ABSTRACT

GUNEY, SELIN. Modeling Nonlinear Price Relationships in Commodity Markets. (Under the direction of Barry K. Goodwin).

Three essays investigate the nonlinear price relationships in commodity markets. The unifying theme of all three essays is that time series econometric models, especially nonlinear time series models, are used.

The first paper presents an empirical analysis of the effect of exchange rate shocks on import and export prices in the forest industry. In particular, exchange rate pass-through for four important tropical timber commodities are considered: sawnwood (hard and soft), plywood, spruce lumber, and logs (hard and soft) for Africa, Southeast Asia and Japan to United States using some linear and non-linear regression approaches taking into account the structural changes.

A nonlinear smooth transition regression (STR) (Teräsvirta 1994, 1998) model, which can be viewed as a generalization of threshold models with a continuous transition function that allows for smooth changes during the transition period rather than discrete changes, is considered. Results suggest evidence for the convenience of the STAR type models (SETAR and LSTAR) to model deviations from LOP in a nonlinear fashion for tropical forest product markets. Reasonable estimates of the threshold values that may be a representation of transaction costs in line with the theoretical arguments in international trade were found. It was also observed that the values of threshold variables greatly vary across different countries.

The second essay provides the empirical results for spatial price dynamics in soybean and corn markets in accordance with the theory of semi-parametric Vector Error Correction Generalized Autoregressive (VECGAM) models and standard VAR models for three North Carolina terminal markets taking into account the nonlinearity of the time trend component. Overall results indicate that the non-parametric drifts coincide with the general price movements, and when compared with the standard VAR results, the addition of nonparametric mean shift affects the overall implication of impulse-responses in a way that the VECGAM model impulse responses tend to imply a smaller degree of reaction towards the shocks and exhibit shorter time of adjustment for the convergence into a stable equilibrium level. Also, the number of significant impulse response coefficients under VECGAM models is larger compared to the standard VAR impulse responses. Responses confirm integration of markets in both VAR and VECGAM models.

The third paper's objective is to investigate the potential of a time series analysis technique, namely the Time Varying Parameter Vector Autoregressive Model (TVPVAR) technique, in the development of daily forecasting models for cattle prices in the presence of structural changes by using a Bayesian approach. More specific objectives include integrating smoothing techniques and stochastic volatility into TVPVAR modeling framework based exclusively on time series for cash-cattle prices and comparing the accuracy of the forecasting performance of this model with the standard VAR model that ignores time variation in parameters and possible time variation in the variance-covariance matrix of disturbance terms to determine if the inclusion of the time varying component

into the conventional VAR structure. Another purpose was to extend the TVPVAR to include stochastic volatility improves the forecast results.

One of the main conclusions from this paper is that letting time variation in VAR models improves the forecast performance. Overall, taking into account expectations about the behavior of cross-the-impulse responses, the process of reaching pre-shock levels and the MNG test results suggest that the nonlinear TVPVAR model is an improvement over the standard VAR forecast for 1 month, 3 months and 9 months ahead horizons for most of the time. Also, the main results are partially consistent with the literature on cattle prices.

Modeling Nonlinear Price Relationships in Commodity Markets

by
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DEDICATION

To my most loved ones—my parents, Sevim Isler Guney and Salih Guney.

BIOGRAPHY

Selin Guney was born in 1982 in Ankara, Turkey. She graduated with honors from Arts and Sciences Faculty, Statistics Department, Gazi University in 2005 with a double major from Faculty of Economic and Administrative Sciences, Department of Econometrics. She obtained her M.A. in Econometrics, Institute of Social Sciences and M.E. in Economics, College of Management from Gazi University and NC State respectively. In 2009, she received a Ph.D. scholarship from Higher Education Council of Turkey.

In August of 2009 she came to the United States to pursue her PhD in Economics with a minor in Statistics at North Carolina State University. As a graduate student, she taught undergraduate courses in economics, econometrics and statistics and received Thank a Teacher Award and Certificate of Accomplishment in Teaching (COAT). She also worked for Rural Advancement Foundation International-USA (RAFI) and had a research project at the North Carolina State University (NCSU) and Gazi University as a research assistant.

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1.1. Introduction

The relationship between exchange rate changes and price adjustments of traded goods across countries—a phenomenon typically referred to as exchange rate pass through—has been investigated in a vast number of academic papers. In efficiently linked international markets, exchange rate shocks and price changes should be perfectly reflected by adjustments that preserve an efficient price equilibrium. Although efficiently linked markets dictate such an equilibrium, more often than not, pass-through effects of exchange rate shocks are found to be imperfect, suggesting undershooting or overshooting in price adjustments.

Trade in tropical forest products is an important source of foreign exchange earnings by many developing countries, particularly those in South Asia and Africa. For example, exports of tropical timber are the second highest source of revenue in Gabon, behind petroleum exports (Terheggen, 2011). Such countries also frequently experience macroeconomic instabilities that may result in volatility in exchange rates. An important aspect of the linkages between primary commodity markets and macroeconomic shocks involves the extent to which commodity prices react to exchange rate changes and to international price shocks. Efficient arbitrage in commodities and in foreign exchange should ensure that, once prices for a homogeneous commodity are expressed in a common currency, shocks should trigger equilibrating adjustments to maintain zero profit conditions.

The focus of interest in linkages of prices and exchange rates has evolved over time. In many cases, a macroeconomic view of pass-through that considers linkages among aggregate price indexes is the focus of attention. In contrast, a micro view, which usually pays attention to the industry or commodity level relationships rather than aggregate ones, is often considered as an important indicator of market performance.

This literature stands on the findings of the phenomenon of Law of One Price (LOP) in the latter case and Purchasing Power Parity (PPP) in the former case. Among the studies that concentrate on the aggregate level relationship and emphasize the importance of macroeconomic conditions are Campa & Goldberg (2002), Choudri and Hakura (2001), Edwards (2006), Gagnon and Ihrig (2004), and Taylor (2000). Examples of the literature focused on micro level relations that examine linkages between import prices and exchange rates at the industry or commodity level include Baldwin (1988), Baldwin and Krugman (1989), Dixit (1989), Dornbusch (1987), and Knetter (1989).

A wide variety of empirical approaches have been applied in evaluations of exchange rate pass through. The simplest approach involves bivariate linear regression (e.g. Uusivuori & Buongiorno, 1991; Vesala, 1992). More recent empirical work has given attention to the time series properties of price and exchange rate data. These studies include Abri and Goodwin (2009), Baharumshah and Habibullah (1995), and Sek and Kapsalyamova (2008). Extensions to a panel context have also been considered (e.g. Hanninen, Toppinen, & Toivonen, 2007). A small number of empirical studies have considered exchange rate pass through in the forest products sector, which is this paper's aim. Among these studies are

Baharumshah and Habibullah (1995), Goodwin et al. (2012), and Hanninen et al. (2000, 2006).

In recent years, this literature has mostly evolved to consider models that take into account the structural changes and regime switching behavior. Such behavior is often taken to represent the effects of transaction costs and other frictions as well as government policies which may inhibit price adjustments. Likewise, the presence of such frictions is often considered to be a characteristic that reveals the overall performance of a market—an indicator that is particularly relevant in developing and transition countries. An example is Legrenzi et al. (2004) who study asymmetric adjustment of real exchange rates.

This paper presents an empirical analysis of the effect of exchange rate shocks on import and export prices in the forest industry. In particular, exchange rate pass-through for four important tropical timber commodities are considered: sawnwood (hard and soft), plywood, spruce lumber, and logs (hard and soft). The trading regions considered in the analysis are Tokyo (Japan), Sapele (Nigeria-Africa), Gabon (Africa), Malaysia (Southeast Asia), and the USA.

The data used in the analysis consist of a set of monthly average prices and exchange rates covering the period from October 1982 to June 2009, leading to a total of 321 observations. The monthly series on domestic and foreign prices were obtained from the Commodity Research Bureau (CRB) and the Food and Agricultural Organization (FAO) while the exchange rates were gathered from International Financial Statistics (IFS) published by International Monetary Fund (IMF).

Nonlinear smooth transition regression (STR) (Teräsvirta 1994, 1998) models, which can be viewed as a generalization of threshold models with a continuous transition function that allows for smooth changes during the transition period rather than discrete changes, are adopted (Hansen, 1999). This approach has several important advantages. It allows researchers to model structural breaks and regime switching and therefore is useful in evaluating gradual regime switching market linkages that account for nonlinearity. Likewise, asymmetric adjustments of exchange rates play an important role in the exchange rate pass through literature. In particular, the appreciation and depreciation of the exchange rate may have different effects on the exchange rate pass through coefficient. This indicates overshooting and/or undershooting behavior and thus is consistent with incomplete or imperfect pass through.

Finally, the STR methodology has been extended recently to multivariate vector autoregressive and error correction models as well as to panel data. Such extensions are considered in this analysis of timber data by evaluating multivariate models and introducing a way to include heterogeneity in disaggregated data for future research. Generalized impulse response functions are used to evaluate the dynamics of adjustments to price and exchange rate shocks.

The analysis indicates varying degrees of imperfect pass through. Both overshooting and undershooting behavior are revealed. The implications of these results for trade in basic commodities among developing countries are discussed in this article. Results are also

discussed within the context of important recent aggregate shocks to the world financial economy. Suggestions for further extensions conclude this article.

1.2. Theoretical Background of Law of One Price

The market price dynamics literature mostly stands on the phenomenon of Law of One Price (LOP) and Purchasing Power Parity (PPP). According to the Law of One Price, identical products should sell for the same common-currency price in different countries, and the assumptions for LOP to hold include the following: costless transportation, distribution and resale. If the LOP holds for some goods such as gold for all countries, then it would be defined as an "integrated world market" (Knetter & Goldberg, 1996). If the LOP holds for all goods that are traded between countries, then the Absolute Purchasing Power Parity theory of exchange rates would also hold for these countries. However, it is clear that the assumptions needed for the strong version of Purchasing Power Parity to hold are very restrictive and unrealistic since it would require the goods in question to enter the basket of goods with the same weight in every country and it also assumes costless and frictionless arbitrage.

As a result of these assumptions, all of which are unlikely to hold, some modifications were made to the LOP and Absolute Purchasing Power Parity which led to Relative PPP that implies that foreign and domestic prices as well as the exchange rates move proportionally to each other (Alper, 2003); also, any frictions in the markets that may affect transportation costs such as trade barriers may lead to stable price differentials in the markets.

The strong version of PPP implies $P = P'e$, where P stands for the domestic prices and P' indicates foreign prices, while the relative PPP implies $P = \alpha e P'$ where α is the real exchange rate or home currency price level as a percentage of foreign price level (Goldberg & Knetter, 1997). Thus, if relative PPP holds, exchange rate fluctuations translate into proportional movements in the domestic price level (i.e. pass through is equal to one) (Anaya, 2000).

Interest in prices and exchange rates was not only limited to a motivation to see if the LOP/PPP holds, but also extended to assess the effects of exchange rate changes on a country's trade balance. Specifically, there was an interest in how a country's trade balance would be affected by the devaluation of a nation's currency. The question of how the devaluation would affect the export prices or from the importer's side if the full effect of devaluation would be passed through the local currency prices led to the concept of "exchange rate pass through (ERPT)"which is defined as the "percentage change in local currency import prices resulting from a one percent change in the exchange rate between the importing and exporting countries"(Goldberg and Knetter, 1997).

If we consider the following generic regression which will be used to assess the relationship between prices and exchange rates:

$$P_T = \alpha + \delta X_T + \gamma E_T + \psi Z_T + \varepsilon_T$$

where P is the local currency import price of a product, E is the exchange rate(importer's currency per unit of exporter's currency)[1], X stands for the measure of the exporter country's cost or price and Z denotes the other control variables, ε is the error term and t denotes the time period.

In this equation, γ is defined as the coefficient of pass-through. ERPT is defined to be "complete" if γ =1 indicating that the effect of exchange rate is completely passed to import prices whereas it is defined as "incomplete" if γ <1 which reflects an incomplete adjustment process. Incomplete pass-through may also be a sign of the largeness of the importer indicating that the importer country has the power to influence the world price.

If γ >1 this reflects the overshooting situation as suggested by Chambers and Just (1980).

1.3. Literature Review

The question dealing with the validity of Law of One Price (LOP), Purchasing Power Parity (PPP) and Exchange Rate Pass-Through (ERPT) has been extensively investigated in the literature since it has important implications both for economists and traders; as its implication being that no persistent opportunities for spatial arbitrage exist. This may help policymakers to decide on the trade policies to be imposed.

[1] Researcher may also consider using foreign exchange future (FX future) instead of exchange rate in the analysis.

The general conclusion underlying this concept is that prices for homogenous products at different geographical locations should not differ more than transport and transaction costs such as insurance, contract fees etc.

However, one obvious reason why the prices of homogenous products may not be the same is the aforementioned transaction and transport costs and other impediments to trade such as tariffs and quotas and as a result of these nonzero costs, deviations from the LOP could contain significant nonlinearities.

Most recently, following these theoretical arguments several studies have employed nonlinear models to investigate the validity of LOP/PPP and ERPT. Among these are Micheal et al (1994), Obstfeld and A.M. Taylor (1997), A.M. Taylor (2001), O'Connel and Wei (2002).In these studies the nonlinear nature of the adjustment process is generally investigated in terms of a threshold autoregressive (TAR) model of some sort and are cumulating evidence in favor of the threshold-type nonlinearity in deviations from the LOP.

Among the studies that use variants of discrete cointegration models of the sort introduced by Balke and Fomby (1997) are Goodwin and Piggott (2001), Lo and Zivot (2001), Sephton (2003) and Park et al (2007) that have found support for the validity of LOP and threshold effects and mentioned that the path of adjustment to equilibrium depends on the size of the shock introduced into the system.

However, since there exists some reasons to think that the patterns of price adjustment in the markets are smooth rather than discrete even though the economic behavior underlying the adjustments is of a discrete nature (i.e. arbitrage is either profitable

or not) (Goodwin et al. 2011) the literature progressed through the usage of smooth transition models instead of discrete models of transition and among the studies taking this approach are Goodwin, Holt and Prestemon (2012) and Enders and Holt (2012).

Beginning from 1980's the ERPT literature mostly involved research investigating the pass-through to the U.S. and progressed from the estimations based on simple OLS models to more advanced models taking into account the non-stationarity, dynamic adjustment processes, asymmetry, simultaneity etc. Among the studies incorporating these issues to exchange rate pass-through estimation are Woo (1984), Hooper and Mann (1989) and Al-Abri and Goodwin (2009).

The dominant approach was to investigate the exchange rate pass through phenomenon at the aggregate level before the rise of imperfect competition and strategic trade theory. These changes led the researches to consider exchange rate pass through concept in the industry level and among the studies taking this approach may be best illustrated by Feenstra (1989) for three different industries; cars, trucks and motorcycles and Pollard and Coughlin (2004) for 30 industries in U.S., Goodwin, Holt and Prestemon (2012) for timber products and Yu (2013) where he investigates how exchange rate pass-through depends on firm heterogeneity in productivity and product differentiation in quality.

Some of the research on ERPT concentrated on the determination of the degree of market power and used the ERPT concept to figure out the market power that a country has and also measure the markups in international markets such as Sumner (1981) that aimed

to measure the monopoly behavior for the cigarette industry of U.S. and Bresnahan (1989) that concluded that the exchange rate as being a demand rotator is an important feature of international studies for the measurement of market power (Goldberg and Knetter,1996).

Recent research using the ERPT concept to measure the market power for countries may also be helpful in understanding the effect of trade and other competition policies. Differences observed in market power across industries or countries would also be useful to figure out the significance of the trade and regulatory policies that will be imposed which may be considered as one of the most important factors that facilitates the segmentation of markets and also the competition structure of the countries in question.

In this paper, price dynamics will be investigated by applying a class of nonlinear, time series models that allow for the gradual adjustment among price linkages.

1.4. STAR Type Models and Data

As economic and financial systems are known to experience structural and behavioral changes, the applied research progressed through the usage of nonlinear time series models rather than the linear models that may leave some aspects of the economic data unexplained.

Due to the existence of structural and behavioral alterations it makes sense to assume that some different time series models may be useful to analyze the empirical data at distinct times.

To model such nonlinear relationships we need to allow for different regimes or states of the world and let the dynamics of the economy to differ in different regimes.

STAR models are a general class of state dependent nonlinear time series models where the transition between states is generated endogenously. These models also include other popular nonlinear models such as Threshold Autoregressive (TAR) and Exponential Autoregressive (EAR) models. For more detailed discussions on this property of STAR type models please see Haggan and Ozaki (1981), Tong (1983), Tsay (1989) and Granger and Terasvirta (1993).

The basic STAR model of order p which is used to investigate The LOP may be stated as follows:

$$Y_t = \phi_{10} + \phi_{11} Y_{t-1} + ... + \phi_{1p} Y_{t-p} + (\phi_{20} + \phi_{21} Y_{t-1} + \phi_{2p} Y_{t-p}) G(S_t; \gamma, c)) + \varepsilon_t$$

where Y_t and ε_t are distributed normally with means and variances $N(\mu, \sigma^2)$ and $N(0, \sigma^2)$ respectively.

In this equation $G(S_t; \gamma, c)$ is the 'transition function' that changes smoothly between zero and one depending on a 'transition' variable S_t, and its properties are determined by the values of the speed of adjustment parameter γ >0 and the location parameter c.

In the STAR modeling framework the variable ΔY_t switches between two regimes in a smooth way, implying that the dynamics of the observations ΔY_t may be determined by both regimes, with one regime having more effect in some times and the other regime

having more effect in other times. So this type of model actually allows for a continuum of regimes and each regime can be related to a different value of transition function $G(S_t;\gamma,c)$.

In practice, generally and throughout this analysis the transition variable S_t is taken to be some function of the dependent variable Y_t.

The basic unit of analysis Y_t used throughout this study is the natural logarithm of the price ratios; ln (P_{it}/P_{jt}) where P_{it} is the nominal import price in country i for the good in question in period t), P_{jt} is the nominal corresponding export price in country j that are expressed in U.S. dollars and t is a time index such that $t=1,.....,T$ where $T=321$.

The transition variable S_t determines the nature of the adjustment or namely the transition process. It is expected that the larger the absolute value of the transition variable the larger the difference in recently observed prices and thus the larger the deviation from a presumed parity condition and potential gains from arbitrage and larger deviations will lead to faster and/or larger market adjustments than smaller ones (Goodwin et al, 2011).

In the literature there are a few choices for the transition function $G(.)$ to be used and one model that has been extensively employed is the Logistic STAR (LSTAR) model where the smooth transition function is a logistic function and may be defined as:

$G(S_t;\gamma,c)=inv(1+\exp(-\gamma(S_t-c))$ where $\gamma>0$

where S_t is the 'transition' variable and its properties are determined by the values of the speed of adjustment parameter $\gamma > 0$ and the 'location' parameter c.

The other alternative for the transition function to be used is the Exponential STAR or ESTAR model in which the transition function is defined as:

$$G(S_t;\gamma,c) = 1 - \exp\left[(-\gamma)(Y_{t-d} - c)\right]^2$$

The parameter c can be interpreted as the threshold and γ determines the speed and the smoothness of the transition for both LSTAR and ESTAR models.

It can be observed that if γ is large both transition functions switch between 0 and 1 more quickly compared to the case where γ is small that implies a very slow and smooth switch between regimes and also as $\gamma \to \infty$ both logistic and exponential functions become binary.

Although there exist some similarity between LSTAR and ESTAR models, they actually exhibit different types of transitional behavior. First of all, the logistic function has a single reflection point while the exponential function has two inflection points which can also be observed from the following figure:

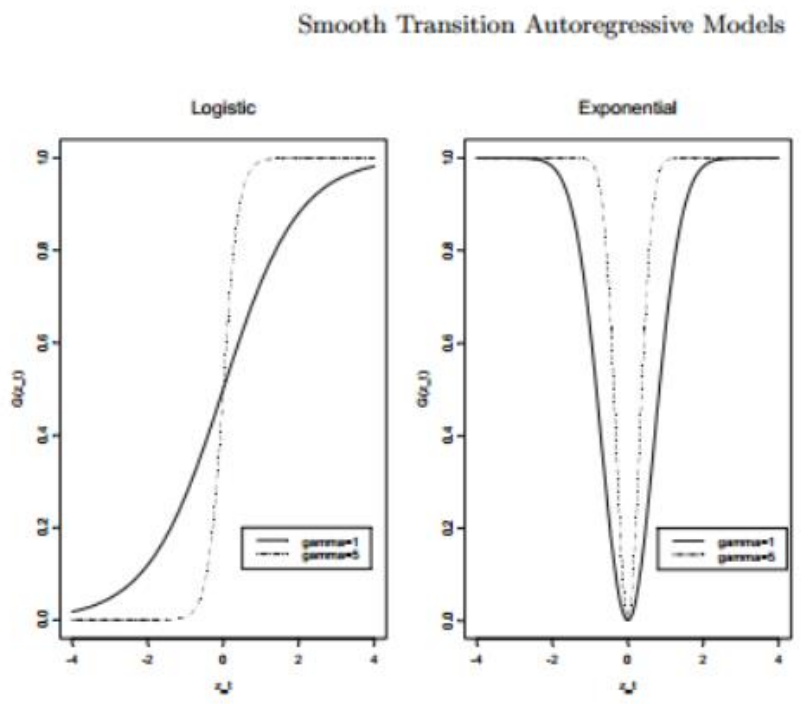

Figure 1.0: Logistic and Exponential Transition Functions

In terms of economic interpretations there are some notable differences between LSTAR and ESTAR models such that LSTAR model is typically related to a couple of regimes (i.e expansive and recessive regimes) with respect to a threshold value and it has the property of being in accordance with an asymmetric business cycle and the variables present a growth with a saturation and associated feedback effects. On the other hand, ESTAR model that includes a symmetric exponential function depicts the sensibility of data to absolute value of transition variable respect to threshold, and then the model lets us to fit in variables with three regimes, a median one and two extremes.

Since the exponential function is symmetric, the ESTAR model switches between two regimes depending on how far away the transition variable S_t is from the threshold c and as a result only the distance between S_t and c matters but not the sign whereas the logistic function is monotonic and the LSTAR model switches between two regimes depending on how much the transition variable S_t is greater or smaller than the threshold c and so both the sign and the distance between S_t and c will be important.

One of the limits of this ESTAR model is that it does not nest as a special case a three-regime self-exciting threshold auto regression (SETAR) which will be explained below since the exponential function approaches the indicator function $I(S_t = c)$ .This property is useful in part because several previous studies of spatial price relationships have successfully employed this model to account for nonlinearities introduced by transaction costs. (see Goodwin and Piggott) (Goodwin et al. 2011).

In contrast to ESTAR models the LSTAR models reduces to a TAR model since the logistic function approaches the indicator function $I(S_t > c)$.

Since the comparison of any nonlinear model will be done with a linear model we will also estimate a linear autoregressive model of order p(AR(p)) and the aforementioned STAR type models will be compared with this model, which may be specified as:

$\Delta Y_t = \Phi 0 + \alpha' X_t + \theta Y_{t-1} + \varepsilon_t$ where $\alpha' = (\phi_1, \phi_2, ... \phi_{p-1})$ and $X_t = (\Delta Y_{t-1}, ..., \Delta Y_{t-p+1})$ or

$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_p Y_{t-p} + \sigma\varepsilon_t$ where the model parameters σ and $\phi = (\mu, \phi_1, \phi_2, ..., \phi_p)$ are independent of time and stays constant over time.

1.4.1. Threshold Autoregressive Models: TAR and SETAR as an Extension of the Autoregressive Model (AR)

To capture nonlinear dynamics, Threshold Autoregressive (TAR) models which are regarded as an extension of autoregressive models (AR) that have been proposed by Tong (1978). These models allow for variations in the model parameters according to the value of weakly exogenous threshold variable S_t.

The TAR model can be presented as follows:

$Y_t = X_t \phi^{(j)} + \sigma^{(j)} \varepsilon_t$ if $r_{j-1} < S_t < r_j$

where $X_t = (1, Y_{t-1}, Y_{t-2}, ...Y_{t-p})$ is a column vector of variables,

$-\infty = r_0 < r_1 < ..... < r_k = +\infty$ are k non-trivial thresholds dividing the domain of S_t into *k+1* different regimes.

If the threshold variable S_t is assumed to be past values of *Y*, e.g. Y_{t-d}, where *d* stands for the delay parameter, the dynamics of the dependent variable depend on the past values of itself and the TAR model is called self-exciting TAR(SETAR).

Thus, for a given threshold r, the probability of the unobservable regime $S_t = 1$ is given by;

$$P\{[S_t = 1 | \{ S_{t-j}{}_{j=1}^{\infty} \}, \{Y_{t-j}\}_{j=1}^{\infty}] \} = I\{Y_{t-d} \le r\} = [\begin{matrix} 1 & Y_{t-d} \le r \\ 0 & Y_{t-d} > r \end{matrix}]$$

In TAR type models a regime change is observed when the threshold variable S_t crosses a certain type threshold and the regime switching is assumed to be sudden and discontinuous. However, sometimes it is more reasonable to assume that these regime switches occur gradually and smoothly which lets us to use smooth transition autoregressive models (STAR) that are obtained by replacing the abrupt changes of TAR type models by a smooth transition function.

In this analysis, the emphasis will be based on the comparison of the results of some nonlinear models such as LSTAR and SETAR models which are widely used in the literature of price relationships and the linear counterpart Linear Autoregressive Models (AR).

1.5. Data

In this paper, the price dynamics will be investigated for four commodities; Sawnwood (Hard and Soft), Plywood, Lumber Spruce, Logs (Hard and Soft) and the exporting regions involved in the analysis are Tokyo (Japan), Sapele (Nigeria-Africa),Gabon (Africa), Malaysia (Southeast Asia) and USA. The data used in the analysis are based on a set of monthly data covering the period from October 1982 to June 2009 leading to a total of 321 observations.

The monthly series on domestic and foreign prices were obtained from Commodity Research Bureau (CRB) and the exchange rates were gathered from International Financial Statistics (IFS) published by International Monetary Fund (IMF).

Trade in tropical forest products is an important source of earnings by many developing countries especially for those in Africa and South Asia. As also indicated by Vincent and Binkley (1972) as well as Douglas (1983), trade in forest products can be an extensive source of employment and income. For example, Gabon, a coastal Central African country located between Cameroon and the Republic of the Congo is the largest African export location of tropical timber consumed in China and trade of tropical timber products constitutes the second highest source of revenue for Gabon. The labor-intensive timber industry is the second largest employer after the state constituting the nearly 28-30% of the active labor force (Wunder, 2003; OECD, 2009). This fact is suitable to consider recent global economic changes and the linkages between primary commodity markets and macroeconomic shocks and the extent to which commodity prices react to changes in exchange rates and price shocks in the international markets.

The production of tropical logs is concentrated with slightly more than 70% of total production taking place in the top-five producer countries including Malaysia, Nigeria (Sapele) and Gabon with percentages 16%,5% and 3% respectively (Terheggen, 2012).

These countries are also the major consumer of their output, i.e. logs are the input for domestic primary wood processing industries producing sawnwood and plywood. For instance, in total, in the Asia-Pacific region 90% of all logs are converted into primary

products (Terheggen, 2012).This high rate indicates that many developing countries including Gabon, Malaysia, Sapele also export an important part of their resources in unprocessed form.

Japan is the most heavily import-dependent country in the world for both primary and secondary forestry products to be able to supply to its highly urbanized population and has a very diverse import base of products. Among the major trading partners with Japan are Malaysia and the United States.

Japan is also the 2nd largest importer of hard and softwood logs based on total value in the world, behind China. After Russia, the U.S. and Malaysia are the next largest suppliers of logs to this country with percentages of 21.2% and 10.4% respectively in 2003.However, we can observe some decline in Japanese imports since 1999,this may be related to the Japanese financial crisis in the late 90's (Source: International Tropical Timber Organization(ITTO)).

Japan is also the 2nd largest importer of lumber behind the U.S. (total value) and mostly imports this commodity from its closest neighbors including Malaysia (39.5%) in 2003 whereas the U.S. exports a minor amount of plywood to Japan and has not been able to have much effect in this market.

1.6. Results

This section provides the empirical results for the test of LOP/ ERPT in accordance with the theory of nonlinear regression for four forest products, namely sawnwood,

plywood, lumber spruce and logs by taking into account the structural changes that may be observed over time.

The major countries investigated are the USA, Japan (Tokyo), Nigeria (Sapele), Malaysia and Gabon and similar or identical products that are traded are examined.

The correlation between plywood prices in the USA and plywood prices in Tokyo seems to be low with a positive Pearson coefficient of magnitude 0.23 and the price development in the two markets has a volatile appearance over the period (Figure 1.1).

Unlike Figure 1.1 we can observe tendency of increasing nominal prices in the log market except between years 1995 and 2005. The Pearson correlation coefficients indicate that there is a moderate and positive relationship between soft log prices in USA and logs prices in Sapele and strong positive relationship between soft log prices in USA and Gabon with coefficients of magnitude 0.43,0.76 respectively and a moderate relationship between hard logs prices in USA and logs prices in Gabon with a positive correlation coefficient of 0.65 and slightly lower correlation with coefficient of magnitude 0.64 with Sapele logs prices (Figure 1.2).

In the sawnwood market the correlations between the nominal prices seem to be high and have a tendency to increase before the end of 90's and follow a considerably stable path until 2005 and tends to increase again. The Pearson correlation between hard sawnwood prices in USA and Malaysia is positive and has a magnitude of 0.85 whereas USA soft sawnwood prices and Malaysia sawnwood prices has a correlation coefficient of 0.80 (Figure 1.3).

Strong similarity can be found in price development between the two markets; USA lumberspruce and Malaysia sawnwood before 2000 and show differences after this period. The USA seems to have more volatile prices compared to Malaysia after 2000 and stability of price seems more significant after 2005 for Malaysia. There exists a moderate positive correlation of a magnitude 0.61 between two prices (Figure 1.4).

Also, time series plots of natural logarithms of relative prices are obtained in Figure 1.5 which indicates that there is considerable volatility in price ratios which suggests the potential for significant market interactions.

So overall we may indicate that the figures show a clear relationship between the prices in each market.

When we carefully examine the figures of the aforementioned prices in each market we can gain some important insights about the general economic condition or changes in the data period and its effects on the prices of tropical forest markets. Tropical forest products manufacturing and industries that are related experienced though times during the 1990s in USA: The general economic recession observed in 1989-1991 resulted in a large amount of plant closings and this was a stimulation of a tendency in the 1980s. However, some large firms with private sources of tropical forest products, benefited from the climbing prices. For example, based on a report of S.G. Warburg & Co. Inc., plywood prices increased 67 percent between 1991 and 1993 and these changes in prices can be clearly observed from the Figures 1.1-1.4.

Economic activity in the USA improved significantly during the first half of 2002 which signaled that economic recession was coming to an end beginning in March 2001. Even though we observed decreases in GDP growth during the 2nd quarter of 2003, some elements such as pleasing monetary policy and strong housing sector raised activity as economy moved through the second half of 2003. Low mortgate rates led to the expectation of strength in the housing sector. Wood product demand was at an all-time high in 2003 due to the strong housing construction (FAO/UNECE, 2004).

We can also observe the effects of the mortgage crisis in 2005-2006 in most of the price pairs which led to the deep recession in 2008. Housing prices fell approximately 30% on average from their mid-2006 peak to mid-2009 and remained at approximately that level as of March 2013 (Fred Database-S&P Case Shiller 20-City Home Price Index) and this incident had a huge effect in the prices of most tropical wood products as can be observed in Figures 1.1-1.4.

We can obtain limited information about a causal relationship between variables using the figures and correlation coefficients because of possible different statistical time series properties. Therefore the analysis of aforementioned price relationships is continued by estimating Logarithmic STAR (LSTAR), Self-Exciting Threshold (SETAR) and Linear Autoregressive (AR) regression models.

The first step of the analysis is to assess the statistical properties of the data such as the existence/nonexistence of unit roots and cointegration in price pairs. To this end the Augmented Dickey Fuller (ADF) and Philips Perron (PP) unit root tests are employed.

According to the results of the ADF unit root test in Table 1.3, USA Soft Sawnwood/Malaysia Sawnwood , USA Lumberspruce/Malaysia Sawnwood, USA Plywood/Tokyo Plywood, USA Hard Logs/Sapele Logs and USA Soft Logs/Sapele Logs price pairs have a unit root and are not stationary at 0.05 significance level.

The Phillips–Perron test is a procedure that might be considered as a generalization of ADF test statistic aiming to figure out the stationarity of the variables and test the null hypothesis of a unit root against an alternative of a stationarity by including a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation. The results given in Table 1.4 also confirm the nonstationarity of the USA Hard Sawnwood/Malaysia Sawnwood, USA Plywood/Tokyo Plywood and USA Soft Logs/Sapele Logs price pairs.

Davidson and MacKinnon (2004) report that the Augmented Dickey–Fuller (ADF) test performs better in finite samples than the Phillips–Perron (PP) test, so we continue the analysis with the first differences of the price pairs that are found nonstationary according to the ADF test statistic.

All first differences of the nonstationary price pairs are found to be stationary with a p value of 0.01 and this fact is also supported by Figure 1.6 where the first differences of the price pairs are displayed.

As specified, LSTAR and SETAR models are nonlinear in parameters so nonlinear estimation methods are called for these models including the first differences of the aforementioned price pairs.

Optimal lag lengths for each of the specified models are chosen by the AIC criterion and same lag length is assumed for each regimes.

Finally, the choice between the mentioned models is done through careful examination of the each model's AIC and MAPE criterions.

The first model proposed was the AR (p) model and this model will be the base model to compare the other models to since a fundamental building block of any non-linear time series model is a typical linear model, here a typical linear autoregressive model.

As an improvement to the AR model, we then applied a SETAR (2; 2, 2) model with threshold delay $\delta = 1$ and an LSTAR model with threshold delay $\delta = 1$ again. For an automatic comparison, we may fit different linear and nonlinear models and directly compare measures of their fit. In this analysis the mentioned nonlinear models are estimated and compared with the linear counterpart in terms of their fit measures specifically AIC and MAPE criterions. The results of these comparisons between the models are presented in Table 1.5.

Following Hansen (1997) to make sure that the results are not affected by the possible outliers that may be observed in the data and the model is well identified, the trim value for the grid search for the estimation of the models was chosen as 0.15, meaning the range for the grid search was chosen as to include the 15th and 85th percentiles.

In principle, we do not expect to have large values of the delay parameter **d** as we do not expect the deviations from LOP to be sticky; throughout this analysis the delay parameter is chosen to be 2, which sets this study apart from some other literature in this area in which the delay parameter d is estimated according to the best fit model but not restricted to unity as has been done in some other previous studies.

From the comparison of all aforementioned models, the SETAR model seems to fit all price pairs best according to AIC criterion whereas the results of the MAPE criterion seems to favor LSTAR model in most price pairs such as USA Soft Sawnwood / Malaysia Sawnwood, USA Plywood /Tokyo Plywood, USA Soft Logs /Gabon Logs and support SETAR model in USA Soft Logs /Sapele Logs, USA Hard Logs /Gabon Logs and USA Lumberspruce/ Malaysia Sawnwood price pairs. According to the MAPE criterion, USA Hard Sawnwood /Malaysia Sawnwood and USA Hard Log /Sapele Logs price pairs are best represented by the linear model.

When there is a contradiction between AIC and MAPE result, models are estimated according to both criteria and evaluated in terms of the significance of the estimated parameters. The best fit models are discussed here. More detailed diagnostics are extracted from these best fit models and are given in Tables 1.6-1.13.

According to Tables 1.8, 1.9, 1.12, and 1.13, it seems that most of the high and low regime coefficients are statistically significant for the USA Lumberspruce /Malaysia Sawnwood, USA Plywood / Tokyo Plywood, USA Hard Logs / Gabon Logs and USA Soft Logs / Gabon Logs price pairs respectively for the SETAR models. The values of the threshold

variables are 0.02128, -0.01935, 0.08986 and -0.32. Persistence from the deviations from LOP that are characterized by nonlinear adjustments depends on whether the exchange rate passes these threshold values—possibly representing the transaction costs—allows us to identify two regimes, high and low. The high regime (second one) is identified as the one in which the increase in lagged percentage change in prices are higher than 0.02128, 0.01935, 0.08986 and -0.32 in absolute terms respectively. Arbitrage is profitable and the process is mean reverting whereas the low (first) regime occurs when the deviations from the LOP are smaller than the threshold values calculated. Arbitrage is not profitable and LOP will not hold as the exchange rates are not likely to move back to equilibrium level.

Table 1.8 shows that for USA Lumberspruce /Malaysia Sawnwood price pair analysis, the low regime includes 72.01% of observations whereas the second high regime includes 27.99%. Results shown in Table 1.9 indicate that in the plywood trade markets between USA and Tokyo, the low regime includes 32.7% of total observations and occurs mainly in the first part of the data sample while the proportion of the data in the high regime (second one) is at about 67.3%. On the other hand, according to Table 1.12, in the logs market between USA (Hard) and Gabon, the low regime includes 92.16% of total observations and the second regime involves only 7.84% part of the data. Table 1.13 shows a similar type of relationship as Table 1.10 in terms of the inclusion of data points in the high and low regime and indicates that for USA Soft Logs / Gabon Logs, the proportion of points in low regime is 10.03% while the high regime includes most of the data points with a 89.97% level. For the USA Soft Logs / Sapele Logs price, the estimated threshold value is 0.0531 and the

proportion of points in low regime is 93.71% and the second high regime includes the 6.29% of the data (as can be seen from Table 1.11). As implied earlier, the low regime may indicate a situation of no trade or may imply that there exist some important barriers to trade such as tariffs and quotas, whereas the high regime may correspond to the case of trade.

As we know, the more far away the prices are from each other, the larger the deviation from a presumed parity condition and potential gains from arbitrage, thus the reason for differences in prices is the transaction costs. According to Table 1.6, if the two possible best models—SETAR and Linear—are compared, the SETAR model seems to fit better in terms of significance of the coefficients for USA Hard Sawnwood / Malaysia Sawnwood price pair; therefore, a SETAR model is assumed for this price pair.

When the same analysis is done for USA Hard Logs / Sapele Logs price pair, the difference between SETAR and Linear models follows the same path wherein the SETAR model is superior to linear model in terms of the significance of estimated parameters (Table 1.10).

According to Table 1.7, the comparison between the LSTAR and SETAR models for price pair of USA Soft Sawnwood / Malaysia Sawnwood favors the usage of SETAR model as the appropriate model since it includes more significant coefficients. Overall, compared to the other models, the SETAR specification mostly accommodates potentially different market adjustments that approximately follow departures from spatial price parity.

It is expected that the larger the value of the transition variable, the larger the difference in recently observed prices will be; thus, the larger is the deviation from the

assumed parity conditions mentioned here, and larger are the potential gains from arbitrage. In this manner, the values of the threshold coefficients provide important insights about the arbitrage opportunities for each country in question; the bigger the coefficient, the more possibility to gain from arbitrage.

The overall results show that nonlinearity and structural change are important features of these markets; price parity relationships implied by the economic theory are generally supported by the estimated models, and the figures of the price pairs presented also supports this conclusion.

The next step in the analysis was to use the out-of-sample forecasting from the aforementioned best fit models and compare the forecasting performance of these models; in addition, using the impulse response functions, the dynamics of these models are investigated further.

The forecasting approach taken here for SETAR and LSTAR models is to evaluate the forecasts for each regime separately in order to see if the nonlinear model can be used to obtain forecasts in a particular regime (see Clements & Smith (1999); van Dijk &Terasvirta (2000); and Tiao & Tsay (1994) for applications of this approach to SETAR models) as there is a possibility that the forecastibility of the time series may be different in different regimes according to the values of the transition variable.

The bootstrap method is chosen to obtain forecasts as they are found more preferable to the naive methods of forecasting and may effectively be used to obtain the confidence intervals using the realizations from bootstrap methods (Clements & Smith,

1997) as empirical forecasts do not always let us to assess the forecasting quality of the STAR type models. So, an estimated SETAR model is used to generate an artificial time series and then forecasts are obtained from these time series using AR (2) model.

It is observed that for most of the price pairs, switching between regimes is not frequent; this fact suggests that the forest market is not jumping back and forth between regimes on a monthly basis, but rather tends to remain in a regime for a long period of time.

Reasonable estimates of the threshold values that may be a representation of transaction costs were found that are in line with the theoretical arguments in international trade. Threshold values obtained show variation across countries and this heterogeneity observed in transaction costs for the same or similar sectors such as using the dollar as our reference currency the estimated threshold values change from %1 to %32 in this analysis may be partly due to the country-specific effects as some countries exhibit relatively higher thresholds for a given sector (Juvenal &Taylor, 2008).

To figure out whether the shocks introduced into this system will have any significant impulse response effects and to assess the time path of these variables, the bootstrap method with 1,000 replications for SETAR and LSTAR models were used. Also, only positive shocks were taken into account in this analysis.

Figures 1.7-1.14 exhibit the graphs of impulse responses for the SETAR models for USA Lumberspruce-Malaysia Sawnwood, USA Plywood-Tokyo Plywood, USA Hard Logs-Sapele Logs, USA Soft Logs-Sapele Logs, USA Hard Logs-Gabon Logs, USA Soft Logs-Gabon

Logs, USA Soft Sawnwood /Malaysia Sawnwood, USA Hard Sawnwood /Malaysia Sawnwood price pairs respectively. In the low (first) regime (Figure 1.7), a shock introduced into the system initially increases USA Lumberspruce-Malaysia Sawnwood price in an increasing rate, but after two periods, the relative price tends to increase at a decreasing rate; thereafter, it converges to its long run equilibrium level at about 40 periods. In the high (second) regime (Figure 1.7), a huge increase of the USA Lumberspruce-Malaysia Sawnwood price is observed in the first 3 periods, and the price ratio immediately turns to its equilibrium level.

For USA Plywood-Tokyo Plywood price ratio (Figure 1.8), some important differences between high and low regime characteristics are observed: a shock introduced into the system will only lead to a slight increase in price ratio in low regime, and it tends to converge to the equilibrium level at about 16 periods, whereas this same shock results in a huge price increase in the initial periods of high regime and a quick turn to equilibrium level in 5 periods only.

The USA Hard Logs-Sapele Logs price pair (Figure 1.9) seems to follow a different path in low and high regimes. A shock introduced into the system leads to an increase in the price ratio in the first 2 periods in the low regime whereas an opposite response is observed in the high regime where the price ratio immediately decreases in the first 2 periods. Thereafter, the price ratio tends to increase and reaches its equilibrium level in about 9 periods in the low regime; however, the high regime needs about 38 periods for this ratio to come to equilibrium level.

USA Soft Logs-Sapele Logs pair also exhibits different behavior in low and high regime (Figure 1.10). In the low regime, it takes a long time for the price pair to recover to its long run equilibrium level and still seems not to catch that level even after 50 periods. In the high regime, after a shock given into the system, the price pair immediately returns to its pre-shock level.

In Figure 1.11, USA Hard Logs-Gabon Logs price ratio tends to exhibit an opposite behavior in the first initial 2 periods after a shock. In the low regime, this shock results in a slight increase in price ratio whereas price ratio decreases in the high regime as a result of a shock. Thereafter, in both regimes it starts to increase towards converging to its long-run equilibrium level. The amount of time needed for the convergence is about two times (30 periods) that of the high regime (15 periods) in the low one.

For USA Soft Logs-Gabon Logs price ratio (Figure 1.12), the response to a shock into the system seems to be completely different from the other in the low and high regimes. In the low regime, the price ratio responds to a shock in a way that leads to a decrease in the initial periods and thereafter continues to decrease further reaching to equilibrium level at about 40 periods. In the high regime, a sharp increase is observed in the initial period that increases continues gradually until the long-run equilibrium is achieved after 15 periods. In Figure 1.13, a similar path for the SETAR model of USA Soft Sawnwood/Malaysia Sawnwood price ratio in the low and high regimes is observed. The price ratio decreases slightly after a shock and immediately reaches to its long run equilibrium level in a few periods. The SETAR model estimated for USA Hard Sawnwood / Malaysia Sawnwood ratio in Figure 1.14

indicates that after a shock, a short period of time is needed for the price pair to come to its long run equilibrium level which is less than 2 months in both regimes.

Here the impulse responses were compared at a mutual level of shock to be able to get clear view of how the basics of the models would vary across regimes. It is also possible to compare the shocks that differed in terms of their sizes in high and low regimes, but this is not preferred here in order to avoid the problem of amplifying the differences in impulse responses.

1.7. Conclusion

This paper attempted to examine the price dynamics of forest products from Africa, Southeast Asia and Japan to the United States using some linear and non-linear regression approaches taking into account the structural changes. Considerable volatility in price ratios were observed, which suggests the potential for significant market interactions between the USA, Africa, Japan and Southeast Asia. The analysis of aforementioned market interactions and price pairs was employed by estimating Logarithmic STAR (LSTAR), Self-Exciting Threshold Autoregressive (SETAR) and Linear Autoregressive (AR) regression models. Optimal lag length for each of the specified models are chosen by applying the AIC criterion. Finally, the choice between the mentioned models are done through careful examination of the each models' AIC and MAPE criterions.

The findings suggest that from this comparison, the SETAR model seems to fit the data best for most price pairs according to AIC and MAPE criteria with the lowest values. When this result was combined with the comparisons of significance of estimated

parameters from various proposed models in case of a contradiction between the results suggested by AIC and MAPE criterions, it was concluded that compared to the other models, SETAR specification accommodates potentially different market adjustments that approximately follow departures from spatial price parity; thus, the SETAR model is thought to better represent this market compared to the other model specifications.

The overall results show that nonlinearity and structural change are important features of these markets; price parity relationships implied by the economic theory are generally supported by the estimated models and the figures of the price pairs used also supports this conclusion. Results suggest evidence for the convenience of the STAR type models (SETAR and LSTAR) to model deviations from LOP in a nonlinear fashion for tropical forest product markets. Reasonable estimates of the threshold values that may be a representation of transaction costs that are in line with the theoretical arguments in international trade were found. It was also observed that the values of threshold variables vary hugely across different countries. The value of the threshold variable is changing between 1% and 32%, which suggests huge differences in potential arbitrage opportunities for countries examined.

For instance, in the soft logs market, the threshold value of the SETAR model is 0.0531 between the USA and Sapele whereas this coefficient is calculated as 0.32 between the USA and Gabon. This fact suggests that the difference in recently observed prices is larger for Gabon, and larger deviations from the parity conditions in Gabon compared to Sapele are observed. Also, a bigger threshold value exposes the fact that Gabon has larger

potential gains from arbitrage and will face a faster adjustment process compared to Sapele, which does not have persistent opportunities for spatial arbitrage. These differences in threshold values may result from region-specific effects for Gabon and Sapele; in general, such effects may be related to country or continent-specific effects (Tables 1.11 and 1.13).

The threshold values dividing the regimes into low and high also provideinformation about countries' trade situations. Taking the same example, in Sapele, if the increase in lagged percentage change in prices of soft log is higher than 5%, the country will be considered in high regime which may indicate the situation of trade and will have potential gains from arbitrage. However, this fact will be valid only for the 6.29% in the data whereas this fact is true for Gabon whenever the lagged percentage change in prices is higher than 32% and the trade situation is observed for the 89.97% of the data points (Tables 1.11 and 1.13).

The results for the hard sawnwood, soft sawnwood and lumber spruce prices in the USA and Malaysia do not show much difference in terms of the values of the threshold variables, opportunities for spatial arbitrage, or the portion of data points in low and high regimes. The threshold values change between 2% and 3%, not suggesting notable differences between these two countries in terms of deviations from parity conditions defined (Tables 1.6, 1.7 and 1.18).

In the hard log markets between the USA, Gabon and Sapele, the estimated threshold values are 0.08 and 0.03 respectively indicate that if the increase in lagged percentage change in prices of hard logs is higher than 8% and 3%, the countries will be

considered in high regime which may indicate the situation of trade and will have potential gains from arbitrage. However, this fact will be valid only for the 92.16 % in the data for Gabon, whereas this fact is true for Sapele for the 10.06% of the data points (Tables 1.10 and 1.12).

Finally, the impulse response analysis for each price pair also supports the changing behavior of price ratios in high and low regimes to a unit shock into the system for almost all price pairs, which may be seen as an another justification to use models taking into account the structural changes to model LOP and ERPT in a nonlinear fashion.

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TABLES AND FIGURES

Table 1.1: Summary Statistics for prices of 321 observations from 1982 to 2009

Variable	Mean	Std Dev	Minimum	Maximum
plywood_tokyo	82891.68	13000.29	62659.19	125233.59
plywood_usa	249.9446000	80.3386335	129.7500000	517.6000000
logs_sapele	17394.73	19307.52	107.0439370	68512.52
logsh_usa	198.0830530	74.4807032	76.4100000	520.8100000
logss_usa	145.3788162	44.6346703	55.8700000	259.9700000
logs_gabon	107579.53	45053.29	42985.82	166617.14
sawnwood_malaysia	1531.15	522.7685327	655.5502800	2147.00
sawnwoodh_usa	554.2112150	203.4422575	169.6300000	940.9700000
sawnwoods_usa	251.8463551	70.0104034	121.1700000	372.6000000
lumberspruce_usa	252.5919315	78.6286909	130.2500000	466.7500000

*Prices in Countries' Home Currency (Yen for Tokyo,Naira (NGN) for Sapele, CFA Frang for Gabon, and Ringgit(MYR) for Malaysia)

Table 1. 2: Pearson Correlation Coefficients

Price Pairs	Pearson Correlation Coefficient
USA Hard Sawnwood-Malaysia Sawnwood	0.84677
USA Soft Sawnwood-Malaysia Sawnwood	0.79695
USA LumberspruceMalaysiaSawnwood	0.60848
USA Plywood-Tokyo Plywood	0.23324
USA Hard Logs-Sapele Logs	0.64165
USA Soft Logs-Sapele Logs	0.42933
USA Hard Logs-Gabon Logs	0.64482
USA Soft Logs-Gabon Logs	0.75728

Table 1.3: Augmented Dickey Fuller (ADF) Unit Root Tests

Price Pairs	ADF Test statistic	p Value(ADF)
USA Hard Sawnwood/Malaysia Sawnwood	-3.5071	0.04232
USA Soft Sawnwood/Malaysia Sawnwood	-3.0911	0.1164
USA Lumberspruce/Malaysia Sawnwood	-2.8318	0.2257
USA Plywood/Tokyo Plywood	-2.7843	0.2458
USA Hard Logs/Sapele Logs	-3.3584	0.06157
USA Soft Logs/Sapele Logs	-1.6022	0.7442
USA Hard Logs/Gabon Logs	-3.7646	0.02113
USA Soft Logs/Gabon Logs	-3.8593	0.0164

Table 1.4: Philips Perron (PP) Unit Root Tests

Price Pairs	Philips- Perron Test statistic	p Value(PP)
USA Hard Sawnwood/Malaysia Sawnwood	-21.0141	0.05514
USA Soft Sawnwood/Malaysia Sawnwood	-36.7174	0.01
USA Lumberspruce/Malaysia Sawnwood	-23.2142	0.03528
USA Plywood/Tokyo Plywood	-20.819	0.05807
USA Hard Logs/Sapele Logs	-22.4924	0.041
USA Soft Logs/Sapele Logs	-8.4204	0.6384
USA Hard Logs/Gabon Logs	-26.3631	0.01811
USA Soft Logs/Gabon Logs	-28.1974	0.01128

Table 1.5: Model Selection Through AIC and MAPE Criterion

Price Pairs	AIC	MAPE
USA Hard Sawnwood /Malaysia Sawnwood		
Linear	-2205.299	1.898770
SETAR	-2205.979	2.059094
LSTAR	-2202.447	2.106865
USA Soft Sawnwood /Malaysia Sawnwood		
Linear	-2232.192	1.989909
SETAR	-2236.514	1.968964
LSTAR	-2229.575	1.698884
USA Lumberspruce /Malaysia Sawnwood		
Linear	-2232.192	1.989909
SETAR	-2236.514	1.698884
LSTAR	-2229.575	1.968964
USA Plywood /Tokyo Plywood		
Linear	-1921.869	1.419646
SETAR	-1926.929	1.567863
LSTAR	-1923.027	1.371151
USA Hard Log /Sapele Logs		
Linear	-2242.767	1.893787
SETAR	-2247.684	2.259924
LSTAR	-2240.168	2.490861

Table 1.5 Continued

USA Soft Logs /Sapele Logs		
Linear	-2164.346	1.555727
SETAR	-2165.463	1.463125
LSTAR	-2160.627	1.597272
USA Hard Logs /Gabon Logs		
Linear	-2223.264	0.7206582
SETAR	-2232.986	0.6724562
LSTAR	-2226.748	0.6836987
USA Soft Logs /Gabon Logs		
Linear	-2166.729	0.9876545
SETAR	-2168.721	0.9847713
LSTAR	-2166.364	0.9689818

Table 1.6: Results of SETAR and LINEAR Model for USA Hard Sawnwood/Malaysia Sawnwood

SETAR Model USA Hard Sawnwood / Malaysia Sawnwood

	Estimate	Std. Error	t value	Pr(>|t|)
const L	0.00011419	0.00145718	0.0784	0.93759
phiL.1	0.39588796	0.06242987	6.3413	7.925e-10 ***
phiL.2	-0.19945091	0.07783983	-2.5623	0.01086 *
const H	-0.00467992	0.00737505	-0.6346	0.52618
phiH.1	0.02846533	0.12022222	0.2368	0.81299
phiH.2	0.12792115	0.14918820	0.8574	0.39185

Signif. codes: 0‘***’0.001 ‘**’0.01‘*’0.05 ‘.’ 0.1 ‘’ 1

Threshold Value: 0.02234

Proportion of points in low regime: 88.36%

High regime: 11.64%

Table 1.6 Continued

LINEAR Model USA Hard Sawnwood / Malaysia Sawnwood				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
const	0.00072208	0.00134493	0.5369	0.59172
phi.1	0.31740038	0.05590563	5.6774	3.106e-08 ***
phi.2	-0.10757305	0.05567077	-1.9323	0.05422 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				

Table 1.7: Results of SETAR and LSTAR Model for USA Soft Sawnwood / Malaysia Sawnwood

SETAR Model USA Soft Sawnwood / Malaysia Sawnwood				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
const L	-0.00082066	0.00180568	-0.4545	0.649790
phiL.1	-0.40518047	0.05708916	-7.0973	8.511e-12 ***
phiL.2	-0.18113770	0.06889214	-2.6293	0.008977 **
const H	0.01258988	0.01532206	0.8217	0.411881
phiH.1	0.27716631	0.20644155	1.3426	0.180375
phiH.2	-0.02320355	0.24418191	-0.0950	0.924355

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Threshold Value: 0.03805				
Proportion of points in low regime: 90.88% High regime: 9.12%				

Table 1.7 Continued

LSTAR Model for USA Soft Sawnwood / Malaysia Sawnwood

	Estimate	Std. Error	t value	Pr(>|z|)
const1	-0.0032847	0.0050323	-0.6527	0.5139328
phi1.1	-0.3945301	0.0641829	-6.1470	7.898e-10 ***
phi1.2	-0.2567382	0.1332510	-1.9267	0.0540138 .
const2	0.0381427	0.0358503	1.0639	0.2873543
phi2.1	0.3516665	0.2682524	1.3110	0.1898734
phi2.2	-0.0880541	0.3538342	-0.2489	0.8034716
gamma	100.0000042	122.7659230	0.8146	0.4153252
th	0.0399837	0.0120122	3.3286	0.0008729 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 1.8: Results of SETAR Model for USA Lumberspruce / Malaysia Sawnwood

USA Lumberspruce / Malaysia Sawnwood

	Estimate	Std. Error	t value	Pr(>|t|)
const L	-0.0104045	0.0070763	-1.4703	0.14247
phiL.1	1.1084454	0.0567769	19.5228	< 2.2e-16 ***
phiL.2	-0.1492092	0.0590933	-2.5250	0.01206 *
const H	-0.1907494	0.0389309	-4.8997	1.538e-06 ***
phiH.1	0.7955181	0.1734814	4.5856	6.539e-06 ***
phiH.2	-1.1611432	0.2904010	-3.9984	7.950e-05 ***

Threshold Value: 0.02128

Proportion of points in low regime: 72.01% High regime: 27.99%

Table 1.9: Results of (SETAR) and LSTAR Model for USA Plywood / Tokyo Plywood

SETAR Model USA Plywood / Tokyo Plywood

	Estimate	Std. Error	t value	Pr(>|t|)	
const L	-0.0154493	0.0079973	-1.9318	0.05428	.
phiL.1	0.1801807	0.0948336	1.9000	0.05835	.
phiL.2	-0.2406931	0.1201924	-2.0026	0.04608	*
const H	0.0087918	0.0040011	2.1973	0.02873	*
phiH.1	0.1431608	0.0679231	2.1077	0.03585	*
phiH.2	-0.3911983	0.0985733	-3.9686	8.964e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Threshold Value: -0.01935

Proportion of points in low regime: 32.7% High regime: 67.3%

LSTAR Model USA Plywood / Tokyo Plywood

	Estimate	Std. Error	t value	Pr(>|z|)
const.L	-0.0784164	0.1074672	-0.7297	0.4656
phiL.1	0.0022688	0.1827971	0.0124	0.9901
phiL.2	-0.6218819	0.5661739	-1.0984	0.2720
const.H	0.1065268	0.1313212	0.8112	0.4173
phiH.1	0.2127073	0.2387743	0.8908	0.3730

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Threshold Value: -0.03751

Table 1.10: Results of SETAR and LINEAR Model for USA Hard Logs / Sapele Logs

SETAR Model USA Hard Logs/Sapele Logs

	Estimate	Std. Error	t value	Pr(>|t|)
const L	-0.02724382	0.01310393	-2.0791	0.03842 *
phiL.1	-0.25110485	0.18129771	-1.3850	0.16702
phiL.2	-0.30627741	0.21942791	-1.3958	0.16376
const H	-0.00054344	0.00179857	-0.3021	0.76274
phiH.1	0.27839503	0.05788211	4.8097	2.35e-06 ***
phiH.2	0.15702840	0.07078693	2.2183	0.02725 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Threshold Value: -0.03362

Proportion of points in low regime: 10.06% High regime: 89.94%

LINEAR Model for USA Hard Log /Sapele Logs

	Estimate	Std. Error	t value	Pr(>|t|)
const	5.1992e-05	1.6784e-03	0.0310	0.97531
phi.1	2.3597e-01	5.5923e-02	4.2196	3.205e-05 ***
phi.2	1.0673e-01	5.5890e-02	1.9096	0.05709 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 1. 11: Results of SETAR Model for USA Soft Logs / Sapele Logs

SETAR Model USA Soft Logs/Sapele Logs				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
const L	-0.0017740	0.0019813	-0.8954	0.371268
phiL.1	-0.2142053	0.0591686	-3.6203	0.000343 ***
phiL.2	-0.0827050	0.0704995	-1.1731	0.241633
const H	0.0258441	0.0244691	1.0562	0.291694
phiH.1	-0.5988918	0.1678859	-3.5673	0.000417 ***
phiH.2	-0.2900146	0.2959269	-0.9800	0.327830

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Threshold Value: 0.0531				
Proportion of points in low regime: 93.71% High regime:6.29%				

Table 1.12: Results of SETAR Model for USA Hard Logs / Gabon Logs

SETAR Model USA Hard Logs/Gabon Logs				
	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
const L	-0.0041124	0.0029150	-1.4108	0.1592910
phiL.1	1.1462939	0.0579367	19.7853	< 2.2e-16 ***
phiL.2	-0.2114007	0.0594169	-3.5579	0.0004313 ***
const H	0.0092989	0.0151864	0.6123	0.5407697
phiH.1	1.6919841	0.1224753	13.8149	< 2.2e-16 ***
phiH.2	-0.7983158	0.1313636	-6.0771	3.529e-09 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Threshold Value: 0.08986				
Proportion of points in low regime: 92.16% High regime: 7.84%				

Table 1.13: Results of SETAR and LSTAR Model for USA Soft Logs / Gabon Logs

SETAR Model USA Soft Logs/Gabon Logs

	Estimate	Std. Error	t value	Pr(>|t|)
const L	-0.292254	0.096356	-3.0330	0.002622 **
phiL.1	0.791375	0.140481	5.6333	3.921e-08 ***
phiL.2	-0.630986	0.275696	-2.2887	0.022759 *
const H	-0.013010	0.005625	-2.3129	0.021375 *
phiH.1	0.684174	0.058855	11.6247	< 2.2e-16 ***
phiH.2	0.248641	0.060175	4.1320	4.615e-05 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Threshold Value: -0.32

Proportion of points in low regime: 10.03% High regime: 89.97%

LSTAR Model for USA Soft Logs/Gabon Logs

	Estimate	Std. Error	t value	Pr(>|z|)
const.L	-0.75950	NA	NA	NA
phiL.1	1.11718	NA	NA	NA
phiL.2	-2.11207	NA	NA	NA
const.H	0.74023	NA	NA	NA
phiH.1	-0.44472	NA	NA	NA
phiH.2	2.27111	NA	NA	NA
gamma	18.76923	NA	NA	NA

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Note: Hessian negative-semi definite

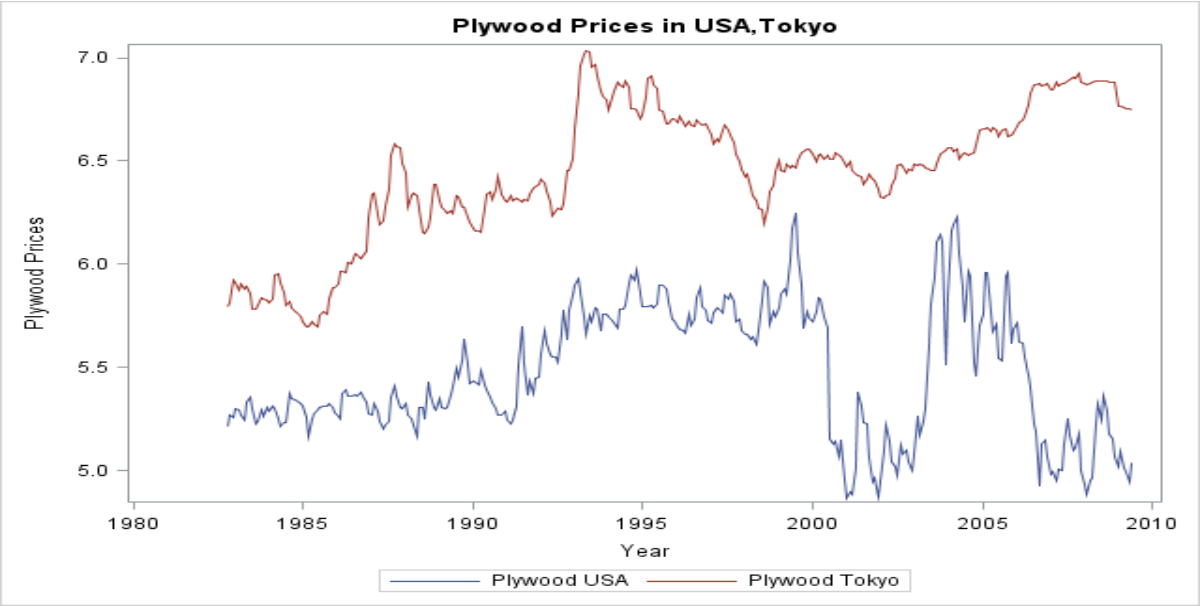


Figure 1.1: Nominal Plywood Prices in USA and Tokyo, 1982:10-2009:6 (Logarithmic Form)

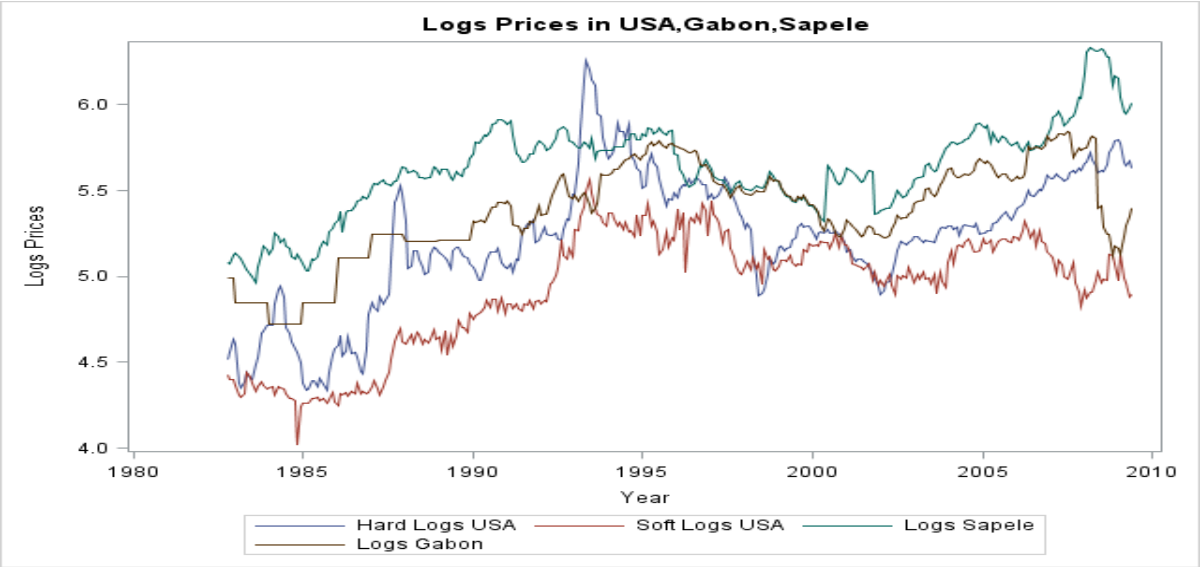


Figure 1.2: Nominal Logs Prices in USA, Gabon and Sapele, 1982:10-2009:6 (Logarithmic Form)

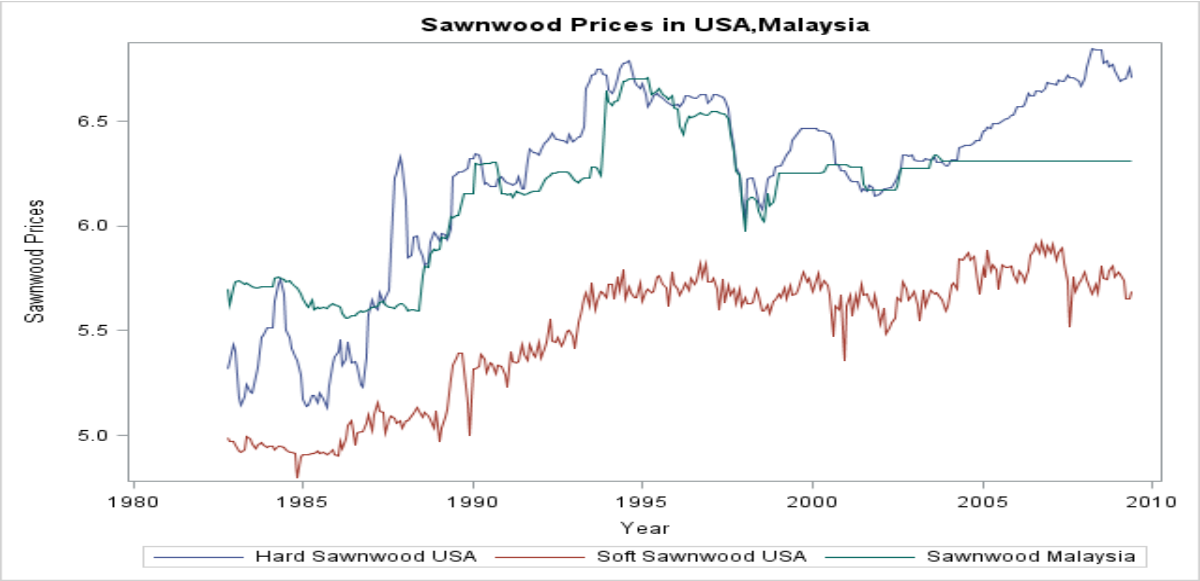


Figure 1.3: Nominal Sawnwood Prices in USA and Malaysia, 1982:10-2009:6 (Logarithmic Form)

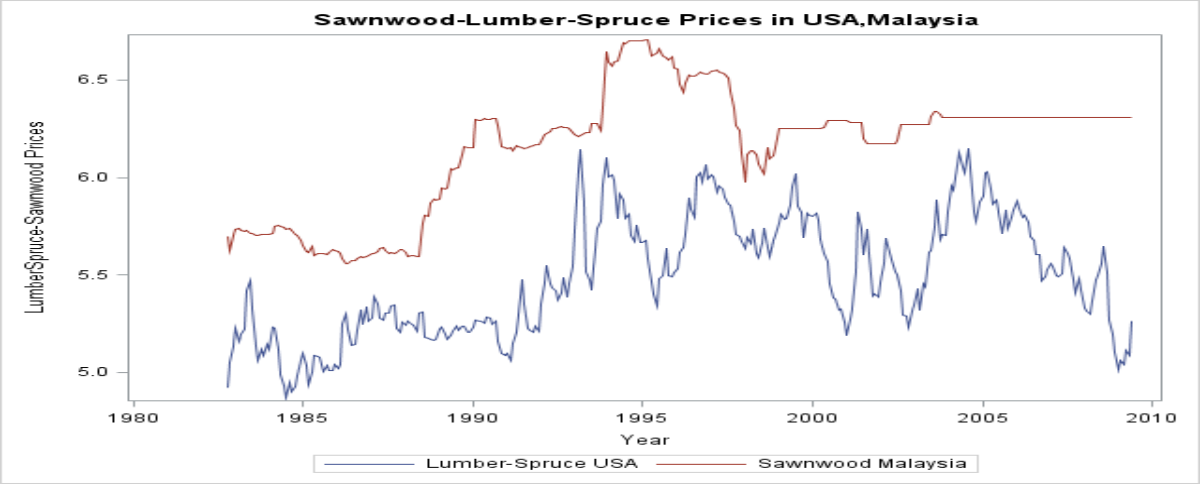
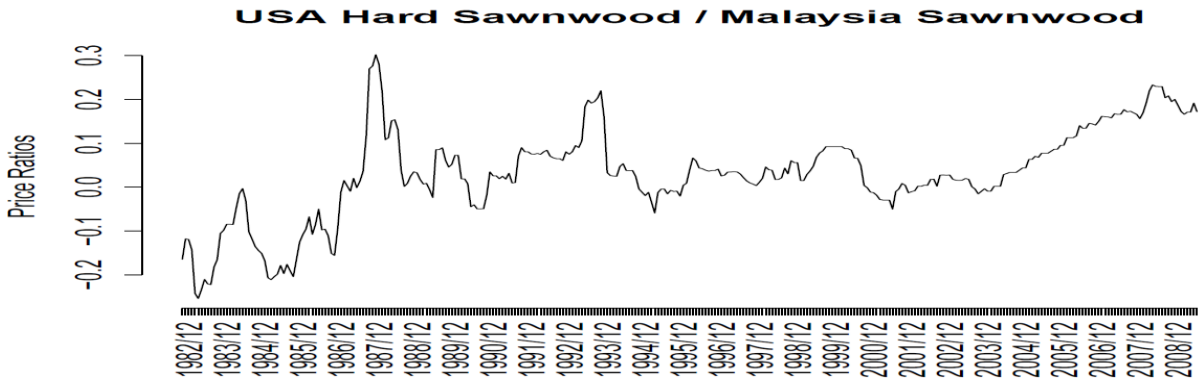
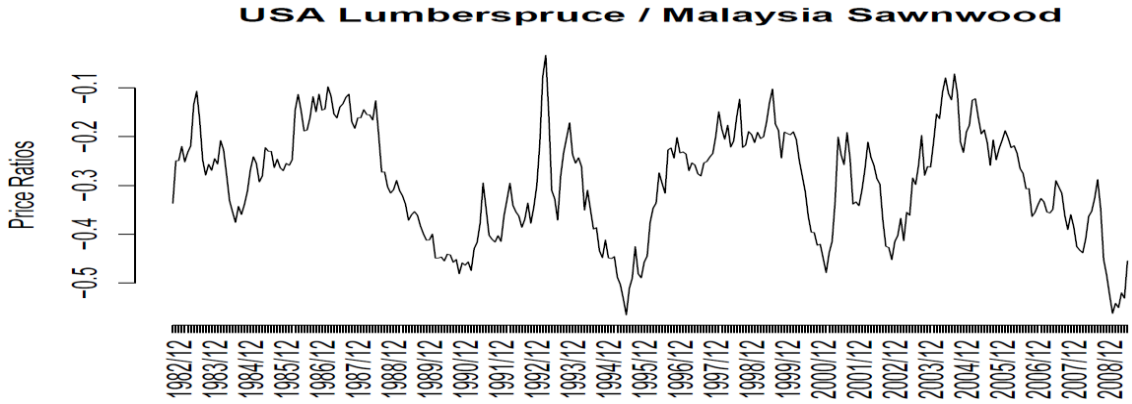
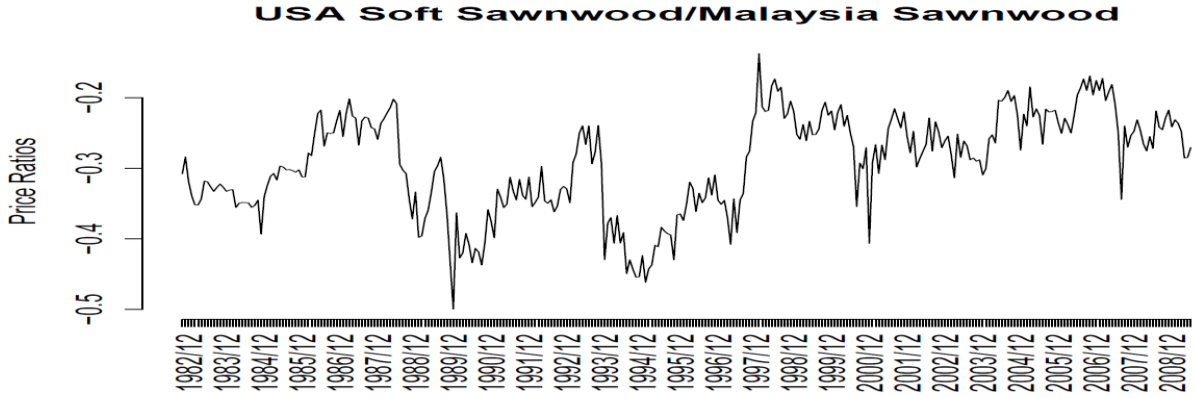


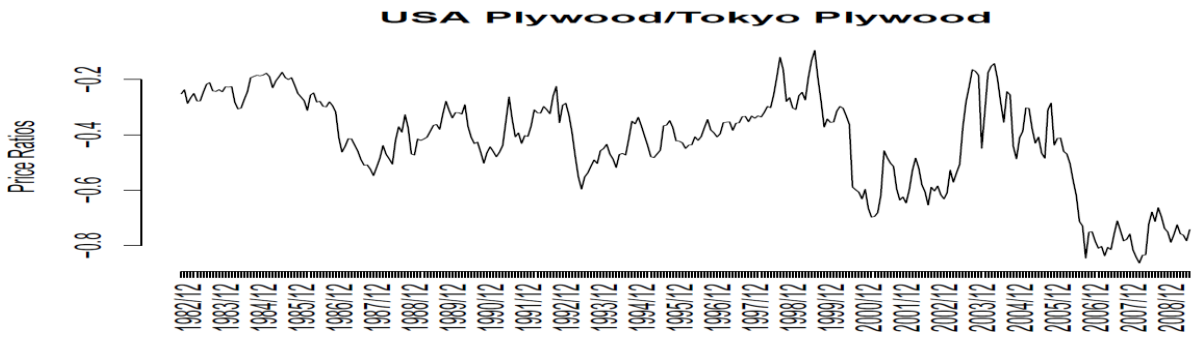
Figure 1.4: Nominal Lumberspruce-Sawnwood Prices in USA and Malaysia, 1982:10-2009:6 (Logarithmic Form)

Figure 1.5: Time Series plots of Natural Logarithms of Relative Prices 1982:10-2009-6


USA Hard Sawnwood / Malaysia Sawnwood
Price Ratios
-0.2 -0.1 0.0 0.1 0.2 0.3
1982/12 1983/12 1984/12 1985/12 1986/12 1987/12 1988/12 1989/12 1990/12 1991/12 1992/12 1993/12 1994/12 1995/12 1996/12 1997/12 1998/12 1999/12 2000/12 2001/12 2002/12 2003/12 2004/12 2005/12 2006/12 2007/12 2008/12


USA Lumberspruce / Malaysia Sawnwood
Price Ratios
-0.5 -0.4 -0.3 -0.2 -0.1
1982/12 1983/12 1984/12 1985/12 1986/12 1987/12 1988/12 1989/12 1990/12 1991/12 1992/12 1993/12 1994/12 1995/12 1996/12 1997/12 1998/12 1999/12 2000/12 2001/12 2002/12 2003/12 2004/12 2005/12 2006/12 2007/12 2008/12


USA Soft Sawnwood/Malaysia Sawnwood
Price Ratios
-0.5 -0.4 -0.3 -0.2
1982/12 1983/12 1984/12 1985/12 1986/12 1987/12 1988/12 1989/12 1990/12 1991/12 1992/12 1993/12 1994/12 1995/12 1996/12 1997/12 1998/12 1999/12 2000/12 2001/12 2002/12 2003/12 2004/12 2005/12 2006/12 2007/12 2008/12


USA Plywood/Tokyo Plywood
Price Ratios
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-0.6
-0.4
-0.2
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
1996/12
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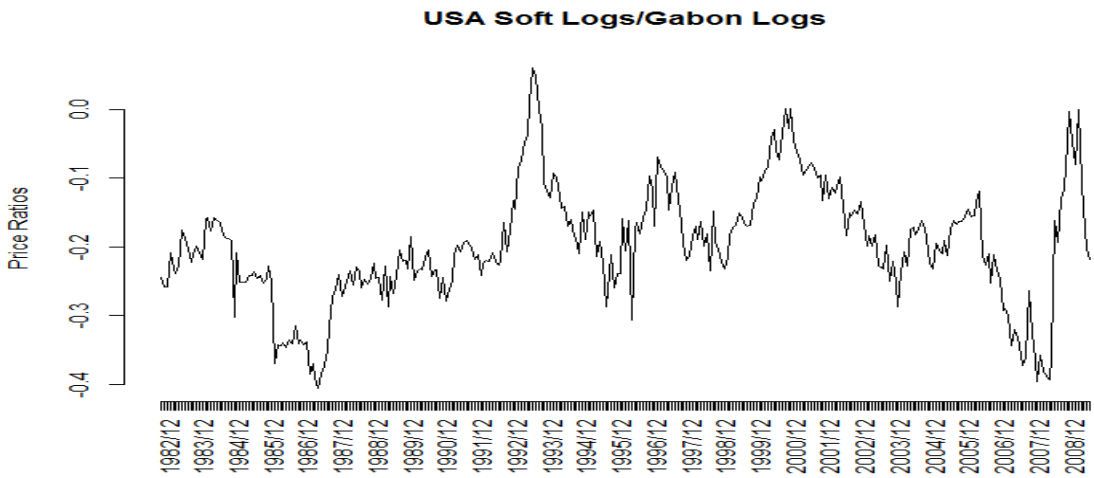
2002/12
2003/12
2004/12
2005/12
2006/12
2007/12
2008/12


USA Soft Logs/Gabon Logs
Price Ratios
-0.4
-0.3
-0.2
-0.1
0.0
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
1996/12
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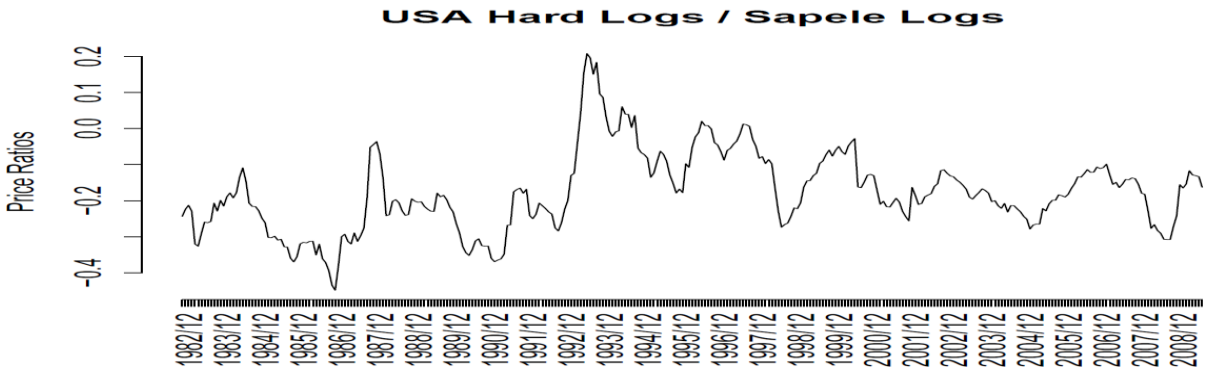
2006/12
2007/12
2008/12


USA Hard Logs / Sapele Logs
Price Ratios
-0.4
-0.2
0.0
0.1
0.2
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
1996/12
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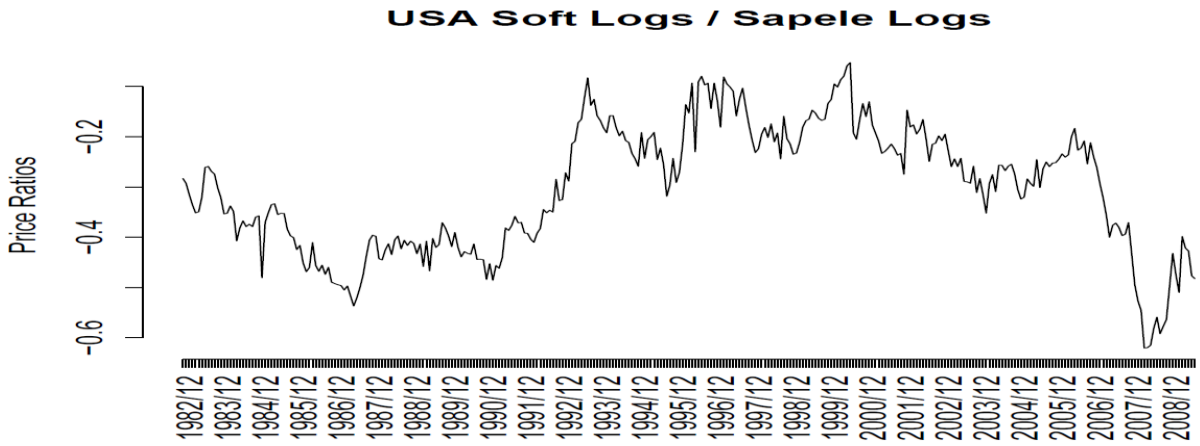
2004/12
2005/12
2006/12
2007/12
2008/12


USA Soft Logs / Sapele Logs
Price Ratios
-0.6
-0.4
-0.2
1982/12
1983/12
1984/12
1985/12
1986/12
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1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
1996/12
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2004/12
2005/12
2006/12
2007/12
2008/12

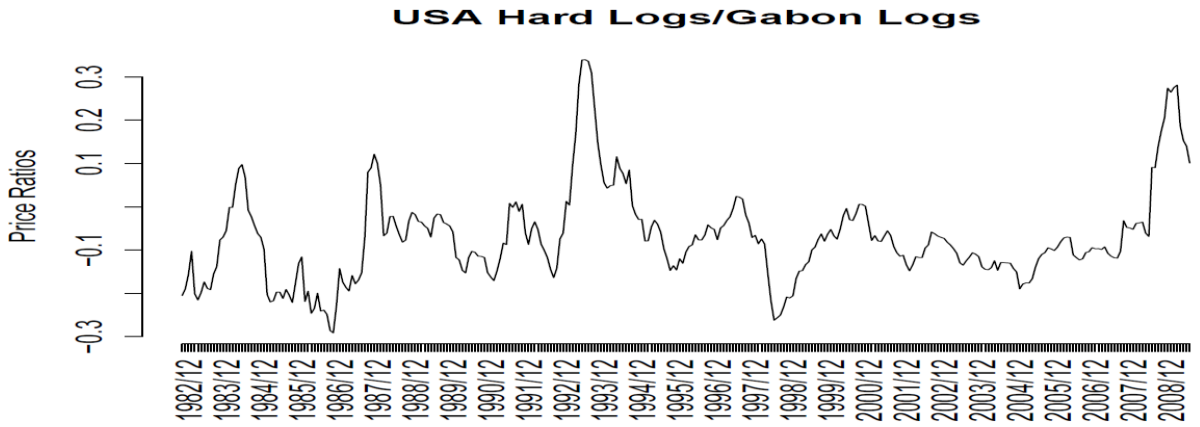
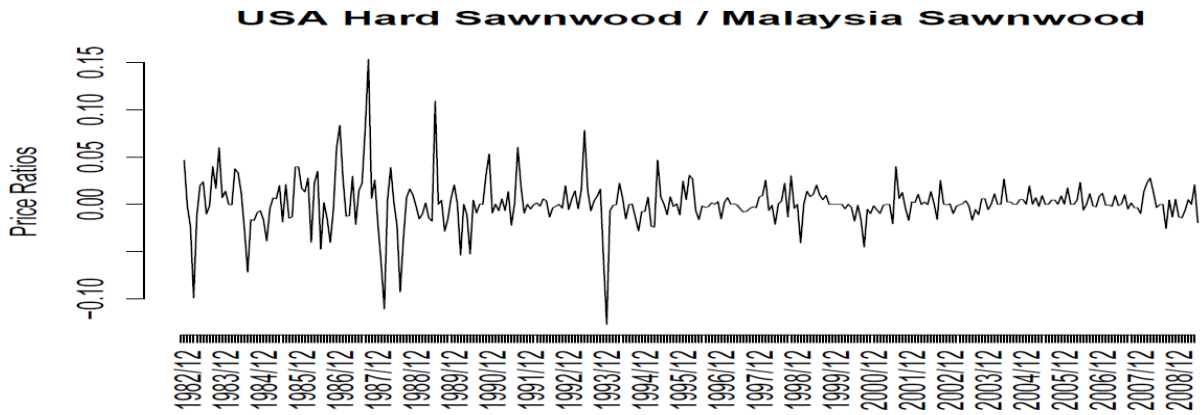

USA Hard Logs/Gabon Logs
Price Ratios
-0.3
-0.1
0.1
0.2
0.3
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
1996/12
1997/12
1998/12
1999/12
2000/12
2001/12
2002/12
2003/12
2004/12
2005/12
2006/12
2007/12
2008/12

Figure 1. 6: Time Series Plots of First Differences of Relative Prices 1982:10-2009-6


USA Hard Sawnwood / Malaysia Sawnwood
Price Ratios
-0.10
0.00
0.05
0.10
0.15
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
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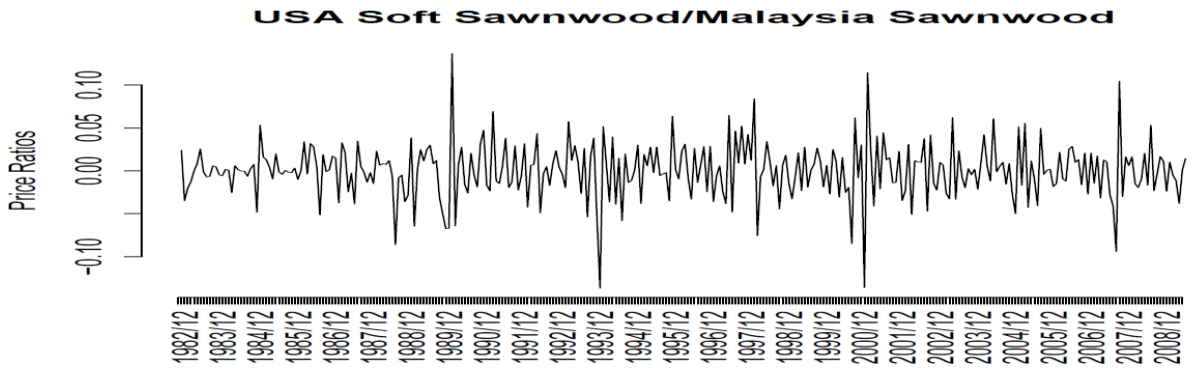
2003/12
2004/12
2005/12
2006/12
2007/12
2008/12


USA Soft Sawnwood/Malaysia Sawnwood
Price Ratios
-0.10
0.00
0.05
0.10
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
1996/12
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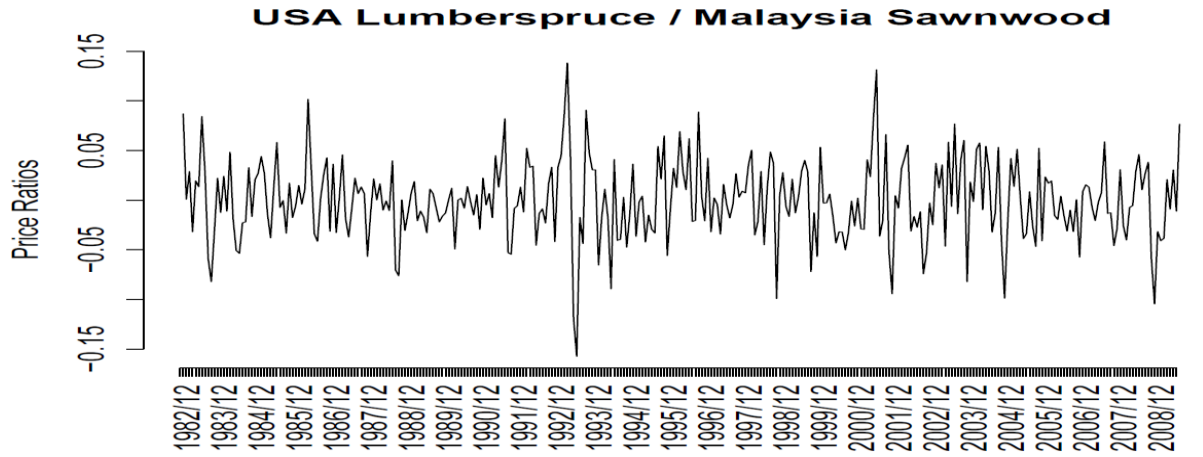
2005/12
2006/12
2007/12
2008/12


USA Lumberspruce / Malaysia Sawnwood
Price Ratios
-0.15
-0.05
0.05
0.15
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
1995/12
1996/12
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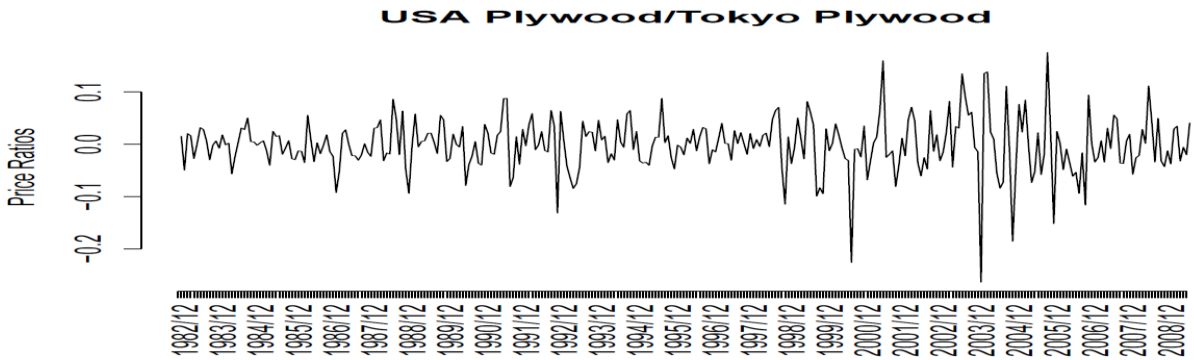
2008/12


USA Plywood/Tokyo Plywood
Price Ratios
-0.2
-0.1
0.0
0.1
1982/12
1983/12
1984/12
1985/12
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1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
1993/12
1994/12
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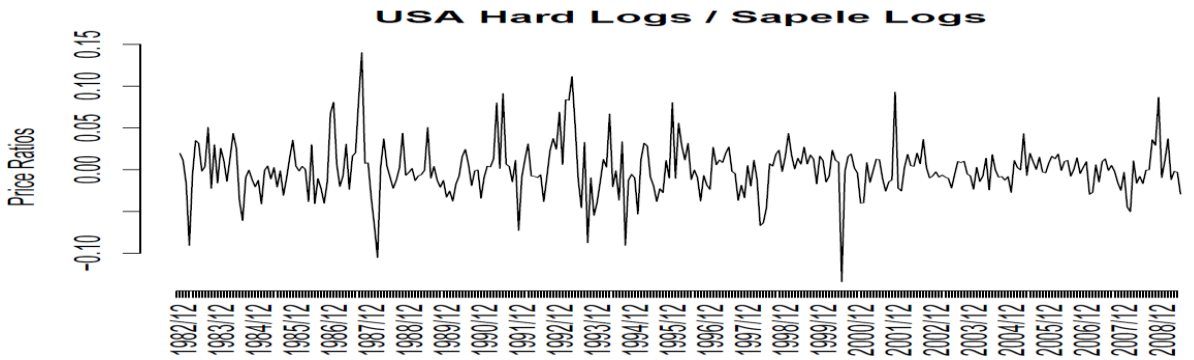
2007/12
2008/12


USA Hard Logs / Sapele Logs
Price Ratios
-0.10
0.00
0.05
0.10
0.15
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
1992/12
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1994/12
1995/12
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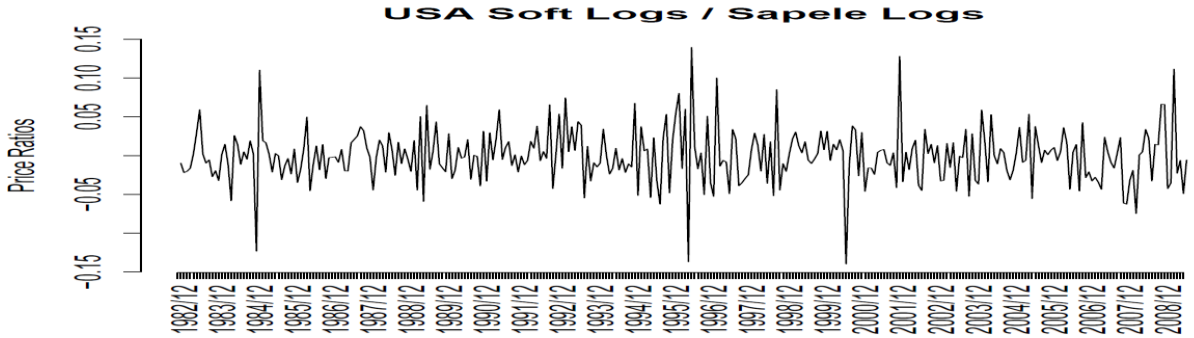
USA Soft Logs / Sapele Logs
Price Ratios
-0.15
-0.05
0.05
0.10
0.15
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
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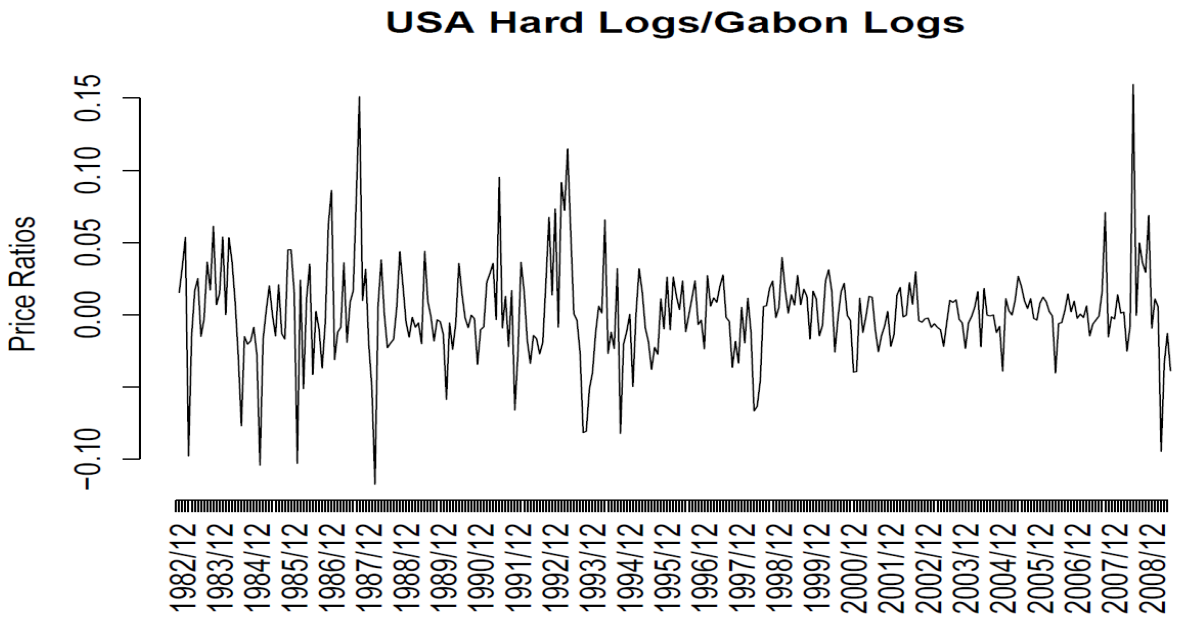
USA Hard Logs/Gabon Logs
Price Ratios
−0.10
0.00
0.05
0.10
0.15
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
1988/12
1989/12
1990/12
1991/12
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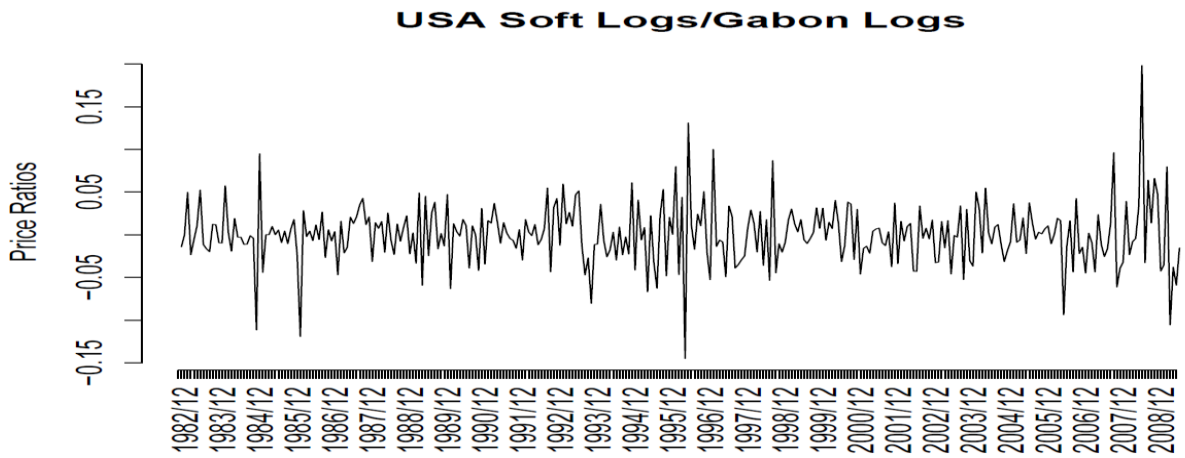
USA Soft Logs/Gabon Logs
Price Ratios
−0.15
−0.05
0.05
0.15
1982/12
1983/12
1984/12
1985/12
1986/12
1987/12
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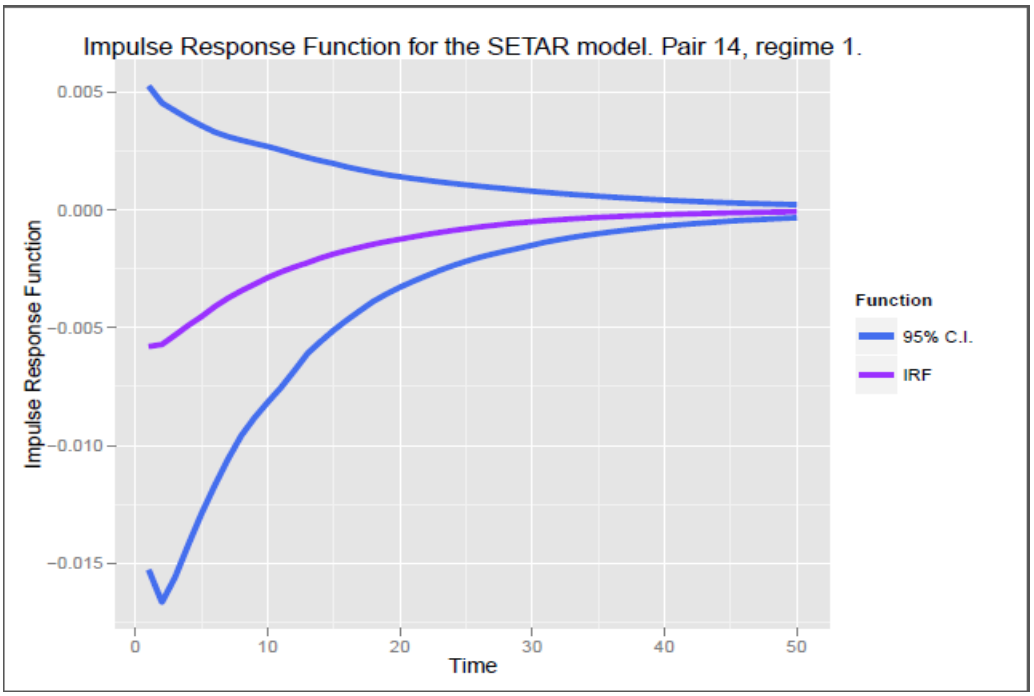


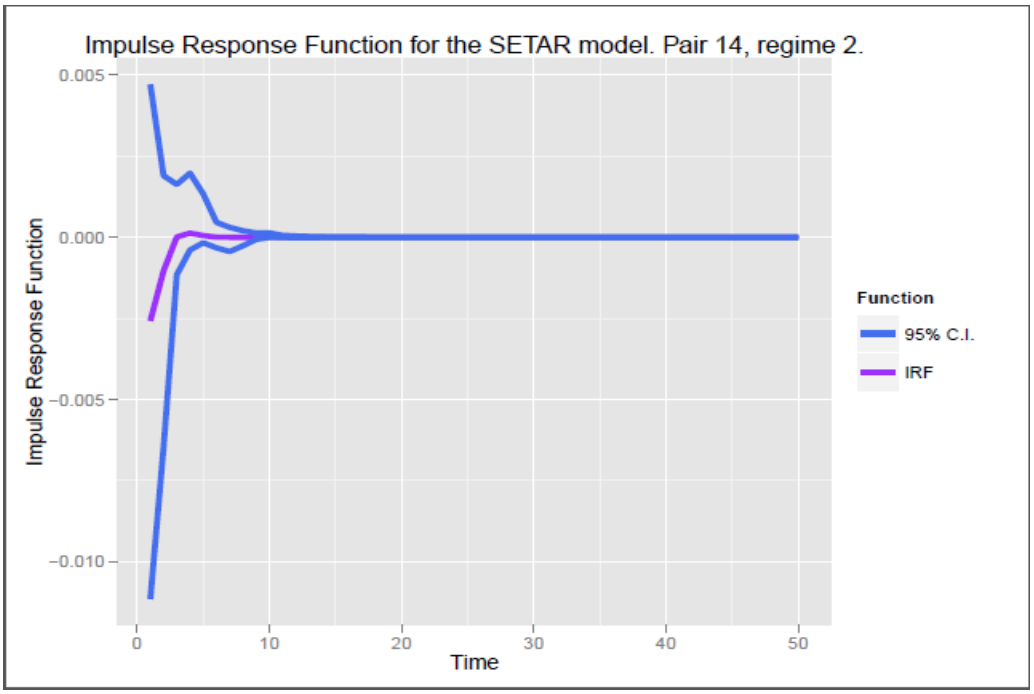
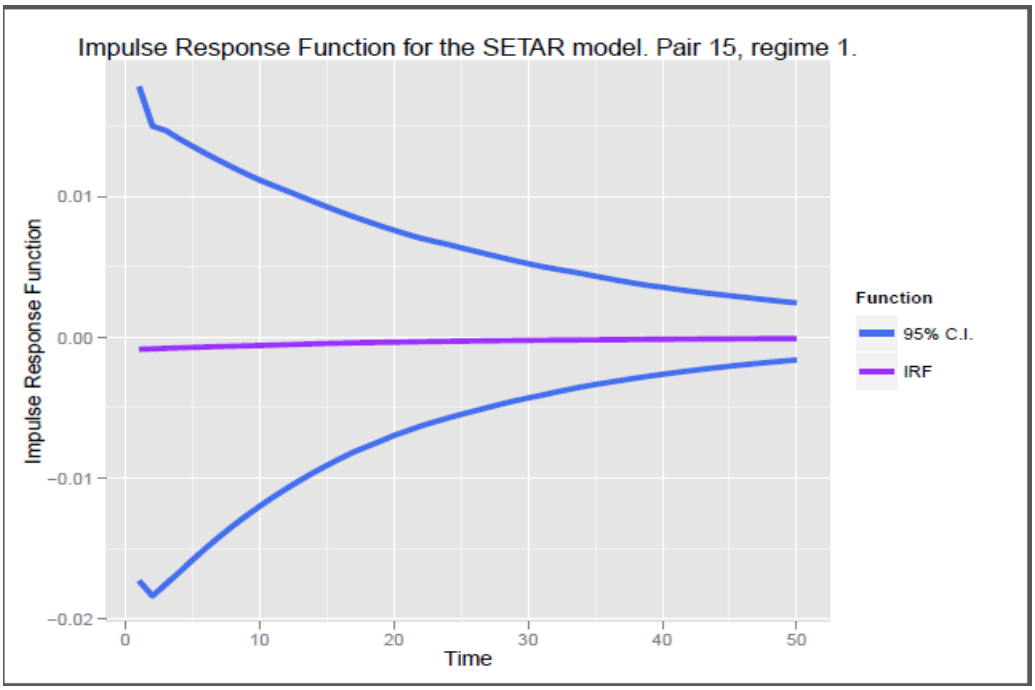


Figure 1. 7: Impulse Response Function for USA Lumberspruce-Malaysia Sawnwood



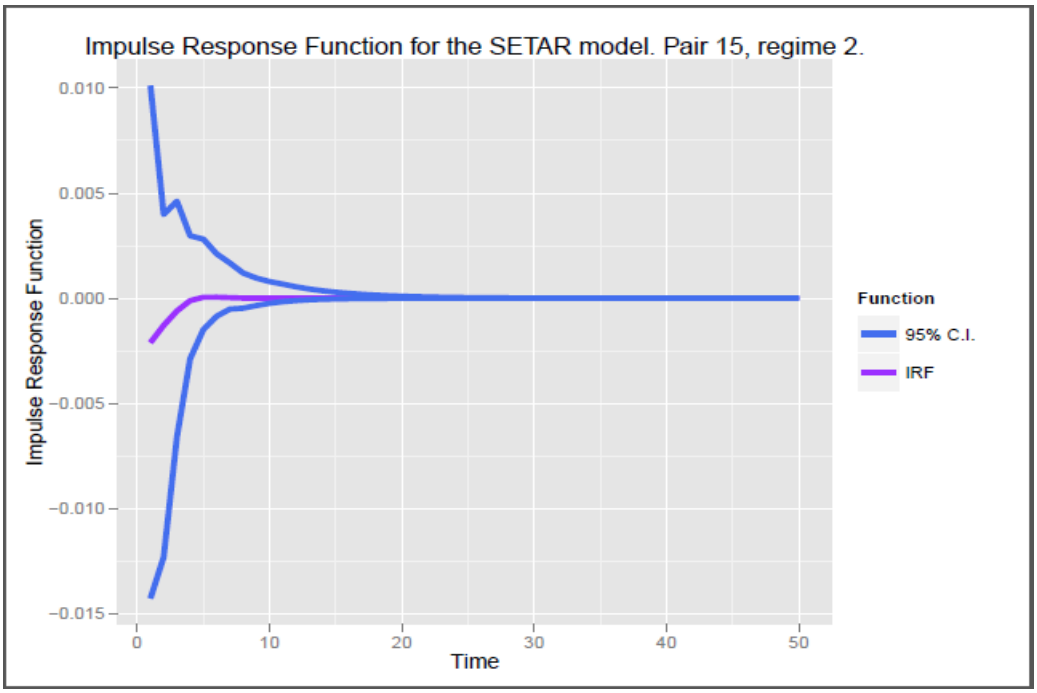
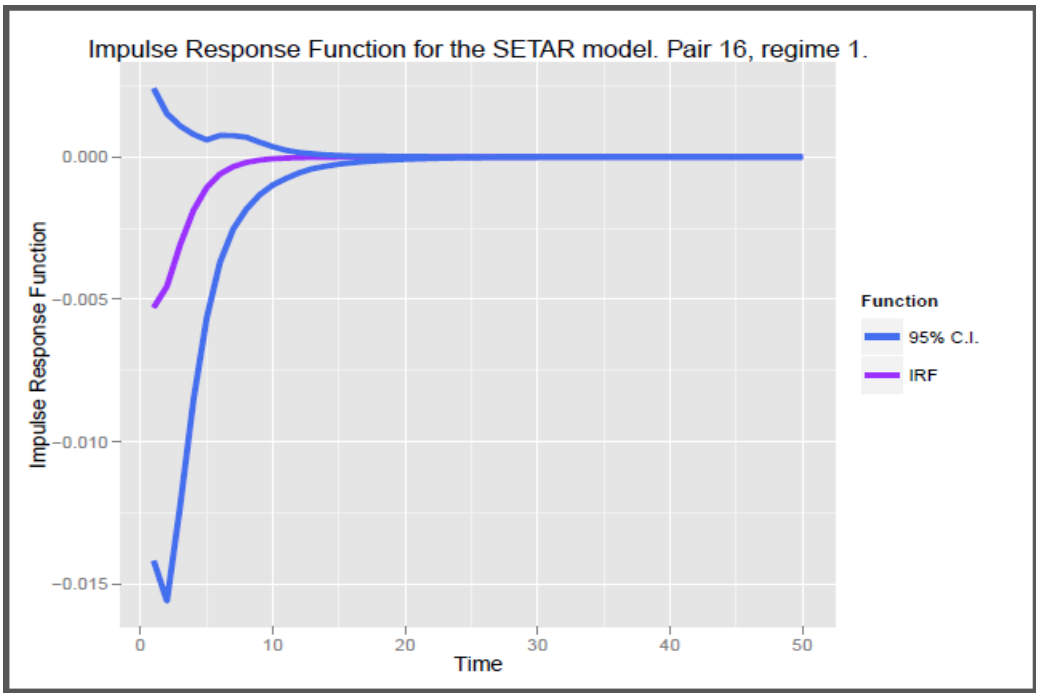


Figure 1. 8: Impulse Response Function for USA Plywood-Tokyo Plywood



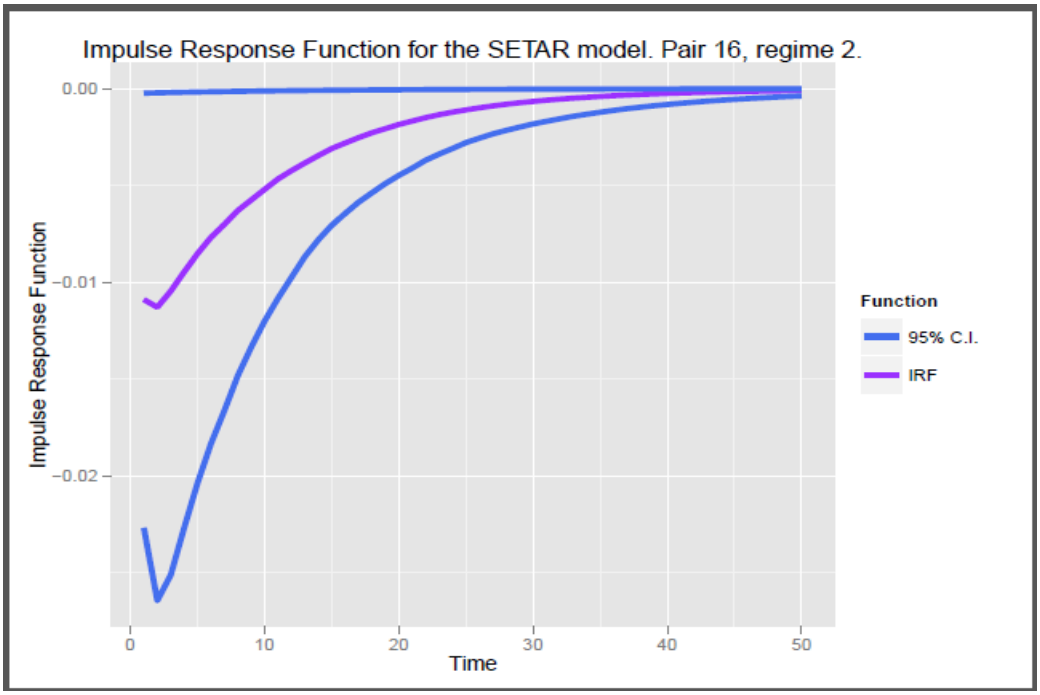
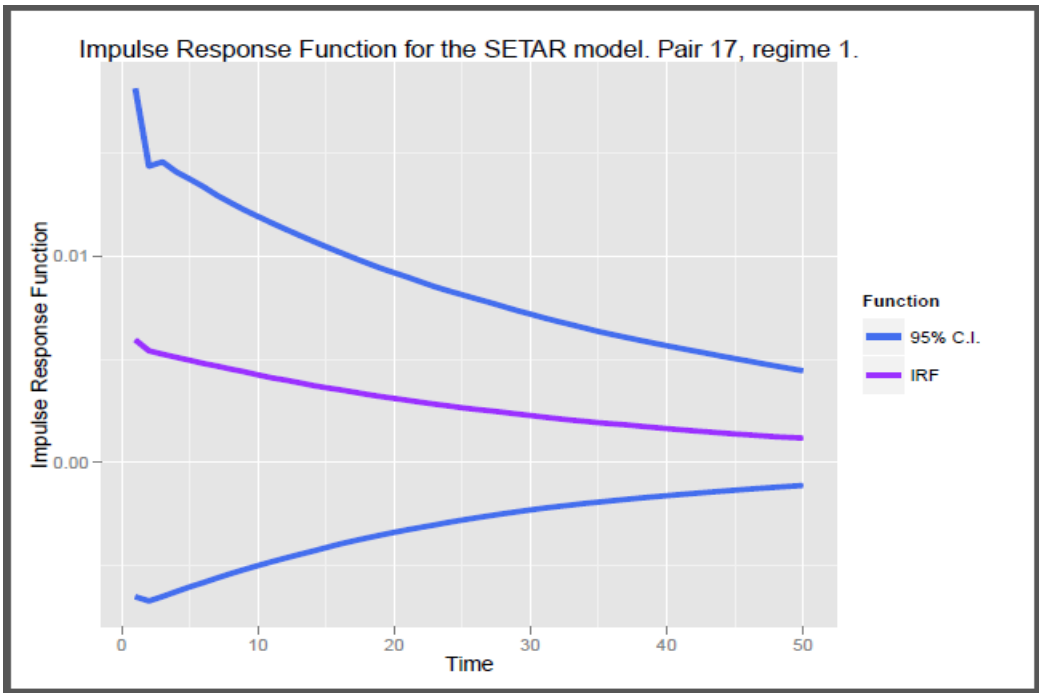


Figure 1. 9: Impulse Response Function for USA Hard Logs-Sapele Logs



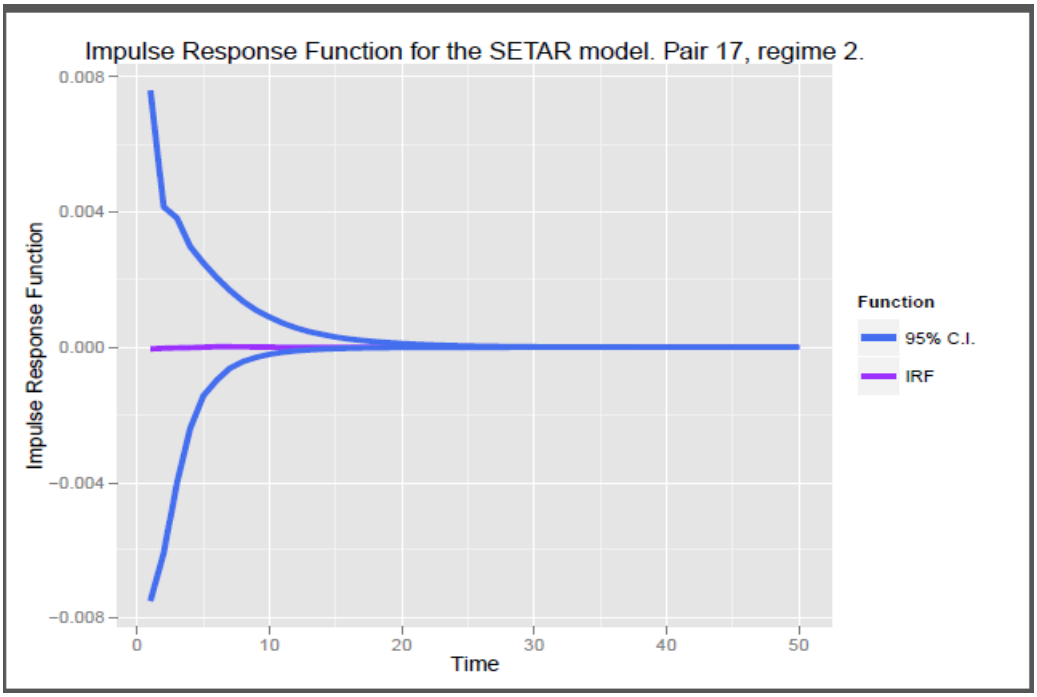
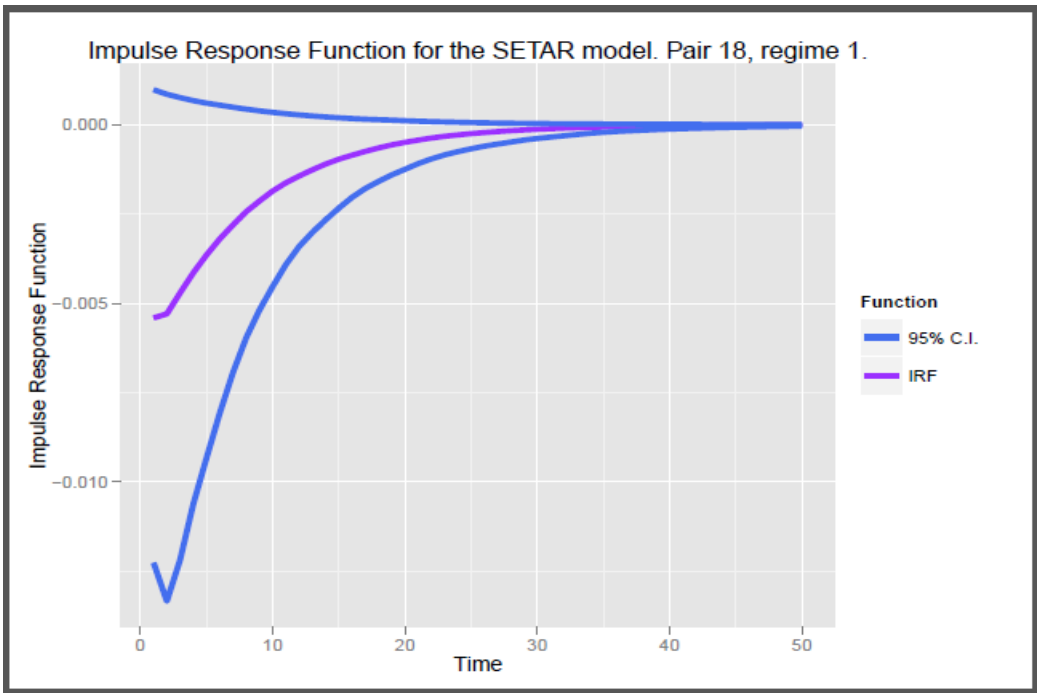


Figure 1. 10: Impulse Response Function for USA Soft Logs-Sapele Logs



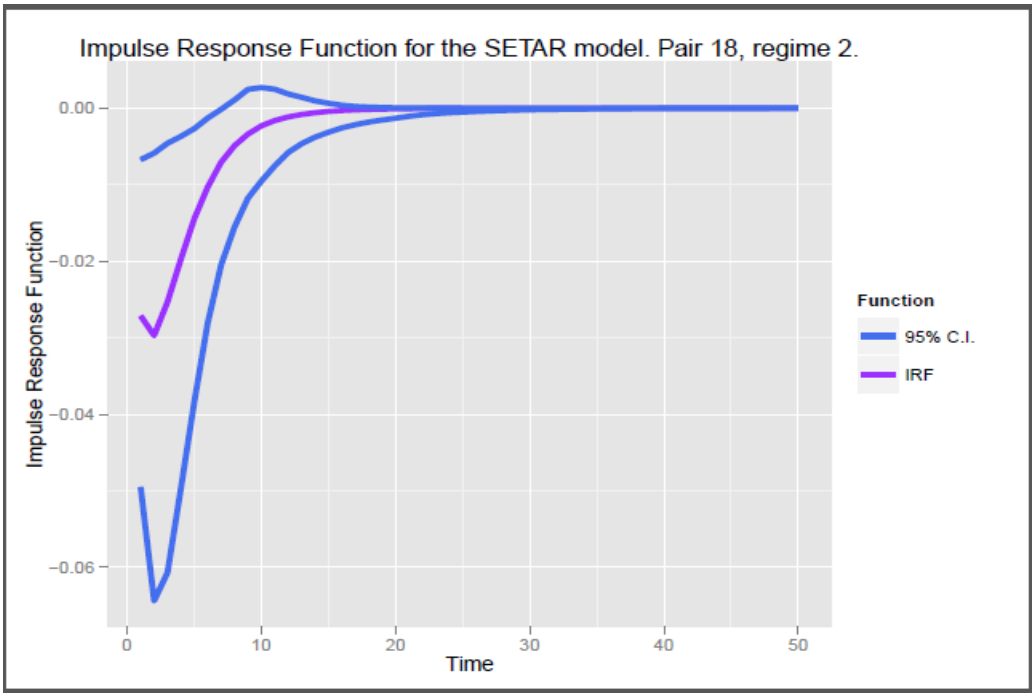
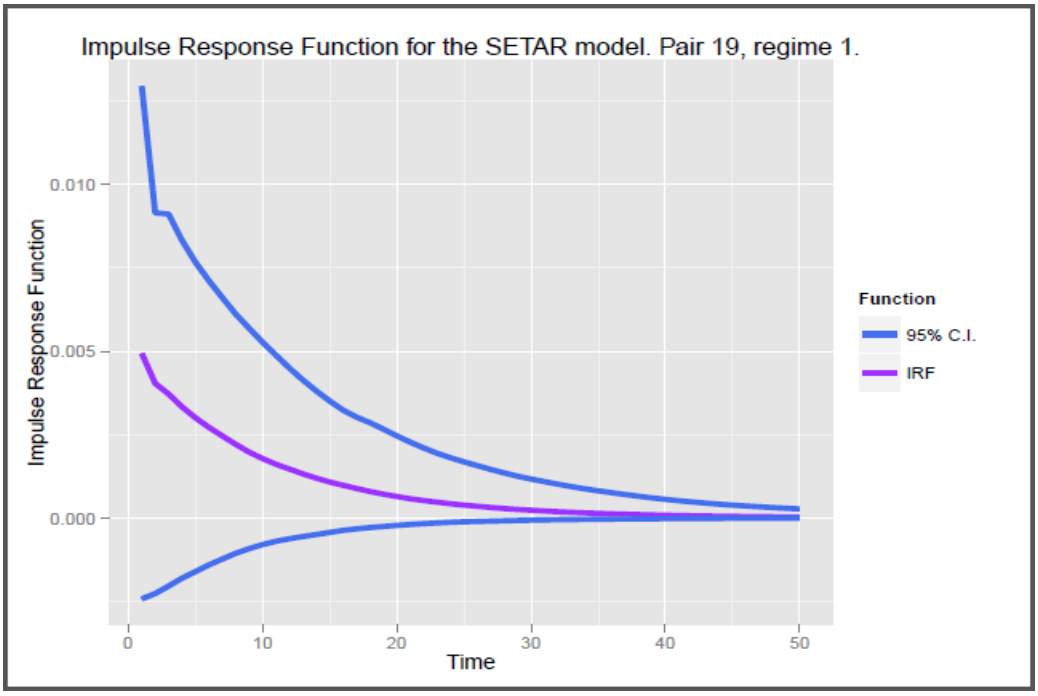


Figure 1. 11: Impulse Response Function for USA Hard Logs-Gabon Logs



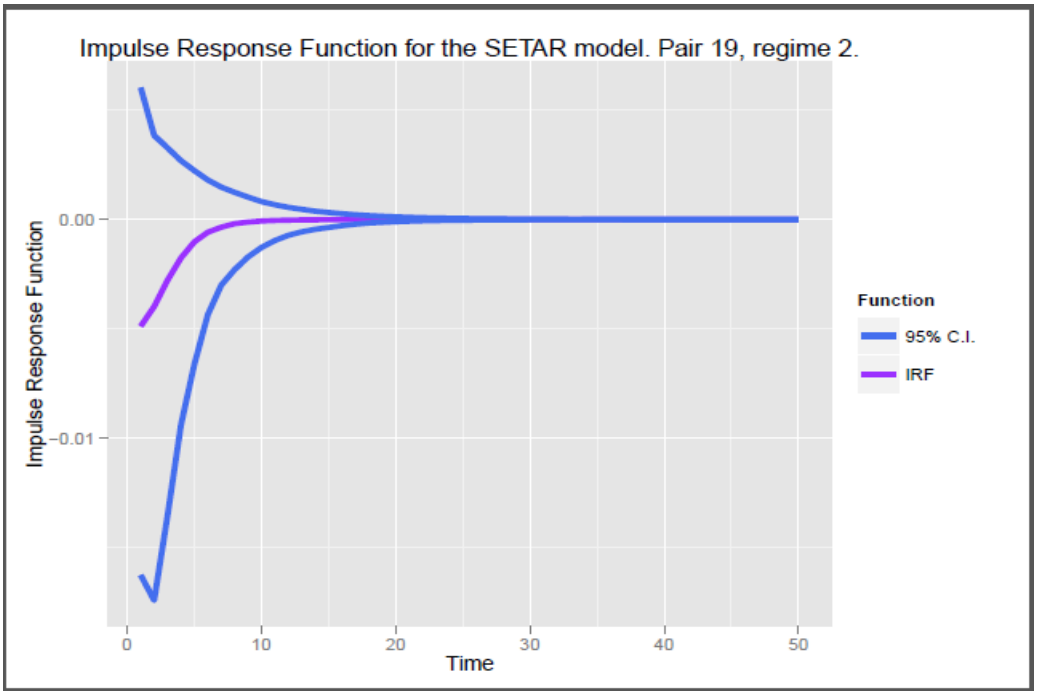
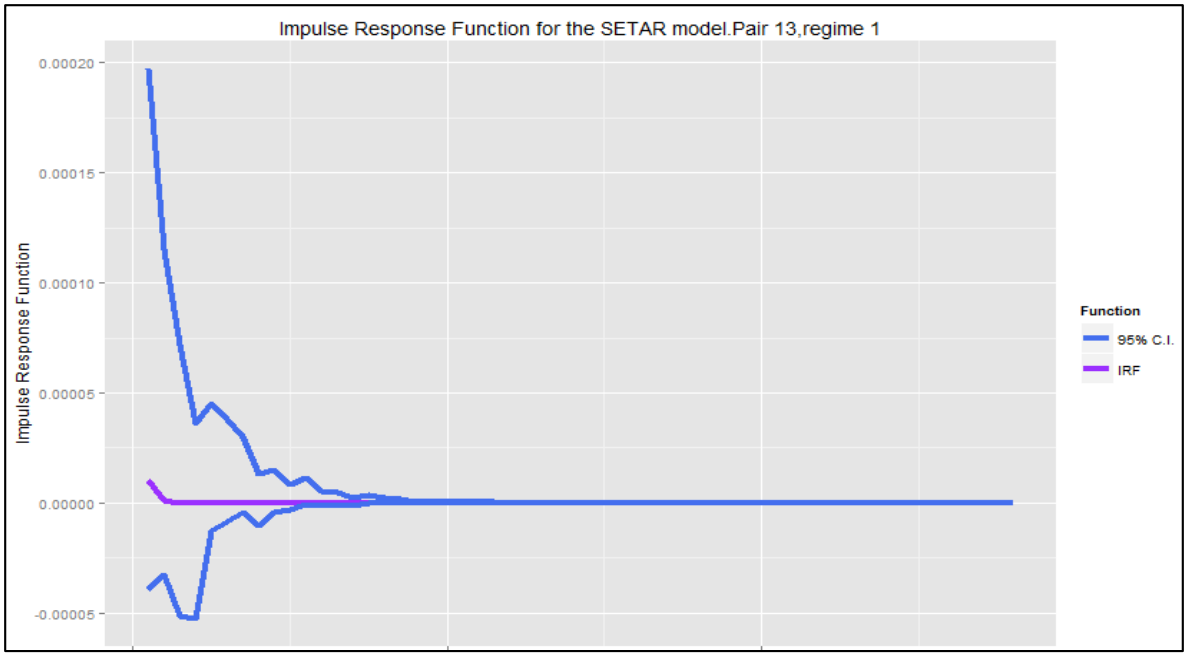


Figure 1. 12: Impulse Response Function for USA Soft Logs-Gabon Logs



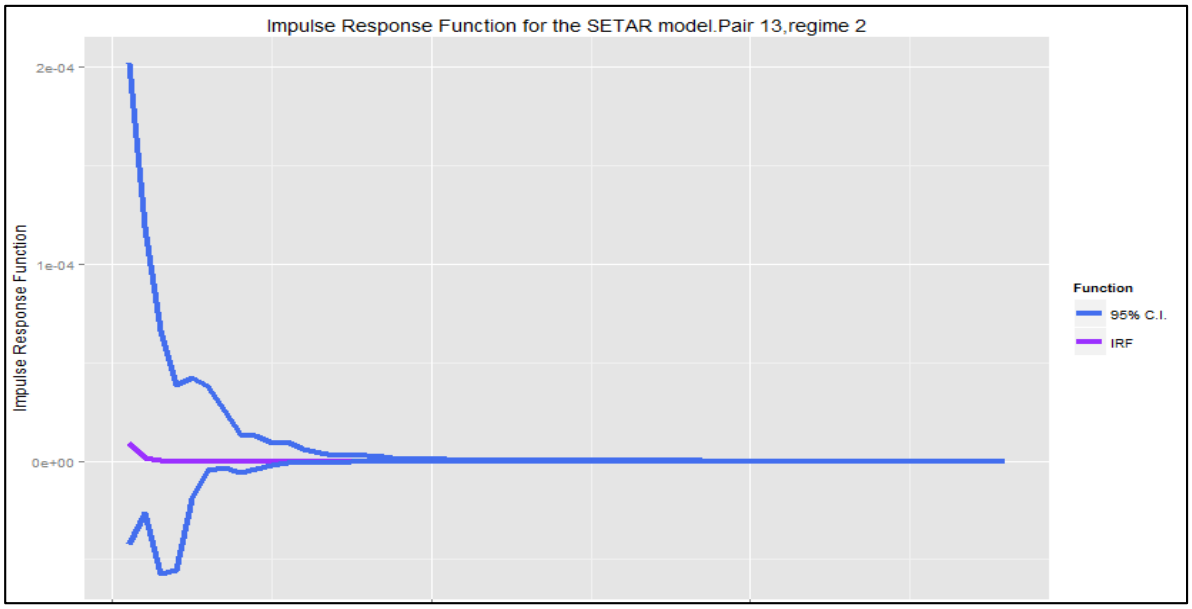
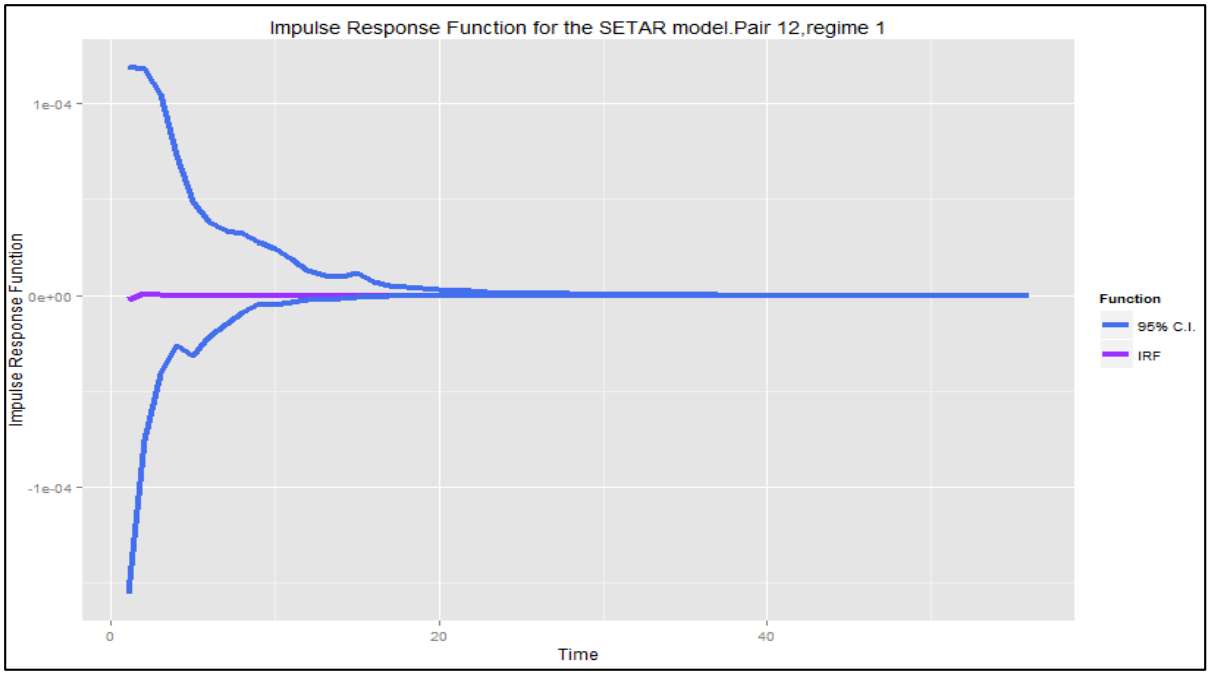


Figure 1.13: Impulse Response Function for SETAR model of USA Soft Sawnwood /Malaysia Sawnwood



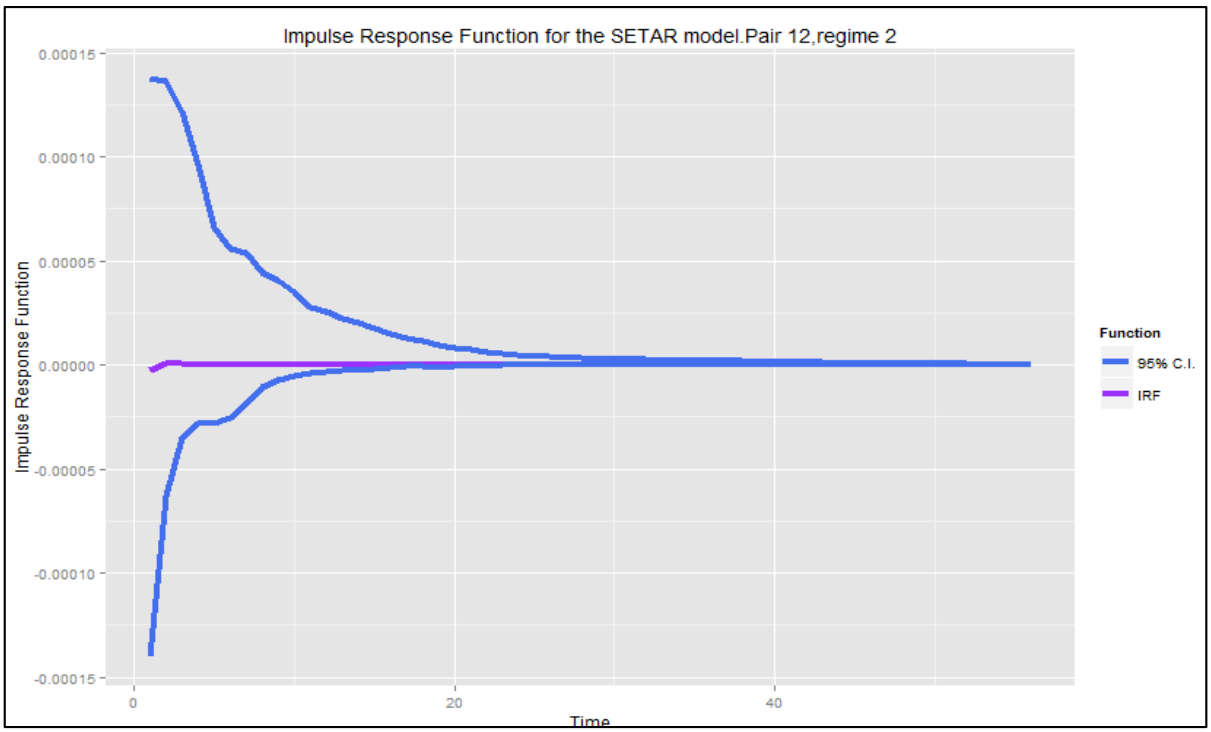


Figure 1.14: Impulse Response Function for SETAR Model of USA Hard Sawnwood / Malaysia Sawnwood

CHAPTER 2: Semi-Parametric Generalized Additive Vector Autoregressive Models of Spatial Price Dynamics

2. 1. Introduction

The empirical literature addressing the behavior of commodity prices over time and across spatially-distinct markets has grown substantially over time. A fundamental axiom of economics—the "Law of One Price"—underlies the arbitrage behavior thought to characterize such relationships. This literature has progressed from a simple consideration of correlation coefficients and linear regression models to classes of models that address particular time-series properties of price data and consider nonlinear price linkages.

In many cases, it seems reasonable to assume that commodity prices act in a way consistent with a stable behavior around a shifting or breaking mean. In recent years, the literature analyzing this phenomenon has focused on models capable of accommodating structural change and mean-shifting behavior to determine the changes of prices over time and across different markets. This mean-shifting behavior and the reasons behind these price movements have been addressed through the application of various specifications (Enders &Holt, 2012; Holt & Terasvirta, 2012; Ng & Voselgang, 2002).

For example, Enders and Holt (2012) applied nonstructural time series models, namely standard vector autoregressive model (VAR) and a more flexible shifting mean VAR (SM-VAR) approach, that allow for smoothly-shifting means; they incorporated the methods outlined by Bai and Perron (1998,2003); Becker, Enders and Hurn (2004,2006); Gonzales &

Terasvirta (2008); and Perron (1989) to capture the timing and nature of the structural breaks (shifts) for a variety of commodity prices.

This literature has involved an evolution in the methods for statistically testing structural change and mean shifting behaviors. Chow tests with known break points have evolved into tests of discrete and gradual mean shifting with unknown break points and variable speeds of adjustment among regimes. These tests address the widely-recognized problems associated with nonstandard test statistics and parameters that may be unidentified under null hypotheses.

The current article proposes a new class of semi-parametric models that accommodate mean-shifting behavior in a vector autoregressive modeling framework. This approach is viewed as a natural next step in the evolution of nonlinear time-series models of spatial and regional price behavior. To this end, recent advances in semi-parametric modeling that have developed methods for additive models that consist of a mixture of parametric and nonparametric components are considered. These vector autoregressive models adopt the Generalized Additive Models (GAM) estimation procedures proposed by Hastie and Tibshirani (1986) and Linton (2000). In particular, the backfitting and integration algorithms developed for GAM model estimation to incorporate a non-parametric mean shift in the linkages describing individual pairs and larger groups of market prices are utilized. The empirical specification involves simple and vector error correction models that relate price differences to lagged values of prices and price differentials.

The current application is to daily data collected from a number of important corn and soybean markets at spatially-distinct markets in North Carolina. These data have been previously utilized to evaluate regional price linkages and spatial market integration (i.e., Goodwin & Piggott, 2001). Impulse response functions are used to evaluate the dynamics of regional price adjustments to localized shocks in individual markets. Implications for regional price adjustments and, in particular, adjustments during recent periods of high volatility, are discussed in the paper. Finally, suggestions for further extensions of the semi-parametric analysis of regime switching behavior are offered.

2. 2. Literature Review

The question dealing with the validity of Law of One Price has been extensively investigated in the literature because it has important implications both for economists and traders; its implication is that no persistent opportunities for spatial arbitrage exist and may help the policymakers to decide on the trade policies to be imposed. The general conclusion underlying this concept is that prices for homogenous products at different geographical locations should not differ more than transport and transaction costs such as insurance, contract fees, etc.

However, one obvious reason why the prices of homogenous products may not be the same is due to the aforementioned transaction and transport costs and other impediments to trade such as tariffs and quotas. As a result, nonzero cost deviations from the LOP should contain significant nonlinearities.

Most recently, following these theoretical arguments, several studies have employed nonlinear models to investigate the validity of the LOP. Among these are Micheal et al. (1994), Obstfeld, O'Connel and Wei (2002), and Taylor (1997, 2001). In these studies, the nonlinear nature of the adjustment process is generally investigated in terms of a threshold autoregressive (TAR) model of some sort; the studies provide cumulative evidence in favor of the threshold-type nonlinearity in deviations from the LOP.

Among the studies that use variants of discrete cointegration models are Balke and Fomby (1997), Goodwin and Piggott (2001), Lo and Zivot (2001), Park et al. (2007), and Sephton (2003), all of whom have found support for the validity of LOP and threshold effects. Additionally, these studies conclude that the path of adjustment to equilibrium depends on the size of the shock introduced into the system. However, there exist some reasons to think that the patterns of price adjustment in the markets are smooth rather than discrete despite the discrete nature of the economic behavior underlying the adjustments (i.e. arbitrage is either profitable or not) (Goodwin et al., 2011). The literature has progressed to publishing the use of smooth transition models instead of discrete models of transition (Enders & Holt, 2012; Goodwin, Holt, & Prestemon, 2012).

In this paper, price dynamics are investigated by using a class of semi-parametric modeling framework that has developed methods for additive models that consist of a mixture of parametric and nonparametric components.

2. 3. Econometric Method and Data

2.3.1. GAM Type Models

Nonparametric regression allows the assumption of linearity to be relaxed, which might be proper for many economic variables, thus allowing visual exploration of the data to uncover structure in the data that might otherwise be missed when evaluated in a parametric form. However, it is a known fact that many forms of nonparametric regression do not work well when the number of independent variables in the model is large; therefore, a large data set is needed to avoid the 'curse of dimensionality,' which is defined as the problem of rapidly increasing variance for increasing dimensionality. One other pitfall of using nonparametric regression is that the interpretation of results and the relationship to be explored between dependent and independent variables is hard to grasp.

To overcome these problems, Stone (1985) proposed additive models that manage an additive approximation to the multivariate regression function. By doing so, the curse of dimensionality problem is overcome because each individual additive term is estimated using a univariate smoother separately, yet the approximation is obtained locally not universally. Also, the interpretation problem is avoided as the estimates of the individual terms explain how the dependent variable changes with the independent variables.

The extensions of the additive model that are valid for wide range of distribution families such as the exponential family have been proposed by Hastie and Tibshirani (1986) through the usage of Generalized Additive Models (GAM) that enable the mean of the dependent variable to depend on an additive predictor through a nonlinear link function.

Following Hastie and Tibshirani (1986), the basic GAM modeling framework which is used to investigate the price relationships may be stated as follows:

Let Y be a response random variable and $X_1, X_2, \ldots\ldots X_P$ be a set of predictor variables. A regression procedure can be viewed as a method for estimating the expected value of Y given the values of $X_1, X_2, \ldots\ldots X_P$. The standard linear regression model assumes a linear form for the conditional expectation:

$$E(Y \mid X_1, X_2, \ldots, X_P) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_P X_P$$

The additive model generalizes the linear model by modeling the conditional expectation as:

$E(Y \mid X_1, X_2, \ldots, X_P) = \beta_0 + \beta_1 S_1(X_1) + \beta_2 S_2(X_2) + \ldots + \beta_P S_P(X_P)$ where $S_i(X)$, $i = 1, 2, \ldots, p$ are smooth functions.

These functions are not given a parametric form but instead are estimated in a nonparametric fashion by using Back-Fitting and Local-Scoring Algorithms.

In this analysis, a smoother for the time trend is used as a tool for summarizing the trend of a response measurement Y as a function of one or more predictor measurements $X_1, X_2, \cdots, X_p$ in a nonparametric fashion thereby satisfying the aim of seeing the mean-shifting behavior of prices in corn and soybean markets for three distinct regions in a vector autoregressive modeling framework. The response variables for the basis of the analysis are the logarithmic prices and the returns for each market in question, whereas the independent variables are taken to be lagged values of prices and returns.

2.3.2. Estimation of Additive Regression Models

2.3.2.1. Backfitting Algorithm

Following Hastie and Tibshirani (1986), the formula used to estimate the smoothing functions $S_0, S_1(.), S_2(.), \ldots, S_P(.)$ in an additive regression model is defined as

$$E(Y \mid X) = S_0 + \sum_{j=1}^{p} S_j(X_j) = E(Y \mid X_1, X_2, \ldots, X_P) = \beta_0 + \beta_1 S_1(X_1) + \beta_2 S_2(X_2) + \ldots + \beta_P S_P(X_P)$$

where $ES_j(X_j) = 0$ for every j.

If the model $Y = S_0 + \sum_{j=1}^{p} S_j(X_j) + \varepsilon$ is assumed to be, in fact, the true model, and the values of $S_0, S_1(.), S_2(.), \ldots, S_{j-1}(.), S_{j+1}(.), \ldots, S_p(.)$ are known, then the partial residuals can be defined as: $R_j = Y - S_0 - \sum_{k \neq j} S_k(X_k)$.

In this case, $E(R_j \mid X_j) = S_j(X_j)$ will hold and it will minimize $E(Y - S_0 - \sum_{k=1}^{p} S_k(X_k))^2$.

In fact, the values of $S_k(.)$'s are unknown, but this provides a way to estimate each $\hat{S}_j(.)$ given the estimates of $\{\hat{S}_i(.), i \neq j\}$. This iterative process suggested by Friedman and Stuetzle (1981) is called the "Backfitting Algorithm".

According to this algorithm, the first step is to initialize the values of smoothing parameters as $S_0 = E(Y)$, $S_1^1(.) \equiv S_2^1(.) \equiv \ldots S_p^1 \equiv 0$, $m = 0$.

Then iterate: $m = m + 1$ for $j = 1$ to p do: $R_j = Y - S_0 - \sum_{k=1}^{j-1} S_k^m(X_k) - \sum_{k=j+1}^{p} S_k^{m-1}(X_k)$

where $S_j^m(X_j) = E(R_j \mid X_j)$.

The iterative process is continued until the sum of residual squares fails to decrease:

$RSS = E(Y - S_0 - \sum_{j=1}^{p} S_j^m(X_j))^2$ fails to decrease (Hastie and Tibshirani, 1986). Here S_j^m stands for the estimate of the S_j at the m th iteration and $ES_j^m(X_j) = 0$ is ensured at every stage by effectively centering the dependent variable Y at the beginning. The RSS does not increase at any stage of the algorithm so convergence is satisfied.

2.3.2.2. Backfitting in the Local Scoring Algorithm

Following Hastie and Tibshirani (1986), for an additive model;

$\eta(X) = S_0 + \sum_{j=1}^{p} S_j(X_j)$ the steps of the General Local Scoring Algorithm can be identified as follows:

The first step is the initialization of the smoothing functions as $S_0 = g(E(Y))$

$S_1^0(.) \equiv S_2^0(.) \equiv \ldots S_p^0 \equiv 0$, $m = 0$ and start the iteration from $m = m + 1$

Then form the adjusted dependent variable $Z = \eta^{m-1} + (Y - \mu^{m-1})(\partial\eta / \partial\mu^{m-1})$, where

$\eta^{m-1} = S_0 + \sum_{j=1}^{p} S_j^{m-1}(X_j)$ and $\eta^{m-1} = g(\mu^{m-1})$.

The next step is to form the weights $W = (\partial\mu / \partial\eta^{m-1})^2 V^{-1}$ and to fit an additive model to Z using the backfitting algorithm with weights W. Doing so provides estimated

functions S_j^m and model η^m; this process will be continued till $Edev(Y, \mu^m)$ fails to decrease.

This algorithm is simply the additive regression backfitting algorithm defined in the previous section with proper weights. In this algorithm, initially the data are transformed using the proper weights and the backfitting algorithm is then applied to the transformed data.

2.3.3. Data

The current application is to daily corn and soybean prices observed at three North Carolina terminal markets. Prices were obtained at Candor, Cofield and Roaring River for the corn markets whereas the prices for the soybean market were obtained at Fayetteville, Cofield and Greenville City. The data span the period 02 November 1981-06 February 2014 for corn and 31 July 1978- 27 May 2010 for soybean. On holidays where all prices were missing in each of the markets mentioned, the observations were omitted from the sample and a smooth continuity of the prices was assumed. The logarithmic transformations of the prices and the returns are taken as the basis for the empirical analysis and the aforementioned cities are chosen based on the data availability.

2.4. Results

This section provides the empirical results for spatial price dynamics in accordance with the theory of semi-parametric Generalized Autoregressive models (GAM) for three

North Carolina terminal markets taking into account the structural changes that may be observed over time.

A tendency of mostly stable prices in the corn markets with some price increases after years 1995 and 2007 (Figure 2.1) were observed. The Pearson correlation coefficients indicate that there is a strong and positive relationship between corn prices in Candor, Cofield and corn prices in Roaring River, with coefficients of magnitude over 0.99 in each market pairs (Table 2.1).

The correlation between soybean prices in Cofield and soybean prices in Fayetteville seems to be strong with a positive Pearson coefficient of magnitude 0.99; the same type of relationship is observed between the prices in Greenville and Cofield and Fayetteville with high correlation coefficients of 0.98 for both (Table 2.2). Price development in the three markets has an almost stable appearance between the periods 1989-1992, 1994-1997 and 2003-2005, while a slight decrease in prices in these markets may be observed after 1998. Years 1992 and 1996 display slight increases in prices, whereas some huge increases are realized after 1992, 1997 and 2007 (Figure 2.2).

Overall, the figures and the correlation coefficients show a clear relationship between the prices in each market. However, only limited information about a causal relationship between variables using the figures and correlation coefficients can be obtained because of possible different statistical time series properties. Therefore, the analysis of aforementioned price relationships is continued by estimating the semi-parametric Vector Generalized Additive Autoregressive (VGAM) regression models.

Before estimating the VGAM models, the first step of the analysis is to assess the time series properties of the variables. In order to determine the existence of any possible unit root, the Augmented Dickey Fuller (ADF) and Philips Perron (PP) unit root tests are employed. Tables 2.3-2.5 show that the logarithmic prices for three corn markets are non-stationary according to both ADF and PP test statistics at the 0.05 significance level. According to Tables 2.6-2.8, on the other hand, the returns in the three corn markets are found to be stationary at the same significance level.

After evaluating non-stationarity of the corn market prices the next step involves checking the possible cointegration relationship(s) among the variables. Table 2.9 indicates that prices in three corn markets are cointegrated of order one according to the cointegration rank test using the trace statistics that are suggested by Johansen (1991). When the same analysis is done with the returns for corn markets, they are found to be cointegrated of an order greater than one (Table 2.10); however, this result does not play an important role since the returns are already found to be stationary.

Similar results are obtained for the soybean markets in terms of the stationarity and cointegration relationships. According to Tables 2.11-2.13, the logarithmic prices in three soybean markets are observed to be nonstationary, whereas the stationarity of returns in these three markets is supported by ADF and PP test statistics in Tables 2.14-2.16. The existence of the cointegration relationship(s) between the prices in the three soybean markets is exhibited in Table 2.17 for the logarithmic prices and in Table 2. 18 for the returns according to the Johansen cointegration test.

As cointegration relationship(s) between the variables were observed, the specification of the GAM models involves VECM that relates price differences to lagged values of prices and price differentials as also suggested by Trenkler, Saikkonen and Lutkepohl (2008). After assessing the time series properties of the variables, the next step is to estimate the GAM models in their vector error representations (VECGAM) as the variables in all markets are found to be nonstationary and cointegrated for logarithmic prices.

As specified, GAM models are nonlinear in parameters, so nonlinear estimation methods are called for and the optimal lag lengths for each of the specified models are chosen by applying the AIC criterion. According to this criterion, the optimal lag length for corn markets is chosen as 6, whereas the optimal lag length is determined as 3 for the soybean markets. The results of the Vector Error Correction representation of GAM models (VECGAM) for the logarithm of the prices and the returns are provided and interpreted separately in Tables 2.19-2.30. The coefficients (c' s and r's) in the given tables represent the estimated VEC coefficients for the logarithmic prices and returns, respectively. According to the Tables 2.19-2.21, it is clear that for the logarithmic prices in Candor and Roaring River corn markets, the smoothed time trends are significant at the 0.05 level; the same fact is observed at the 0.1 level for Cofield corn market. This fact is also supported by the Chi-Square significance test and their corresponding p values. Figures 2.3-2.5 show that the smoothing components of the logarithmic prices in these three markets indicate how the trend is moving nonparametrically. The means are moving in a way that allows for

capture of the movements nonparametrically by smoothing components that also show correspondence with the movements of the corn prices in logarithmic terms given in Figure 2.1.

When the same analysis is done with the returns in these three markets, the expectations about the volatility of nonlinear trends around zero seem to be satisfied. The existence of a trend in returns is not expected, which is confirmed by the examination of the nonlinear time trend coefficients in Tables 2.22-2.24. These tables also show insignificant coefficients and corresponding Chi-Square significance test statistic values; also, careful examination of Figures 2.6-2.8 shows the smoothing components of the returns. These findings coincide with the fact that returns should not be forecastable.

Tables 2.25-2.27 show the significance of the smoothed time trends for the logarithmic prices in Fayetteville and Greenville soybean markets at the 0.05 significance level with corresponding p values smaller than 0.005; however, a p value of 0.4973 indicates that the smoothed time trend is not significant for the Cofield corn market. The same conclusion may be obtained through the examination of the Chi-Square significance test statistic and corresponding p value. The movements in the mean of the logarithmic prices in most soybean markets may be captured by the smoothing components in a nonparametric fashion; this fact is also supported by Figures 2.9-2.11, all of which show the smoothing components, and by Figure 2, which exposes the movement of soybean prices in these three soybean markets.

The insignificant time trend coefficients for the returns indicated in Tables 2.28-2.30 with p values of 0.0563, 0.728 and 0.2293 for Fayetteville, Cofield and Greenville respectively confirm the expectations about the nonexistence of trends in the returns in these three soybean markets; this fact is supported with the corresponding Chi-Square values. According to Figures 2.12-2.14, the nonlinear trend just oscillates around zero.

The overall conclusions reported in the regression results are also supported by the information that may be obtained from the figures that indicate that a smoothed nonlinear time trend is an important feature of these markets and has a significant role in explaining spatial and regional price behavior. Mean-shifting behavior in a vector autoregressive modeling framework that is accommodated by semi-parametric models is generally supported by the estimated models, and the figures of the smoothing components plotsalso support this conclusion.

The out-of-sample forecasting from the aforementioned models were obtained and the forecasting performance of these models was investigated. By using the impulse response functions, the dynamics of these models were also revealed. For this purpose, the orthogonolized impulse responses and 95% confidence bands were calculated recursively using bootstrapping method with 10.000 replications. One standard shock was put to the first observation and then the change in the dependent variables were recursively estimated. The impulse response results of the standard VAR and VECMGAM models were then compared in order to determine whether the usage of semi-parametric nonlinear models has any benefit over the standard linear models.

The orthogonalized impulse-response functions of the logarithmic prices and returns for standard VAR models in each markets are shown in Figures 2.15-2.17, which show the prices for Candor, Cofield and Roaring River corn markets whereas Figures 2.18-2.20 give the orthogonalized impulse responses for the returns in these three corn markets respectively. From the investigation of these standard VAR impulse responses, it is observed that compared to the bootstrapped VECGAM impulse responses given in Figures 2.27-2.32, for almost all the markets under investigation, the return of the prices into their long run equilibrium levels either takes long time, or prices do not even end up at any equilibrium level (i.e unreasonable estimates are obtained from standard VAR model impulse responses). Similar conclusions are obtained for the soybean markets through a careful examination of Figures 2.21-2.23 for logarithmic prices and Figures 2.24-2.26 for returns in standard VAR models of Fayetteville, Cofield and Greenville markets respectively. The results of the impulse responses corresponding to the standard VAR models will not be interpreted here in detail. Instead, the focus is on the interpretation of the impulse responses obtained from the VECMGAM models given in Figures 2.27- 2.38.

For the logarithmic prices in the Candor corn market, it is observed that a shock introduced into the system initially increases the price level and then immediately leads to a decrease and tends to reach the equilibrium level with little volatility (Figure 2.27). The Cofield corn market follows an almost identical path, and both markets seem to reach the equilibrium level after about 2 months (Figure 2.27 and Figure 2.28). According to Figure 2.29 the Roaring River corn market also exhibits the same behavior, with the only difference

being that it is less volatile at the initial periods of the shock (after 10 days). The returns in Cofield and Roaring River corn markets exactly show the same action towards the shocks in a way that after a modest decrease in prices, they tend to stay stable after 40 days and not reach the equilibrium level, whereas the return in Candor corn market stays stable for a few days and declines afterwards (Figures 2.31-2.32).

The behaviors of logarithmic prices in soybean markets as a result of a shock are exhibited in Figures 2.33-2.35 for Fayetteville, Cofield and Greenville markets, respectively. A shock introduced into the system immediately leads to an increase in price levels and is followed by a decrease towards the equilibrium point with modest volatilities in price ratios in first 3 weeks; the price reaches the equilibrium point in 3 months. The price path seems to be similar for Fayetteville and Cofield markets, whereas the Greenville market exhibits more volatility in the first 2 weeks. For the logarithmic prices, compared to the corn markets, the soybean markets need less time to converge to the equilibrium level. According to the Figures 2.36-2.38, returns in all three soybean markets go in the same direction with initial slight increases in price levels followed by continuous decreases.

When the impulse responses of standard VAR models with VECGAM model results are compared, several differences are notable. First, under standard VAR assumptions, for some markets, the return of the prices to their long run equilibrium levels is not observed. This does not satisfy the expectations about the convergence of the prices to an equilibrium level, which suggests unreasonable estimates are obtained from standard VAR model impulse responses; this is true mostly for the corn markets. Second, through comparisons of

the reasonable estimates obtained from the standard VAR responses and VECGAM responses, it is observed that exogenous shocks tend to be more modest in semi-parametric VECGAM models. The reasonable standard VAR models' impulse response graphics tend to imply a greater degree of reaction to exogenous shocks than VECGAM models' impulse responses. Additionally, short-run reactions often involve a small degree of volatility which may take a few days to die out just before emerging to the equilibrium levels in semi-parametric VECGAM models contrary to the standard ones.

Lastly, the cross impulse responses of the VECGAM models for the logarithmic prices in both corn and soybean markets support evidence of convergence of prices into an equilibrium level whenever there is a shock introduced into the system in either of the markets.

2.5 Conclusions

This paper made an initial attempt to examine the price dynamics in soybean and corn markets in three distinct markets using semi-parametric VECGAM regression approaches taking into account the nonlinearity of the time trend component.

The optimal lag lengths for each of the specified models are chosen by applying the AIC criterion and the suitable lag length for corn markets is chosen as 6 whereas the optimal lag length is determined as 3 for the soybean markets. The results of the VECGAM models for the logarithm of the prices and the returns are given and interpreted separately.

For the logarithmic prices in Candor, Cofield and Roaring River corn markets, the smoothed time trend is found to be significant, and the smoothing components of the

logarithmic prices in these three markets show how the trend is moving nonparametrically; this trend implies that there is a mean that is moving in a way that can be captured nonparametrically. The existence of trend in returns is not expected for these three corn markets, which is confirmed by the examination of the nonlinear time trend coefficients.

For the Fayetteville, Cofield and Greenville soybean markets, the significance of the smoothed time trend for the logarithmic prices is observed. The movements in the mean of the logarithmic prices in these three soybean markets may also be obtained by the help of smoothing components in a nonparametric fashion. The nonexistence of trend in the returns in these three soybean markets is again observed.

Overall results indicate that the non-parametric drifts coincide with the general price movements, and when compared with the standard VAR results, the addition of nonparametric mean shift affects the overall implication of impulse-responses. The VECGAM model impulse responses tend to imply a smaller degree of reaction towards the shocks and exhibit shorter time of adjustment for the convergence into a stable equilibrium level. Also, the number of significant impulse response coefficients under VECGAM models is larger compared to the standard VAR impulse responses. The convergence of the prices into an equilibrium level is supported by the examination of cross impulse responses in both corn and soybean markets.

Because price data are non-stationary, shocks introduced into the system may cause transitory or permanent responses. This fact indicates that the shocks may permanently change the time path of the variables. The responses are consistent with convergence of

prices into an equilibrium level in the long run implying the market integration in these markets. When cross impulse responses are examined, it is observed that a shock in one market provokes responses in the other markets and most of the time prices tend to equalize over time. For instance, a shock to the Candor corn market evoke to responses in the Cofield and the Roaring River market and over time prices tend to converge to one another after a period of short term adjustments (Figures 2.15-2.17).

Prices in the soybean markets tend to follow the same path in terms of the convergence behavior. Figures 2.21-2.23 show that whenever a shock is introduced in one of the soybean markets the others immediately respond to this shock and tend to reach an equilibrium level after a short period of time implying market integration.

Even though prices in some markets may not converge to absolute equality such the impulse responses still show behavior consistent with convergence (Figure 2.16 and Figure 2.22).

In sum, responses confirm integration of markets in both VAR and VECGAM models and VECGAM model impulse responses tend to imply a smaller degree of reaction towards the shocks and exhibit shorter time of adjustment for the convergence into a stable equilibrium level. Speed of adjustment may be related to the efficiency of the market system and may imply well-functioning markets. However, we should keep in mind that speed of adjustment is just one dimension of integration that might be a concern for policy makers for food distribution planning, transport regulations, price stabilization policy etc. and effect government intervention decisions.

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TABLES AND FIGURES

Table 2.1: Correlation Coefficients of Corn Markets

ρ	Candor	Cofield	Roaring River
Candor	1	0.99564	0.99636
Cofield	0.99564	1	0.99220
Roaring River	0.99636	0.99220	1

Table 2.2: Correlation Coefficients of Soybean Markets

ρ	Fayetteville	Cofield	Greenville
Fayetteville	1	0.98859	0.98475
Cofield	0.98859	1	0.98549
Greenville	0.98475	0.98549	1

Table 2.3: ADF and PP Unit Root Tests for Candor Corn Markets (Logarithmic Prices)

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	0.0659	0.6977	0.06	0.7019
	6	0.0033	0.6832	0.00	0.6835
Single Mean					
	1	-7.0165	0.2717	-1.89	0.3344
	6	-8.0518	0.2121	-2.03	0.2751
Trend	**1**	-11.6670	0.3271	-2.43	0.3647
	6	-13.7017	0.2278	-2.63	0.2680

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr<Tau**	**F**	**Pr > F**
Zero Mean	**1**	0.0232	0.6878	0.02	0.6894		
	6	-0.0909	0.6618	-0.09	0.6510		
Single Mean	**1**	-6.9566	0.2756	-1.84	0.3586	1.87	0.5920
	6	-5.0801	0.4254	-1.44	0.5637	1.09	0.7926
Trend	**1**	-11.9825	0.3098	-2.43	0.3620	2.96	0.5839
	6	-12.1681	0.2998	-2.47	0.3414	3.28	0.5201

Table 2.4: ADF and PP Unit Root Test for Cofield Corn Markets (Logarithmic Prices)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-0.3384	0.6055	-0.25	0.5959		
	6	-0.2143	0.6337	-0.20	0.6126		
Single Mean	**1**	-9.9581	0.1336	-2.23	0.1959	2.59	0.4083
	6	-5.9602	0.3481	-1.59	0.4855	1.31	0.7368
Trend	**1**	-16.3009	0.1390	-2.84	0.1857	4.02	0.3699
	6	-12.9836	0.2594	-2.51	0.3216	3.29	0.5175

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-0.2069	0.6354	-0.16	0.6273
	6	-0.2468	0.6264	-0.19	0.6177
Single Mean	**1**	-8.8448	0.1751	-2.14	0.2287
	6	-9.6554	0.1439	-2.23	0.1948
Trend	**1**	-14.0230	0.2147	-2.66	0.2543
	6	-15.6753	0.1570	-2.81	0.1945

Table 2.5: ADF and PP Unit Root Test for Roaring River Corn Markets (Logarithmic Prices)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	0.0258	0.6884	0.02	0.6901		
	6	-0.0229	0.6772	-0.02	0.6748		
Single Mean	**1**	-6.6903	0.2935	-1.78	0.3915	1.74	0.6253
	6	-4.9202	0.4408	-1.39	0.5876	1.04	0.8043
Trend	**1**	-12.9567	0.2608	-2.53	0.3112	3.22	0.5308
	6	-13.2963	0.2452	-2.57	0.2951	3.53	0.4680

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	0.1238	0.7114	0.12	0.7193
	6	0.0551	0.6952	0.05	0.6982
Single Mean	**1**	-6.5051	0.3066	-1.81	0.3755
	6	-7.5474	0.2394	-1.95	0.3097
Trend	**1**	-11.8242	0.3184	-2.44	0.3577
	6	-14.0036	0.2155	-2.65	0.2566

Table 2.6: ADF and PP Unit Root Test for Candor Corn Markets (Returns)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-254.130	0.0001	-11.26	<.0001		
	6	-970.275	0.0001	-7.41	<.0001		
Single Mean	**1**	-254.919	0.0001	-11.25	<.0001	63.33	0.0010
	6	-1026.76	0.0001	-7.41	<.0001	27.47	0.0010
Trend	**1**	-254.914	0.0001	-11.24	<.0001	63.13	0.0010
	6	-1040.63	0.0001	-7.41	<.0001	27.46	0.0010

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-307.175	0.0001	-17.41	<.0001
	6	-320.927	0.0001	-17.44	<.0001
Single Mean	**1**	-307.585	0.0001	-17.40	<.0001
	6	-320.765	0.0001	-17.43	<.0001
Trend					
	1	-307.579	0.0001	-17.37	<.0001
	6	-320.742	0.0001	-17.40	<.0001

Table 2.7: ADF and PP Unit Root Test for Cofield Corn Markets (Returns)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-221.083	0.0001	-10.48	<.0001		
	6	-30344.0	0.0001	-8.03	<.0001		
						54.88	0.0010
Single Mean	**1**	-221.537	0.0001	-10.48	<.0001		
	6	-301098	0.0001	-8.02	<.0001	32.20	0.0010
Trend	**1**	-221.541	0.0001	-10.46	<.0001	54.70	0.0010
	6	112484.6	0.9999	-8.01	<.0001	32.18	0.0010

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-275.231	0.0001	-15.73	<.0001
	6	-271.510	0.0001	-15.71	<.0001
Single Mean	**1**	-275.501	0.0001	-15.72	<.0001
	6	-271.366	0.0001	-15.69	<.0001
Trend	**1**	-275.513	0.0001	-15.69	<.0001
	6	-271.388	0.0001	-15.67	<.0001

Table 2.8: ADF and PP Unit Root Test for Roaring River Corn Markets (Returns)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-252.557	0.0001	-11.22	<.0001		
	6	-1781.24	0.0001	-7.78	<.0001		
Single Mean	**1**	-253.410	0.0001	-11.22	<.0001	62.96	0.0010
	6	-1985.37	0.0001	-7.77	<.0001	30.26	0.0010
Trend	**1**	-253.433	0.0001	-11.20	<.0001	62.77	0.0010
	6	-2154.92	0.0001	-7.79	<.0001	30.40	0.0010

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-292.618	0.0001	-16.57	<.0001
	6	-304.534	0.0001	-16.62	<.0001
Single Mean	**1**	-293.058	0.0001	-16.57	<.0001
	6	-304.251	0.0001	-16.61	<.0001
Trend	**1**	-293.057	0.0001	-16.54	<.0001
	6	-304.257	0.0001	-16.59	<.0001

Table 2.9: Johansen Cointegration Results for Corn Markets (Logarithmic Prices)

Cointegration Rank Test Using Trace						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.1953	98.5343	29.38	Constant	Linear
1	**1**	0.0884	30.9580	15.34		
2	**2**	0.0069	2.1672	3.84		
Cointegration Rank Test Using Trace Under Restriction						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.1955	99.1292	34.80	Constant	Constant
1	**1**	0.0884	31.4753	19.99		
2	**2**	0.0086	2.6846	9.13		

Table 2.10: Johansen Cointegration Results for Corn Markets (Returns)

Cointegration Rank Test Using Trace						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.4599	432.0819	29.38	Constant	Linear
1	**1**	0.4199	241.1388	15.34		
2	**2**	0.2081	72.3283	3.84		
Cointegration Rank Test Using Trace Under Restriction						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.4599	432.0849	34.80	Constant	Constant
1	**1**	0.4199	241.1416	19.99		
2	**2**	0.2081	72.3287	9.13		

Table 2.11: ADF and PP Unit Root Tests for Fayetteville Soybean Market (Logarithmic Prices)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-0.1909	0.6389	-0.35	0.5592		
	3	-0.2124	0.6340	-0.36	0.5537		
Single Mean	**1**	-17.3490	0.0207	-2.92	0.0448	4.27	0.0708
	3	-23.0022	0.0050	-3.21	0.0209	5.15	0.0330
Trend	**1**	-17.3628	0.1114	-2.92	0.1587	4.26	0.3213
	3	-23.0247	0.0337	-3.21	0.0856	5.15	0.1431

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-0.2334	0.6293	-0.40	0.5392
	3	-0.2376	0.6283	-0.40	0.5383
Single Mean	**1**	-19.4907	0.0120	-3.18	0.0228
	3	-21.3825	0.0074	-3.32	0.0151
Trend	**1**	-19.4994	0.0718	-3.17	0.0925
	3	-21.3918	0.0481	-3.32	0.0658

Table 2.12: ADF and PP Unit Root Tests for Cofield Soybean Market (Logarithmic Prices)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-0.2468	0.6262	-0.42	0.5308		
	3	-0.2537	0.6247	-0.43	0.5268		
Single Mean	**1**	-18.8481	0.0141	-3.03	0.0338	4.60	0.0504
	3	-21.9223	0.0065	-3.13	0.0263	4.90	0.0410
Trend	**1**	-19.1741	0.0769	-3.06	0.1181	4.70	0.2331
	3	-22.3295	0.0392	-3.16	0.0959	4.99	0.1742

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-0.2716	0.6206	-0.45	0.5182
	3	-0.2695	0.6211	-0.45	0.5186
Single Mean	**1**	-19.2746	0.0127	-3.14	0.0256
	3	-20.3189	0.0097	-3.22	0.0204
Trend	**1**	-19.5710	0.0708	-3.16	0.0948
	3	-20.6386	0.0565	-3.24	0.0783

Table 2.13: ADF and PP Unit Root Tests for Greenville Soybean Market (Logarithmic Prices)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-0.2487	0.6258	-0.38	0.5445		
	3	-0.2711	0.6207	-0.42	0.5318		
Single Mean	**1**	-20.9601	0.0083	-3.21	0.0210	5.15	0.0332
	3	-24.7746	0.0032	-3.32	0.0151	5.53	0.0223
Trend	**1**	-21.0728	0.0515	-3.21	0.0839	5.18	0.1358
	3	-24.9153	0.0222	-3.33	0.0636	5.56	0.0895

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-0.3628	0.5999	-0.53	0.4869
	3	-0.3526	0.6022	-0.52	0.4883
Single Mean	**1**	-23.4970	0.0044	-3.51	0.0086
	3	-24.6728	0.0033	-3.60	0.0066
Trend	**1**	-23.5435	0.0301	-3.51	0.0406
	3	-24.7182	0.0232	-3.59	0.0326

Table 2.14: ADF and PP Unit Root Test for Fayetteville Soybean Market (Returns)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-234.595	0.0001	-10.80	<.0001		
	3	-208.625	0.0001	-7.52	<.0001		
Single Mean	**1**	-234.598	0.0001	-10.78	<.0001	58.07	0.0010
	3	-208.629	0.0001	-7.51	<.0001	28.17	0.0010
Trend	**1**	-234.587	0.0001	-10.76	<.0001	57.88	0.0010
	3	-208.622	0.0001	-7.49	<.0001	28.08	0.0010

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-297.261	0.0001	-18.46	<.0001
	3	-308.105	0.0001	-18.38	<.0001
Single Mean	**1**	-297.273	0.0001	-18.43	<.0001
	3	-308.120	0.0001	-18.35	<.0001
Trend	**1**	-297.271	0.0001	-18.39	<.0001
	3	-308.114	0.0001	-18.32	<.0001

Table 2.15: ADF and PP Unit Root Test for Cofield Soybean Market (Returns)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-258.681	0.0001	-11.32	<.0001		
	3	-256.323	0.0001	-7.94	<.0001		
Single Mean	**1**	-258.712	0.0001	-11.30	<.0001	63.85	0.0010
	3	-256.388	0.0001	-7.92	<.0001	31.40	0.0010
Trend	**1**	-258.746	0.0001	-11.28	<.0001	63.63	0.0010
	3	-256.494	0.0001	-7.91	<.0001	31.31	0.0010

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-273.550	0.0001	-16.95	<.0001
	3	-275.061	0.0001	-16.95	<.0001
Single Mean	**1**	-273.574	0.0001	-16.92	<.0001
	3	-275.081	0.0001	-16.92	<.0001
Trend	**1**	-273.587	0.0001	-16.89	<.0001
	3	-275.085	0.0001	-16.89	<.0001

Table 2.16: ADF and PP Unit Root Test for Greenville Soybean Market (Returns)

Augmented Dickey-Fuller Unit Root Tests							
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**	**F**	**Pr > F**
Zero Mean	**1**	-291.553	0.0001	-12.81	<.0001		
	3	-238.405	0.0001	-7.93	<.0001		
Single Mean	**1**	-291.486	0.0001	-12.79	<.0001	81.78	0.0010
	3	-238.380	0.0001	-7.91	<.0001	31.31	0.0010
Trend	**1**	-291.406	0.0001	-12.77	<.0001	81.82	0.0010
	3	-238.456	0.0001	-7.90	<.0001	31.17	0.0010

Phillips-Perron Unit Root Tests					
Type	**Lags**	**Rho**	**Pr < Rho**	**Tau**	**Pr < Tau**
Zero Mean	**1**	-285.976	0.0001	-18.30	<.0001
	3	-289.475	0.0001	-18.27	<.0001
Single Mean	**1**	-286.000	0.0001	-18.27	<.0001
	3	-289.505	0.0001	-18.23	<.0001
Trend	**1**	-285.934	0.0001	-18.23	<.0001
	3	-289.406	0.0001	-18.20	<.0001

Table 2.17: Johansen Cointegration Results for Soybean Market (Logarithmic Prices)

Cointegration Rank Test Using Trace						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.3665	152.1257	29.38	Constant	Linear
1	**1**	0.0891	33.9097	15.34		
2	**2**	0.0369	9.7402	3.84		
Cointegration Rank Test Using Trace Under Restriction						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.3679	152.8119	34.80	Constant	Constant
1	**1**	0.0894	34.0100	19.99		
2	**2**	0.0369	9.7402	9.13		

Table 2.18: Johansen Cointegration Results for Soybean Market (Returns)

Cointegration Rank Test Using Trace						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.4402	358.0961	29.38	Constant	Linear
1	**1**	0.4104	208.3918	15.34		
2	**2**	0.2438	72.0952	3.84		
Cointegration Rank Test Using Trace Under Restriction						
H0: Rank=r	**H1: Rank>r**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
0	**0**	0.4403	358.1357	34.80	Constant	Constant
1	**1**	0.4104	208.4227	19.99		
2	**2**	0.2439	72.1180	9.13		

Table 2.19: GAM Results of Logarithmic Prices in Candor Corn Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.01731	0.00601	2.88	0.0043
dc2	0.44671	0.04077	10.96	<.0001
dc3	0.51073	0.04451	11.47	<.0001
dc1_1	-0.58676	0.11977	-4.9	<.0001
dc1_2	-0.39897	0.0753	-5.3	<.0001
dc1_3	-0.26481	0.06492	-4.08	<.0001
dc1_4	-0.06909	0.06062	-1.14	0.2554
dc1_5	-0.10783	0.05759	-1.87	0.0622
dc2_1	0.01251	0.05342	0.23	0.815
dc2_2	0.08312	0.05257	1.58	0.115
dc2_3	0.0094	0.05218	0.18	0.8572
dc2_4	-0.1194	0.05162	-2.31	0.0215
dc2_5	-0.02735	0.04663	-0.59	0.558
dc3_1	0.36668	0.05798	6.32	<.0001
dc3_2	0.31676	0.07206	4.4	<.0001
dc3_3	0.33526	0.06407	5.23	<.0001
dc3_4	0.21128	0.06902	3.06	0.0024
dc3_5	0.18825	0.05898	3.19	0.0016
Linear(u1_1)	0.17942	0.10215	1.76	0.0801
Linear(t)	0.00003936	0.00002207	1.78	0.0755
Linear(c1_1)	-0.01947	0.00633	-3.08	0.0023

Note: c1: Candor, c2: Cofield, c3: Roaring R.

Table 2.20: GAM Results of Logarithmic Prices in Cofield Corn Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.02007	0.00616	-3.26	0.0013
dc1	0.6652	0.05788	11.49	<.0001
dc3	0.32199	0.0601	5.36	<.0001
dc1_1	0.40506	0.07193	5.63	<.0001
dc1_2	0.30252	0.07393	4.09	<.0001
dc1_3	0.18022	0.07256	2.48	0.0136
dc1_4	-0.01	0.07082	-0.14	0.8878
dc1_5	0.16361	0.06542	2.5	0.013
dc2_1	-0.00425	0.07478	-0.06	0.9547
dc2_2	-0.251	0.05847	-4.29	<.0001
dc2_3	-0.19281	0.05828	-3.31	0.0011
dc2_4	0.0641	0.06251	1.03	0.306
dc2_5	-0.00938	0.05492	-0.17	0.8645
dc3_1	0.11778	0.07169	1.64	0.1015
dc3_2	-0.0106	0.07832	-0.14	0.8925
dc3_3	-0.08345	0.07718	-1.08	0.2805
dc3_4	-0.09824	0.07457	-1.32	0.1888
dc3_5	-0.24427	0.06632	-3.68	0.0003
Linear(u2_1)	-0.4531	0.07303	-6.2	<.0001
Linear(t)	-0.0000552	0.00002472	-2.23	0.0263
Linear(c2_1)	0.02398	0.00668	3.59	0.0004

Note: c1: Candor, c2: Cofield, c3: Roaring R.

Table 2.21: GAM Results of Logarithmic Prices in Roaring River Corn Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.00941	0.00625	1.51	0.1334
dc1	0.62572	0.05382	11.63	<.0001
dc2	0.26809	0.05122	5.23	<.0001
dc1_1	0.19149	0.06962	2.75	0.0063
dc1_2	0.18738	0.07156	2.62	0.0093
dc1_3	0.13149	0.06843	1.92	0.0557
dc1_4	0.00717	0.06655	0.11	0.9143
dc1_5	0.03106	0.06478	0.48	0.6319
dc2_1	0.32771	0.05643	5.81	<.0001
dc2_2	0.19071	0.06713	2.84	0.0048
dc2_3	0.20679	0.0592	3.49	0.0006
dc2_4	0.18596	0.05315	3.5	0.0005
dc2_5	0.0537	0.05284	1.02	0.3104
dc3_1	-0.60612	0.12089	-5.01	<.0001
dc3_2	-0.42341	0.06765	-6.26	<.0001
dc3_3	-0.37183	0.06939	-5.36	<.0001
dc3_4	-0.16524	0.06615	-2.5	0.0131
dc3_5	-0.09441	0.0611	-1.55	0.1234
Linear(u3_1)	0.07375	0.10851	0.68	0.4973
Linear(t)	0.0000479	0.00002405	1.99	0.0474
Linear(c3_1)	-0.01326	0.00651	-2.04	0.0428

Note: c1: Candor, c2: Cofield, c3: Roaring R.

Table 2.22: GAM Results of Returns in Candor Corn Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.00389	0.00329	-1.18	0.2386
dr2	0.35064	0.04038	8.68	<.0001
dr3	0.58181	0.04483	12.98	<.0001
dr1_1	-1.06288	0.07263	14.63	<.0001
dr1_2	-0.78586	0.0923	-8.51	<.0001
dr1_3	-0.59671	0.09543	-6.25	<.0001
dr1_4	-0.33733	0.08156	-4.14	<.0001
dr1_5	-0.03483	0.0578	-0.6	0.5473
dr2_1	0.12577	0.06839	1.84	0.067
dr2_2	0.0416	0.08168	0.51	0.611
dr2_3	-0.0834	0.08391	-0.99	0.3211
dr2_4	-0.10579	0.06743	-1.57	0.1178
dr2_5	-0.14833	0.05013	-2.96	0.0034
dr3_1	0.94677	0.07971	11.88	<.0001
dr3_2	0.71708	0.08697	8.25	<.0001
dr3_3	0.66242	0.08871	7.47	<.0001
dr3_4	0.35441	0.07649	4.63	<.0001
dr3_5	0.09597	0.05257	1.83	0.069
Linear(u1_1)	-0.72942	0.11311	-6.45	<.0001
Linear(t)	0.00001413	0.00001776	0.8	0.4269
Linear(r1_1)	0.59333	0.11533	5.14	<.0001

Note: r1: Candor, r2: Cofield, r3: Roaring R.

Table 2.23: GAM Results of Returns in Cofield Corn Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.00392	0.0037	-1.06	0.2904
dr1	0.59113	0.05424	10.9	<.0001
dr3	0.36584	0.05653	6.47	<.0001
dr1_1	0.80888	0.08373	9.66	<.0001
dr1_2	0.86462	0.10205	8.47	<.0001
dr1_3	0.65057	0.10484	6.21	<.0001
dr1_4	0.28346	0.0919	3.08	0.0022
dr1_5	0.25573	0.06206	-4.12	<.0001
dr2_1	-1.02066	0.07107	14.36	<.0001
dr2_2	-0.97225	0.08049	12.08	<.0001
dr2_3	-0.81564	0.07973	10.23	<.0001
dr2_4	-0.42513	0.07047	-6.03	<.0001
dr2_5	-0.22684	0.05242	-4.33	<.0001
dr3_1	0.51561	0.09196	5.61	<.0001
dr3_2	0.36848	0.10422	3.54	0.0005
dr3_3	0.2333	0.10552	2.21	0.0279
dr3_4	0.11819	0.08927	1.32	0.1866
dr3_5	-0.16592	0.06075	-2.73	0.0067
Linear(u2_1)	-0.79584	0.08593	-9.26	<.0001
Linear(t)	0.00001697	0.00002005	0.85	0.398
Linear(r2_1)	0.50873	0.09299	5.47	<.0001

Note: r1: Candor, r2: Cofield, r3: Roaring R.

Table 2.24: GAM Results of Returns in Roaring River Corn Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.00283	0.00395	-0.72	0.4739
dr1	0.61472	0.0532	11.56	<.0001
dr2	0.22137	0.04996	4.43	<.0001
dr1_1	0.60888	0.08887	6.85	<.0001
dr1_2	0.59247	0.11169	5.3	<.0001
dr1_3	0.40141	0.10886	3.69	0.0003
dr1_4	0.10622	0.09287	1.14	0.2537
dr1_5	0.07687	0.06646	1.16	0.2485
dr2_1	0.41595	0.07084	5.87	<.0001
dr2_2	0.30872	0.09608	3.21	0.0015
dr2_3	0.28054	0.09607	2.92	0.0038
dr2_4	0.29241	0.07452	3.92	0.0001
dr2_5	0.08116	0.06272	1.29	0.1968
dr3_1	-1.04293	0.07837	13.31	<.0001
dr3_2	-0.97337	0.09431	10.32	<.0001
dr3_3	-0.78486	0.10037	-7.82	<.0001
dr3_4	-0.45606	0.08752	-5.21	<.0001
dr3_5	-0.24229	0.0585	-4.14	<.0001
Linear(u3_1)	-0.39552	0.16763	-2.36	0.019
Linear(t)	0.00001375	0.0000211	0.65	0.5151
Linear(r3_1)	0.2283	0.16079	1.42	0.1568

Note: r1: Candor, r2: Cofield, r3: Roaring R.

Table 2.25: GAM Results of Logarithmic Prices in Fayetteville Soybean Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.04498	0.01796	-2.5	0.013
dc2	0.63922	0.0434	14.73	<.0001
dc3	0.29309	0.04114	7.12	<.0001
dc1_1	-0.20682	0.07753	-2.67	0.0082
dc1_2	0.12418	0.06584	1.89	0.0605
dc2_1	0.26419	0.05801	4.55	<.0001
dc2_2	-0.12538	0.06324	-1.98	0.0486
dc3_1	0.37865	0.0465	8.14	<.0001
dc3_2	0.11411	0.0344	3.32	0.0011
Linear(u1_1)	-0.52118	0.08948	-5.82	<.0001
Linear(t)	0.00003313	0.00001681	1.97	0.0499
Linear(c1_1)	0.02251	0.00963	2.34	0.0203

Note: c1: Fayetteville, c2: Cofield, c3: Greenville

Table 2.26: GAM Results of Logarithmic Prices in Cofield Soybean Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.00391	0.02349	-0.17	0.8678
dc1	0.66258	0.05086	13.03	<.0001
dc3	0.29719	0.04679	6.35	<.0001
dc1_1	0.37839	0.07793	4.86	<.0001
dc1_2	0.06929	0.06015	1.15	0.2504
dc2_1	-0.25378	0.13379	-1.9	0.0591
dc2_2	-0.16238	0.05809	-2.8	0.0056
dc3_1	0.06128	0.06333	0.97	0.3342
dc3_2	0.051	0.04084	1.25	0.2129
Linear(u2_1)	-0.17621	0.13901	-1.27	0.2062
Linear(t)	0.00001189	0.00001749	-0.68	0.4973
Linear(c2_1)	0.00284	0.01286	0.22	0.8256

Note: c1: Fayetteville, c2: Cofield, c3: Greenville

Table 2.27: GAM Results of Logarithmic Prices in Greenville Soybean Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.13277	0.03213	-4.13	<.0001
dc1	0.37712	0.07617	4.95	<.0001
dc2	0.61719	0.07542	8.18	<.0001
dc1_1	0.03496	0.09117	0.38	0.7017
dc1_2	0.1298	0.07677	1.69	0.0922
dc2_1	0.5369	0.09294	5.78	<.0001
dc2_2	-0.24278	0.09221	-2.63	0.009
dc3_1	0.50434	0.14139	3.57	0.0004
dc3_2	0.12062	0.06433	1.88	0.062
Linear(u3_1)	-1.15072	0.17229	-6.68	<.0001
Linear(t)	0.0000489	0.00002427	2.01	0.0451
Linear(c3_1)	0.07174	0.0174	4.12	<.0001

Note: c1: Fayetteville, c2: Cofield, c3: Greenville

Table 2.28: GAM Results of Returns in Fayetteville Soybean Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.00499	0.0028	-1.78	0.0762
dr2	0.68129	0.0368	18.51	<.0001
dr3	0.23138	0.03544	6.53	<.0001
dr1_1	-1.31991	0.0646	20.43	<.0001
dr1_2	-0.41556	0.0473	-8.79	<.0001
dr2_1	0.76559	0.05502	13.91	<.0001
dr2_2	0.20863	0.04522	4.61	<.0001
dr3_1	0.46516	0.03908	11.9	<.0001
dr3_2	0.2932	0.02984	9.83	<.0001
Linear(u1_1)	-0.9612	0.08149	-11.8	<.0001
Linear(t)	0.00003532	0.00001841	1.92	0.0563
Linear(r1_1)	0.88064	0.08574	10.27	<.0001

Note: r1: Fayetteville, r2: Cofield, r3: Greenville

Table 2.29: GAM Results of Returns in Cofield Soybean Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	0.00116	0.00332	0.35	0.7271
dr1	0.70098	0.0461	15.21	<.0001
dr3	0.22776	0.04308	5.29	<.0001
dr1_1	0.75033	0.07785	9.64	<.0001
dr1_2	0.29422	0.06051	4.86	<.0001
dr2_1	-0.72466	0.06214	11.66	<.0001
dr2_2	-0.3181	0.05391	-5.9	<.0001
dr3_1	0.06777	0.05406	1.25	0.2113
dr3_2	0.03068	0.04211	0.73	0.467
Linear(u2_1)	-0.06209	0.11934	-0.52	0.6034
Linear(t)	0.00000756	0.00002171	-0.35	0.728
Linear(r2_1)	-0.10348	0.1221	-0.85	0.3976

Note: r1: Fayetteville, r2: Cofield, r3: Greenville

Table 2.30: GAM Results of Returns in Greenville Soybean Market

Parameter	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	-0.00504	0.00405	-1.24	0.2152
dr1	0.35445	0.07176	4.94	<.0001
dr2	0.53167	0.07118	7.47	<.0001
dr1_1	0.17005	0.10373	1.64	0.1024
dr1_2	0.00004707	0.07283	0	0.9995
dr2_1	0.74151	0.1016	7.3	<.0001
dr2_2	0.34737	0.06819	5.09	<.0001
dr3_1	-0.86413	0.05457	15.84	<.0001
dr3_2	-0.32712	0.03797	-8.62	<.0001
Linear(u3_1)	-0.71026	0.11451	-6.2	<.0001
Linear(t)	0.00003197	0.00002653	1.21	0.2293
Linear(r3_1)	0.47725	0.12783	3.73	0.0002

Note: r1: Fayetteville, r2: Cofield, r3: Greenville

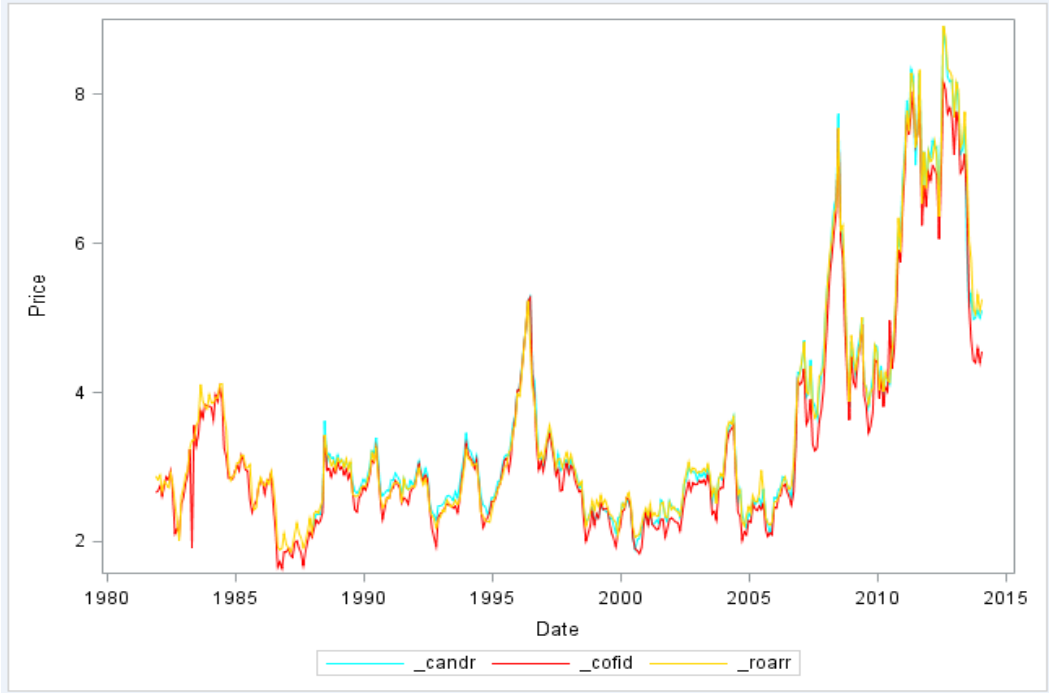


Figure 2.1: Corn Markets

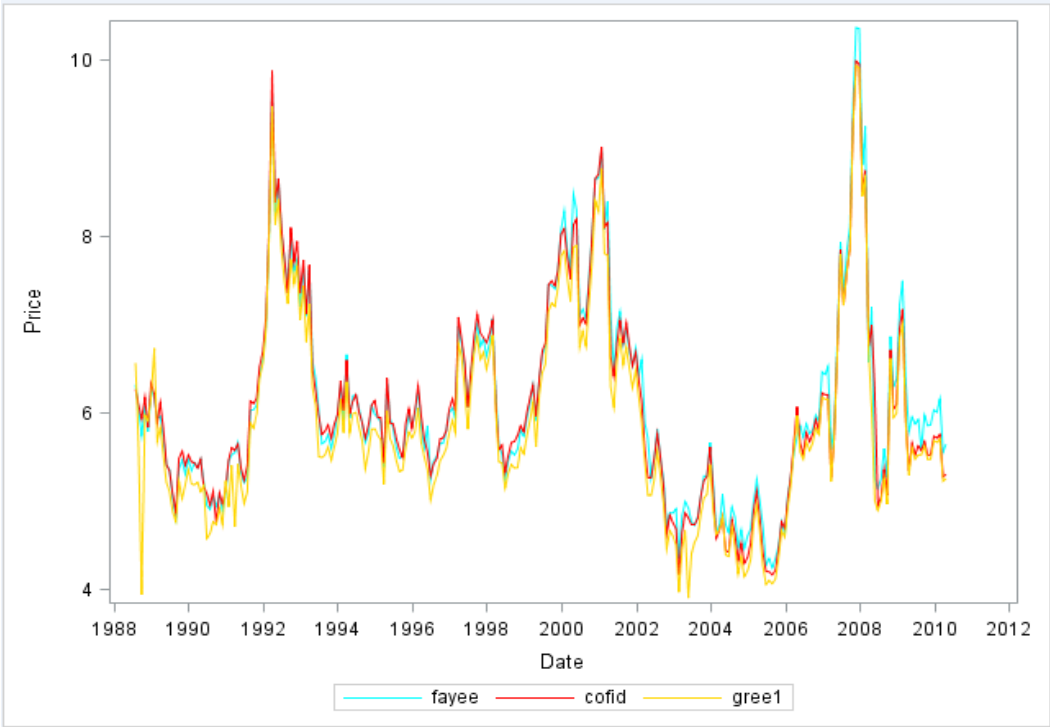
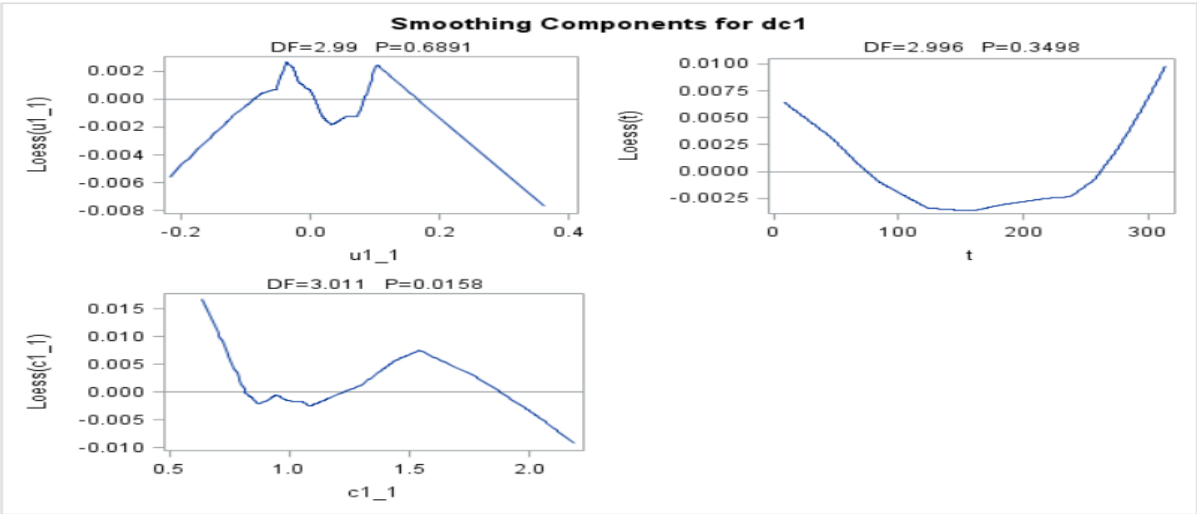


Figure 2.2: Soybean Markets



Note: c1: Candor

Figure 2.3 : Smoothing Component for Logarithmic Prices in Candor Corn Market

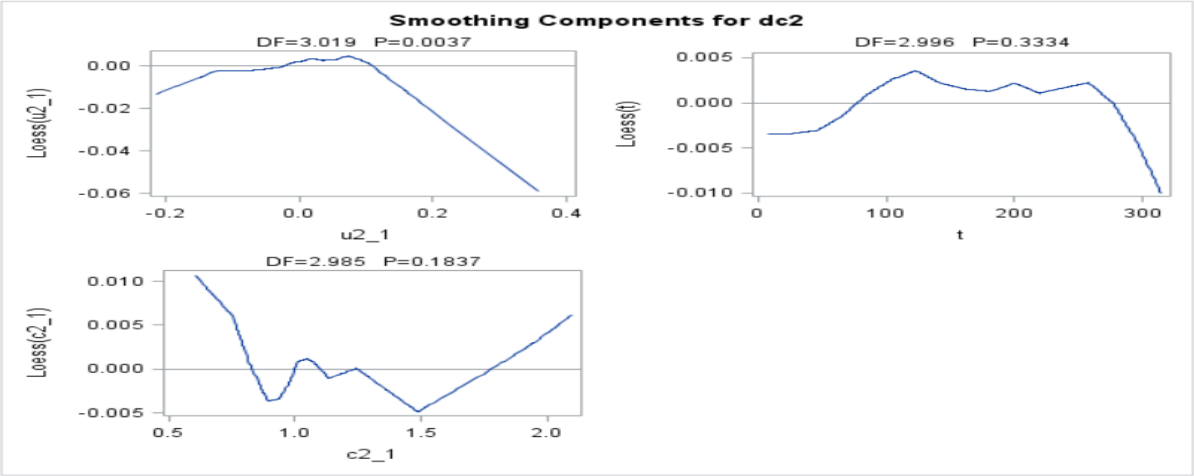


Figure 2.4 : Smoothing Component for Logarithmic Prices in Cofield Corn Market

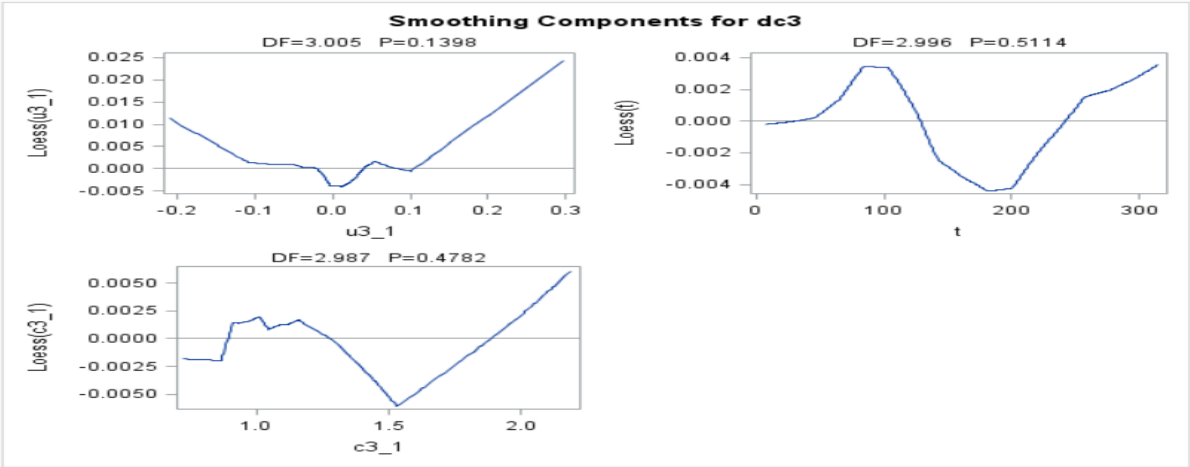
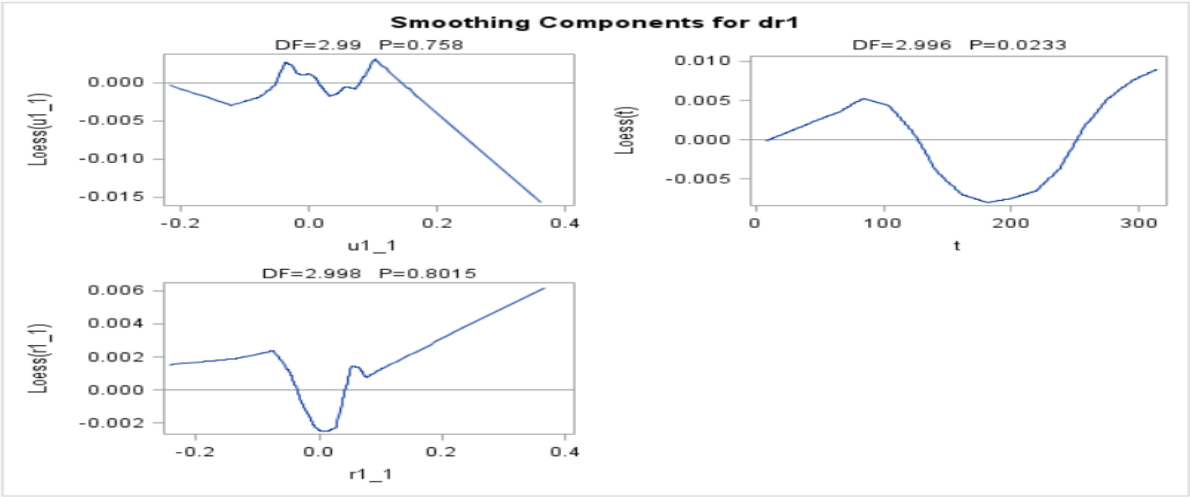
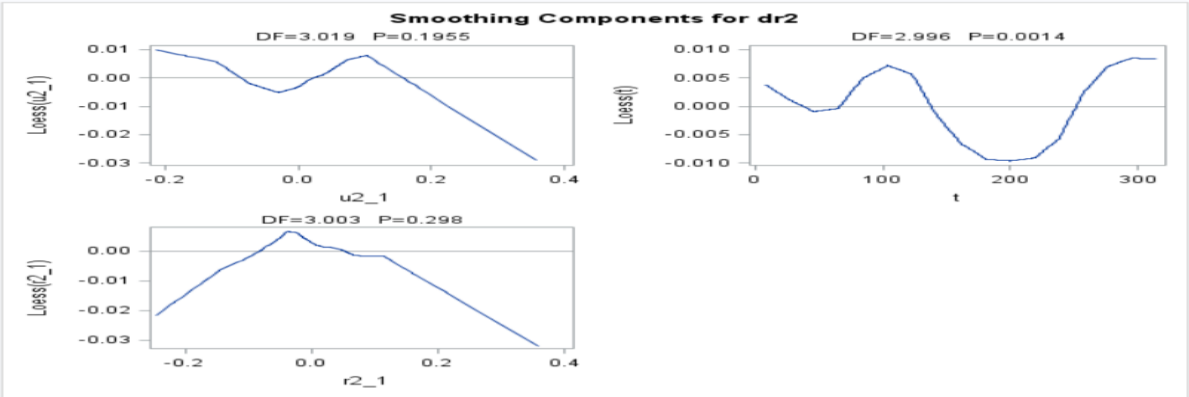


Figure 2.5 : Smoothing Component for Logarithmic Prices in Roaring River Corn Market



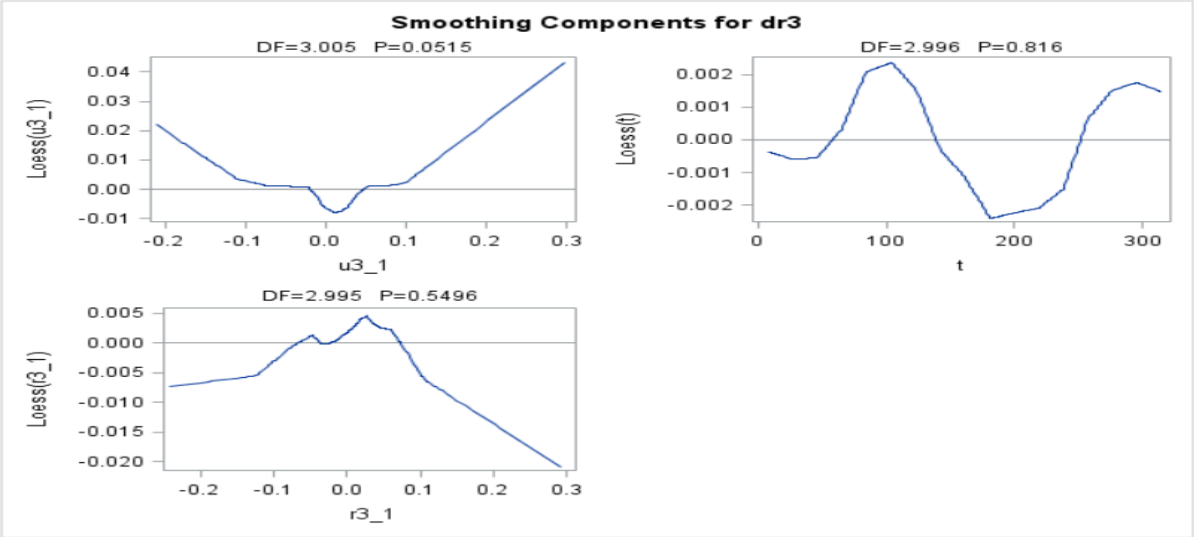
Note: r1: Candor

Figure 2.6 : Smoothing Component for Returns in Candor Corn Market



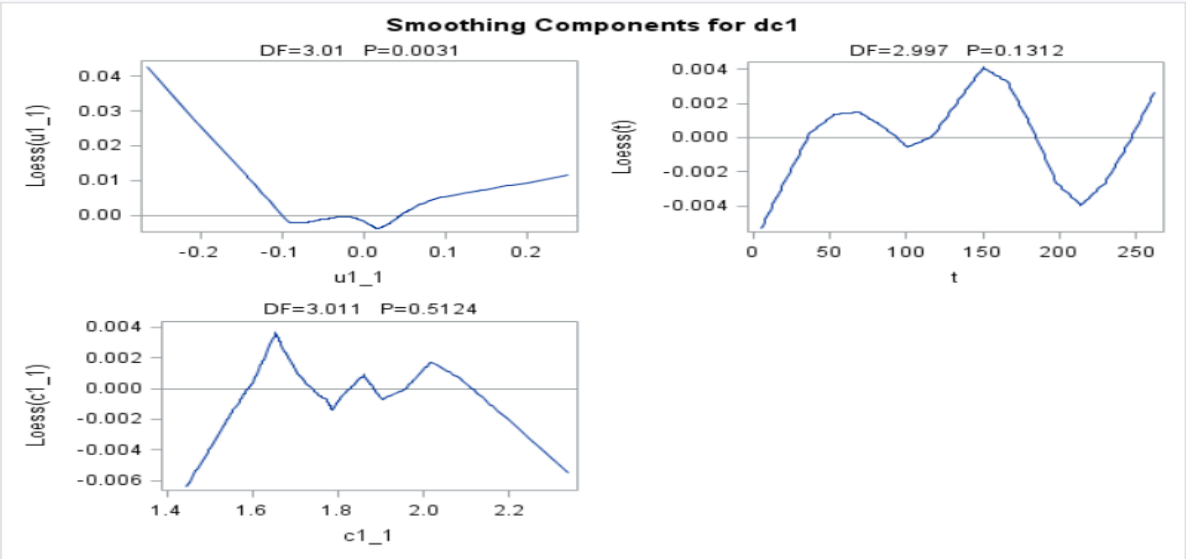
Note: r2: Cofield

Figure 2.7 : Smoothing Component for Returns in Cofield Corn Market



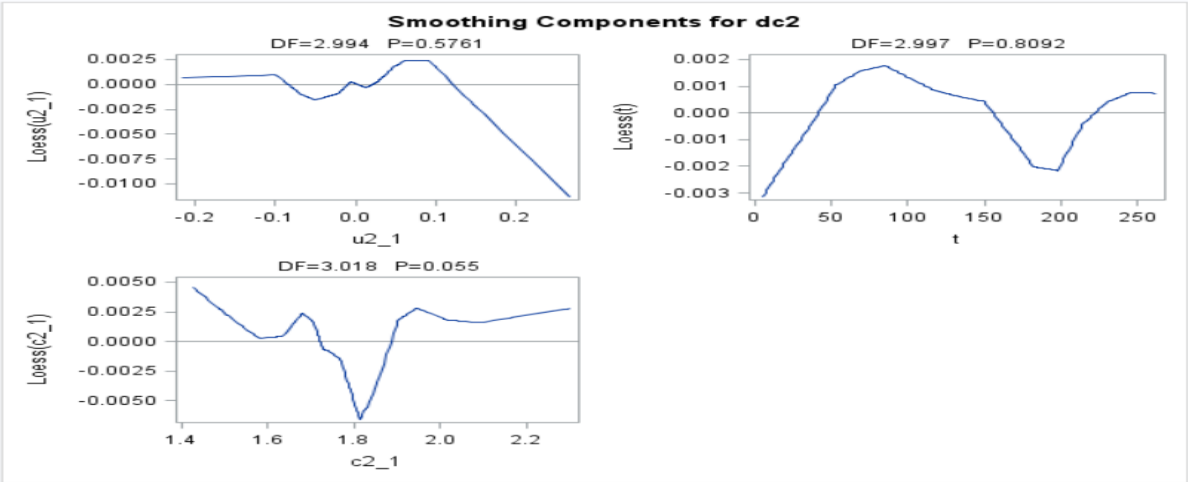
Note: r3: Roaring River

Figure 2.8 : Smoothing Component for Returns in Roaring River Corn Market



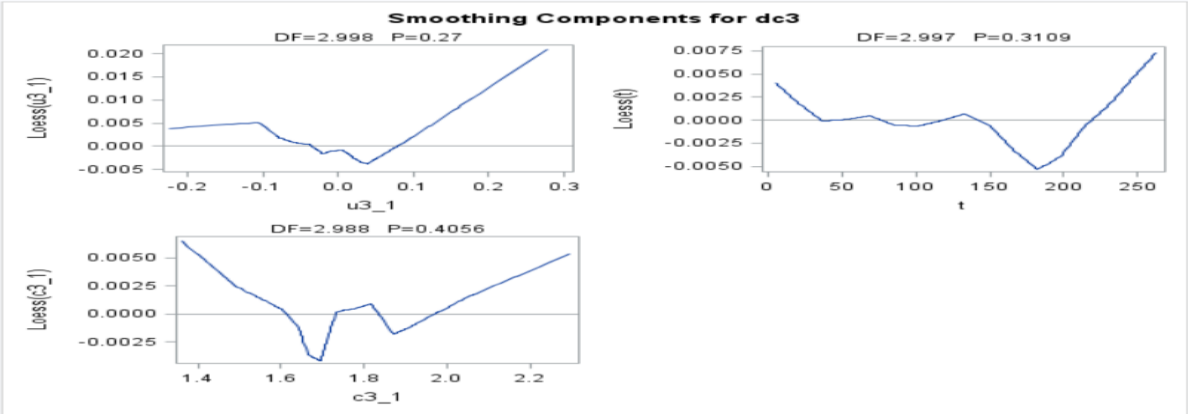
Note: c1: Fayetteville

Figure 2.9 : Smoothing Component for Logarithmic Prices in Fayetteville Soybean Market



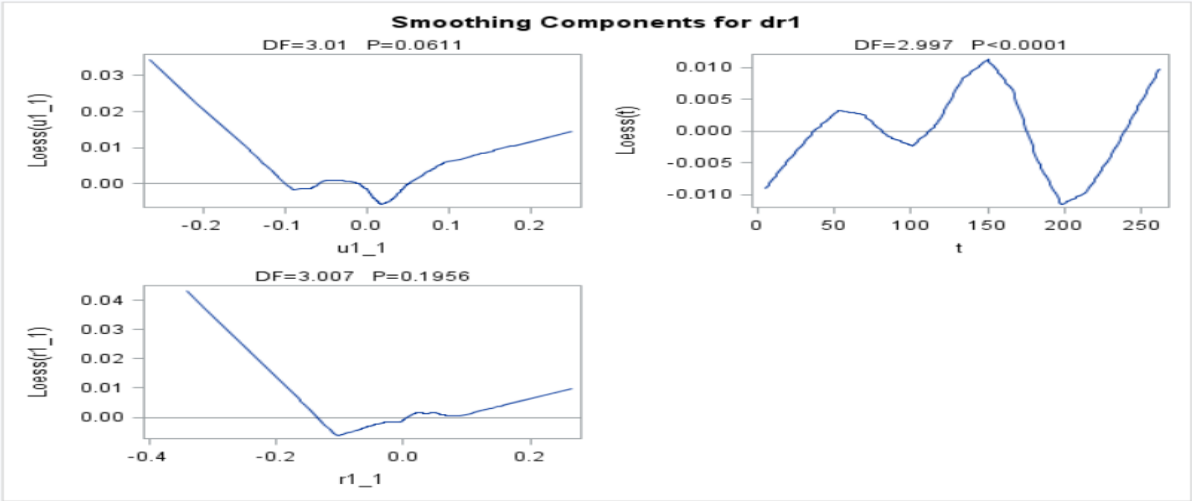
Note: c2: Cofield

Figure 2.10 : Smoothing Component for Logarithmic Prices in Cofield Soybean Market



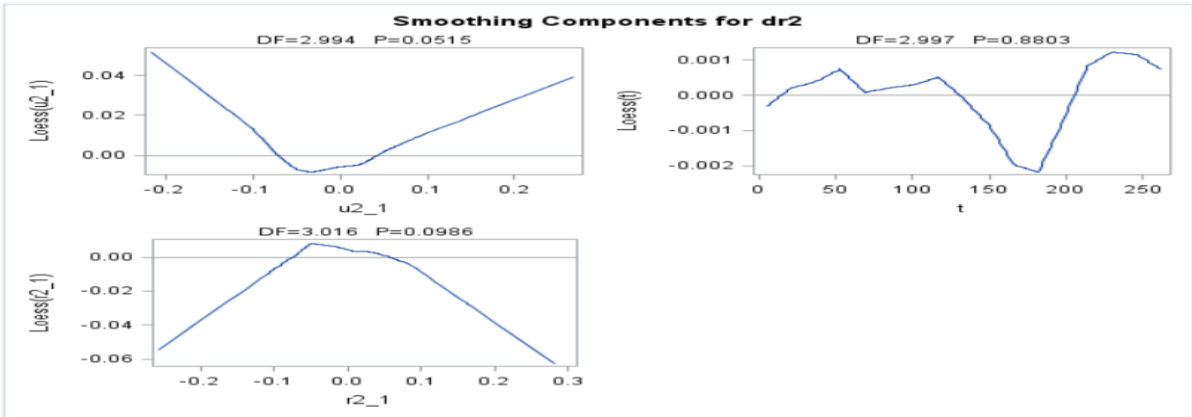
Note: c3: Greenville

Figure 2.11 : Smoothing Component for Logarithmic Prices in Greenville Soybean Market



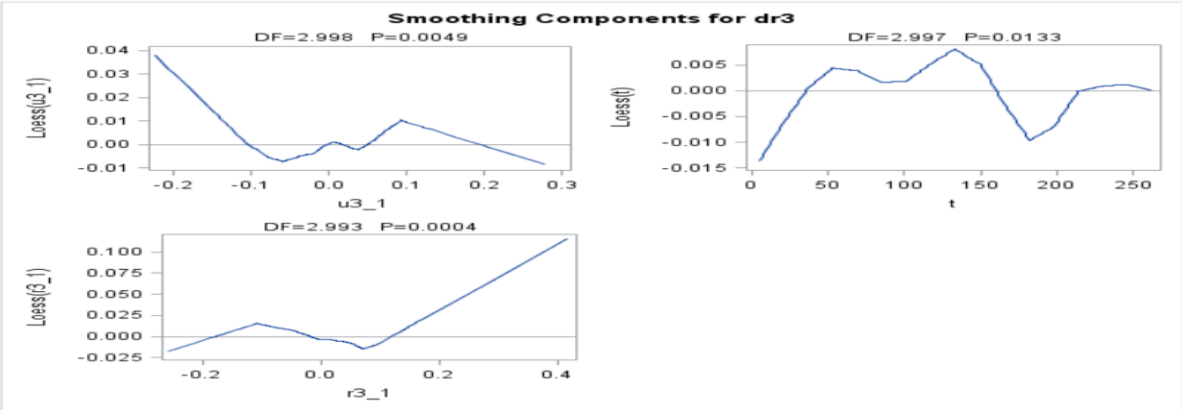
Note: r1: Fayetteville

Figure 2.12 : Smoothing Component for Returns in Fayetteville Soybean Market



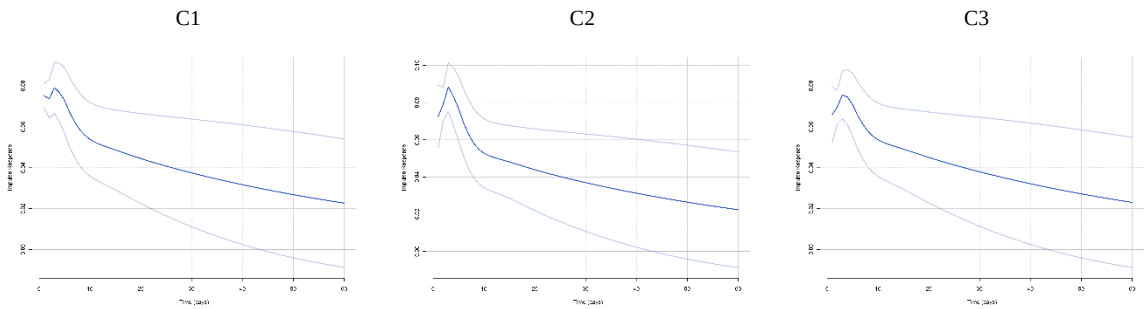
Note: r2: Cofield

Figure 2.13 : Smoothing Component for Returns in Cofield Soybean Market



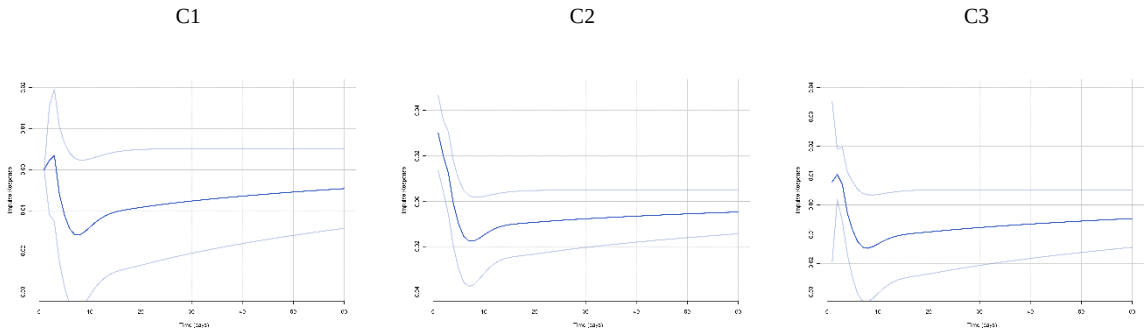
Note: r3: Greenville

Figure 2.14 : Smoothing Component for Returns in Greenville Soybean Market



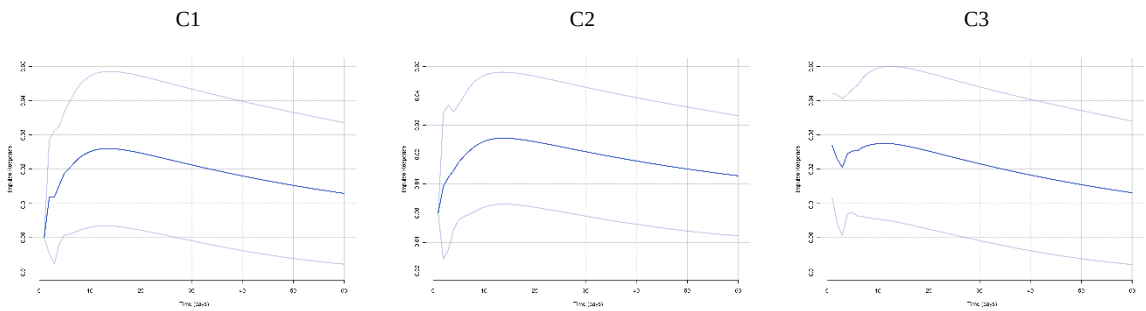
Note: c1: Candor, c2: Cofield, c3: Roaring R

Figure 2.15: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Candor CornMarkets



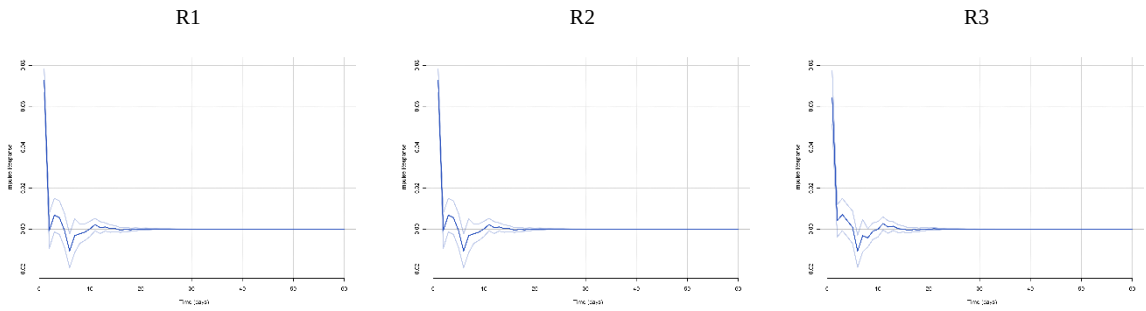
Note: c1: Candor, c2: Cofield, c3: Roaring River

Figure 2.16: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Cofield Corn Markets



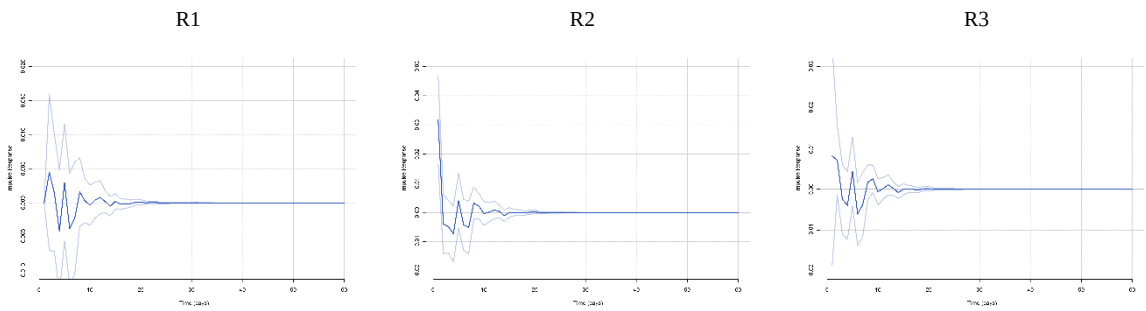
Note: c1: Candor, c2: Cofield, c3: Roaring River

Figure 2.17: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Roaring River Corn Markets



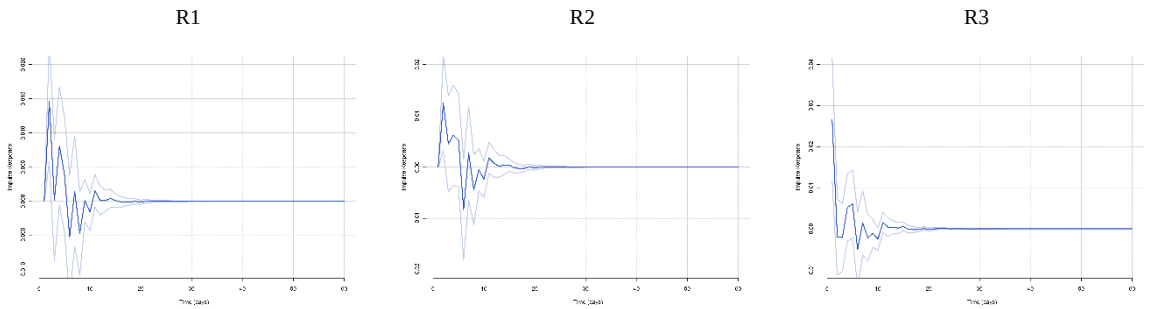
Note: r1: Candor, r2: Cofield, r3: Roaring R

Figure 2.18: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Candor Corn Markets



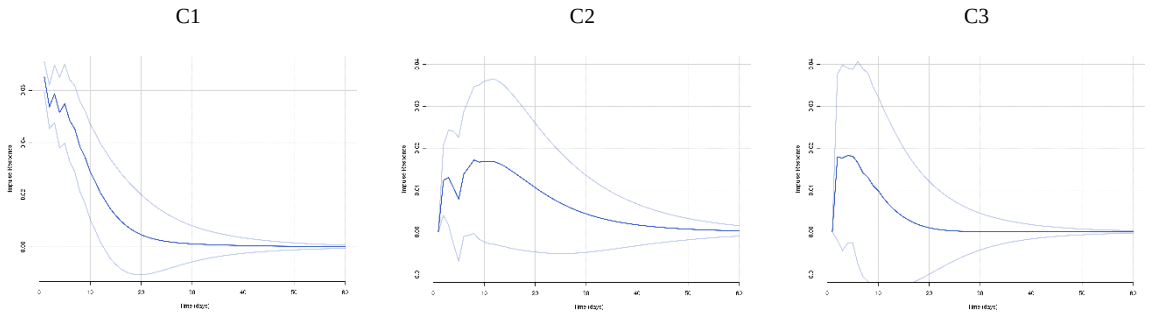
Note: r1: Candor, r2: Cofield, r3: Roaring River

Figure 2.19: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Cofield Corn Markets



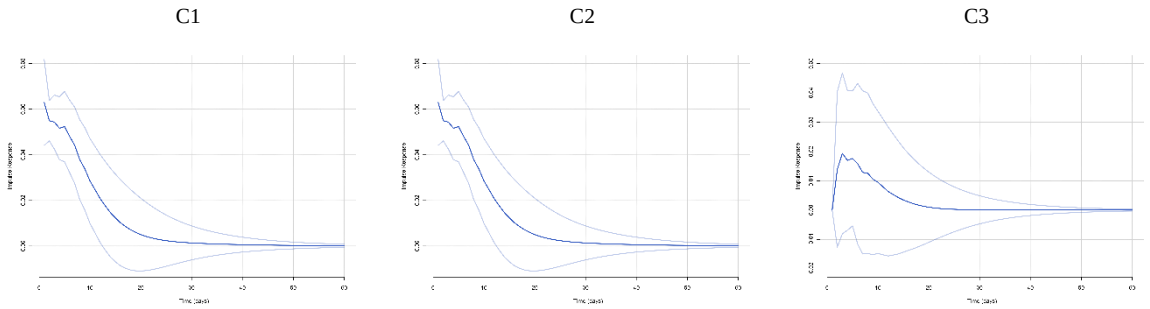
Note: r1: Candor, r2: Cofield, r3: Roaring River

Figure 2.20: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Roaring River Corn Markets



Note:c1:Fayetteville,c2:Cofield,c3:Green

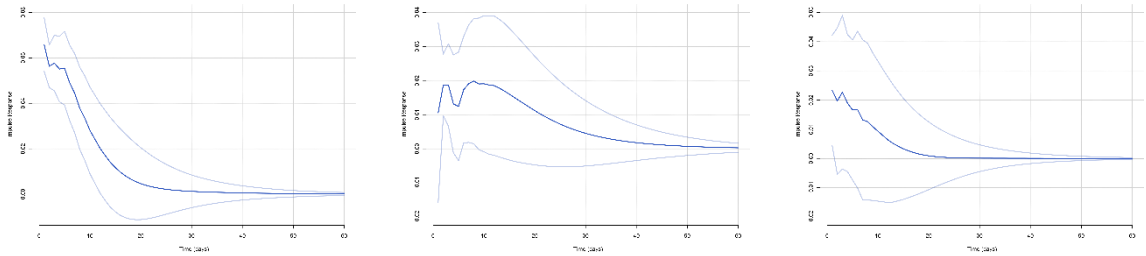
Figure 2.21: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Fayetteville Soybean Market



Note: c1: Fayetteville, c2: Cofield, c3: Greenville

Figure 2.22: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Cofield Soybean Market

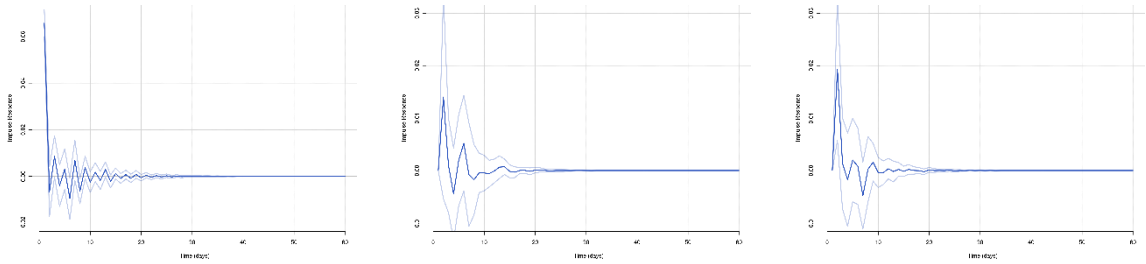
C1 C2 C3



Note: c1: Fayetteville, c2: Cofield, c3: Greenville

Figure 2.23: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Greenville Soybean Market

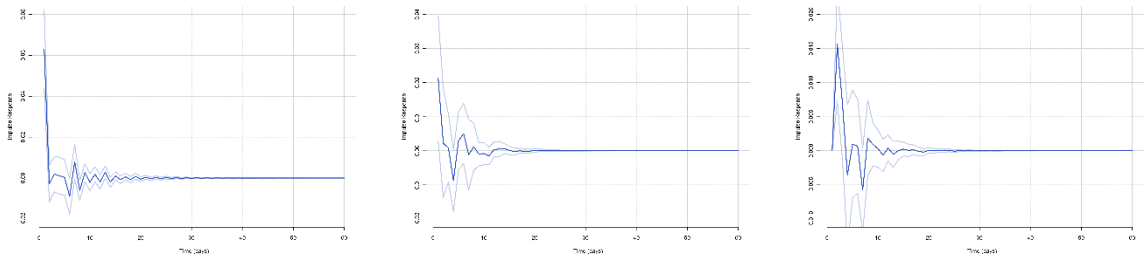
R1 R2 R3



Note: r1:Fayetteville,r2:Cofield, r3: Green

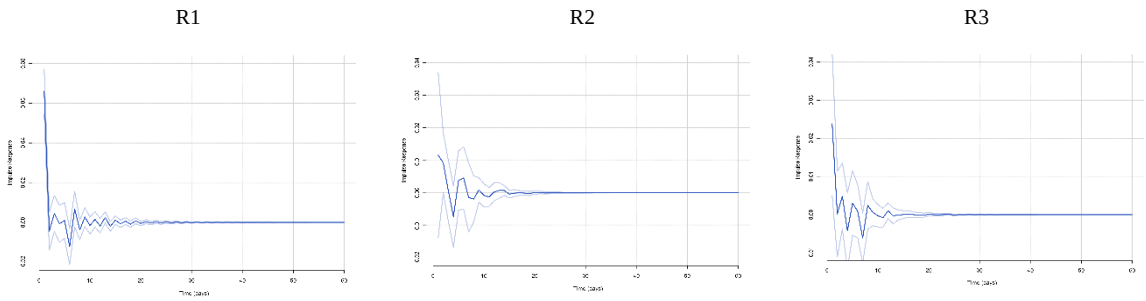
Figure 2.24: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Fayetteville Soybean Market

R1 R2 R3



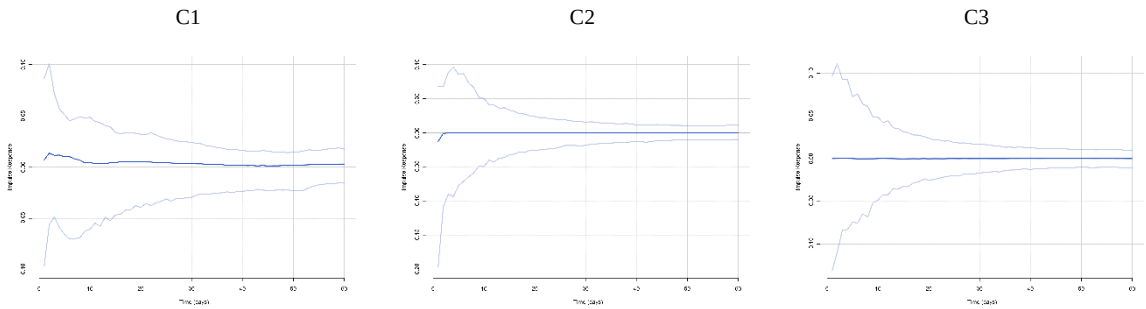
Note: r1: Fayetteville, r2: Cofield, r3: Greenville

Figure 2.25: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Cofield Soybean Market



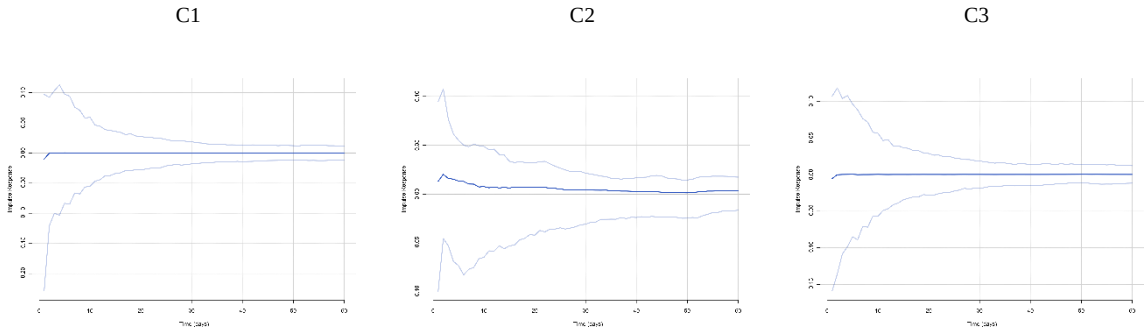
Note: r1:Fayetteville,r2:Cofield, r3: Green

Figure 2.26: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Greenville Soybean Market



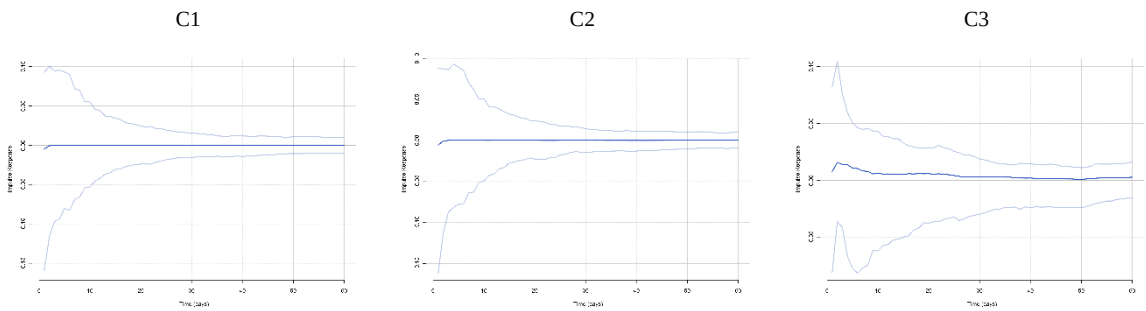
Note: c1: Candor, c2: Cofield, c3: Roaring River

Figure 2.27: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Candor Corn Markets (VECGAM)



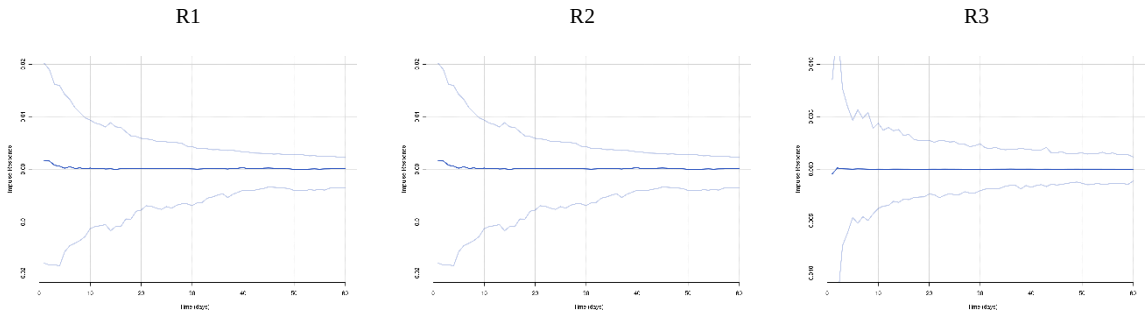
Note: c1: Candor, c2: Cofield, c3: Roaring River

Figure 2.28: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Cofield Corn Markets (VECGAM)



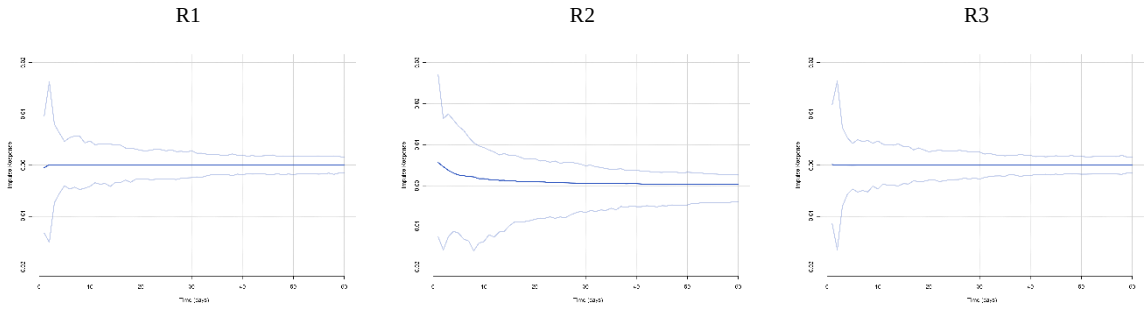
Note: c1: Candor, c2: Cofield, c3: Roaring R

Figure 2.29: Response to Orthogonalized Impulse and %95 Confidence Bands for Roaring River Corn Markets (VECGAM)



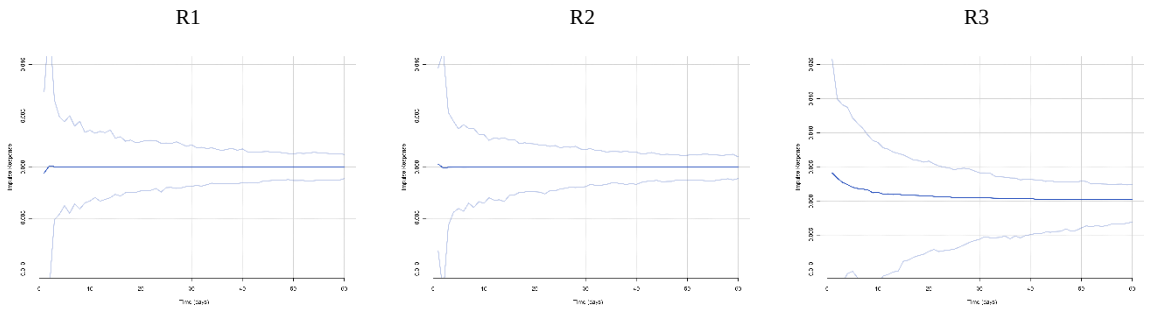
Note: r1: Candor, r2: Cofield, r3: Roaring R.

Figure 2.30: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns Candor Corn Markets (VECGAM)



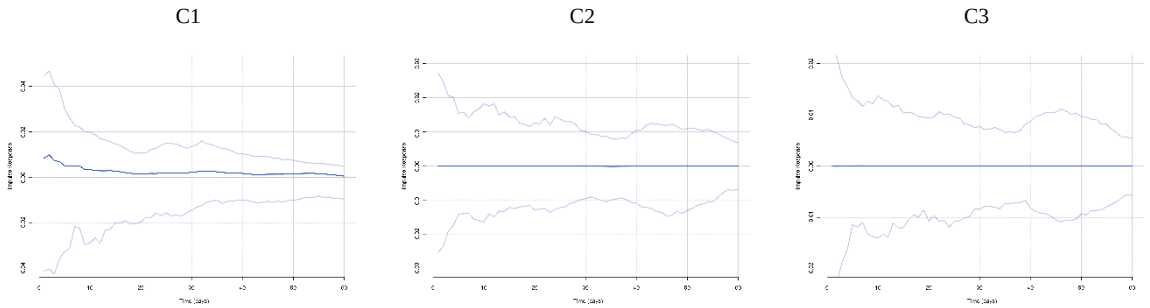
Note: c1: Candor, c2: Cofield, c3: Roaring R.

Figure 2.31: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Cofield Corn Market (VECGAM)



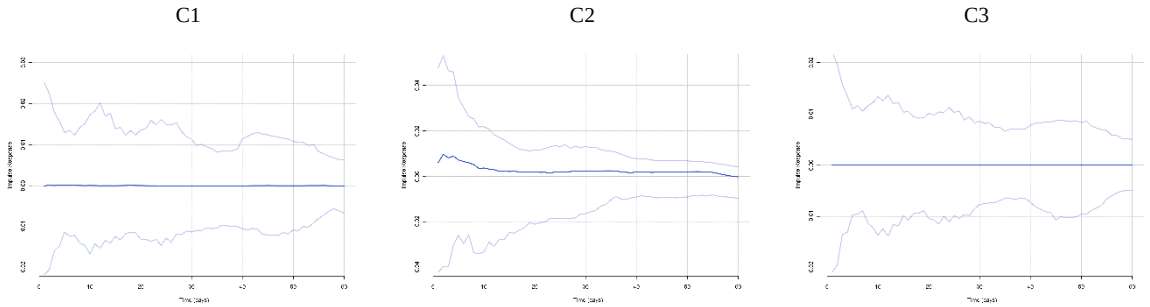
Note: c1: Candor, c2: Cofield, c3: Roaring R.

Figure 2.32: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Roaring River Corn Market (VECGAM)



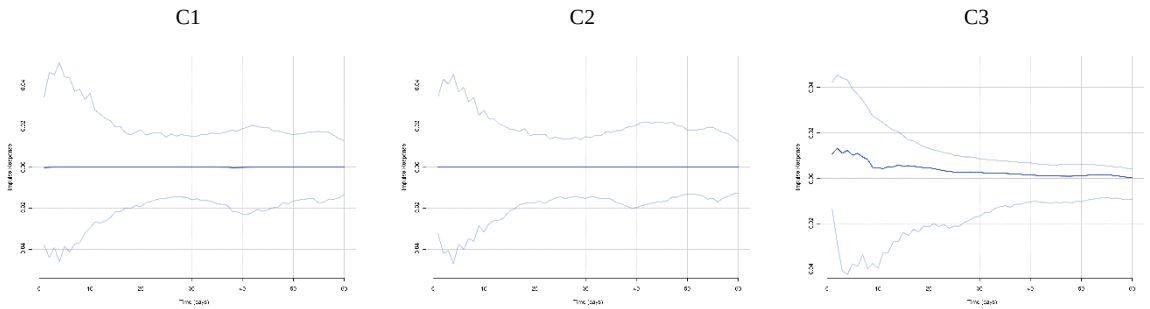
Note: c1:Fayetteville,c2:Cofield,c3: Green

Figure 2.33: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Fayetteville Soybean Market (VECGAM)



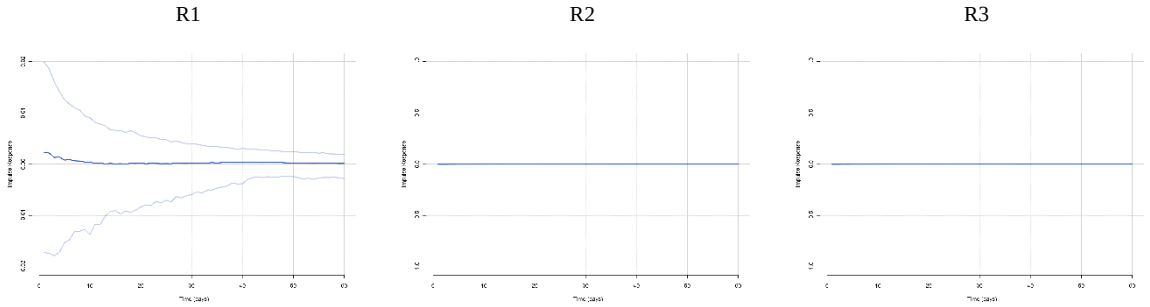
Note: c1: Fayetteville, c2: Cofield, c3: Greenville

Figure 2.34: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Cofield Soybean Market (VECGAM)



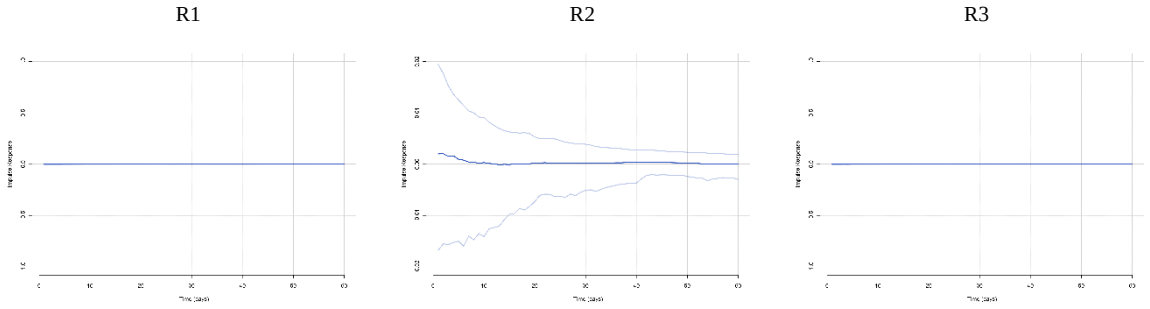
Note: c1: Fayetteville, c2: Cofield, c3: Greenville

Figure 2.35: Response to Orthogonalized Impulse and %95 Confidence Bands for Logarithmic Prices in Greenville Soybean Market (VECGAM)



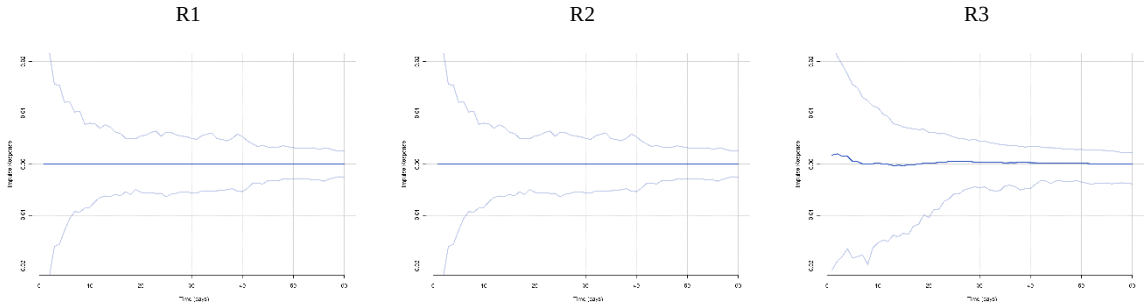
Note: r1: Fayetteville, r2: Cofield, r3: Greenville

Figure 2.36: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Fayetteville Soybean Market (VECGAM)



Note: r1: Fayetteville, r2: Cofield, r3: Greenville

Figure 2.37: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Cofield Soybean Market (VECGAM)



Note: r1: Fayetteville, r2: Cofield, r3: Greenville

Figure 2.38: Response to Orthogonalized Impulse and %95 Confidence Bands for Returns in Greenville Soybean Market (VECGAM)

CHAPTER 3: An Evaluation of Price Forecasts of the Cattle Market under Structural Changes

3.1. Introduction

Changes in commodity prices will have a direct effect on the revenues, cost and profits of agricultural businesses and agricultural producers. Optimal and efficient forecasts of agricultural prices help firms to improve the economic decision process such as planning business operations and investment, marketing, and lending decisions; governments also use this information to establish a proper agricultural policy and hence, the forecasts affect social welfare (Kenyon, Jones, & McGuirk, 1993; Stein, 1981), and systematic errors in forecasts could lead to a misallocation of scarce resources (Stein, 1981).

Because of the aforementioned importance of accurate forecasting of cattle prices, there is a vast literature concentrating on the forecasts of cattle prices in the U.S.A. that have used different techniques and methodologies. Most commonly-used approaches to model livestock sectors have ignored the possibility of structural breaks that are expected to occur for several reasons in this industry, including the merging of some important firms, changes in the beef packing industry, important changes in U.S. meat consumption behaviors related to health concerns, outbreaks of animal diseases, effects of quotas imposed by the government, and the effects of government interventions following import or export bans.

The institutional changes motivating the structural breaks have had a significant impact on cattle prices. For example, after the May 2003 BSE (Bovine Spongiform

Encephalopathy) discovery in Canada, the United States banned live animal imports from that country because Canada was not regarded as a minimal-risk region. Federal court approved removal of the ban on July 14, 2005; however, it was observed that the monthly volumes were much less than during the pre-BSE period. This fact had an impact on the prices of cattle. The effects of three important incidents—namely, the 1989-1991 recession, the mortgage crisis in 2005-2006 in USA, and world economic crisis in 2008-2009—and their effects on the cattle prices will be investigated further in this analysis.

The specific purpose of this paper is to investigate the potential of a time series analysis technique, namely the Time Varying Parameter Vector Autoregressive Model (TVPVAR) technique, in the development of daily forecasting models for cattle prices in the presence of structural changes. More specific objectives are to integrate smoothing techniques and stochastic volatility into TVPAR modeling framework based exclusively on time series for cash-cattle prices, and to compare the accuracy and evaluate the forecasting performance of this model with the standard VAR model based on forecast accuracy measures.

3.2. Data

Reviewing the empirical work concentrated on the US cattle industry (i.e. Marsh, 1983; Nelson & Spreen, 1978; Ospina & Shumway, 1981; Ziemer and White, 1982), it is observed that many common variables have been investigated, including prices and/or amounts of live cattle, prices and/or amounts of hogs to consider the effect of a substitute

for cattle, beef imports, corn prices, soybean prices, and variables reflecting income levels to investigate and forecast cattle prices.

Economic conditions in other sectors may have indirect effects in cattle industry such as the conditions related to the grains market or dairy products. So the cattle industry may be regarded as a good example of interdependence of different industries. Mutual dependence of this nature is important in agriculture and must be taken into account in order to get a full understanding of changes. Actually, the effects of feed grain and dairy policies may be as great as or even greater than the direct effects of the import quota set on cattle products (Arzac & Wilkinson, 1979; Ospina & Shumway, 1981). Ospina and Shumway found that beef supplies are more responsive to changes in corn prices than to changes in their own price.

The nominal daily prices of cattle, broilers, hogs, corn, soybean and per capita income comprise the information set for the VAR models for the period 1991-2013, and the logarithms of the variables were taken as the basis of the analysis. The daily prices of cattle, hogs, broilers, corn and soybean are obtained from the Commodity Research Bureau (CRB) database and SP 500 index, which is suitable to proxy daily U.S. Gross Domestic Products (GDP), is taken from Federal Reserve Bank of St. Louis-FRED.

The multivariate expected interactions between these series are as follows: the demand forces that have influences on the price of cattle are reflected through per capita income. As also suggested by Marsh (1985) as well as Spreen and Shonkwiler (1981), cattle

prices are sensitive to feed prices, so prices of soybeans and corn are also involved in the models under analysis in this article.

The argument over whether the price of corn should be considered as an exogenous or endogenous variable was considered. Because of the fact that cattle feed is a significant end use for corn, the relationship between these variables has to considered bidirectional; there also are some reasons why it can be evaluated as endogenous. We may regard the effect of cattle price on corn price as indirect because it is going be the quantity of cattle but not the price of cattle affecting demand for corn. Also, the weather conditions have a strong effect on corn prices, so the demand side effects from the cattle industry may be considered to be of secondary importance (Fanchon & Wendel, 1992). However, since the econometric model that is employed in this paper includes the lagged endogenous variables, that is not of concern here.

3.3. Literature Review and Methodology

3.3.1. Literature Review

Various proposed forecasting methods have been discussed (Allen, 1994; Gerlow, Irwin, & Liu, 1993; Harris & Leuthold, 1985; Helmers & Held, 1977; Nelson & Spreen, 1978) and applied in the livestock economics literature. Among the most commonly-used approaches to model livestock sectors is to build a structural model. However, time series models differ from the structural models in terms of the restrictions imposed. The specific time series model adopted for this study, a VAR methodology, may be regarded as a reduced form of a structural model evaluating all variables in the model as being

endogenous. This approach has some advantages over the structural models that use variables that are changing exogenously in the model. Such structural models have been criticized by Sims (1980) since the number of restrictions imposed to obtain a structural model is large, which then causes the models to be over-identified; in addition, the restrictions imposed to accomplish identification are generally not believable. Even though structural models may provide satisfying explanations for historical data, they generally offer modest and sometimes quite poor real time forecasts (Cooper, 1972).

Forecasting prices with structural econometric models requires forecasts of the relevant exogenous and lagged endogenous variables which are considered to be exogenous in estimation. While these forecasts can be obtained in a recursive manner, forecasts of exogenous variables often present problems for econometric model users (Jin, Power, & Elbakidze, 2008). Hence, the literature on forecasting cattle prices has progressed from structural models to the univariate ARIMA models proposed by Box and Jenkins that are based on current and past observations of the particular data series in question with no exogenous variables included. Several studies that adopted this approach to forecast cattle prices in the USA hog prices (Allen, 1994; Gerlow, Irwin, & Liu, 1993; Goodwin, 1992; Harris & Leuthold, 1985; Kohzadia, Boyd, Kermanshahi, & Kaastra, 1996; Leuthold, et al., 1970; Oliveira, O'Connor & Smith, 1979). Oliveira, Buongiorno and Kmiotek (1977) compared cattle prices to lumber prices.

Although there exists some literature suggesting that the ARIMA models perform best among the individual models for forecasting commodity prices (see Brandt & Bessler

(1983) for hog prices), numerous authors agree that the usage of ARIMA models should only be supplementary and should not be considered as a replacement for traditional econometric models as they do not involve casual structures implied by the economic theory; thus, they will not be useful to test hypotheses of any kind nor to establish confidence intervals for the parameter estimates obtained. Also, some researchers have concluded that the accuracy of the ARIMA results has been ambiguous in a sense that these models are found to be different in the short run and in the long run as well as found to depend on the prices chosen (i.e., future prices vs. cash prices). Most of the literature implies that the models for the cash prices seem to be more accurate in the short run, whereas models depending on future prices seem to be more accurate in the long horizon (ex. Oliveira & Smith, 1979). Also as indicated by Oliveira, O'Connor, and Smith (1979), "The potential for error increases greatly as the forecast horizon increases and that ARIMA models may differ in accuracy among regions." Thus, a logical improvement of these univariate models would be the augmentation of multivariate time series models specifically for short term forecasts (Pierce, 1971).

However, some opposite opinions also exist in the literature such as Dorfman and McIntosh (1990), who suggest that “structural econometrics may not be superior to time series techniques even when the structural modelers are given the elusive true model.” Kohzadia et al. (1996) indicate that ARIMA models have attracted researchers because it is a parsimonious approach which can represent both stationary and non-stationary stochastic processes. Their work suggests the use of Neural Network models for forecasting the US

monthly live cattle and wheat cash prices and concludes that ARIMA technique is inferior to Neural Network modeling since data may contain non-linear or chaotic behavior that cannot be fully captured by the linear ARIMA model.

Actually, it is a known fact that some problems with the estimation of nonstationary data may be encountered; however, recent work suggests that this problem may be overcome if the variables in question are also cointegrated. There exist some approaches proposed by econometricians to conquer this problem, some of which include the asymptotic distribution theory developed by Philips and Durlauf (1986), Sims et al. (1990), Stock (1987), and West (1988). They show that it is possible to get consistent estimates by OLS; therefore, straightforward estimation of a VAR model with raw data (nonstationary) is convenient. One drawback to using VAR methodology with nonstationary data is that finite sample bias may be observed, but this problem can also overcome if a large data set is used.

Using the concept of cointegration and believing the use of VAR models' convenience for nonstationary and cointegrated data, Bessler and Covey (1991) estimate COVAR models for the US cattle future and cash prices; their study indicates that the previous literature that suggests that incorporation of cointegration relationships in the forecasts improves the long-range forecasts when compared with the models that exclude the cointegration restrictions is valid. A literature review regarding tests of cointegration and its VAR representations may be obtained from Bessler and Covey (1991). Their results for the existence of cointegration between these two prices are mixed depending on the horizons and methods applied. In their empirical analysis, they also add the error correction

model (ECM) for comparing the forecasting accuracies of VAR and ECM models. Contrary to the previous literature, their results imply that the error-correction model (ECM)'s forecasts do not outperform forecasts from a restricted VAR in first differences of cash and nearby futures prices. For other articles using ECM/VECM models to forecast cattle prices see Fanchon & Wendel (1992), Jin Power, and Elbakidze (2008), and Zapata and Garcia (1990).

The literature then progressed to the usage of composite model approaches that suggest combining the time series and econometric techniques in order to gain some efficiency. This theory suggests that by the combination of regression analysis and time series analysis, the researcher will be able to get more accurate forecasts than if either technique were used alone. Among the studies that support this view are Allen (1994), Brandt and Bessler (1983), and Sanders and Manfredo (2003). Although this view seems to be the dominant one, there exists some research which claims that the composite models do not perform well enough when compared with the individual forecasting methods (See Harris & Leuthold (1985) for an application to cattle and hog prices for USA).

In sum, even though there is no clear agreement on the best forecasting technique, the decision may be based on the interests of the author; if the aim is solely forecasting, the Box-Jenkins methodology can be used, keeping in mind that they have no underlying economic theory. In contrast, if the aim is to explain the behavior of an economic system, this method may not be preferable. None of the research summarized here except Harris and Leuthold (1985) and Goodwin (1992) integrates explicitly the structural breaks that are expected to occur in the cattle industry for the USA or directly test for them.

There are several reasons to suspect structural breaks in the cattle industry. These include changes in marketing structures (ex. merging of some firms), geographical changes of markets, significant changes in U.S. meat consumption behaviors related to health concerns, effects of quotas imposed by the government, changes in beef packing industry, effects of government interventions in dairy product prices or grain prices, outbreaks of animal disease such as Bovine Spongiform Encephalopathy (BSE), and following import or export bans.

The procedures used to develop the VAR models and the time varying extensions that take into account the possible structural breaks which forms the basis of this empirical analysis will be briefly described before starting the empirical analysis.

3.3.2. VAR Methodology and its Time-Varying Extension

For a set of n time series variables $y_t = (y_{1t}, y_{2t,}...,y_{nt})'$, a VAR model of order p (VAR (p)) can be written as:

$y_t = A_1 y_{t-1} + A_2 y_{t-2} + ... + A_p y_{t-p} + u_t$ where the A_i's are (nxn) coefficient matrices and $u_t = (u_{1t}, u_{2t},...,u_{nt})'$ is an unobservable i.i.d. zero mean error term (Enders, (2008)).

For the specification of the VAR model the first step is to decide on the variables that enter the VAR model. To overcome the omitted variable(s) problem caused by the misspecification of the model that may cause serially correlated error terms, this stage should be given enough importance.

Also, in order to implement the VAR, the optimal number of lags should be specified. A variety of criteria including Akaike (AIC) or Schwarz (SBC) are available. However, it should be noted that if there exist any omitted variables in the system, increasing the number of lags does not solve the correlated residual problem.

VAR models can be used to obtain impulse responses defined as the time path responses to exogenous shocks to any of the variables in the system by using models' Moving Average (MA) representation (Hakkio & Morris, 1984), which would be helpful for policymakers and agricultural producers for future planning. However, even if there is no problem with omitted variables and the optimal number of lags are included in the model, residuals can still reflect a problem, and inaccuracy and bias in the forecasts caused by structural breaks may be encountered. At this stage, it is preferable to use less restrictive forecasting methods which allow the coefficients to change over time according to economic environment and taking into account the structural changes.

A generalization of VAR models which let the coefficients change over time called time varying coefficients (parameters) VAR (TVPVAR) will be useful for this purpose.

For a vector of time series Y_t, TVPVAR model is represented as follows:

$Y_t = A_0,_t + A_{1,t}Y_{t-1} + ... + A_{p,t}Y_{t-p} + \varepsilon_t$ where ε_t is assumed to follow a Gaussian distribution with zero mean and Σ_t is the time-varying covariance matrix of ε_t.

If the coefficients matrix $A_t = \left[A_{0,t}, A_{1,t}, A_2,_t ,..., A_p,_t\right]$ and $\theta_t = vec(A_t^{'})$ where $vec(.)$ is the column stacking operator, it is proposed:

$\theta_t = \theta_{t-1} + w_t$ where w_t follows a Gaussian white noise process with zero mean and covariance matrix Ω.

Let $\sum_t = F_t D_t F_t'$ and σ_t to be the vector of the diagonal elements of $D_t^{1/2}$ and $\phi_{i,t}, i = 1,...,n-1$ to be the column vector consisting of the non-zero and non-one elements of the (i+1)-th row of F_t^{-1} then assume that log σ_t = log $\sigma_{t-1} + \xi_t$ and $\phi_{i,t} = \phi_{i,t-1} + \psi_{i,t}$ where $\psi_{i,t}$ and ξ_t are Gaussian white noise processes with zero mean and having a covariance matrices of Ξ and Ψ respectively.

Let $\phi_t = [\phi'_{1,t},...,\phi'_{n-1,t}]$, $\psi_t = [\psi'_{1,t},...,\psi'_{n-1,t}]$ and Ψ be the covariance matrix of ψ_t. Assume that $\psi_{i,t}$ is independent of $\psi_{j,t}$ for $i \neq j$ and ξ_t, w_t, ψ_t and ε_t are independent at all lags and leads.

The most important property of the TVPVAR models is that since the second moments (variances and covariances) and impulse response functions are changing over time, they imply that the effects and the augmentation and/or contributions of a shock may vary over time. More generally, the TVPVAR modeling framework considers a situation where all of the parameters in the model can change according to economic enviroment; however, as in Enders and Holt (2012), some literatureestricts attention to the case where only the intercept term is allowed to change over time. So the attention and focus of these papers are based on modeling time series variables with shifting means only.

Then, in a multivariate setting, the shifting mean vector autoregression (SM-VAR) is defined as follows:

$Y_t = \tilde{\delta}(t) + \sum_{j=1}^{p} \Theta_j Y_{t-j} + \varepsilon_t$ where $Y_t = (Y_{1t},...,Y_{nt})'$ is (n x 1) vector of observations, Θ_j is (n x n) parameter matrix (j =1,...,p) and ε_t is i.i.d. with zero mean and (n x n) positive definite covariance matrix Σ.

In this equation $\tilde{\delta}_t = (\delta_1(t^*),..., \delta_n(t^*))'$ is a (n x 1) time-varying intercept vector and a classical component may be given as:

$\tilde{\delta}_j(t) = \delta_{0j} + \sum_{i=1}^{k_j} \delta_{ji} G(t^*; \eta_{ji}, c_{ji})$ for j =1,...,n where G stands for the transition function to be chosen.

3.3.3. Time Varying Parameter VAR's with Stochastic Volatility

This type of VAR model is a class of multivariate models where the sources of the time variation are defined as both the coefficients and the variance covariance matrix of the innovations; this is a more flexible approach in terms of the ability to distinguish between systematic and non-systematic parts of any policy change and their effects on the rest of the economy. The model enables the time variation of the relationships among variables to be reflected in a simultaneous way as well as the heterokedasticity of the innovations of the model.

This model may be considered as an improvement to the VAR models used by Cogley and Sargent (2003), Sims (1993), and Stock and Watson (1996) wherein the aim was to estimate the VAR model with drifting coefficients. TVPVAR model is also superior to stochastic volatility models used by Chib, Nardari and Shephard (2002). These models either

assume that the covariances do not evolve independently, or they assume simultaneous relations among the variables are taken to be time invariant. The TVPVAR model also has advantages over the models which ignore the potential heteroskedasticity of the innovations such as the model proposed by Boivin (2001) or models that take into account the stochastic volatility but neglect time varying coefficients such as Uhlig (1997).

Also from the perspective of modeling any possible structural breaks or changes, this model favors smooth and continuous drifting coefficients rather than discrete, abrupt changes which are expected to occur in many situations and represent the existence of learning-type behaviors. Integrating both time varying coefficients and time varying variance and covariance matrixes of the additive innovations makes it possible to obtain possible heterokedastic shocks. It is also possible to assess any nonlinearities that may be observed in the simultaneous relations in the model, as the drifting coefficients are useful for capturing nonlinearities in the lag structure; stochastic volatility is able to catch the heteroskedasticity of the shocks and contemporaneous relations between the variables.

The estimation of the model requires numerical methods and an efficient Markov Chain Monte Carlo (MCMC) algorithm for the posterior of the parameters which will be introduced after the model is presented. The Bayesian method has the advantage of coping with the high dimension of the parameters and the nonlinearities of the model and also provides smoothed estimates by using the MCMC algorithm; this way, estimates are attained on the entire data as opposed to the methods using filtered estimates that only uses the information in the subsample chosen.

According to Primiceri (2005), the time varying parameter VAR with stochastic volatility model can be defined as follows:

$$y_t = c_t + B_{1t} y_{t-1} + \ldots\ldots\ldots + B_{k,t} y_{t-k} + u_t \qquad t = 1, \ldots\ldots\ldots\ldots, T$$

where y_t : Vector of observed endogenous variables (nx1)

c_t : Vector of time varying coefficients multiplying constant terms (nxn)

$B_{i,t}$: Time varying coefficients (nxn) $i = 1, \ldots\ldots\ldots, k$

u_t : Heteroskedastic unobservable shocks with variance covariance matrix Ω_t

Considering $A_t \Omega_t A_t' = \sum_t \sum_t'$ where A_t is defined as a lower triangular matrix;

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n1,t} & \cdots & \alpha_{nn-1,t} & 1 \end{bmatrix}$$

and $\sum_t$ is the diagonal matrix;

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix}.$$

It follows that $y_t = c_t + B_{1,t} y_{t-1} + \ldots + B_{k,t} y_{t-k} + A_t^{-1} \sum_t \varepsilon_t$, $V(\varepsilon_t) = I_n$ or if we stack all the right hand side coefficients in a vector B_t this model can be re-expressed as:

$$y_t = X_t' B_t + A_t^{-1} \sum_t \varepsilon_t,$$

$X_t' = I_n \otimes [1, y_{t-1}', \ldots, y_{t-k}']$ where $\otimes$ represents the Kronecker product.

Let α_t: Non-zero and non-one elements of the matrix A_t and σ_t: Vector of diagonal elements of $\sum_t$ then the dynamics of the model's time varying parameters will be specified as:

$$B_t = B_{t-1} + v_t \ , \ \alpha_t = \alpha_{t-1} + \varsigma_t \ , \ \log \sigma_t = \log \sigma_{t-1} + \eta_t$$

The elements of the vector B_t and the free elements of the vector A_t are modeled as random walks whereas σ_t are assumed to have geometric random walks, which is an alternative to ARCH models.

All the innovations are assumed to be jointly normally distributed where I_n is an identity matrix of dimension n and Q, S and W are positive definite matrices. The variance-covariance matrix is defined as:

$$V = Var\begin{bmatrix} \varepsilon_t \\ v_t \\ \varsigma_t \\ \eta_t \end{bmatrix} = \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix}$$

This paper takes into consideration the case where S is block diagonal, which means that the estimated coefficients of the simultaneous relationships evolve independently in each equation.

3.3.4. Tests of Structural Breaks (Changes)

To prevent inaccuracy and bias problems in the estimation process, the determination of structural breaks was given great importance during modeling which was

assisted by the vast literature concentrated on the determination of structural breaks (changes) and their possible effects on the estimated coefficients.

Perron (1989) showed that the standard ADF unit root tests were invalid when a break in the trend function of a time series is present and introduced a variety of unit root tests that are proper when a break in the trend function exists. Perron (1989) claimed that the series may show stable fluctuations around a deterministic trend and proposed an alternative method to standard ADF tests. This test concentrates on three different models that take into account the breaks occurring only in the mean of the trend function (Model A), occurring only in the slope of the trend function (Model B), and both in the mean and the slope of the trend function (Model C). However, one pitfall of Perron's claims is that this test assumes only one structural break; another is that the time of this break is assumed to be known à priori.

Christiano (1992) criticizes Perron's (1989) apriority assumption and claims that the break point has to be estimated endogenously rather than making the apriority assumption. After Christiano's work on structural breaks assuming endogeneity, some research has internalized this endogeneity assumption. Among these are Banarjee, Lumsdaine and Stock (1992), Perron and Vogelsang (1992), Perron (1997a), Vogelsang and Perron (1998), and Zivot and Andrews (1992). All of the aforementioned models assume that the timing of the structural break is not known à priori and has to be estimated endogenously. Zivot and Andrews (1992) proposed a unit root test to figure out the timing of the structural break in the trend function endogenously using the aforementioned three models proposed by

Perron (1989). Different from Perron (1989), the models proposed by Zivot and Andrews do not include the dummy variables showing the instant break in the intercept term and their method is date-dependent. According to this approach, the point that has the smallest t-statistics of the unit root null hypothesis among the all possible structural break points is defined as the break point.

On the other hand, Perron and Vogelsang (1992) tested the timing of the structural change in the mean of the series that do not include trend, assuming the time of the structural change is not known à priori. They proposed test statistic based on the data dependent approach used by Zivot and Andrews (1992). Opposite to Perron and Vogelsang's (1992) approach, Perron (1997a) developed a unit root test statistic for the series that included trend by using the three models proposed by Perron (1989). Perron (1997a) concentrated on a method that suggests choosing the point with the highest t statistics among all possible choices as the breaking point.

Among the tests limiting the number of break points to one is Andrews (1993), where he considers tests for parameter instability and structural change with an unknown break point in nonlinear parametric model. Both Andrews and Hansen (1992) developed alternative test statistics to overcome the problem of nonstandard inferential problems of sort introduced by Davies (1977) which indicates that the test statistic is a supremum, and since parameters associated with alternative regimes are unobserved under the null hypothesis of no structural break , it does not have the usual standard F or χ^2 statistics; this sort of problem is associated with some commonly-used structural tests such as the

standard Chow (1960) test. They solved this problem by using either limiting distributions or simulated critical values of the test statistic. Andrews used Wald, Lagrange multiplier and likelihood ratio-like tests, and the change point was assumed to be completely unknown or to lie in a restricted interval; thus, tests for both pure and partial structural changes were investigated. This test assumes that the regressors are stationary and excludes the structural changes in the marginal distribution of regressors. It does not have the power to make the distinction between structural change in the conditional and marginal distributions. Hansen (2000) fixed this problem and derived a test statistic that allows for structural change in the marginal distribution of the regressors.

Among the approaches that aim to determine the structural breaks with unknown points have been developed within the context of cumulative sums (CUSUM) which contain cumulative sums of standardized residuals or CUSUM squared (CUSUM-sq) proposed by Brown, Durbin and Evans (1975) and Ploberger and Kramer (1992). Another way to detect a structural change is to analyze moving sums of residuals, called MOSUM processes, where the fluctuation process does not contain the sum of all residuals up to a certain time t, but is the sum of a fixed number of residuals in a data window whose size is determined by the bandwidth parameter $h \in (0,1)$.

The common property of all the tests mentioned so far is that they assume that there is only one structural break (change) and determine the change point endogenously, so if there is more than one structural change in the series, none of these tests gives proper results.

To overcome this problem, Lumsdaine and Papell (1997) extended Zivot and Andrews' (1992) approach to the case of two break points, whereas Clemente, Montanes and Reyes (1998) improved Perron and Vogelsang's (1992) methodology to include two change points. For both tests, the null hypothesis indicates that the series has a unit root without any breaks, whereas the alternative hypothesis claims that the series are stationary with two break points. Besides, the critical values are obtained under the null hypothesis indicating no structural breaks. This is criticized by Lee and Strazicich (2003), who developed a unit root test allowing for two structural breaks in the trend function of the series both under null and alternative hypothesis that is based on minimum Lagrange Multipliers (LM).

Ohara (1999) extends the work of Zivot and Andrews (1992) to the case of *m* structural breaks and proposes a unit root test for the multiple changes in the trend function. However, this approach is not preferred because of the difficulties in computation in the estimation process when there are more than two structural breaks. The method proposed by Bai and Perron (1998, 2003a) is more preferred in the literature because their approach investigates the multiple structural breaks for the linear regression model that is obtained by minimizing the sum of squared errors. Their procedure is based on dynamic programming which may be seen as a more efficient technique compared to other alternative approaches.

As the literature on detecting structural breaks progressed, the models taking into account the gradual changes rather than the discrete ones have been proposed. Lin and Terasvirta (1994) suggest using transition functions that define a function of t which is

allowed to shift gradually, and thus allows the change to be transitory or permanent based on the specification of the transition function. The inclusion of multiple transition functions also gives the flexibility to incorporate multiple overlapping structural changes.

Recent advances led to the nonparametric or semi-parametric representations of structural changes. An example is the Generalized Additive Models (GAM) proposed by Hastie and Tibshirani (1986) where they used the backfitting and local scoring algorithms for the estimation of the models.

The motivation in this current analysis to use a Time-Varying Parameter Vector Autoregressive Model (TVPVAR) is to allow model dynamics to change over time since economic dynamics are more likely to evolve in time rather than being constant; that parameter constancy is not expected in many situations. This approach gives flexibility in estimation and has been used before by Goodwin (1992) to forecast cattle prices in the presence of structural breaks as well as Bessler and Kling (1989) to forecast slaughter and feeder cattle prices; both studies confirmed that letting time variation in VAR models improved the forecast performance.

The analysis considers the extension of TVPVAR models to the case of stochastic volatility modeling scheme to consider the heteroskedasticity of additive innovations.

3.3.5. Forecast Evaluations

3.3.5.1. Traditional Statistical Loss Function Measures for Forecast Accuracy

The traditional statistical loss function measures of forecast accuracy may be categorized into three groups such as scale-dependent errors, percentage errors and scaled

errors. The first group—scale-dependent errors—just basically depends on the error term that is defined as the difference between the actual value and the fitted value of the variable i.e. $e_i = y_i - \hat{y}_i$ where y_i denotes the ith observation and $\hat{y}$ is the corresponding forecast of y_i.

Among the most commonly used, scaled-dependent errors are mean absolute error (MAE) and root mean squared error (RMSE), which are defined as:

$MAE = mean(|e_i|)$ and $RMSE = \sqrt{mean(e_i)^2}$

Scaled-dependent errors are not useful to compare series that are measured in different scales, so the percentage errors that have the advantage of being scale-independent are mostly preferred to compare the forecast accuracy of series that are on different scales.

The most popular percentage error is the mean absolute percentage error (MAPE), which is defined as $mean(|p_i|)$ where $p_i = 100e_i / y_i$.

However, since this measure has the disadvantage of asymmetry and is influenced by outliers, symmetric MAPE (sMAPE) is proposed by Armstrong (1985) to overcome these problems. sMAPE is defined as:

$sMAPE = [mean(200(y_i - \hat{y}_i)/(y_i + \hat{y}_i)]$

This measure is widely used in the literature even though it has some pitfalls such that in the case that y_i is close to zero, $\hat{y}_i$ is also likely to be close to zero making the calculation inconsistent. As an alternative to these measures, Hyndman and Koehler (2006)

proposed to use scaled errors such as mean absolute scaled error (MASE) and mean squared scaled error (MSSE) for seasonal and non-seasonal time series.

3.3.5.2. Tests of Forecast Equivalence

Although the traditional statistical loss function measures for forecast accuracy are widely used in the literature, none of them indicates whether the forecast obtained from one model is statistically better than the other. However, there are some approaches that aim to compare the forecast equivalence such as Ashley et al. (1980) (AGS) and Diebold and Mariano (1995) (MGN).

The procedure for the AGS test that is also defined by Goodwin (1992) and Bessler and Brandt (1992) may be summarized as follows:

The AGS test is the test of equality of mean squared errors (MSE) of two different models against the alternative that model 2's MSE is lower than model 1's MSE.

If we define $d_t = \alpha_1 + \alpha_2(s_t - smean) + \eta_t$ the test is performed by jointly testing the significance of the parameters $\alpha_1$and α_2 in the regression where *dt* is the difference between the forecast errors related to models 1 and 2 respectively i.e. e_1 and e_2, *st* is the sum of forecast errors e_1 and e_2, *smean* =sample mean of *st* , and η_t is a white noise process.

The test statistic for the AGS test is calculated as T S = ((SSER − SSEUR)/(k − 1))/(SSEUR/(n − k)) where SSEUR denotes the sum of squared residuals from the unrestricted model, *SSER* is the sum of squared residuals from the model that restricts α_1 =

$\alpha_2 = 0$, *n* is the number of observations in the sample, and *k* is the number of variables in the regression model. The AGS test statistic has an F distribution with 2 and n − 2 degrees of freedom under the assumption of normality and contemporaneously and serially uncorrelated error terms.

The assumption of contemporaneously uncorrelated error terms has been relaxed by the MGN test proposed by Diebold and Mariano (1995). This function also corrects for the autocorrelation that multi-period forecast errors usually have by using Newey-West type estimator for sample variance of the loss differential; the test also is robust to non-normality. In order to get pair-wise comparisons of forecast evaluations of competing models, the MGN test in addition to the traditional statistical loss function measure RMSE.

The test statistic of MGN test may be computed as following:

$MGN = \frac{\hat{\rho}_{sd}}{(1-\hat{\rho}_{sd})^{12}}(n-1)^{12}$ where $\hat{\rho}_{sd}$ is the estimated correlation coefficient between

$s = e_1 + e_2$

and $d = e_1 - e_2$ with e_1 and e_2 being the forecast errors for model 1 and model 2 respectively. Diebold and Mariano (1995) showed that this test is distributed normally .

3.4. Empirical Results

In order to get a general idea about the linear relationships between variables, the Pearson correlation coefficients given in Table 3.2 can be used. According to this table, cattle prices are highly correlated with hogs, broiler, corn and soybean prices with values of correlation coefficients over 0.80; however, the correlation coefficient of cattle prices and

the SP500 index is 0.50, which only suggests a moderate relationship between these two variables.

The second step of the empirical analysis consists of checking some time series properties of the data. The stationarity of the variables and possible cointegration relationship(s) between the variables are taken into consideration. To determine whether the variables are stationary, the Augmented Dickey Fuller (ADF) and Philips Perron (PP) test are employed; these results are presented in Table 3.3 and Table 3.4 for the levels and the first differences of the variables respectively. The results indicate that the null hypothesis of stationarity can still be rejected and thus conclude that the variables are not stationary in levels. When the same analysis is done with the first differences, stationarity is obtained, and it is determined that the variables are stationary in first differences, i.e., the variables are integrated of order one; I(1).These facts are supported by the careful examination of Figure 3.1 and Figure 3.2 that represent the path of the variables in levels and first differences respectively.

Figure 3.1 shows that the variables' means are not steady, and they show fluctuations over time and also tend to increase for almost all prices. The means of the first differenced variables exhibited in Figure 3.2 seem steadier, which supports the conclusions about the nonstationarity of the variables. Some structural changes / shifts in years 1991, 2005 and 2009 that can be related to recession in 1989-1991, Mortgage Crisis of 2005-2006 and world economic crisis realized in 2008-2009 that initially originated in the USA and then spread to the whole world, can be observed.

The economic crises/recessions observed in the data period had important direct and indirect effects in the U.S. agriculture. For instance, declining incomes around the world as a result of the 2008-2009 worldwide recession had lowered the demand for U.S. agricultural exports and ended up with lower agricultural export levels and prices for agricultural markets. This may be considered as one of the indirect international effects of these crises not based solely on changes in the U.S. economy. One of the specific reasons leading to this outcome is the change in the exchange rate of U.S. dollar; the short term effect of the crisis was to appreciate the U.S. dollar against other currencies belonging to the countries that U.S trades with such as China and South Korea because money from these countries flow into U.S. as U.S. is regarded as a safer place to invest under their current bad economic conditions. A stronger dollar makes U.S. agricultural products more expensive in foreign markets and reduces the competitive power of U.S. agricultural products, therefore resulting in lower export levels and lower prices.

Among the other indirect effects is the declining energy prices resulted from the decreases in economic activities due to economic crisis or recession. It is expected that the changes in the energy prices will not affect each sector in the same way. All producers except the ones producing feedstock crops such as corn and soybean are likely to benefit from energy price decreases; however, a fall in the energy prices will lower the prices of corn and soybean by cutting down the price of biofuels, and these producers will be the losers of this price reduction.

On the other hand, producers of meat and other livestock products such as cattle that use corn and soybean as a feedstock will benefit from the decrease of energy prices resulting from the declining economic activity. The direct effects of the crisis will come from the changes in the composition of demand due to declines in incomes. For instance, as a result of their lower income, people will be more likely to substitute more expensive meat products such as beef with cheaper meat products like hogs and broilers.

The financial institutions' positions under economic recession or crisis should also be taken into account. Financial crises such as the one observed in 2005-2006 will be likely to affect the farmers as they may alter the financial institutions' ability to lend to farmers; agricultural businesses, in turn, may decrease the demand of farmers for agricultural inputs used in production and limit some agricultural businesses that rely on credits or loans.

Figure 3.2 shows that the data supports the aforementioned direct and indirect effects caused by 1989-1991 recession in U.S. and 2008-2009 world economic crisis; the declining prices of corn, soybean and SP 500 index considered as a proxy for GDP that resulted from the declining economic activity and declining energy prices caused by recession can be observed.

In evaluating cattle, hogs and broiler prices in detail besides the mentioned declined activity in these markets that led to the changes in composition of meat demand, there also exists a significant factor that hugely affected the prices of these commodities: namely, animal disease outbreaks such as BSE and AI completely altered consumer confidence to consume these products and also changed the competition power of the countries that

traded with the U.S., resulting in some extra precautions on meat exports (Piggott & Marsh, 2014).

For instance, the 2003 detection of a cow in the state of Washington with BSE followed with additional outbreaks in 2005 and 2006 greatly influenced the U.S. beef trade, as consumer confidence was shaken; also, some countries such as Japan took extra precautions and either completely closed or limited their imports from U.S. This influenced the other countries' competition power against U.S. and, of course, resulted in demand and price declines for U.S. meat products. This fact can be easily observed from Figure 3.2 where the cattle prices hit the bottom in 2003 and price increases occur in the hog and broiler industries, as these industries benefited from beef trade difficulties due to the fact that customers switched to consumption of hog/pork and broilers. The U.S. hog/pork industry was the main benefiting actor of these incidences because the broilers industry also experienced AI outbreaks that decreased the demand for broilers in Asia and Eastern Europe and caused only short term disruption of consumption.

The next step of analysis involves checking any possible cointegration relationship(s) among variables. Johansen's cointegration test is employed for this purpose. The results of the test are given in Table 3.5 and show no cointegration relationship between the variables.

One drawback to use VAR type models with nonstationary data is that finite sample bias may be observed. There are some approaches proposed to estimate such models including vector error correction (VEC) models that difference the data to achieve

stationarity and include an error correction term to compensate for the long run information lost because of differencing the data. The second approach proposed is to estimate VAR models with raw data in levels if the non-stationary data is also cointegrated because recent theoretical work shows that estimation with such data will allow for consistent parameter estimates (Fanchon and Wendel, 1992). The third approach proposed as a solution to the mentioned problem is to use a Bayesian approach. Bayesian parameter estimates are not affected by non-stationarity (Sims, 1989); however, some researchers including Engle and Yoo (1987) argue that Bayesian analysis is not suitable for data that is also cointegrated. The reasoning behind Engle and Yoo (1987)'s work is that standard prior used in Bayesian analysis is approaching standard VAR model with differenced data and this model is mis-specified for data that is cointegrated because it does not involve an error correction term. Therefore, this technique is an option in this paper as no cointegration relationship(s) among the variables is observed. In sum, the nonstationarity of the variables and nonexistence of cointegration relationships support the use of Bayesian techniques for the current analysis (Fanchon and Wendel, 1992).

The analysis continues with concentrating on dynamic Bayesian TVPVAR model estimated using Markov Chain Monte Carlo (MCMC) method based on a Gibbs sampler that allows the parameters to vary over time, as the economic dynamics are expected to evolve in time rather than being constant; this integrates the volatility concept in VAR estimation.

To account for structural breaks that are expected to occur for several reasons in the U.S. cattle industry such as changes in marketing structure, changes in beef packing

industry, government interventions in grain markets affecting cattle prices etc., it is desired to incorporate a smooth transition function to model transition between regimes that characterizes structural change in forecasting cattle prices. TVPVAR model serves this aim implicitly by its time-varying structure that allows for both temporary and permanent shifts in the parameters in a flexible and robust way.

As the first step of any kind of VAR estimation is to determine the appropriate lag length(s), the minimum information criterion based on AIC was used, resulting in a lag of 9 as optimal given a maximum lag length of 12. So, standard VAR and TVPVAR with stochastic volatility models include a constant and 9 lags of the dependent variables.

Initially, the standard VAR models that neglect the existence of structural breaks and stochastic volatility are estimated to compare the forecasting performance of these models with TVPAR modeling framework that includes stochastic volatility to assess the importance of expected smooth structural changes and varying covariance matrices indicating possible changes of the volatility of disturbances. The impulse responses obtained from standard VAR forecasts are given in Figures 3.3-3.21 for three different horizons.

The details of the usual VAR impulse response graphics are considered in detail here; instead, the emphasis is on the simulated out-of sample forecast differences between standard VAR impulse responses and the impulse responses obtained from the TVPVAR models presented in Figures 3.23- 3.28 in addition to the contributions expected by including time variation and stochastic volatility in disturbance terms. The forecast horizons used for comparison are chosen as 30 (approximately one month), 60 (app. 2 months), 90

(app. 3 months), 120 (app.4 months) and 180 (app. 6 months) for the paper, but only 3 horizons (1 month, 3 months and 6 months) are interpreted here. The impulse responses belonging to the remaining horizons can be obtained from the author if requested.

For standard VAR models, the impulse responses are obtained for each set of two variables, whereas for the TVPVAR models, impulse responses are computed in an additional dimension such that they are calculated at all points in time using the time-varying parameters in a recursive fashion. To compute recursive innovations, already-calculated time-varying coefficients are accounted from existing date to future periods, and the forecasts are computed recursively with expansion of the sample each day.

Figure 3.22 presents a plot of the posterior means of the standard deviation of residuals of TVPVAR equations for each variable. Some important features may be obtained from this graph before comparing two models in details. First of all, the time varying paths of residuals are easily observed, which implies different variances for different periods of time that support the inclusion of time varying components into the model.

The later periods exhibit substantially higher volatility, especially for soybean and corn markets as well as for SP-500 index. The hogs and broilers markets exhibit the opposite behavior, showing that the volatility for these markets seems to be higher in the initial periods of the study.

Figures 3.23-3.28 show the impulse responses of each variable in three different dates of the sample: 1 month, 3 months and 9 months respectively for TVPVAR with stochastic volatility and allows for observation of the evolution of responses in short,

medium and long run periods. In the short period (1 month), there exist some notable differences between impulse responses of two models for the soybean market. The response of cattle prices to a shock in the soybean market tends to be more volatile in the TVPVAR modeling framework compared to standard VAR model and also leads to a decrease in cattle prices, whereas the response of cattle behaves quite differently in the VAR model. Cattle prices increase initially in this market after a shock is given and seem more stable over the time period.

A similar opposite kind of response is also observed in the corn markets. There is a huge decrease in corn prices in the initial period of time after the shock in the TVPVAR model, whereas corn prices seems to increase slightly in the VAR model. One other distinction for these markets is that for the later periods in this horizon, the TVPVAR model exhibits much more volatility compared to the standard VAR model.

The other responses work in the same direction with some differences observed in the horizon. The soybean price initially increases as a result of a shock in the soybean market and exhibits some volatility over the period, but it then ends up close to a pre-shock level in the TVPVAR modeling framework. However, this tendency to reach pre-shock level is not realized in the standard VAR model, as observed.

The response of price index SP-500 seems more volatile and tends to reach an equilibrium level in the TVPVAR model, whereas the price index always stays above the equilibrium levels in the standard model for the whole 1 month period, again not satisfying the expectations. When examining the responses of hogs and broilers to a shock in soybean

prices, only some slight differences were shown. More volatility exists in the TVPVAR modeling framework compared to the standard model, though they tend to show the same type of reaction to the shocks (i.e.. decreases in hog prices and increases in broiler prices).

For the hogs market, what is shown from the impulse responses is completely different for all variables considered. For instance, when a shock is given to the cattle market, the hog prices tends to increase for about 1 week and gradually decrease; it takes more than 1 month to reach an equilibrium level in TVPVAR framework. However, in the standard model, hog prices tend to return to pre-shock level in the very initial periods with only a slight increase in price levels. The self-response of hog prices to a shock does not seem to end up at pre-shock level at this horizon for the standard VAR model, but tends to be volatile around zero with initial price decreases in the TVPVAR model.

The broiler market also exhibits differences to the shocks introduced in the system. For the standard model, after reaching the pre-shock level after only a few days, it seems to get further and further from this level. In the TVPVAR model, the price reaches the pre-shock level with volatilities in the first 3 weeks of horizon.

Departures from the pre-shock level are also observable in the corn, soybean and SP-500 prices after a shock given to hog prices in the short run. The conclusion gained from the impulse responses related to these markets is that in the TVPVAR modeling scheme the prices show volatilities around the pre-shock level; however, in the standard model, they depart from these levels after a few weeks.

The trend of responses in broilers markets in short run horizon also shows proof of different actions for two models considered in this paper. In all of the markets, it is observed that in the TVPVAR framework, prices come back to their pre-shock levels as opposite to the standard models. For the cattle market, the prices are always above the pre-shock levels and never get close; this conclusion is also true for the VAR model with the only difference being the volatilities in the whole horizon after a shock given to broiler prices.

Hog prices in the short run are volatile around zero and catch pre-shock levels with slight decreases in price levels in the TVPVAR model. An opposite reaction is exhibited in the standard model without catching pre-shock price level and show moderate price increases. Own response of broiler prices also differ between two models; as mentioned before, in the standard model, the price level never catches the pre-shock level. However, the price approaches this level with some volatilities in the initial periods in the TVPVAR model. Corn markets show a similar path in the TVPAR modeling framework and corn prices catch the pre-shock level in 2 weeks but get further from that level in the later periods in the standard model.

The soybean market behaves completely different under the two models with respect to reaching to pre-shock level such that the standard model shows ongoing increases in price levels and a divergence behavior away from the equilibrium; however, according to the TVPVAR framework, the soybean price catches that level in about 3 weeks but shows only slight departures from that level as time goes by. As a result of a shock to

broiler prices, SP-500 exhibits little volatility in the initial periods of the horizon and starts to get away from pre-shock level afterwards in the standard model, whereas the equilibrium level is caught some volatile decreasing prices in the time varying framework.

Considering the cattle market in response to a shock in corn prices, similar responses are shown in both models. In both models, cattle prices do not seem to come to pre-shock level and are always located above that level with only difference observed is VAR model exhibits more stable price movements.

Hog prices in response to a shock in corn prices show similar paths in terms of the changes in prices except the fact that TVPVAR seems to catch the pre-shock level in 1 month, whereas in standard model the price level diverges from that level in further periods.

One notable difference between the way broiler prices act as a result of a shock given to corn prices is that VAR model responses seem to be not affected at all from this shock and stay stable in all periods. However, TVPVAR model responses just suggest highly volatile prices.

The own response of corn price to a shock in its own price exhibits some similarities between the two models in a way that both prices tend to stay above the pre-shock level and VAR model seems to never catch it, whereas in TVPVAR model the price level gets close to that level in future horizons.

Volatility around equilibrium level is the basic feature of soybean response to a shock given to corn prices for TVPVAR model. The impulse response graphics of the

standard model is quite different then TVPVAR, suggesting that the price level of soybeans is always above the pre-shock level with slight increases in the initial period, but never reaches or gets closer to that initial price level.

SP-500 stays volatile around the pre-shock level in TVPVAR model, whereas it is always stable above a level greater than the equilibrium point in standard model after a shock introduced in corn prices, which is as expected. The basic differences in responses from a shock given to the SP-500 index emerges from cattle and hogs markets. Cattle prices seem to be volatile around pre-shock level after an initial decrease in price level in the first 4-5 days in the time varying model, whereas in the standard model, the cattle price reaches the pre-shock level in 2 weeks and tend to stay there. In addition to that, little volatilities are observed in the first week after the shock and cattle prices show an increasing trend.

Hog prices are not stable in the first week but seem to be volatile around pre-shock price level in 1 month in TVPVAR model, just opposite to the standard model that exhibits an increasing trend and a divergence behavior from the pre-shock level as a result of a shock in SP-500.

Responses of broilers and corn markets follow a similar path both in the TVPVAR and standard VAR models. In the time varying model, they are not stable and tend to reach the pre-shock level, but the model does not catch it and divergence from that level with an increasing trend in prices is observed for the standard models.

Self-response of SP-500 also shows a similar path for both models in a way that they tend to stay above the pre-shock level over the horizon with one difference being more volatile in the time varying structure.

The results that stand out for the analysis of the prices in return to a shock given to cattle prices are mostly similar to the previous results obtained from two models. The cattle prices in both models exhibit the same initial decreases in the first week followed by minor increases in the second week and reach pre-shock level in TVPVAR but not in VAR after a shock given to cattle prices.

Hog and broiler prices are again volatile around pre-shock level in the time varying model in response to a shock in cattle prices, whereas an increasing trend that leads to a price level which is above the pre-shock level for the rest of the horizon in standard model is observed.

Corn and soybean prices tend to exhibit moderate price increases and converge to the pre-shock level with volatilities observed as a result of shock applied to cattle prices.

The responses of SP-500 in both models show some similarities as well as differences. First of all, they follow the same path in terms of the initial increases followed by decreases in the first 2 weeks. Second, the process of reaching the pre-shock level is different such that in TVPVAR model, the price level gets closer to that level, but in the standard model we can observe the divergence of prices from that level.

A few results stand out from the comparison of these two models before evaluating their longer run (3 months, 6 months) forecast performances. Initially, for the short run (1

month), most of the time in the TVPVAR models, the prices reach to their pre-shock levels as opposed to the standard VAR models that ignore time variation and stochastic volatility of the disturbances. Apart from that, our expectations about the way that these prices interact with each other in the market are also mostly supported in the TVPVAR framework compared to the standard VAR models.

When we check the longer horizon impulse response results, obviously over time, the path (behavior) of responses do not change much for the initial periods, but they tend to become more stable over larger horizons in TVPVAR modeling framework, signaling that the estimated coefficients do not show much time variation for larger forecast horizons after the short term. They are still able to be predicted in a robust way with these models. So, with all the other reasons considered such as expectations about the behavior of impulse responses, especially the cross impulse responses and the time needed to reach the pre-shock levels, the TVPVAR modeling is superior to the standard VAR model in terms of forecasting. Also of note is that time varying variance and covariance matrixes play an important role for analyzing long run responses. For larger horizons, the standard errors of the forecasts get larger in TVPVAR model, but this should not be surprising as the out of sample parameters have to be simulated recursively, which may introduce some accumulated uncertainty for forecasts in longer horizons taken into consideration.

Even though there are enough reasons to conclude that TVPVAR model is superior to the standard VAR model, the last step in the analysis involves comparing the forecasting performances of these two models based on a test of forecast equivalence proposed by

Diebold and Mariano (1995). Table 3.6 presents the results of MNG test for 3 different horizons. According to these test results, the null hypothesis of equality of forecast accuracy is rejected under the general assumptions that also take into account the autocorrelation problem that might be observed in large horizons and non-normality problem. The test results suggest using TVPVAR framework for some but not all of the cases compared to the standard VAR. According to the MNG test results, for all horizons, the TVPVAR modeling is superior to VAR modeling only in two cases: hogs and soybean prices. Root mean squared errors (RMSE) were also obtained to see forecast accuracy differences between two models. The results exhibited in Table 3.9 provides the same conclusion: the TVPVAR model has more forecast accuracy for hogs and soybean prices, but this fact is not supported for the rest of the prices.

The last step of the analysis involves checking the diagnostics of the models compared. For this purpose, only the results from the long horizon (6 months) were used. The results of Ljung-Box Q Autocorrelation test and Jacque-Berra Normality test are given in Tables 3.7-3.8 respectively. According to Table 3.7, VAR models exhibit more autocorrelation problems compared to the TVPVAR model, whereas non-normality behavior is only observed in VAR modeling framework but not in TVPVAR which is a supplemental support to prefer TVPVAR for forecasting.

Overall, taking into account expectations about the behavior of cross the impulse responses, the process of reaching to pre-shock levels and the MNG test results suggest

that the nonlinear TVPVAR model improves over the standard VAR forecast for 1 month, 3 months and 9 months ahead horizons for most of the time.

3.5. Discussion

Changes in the commodity prices have an important effect on the revenues, cost, and profits of the agricultural businesses and agricultural producers; therefore, optimal and efficient forecasts of agricultural prices help firms to improve the economic decision process and play an important role in planning formation.

The purpose of this paper was to investigate the potential of a time series analysis technique, namely the Time Varying Parameter Vector Autoregressive Model (TVPVAR) technique, in the development of daily forecasting models for cattle prices in the presence of structural changes. More specific objectives included integrating smoothing techniques and stochastic volatility into TVPVAR modeling framework based exclusively on time series for cash-cattle prices. The goal was to then compare the accuracy of the forecasting performance of this model with the standard VAR model that ignores time variation in parameters and possible time variation in the variance-covariance matrix of disturbance terms to determine if the inclusion of the time varying component into the conventional VAR structure and also the extension of the TVPVAR to include stochastic volatility improves the forecast results.

To prevent inaccuracy and bias problems in the estimation process, the determination of structural breaks was given great consideration, the relevant literature

progressed from models taking into account single and discrete changes to more advanced models concentrating on multiple and gradual changes.

For the purpose of this paper, the structural breaks were integrated into the analysis with the help of smooth transition functions that are integrated into TVPVAR models, allowing for modeling dynamic changes over time and also allowing both gradual and sudden changes to be integrated into the analysis since economies are expected to evolve in time rather than being constant, and that parameter constancy is not expected in many of the situations.

Impulse-response functions that trace out the response of current and future values of each of the variables in the model to a one-unit increase (or to a one-standard deviation increase, when the scale matters) in the current value of one of the VAR errors were obtained to observe the long run effects and the time paths of variables. The responses were examined in detail for three different horizons in order to compare the forecast performances for longer periods of time. The main conclusion obtained from the impulse response results is that integrating the time variation and a variance-covariance matrix that allows the disturbances to change over time improved the forecast results both in the short and long run; this conclusion is supported by the expectations about the path of cross impulse responses and also MNG and diagnostic test results.

One of the main conclusions obtained from this paper is that letting time variation in VAR models improve the forecast performance. Also, from the evaluation of impulse responses, some insights about the market interactions can be obtained. According to the

orthogonalized impulse responses for short run (1 month), these can be summarized as follows:

From Figure 3.6 it may be noted that after the shock on corn price, only soybeans and GDP have initial increases in the first three days, whereas the responses of the other variables become insignificant when taking into account the confidence band.

Figure 3.3 shows that soybean has a price response which is expected, yet most of the markets have insignificant responses. However, an unusual result obtained is that a shock introduced in the soybean market leads to an increase in GDP in the first week.

In Figure 3.8, the impulse responses from shocks to cattle prices on each market are determined for each estimated period. The results suggest that a shock in the cattle market leads to an increase in the hog prices which is expected because of the possible substitution effect between these goods. As the price of cattle increases, people may be more likely to consume hogs which can be regarded as a substitute for beef. Broiler prices increase on the fourth day before this increase becomes insignificant. The responses of the other variables become insignificant when taking into account the confidence band. An unusual result is that a shock in live cattle prices does not produce any significant response function on both corn and soybean prices.

Unexpected results regard the anticipated relationships between hog and all other prices. For instance, a shock introduced in the hogs market does not seem to produce any significant effect on any price except its own price, which is not likely to occur (Figure 3.4).

The broiler market shows exactly the same behavior with insignificant responses (Figure 3.5).

The results obtained from the impulse responses to a shock in GDP are in accordance with expectations. Figure 3.7 shows that after a shock in GDP, none of the responses seem significant when the confidence bands are taken into account.

In sum, the main results are partially consistent with the literature on cattle prices. As already indicated, this paper took a Bayesian approach. This methodology does not require stationary variables as long as the condition of no cointegration is satisfied. For future research, analysts may want to observe the results considering stationarity and also may prefer to use different priors.

Also, we like to note that many insignificant impulse response results are obtained from the TVPVAR models. This might be due to the sensitivity of impulse responses to seemingly innocent prior assumptions because many common priors imply that posterior densities for impulse responses have no moments (Koop et al. 1994) or correlated independent variables (Auer, 2014) leading to inaccurate and insignificant IRF's (Curse of Dimensionality Problem). The seemingly high correlation coefficients may lead us to spurious relationships as suggested by Granger and Newbold (1974).Researcher might attempt to try the analysis with different priors or overcome the autocorrelation problem to overcome the problem of insignificant impulse response results.

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TABLES AND FIGURES

Table 3.1: Summary Statistics for Data Covering Period 1991:Q1-2013:Q2

Variables	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Cattle	0.7265	0.8424	0.9566	1.0020	1.1060	1.5530
Hogs	0.3477	0.7939	0.9699	1.0010	1.1860	1.6540
Broilers	0.7598	0.8488	0.9287	1.0010	1.1640	1.6430
Corn	0.4890	0.6492	0.7995	1.0030	1.1310	2.5320
Soybean	0.5599	0.7298	0.8176	1.0000	1.2130	2.2300
SP 500	352.30	676.5	1113.0	1005.0	1287.0	1607.0

Table 3.2: Pearson Correlation Coefficients

	cattle	hogs	broiler	corn	soybean	SP500
cattle	1.0000000	0.8185905	0.8143351	0.8003852	0.8127766	0.4862240
hogs	0.8185905	1.0000000	0.7681042	0.6801547	0.6829798	0.5741698
Broiler	0.8143351	0.7681042	1.0000000	0.7457851	0.8279083	0.6147556
corn	0.8003852	0.6801547	0.7457851	1.0000000	0.9451792	0.3437792
Soybean	0.8127766	0.6829798	0.8279083	0.9451792	1.0000000	0.3706160
SP500	0.4862240	0.5741698	0.6147556	0.3437792	0.3706160	1.0000000

Table 3.3: Augmented Dickey Fuller (ADF) Unit Root Tests (Levels)

Variables in Levels	**ADF Test statistic**	**p Value(ADF)**
Cattle	-1.6286	0.7291
Hogs	-4.1886	0.01
Broilers	-1.9398	0.601
Corn	-1.328	0.8528
Soybean	-1.3024	0.8634
SP 500	-2.3951	0.4135
Alternative Hypothesis: Stationary		
Variables in First Differences	**ADF Test statistic**	**p Value(ADF)**
Cattle	-4.2044	0.01
Hogs	-4.209	0.01
Broilers	-4.1557	0.01
Corn	-4.6239	0.01
Soybean	-4.7239	0.01
SP 500	-3.2832	0.07933
Alternative Hypothesis: Stationary		

Table 3.4: Philips Perron (PP) Unit Root Tests (Levels and First Differences)

Variables in Levels	**PP Test statistic**	**p Value(PP)**
Cattle	-7.2994	0.6904
Hogs	-24.853	0.01883
Broilers	15.8684	0.1868
Corn	-8.0188	0.6482
Soybean	-8.4442	0.6231
SP 500	-7.4915	0.6791
Alternative Hypothesis: Stationary		
Variables in First Differences	**PP Test statistic**	**p Value(PP)**
Cattle	-96.6438	0.01
Hogs	63.5993	0.01
Broilers	-71.7218	0.01
Corn	60.2401	0.01
Soybean	-57.5663	0.01
SP 500	50.8997	0.01
Alternative Hypothesis: Stationary		

Table 3.5: Johansen Cointegration Test Results

Cointegration Rank Test Using Trace						
H0:	**H1:**	**Eigenvalue**	**Trace**	**5% Critical Value**	**Drift in ECM**	**Drift in Process**
Rank=r	**Rank>r**					
0	**0**	0.3335	82.4715	93.92	Constant	Linear
1	**1**	0.2313	47.171	68.68		
2	**2**	0.1251	24.2845	47.21		
3	**3**	0.0721	12.6601	29.38		
4	**4**	0.0437	6.1492	15.34		
5	**5**	0.0257	2.2652	3.840		

Table 3.6: Diebold and Mariano Forecast Equivalence Test Results

Horizon	**h= 180**	**h= 90**	**h=30**
C1	-61.48	-52.52	-51.52
C2	2.35	2.61	3.28
C3	-65.13	-56.67	-50.19
C4	-30.61	-37.20	-36.79
C5	0.96	1.14	1.61
C6	-43.02	-54.27	-52.92

Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

Table 3.7: Ljung-Box Q Autocorrelation Test statistic Results (p values)

	c1	c2	c3	c4	c5	c6
TVPVAR	0.0175 *	0.7569**	0.00017993*	0.0929**	0.0929**	0.4987**
VAR	0.00040338 *	0.000033563*	0.0419*	0.2545**	0.1759**	0.0022*
* Reject H0 **Not able to reject H0						

Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

Table 3.8: Jacque-Berra Normality Test statistic Results (p values)

	c1	c2	c3	c4	c5	c6
TVPVAR	0.0659**	0.5**	0.1281**	0.4682**	0.5**	0.5**
VAR	0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
* Reject H0 **Not able to reject H0						

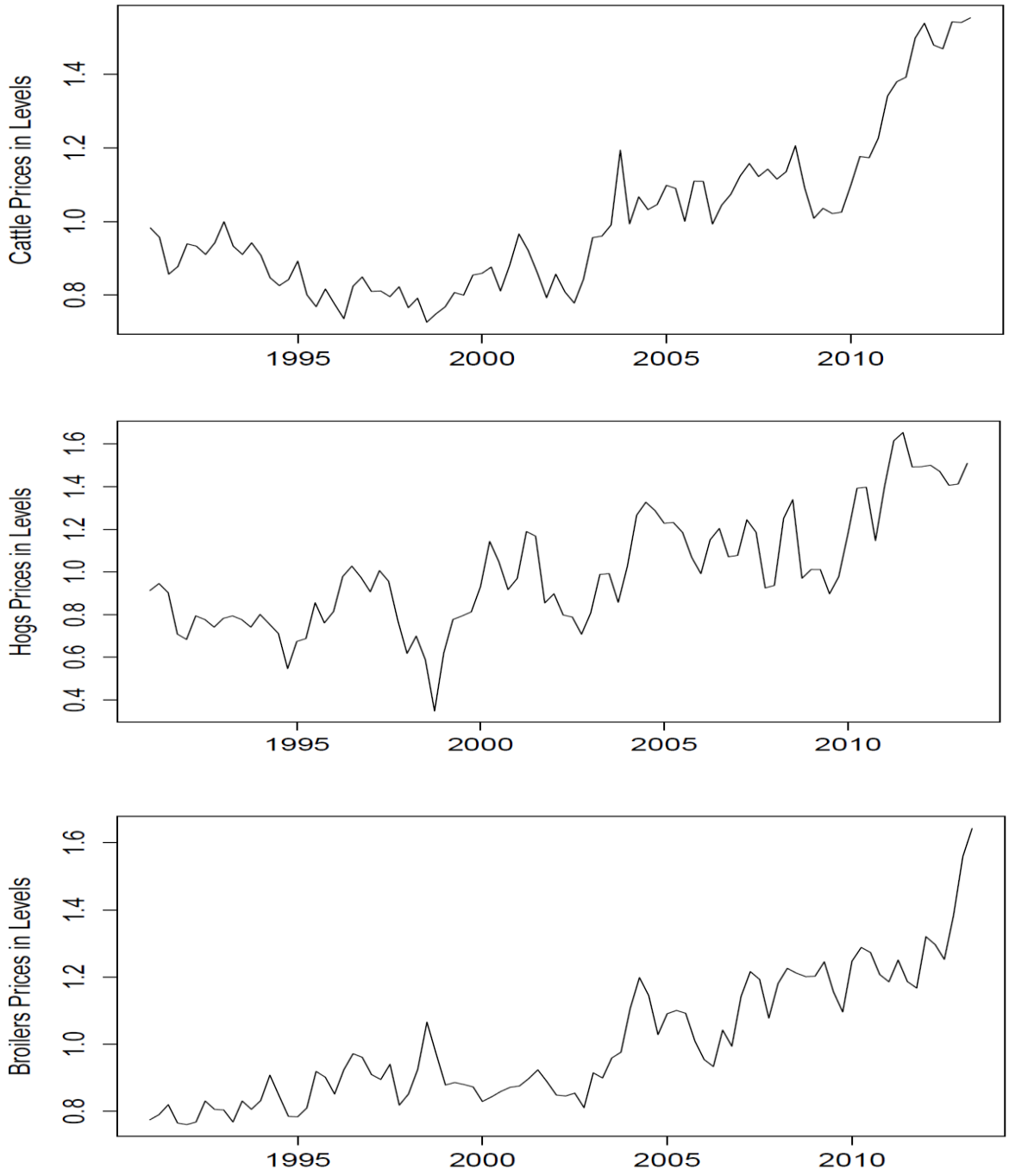
Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

Table 3.9: Root Mean Squared Errors (RMSE) Results

	VAR	TVPVAR
C1	0.0113	0.0475
C2	0.0219	0.0156
C3	0.0112	0.2599
C4	0.018	0.0448
C5	0.0153	0.0142
C6	0.0116	0.1122

Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

Figure 3.1: Time Series of the Variables in Levels


Cattle Prices in Levels
0.8
1.0
1.2
1.4
1995
2000
2005
2010
Hogs Prices in Levels
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1995
2000
2005
2010
Broilers Prices in Levels
0.8
1.0
1.2
1.4
1.6
1995
2000
2005
2010

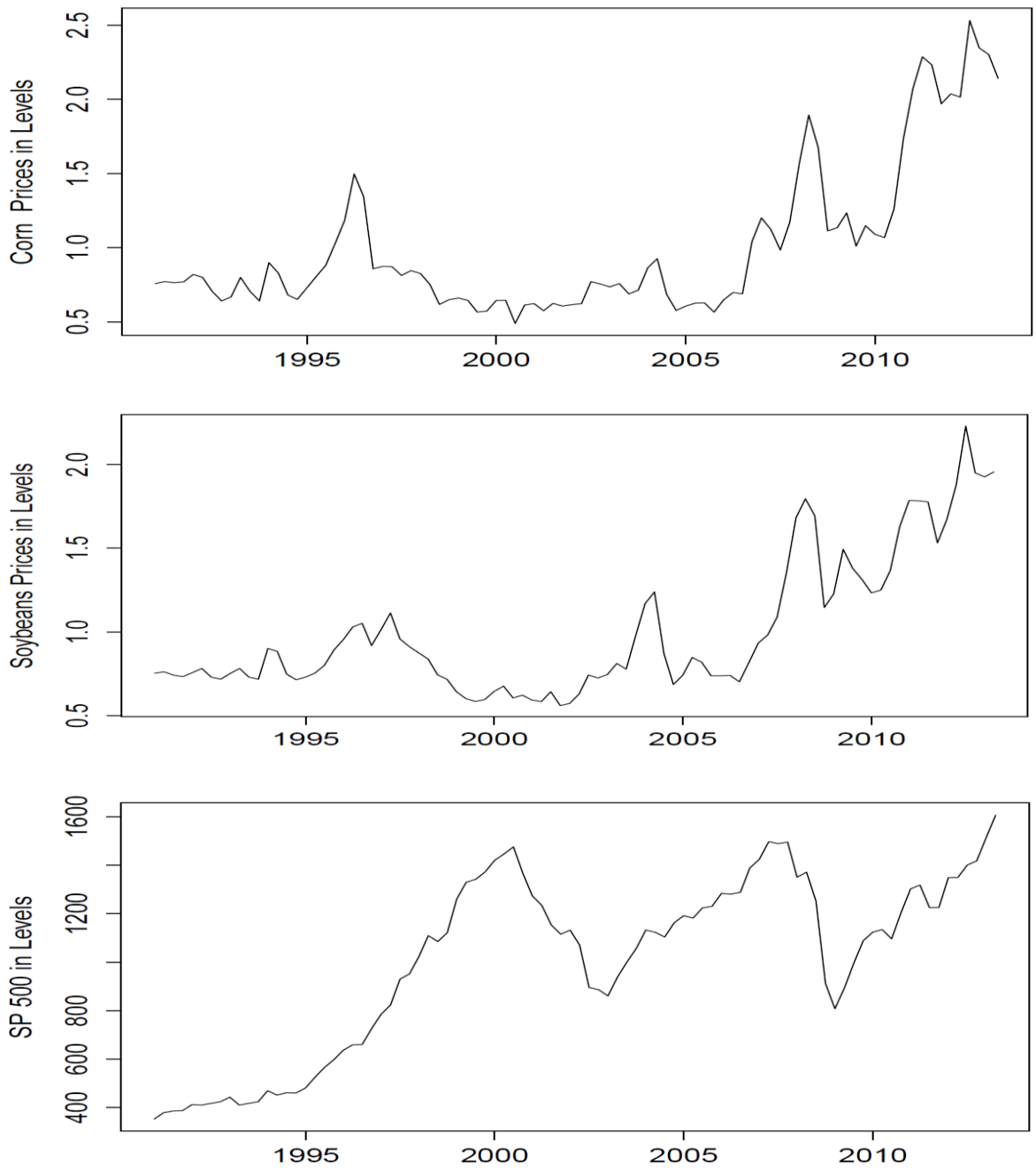
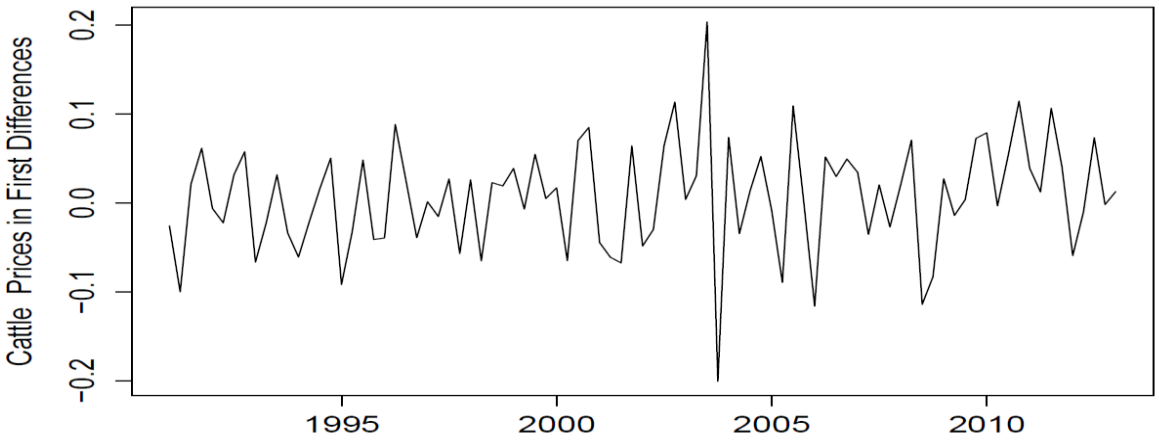
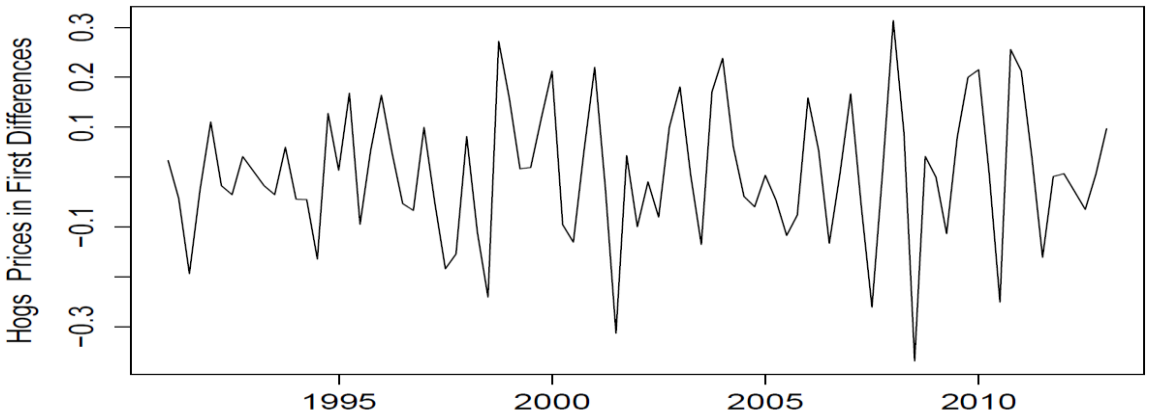
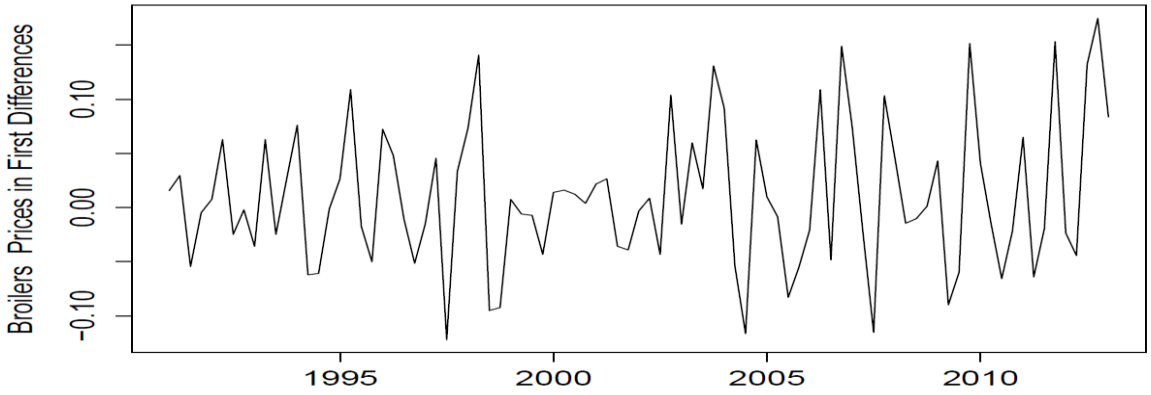

Corn Prices in Levels
0.5
1.0
1.5
2.0
2.5
1995
2000
2005
2010
Soybeans Prices in Levels
0.5
1.0
1.5
2.0
1995
2000
2005
2010
SP 500 in Levels
400
600
800
1200
1600
1995
2000
2005
2010

Figure 3.2: Time Series of the Variables in First Differences


Cattle Prices in First Differences
0.2
0.1
0.0
-0.1
-0.2
1995
2000
2005
2010

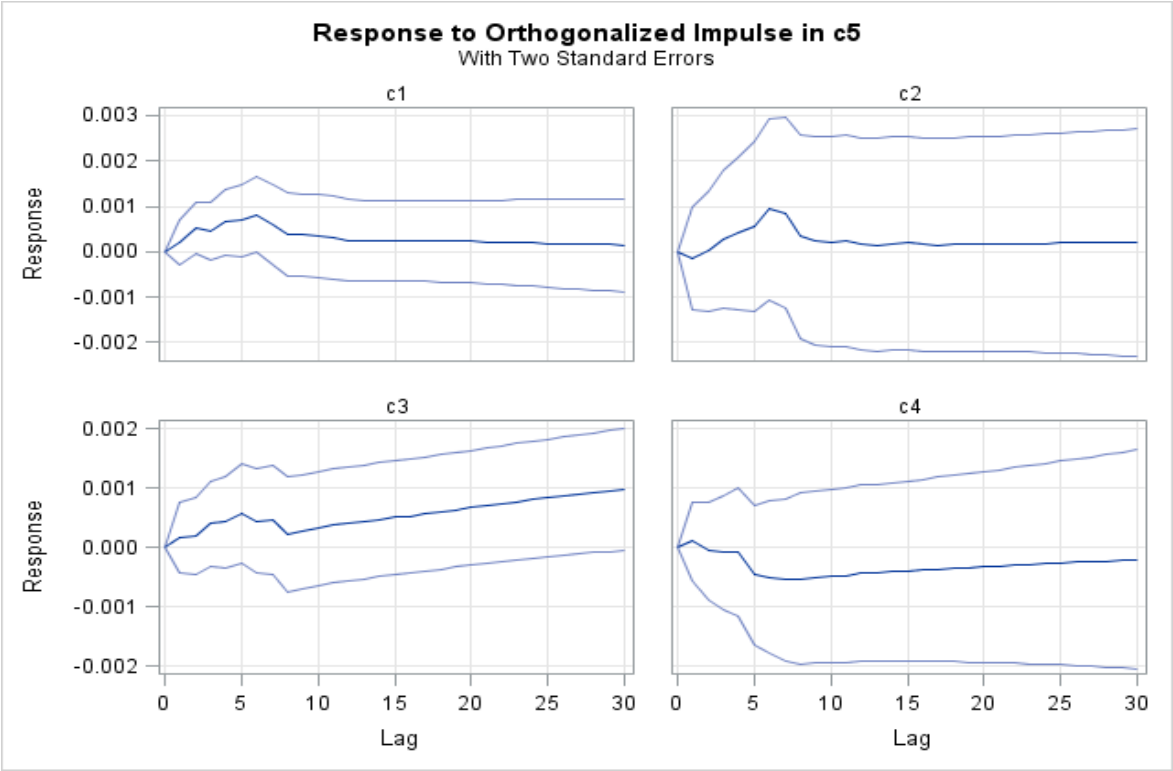

Hogs Prices in First Differences
0.3
0.2
0.1
-0.1
-0.3
1995
2000
2005
2010

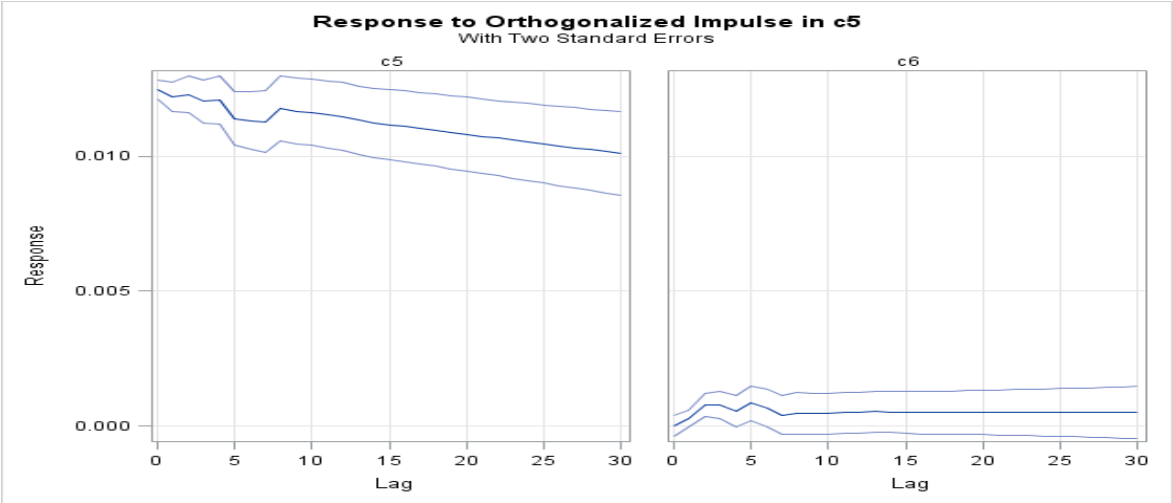

Broilers Prices in First Differences
0.10
0.00
-0.10
1995
2000
2005
2010


Corn Prices in First Differences
-0.6
-0.4
-0.2
0.0
0.2
0.4
1995
2000
2005
2010


Soybeans Prices in First Differences
-0.4
-0.2
0.0
0.2
1995
2000
2005
2010

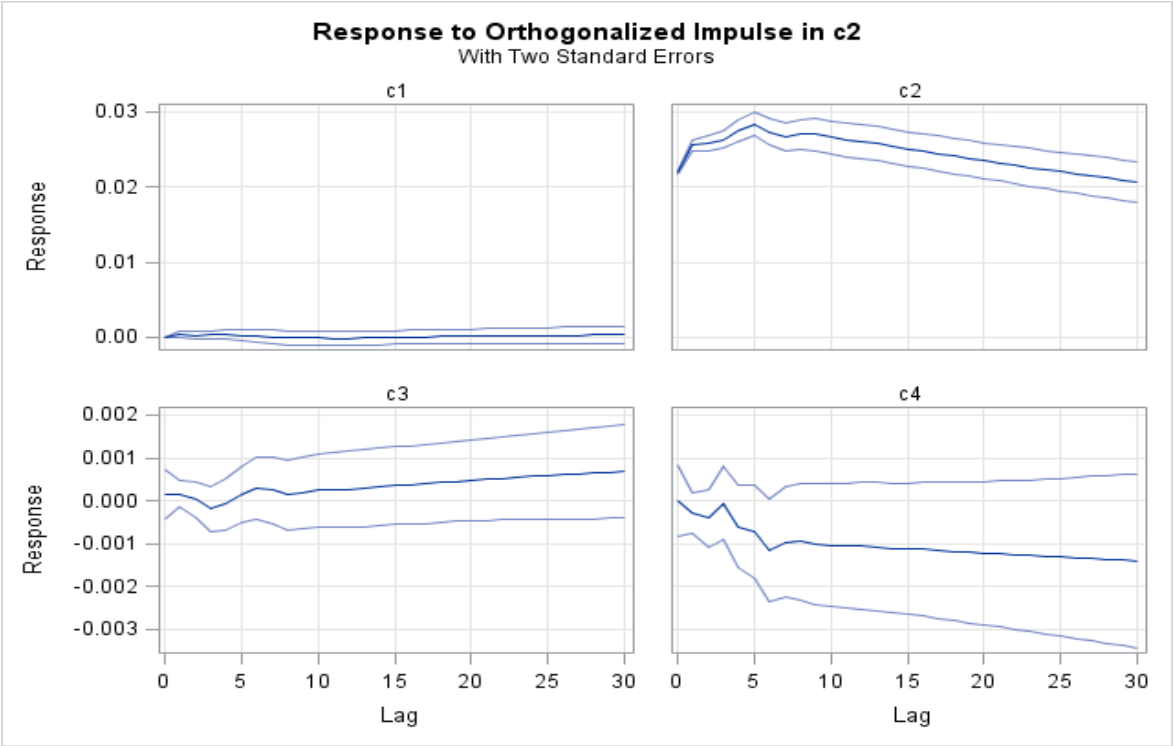

SP 500 Prices in First Differences
-300
-200
-100
0
100
1995
2000
2005
2010

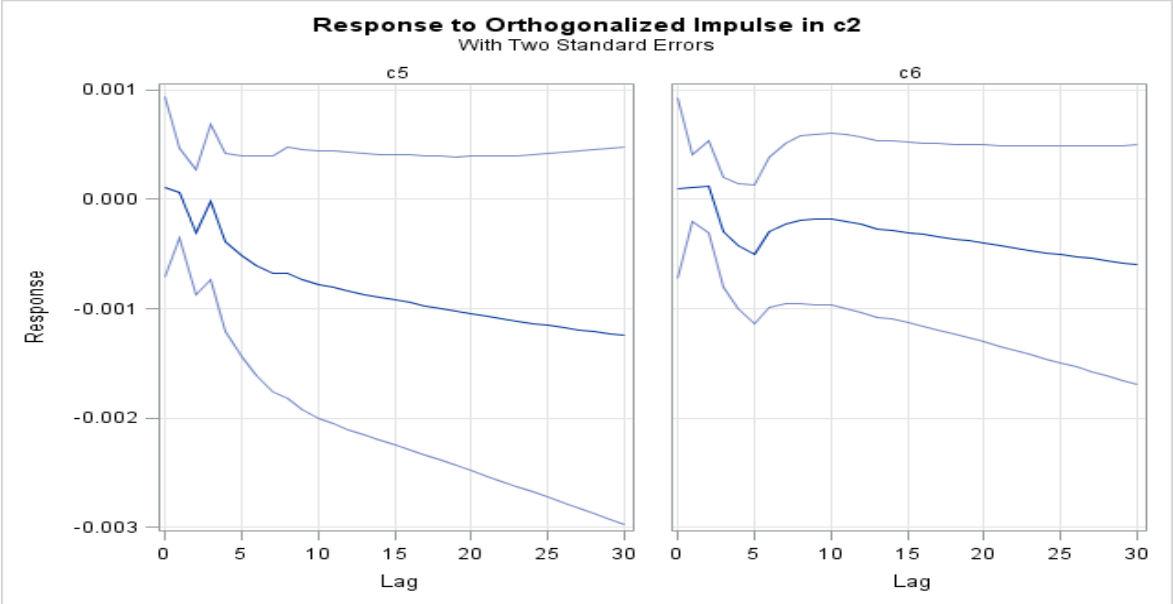




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

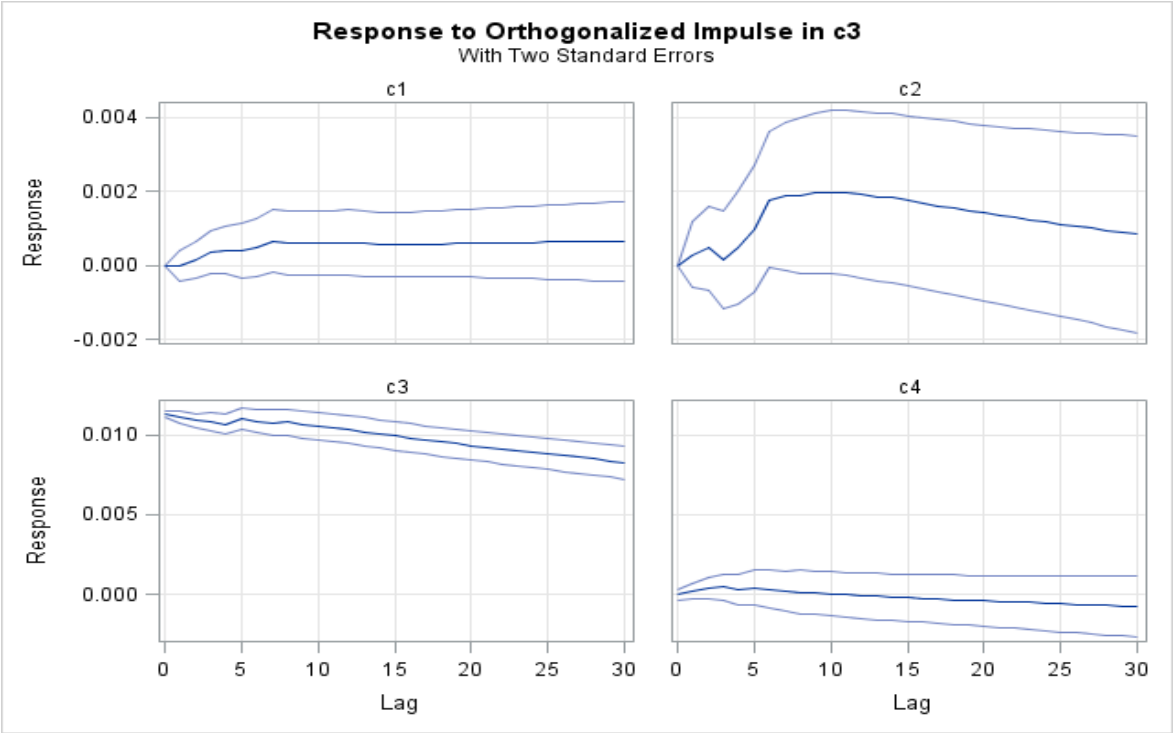
Figure 3.3: Response to Orthogonalized Impulse in Soybean Prices (1 month)

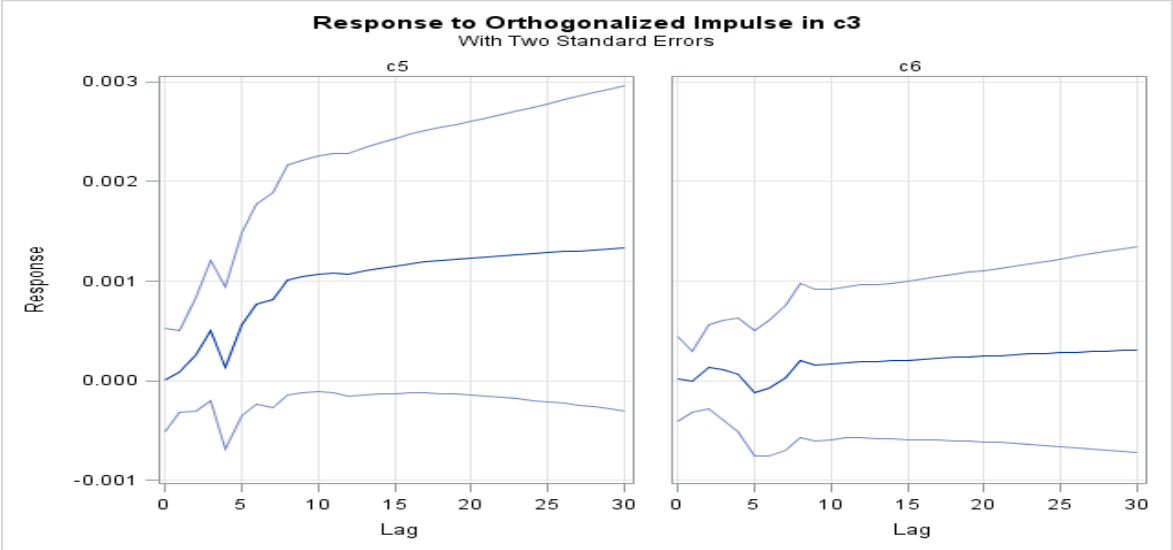




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

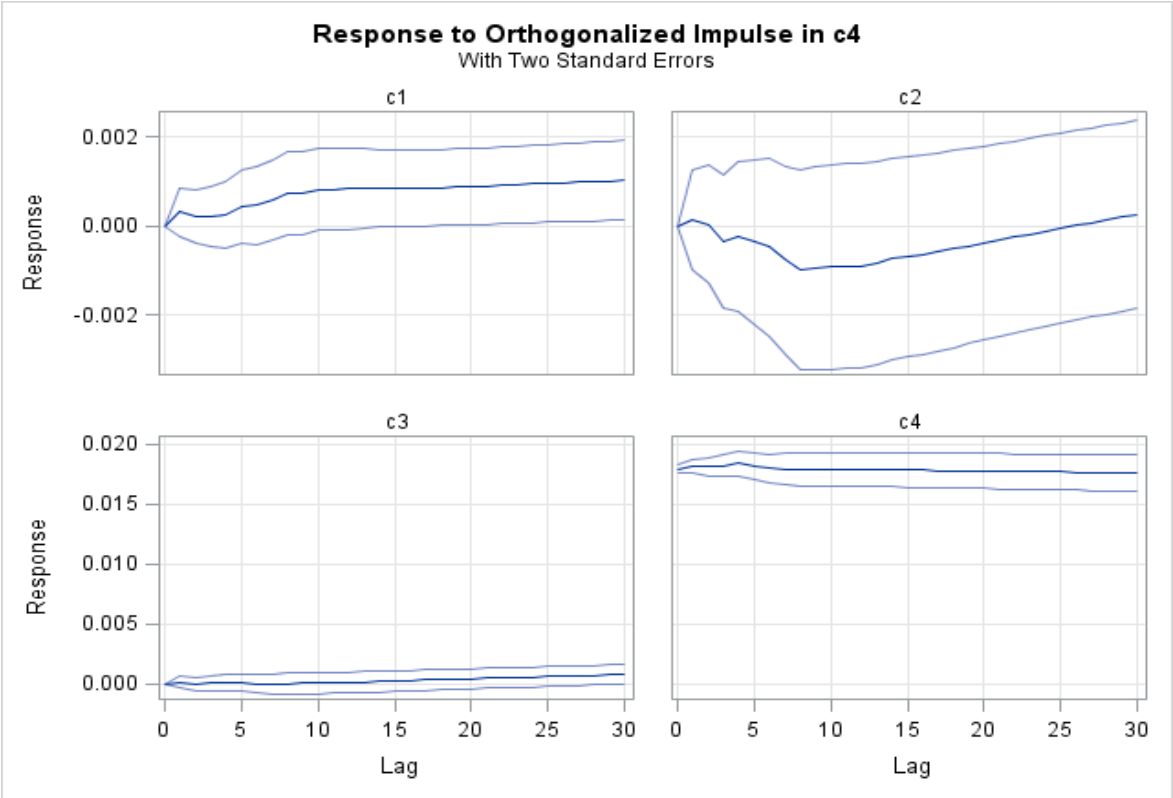
Figure 3.4: Response to Orthogonalized Impulse in Hog prices (1 month)

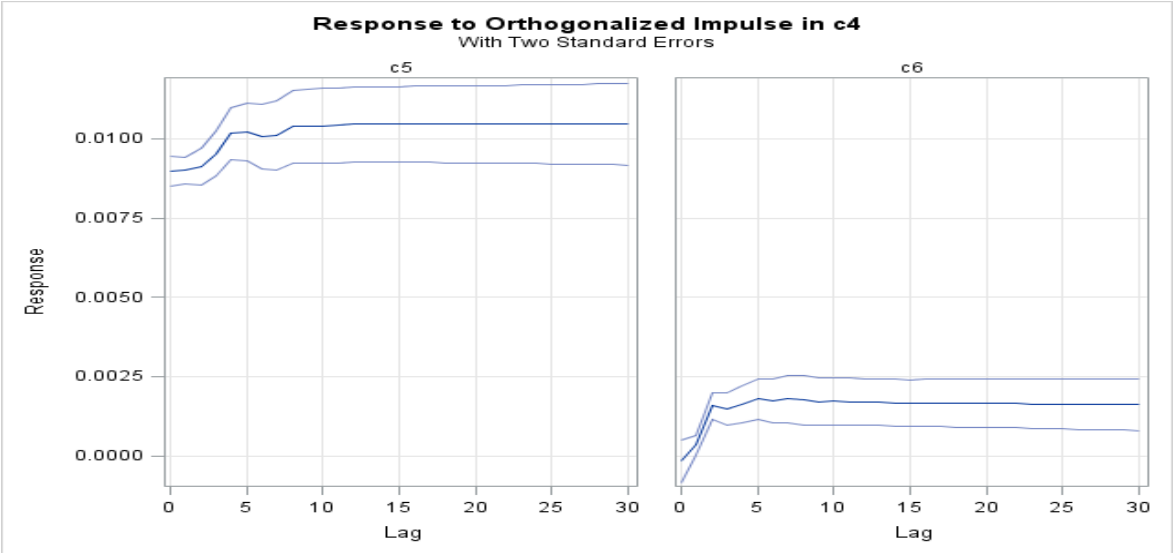




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

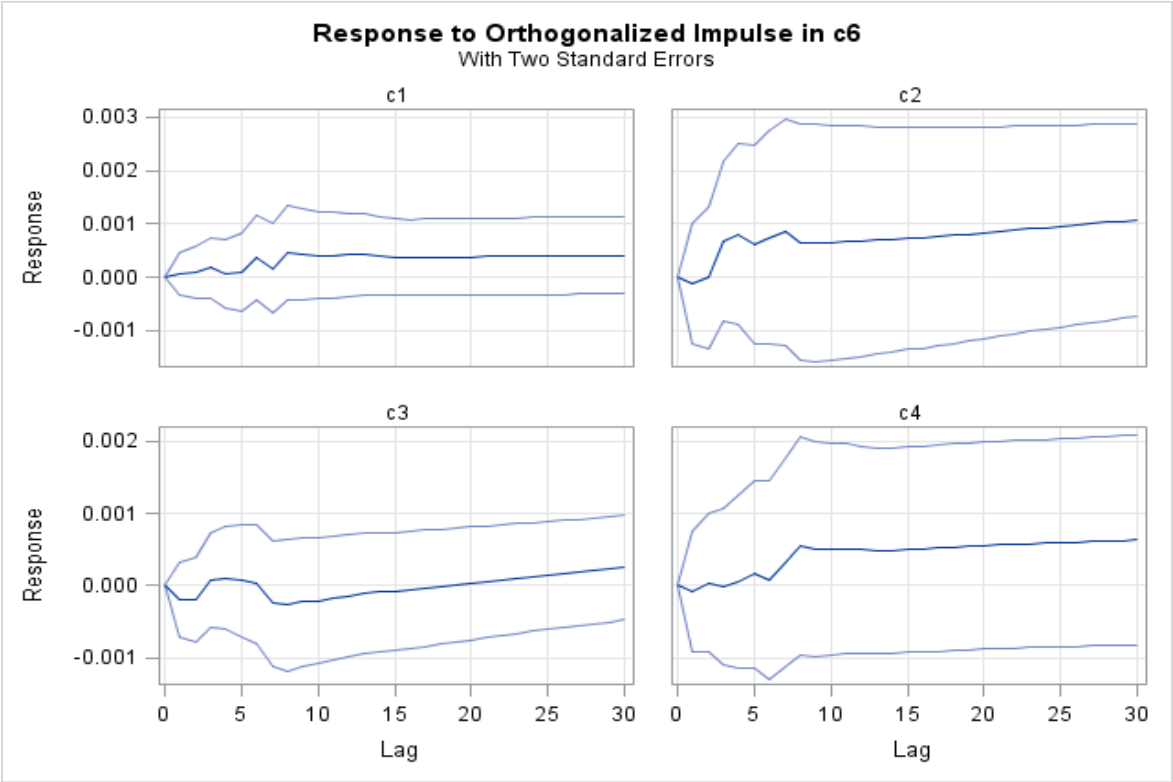
Figure 3.5: Response to Orthogonalized Impulse in Broiler prices (1 month)

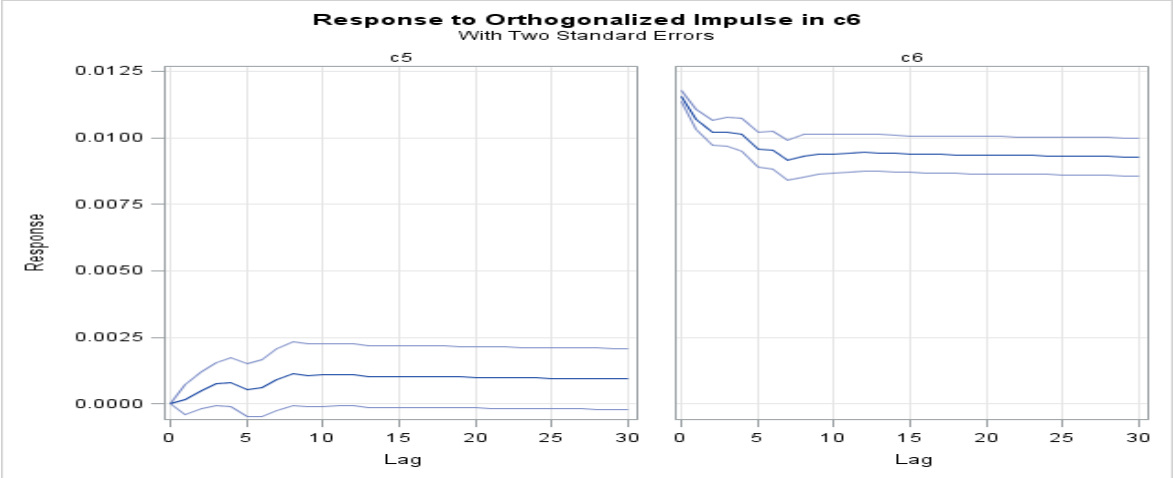




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

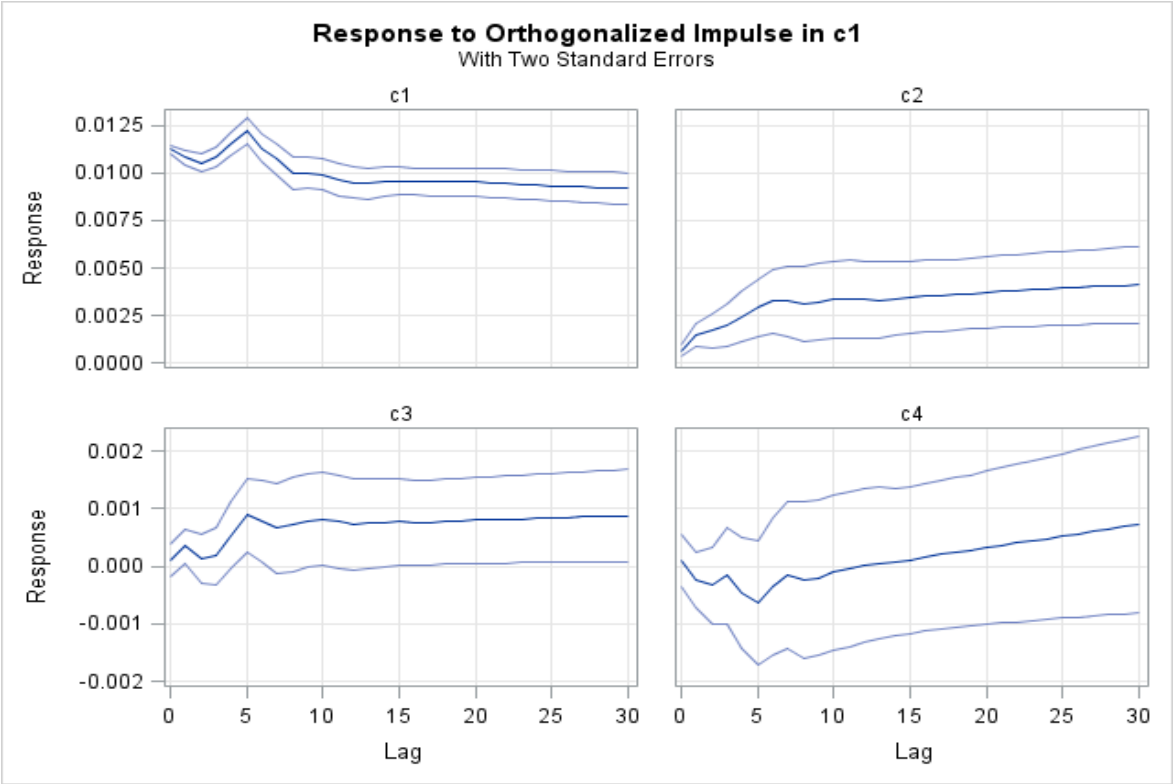
Figure 3.6: Response to Orthogonalized Impulse in Corn Prices (1 month)

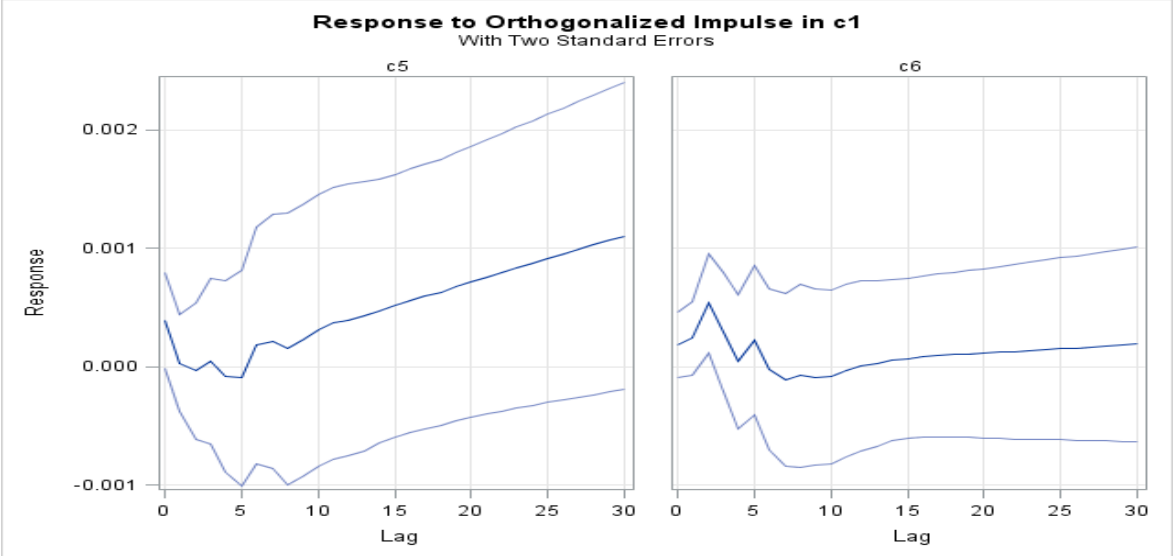




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

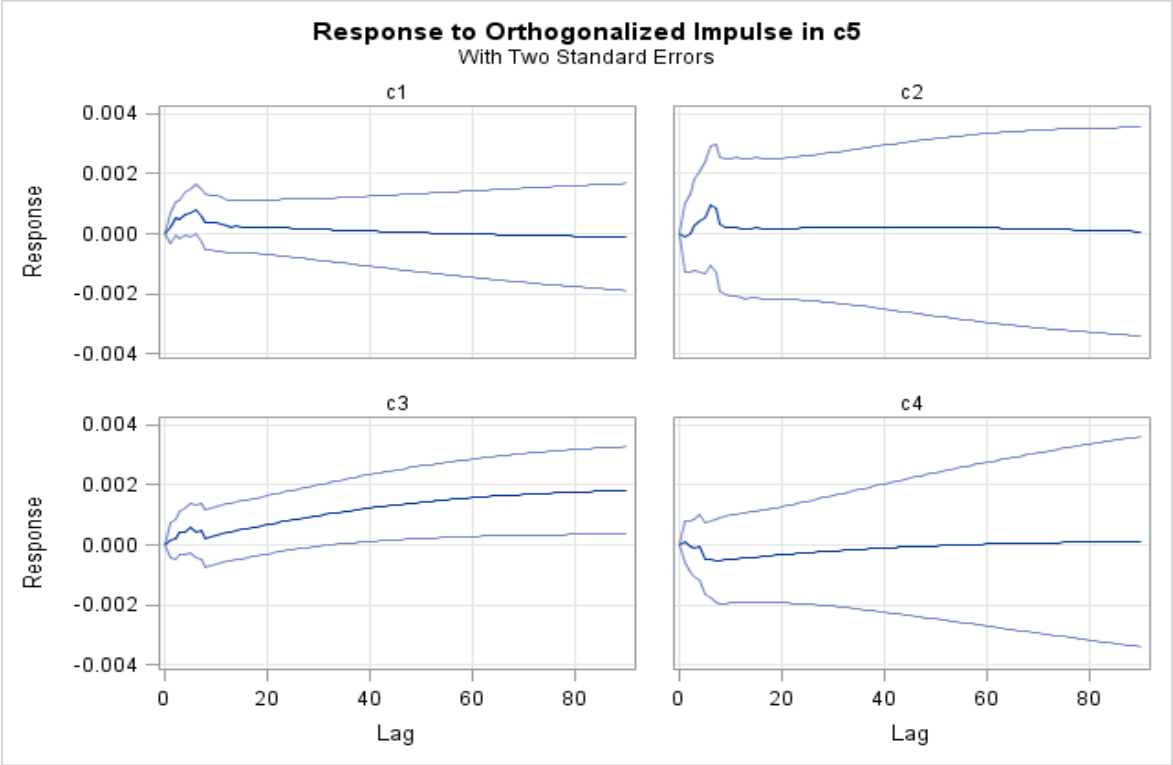
Figure 3.7: Response to Orthogonalized Impulse in SP_500 Index (1 month)

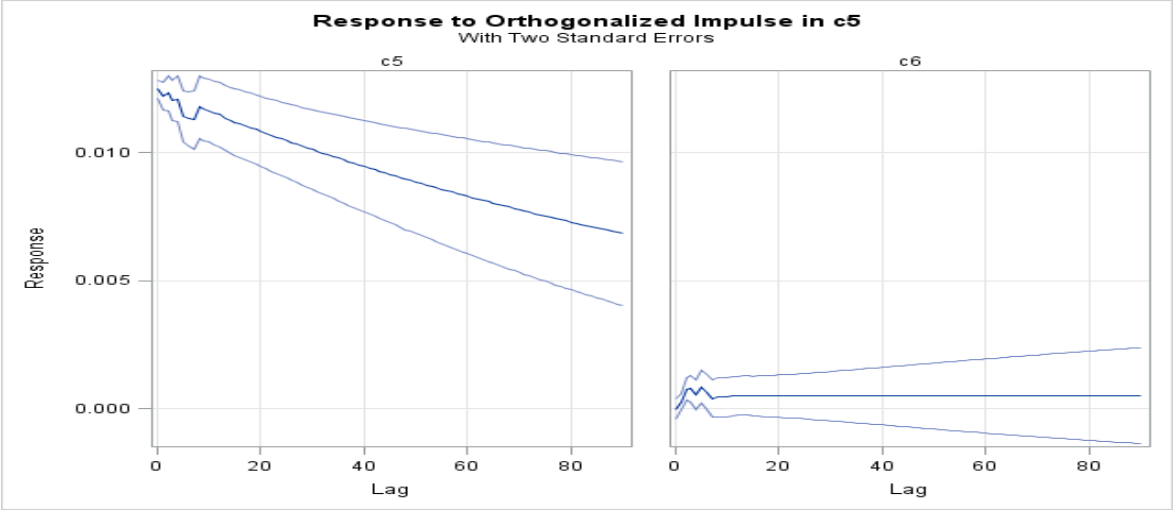




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

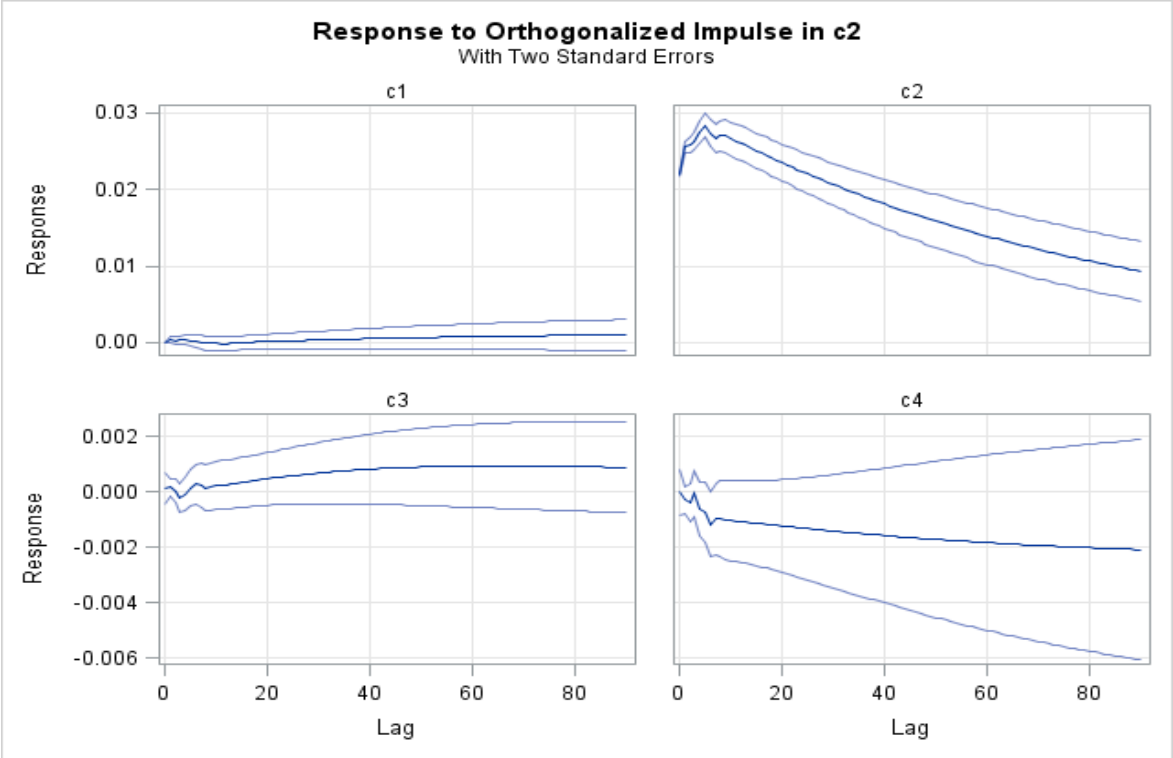
Figure 3.8: Response to Orthogonalized Impulse in Cattle Prices (1 month)

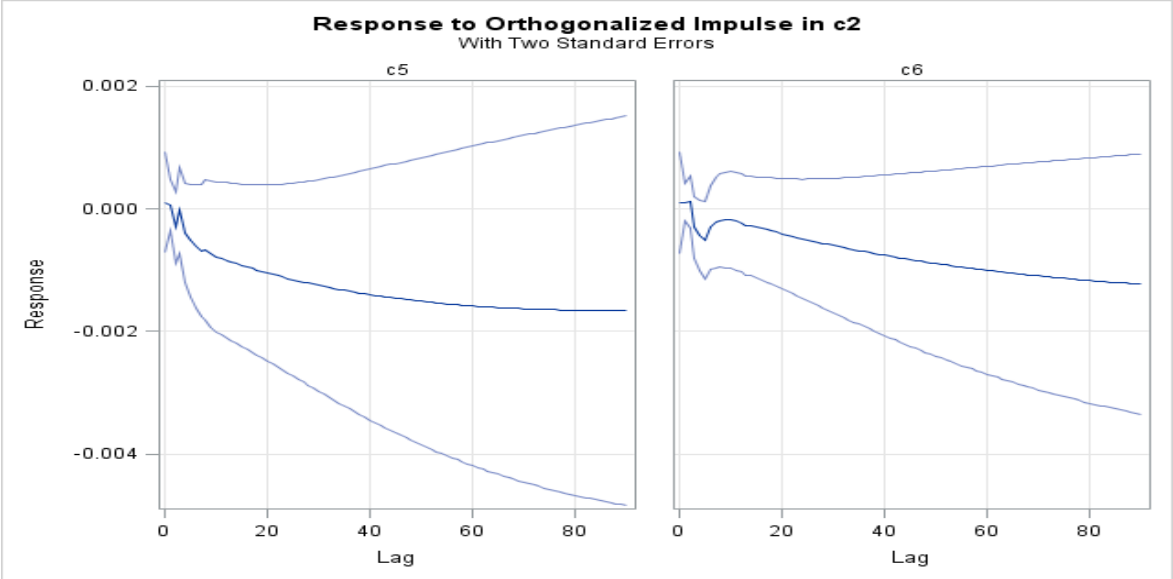




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

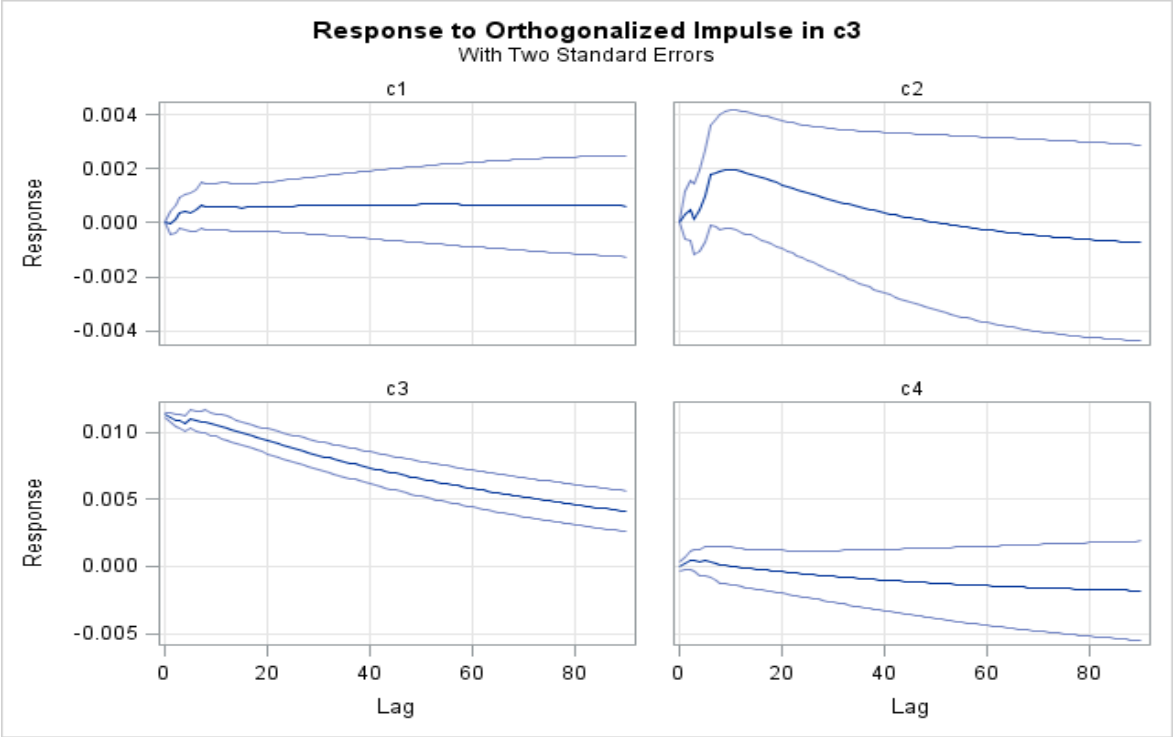
Figure 3.9: Response to Orthogonalized Impulse in Soybean Prices (3 months)

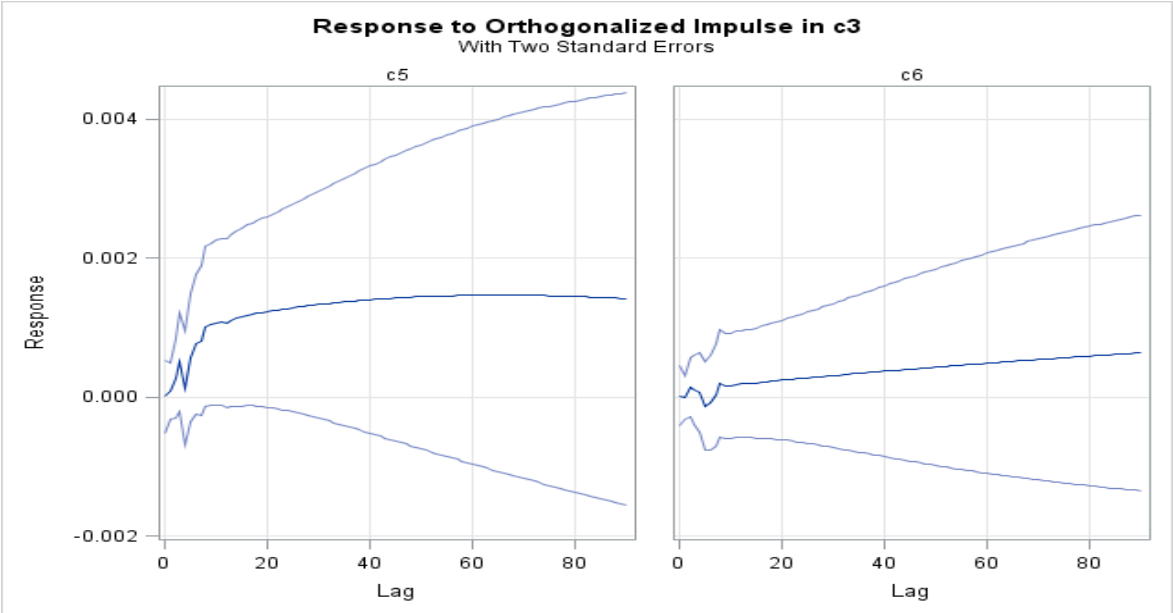




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

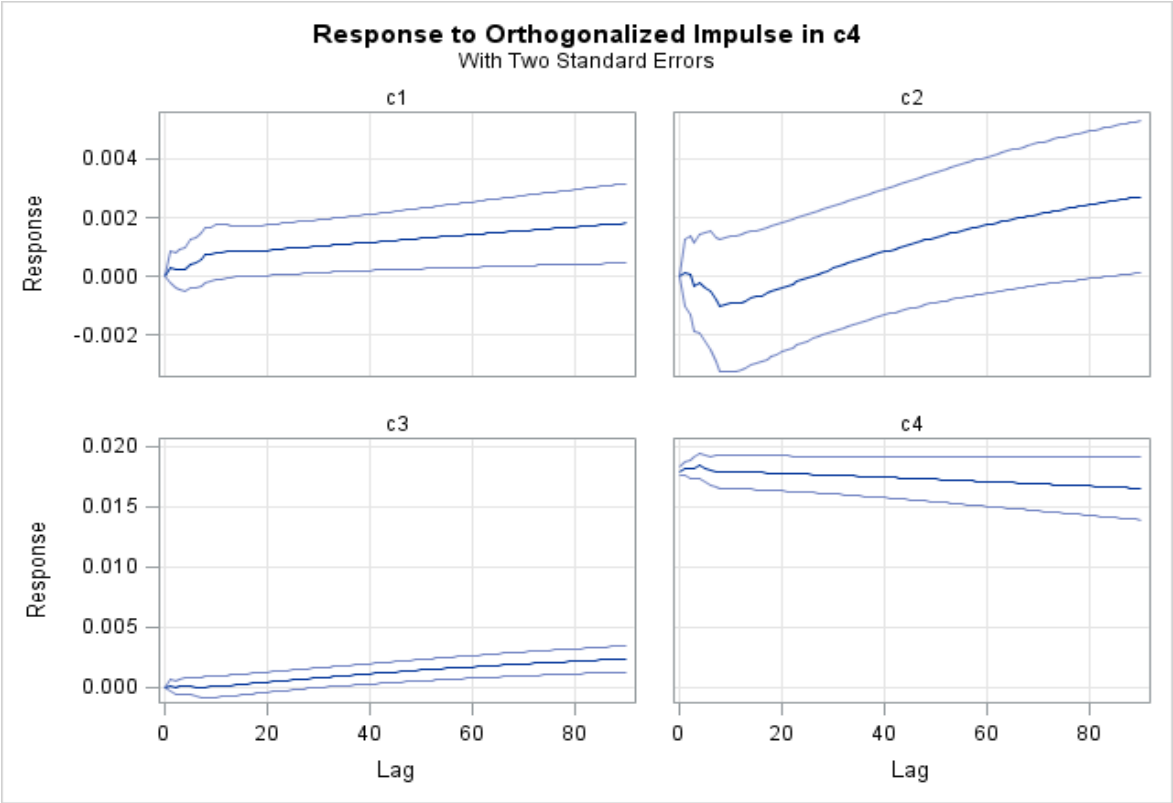
Figure 3.10: Response to Orthogonalized Impulse in Hog prices (3 months)

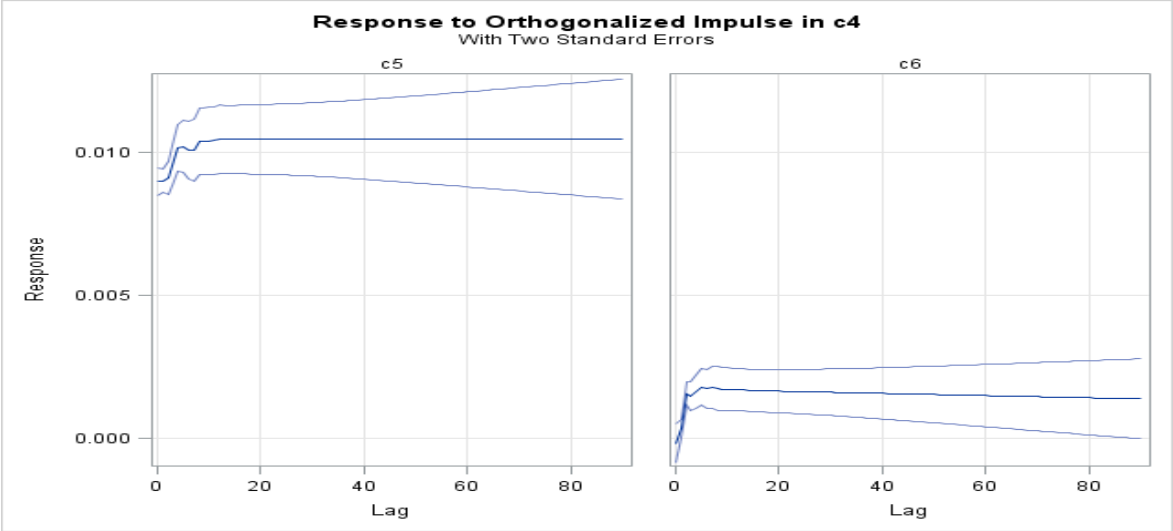




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

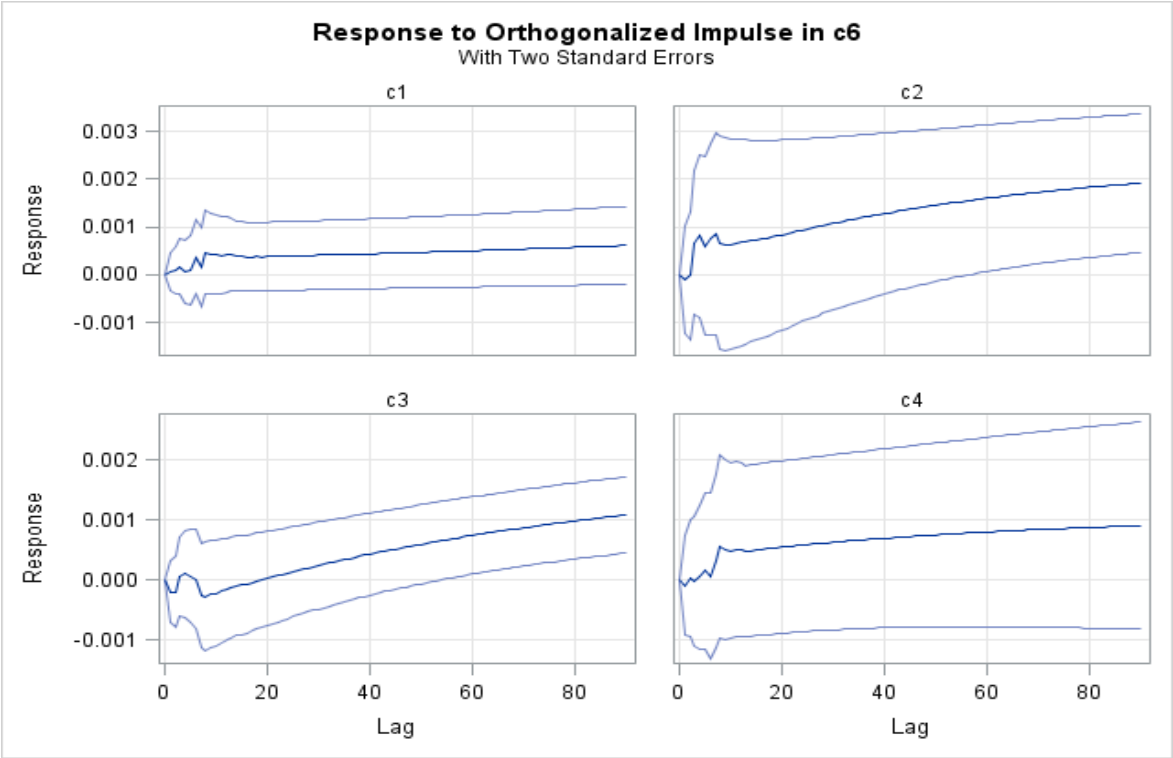
Figure 3.11: Response to Orthogonalized Impulse in Broiler prices (3 months)

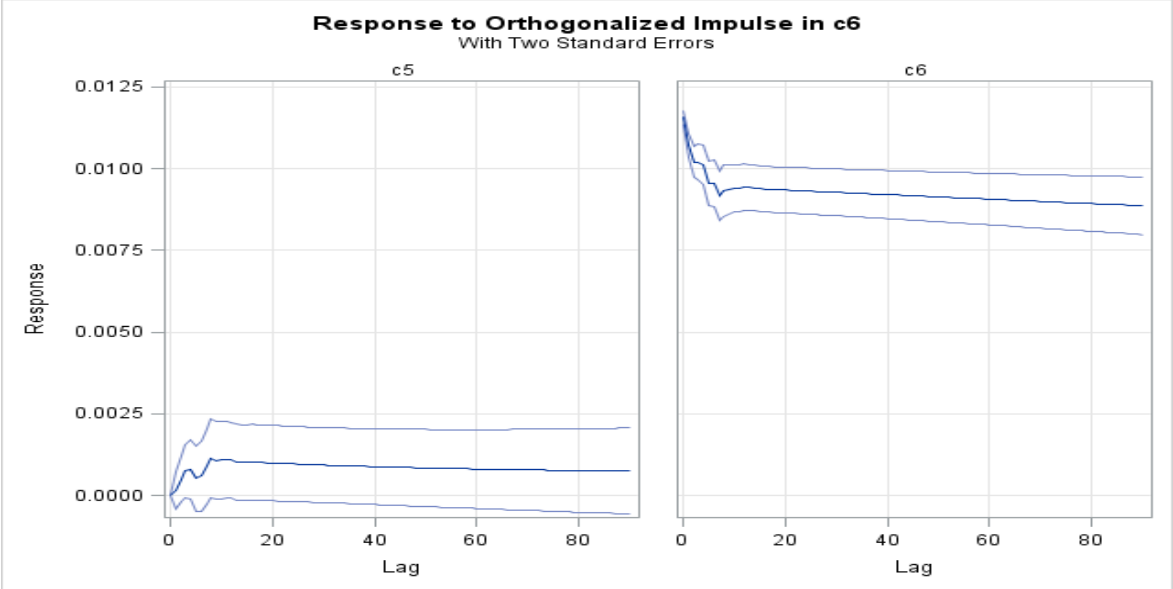




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

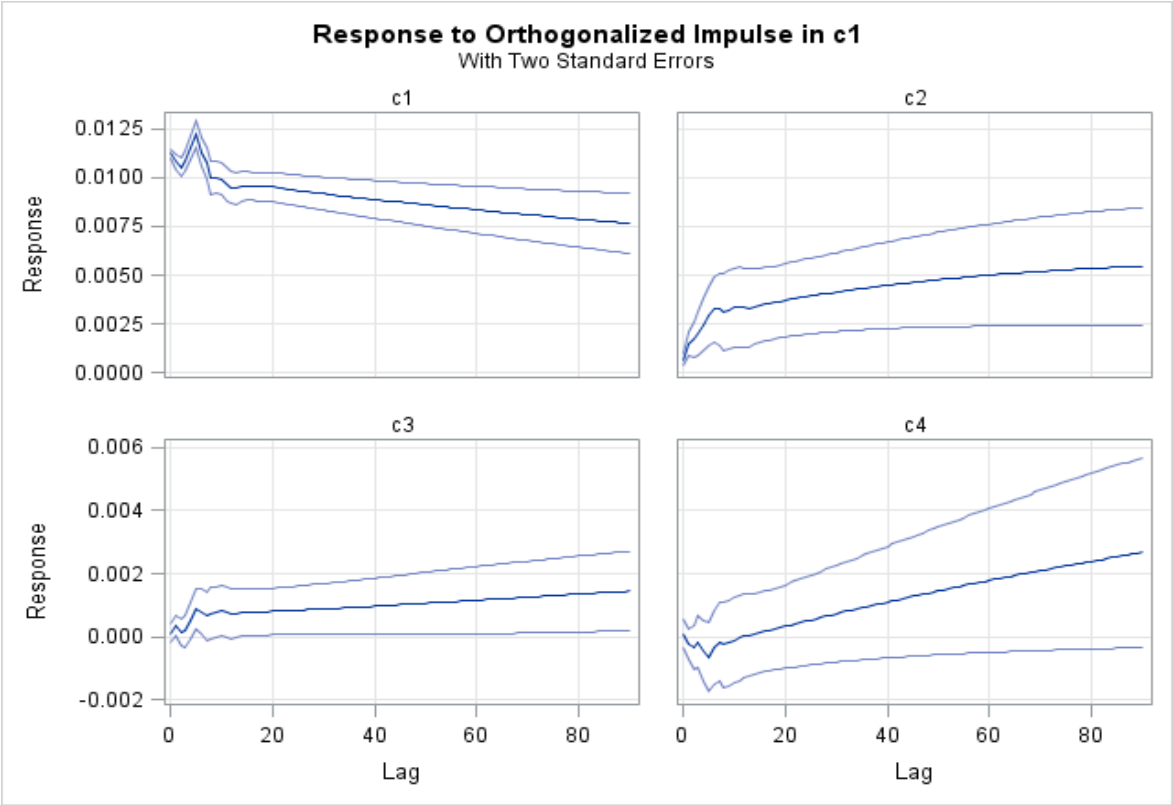
Figure 3.12: Response to Orthogonalized Impulse in Corn Prices (3 months)

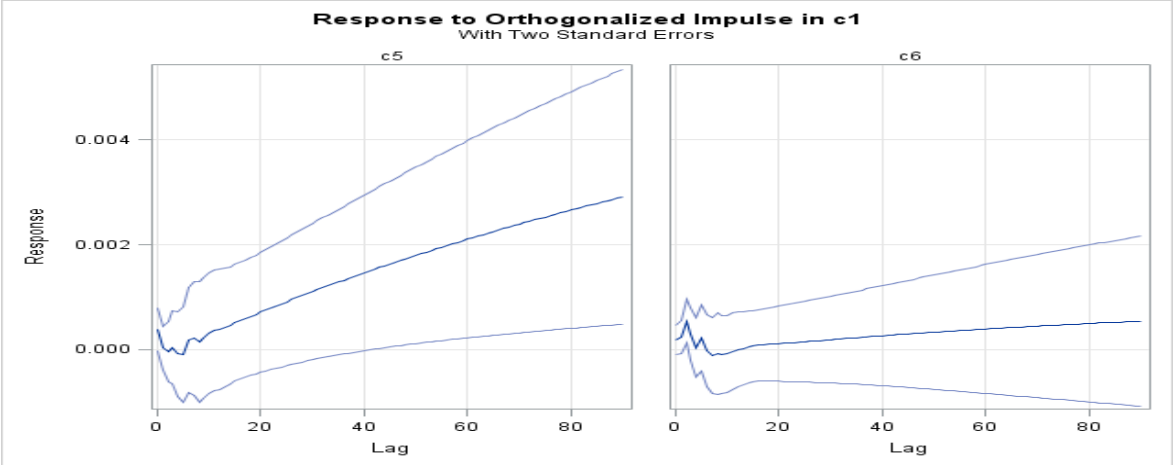




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

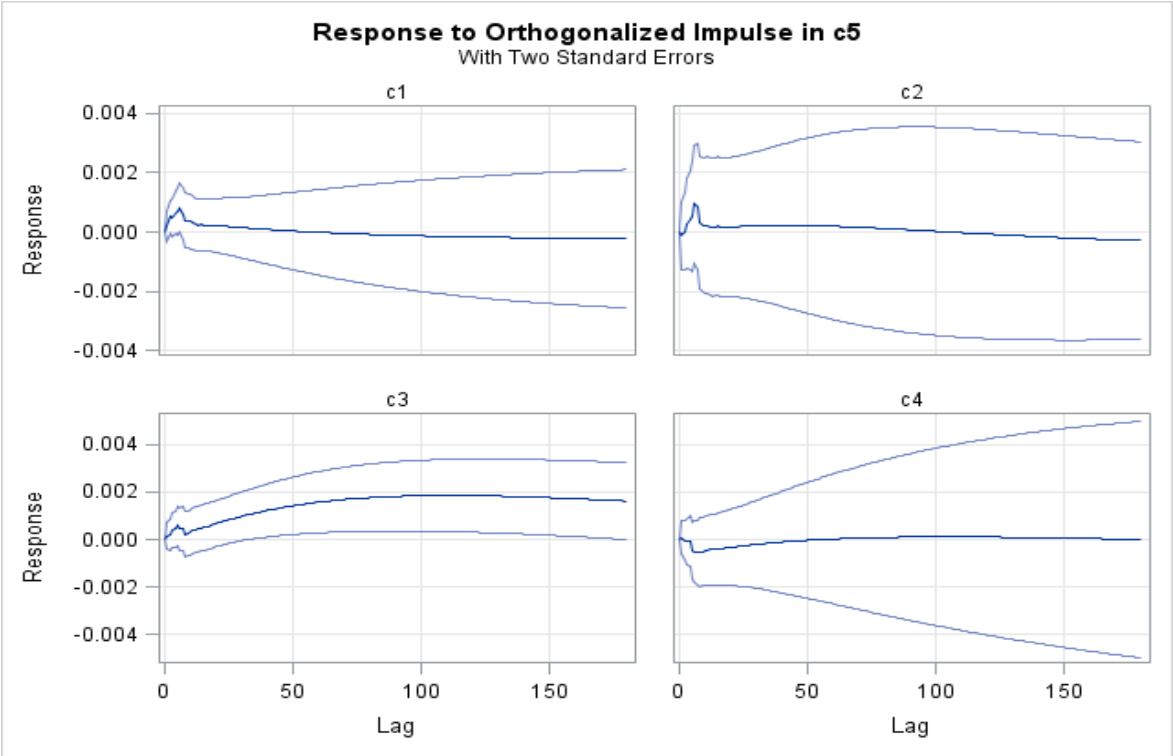
Figure 3.13: Response to Orthogonalized Impulse in SP_500 Index (3 months)

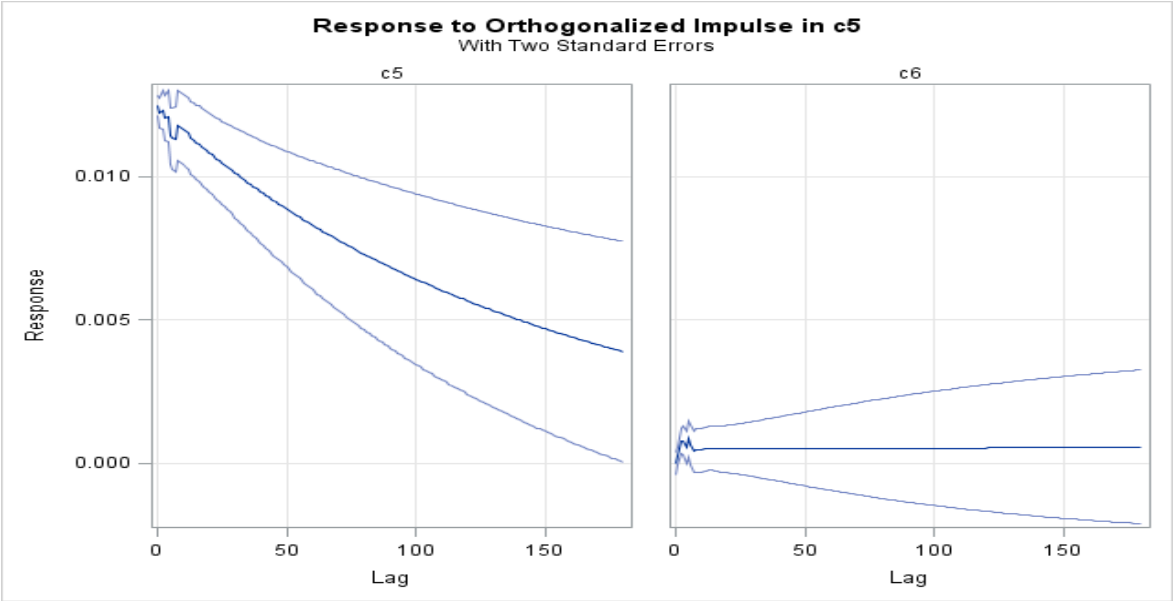




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

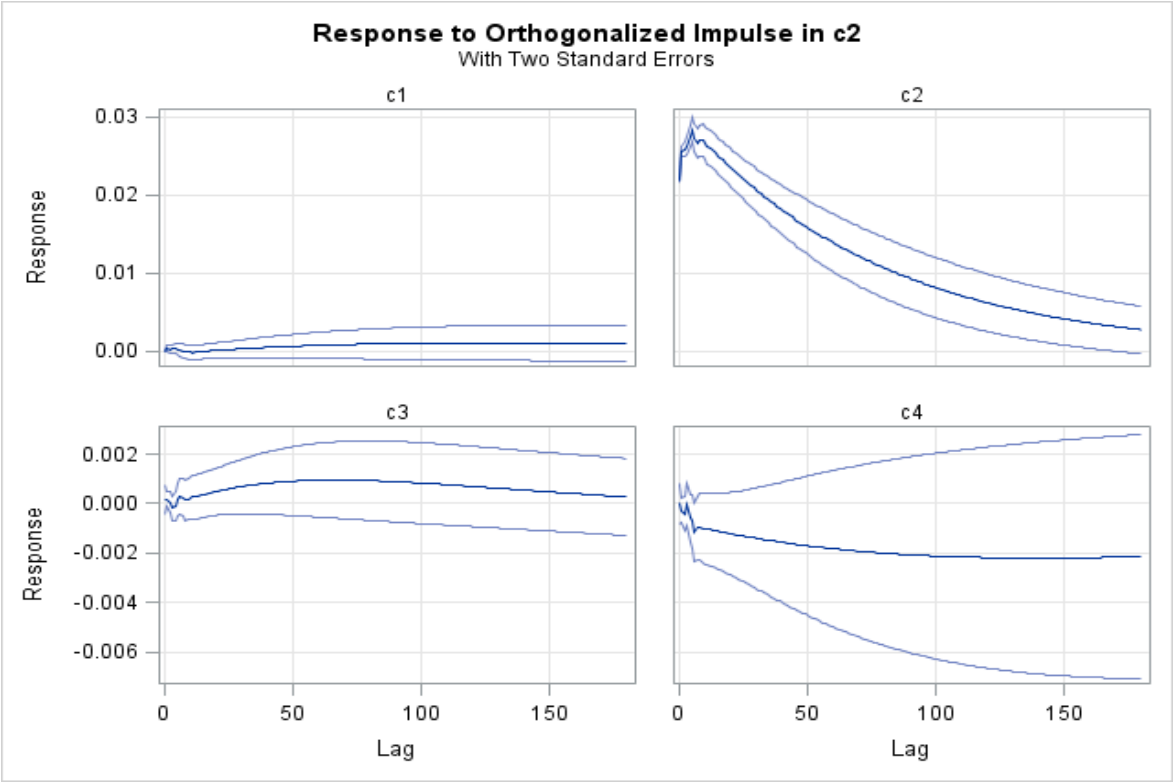
Figure 3.14: Response to Orthogonalized Impulse in Cattle Prices (3 months)

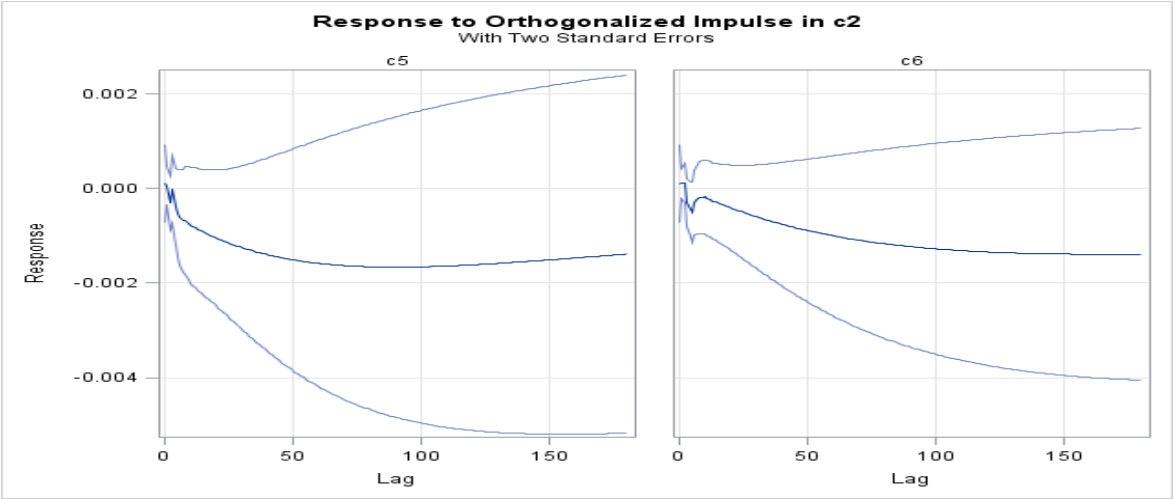




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

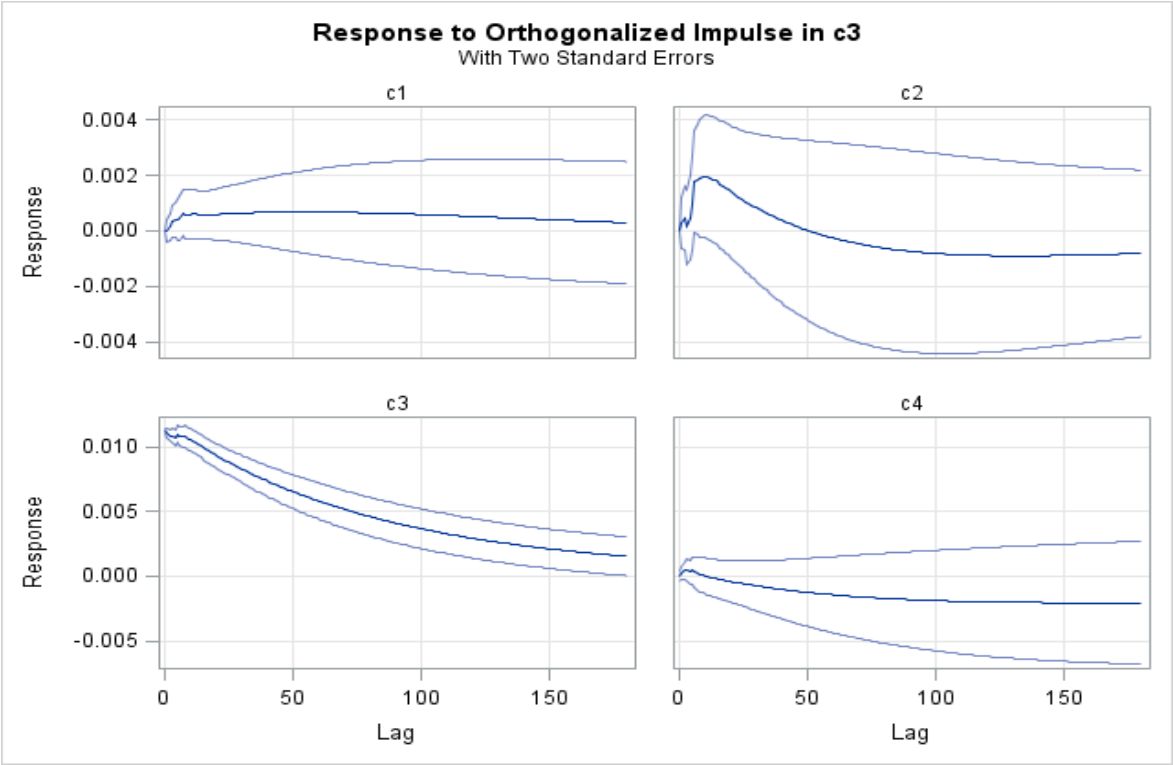
Figure 3.15: Response to Orthogonalized Impulse in Soybean Prices (6 months)

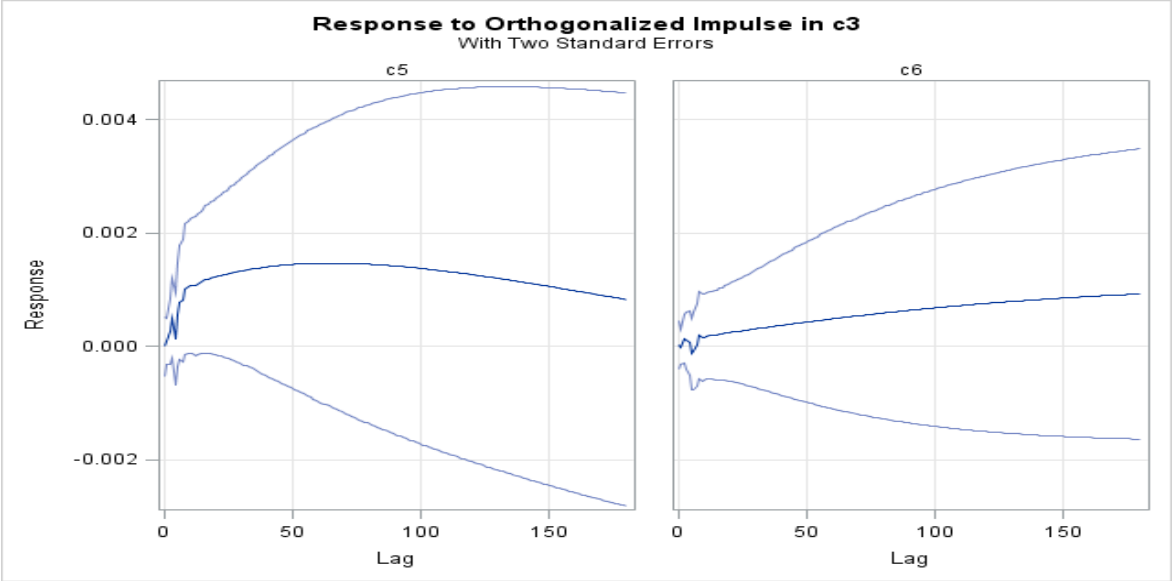




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

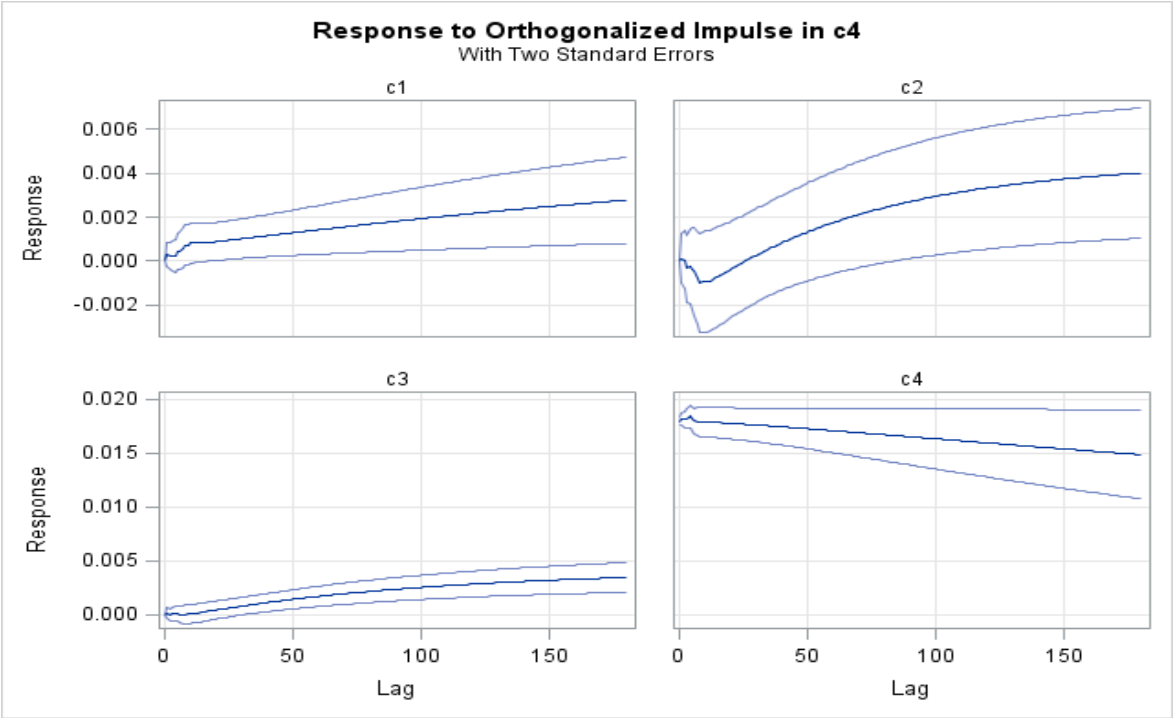
Figure 3.16: Response to Orthogonalized Impulse in Hog prices (6 months)

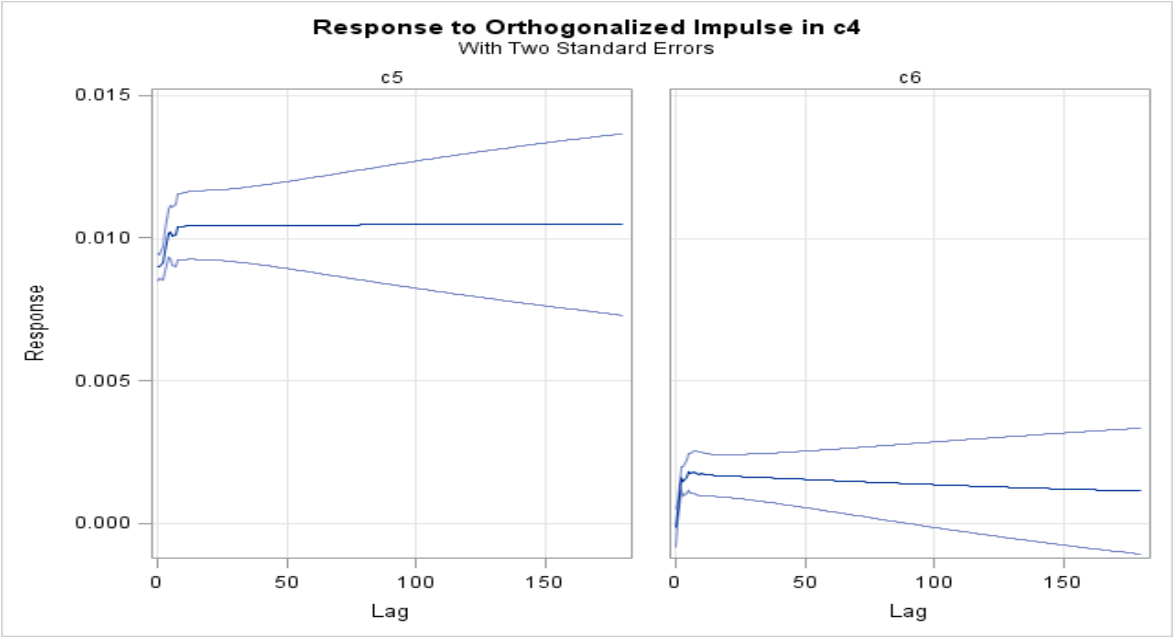




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

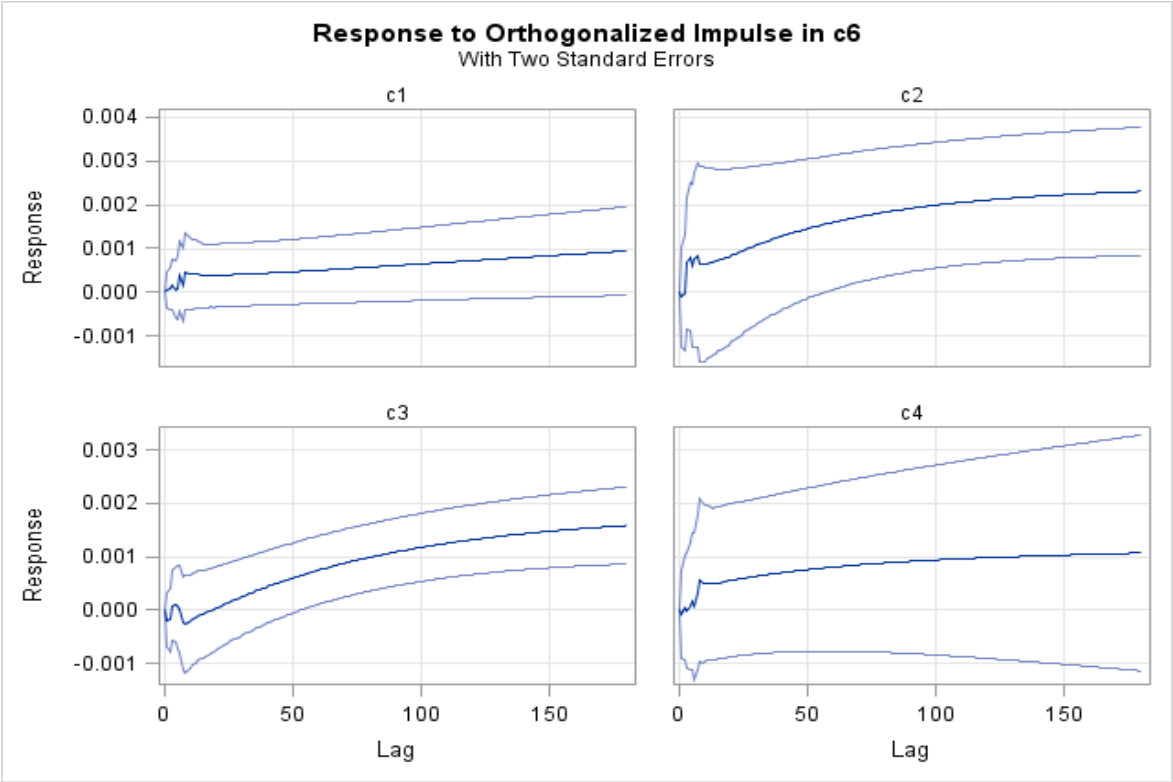
Figure 3.17: Response to Orthogonalized Impulse in Broiler prices (6 months)

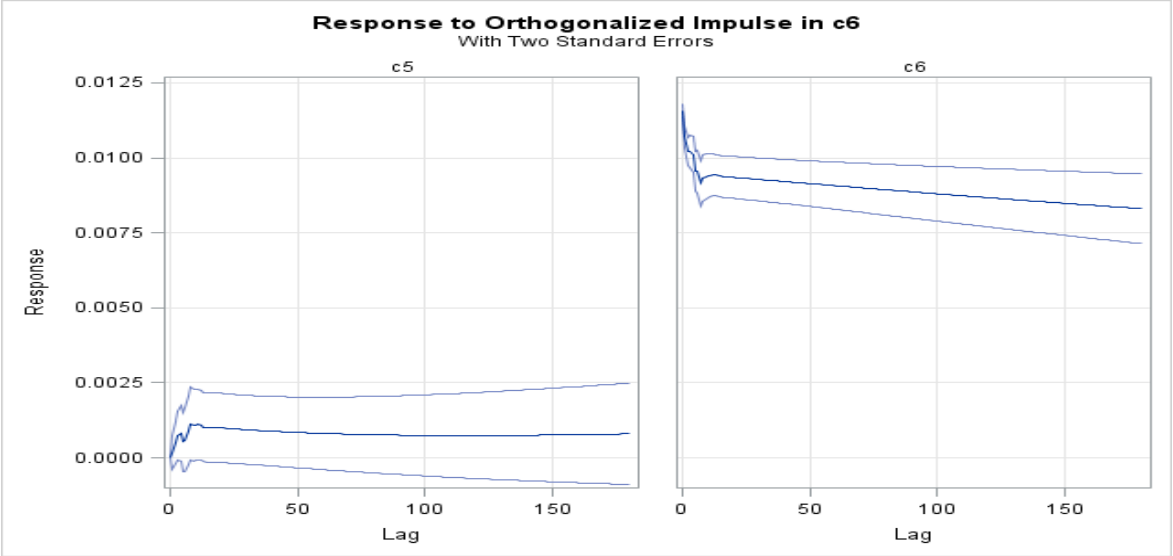




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

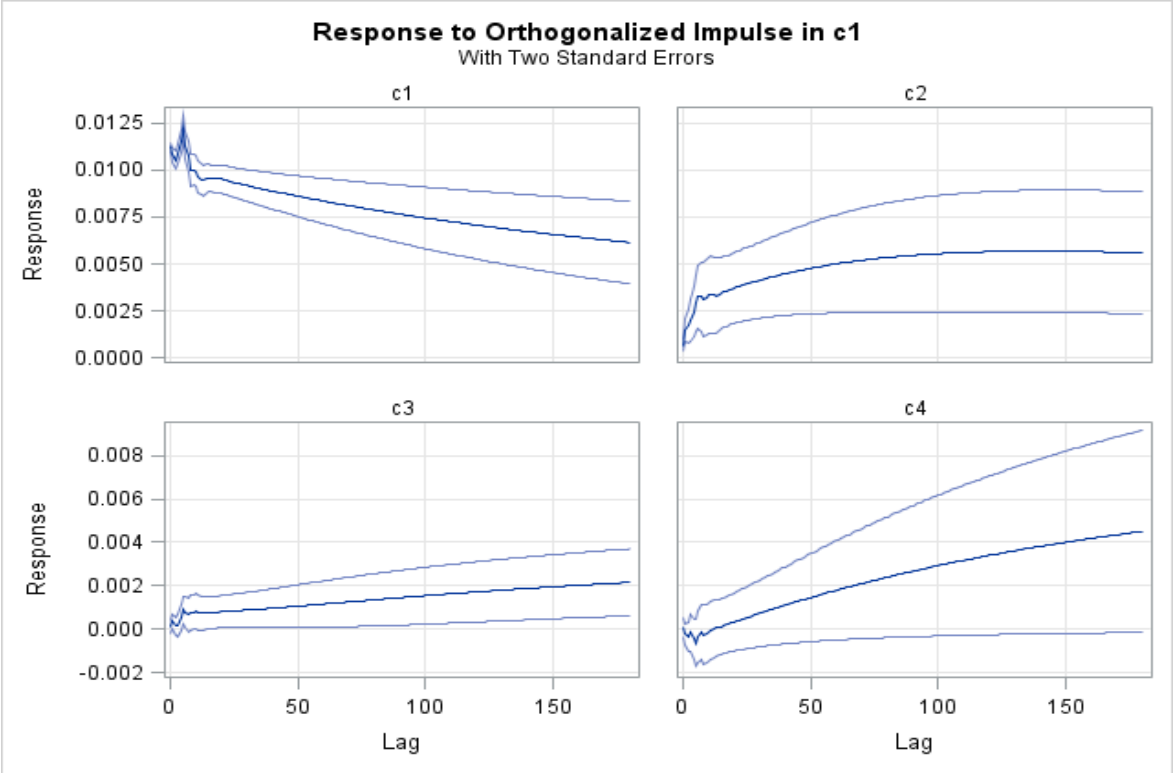
Figure 3.18: Response to Orthogonalized Impulse in Corn Prices (6 months)

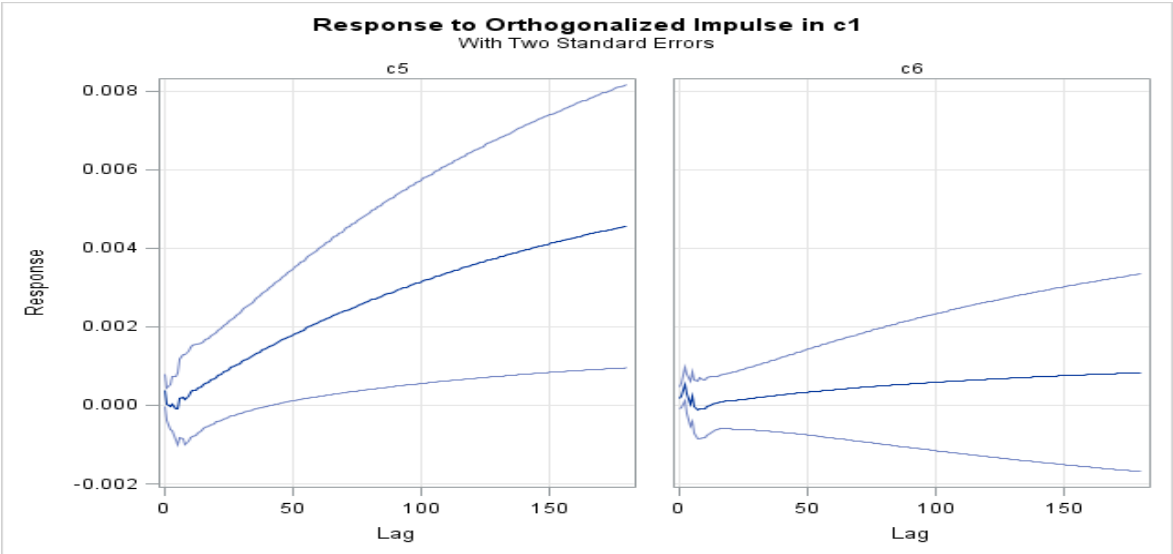




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

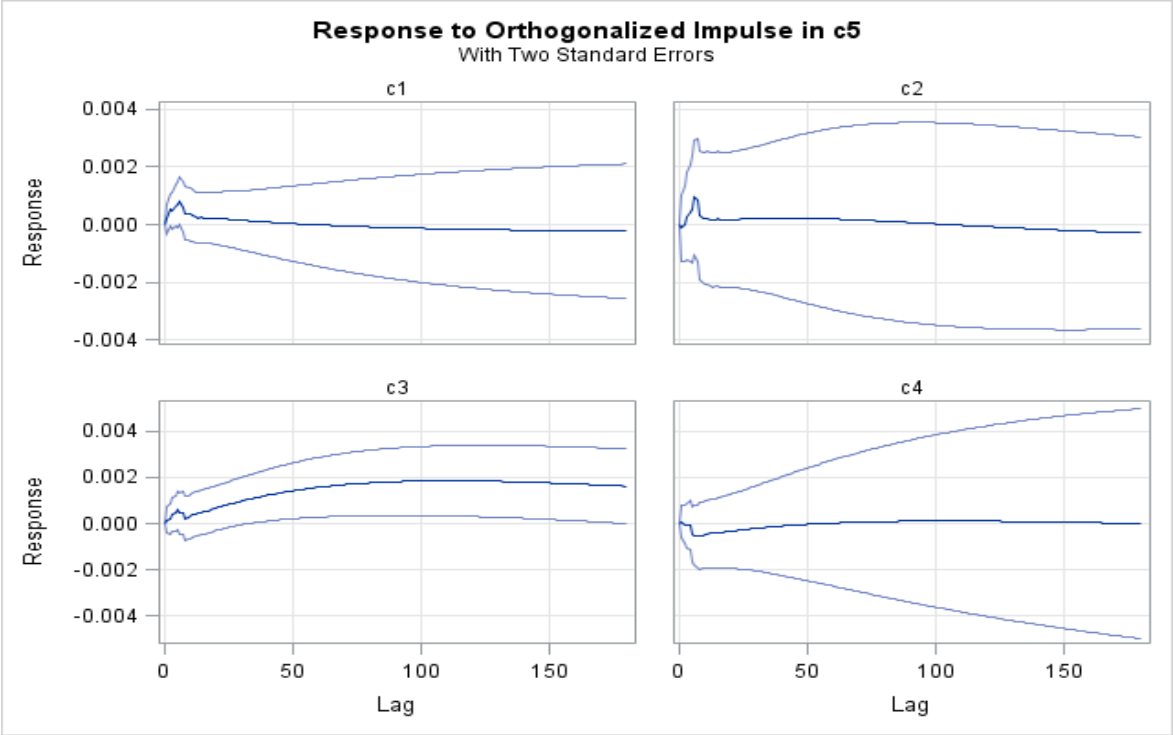
Figure 3.19: Response to Orthogonalized Impulse in SP_500 Index (6 months)

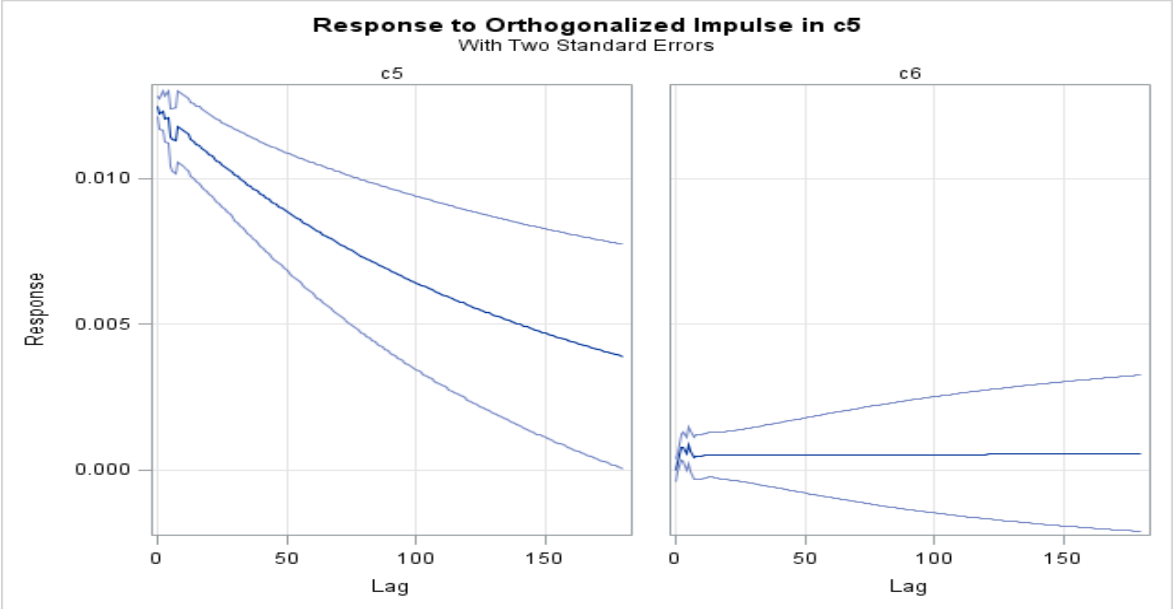




Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

Figure 3.20: Response to Orthogonalized Impulse in Cattle Prices (6 months)





Note: c1= cattle prices, c2=hog prices, c3=broiler prices c4=corn prices, c5=soybean prices, c6= SP500 index

Figure 3.21: Response to Orthogonalized Impulse in Soybean Prices (6 months)

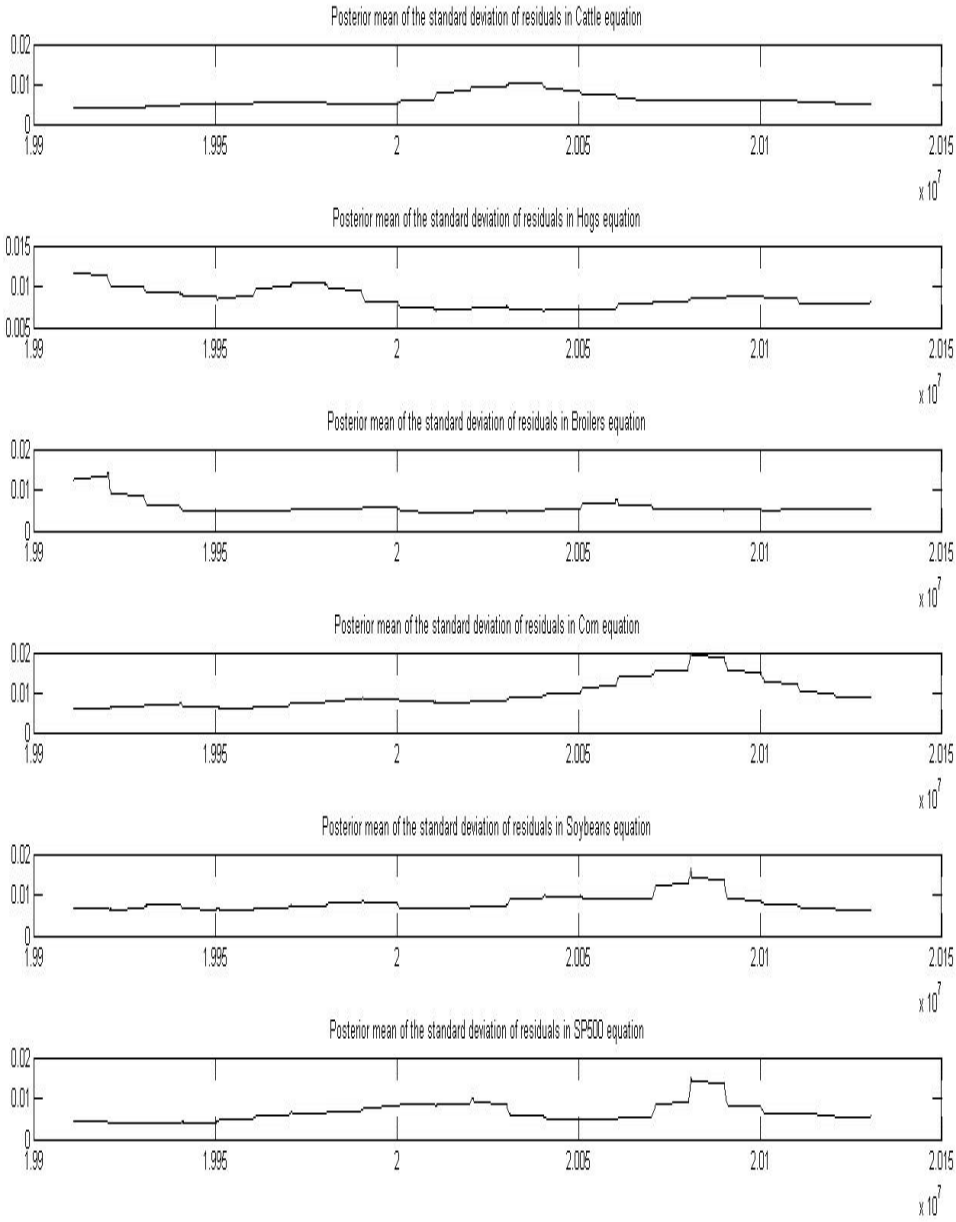


Figure 3.22: Posterior means of the standard deviation of residuals of TVPVAR equations

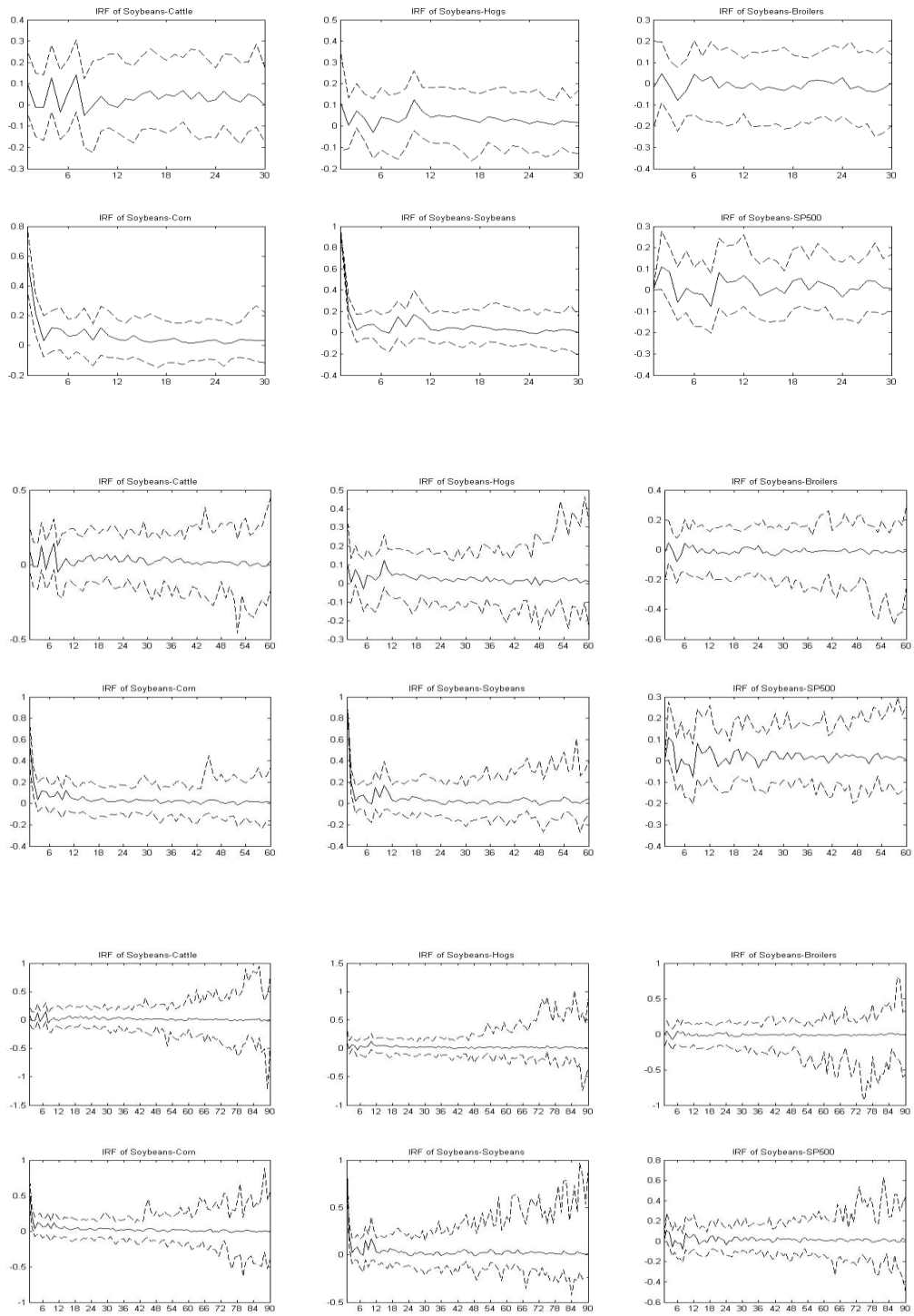


Figure 3.23: Response to Impulse in Soybean Prices TVPVAR Model (1, 3, 9 month(s))

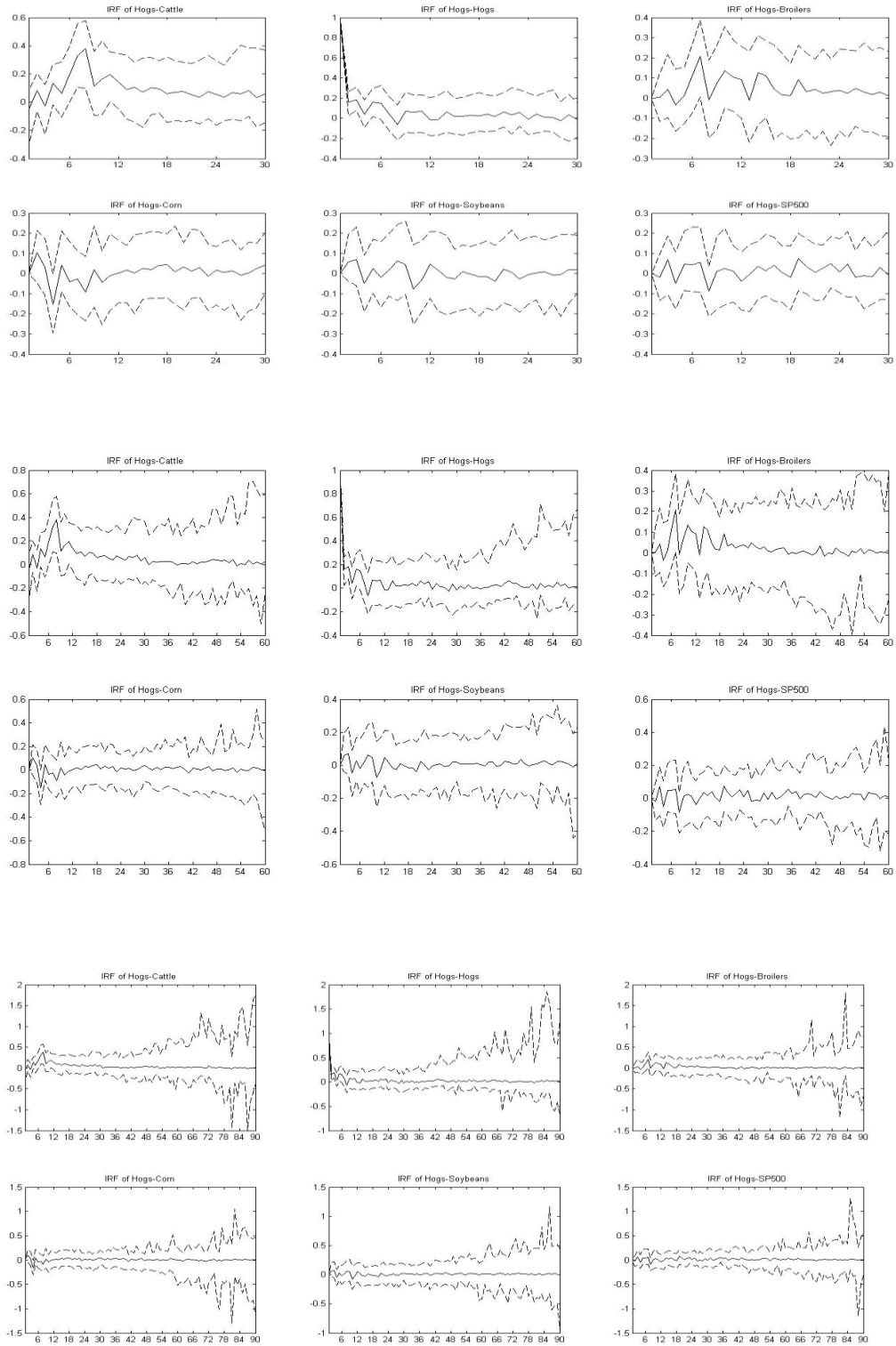


Figure 3.24: Response to Impulse in Hog prices TVPVAR Model (1, 3, 9 month(s))

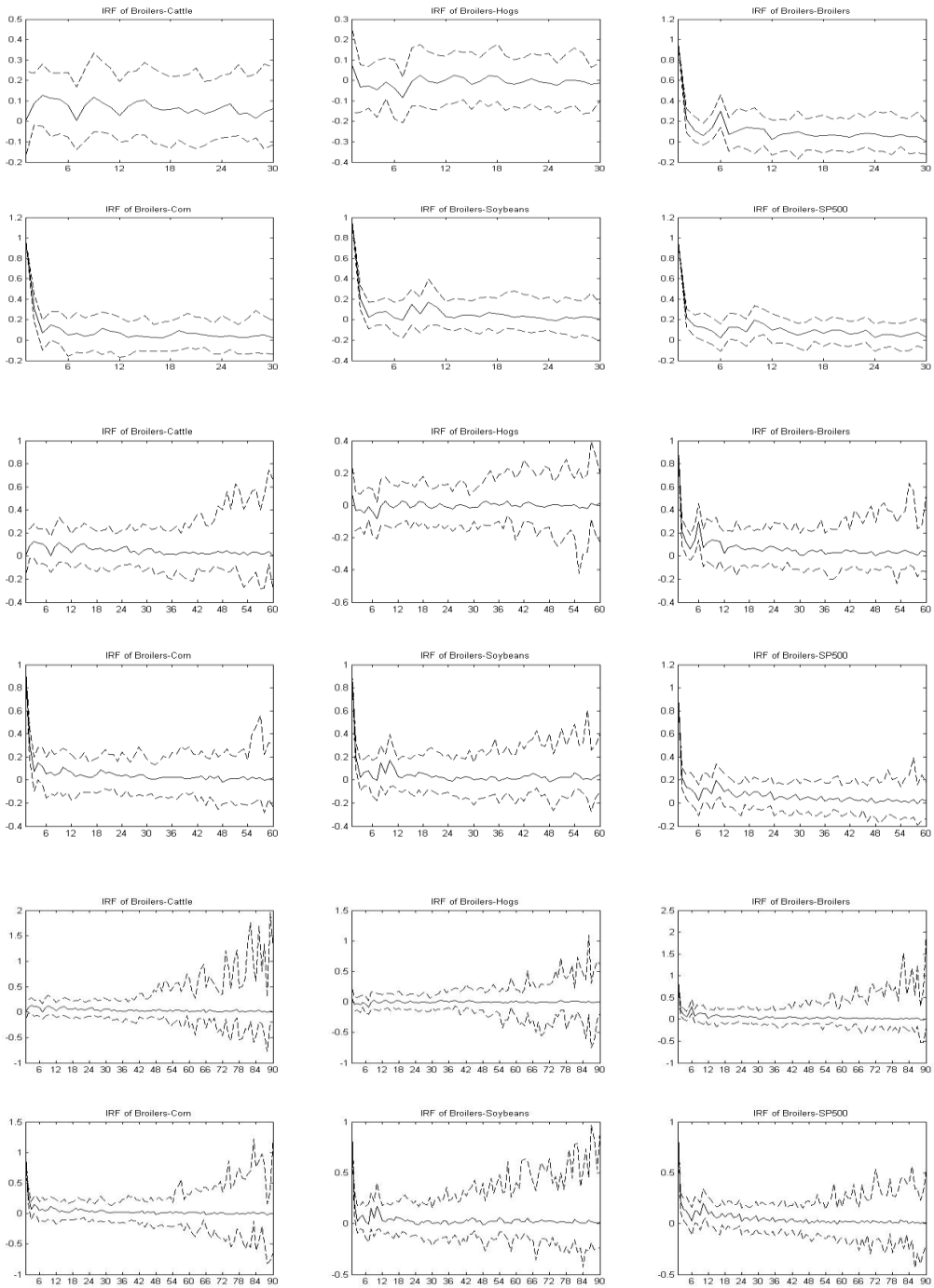


Figure 3.25: Response to Impulse in Broiler prices TVPVAR Model (1, 3, 9 month(s))

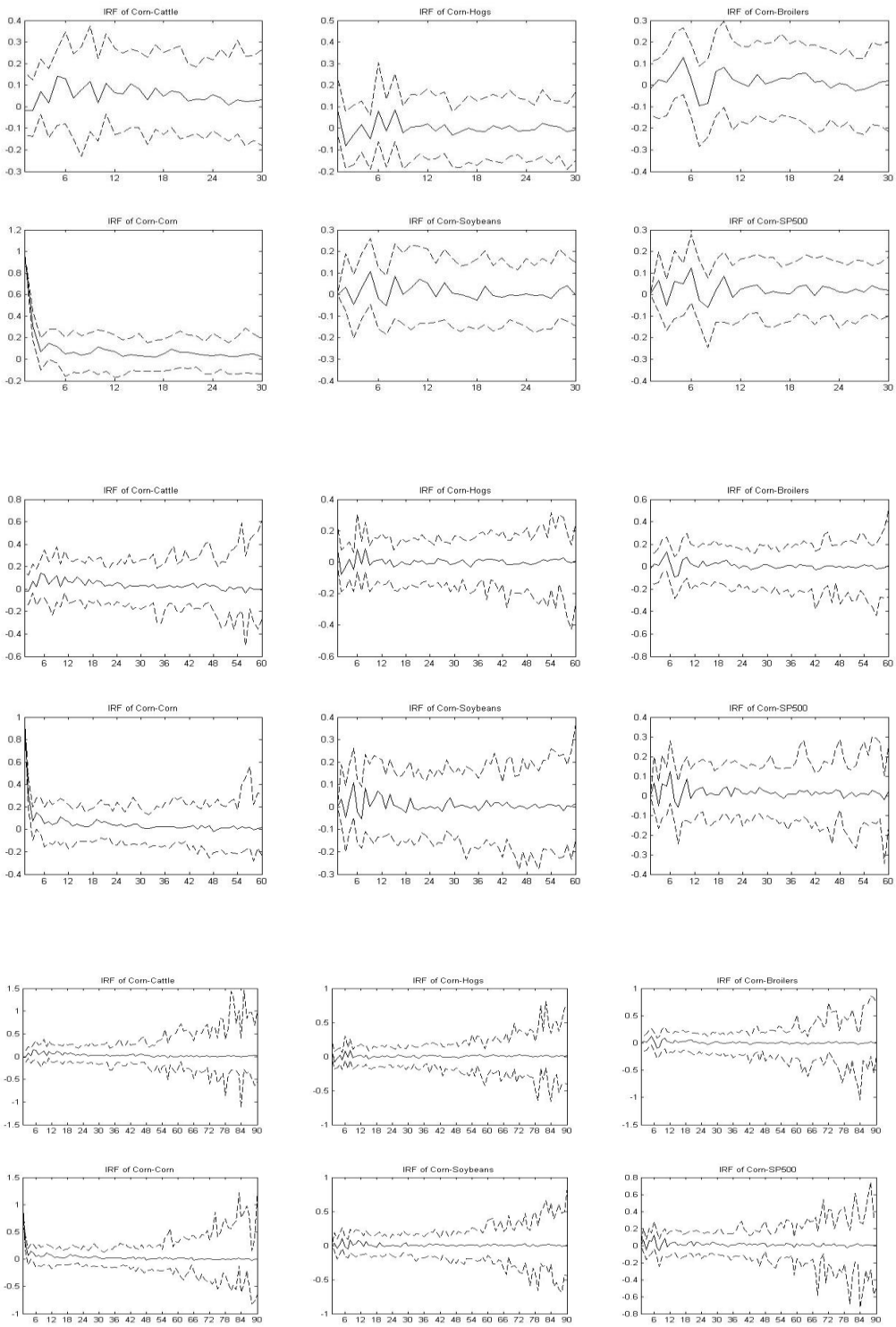


Figure 3.26: Response to Impulse in Corn Prices TVPVAR Model (1, 3, 9 month(s))

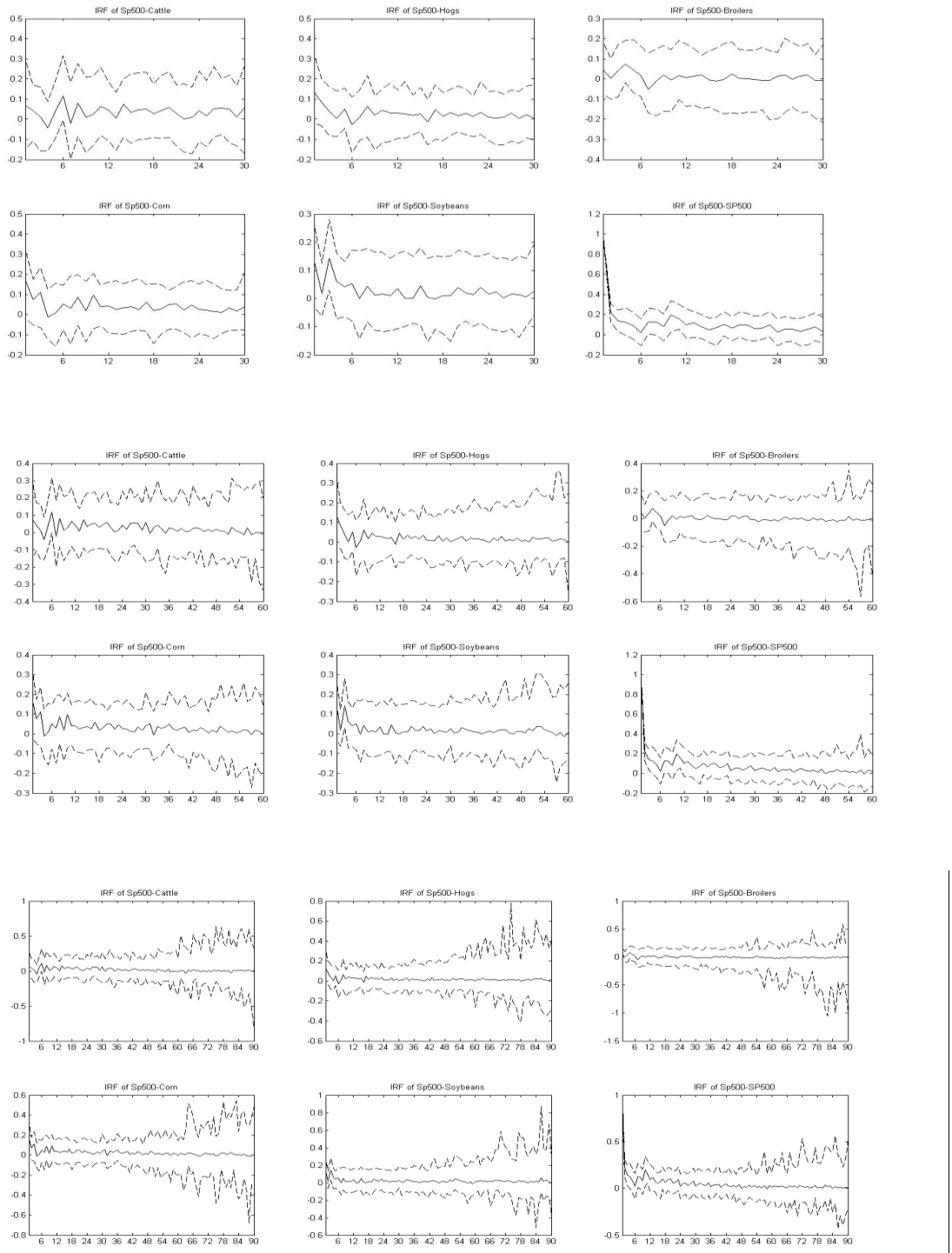


Figure 3.27: Response to Impulse in SP_500 Index TVPVAR Model (1, 3, 9 month(s))

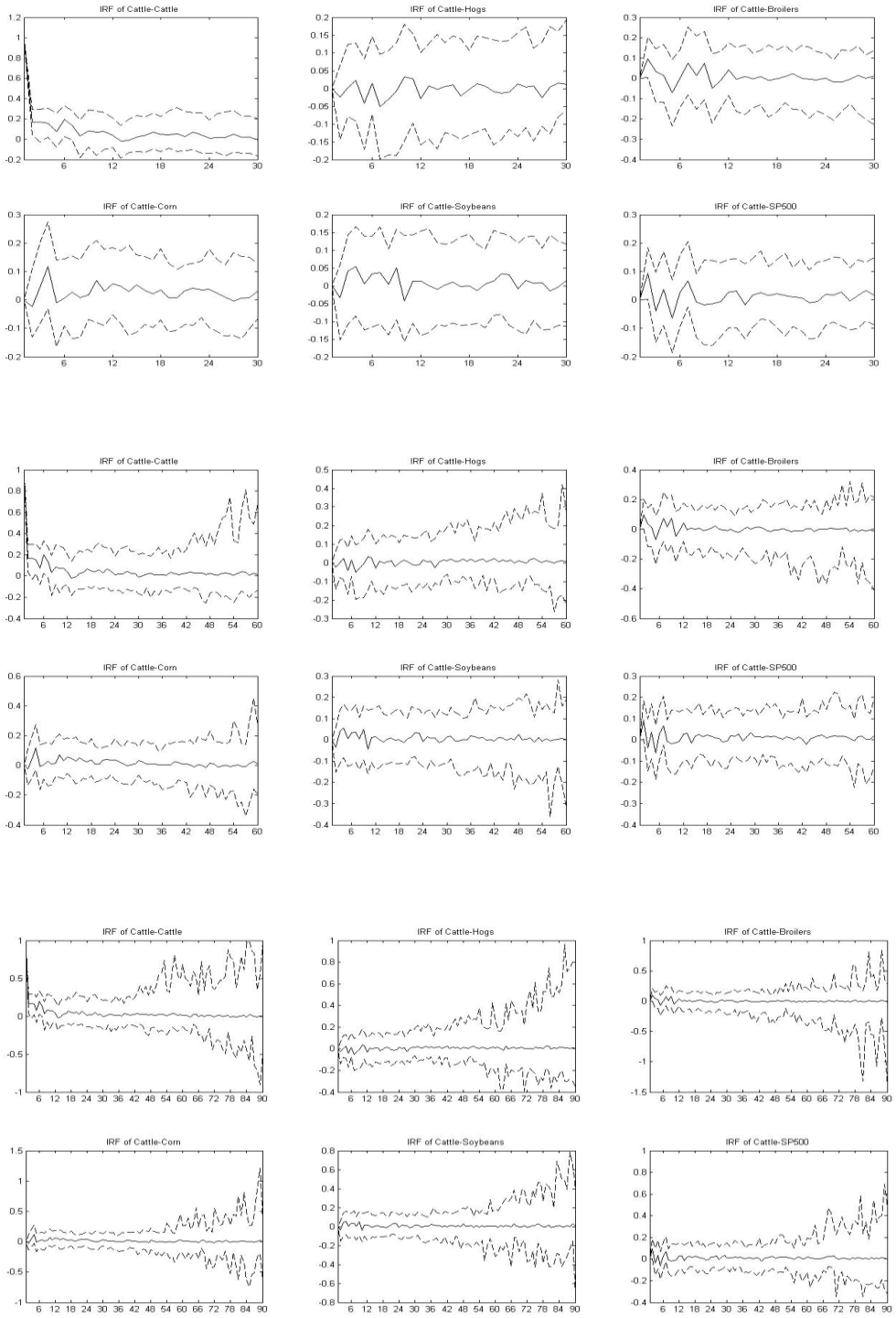


Figure 3.28: Response to Impulse in Cattle Prices TVPVAR Model (1, 3, 9 month(s))