granger-causality reveals causation from past to present.

Structural restrictions derived from economic theory

To estimate a structural VAR, we need to place certain identifying restrictions using nonsample information. This is because a VAR is a reduced-form model, therefore impulse response functions from a VAR are non-unique. Moreover, the components of the innovations may be correlated, so the IRFs could be misleading. Two common approaches to the imposition of identifying restrictions and therefore obtain unique IRFs are the Choleski factorization and the Bernanke-Sims method. The Choleski factorization may not always be appropriate because it is arbitrary: it imposes a recursive structure. The Bernanke-Sims approach assumes that economic theory (i.e., nonsample information) can provide the researcher with guidance on what contemporaneous, identifying restrictions to place. The challenge with this approach is whether the restrictions are correct. In this paper we compare the results obtained from two approaches: Bernanke-Sims and DAGs.

Further details on the present-used framework can be found in Lutkepohl (2005, pp.358-68). Suppose that the commodity prices are generated by an unobservable process that can be described using the following model:

$$AY_t = BY_{t-1} + Dv_t$$

where Y_{t-1} are endogenous, and v_t are IID orthogonal,“primitive”, shocks, such that $\mathbb{E}[v_t v_t'] = \Lambda$, a diagonal matrix. Generally, it is assumed that the matrix **D=I**, i.e. the identity matrix. The researcher, however, only observes the following relationship:

$$Y_t = \Gamma Y_{t-1} + u_t$$

where Γ is a matrix of coefficients estimated using a VAR model and u_t are the residuals from the VAR model estimation such that $\mathbb{E}[u_t u_t'] = \Sigma$, a real, symmetric matrix which is estimated as $\hat{\boldsymbol{\Sigma}}$**.** Calculating impulse response functions from the u_t residuals is clearly misleading due to the contemporaneous correlation between residuals associated with different variables. Instead, consider that we may rewrite the observable relationship as follows:

$$Y_t = A^{-1}BY_{t-1} + A^{-1}Dv_t$$

where $[u_t u_t'] = A^{-1}\mathrm{D}\Lambda\mathrm{D}'(\mathrm{A}')^{-1}$. Under the Choleski decomposition, it is assumed that $\Sigma = PP'$ for a lower diagonal **P**. This implies a recursive structure, which may not be a reasonable restriction.

To obtain correctly identified impulse response functions together with the innovation accounting and variance decomposition, we need to specify the matrix **A** such that $\boldsymbol{\Lambda}$ is diagonal. We consider both the Cowles Commission-inspired approach of imposing restrictions from economic theory (i.e., a structural economic model) as well as the Bernanke-Sims approach of imposing restrictions based on a causal ordering derived from nonsample information or, in this case, the application of DAGs to determine the causal structure of the system of commodity prices.

One limitation of using restrictions derived from a structural model is that since some variables, e.g. quantities, are only recorded at a monthly or quarterly frequency, the number of observations is smaller and there few degrees of freedom available for such a VAR model.

From above, note that $\boldsymbol{\Sigma} = \mathbf{A}^{-1}\mathbf{D}\,\boldsymbol{\Lambda}\,\mathbf{D}'(\mathbf{A}')^{-1}$ and, assuming that **D=I** and further normalizing to one the variances of the structural innovations v_t , then we may write

$\Sigma = A^{-1}(A')^{-1}$. It follows that the VAR residuals are: $u_t = \mathbf{A}^{-1} v_t$ or equivalently, that the structural shocks are: $v_t = \mathbf{A}u_t$. This is known in the literature as the A-model (see e.g., Lutkepohl, 2005, p. 358-62).

The causal ordering found by the DAGs suggests the following specification for the system of nine commodity price series (ethanol is presently excluded):

$v_{corn} = u_{corn} + a_{13}u_{wheat}$

$v_{soybeans} = a_{21}u_{corn} + u_{soybeans} + a_{23}u_{wheat}$

$v_{wheat} = a_{31}u_{corn} + u_{wheat}$

$v_{cattle} = u_{cattle}$

$v_{hogs} = a_{54}u_{cattle} + u_{hogs}$

$v_{fert} = u_{fert}$

$v_{crude} = u_{crude} + a_{67}u_{heating}$

$v_{heating} = a_{76}u_{crude} + u_{heating}$

$v_{natural} = a_{85}u_{fert} + a_{87}u_{heating} + u_{natural}$

The estimation of the parameters in the matrix **A** is done numerically. The matrix **A** is vectorized and expressed in a form that can be evaluated for just- or over-identification (see e.g. Amisano and Giannini, 1997). The results of the structural VAR model estimation are omitted from the present paper but will be detailed in an updated version.

Changes in energy-agricultural price relationships: inclusion of ethanol price data

One of the present paper's research questions is: How has the ethanol and biofuel expansion affected, if at all, the relationship between agricultural and energy prices? To this end, we reconsider the complete system of price series using weekly data from 2005 to

2009 (T=194). We use all nine price series described earlier in addition to ethanol. The optimal VAR model, based on Likelihood Ratio tests, uses four lags. The results from Granger-causality tests, at the 5% level of significance, are presented in **table 2** and suggest the following relationships:

- Corn prices Granger-cause wheat prices and heating oil prices
- Soybean prices Granger-cause corn prices
- Wheat prices Granger-cause soybean prices and crude oil prices
- Live cattle prices Granger-cause heating oil prices
- Lean hog prices Granger-cause crude oil and heating oil prices
- Fertilizer prices Granger-cause corn, soybean, live cattle, heating oil and natural gas prices
- Crude oil, heating oil and natural gas prices do not Granger-cause any other price series
- Ethanol prices do not Granger-cause any other price series

These results appear surprising: for example, why are energy and ethanol prices unrelated to other series? In contrast, a very different picture of (contemporaneous) causal relationships emerges from the application of DAGs to the VAR innovations:

- Corn prices are a direct cause of wheat prices and natural gas prices
- Soybean prices are a direct cause of corn prices
- Wheat prices are a direct cause of corn prices
- Ethanol prices are a direct cause of corn prices
- Live cattle prices are a direct cause of wheat prices

- Crude oil price are causally related to heating oil prices but the direction is indeterminate
- Heating oil prices are a direct cause of natural gas prices and are causally related to crude oil prices
- Natural gas prices are a direct cause of corn prices

Therefore, the principal causal chain as determined by DAGs is: crude oil →heating oil→natural gas→corn →wheat. Another chain runs from cattle prices to wheat prices to corn prices. Corn prices, in fact, appear to be a "sink" in the sense that they are predicted by several different variables but do not themselves predict other variables. Therefore, the DAG causal ordering suggests the following specification, usable for the estimation of structural shocks, for the system of ten commodity price series, including ethanol:

$v_{corn} = u_{corn} + a_{12}u_{soybeans} + a_{13}u_{wheat} + a_{19}u_{natural} + a_{1,10}\, u_{ethanol}$

$v_{soybeans} = u_{soybeans}$

$v_{wheat} = a_{31}u_{corn} + u_{wheat} + a_{34}u_{cattle}$

$v_{cattle} = u_{cattle}$

$v_{hogs} = u_{hogs}$

$v_{fert} = u_{fert}$

$v_{crude} = u_{crude} + a_{67}u_{heating}$

$v_{heating} = a_{76}u_{crude} + u_{heating}$

$v_{natural} = a_{81}u_{corn} + a_{87}u_{heating} + u_{natural}$

$v_{ethanol} = u_{ethanol}$

Using this causal ordering, a structural VAR model is estimated. Using standard notation, the **A** matrix is specified using the above ordering and is expressed in vec form with six “free” parameters (the above a_{31}, a_{34}, …, a_{87}) while the **B** matrix is expressed as a diagonal with ten “free” parameters. The estimation results are omitted from the present paper but will be detailed in an updated version**.**

Impulse response functions

Once the orthogonalized, structural shocks have been computed, it is possible to obtain the impulse response functions that represent the individual effect on all variables of a random shock occurring in one selected variable. The results are presented in **figures 13 to 22** for each of the ten price variables studied in this paper. We summarize the results as follows:

- A one standard deviation (positive) shock to the futures price of corn has a substantial impact on the price (index) of fertilizer as well as the price of ethanol: in fact, the impact appears to increase over time. It also has a short-lived impact on the price of lean hogs.
- A shock to soybean prices has a marked effect on fertilizer, wheat, and corn.
- A shock to wheat prices particularly affects corn and fertilizer.
- Shocks to cattle prices appear to be weak and short-lived.
- A shock to hog prices has a short-lived impact on corn, soybean and wheat prices but is otherwise short-lived.
- A shock to fertilizer prices is persistent and appears to lead to long-lived impacts on grain/oilseed prices.
- A shock to crude oil prices has a marked effect on fertilizer prices.
- A shock to heating oil prices a substantial effect on natural gas and fertilizer prices as well as a large but short-lived effect on crude oil prices.

- A shock to natural gas prices has a persistent effect on fertilizer and heating oil prices.
- A shock to ethanol prices has a persistent effect on crude oil prices and a clear but short-lived effect on corn prices , as well as a smaller effect on fertilizer prices.

Conclusion

This paper examines the relationship between agricultural and energy prices with the objective of determining what commodities have been the main drivers of the recent commodity bull cycle and whether the relationship has changed in the last ten years. To this end, we estimate structural VAR models of a system of ten agricultural and energy commodity price /price index variables. For the structural identification, we consider restrictions derived from economic theory as well as from a causal ordering obtained from an application of Directed Acyclic Graphs to the innovations of the reduced-form VAR model. We study the estimates of the structural VAR as well as the orthogonalized impulse response functions and lastly we contrast the results of DAGs on the contemporaneous causal ordering with the results from Granger-causality F-tests. Our preliminary results suggest that the energy and agricultural sectors are less obviously connected than what would appear from a direct examination of common price trends. More work is needed to verify this hypothesis.

Table 1: Results of Granger-causality Wald tests, nine price series (ethanol excluded), 1/2001-3/2009. A p-value implies the null of no Granger-causality is rejected. Empty cells imply p>0.10.

Variable	C	SB	W	LC	LH	FR	CL	HO	NG
Corn	0.001	0.02	0.001	.	.	.	.	0.04	0.03
Soybeans	.	0.001	0.001	.	.	.	.	.	0.001
Wheat	.	0.01	0.001	0.001	.	.	.	.	0.001
Live cattle	.	.	0.001	0.001		.	0.05	.	0.001
Lean hogs	.	.	0.02	.	0.001	.	.	.	0.001
Fertilizer index	.	.	.	.	.	0.001	.	.	.
Crude oil	.	.	.	.	.	.	0.001	.	.
Heating oil	0.04	0	.	.	.	.	.	0.001	0.001
Natural gas	0	.	.	.	.	.	.	0.001	0.001

Table 2: Results of Granger-causality Wald tests, ten price series, 5/2005-3/2009. A p-value implies the null of no Granger-causality is rejected. Empty cells imply p>0.10.

Variable	C	SB	W	LC	LH	FR	CL	HO	NG	ETH
Corn	0.001	0.01	.	.	.	0	.	.	.	.
Soybeans	.	0.001	0.02	.	.	0	.	.	.	.
Wheat	0.06	0.05	0.001	.	.	.	.	.	0.1	.
Live cattle	0.1	0	.	0.001	.	0.01	.	.	.	.
Lean hogs	.	.	.	.	0.001	.	0.05	.	.	.
Fertilizer index	.	.	.	.	.	0.001	.	.	.	.
Crude oil	0.03	.	0.05	.	0.02	.	0.001	.	.	.
Heating oil	0.02	.	0.09	0.02	0.03	0.02	.	0.001	.	.
Natural gas	.	.	.	.	.	0.01	.	.	0.001	.
Ethanol	.	0.09	.	0.03	.	.	.	.	.	0.001

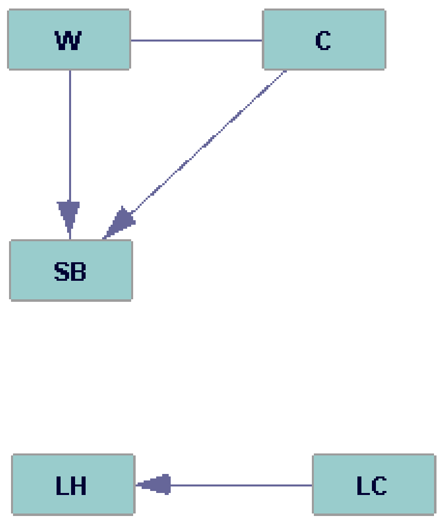

Figure 1: Directed acyclic graph of causal structure between the white noise residual series of nine commodity prices estimated in a VAR(5) model using data over the period 2001-2009. An arrow designates a direct cause while a simple line designates a bidirectional relationship or “feedback”. Legend: C: corn, CL: crude oil, FR: fertilizer price index, HO: heating oil, LC: live cattle, LH: lean hogs, NG: natural gas, SB: soybeans, W: wheat. Source: Data collected from Thomson Datastream and USDA-NASS. Computational implementation in Tetrad IV.

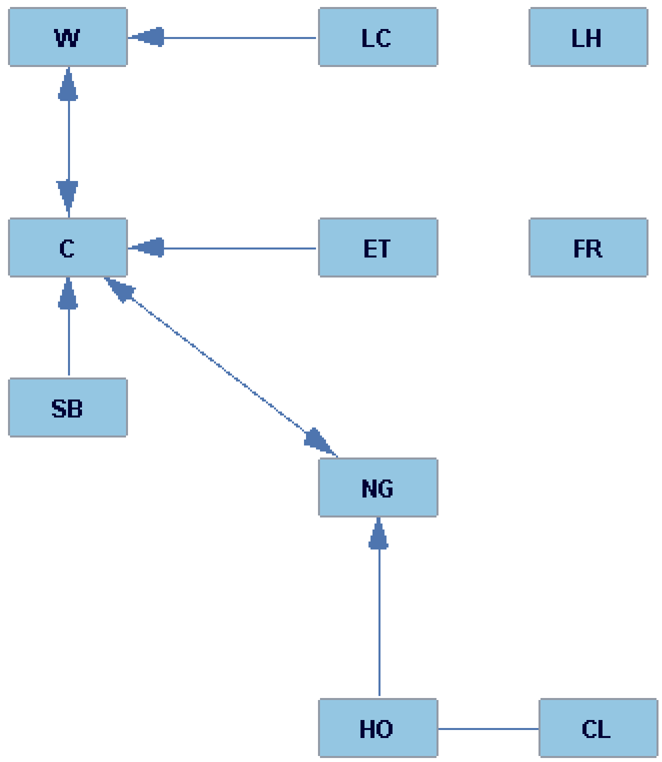

Figure 2: Directed acyclic graph of causal structure between the white noise residual series of ten commodity prices estimated in a VAR(5) model using data over the period 2005-2009. An arrow designates a direct cause while a simple line designates a bidirectional relationship or “feedback”. Legend: C: corn, CL: crude oil, ET: ethanol, FR: fertilizer price index, HO: heating oil, LC: live cattle, LH: lean hogs, NG: natural gas, SB: soybeans, W: wheat. Source: Data collected from Thomson Datastream and USDA-NASS. Computational implementation in Tetrad IV.

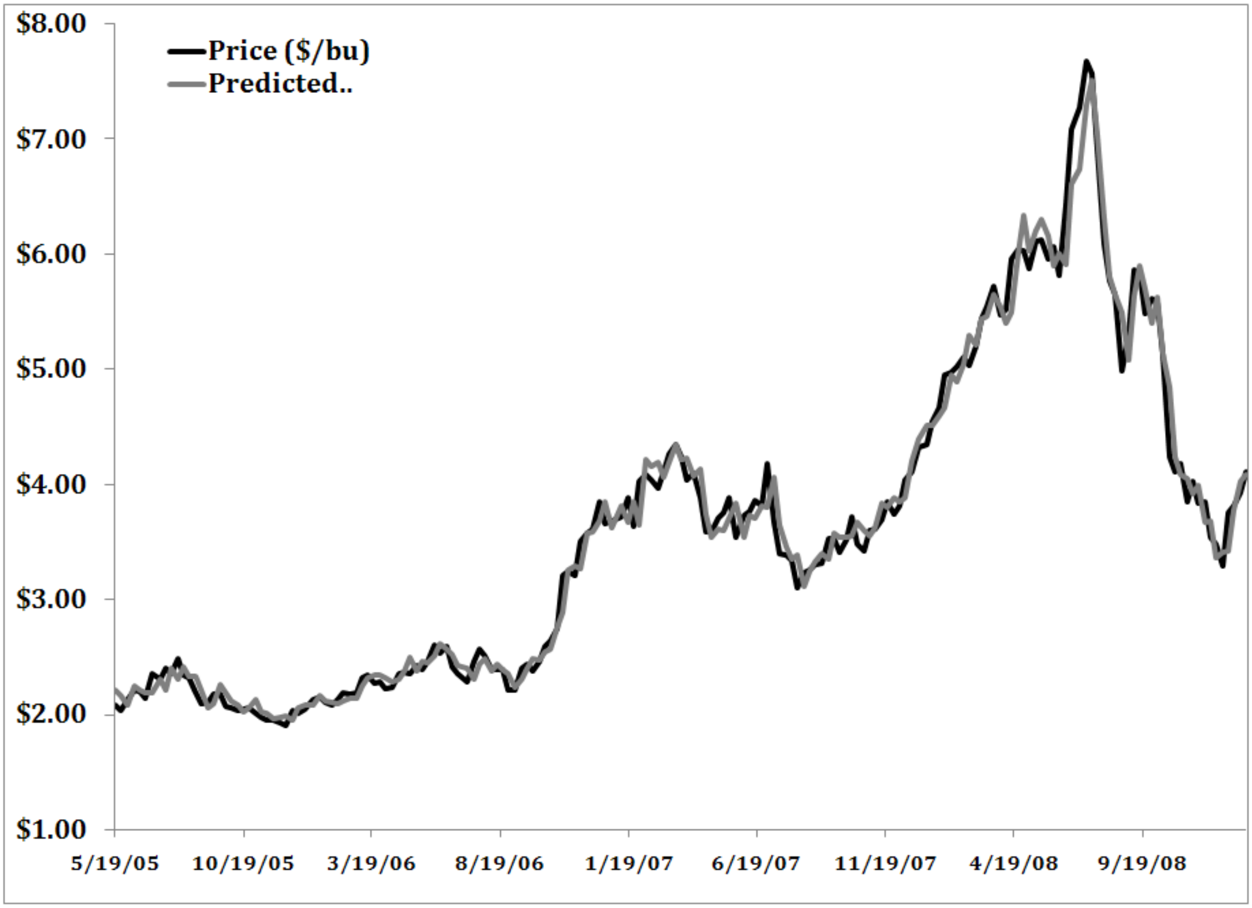

Figure 3: Corn futures price and predicted price (VAR model), 5/2005-3/2009.

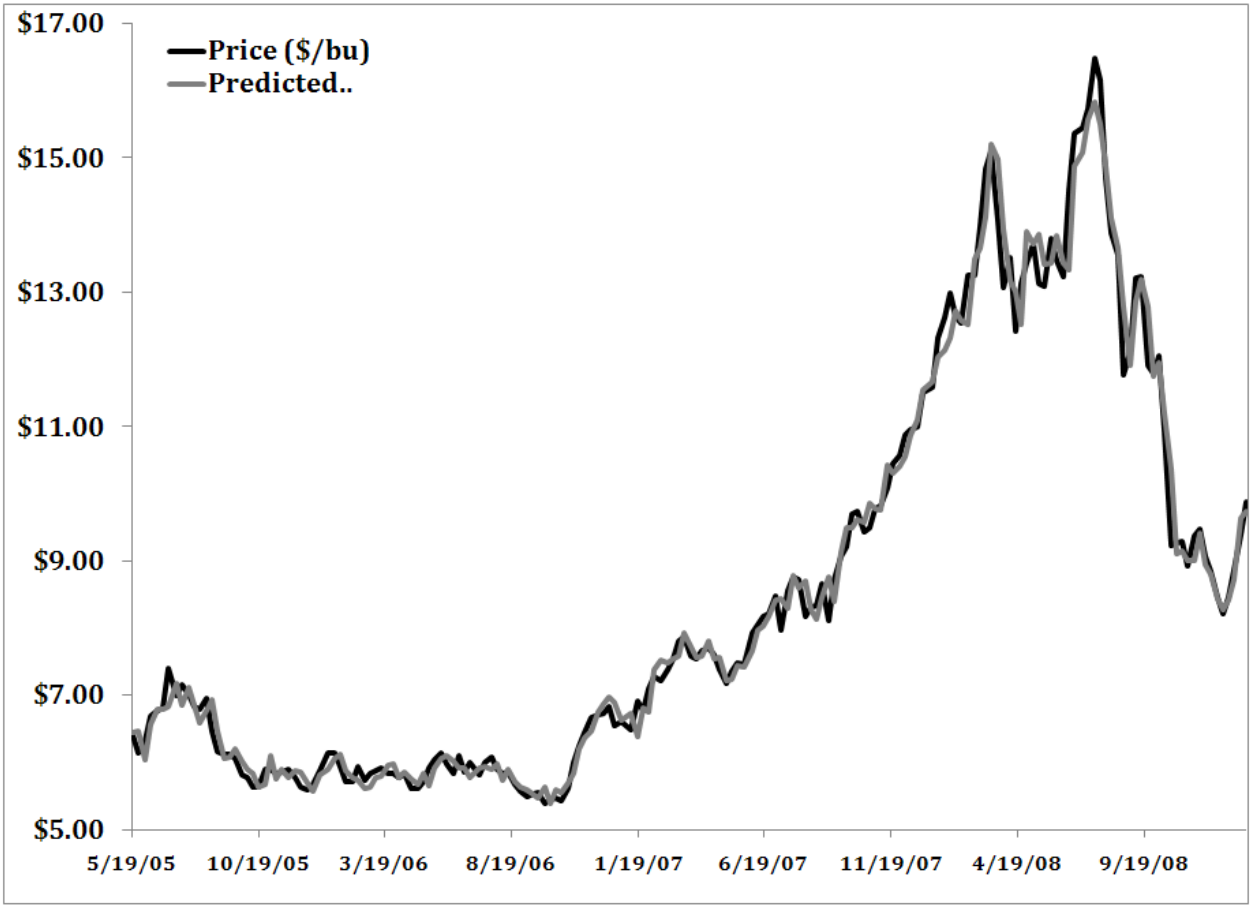

Figure 4: Soybean futures price and predicted price (VAR model), 5/2005-3/2009.

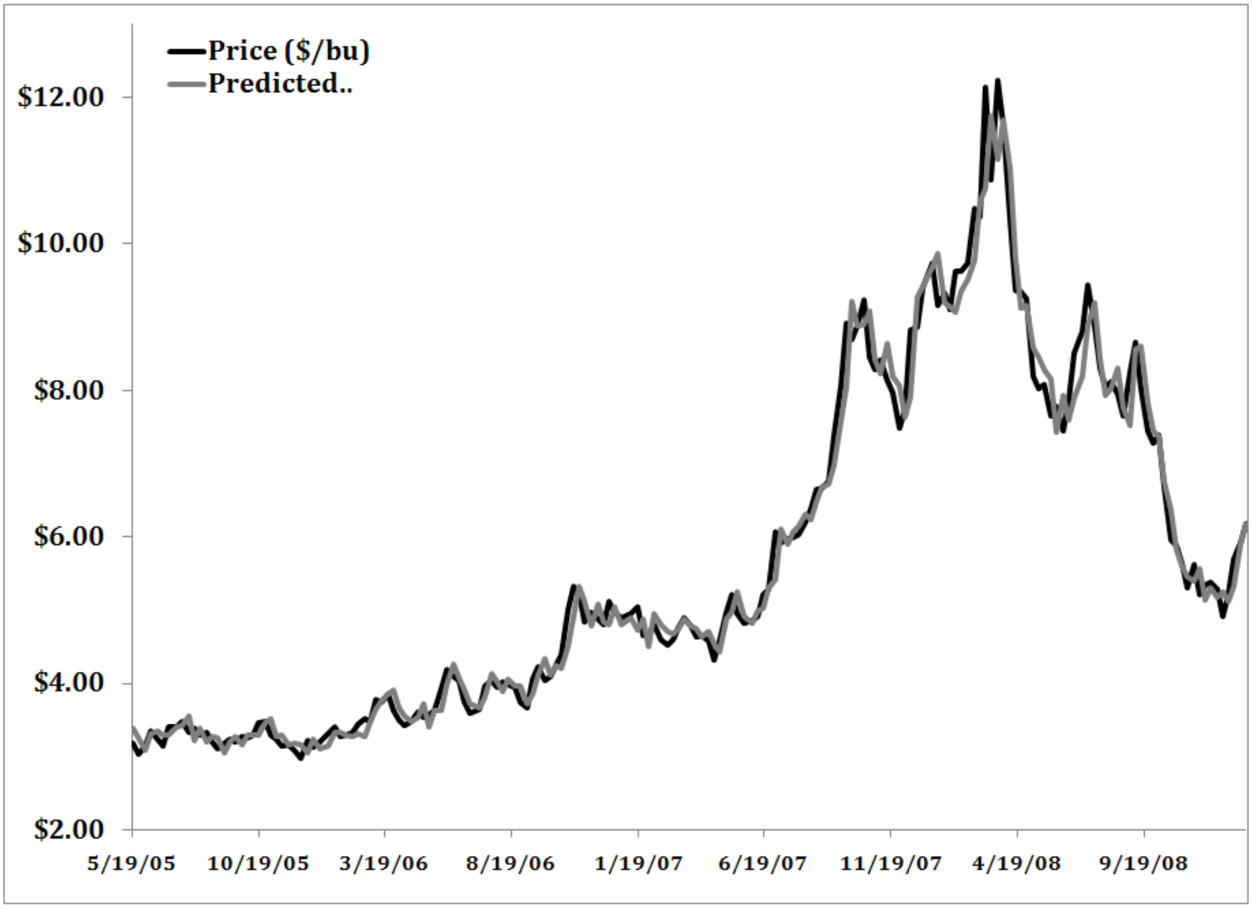

Figure 5: Wheat futures price and predicted price (VAR model), 5/2005-3/2009.

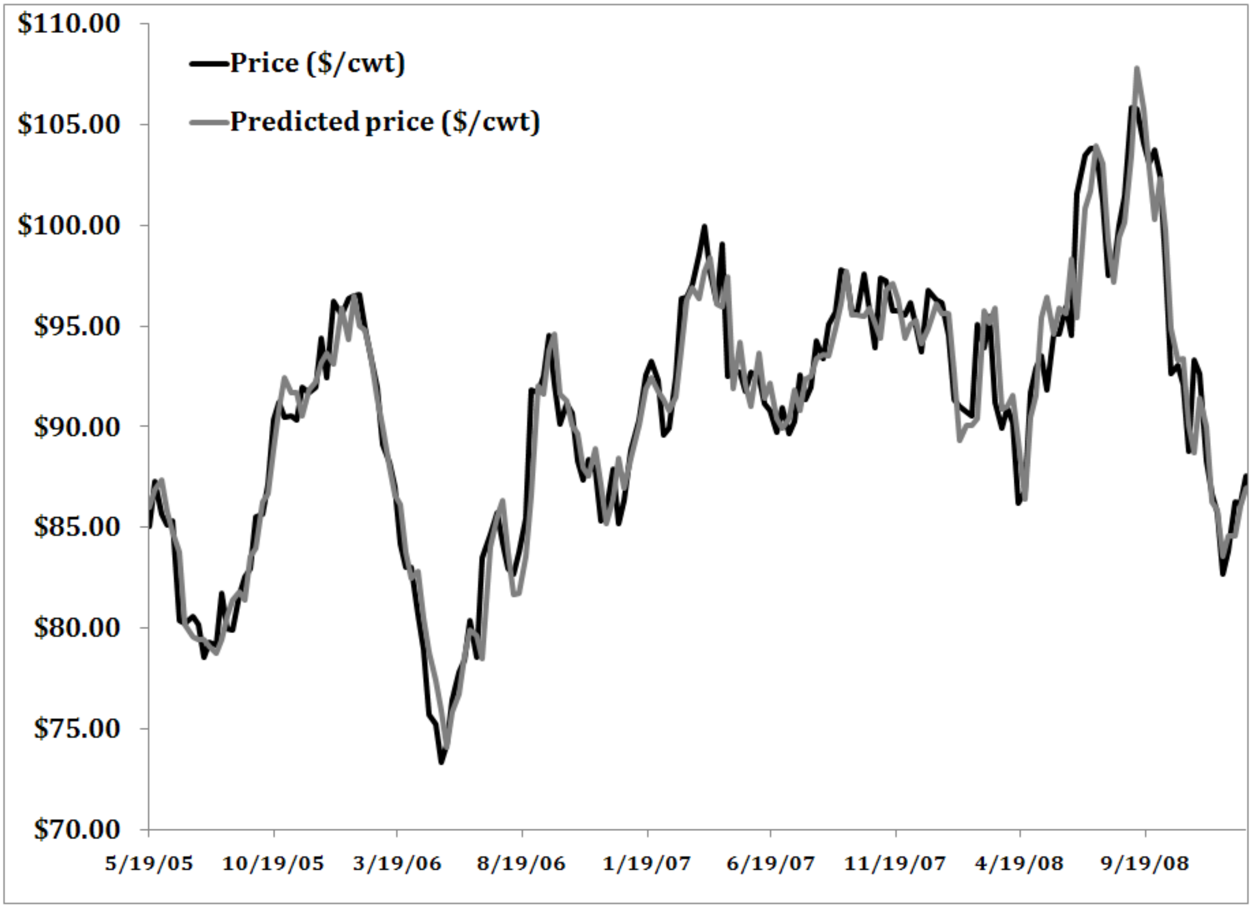

Figure 6: Live cattle futures price and predicted price (VAR model), 5/2005-3/2009.

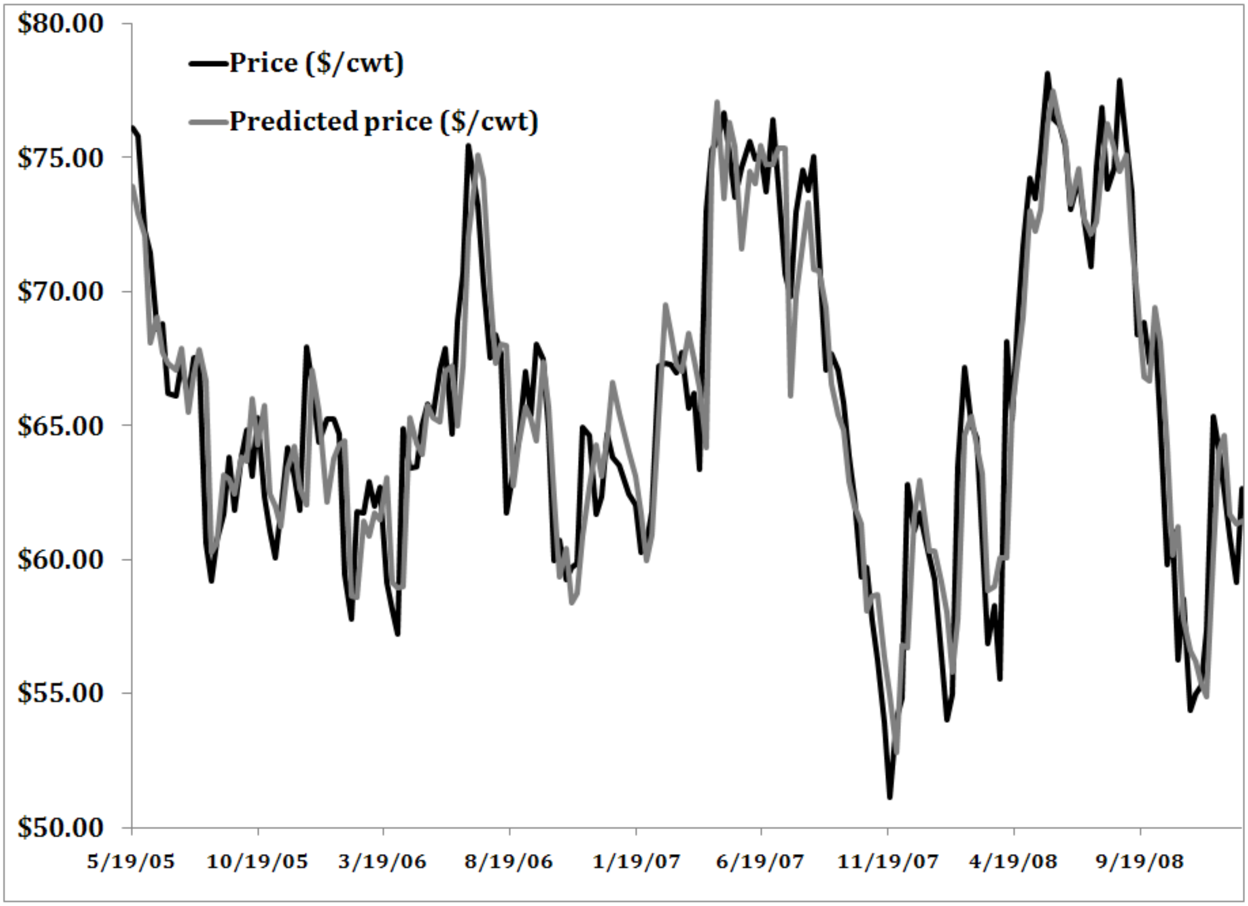

Figure 7: Lean hogs futures price and predicted price (VAR model), 5/2005-3/2009.

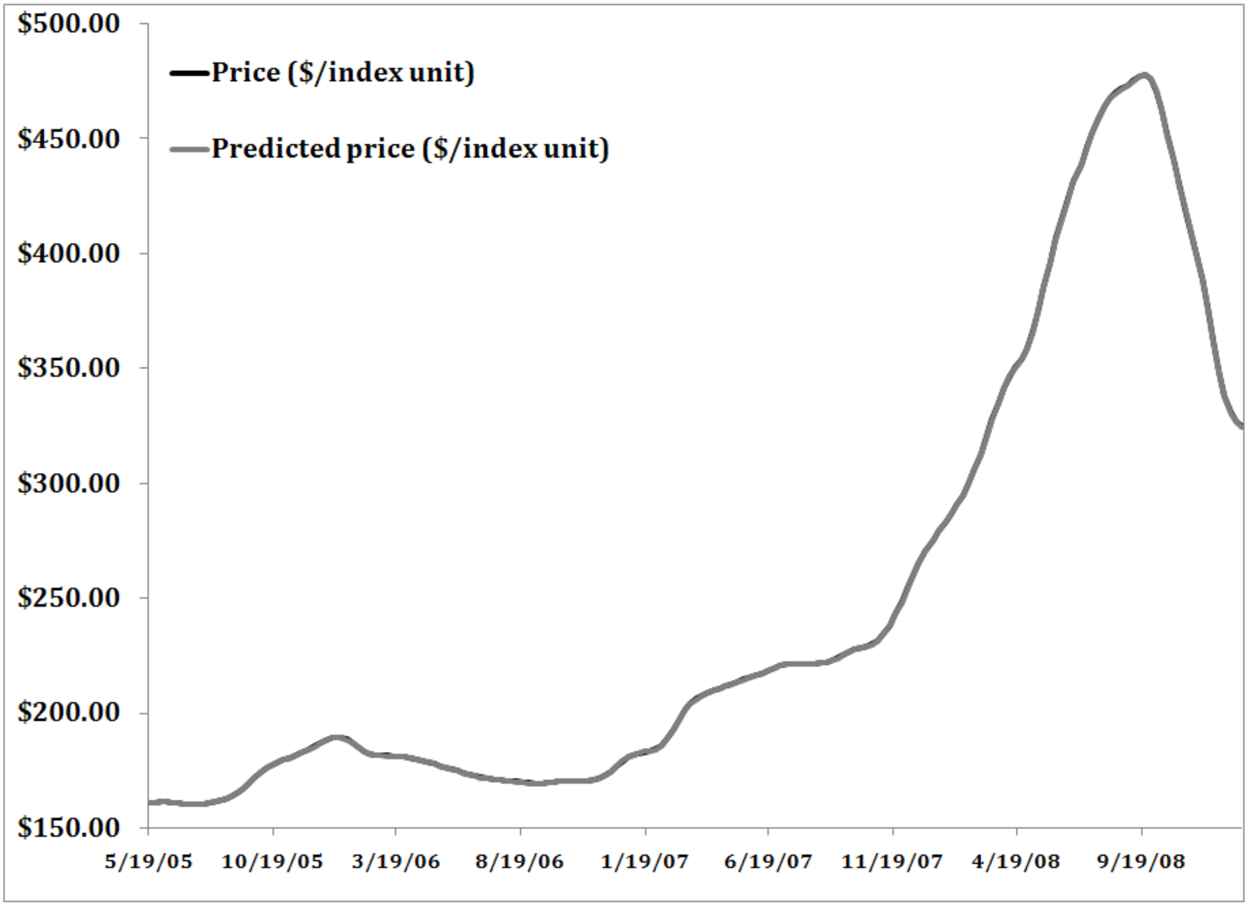

Figure 8: Fertilizer index price and predicted price (VAR model), 5/2005-3/2009.

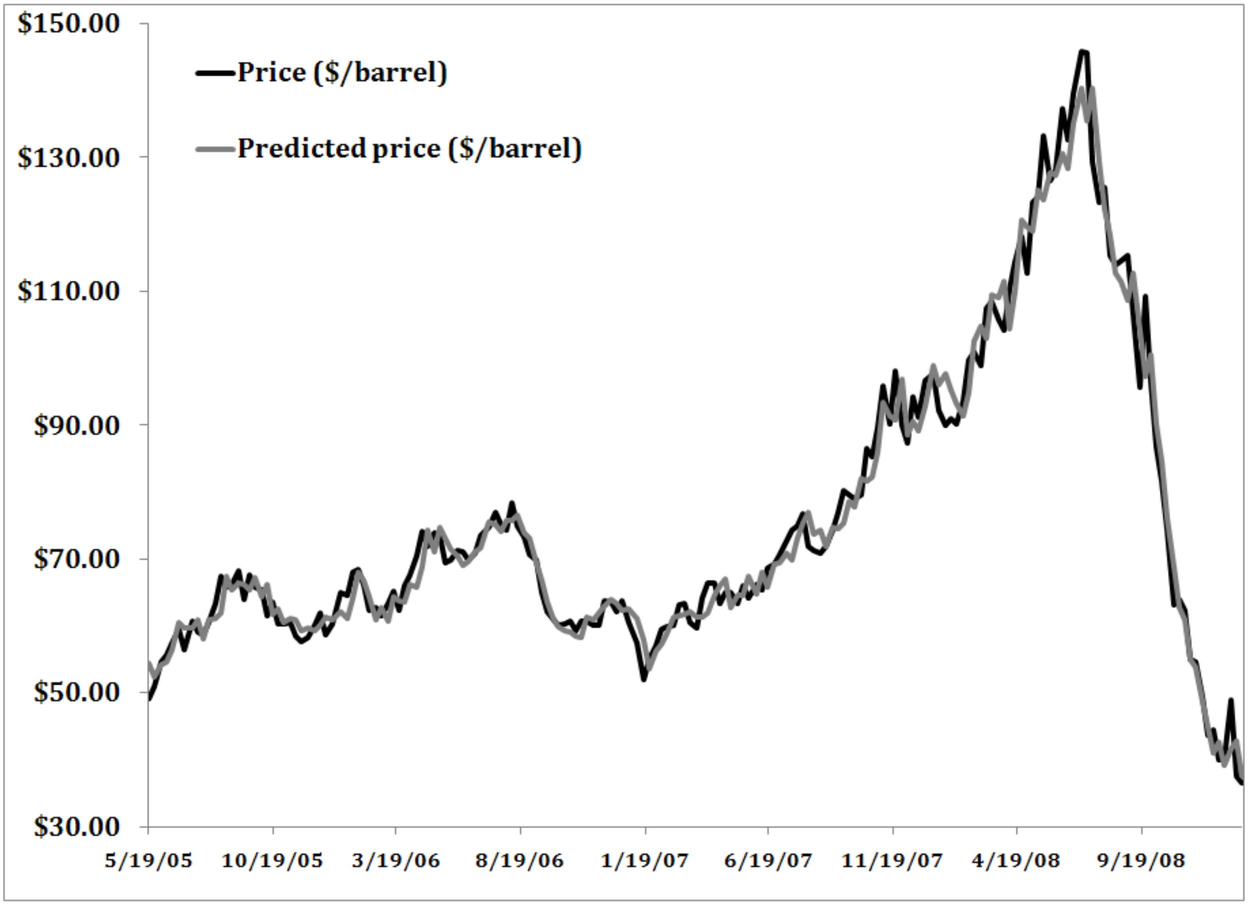

Figure 9: Light crude oil futures price and predicted price (VAR model), 5/2005-3/2009.

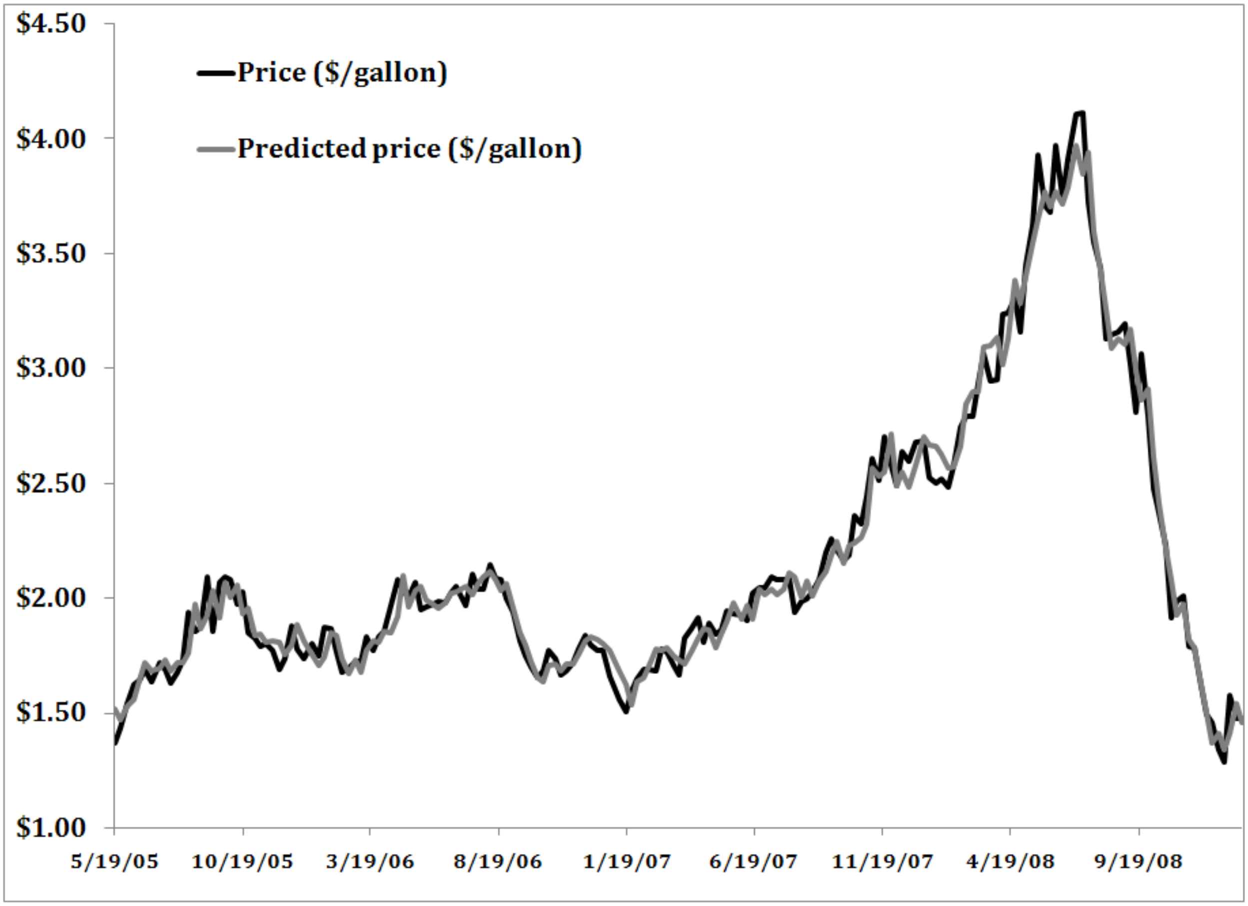

Figure 10: Heating oil futures price and predicted price (VAR model), 5/2005-3/2009.

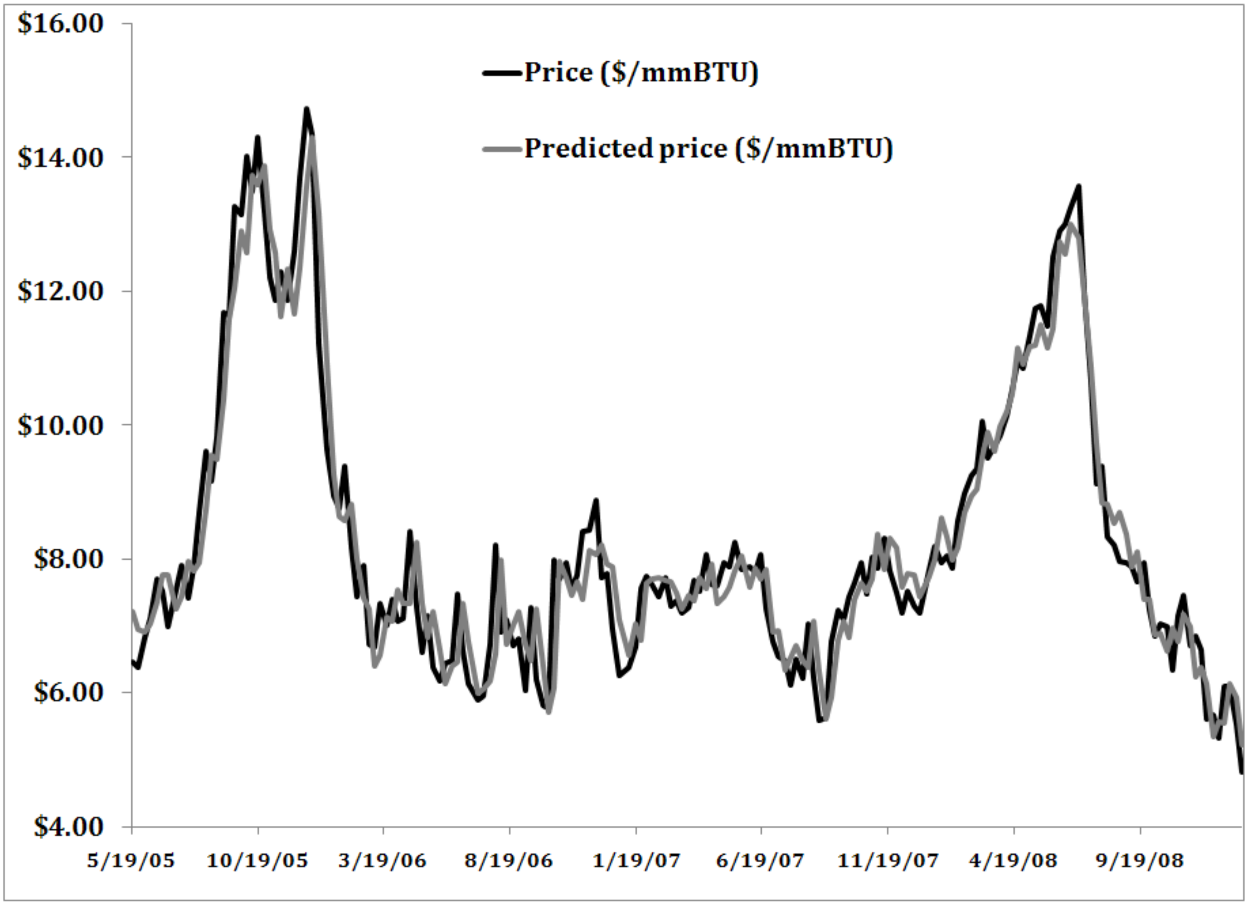

Figure 11: Natural gas futures price and predicted price (VAR model), 5/2005-3/2009.

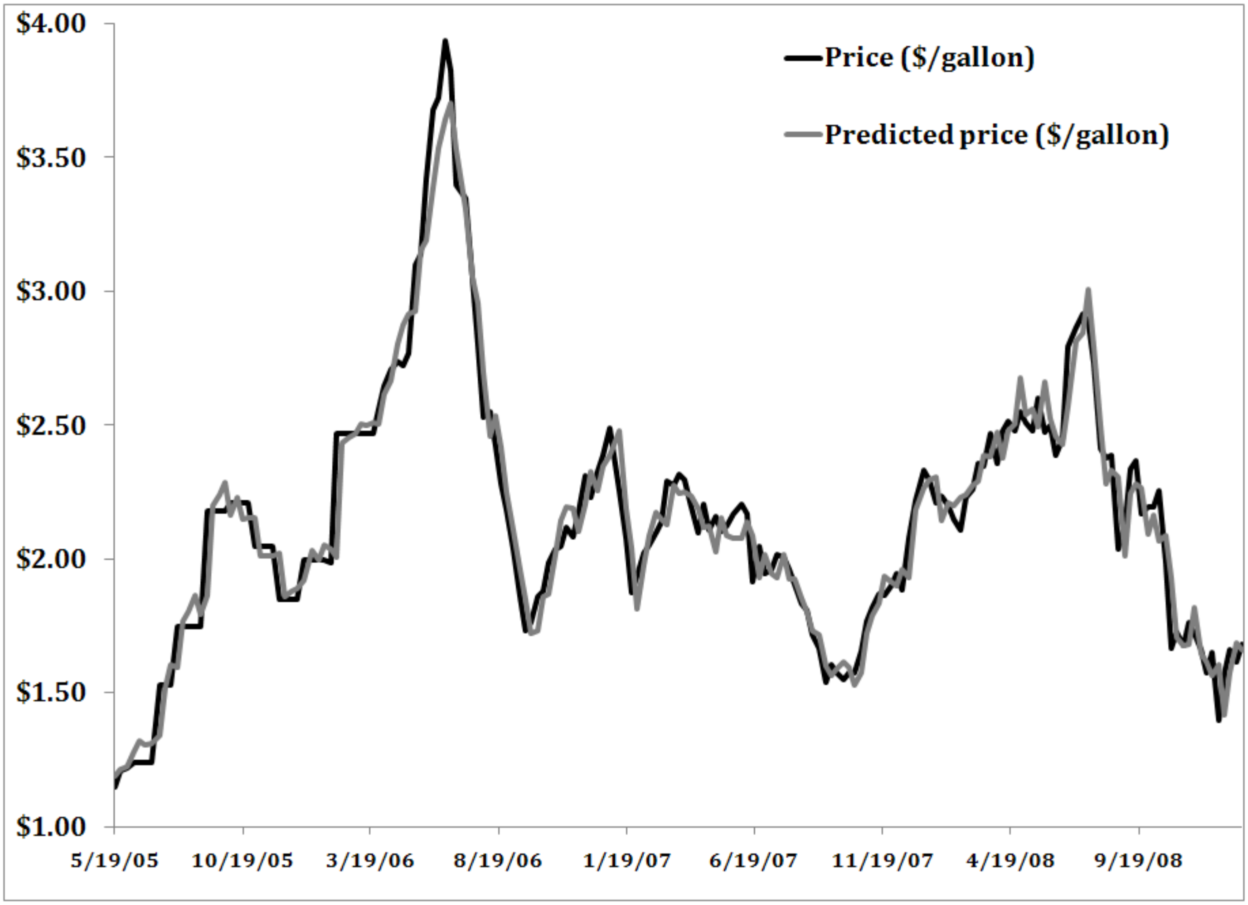

Figure 12: Ethanol futures price and predicted price (VAR model), 5/2005-3/2009.

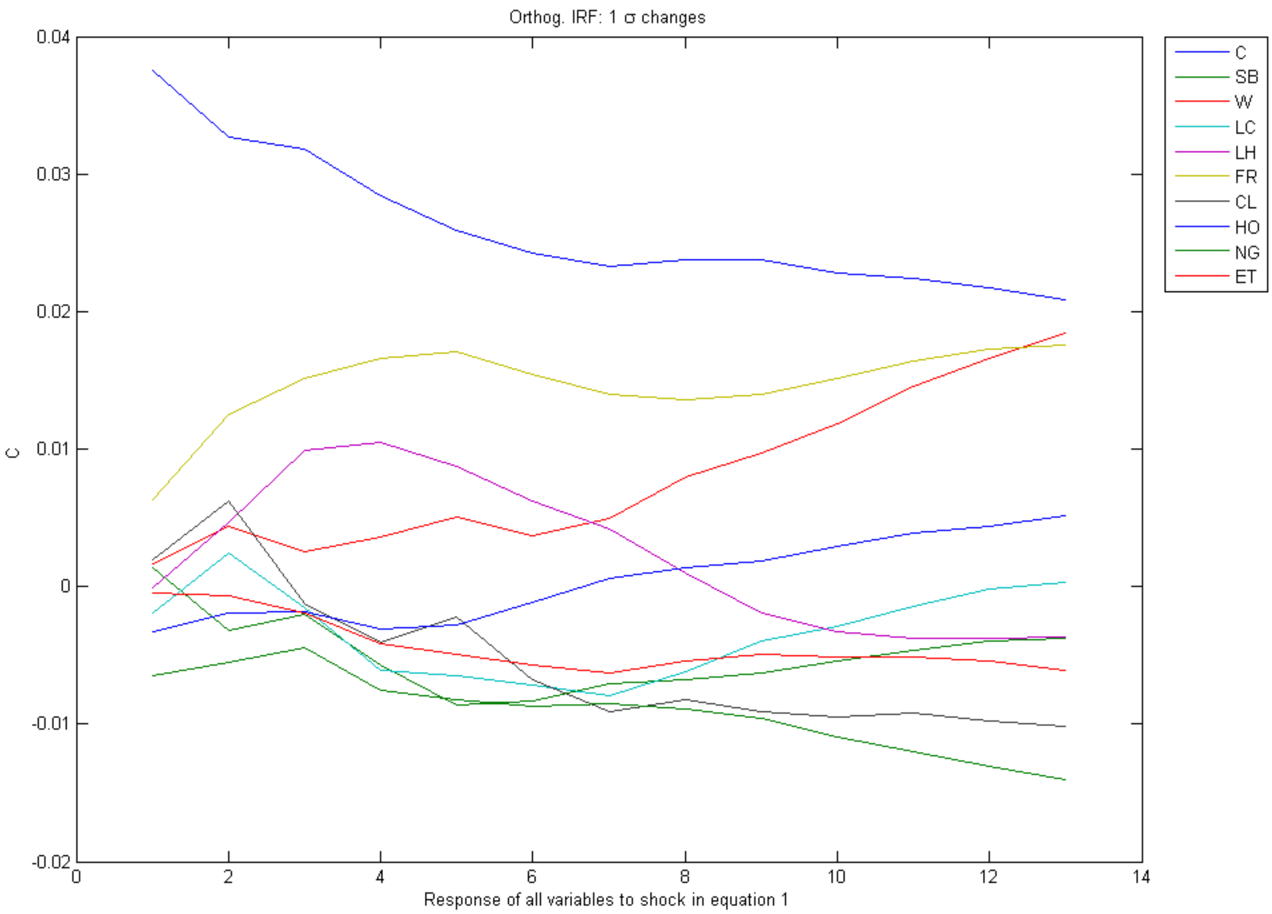

Figure 13: Impulse response functions for corn price

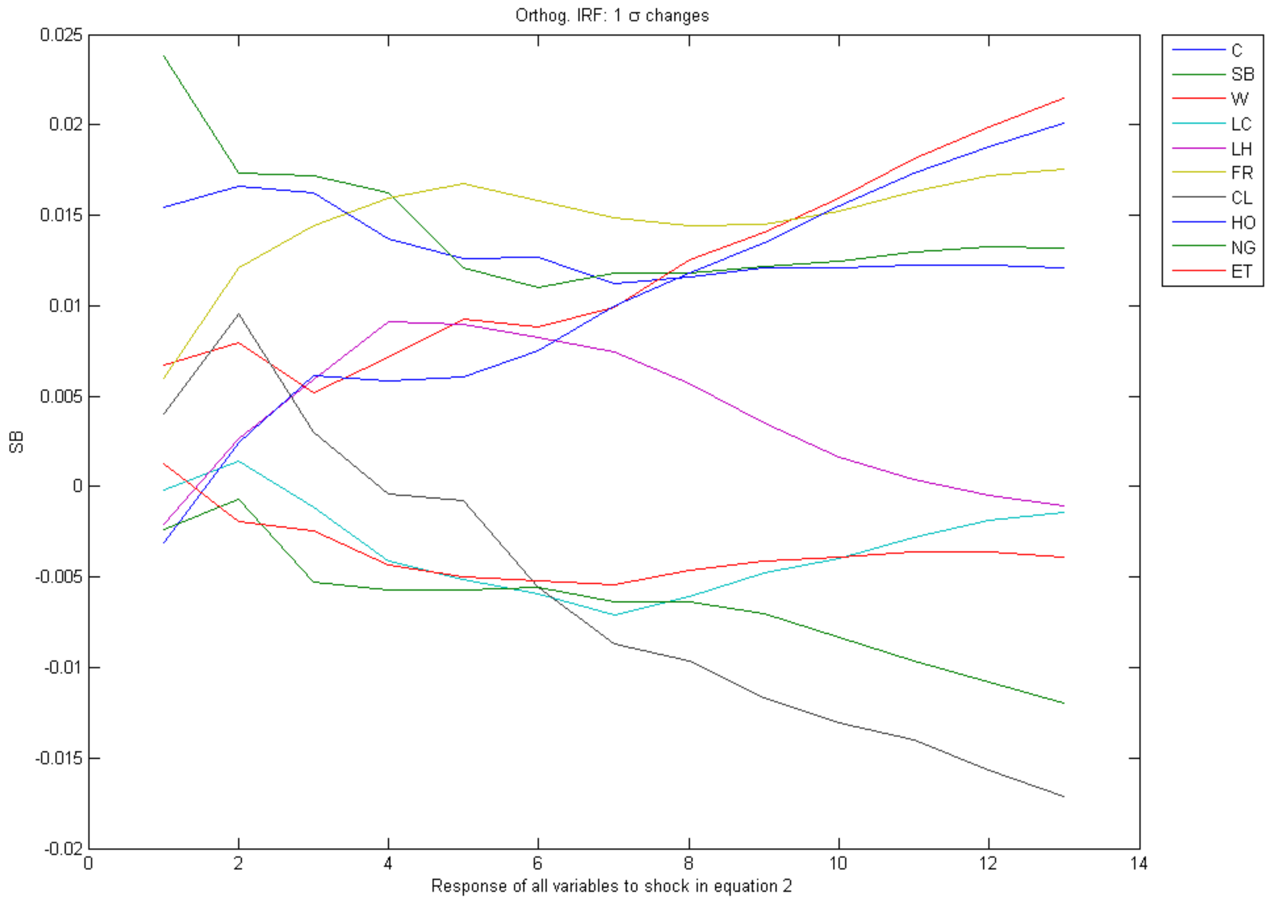

Figure 14: Impulse response functions for soybean price

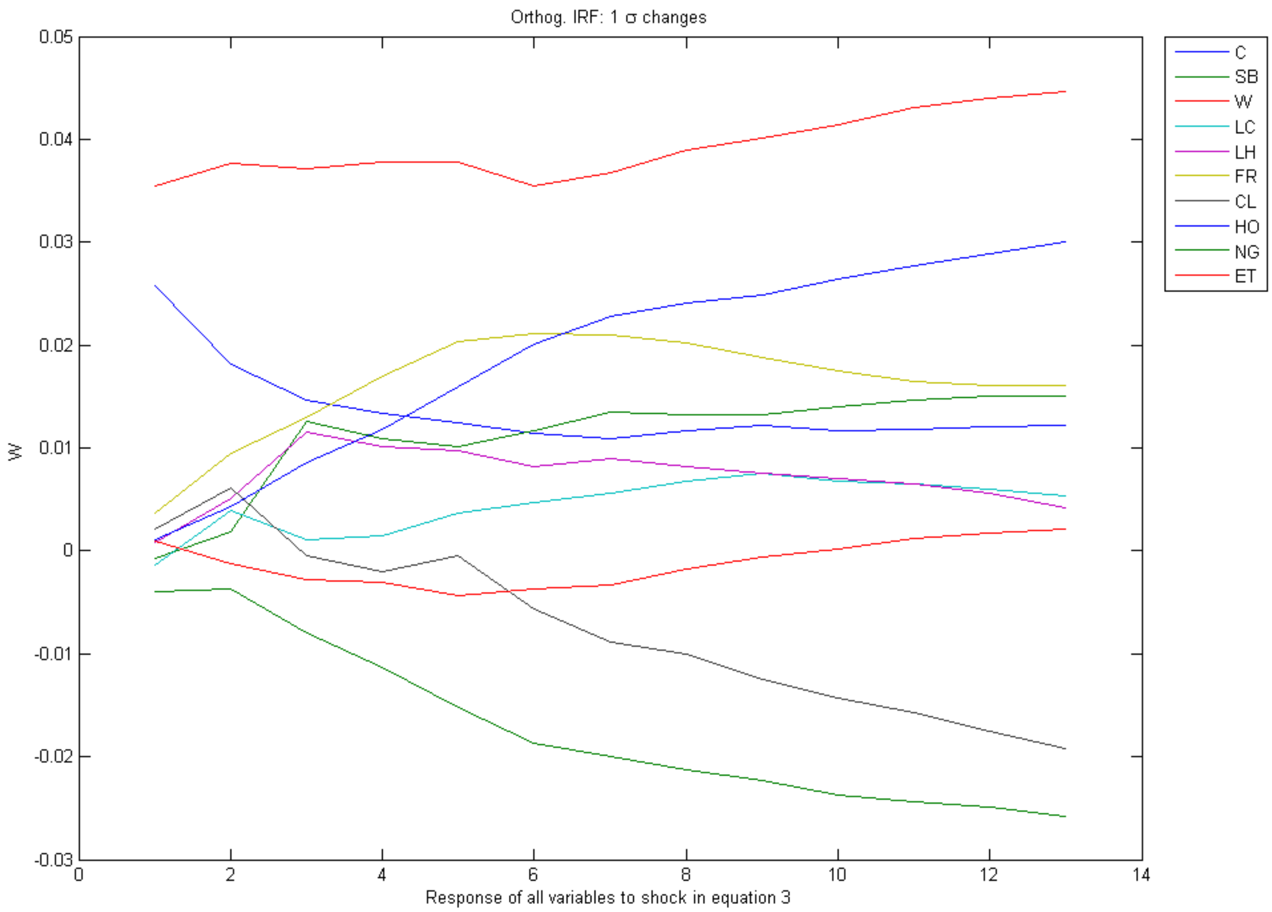

Figure 15: Impulse response functions for wheat price

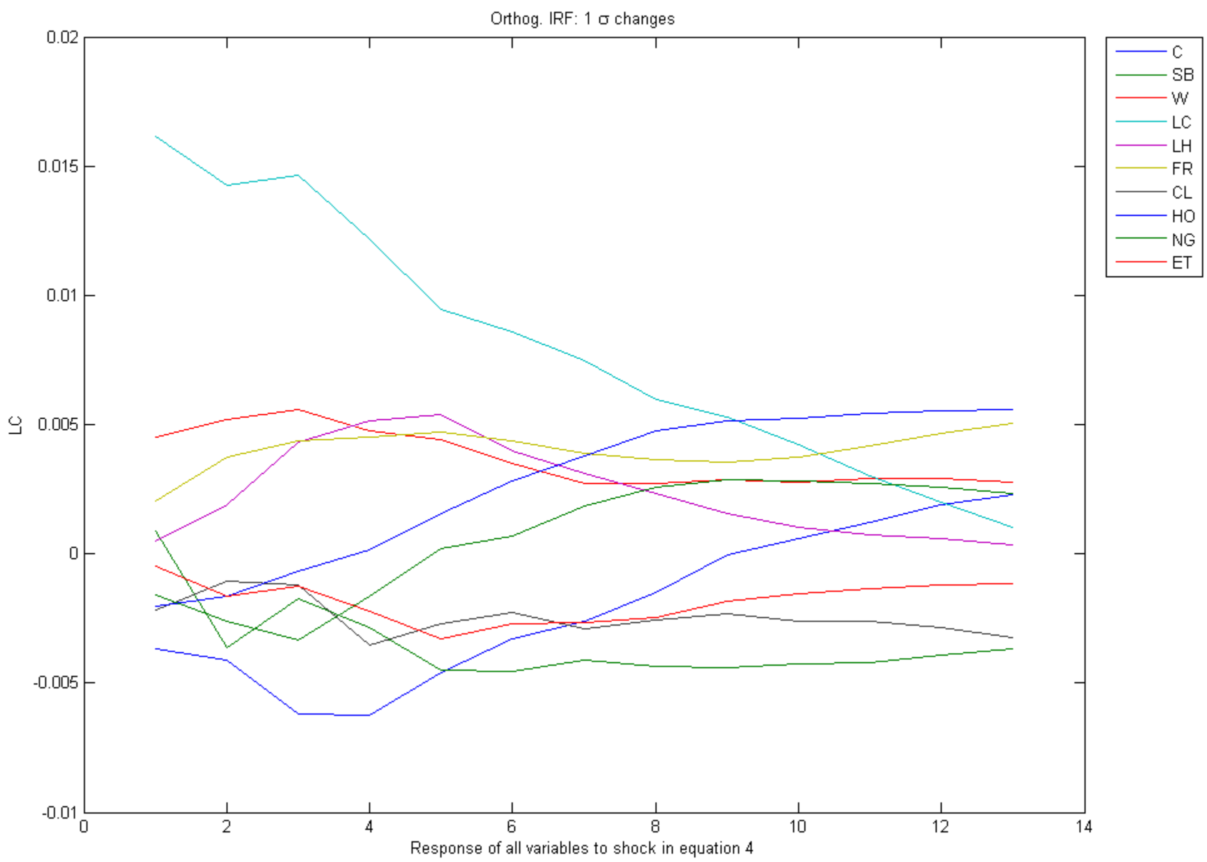

Figure 16: Impulse response functions for live cattle price

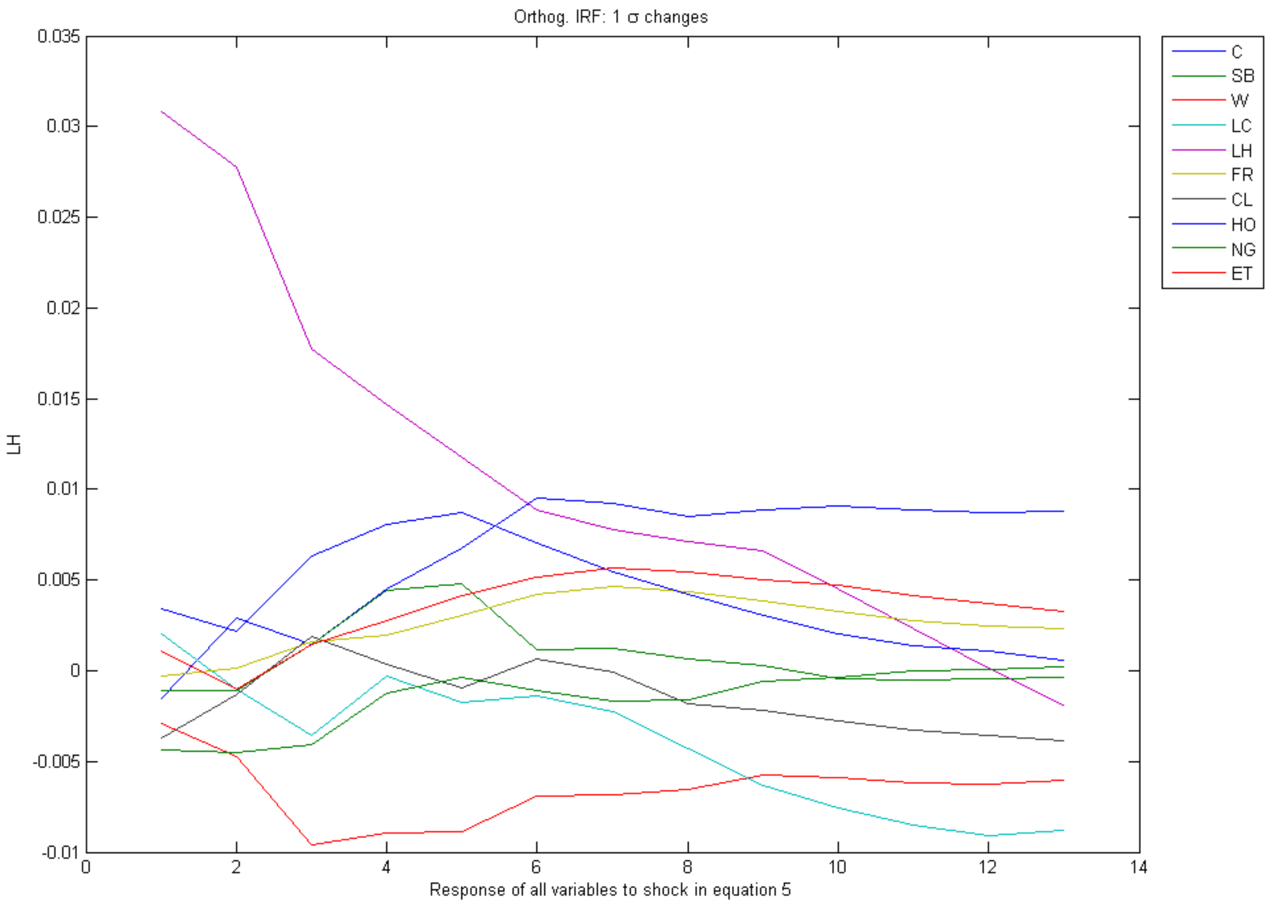

Figure 17: Impulse response functions for lean hogs price

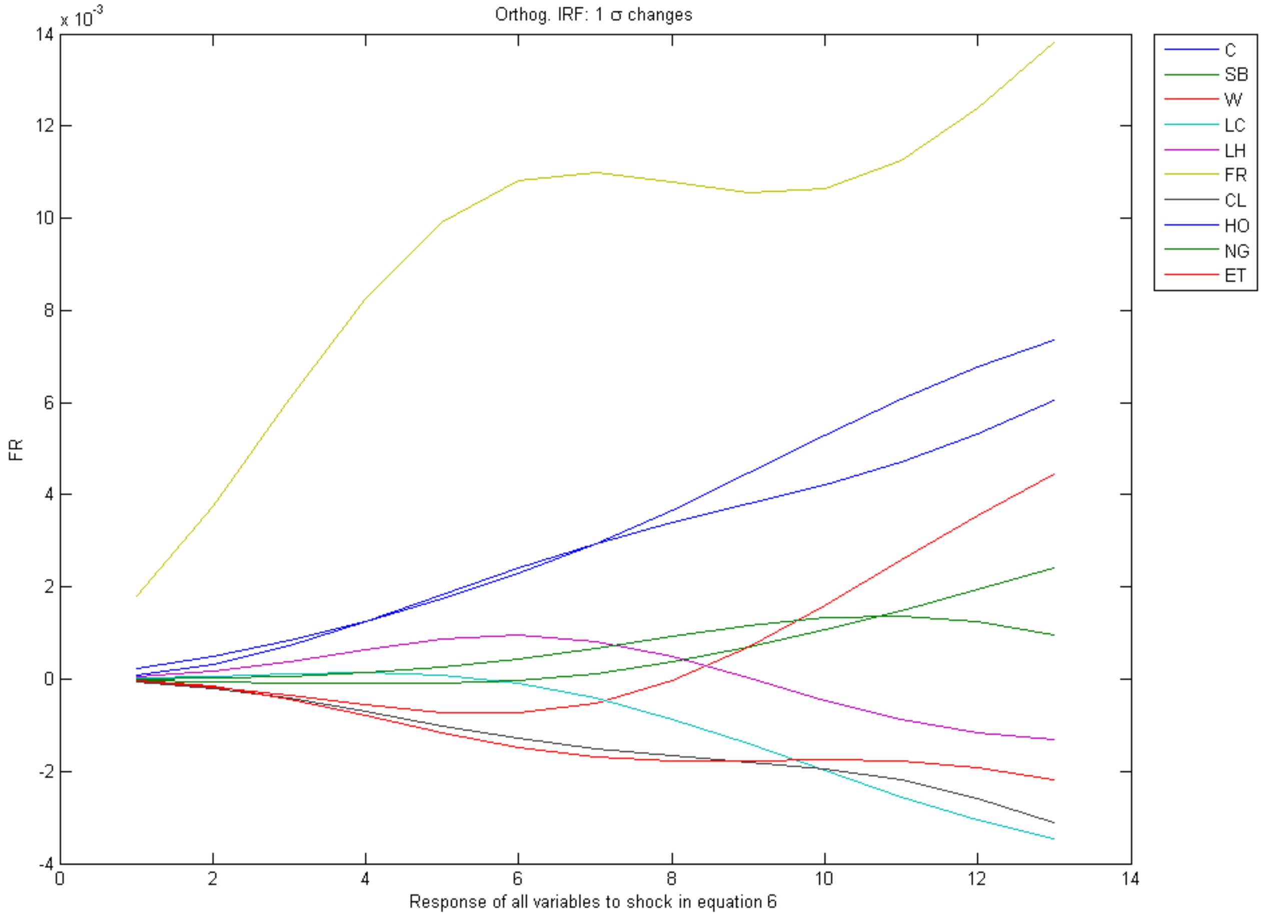

Figure 18: Impulse response functions for fertilizer price index

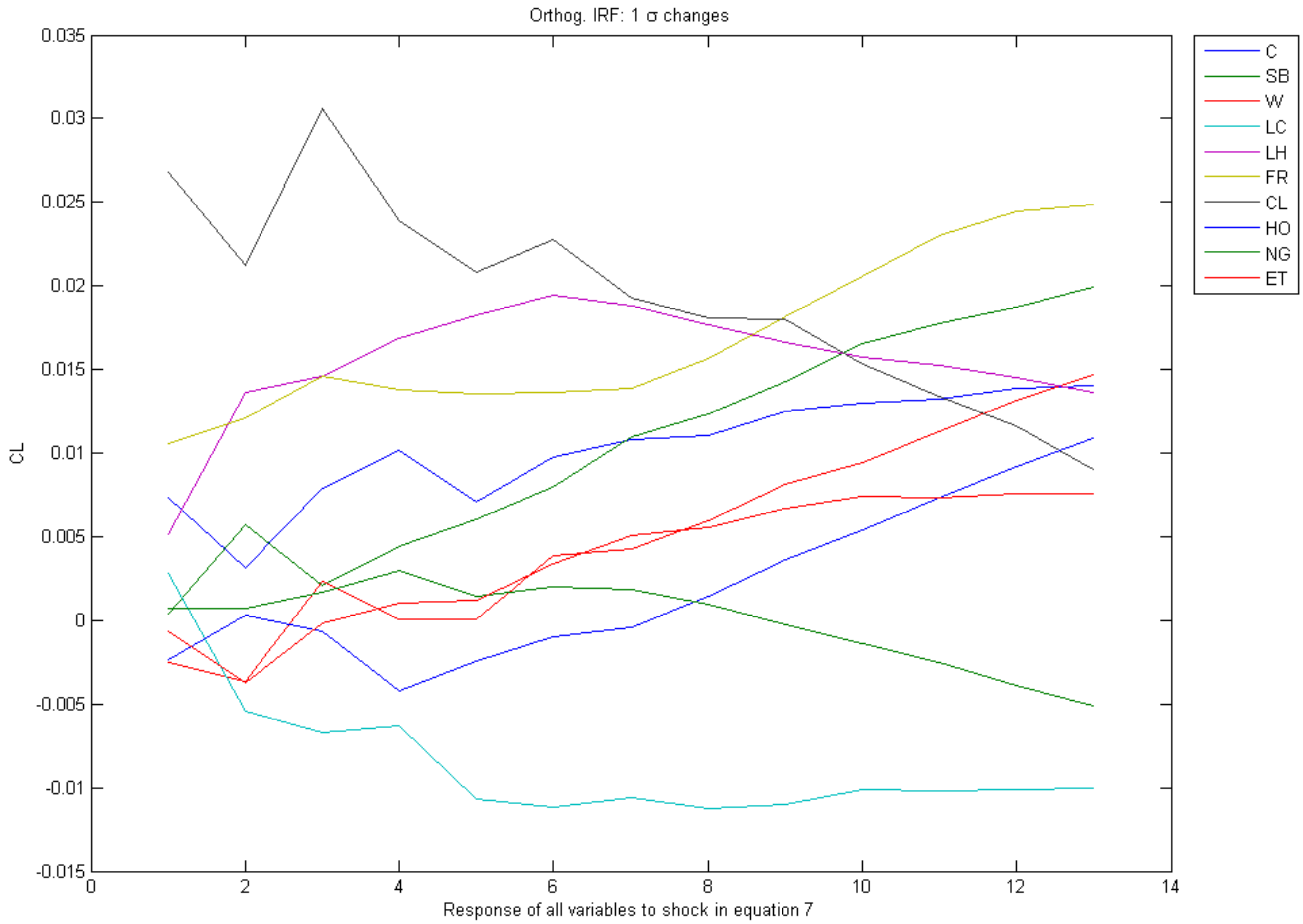

Figure 19: Impulse response functions for light crude oil price

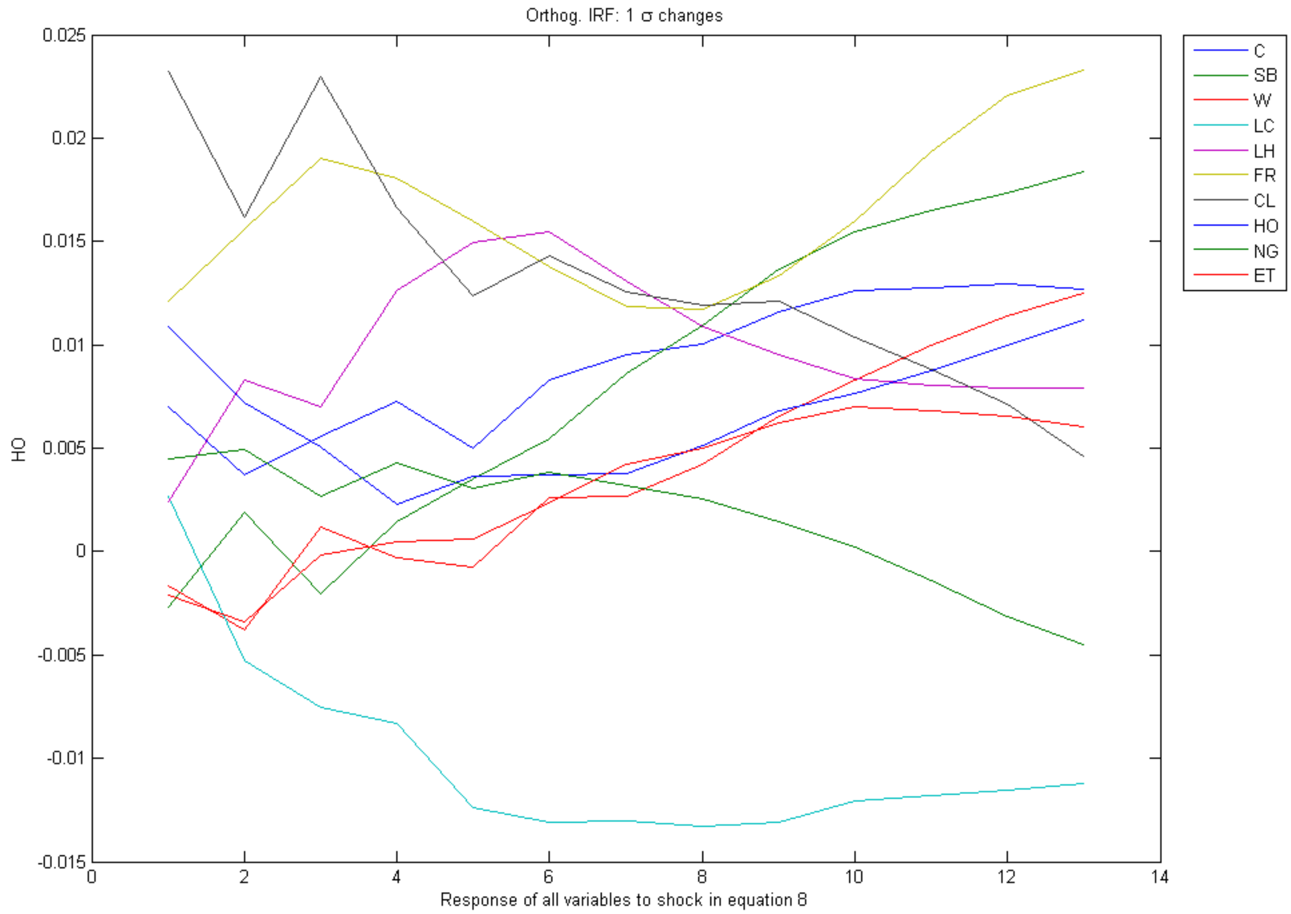

Figure 20: Impulse response functions for heating oil price

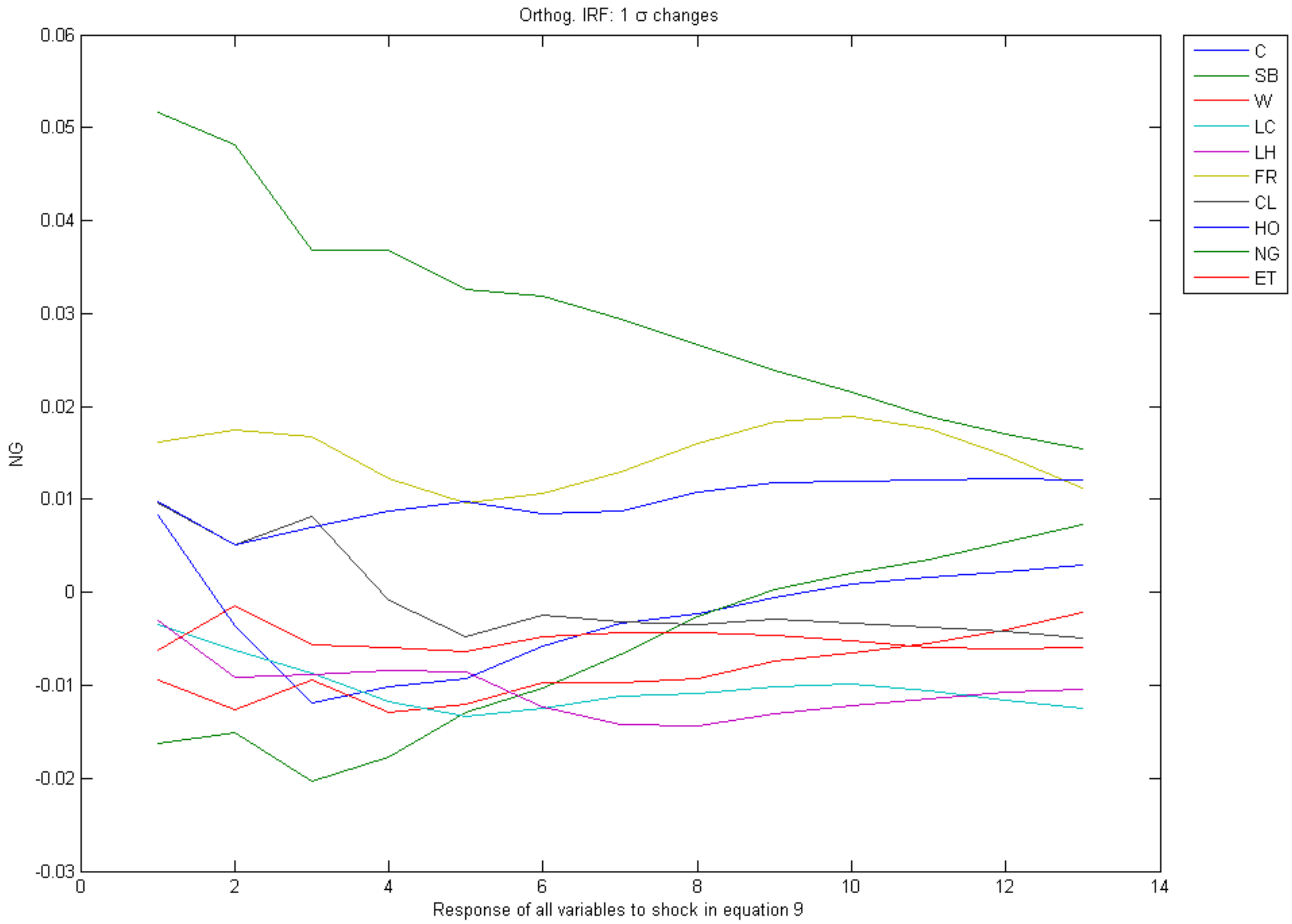

Figure 21: Impulse response functions for natural gas price

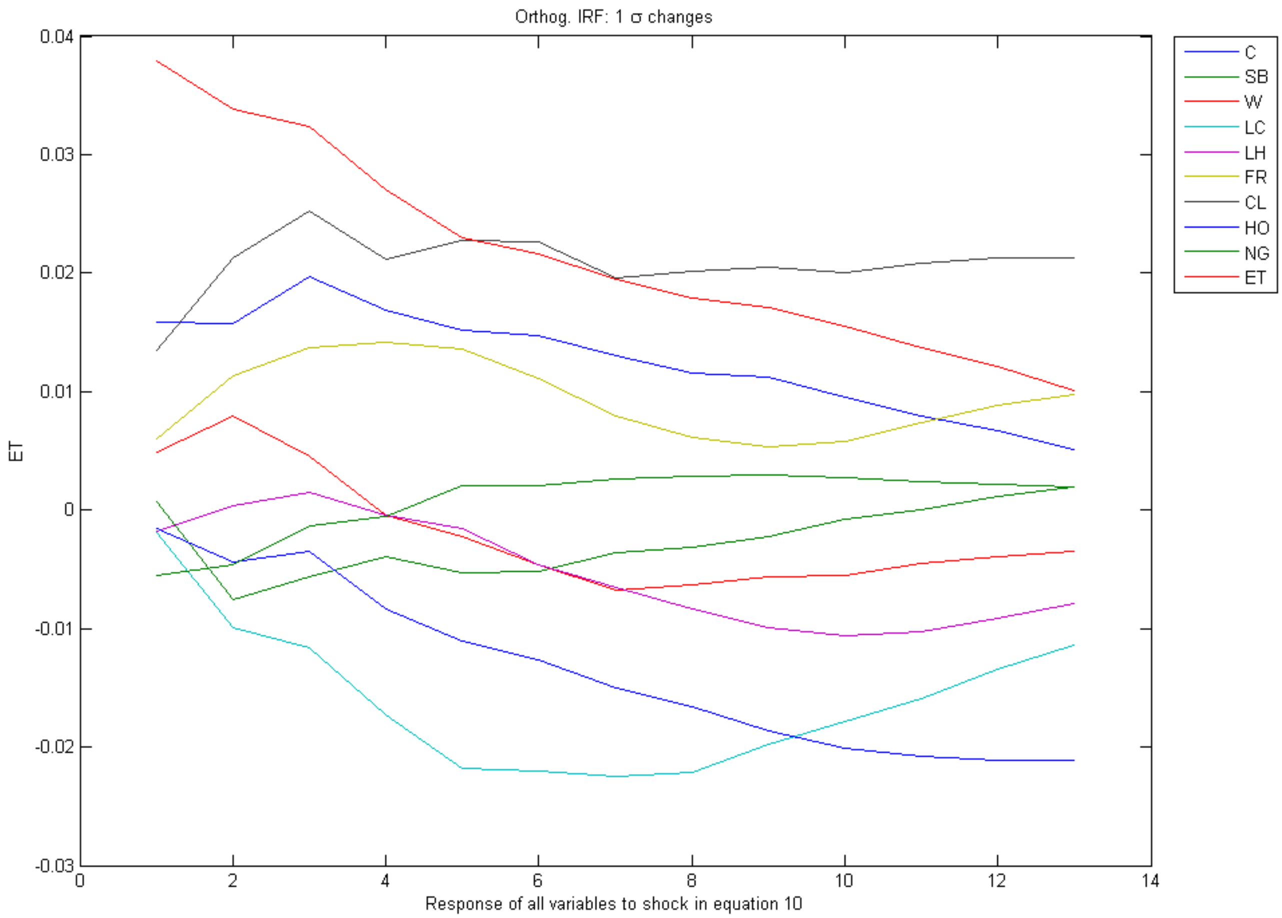

Figure 22: Impulse response functions for ethanol price

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