IMPLIED VOLATILITY SPILLOVER IN AGRICULTURAL AND ENERGY MARKETS

by

CLAIRE LUENSMANN

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Dr. Ted C. Schroeder

Abstract

In recent years, the agricultural markets have been subject to increased prices and unusual levels of elevated volatility. One likely driver of this is the mandated ethanol expansion in the Energy Policy Act of 2005. Previous research has identified relationships in market prices and variability between the energy and grain markets, but little has been done to evaluate volatility spillover across a broader spectrum of agricultural commodities. Additionally, few studies have assessed causal linkages across market implied volatilities.

This research examines implied volatility spillover in futures markets across major agricultural commodities and energies. The analysis also determines the time path and magnitude of volatility translation across the markets and compares the causal relationships between pre-ethanol boom and post-ethanol boom time periods. Granger causality tests are conducted using multivariate and bivariate vector autoregressive modeling techniques, and impulse response functions are employed to obtain time paths of the reactions.

Overall, results indicate that strong implied volatility spillover relationships exist between the grain markets and between the live cattle and feeder cattle markets. The analysis also finds that the agricultural markets have evolved from lean hogs being the primary volatility leader in the pre-ethanol boom era to corn being the primary volatility leader in the post-ethanol boom era. Despite a high correlation between crude oil and corn volatilities in the post-ethanol boom time period, the causal linkage between the two commodities' volatilities may not be as definite as other literature suggests.

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Chapter 1 - Introduction

Elevated volatility in agricultural commodity markets has dominated producer, market analyst, and farm policy forum discussions in recent years. Grain price percentage increases from 2006 to 2008 were among the highest recorded historically (Sumner 2009). Continued globalization, growth in developing countries, speculation within the commodity markets, instantaneous information exchange, major droughts, substantial trade disruptions, and consumer reactions to food safety events are examples of potential drivers of increased commodity market variability. Recent changes to energy policy, including the Energy Policy Act of 2005, have restructured the biofuels industry and thus have had major impacts on the agricultural industry as well. Fluctuations in commodity market volatility alter the risk exposure of agricultural producers, processors, and biofuel refineries and affect their hedging and investing decisions. Policymakers should consider the linkages between these markets when proposing and evaluating farm and energy policies. Of considerable interest to these key players throughout the food and fuel industries is how volatility in one market might affect volatility in other markets. That is, understanding the magnitude of volatility spillover across commodities is essential for risk management and policy analysis.

Two basic methods of estimating volatility include calculating the volatility that is implied by the market based on the other known factors in an option pricing model or calculating the variance of an historical price series. The most well-known options pricing model that is frequently used in the finance industry was introduced by Black and Scholes in 1973. In recent years, the Black-Scholes theory has been expanded upon to produce more accurate implied volatility measures. Implied volatility is the market-determined expected commodity price risk. As such, implied volatility provides a direct measure of market participants' expectations regarding market uncertainty. Implied volatility is typically a more reliable measure of risk than historical volatility in the short-term since it is forward-looking, and analyzing implied volatility spillover can provide valuable insight into how the markets are interconnected.

1.1 Energy Policy Act of 2005

In August 2005, the federal government passed the Energy Policy Act to address issues related to energy production and reform the government's role in the energy sector. One of the provisions of the Energy Policy Act was the Renewable Fuel Standard which required a minimum volume of renewable fuel to be included in all motor fuel sold in the United States. At first, the goal of the Renewable Fuel Standard was to achieve production of 7.5 billion gallons of biofuel per year by 2012, up from 1 billion gallons per year in the late 1990s. However, after the initial success of the policy, the government expanded on the Renewable Fuel Standard in the energy bill of 2007 to target production of 36 billion gallons of biofuel per year by 2022. At the time, the government anticipated fuel consumption to continue to rise and hoped to attain a minimum blend ratio of 10 percent biofuel to 90 percent gasoline (EPA 2013). Ethanol, also known as conventional biofuel, was introduced in the early 1980s and is commonly produced in the United States using corn.

Because of this increase in biofuel production, in which corn has been an important input, and subsequently an increase in the demand for corn, it has been speculated by many economists that the relationship between corn prices and energy prices has strengthened and higher crude oil prices may have contributed to the corn price spike of 2008. As the amount of available agricultural land in the United States is relatively fixed, fluctuations in the corn market likely transferred to other agricultural crops. Livestock markets too may have been affected since corn is commonly used as a feedstuff in livestock rations.

1.2 Objectives

This study is designed to specifically identify the dynamic and causal relationships of implied volatility in futures markets across major agricultural commodities and energies. In particular, dynamic relationships between implied volatilities on option contracts of these futures markets are investigated to determine how changes in volatility across markets are related.

Specific objectives that are achieved in this analysis include:

1. Quantify contemporaneous correlations between implied volatilities in the commodity and energy markets.
2. Determine which markets have been leaders in volatility discovery and which markets have tended to lag.
3. Evaluate these volatility spillovers before and after the passage of the Energy Policy Act of 2005 and across both time periods.
4. Analyze the time path and magnitude of volatility translation across markets.

1.3 Motivation

Determining the dynamics and lead-lag relationships among major agricultural commodity markets will provide useful information for producers, traders, market analysts, and policymakers. Producers and market analysts will benefit from understanding volatility spillovers as they formulate risk management strategies. Traders and speculators can use this information to predict how present changes in implied volatilities in one market may affect future options premiums in another market. Similarly, policymakers should consider this information when proposing policies for one industry that could impact another industry. Additionally, this study will motivate further research as this topic has not been fully explored in commodity markets.

Chapter 2 - Literature Review

Several studies have documented the nature of increased commodity price levels and associated price variability and a few studies have assessed price spillovers across agricultural commodities. However, little has been done to determine how market variability translates across agricultural commodities. The work that has been completed related to volatility spillover focuses on the financial markets (Christiansen 2007; Baele 2005; Hong 2001; Ng 2000) or relationships between the energies and the corn, wheat, or soybean markets. Additionally, most of these studies have examined the spillover effects of historical variations in price rather than implied volatilities. This chapter will focus on the literature most relevant to this thesis which analyzes commodity price movements over time or evaluates price or volatility spillovers in the energy and commodity markets. However, it is first necessary to review literature that discusses varying methods of calculating volatility.

2.1 Methods of Calculating Volatility

There are many simple and complex methods used to forecast the volatility of returns on financial derivatives. As was pointed out in Chapter 1, these results can be classified as either implied or historical.

2.1.1 Implied Volatility

An option is a contract that gives the buyer of the option the right to buy or sell an underlying commodity or stock at a specific exercise price. Options are used to defer risk from the buyer of the option to the seller of the option. Therefore, the option price, or premium, represents the option buyer's maximum willingness-to-pay for the reduction of risk and the option seller's minimum willingness-to-accept for his gamble. If the buyers of options feel more uncertain about future market prices, they are willing to pay a higher option premium to avoid risk (Purcell and Koontz 1999). Buyer uncertainty is analogous to market volatility. Implied volatility is the market consensus volatility since the market price of an option underlying its given futures contract is used to calculate the volatility estimate (Stoll and Whaley 1993).

The Black-Scholes options pricing model considers five variables to solve for an option's theoretical premium: 1) current underlying commodity futures price, 2) the option's exercise price, 3) the riskless interest rate, 4) time until expiration of the option, and 5) market volatility (Black and Scholes 1973). Since an option's premium is market determined, and together with the first four variables, is known at any given time, the Black-Scholes formula can be inverted to solve for the volatility implied by the option premium, referred to as the implied volatility (Giot 2003). Traded options for each commodity have varying exercise prices, expiration dates, and premiums, and not all of these options will necessarily reveal the same implied volatility when using the Black-Scholes theory. This is because the formula assumes that the option premium and underlying commodity price are observed at the same time, when in fact it, is very rare that the options trade and futures trade on the underlying commodity are made at the exact same time (Stoll and Whaley 1993). Even if these prices were observed simultaneously, the formula would still return differing volatilities for different options on the same underlying commodity. Options market makers always desire a rate of return on their capital and therefore set the selling price (ask) above the buying price (bid). As a result, when a trade takes place, a buyer is agreeing to purchase at the lowest ask price or a seller is agreeing to sell at the highest bid price. Since there is no way to discern whether a trade was made at the ask price or the bid price, one must assume in the Black-Scholes formula that the ask price and the bid price are equal and there is consequently some error in the calculated implied volatility (Stoll and Whaley 1993).

To combat these issues, most implied volatility calculations take into account several of the options available for a futures contract. These calculations typically give more weight to at-the-money options (options in which the current underlying commodity price is near the exercise price) than out-of-the-money options or in-the-money options since out-of-the-money and in-the-money options are less reliable and less frequently traded (Kolb and Overdahl 2007). The Black-Scholes formula is infamous for unreliably predicting implied volatility on in-the-money and out-of-the-money options. This problem, known as volatility smile, occurs as a result of Black-Scholes theory's failure to consider variation in exercise price and time to expiration. In more recent years, mathematicians have developed options pricing methods very similar to Black-Scholes that correct for the volatility smile. The implied binomial and trinomial tree models are examples that extend upon the familiar Black-Scholes theory to allow the future commodity price to vary based on time to expiration and a derived probability function (Derman, Kani, and Chriss 1996).

2.1.2 Historical Volatility

Historical volatility calculations range from simple to extremely complex mathematical models. An easy method often used by options traders is performed by calculating the variance of the rate of return on a commodity over a period of time (Stoll and Whaley 1993). Two more complex historical volatility calculation methods frequently used by economists are generalized autoregressive conditional heteroskedasticity (GARCH) and stochastic volatility (SV) models. GARCH is a time-series estimation procedure that is used in this context to calculate the conditional variance of a price series. Sometimes, implied volatility is used as an explanatory variable in GARCH models to improve accuracy, but with mixed results (Koopman, Jungbacker, and Hol 2005). While SV models tend to be harder to work with and are less commonly used, they are based on a continuous time process and thus tend to fit options prices more naturally. SV models are typically estimated using Monte Carlo techniques and have been found to return more accurate results than the GARCH method (Du, Yu, and Hayes 2011; Koopman, Jungbacker, and Hol 2005).

2.1.3 Comparing Methods

Although implied and historical volatilities are two methods of evaluating market volatility of returns, they are not simply two different calculations that indicate the same thing. Implied volatility uses the option premium to quantify options buyers' uncertainty based on their willingness to pay to defer their risk. In this way, it is the measure of the risk that is specified by the insurance premium. In contrast, historical volatility measures past price variation realized in a market over a period of time.

A widely accepted notion in the finance industry is that implied volatility is a superior method of forecasting future price variance compared to historical volatility. Kolb and Overdahl (2007) use the example of the stock market crash of 1987 to illustrate the advantages of using implied volatility. On October 19, 1987, the stock market lost 22 percent of its value. Had one calculated a stock's historical volatility on October 20, 1987 using a year's worth of daily or weekly price data, the estimate would clearly be too low. The implied volatility on October 20, 1987, however, would be much more accurate in reflecting market sentiment, especially in the short-term. Despite this notion, the best method of forecasting volatility has been widely debated by economists. Past literature reviews and comparisons of implied and historical volatility models have been mixed. While many studies have analyzed this topic, this section will only highlight a few of the most relevant.

Canina and Figlewski (1993) argue that it is illogical to apply an approach, like the Black-Scholes theory, that assumes a constant volatility to a situation in which volatility must be forecast because it changes over time. In their analysis of daily closing prices for options on the Standard and Poors 100 Index between March 1983 and March 1987, they find that implied volatilities calculated using a binomial model have little or no correlation with actual realized volatilities. In an article written specifically to question Canina and Figlewski's (1993) results, Christensen and Prabhala (1998) come to an opposing conclusion. Using the same methodology, their study of average monthly options premiums on the Standard and Poors 100 Index between November 1983 and May 1995 finds that implied volatility does predict future realized volatility, whereas historical volatility has much less explanatory power. They attribute this to their use of a longer time period and non-overlapping data due to the lower frequency (monthly as opposed to daily) relative to Canina and Figlewski's (1993) research. Christensen and Prabhala (1998) also note that other studies often focus on implied volatility's problems predicting future realized volatility, when they should focus on its high degree of accuracy in predicting future implied volatility.

Literature by Andersen and Bollerslev (1998), Giot (2002), Manfredo and Sanders (2004), Agnolucci (2009), and Brittain, Garcia, and Irwin (2011) compare implied volatilities to conditional volatilities calculated using the GARCH process. GARCH has faced some scrutiny due to claims of its inability to provide satisfactory out-of-sample forecasts (Agnolucci 2009). However, in evaluating daily exchange rates from October 1987 to September 1992, Andersen and Bollerslev (1998) discover that volatility forecasts from GARCH and SV methods typically correlate closely to realized volatility and account for 50 percent of its variability. These results improve as frequency of the data increases. Agnolucci (2009) also compares Black-Scholes volatilities to GARCH volatilities calculated on daily crude oil futures between December 1991 and February 2005 and determines that GARCH-type models perform better.

Giot (2002) analyzes daily cacao, coffee, and sugar futures contracts between January 1994 and December 1999. After evaluating both implied volatilities and GARCH volatilities in Value-at-Risk models, he concludes that implied volatilities have high information content and perform “as well” as the more complex GARCH processes. Manfredo and Sanders (2004) examine weekly live cattle volatilities between January 1986 and November 1999 using the two methods and find that both are biased and inefficient forecasts, but the implied volatility forecasts systematically improve over time. Brittain, Garcia, and Irwin (2011) show that implied volatility forecasts for daily live and feeder cattle futures contracts between October 1984 and January 2008 are consistently upwardly biased and inefficient, but still outperform GARCH forecasts. Interestingly, they also find that implied volatility forecasts for the live cattle market are considerably less accurate than the implied volatility forecasts for the feeder cattle market, which has about five times less trading volume.

Despite economists’ efforts, there is no consensus on the most accurate method of forecasting market volatility. Accuracy of volatility forecasts likely depends on the market and time period that is analyzed. There are advantages and disadvantages to each model for calculating volatility. This thesis uses the implied trinomial model because it is the method preferred by financial institutions and traders. Implied volatility spillover also has not been fully explored as it is used less frequently than historical volatility in previous economic literature.

2.2 Commodity Price Variation in Recent Years

Prices of agricultural commodities have been more variable in recent years than throughout most of history. In particular, prices more than tripled between 2006 and mid-2008, plummeted in November 2008, and have since sustained unusually high volatility. Economists have attempted to provide explanations for this sudden market instability, but there has been no consensus on attributing these price movements to any certain factors. Some fundamental drivers, other than biofuels policies, that have been suggested include exchange rate movements, a speculative price bubble, increased globalization, income expansion in developing countries, European agricultural policy changes, and weather shocks.

Devlin, Woods, and Coates (2011) analyze historical volatilities in the food, metals, crude oil, and agricultural materials markets over the last century and find that the 2008 price spike was not unprecedented. A price boom in the 1930s was a bounce back from the Great Depression and a spike in the 1970s can be attributed to a number of supply shocks that afflicted the markets at the time. They also set out to determine whether an increase in market speculation could have caused the recent increase in volatility. Studies by Sanders and Irwin (2010) and others use data from the U.S. Commodity Futures Trading Commission and Granger causality tests to examine the relationship between commodity fund positions and commodity prices and find that the number of fund positions does not have an effect on volatility in the markets. Devlin, Woods, and Coates (2011) also point out that commodity markets that are not actively traded, such as coal and iron ore, appreciated as much during the price spike in 2008 as the more actively traded markets. Most convincing is the observation that during the price increase, there was not a corresponding accumulation of physical stocks. If speculation was indeed the key driver of the price spike, commodity inventory should have been building. Stocks of agricultural commodities actually declined during this time period, and this indicates that it is more likely that a demand shock was the primary cause of the increased volatility.

Wright (2011) critically analyzes several of potential drivers of the price movements. He does not believe that agricultural commodity prices became more variable in recent years solely because crude oil prices have also become more variable, as some other economists have claimed (Headey and Fan 2008). Wright (2011) points out that historically, commodity prices have not always followed crude oil prices. He also notes that crude oil prices would have affected commodity production only if producers had cut back on farm inputs, like fertilizer. However, this was not the case during the price spike in 2008. Wright also does not believe that international population and income growth or a speculative bubble could have alone produced such large reactions in the market. He proposes that the only possible explanation for the price spike is the 2005 biofuels mandate that came at a time when stocks were low. He states that only two other large exogenous shocks have stricken the grain markets since 1971, and both occurred when stocks of grain were high. Wright (2011) suggests that as long as biofuel mandates continue as planned, over time the commodity markets should reach a less volatile equilibrium with a higher price point.

In 2010, Gilbert and Morgan set out to determine if the conditional volatility of food prices had increased between 2007 and 2009 or if higher prices had been observed without a change in expected volatility. Using the GARCH framework, Gilbert and Morgan (2011) find increases in conditional volatility for corn, soybeans, wheat, rice, sorghum, beef, and other foods, albeit only the increase in the conditional volatility of soybean oil is significant at the 10 percent level. However, when comparing decades, they discover that agricultural price volatility was actually lower in the 1990s and 2000s than in the previous two decades, with an exception in the rice market. For this reason, Gilbert and Morgan (2011) do not dismiss that agricultural volatility levels could return to historical normalcy.

In an article in Choices magazine, Irwin and Good (2009) present an opposing view. They suggest that the Energy Policy Act of 2005 caused the agricultural markets to undergo a great deal of structural change and believe that a new era of elevated crop prices and volatility has begun. They compare 2007 and 2008 nominal prices and variability to market conditions in two previous periods when structural change had occurred: in 1947 after World War II and from 1973 to 1975 following changes in exchange rate policies and rapid inflation. They project average nominal grain prices and volatilities for the new era based on these two previous periods of change. Irwin and Good (2009) also found that between September 2007 and March 2009, there was a high degree of correlation between ethanol and corn prices. They go so far as to state that the price of corn should be evaluated as a function of the price of ethanol in the future.

Sumner (2009) also analyzes historical commodity price movements, but in real terms. He compares 2006, 2007, and 2008 corn and wheat prices to historical prices dated back to 1866 and adjusted for a 1948 base. His analysis shows a distinct downward trend that began after World War II with dramatic price movements associated with war and macroeconomic shocks. Sumner (2009) finds that the price level associated with the price spike of 2008 is relatively unremarkable and real prices are comparable to corn and wheat real prices in the 1980s. However, when he observes variability by calculating the percentage deviation of the real price from a three-year moving average of past prices, Sumner (2009) discovers that the recent spike was exceeded by only four other instances in history. At 60 percent, this price rise is very large by historical standards. When compared to the price increase of the 1970s, the 2008 spike was much more precipitous. Based on his historical observations, Sumner (2009) believes that real prices should return to the long-term trend reduction, though it is likely to take some time. He suggests that in order to keep up with demand increases, the government should invest more in agricultural research to ensure long-term productivity growth.

While there is no doubting that crude oil and agricultural prices have been more volatile in recent years, the question remains whether this shock to the markets was truly unprecedented and unpredictable. Undeniably, the Energy Policy Act of 2005 played a role in the 2008 price spike, but the extent of its impact on the markets has been heavily debated. Likely many factors were influencing the energy and agricultural sectors during that time and created what Heady and Fan (2008) refer to as a "perfect storm." Some economists argue that a new era of increased volatility began in 2008 due to structural change in the markets (Irwin and Good 2009), whereas others believe volatility will subside and prices will return to follow historical trends (Gilbert and Morgan 2010; Sumner 2009). While this thesis will not attempt to identify the factors responsible for the volatility surge or project the future of price stability, it is important to be aware of market behavior during the time period analyzed.

2.3 Price and Volatility Spillover in the Energy and Agricultural Markets

Because the 2008 price spike and since-sustained level of high volatility in the commodity markets have generated chaos in the energy and agricultural industries in recent years, several economists have estimated spillover effects crude oil and biofuels markets may have had on agricultural markets, including corn, soybeans, and wheat. These studies have used varying approaches and techniques with mixed results. This literature is discussed in this section.

Many of the papers reviewed below use Granger causality tests to analyze causal relationships between prices or volatilities. This method of determining the direction of causality or feedback between time series was introduced by Granger (1969). The Granger test does not truly reveal causality, but it does indicate whether there is a lead or lag relationship between two variables. Granger causality tests are the primary method of analysis used in this research, and details and mechanisms of the test are discussed more extensively in Chapter 4.

2.3.1 Previous Studies on Price Spillover

Saghaian (2010) analyzes monthly prices in the crude oil, ethanol, corn, soybeans, and wheat markets between January 1996 and December 2008. He finds strong correlation between crude oil and ethanol prices alone and between agricultural commodities alone, but not between fuel and agricultural prices. Saghaian (2010) uses Johansen's cointegration method, a vector error correction model (VECM), and TETRAD IV software to test for causal links between the price series. He finds causality only from the corn and soybean markets to the wheat market. Saghaian (2010) also evaluates the price series using Granger causality tests with two lags. He finds a strong unidirectional relationship from crude oil to ethanol and a strong bidirectional relationship between corn and ethanol. Crude oil prices Granger cause all three of the grains' prices. He also determines that soybeans and wheat unidirectionally Granger cause ethanol. Between the agricultural commodities, corn and wheat Granger cause soybean prices and corn and wheat have a bidirectional relationship. Although these results are mixed, they are still useful. Likely the Granger tests are picking up on the strong correlation, and therefore, Saghaian (2010) concludes that causation between the price series is questionable.

A similar study by Zhang, Lohr, Escalante, and Wetztein (2009) uses those same methods along with impulse response functions (IRFs) to conclude that gasoline prices directly affected the prices of crude oil and ethanol from March 1989 to December 2007. They find no long-run relations between the energies and corn and soybean prices during this time period. They also analyze the data as it is split into two time periods: pre-ethanol boom (1989-1999) and post-ethanol boom (2000-2007). Interestingly, their results show that corn Granger caused crude oil in the short-run prior to the boom, but not post-boom. The only other linkage is the causality from crude oil to ethanol which is significant in the post-boom period. They suggest the disconnect between fuel and grain prices is due to corn showing limited response to any price shocks. The IRFs indicate that corn prices always quickly converge to their long-run equilibrium.

Analysis of crude oil and corn prices by Muhammad and Kebede (2009) determined that there was very little relationship between the two prior to the Energy Policy Act of 2005. Between 1990 and 2004, less than 2 percent of the movement in corn prices was explained by crude oil price changes. Between 2005 and 2008 however, that number jumped to 60 percent and correlation between the two commodities was strong. When crude oil prices fell in late 2008, corn prices did not fall as hard, and this suggests that the relationship between crude oil and corn is stronger when prices are rising and weaker when they are declining. Muhammad and Kebede (2009) assert that between June 2007 and July 2008, 54 percent of corn and 49 percent of soybean price changes can be attributed to growth in the biofuels sector. This translates to 3 to 4 percent of price increases in retail foods. They believe that the livestock industry may be one of the most negatively affected by the Energy Policy Act of 2005, since their input costs, namely feed grains, have increased in recent years, but livestock prices have not risen by the same magnitude. However, they did not test this hypothesis.

2.3.2 Previous Studies on Volatility Spillover

Trujillo-Barrera, Mallory, and Garcia (2012) examine the crude oil, ethanol, and corn markets from July 2006 to November 2011. By calculating weekly percentage price changes, they analyze stationarity, correlation, and cointegration of the variability in the price series.

Augmented Dickey Fuller (ADF) and Phillips-Pherron unit root tests reveal that the prices themselves are nonstationary, but returns are stationary. They find significant correlation between all three of the markets and discover cointegration between corn and ethanol prices.

Trujillo-Barrera, Mallory, and Garcia (2012) then use a GARCH model and a vector error correction model (VECM) to estimate the conditional volatilities and determine spillovers. Their largest conditional volatilities are not-surprisingly found to be at the end of 2008 and the beginning of 2009. The results indicate that there is volatility spillover from the crude oil market to the ethanol and corn markets and from the corn market to the ethanol market. Trujillo-Barrera, Mallory, and Garcia (2012) also measure the strength of volatility transmission by defining and calculating volatility spillover ratios which measure the portion of conditional variability in one market that can be attributed to another market at a certain point in time. These ratios determine that the effect of crude oil volatility on corn and ethanol volatility averaged about 15 percent, but reached peaks of nearly 45 percent during periods of high uncertainty.

Using similar methodology, Wu, Guan, and Myers (2011) examine volatility spillover between January 1992 and June 2009 using mid-week closing prices from the corn cash market and corn and crude oil futures markets. Unlike most other studies, they use three different parameterizations. Firstly, they assume that spillovers are constant throughout the entire period. Secondly, they use a dummy variable to indicate whether the data was from after the Energy Policy Act of 2005 was passed or otherwise. Thirdly, they allow the parameters to vary based on a lagged consumption ratio of ethanol to gasoline to indicate size of the spillovers between markets.

Wu, Guan, and Myers (2011) found that correlation between crude oil and corn markets changed from being weakly negative to strongly positive over the time period they analyzed.

However, they find no cointegration between crude oil and corn prices. The results of their first test for the entire time period show relatively small spillovers in any of the markets. Their second test reveals that the Energy Policy Act of 2005 greatly strengthened the connection between crude oil and corn markets and caused volatility spillover to occur from crude oil to corn. The third test finds that more substantial spillovers occur from crude oil to corn when the ethanol to gasoline consumption ratio is high. In all three tests, the crude oil market had similar impacts on the corn cash and corn futures markets.

A study by Du, Yu, and Hayes (2011) assesses the sources of crude oil price variability and evaluates volatility spillover between the crude oil, corn, and wheat markets. They estimate a bivariate SV model using Bayesian techniques and use weekly average futures prices in two periods: November 1998 to October 2006 and October 2006 to January 2009. The study determines that in the first period, crude oil and the agricultural commodities have a negative correlation and little spillover. However, in the second period there is high correlation and positive spillover coefficients between variability in crude oil and corn and variability in crude oil and wheat. Additionally, Du, Yu, and Hayes (2011), run a univariate SV model with Merton jump to relate crude oil volatility to variables including crude oil inventory, a speculation index, and scalping, which is the action of opening and closing a contract position in a short period of time. They find that, as expected, crude oil inventory discourages variability in the crude oil market, whereas speculation and scalping increase variability.

Harri and Hudson used a methodical framework similar to that which is used in this thesis in 2009. They employ the GARCH method to compute conditional variances for daily crude oil prices, corn prices, and exchange rates between April 2003 to March 2006 and April 2006 to March 2009. Like in other studies, they find a cointegrating relationship between crude oil and corn in the second era, but not in the first. They use a vector autoregressive (VAR) model to evaluate volatility spillover and perform both Granger causality tests and cross-correlation function (CCF) tests of the squared residuals. They discover that in the first period, crude oil prices Granger cause exchange rates, but not corn prices. There are no other causal relationships in prices or variance in the first era. In the second period, Harri and Hudson (2009) find that crude prices Granger cause corn prices and exchange rates. The effect of crude oil prices on exchange rates is more prominent in the second period than in the first period. They also determine that crude oil price variance leads corn price variance. The CCF tests of squared residuals show a relationship between crude oil volatility and corn volatility in the second period as well.

In their analysis, Hertel and Beckman (2011) take a unique approach and use stochastic simulations and an applied general equilibrium model to examine the linkage between energy and agricultural markets given different policy specifications. Their scenarios include a binding Renewable Fuel Standard in 2015 versus a non-binding Renewable Fuel Standard in 2015 and a maximum blend ratio of biofuel to gasoline in 2015 versus no maximum blend ratio of biofuel to gasoline in 2015. This maximum blend ratio is a constraint set by refineries and car manufacturers since they claim there is only a certain amount of ethanol that can be blended with gasoline before problems arise logistically and mechanically. This problem is commonly referred to as the blend wall. Like most other studies, Hertel and Beckman (2011) find that the relationship between crude oil and corn strengthened after the passage of the Energy Policy Act of 2005. Their analysis shows that crude oil volatility has been transferred to the corn market in recent years, but they believe the future of this linkage will depend on the future of energy policy. They discover that a binding Renewable Fuel Standard will cause volatility to increase in the agricultural markets in the case of low crude oil prices, as ethanol producers will be unable to cut production. This binding Renewable Fuel Standard could increase volatility in the coarse grains market by 25 percent. Similarly, a maximum blend ratio will increase agricultural commodity volatility when crude oil prices are high, because ethanol producers cannot capitalize on this. Hertel and Beckman (2011) estimate that if both the Renewable Fuel Standard and the blend wall are binding in 2015, volatility in the coarse grains markets will be about 57 percent higher in response to corn supply shocks than in a non-binding scenario.

While most of these studies show strong price or volatility spillover effects between crude oil and corn in their self-defined post-ethanol boom periods (Trujillo, Barrera, Mallory, and Garcia 2012; Wu, Guan, and Myers 2011; Du, Yu, and Hayes 2011; Harri and Hudson 2009; Muhammad and Kebede 2009) some of the analysts find no spillover effects at all (Zhang, Lohr, Escalante, and Wertztein 2009). Results vary based on the time periods chosen to analyze and the method used to calculate volatility. To date, no literature has been published that evaluates spillover in the energy and agricultural markets using implied volatilities calculated with the Black-Scholes formula or trinomial formula method. There are also no known studies that consider spillover between grain and livestock commodities a primary source of interest. This research will expand upon what others have done with historical volatilities to fill that need.

Chapter 3 - Data

3.1 Source and Overview

The data used in this analysis were obtained from the Bloomberg Professional service data terminals. They include a daily series of futures contracts' closing prices and put and call options contracts' implied volatilities for corn, soybeans, live cattle, feeder cattle, and lean hogs from the CME Group, hard red winter wheat from the Kansas City Board of Trade (KCBT), cotton from the Intercontinental Exchange (ICE), and light sweet crude oil and natural gas from the New York Mercantile Exchange (NYMEX) over the period beginning January 3, 1995 and ending December 31, 2012. Bloomberg calculates options' implied volatilities using the implied trinomial method for American options. In the implied trinomial calculations, Bloomberg uses the underlying future's last trade price and the option's last trade price. The implied volatility reported is then a weighted average of the implied volatilities of the two put or call options closest to the at-the-money strike.

A small percentage of daily implied volatility observations were missing from the initial data set for live cattle, feeder cattle, and lean hogs. The reasoning behind this is unknown, although it could be due to low trade volume on specific contracts in certain years since Bloomberg has a minimum volume of trades that must be completed each day to calculate an implied volatility. These missing data points were gathered from the Commodity Research Bureau (CRB) DataCenter. The implied volatility series assembled via Bloomberg and the series collected from CRB DataCenter were often identical and nearly perfectly correlated. Prices and available implied volatilities were also compared manually and were nearly identical in most cases, often times to the tenths decimal place. For this reason, the replacement data was preferred to blank observations and should not have biased the outcome of the results in any way.

Daily volatilities for put and call options on the same contracts were averaged to consolidate data into one daily value that reflected price risk. Weekly averages were then calculated for both prices and volatilities. For each commodity, the series to analyze was defined as a single implied volatility sequence that consisted of the implied volatility for the futures contract expiring in four or five months depending on the contract months available for the commodity. In the event that the commodity had a contract expiring in four months and a contract expiring in five months, the contract expiring in four months was used. In only a few instances, there were no contracts expiring in four or five months, and in these cases the contract expiring in six months was used. In this way, there is a similar forward horizon for all commodities and problems associated with implied volatility variation that can occur near contract expiration time periods are avoided. Daily last trade prices for all commodities were also defined in a similar manner. For example, feeder cattle contracts are traded for the months of January, March, April, May, August, September, October, and November. In January, the May contract is four months from expiration, so prices and volatilities on the May contract were used. In February, there are no contracts expiring in four to five months since feeder cattle contracts are not traded for June or July. In this case, August contract data were used. In April, the August contract is four months from expiration and the September contract is five months from expiration. The August contract data were also used in this scenario. In August, there is no contract that expires in four months, but the January contract expires in five months. Therefore, in August, the January contract data were used. Table 3.1 illustrates this further for each commodity. In Table 3.1 and hereon throughout this thesis, LC refers to live cattle, FC refers to feeder cattle, LH refers to lean hogs, CO refers to crude oil, and NG refers to natural gas.

The markets that were selected for this study are major agricultural markets that are related in that one is a common input for another (e.g., corn and cattle) or they are substitutes in production (e.g., corn, soybeans, and cotton). Crude oil and natural gas were also included because of the connections that exist between the energy and agricultural markets which were discussed extensively in earlier chapters of this thesis. Ideally, the ethanol market would have been represented in this research as well. However, ethanol volatilities were omitted since ethanol futures contracts were not traded at all until 2005 and due to low trade volume, prices and volatilities for those contracts have not been reported consistently even in more recent years.

3.2 Preliminary Analysis

This section will summarize the data used in this thesis and provide the results of preliminary analysis including descriptive statistics and correlation matrices. The implied volatilities series were analyzed over three time periods: the entire January 1995 to December 2012 period, pre-ethanol boom (January 1995 to December 2005), and post-ethanol boom (January 2006 to December 2012). A few different dates for the division of the time series were evaluated, and the results were found to be somewhat sensitive to the time period that was chosen. The division of the time series between 2005 and 2006 was selected as it is consistent with what has been used in most previous literature. All preliminary analysis was conducted using SAS analytics software.

3.2.1 Descriptive Statistics

Descriptive statistics were calculated for all nine price and volatility variables over the three time periods. Across the aggregate time frame, there were 943 total weekly price observations and 943 total weekly implied volatility observations that were considered. This is equivalent to one observation per week (the weekly average price or implied volatility) over the 18 year (1995-2012) time span. Subsets of the aggregate data were analyzed in the pre-ethanol boom and post-ethanol boom eras. The descriptive statistics are presented in Table 3.2 and Table 3.3.

Over time, the livestock markets have been the least volatile and the energy markets have been the most volatile. In comparing the pre-ethanol boom and post-ethanol boom time periods, it appears that corn, soybeans, wheat, and cotton are the only commodities that experienced a significant shift in their mean volatility; however, all nine markets realized increases in their mean prices between the two time frames. Most of the commodity price series, with the exception of natural gas, began trending upward in the mid-2000s. Plots of the price series and implied volatilities are contained in Figures 3.1 through 3.9.

Major news events have caused some large spikes in implied volatility in the some of the markets. For example, following the announcement that a cow with bovine spongiform encephalopathy had been imported into the United States in December of 2003, implied volatilities in the live cattle and feeder cattle markets increased by approximately 68 percent and 100 percent, respectively. Similarly, a volatility spike of approximately 87 percent arose in December of 1998 in the lean hogs market after hog prices tumbled to a historic low in real dollars because of a surplus in the market. The lean hogs market also saw a precipitous increase in volatility during the H1N1 “swine” flu outbreak in 2009. In July of 2008, prices in the crude oil market fell abruptly by more than 50 dollars per barrel and volatilities increased after it was broadcasted that the presidential ban on U.S. offshore oil drilling would be lifted. Natural gas has been the most consistently volatile market over the years, probably because of its varying availability in the United States.

3.2.2 Contemporaneous Correlations

Contemporaneous correlation was evaluated between prices in all nine markets using the Pearson correlation coefficient. The same was done to examine relationships between implied volatilities. Correlation is a measure of linear dependence between each of the price or implied volatility series. A correlation coefficient of 1 indicates perfect positive linear correlation, whereas a correlation coefficient of -1 indicates perfect negative linear correlation. A value of 0 means there is no linear dependence between the volatility in the two markets. Tables 3.4 through 3.9 show the contemporaneous correlations in the data during the three time frames.

A main finding in the agricultural price series is that correlation between the grains and cattle prices changed from moderately negatively correlated in the pre-ethanol boom time period to strongly positively correlated in the post-ethanol boom time period. Nearly all of the implied volatility series for the agricultural commodities are positively linearly correlated in both the pre-ethanol boom and post-ethanol boom time periods. The correlation coefficients either remain close to the same or greatly increase from the pre-ethanol boom era and post-ethanol boom era, indicating that the volatility relationships between the agricultural markets strengthened over time. Across the time periods, the strongest price and volatility correlations occur, predictably, between the live cattle and feeder cattle markets. Corn, soybeans, and wheat are also very highly correlated in both price and volatility

Interestingly, the correlation between the crude oil market and the grain markets transformed from weakly negative, uncorrelated, or weakly positive pre-ethanol boom to strongly positive post-ethanol boom. The crude oil and corn relationship in particular changed from weakly negative in the first era to strongly positive, with correlation coefficients of 0.703 for price and 0.574 for volatility, in the second era. This is evidence that the Energy Policy Act of 2005 indeed strengthened the bond between the crude oil and corn markets. A strongly positive relationship between natural gas and livestock prices evolved into a moderately negative one. The correlation between crude oil volatility and natural gas volatility diminished over time, and natural gas volatility is weakly correlated with the agricultural commodities' volatility, except in the case of lean hogs.

In summary, there does appear to have been an upward shift in the mean prices and implied volatilities of all commodities, but especially in the grain markets, from the pre-ethanol boom time period to the post-ethanol boom time period. The agricultural and crude oil markets are experiencing an increasing trend in price movement that began in the mid-2000s, and correlation between the agricultural and crude oil market has notably increased over time. All of this is consistent with the hypothesis that the Energy Policy Act of 2005 strengthened the link between the grain and crude oil markets, as other economists have suggested.

Table 3.1, Contracts Used to Achieve Forward Horizon

Month	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Jan	May	May	May	May	Jun	May	Jun	May	May
Feb	Jul	Jul	Jul	Jul	Jun	Aug	Jun	Jun	Jun
Mar	Jul	Jul	Jul	Jul	Aug	Aug	Jul	Jul	Jul
Apr	Sep	Aug	Sep	Oct	Aug	Aug	Aug	Aug	Aug
May	Sep	Nov	Sep	Oct	Oct	Sep	Oct	Sep	Sep
Jun	Dec	Nov	Dec	Oct	Oct	Oct	Oct	Oct	Oct
Jul	Dec	Jan	Dec	Dec	Dec	Nov	Dec	Nov	Nov
Aug	Dec	Jan	Dec	Dec	Dec	Jan	Dec	Dec	Dec
Sep	Mar	Mar	Mar	Mar	Feb	Jan	Feb	Jan	Jan
Oct	Mar	Mar	Mar	Mar	Feb	Mar	Feb	Feb	Feb
Nov	Mar	Mar	Mar	Mar	Apr	Mar	Apr	Mar	Mar
Dec	May	May	May	May	Apr	Apr	Apr	Apr	Apr

Table 3.2, Descriptive Statistics for Futures Prices

	Units	# Obs.	Mean	Standard Deviation	Minimum	Maximum
1995-2012						
Corn	(¢/bu)	943	342.97	154.26	188.25	824.10
Soybeans	(¢/bu)	943	786.10	309.69	417.69	1748.50
Wheat	(¢/bu)	943	488.62	200.26	277.45	1215.50
Cotton	(¢/lb)	943	68.20	22.29	30.92	195.77
Live Cattle	($/cwt)	943	83.36	18.63	59.27	137.48
Feeder Cattle	($/cwt)	943	96.01	23.69	51.96	163.50
Lean Hogs	($/cwt)	943	66.24	12.78	34.04	103.22
Crude Oil	($/bbl)	943	48.98	31.05	11.71	143.58
Natural Gas	($/mmBtu)	943	4.77	2.59	1.47	14.50
Pre-Ethanol Boom (1995-2005)						
Corn	(¢/bu)	576	252.02	43.10	188.25	424.00
Soybeans	(¢/bu)	576	599.57	115.24	417.69	1026.85
Wheat	(¢/bu)	576	361.21	63.99	277.45	651.25
Cotton	(¢/lb)	576	62.46	14.37	30.92	103.81
Live Cattle	($/cwt)	576	71.70	7.99	59.27	94.61
Feeder Cattle	($/cwt)	576	82.01	13.21	51.96	114.71
Lean Hogs	($/cwt)	576	60.35	9.66	34.04	82.78
Crude Oil	($/bbl)	576	27.28	12.22	11.71	69.37
Natural Gas	($/mmBtu)	576	3.99	2.39	1.47	14.50
Post-Ethanol Boom (2006-2012)						
Corn	(¢/bu)	367	485.72	157.73	215.88	824.10
Soybeans	(¢/bu)	367	1078.85	292.04	557.00	1748.50
Wheat	(¢/bu)	367	688.59	176.46	376.35	1215.50
Cotton	(¢/lb)	367	77.20	28.65	41.39	195.77
Live Cattle	($/cwt)	367	101.66	15.59	75.43	137.48
Feeder Cattle	($/cwt)	367	117.99	19.42	87.52	163.50
Lean Hogs	($/cwt)	367	75.48	11.56	44.47	103.22
Crude Oil	($/bbl)	367	83.04	18.52	42.74	143.58
Natural Gas	($/mmBtu)	367	6.01	2.39	2.24	13.79

Table 3.3, Descriptive Statistics for Implied Volatilities

	Units	# Obs.	Mean	Standard Deviation	Minimum	Maximum
1995-2012						
Corn	%	943	27.39	7.71	6.41	47.81
Soybeans	%	943	24.74	6.75	10.85	53.28
Wheat	%	943	27.12	6.63	16.59	54.81
Cotton	%	943	26.17	7.89	11.86	61.55
Live Cattle	%	943	14.71	3.26	9.53	36.46
Feeder Cattle	%	943	13.85	3.24	7.27	34.69
Lean Hogs	%	943	23.12	5.46	14.98	55.77
Crude Oil	%	943	34.06	9.31	6.18	85.38
Natural Gas	%	943	46.69	11.09	26.76	80.23
Pre-Ethanol Boom (1995-2005)						
Corn	%	576	23.29	5.45	6.41	40.43
Soybeans	%	576	22.55	5.11	10.85	38.82
Wheat	%	576	23.20	3.40	16.59	42.75
Cotton	%	576	23.56	5.59	11.86	38.07
Live Cattle	%	576	14.41	3.63	9.53	36.46
Feeder Cattle	%	576	13.24	3.41	7.27	34.69
Lean Hogs	%	576	23.39	6.19	14.98	55.77
Crude Oil	%	576	32.92	7.65	6.18	57.79
Natural Gas	%	576	46.11	11.10	26.76	79.26
Post-Ethanol Boom (2006-2012)						
Corn	%	367	33.82	6.21	20.40	47.81
Soybeans	%	367	28.19	7.53	16.14	53.28
Wheat	%	367	33.27	5.74	22.11	54.81
Cotton	%	367	30.27	9.14	17.91	61.55
Live Cattle	%	367	15.18	2.49	9.63	25.20
Feeder Cattle	%	367	14.80	2.68	10.28	25.79
Lean Hogs	%	367	22.70	4.03	15.16	47.14
Crude Oil	%	367	35.85	11.21	23.95	85.38
Natural Gas	%	367	47.59	11.01	29.88	80.23

Figure 3.1, Corn Market Prices and Volatility (1995-2012)

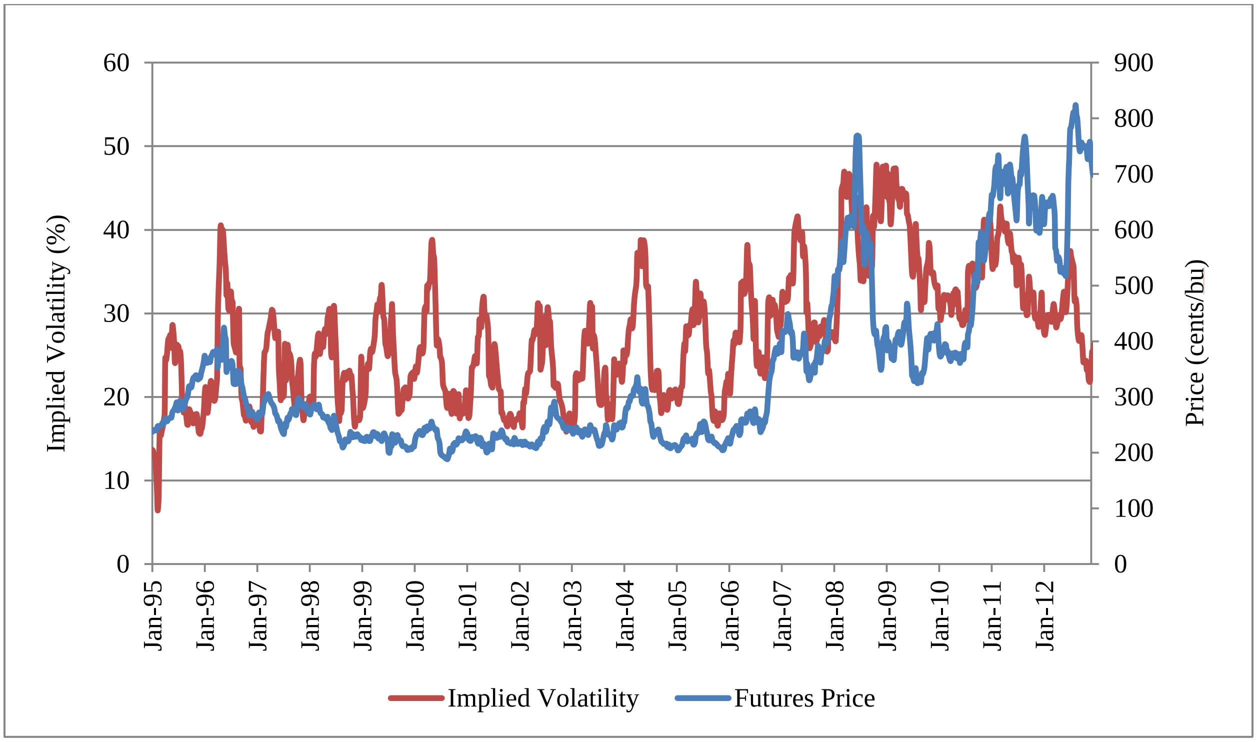


Figure 3.2, Soybeans Market Prices and Volatility (1995-2012)

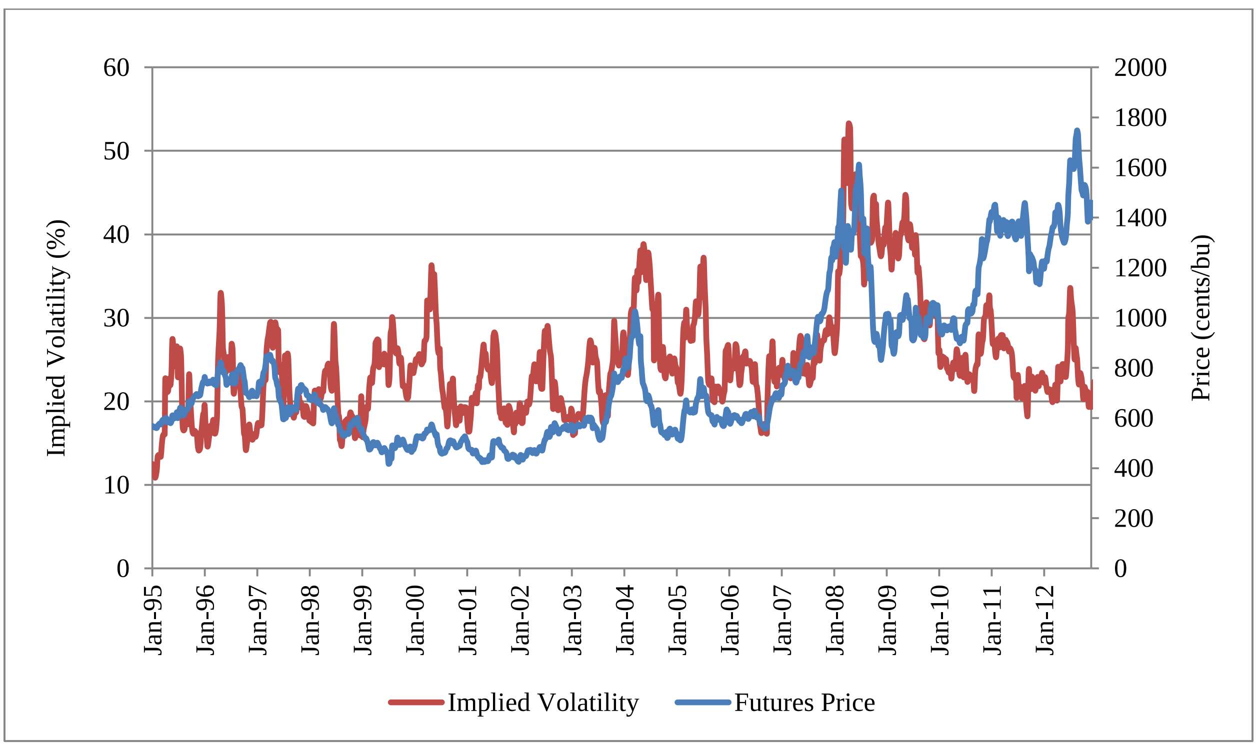


Figure 3.3, Wheat Market Prices and Volatility (1995-2012)

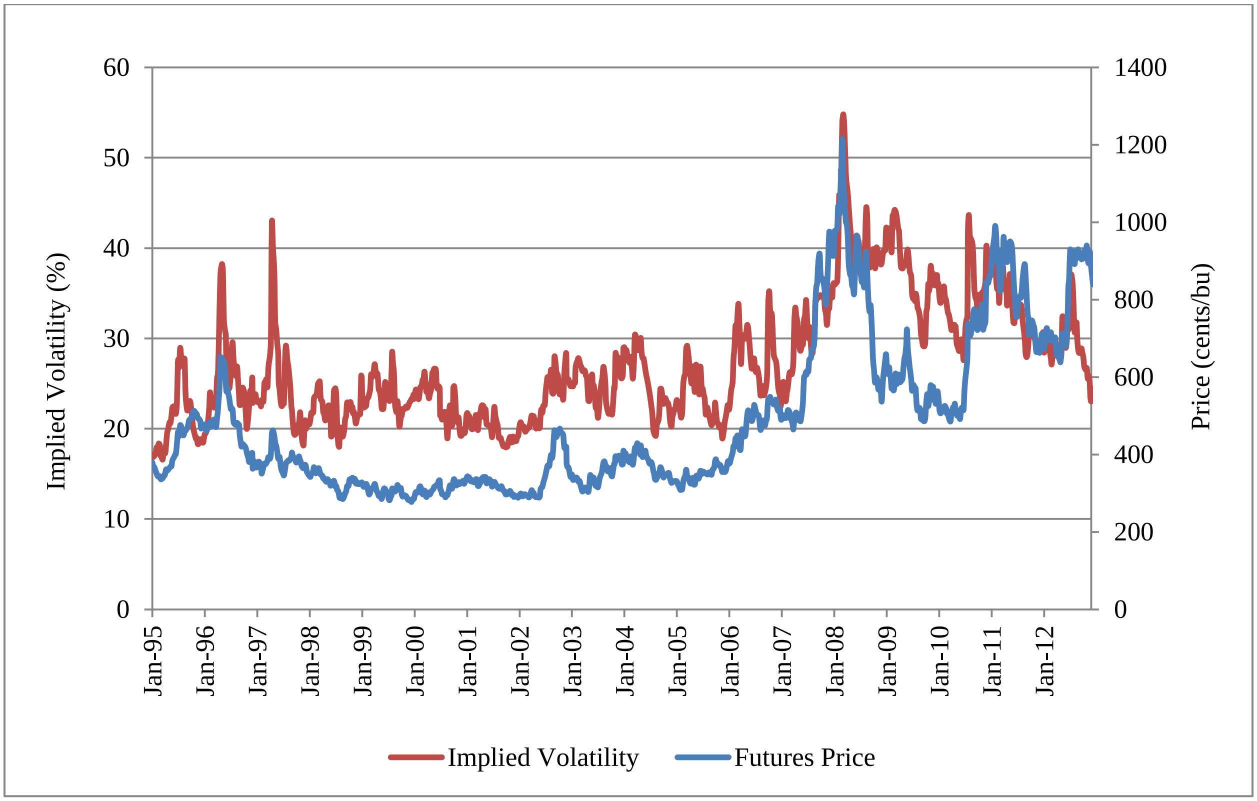


Figure 3.4, Cotton Market Prices and Volatility (1995-2012)

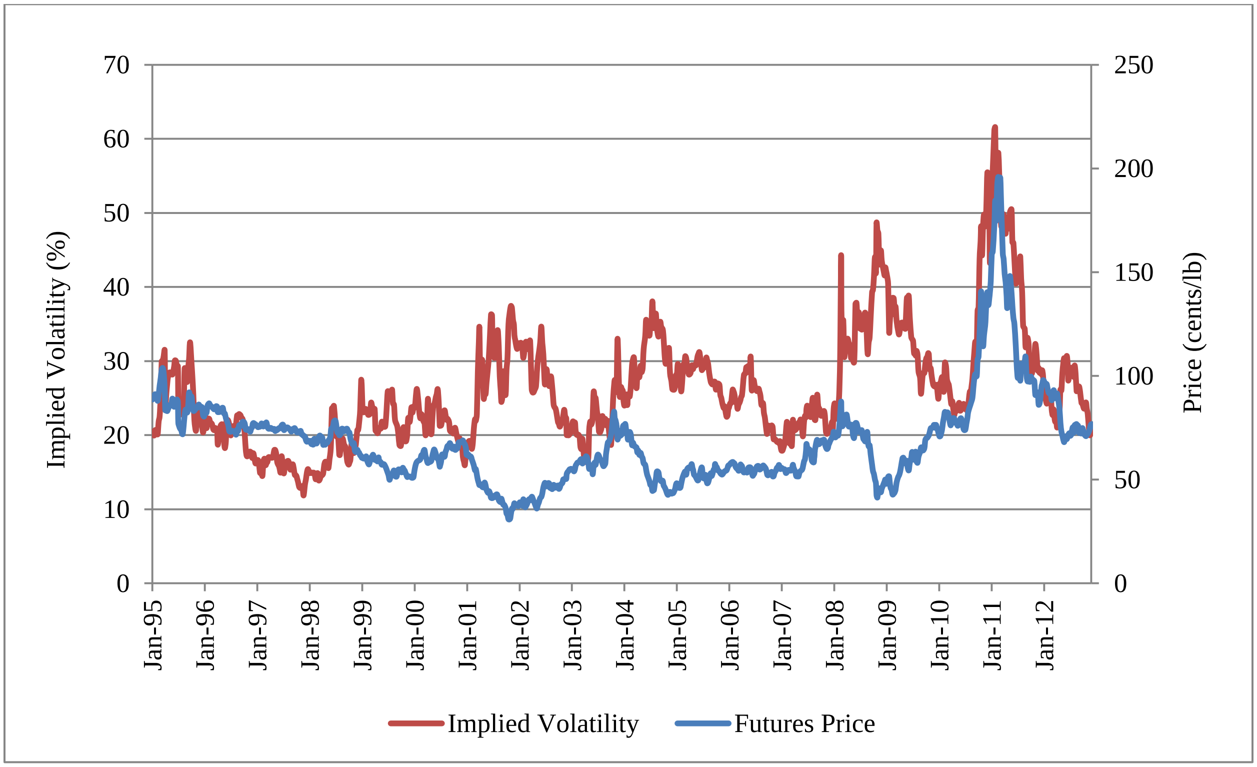


Figure 3.5, Live Cattle Market Prices and Volatility (1995-2012)

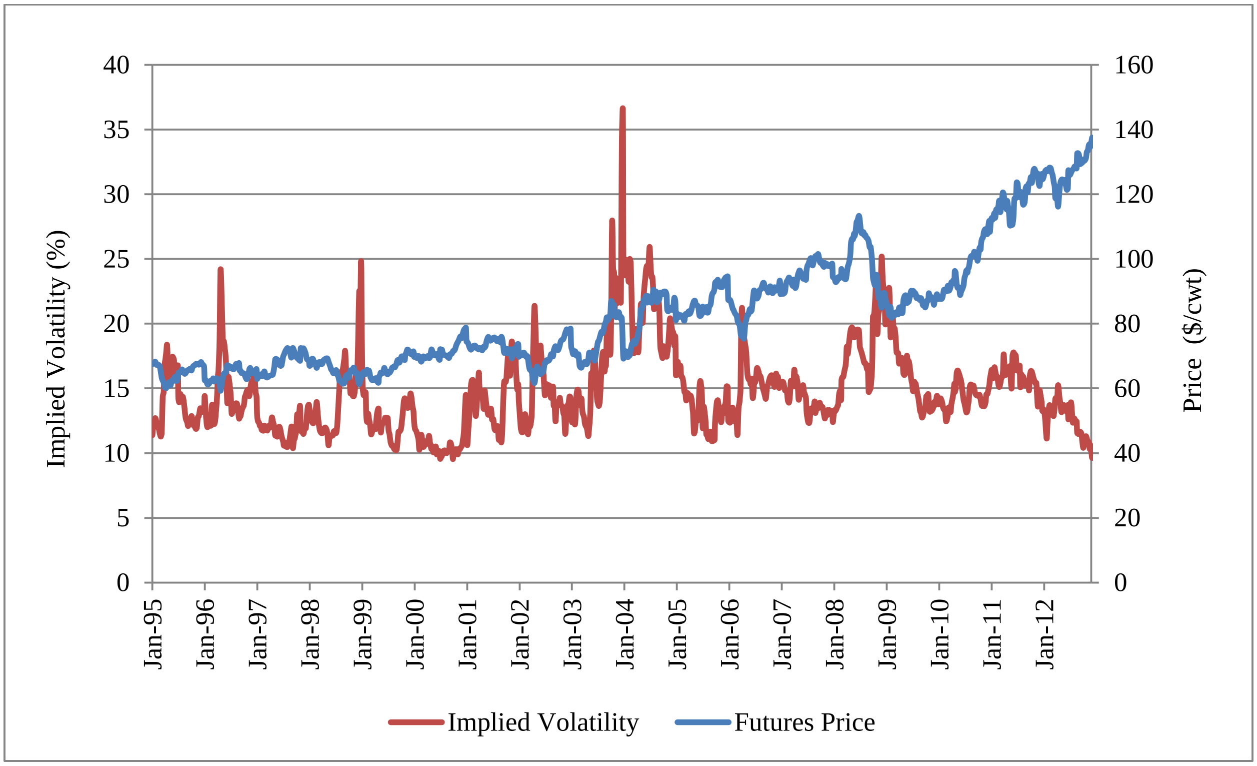


Figure 3.6, Feeder Cattle Market Prices and Volatility (1995-2012)

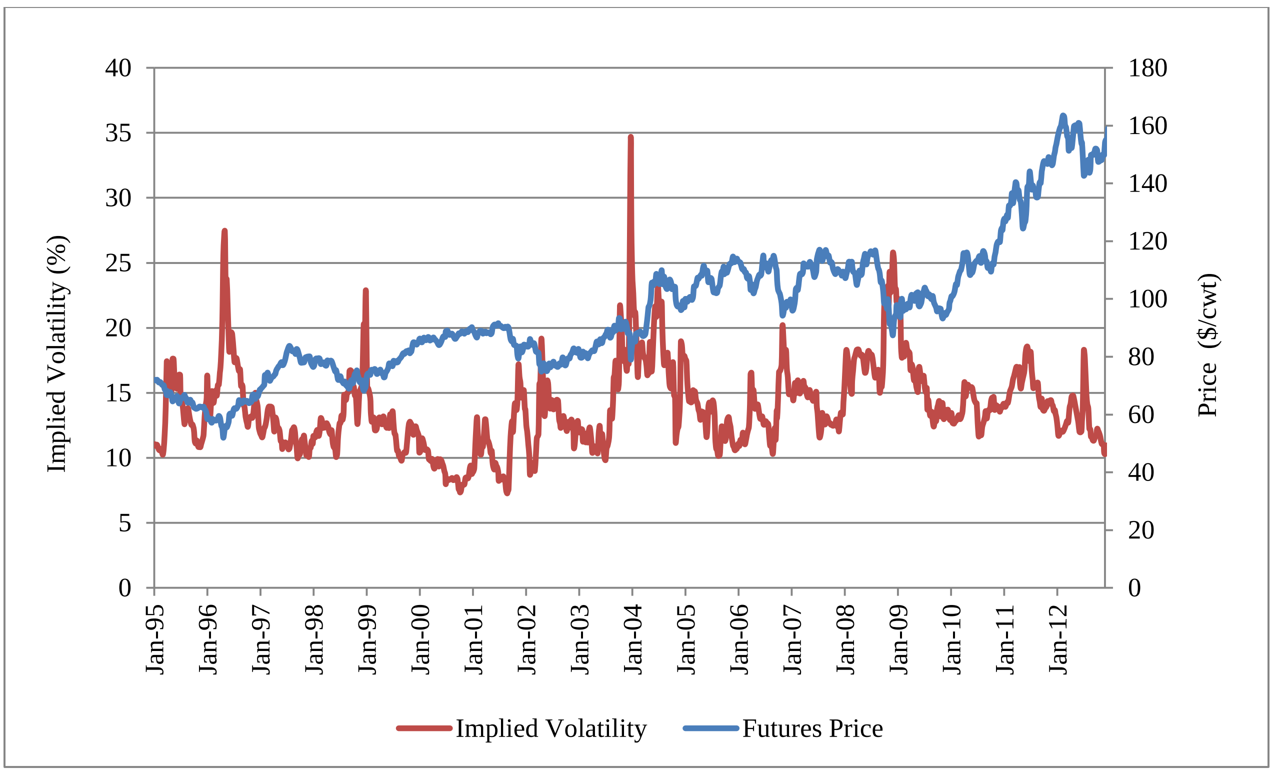


Figure 3.7, Lean Hogs Market Prices and Volatility (1995-2012)

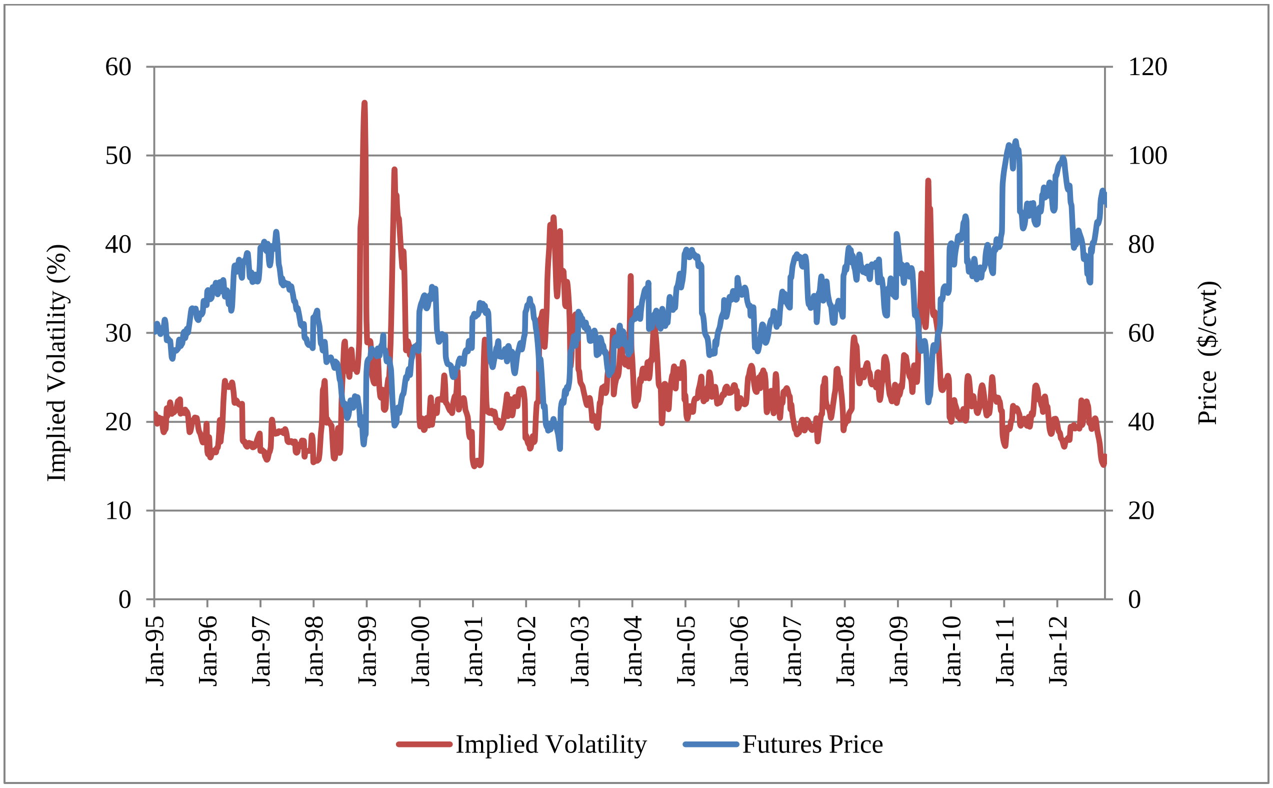


Figure 3.8, Crude Oil Market Prices and Volatility (1995-2012)

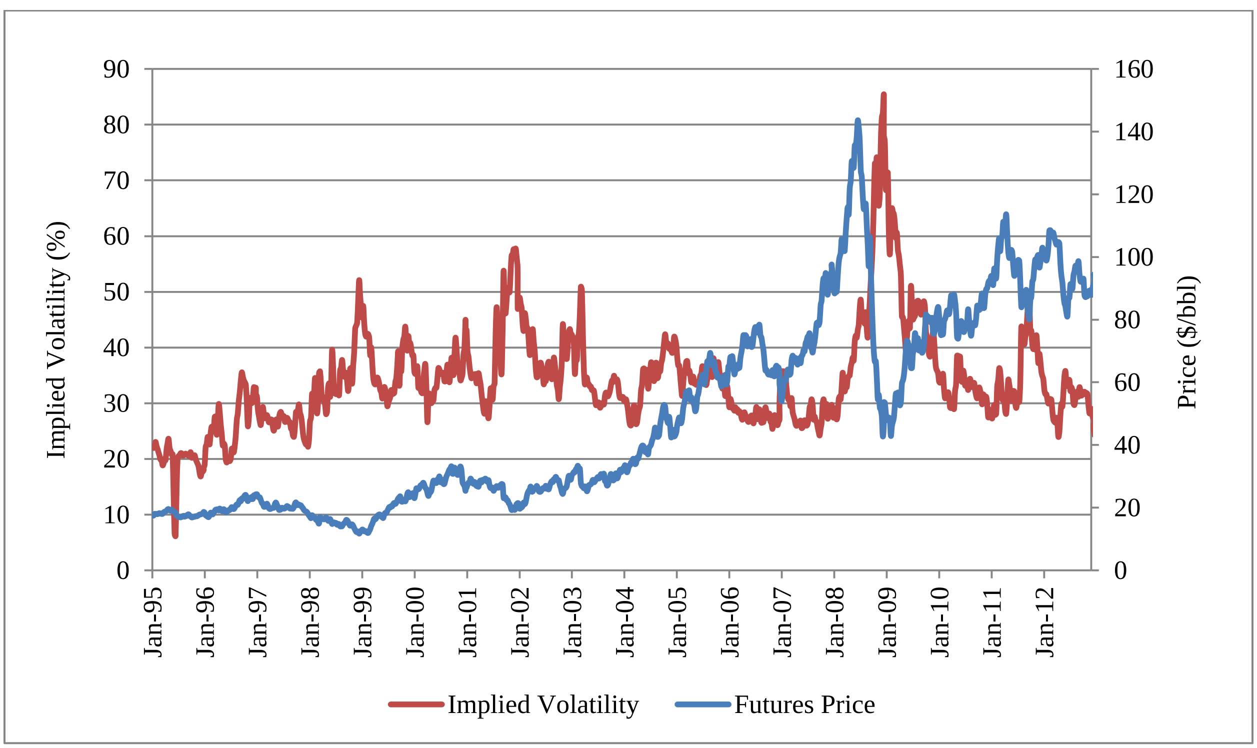


Figure 3.9, Natural Gas Market Prices and Volatility (1995-2012)

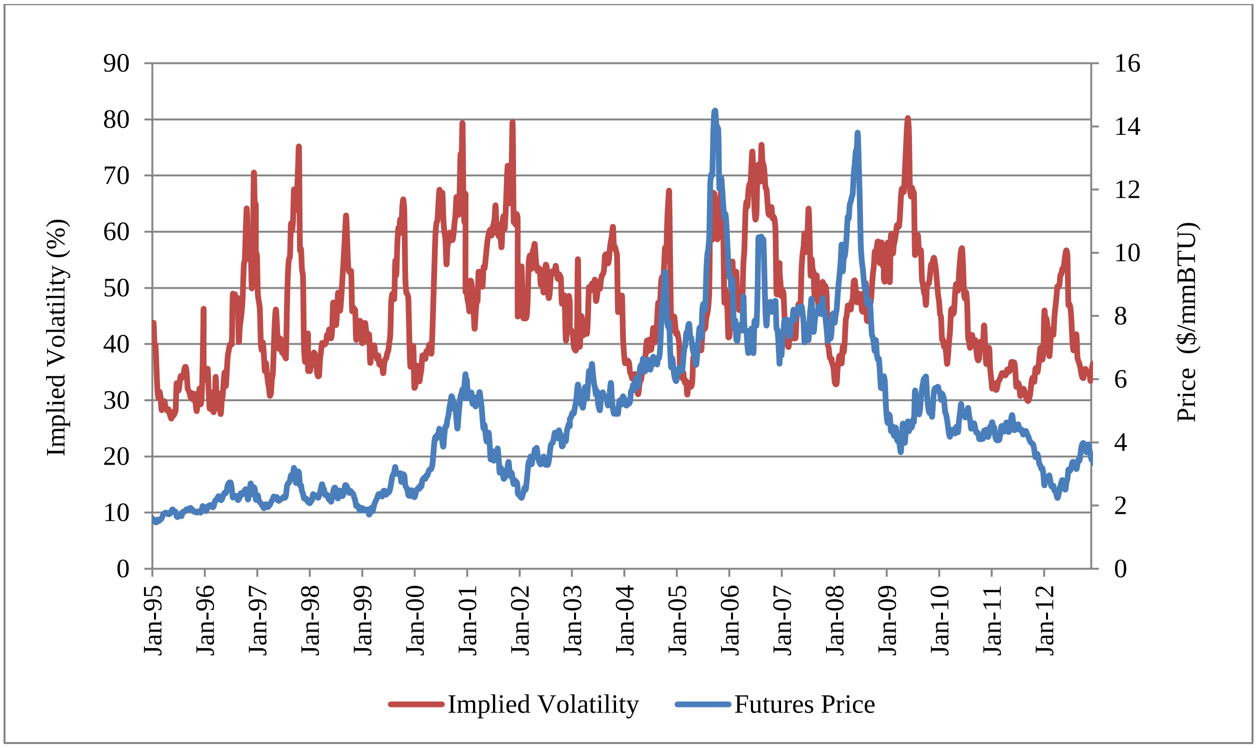


Table 3.4, Correlation Matrix of Prices (1995-2012)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	1	-	-	-	-	-	-	-	-
Soybeans	0.954	1	-	-	-	-	-	-	-
Wheat	0.915	0.925	1	-	-	-	-	-	-
Cotton	0.624	0.601	0.555	1	-	-	-	-	-
LC	0.846	0.835	0.794	0.402	1	-	-	-	-
FC	0.723	0.727	0.668	0.304	0.961	1	-	-	-
LH	0.735	0.723	0.658	0.585	0.703	0.652	1	-	-
CO	0.793	0.825	0.830	0.379	0.899	0.864	0.649	1	-
NG	0.096	0.163	0.266	-0.205	0.369	0.388	0.116	0.558	1

* indicates results were found to be insignificant at the 10% level.

Table 3.5, Correlation Matrix of Prices (Pre-Ethanol Boom: 1995-2005)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	1	-	-	-	-	-	-	-	-
Soybeans	0.761	1	-	-	-	-	-	-	-
Wheat	0.872	0.674	1	-	-	-	-	-	-
Cotton	0.621	0.599	0.544	1	-	-	-	-	-
LC	-0.337	0.674*	-0.124	-0.446	1	-	-	-	-
FC	-0.589	-0.211	-0.450	-0.604	0.903	1	-	-	-
LH	0.379	0.490	0.370	0.264	0.180	0.064*	1	-	-
CO	-0.308	0.032*	-0.112	-0.417	0.860	0.841	0.234	1	-
NG	-0.345	-0.019*	-0.130	-0.411	0.857	0.830	0.123	0.929	1

* indicates results were found to be insignificant at the 10% level.

Table 3.6, Correlation Matrix of Prices (Post-Ethanol Boom: 2006-2012)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	1	-	-	-	-	-	-	-	-
Soybeans	0.929	1	-	-	-	-	-	-	-
Wheat	0.794	0.850	1	-	-	-	-	-	-
Cotton	0.621	0.573	0.520	1	-	-	-	-	-
LC	0.875	0.793	0.624	0.536	1	-	-	-	-
FC	0.712	0.646	0.448	0.482	0.929	1	-	-	-
LH	0.722	0.612	0.463	0.709	0.730	0.722	1	-	-
CO	0.703	0.737	0.685	0.540	0.634	0.541	0.483	1	-
NG	-0.358	-0.359	-0.047*	-0.387	-0.459	-0.529	-0.483	0.080*	1

* indicates results were found to be insignificant at the 10% level.

Table 3.7, Correlation Matrix of Implied Volatilities (1995-2012)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	1	-	-	-	-	-	-	-	-
Soybeans	0.796	1	-	-	-	-	-	-	-
Wheat	0.830	0.713	1	-	-	-	-	-	-
Cotton	0.534	0.478	0.485	1	-	-	-	-	-
LC	0.309	0.384	0.271	0.400	1	-	-	-	-
FC	0.460	0.460	0.437	0.386	0.838	1	-	-	-
LH	0.087	0.237	0.088	0.133	0.292	0.233	1	-	-
CO	0.261	0.360	0.256	0.385	0.297	0.247	0.306	1	-
NG	-0.077	0.031*	-0.075	-0.049	0.039*	-0.141	0.217	0.364	1

* indicates results were found to be insignificant at the 10% level.

Table 3.8, Correlation Matrix of Implied Volatilities (Pre-Ethanol Boom: 1995-2005)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	1	-	-	-	-	-	-	-	-
Soybeans	0.793	1	-	-	-	-	-	-	-
Wheat	0.593	0.508	1	-	-	-	-	-	-
Cotton	0.091	0.340	-0.119	1	-	-	-	-	-
LC	0.136	0.277	0.176	0.385	1	-	-	-	-
FC	0.256	0.283	0.341	0.251	0.842	1	-	-	-
LH	0.098	0.172	0.141	0.236	0.297	0.264	1	-	-
CO	-0.163	-0.048*	-0.141	0.288	0.083	-0.088	0.304	1	-
NG	-0.322	-0.203	-0.344	0.033*	-0.072	-0.300	0.125	0.502	1

* indicates results were found to be insignificant at the 10% level.

Table 3.9, Correlation Matrix of Implied Volatilities (Post-Ethanol Boom: 2006-2012)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	1	-	-	-	-	-	-	-	-
Soybeans	0.761	1	-	-	-	-	-	-	-
Wheat	0.762	0.774	1	-	-	-	-	-	-
Cotton	0.637	0.393	0.525	1	-	-	-	-	-
LC	0.699	0.585	0.484	0.484	1	-	-	-	-
FC	0.723	0.631	0.542	0.467	0.840	1	-	-	-
LH	0.347	0.538	0.337	0.131	0.318	0.231	1	-	-
CO	0.574	0.604	0.440	0.403	0.650	0.663	0.412	1	-
NG	-0.025*	0.228	-0.076*	-0.202	0.272	0.117	0.471	0.219	1

* indicates results were found to be insignificant at the 10% level.

Chapter 4 - Econometric Procedures

The primary focus of this research is to determine lead or lag implied volatility relationships between commodity markets before and after the passage of the Energy Policy Act of 2005 and analyze the time path and magnitude of this volatility translation across markets. This chapter discusses the econometric models that were developed to accomplish these objectives. The methodology used in this thesis is similar to that found in many other works that examine causal relationships between time series (Ji and Chung 2012; Trujillo-Barrera, Mallory, and Garcia 2012; Saghaian 2010; Zhang, Lohr, Escalante, and Wetztein 2009; Harri and Hudson 2009). Multivariate and bivariate vector autoregressive models were estimated and Granger causality tests were performed using SAS analytics software. Both the multivariate and bivariate methods were evaluated and the results may be found in Chapter 5.

4.1 Testing for Stationarity

Prior to conducting Granger causality tests, a unit root test was performed to determine if the individual implied volatility series were stationary. Nonstationarity indicates that a time series' means and variances are changing over time. When nonstationarity is found, the data series is time-differenced to create stationary series.

An augmented Dickey-Fuller (ADF) test was conducted to test for stationarity using the following ordinary least squares (OLS) regression (Cheung and Lai 1995):

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 trend + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + e_t \tag{4.1}$$

where y_t is the implied volatility series. A trend variable was also included, and y_{t-i} was determined using the Akaike information criterion (AIC) to find the optimal number of lags to include in the model. The presence of a unit root is indicated by the results of a t-test for α_1. Results of the ADF tests are contained in Table 4.1.

Over the 1995 to 2012 aggregate time period and during the pre-ethanol boom period, all of the implied volatility series were stationary at the 90 percent confidence level. As predicted based on the appearance of the upward trend in prices and volatility that began in the mid-2000s, the volatility series were nonstationary in the 2005 to 2012 period. Therefore, the series in the post-ethanol boom period were first-differenced and the ADF test was performed again. The ADF statistics showed that the implied volatility series in the later period were stationary after the first-differencing. As a result, all Granger causality tests and associated lead-lag econometrics were conducted using stationary data series.

4.2 Granger Causality Tests

To identify volatility spillovers between the commodity markets, Granger causality tests are used in this study. Granger (1969) defines causality as the ability of a series of historical data, *y*, to improve the prediction accuracy of another series, *x*. As long as the information included in *y* is unique to the function, *y* causes *x*. The Granger test is not truly a causal test because of the possibility that series *x* and *y* are both driven by a third variable, but it does indicate the lead or lag relationship between *x* and *y*. Granger causality can be directional (*y* causes *x*, but *x* does not cause *y*) or bidirectional (*y* causes *x*, and *x* causes *y*), or it can be that no direction is determinable. Although Granger causality is not a measure of actual causality between two time series, a directional Granger relationship between *y* and *x* indicates that the previous values of *y* could be useful in predicting future values of *x* (Ji and Chung 2012). While there are several methods to test for Granger causality, this study uses VAR models.

4.2.1 Multivariate VAR Models

The multivariate VAR model tests the implied volatility relationships between all nine commodity markets simultaneously. It consists of nine equations, one for each implied volatility series regressed against lags of itself and all the other series in the model using the OLS technique. The VAR model can be specified as:

$$y1_t = \beta_{10} + \sum_{i=1}^{n} \beta1_{1i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{1i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{1i}\, y9_{t-i} \ + e1_t$$

$$y2_t = \beta_{20} + \sum_{i=1}^{n} \beta1_{2i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{2i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{2i}\, y9_{t-i} \ + e2_t$$

$$y3_t = \beta_{30} + \sum_{i=1}^{n} \beta1_{3i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{3i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{3i}\, y9_{t-i} \ + e3_t$$

$$y4_t = \beta_{40} + \sum_{i=1}^{n} \beta1_{4i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{4i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{4i}\, y9_{t-i} \ + e4_t$$

$$y5_t = \beta_{50} + \sum_{i=1}^{n} \beta1_{5i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{5i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{5i}\, y9_{t-i} \ + e5_t \tag{4.2}$$

$$y6_t = \beta_{60} + \sum_{i=1}^{n} \beta1_{6i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{6i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{6i}\, y9_{t-i} \ + e6_t$$

$$y7_t = \beta_{70} + \sum_{i=1}^{n} \beta1_{7i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{7i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{7i}\, y9_{t-i} \ + e7_t$$

$$y8_t = \beta_{80} + \sum_{i=1}^{n} \beta1_{8i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{8i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{8i}\, y9_{t-i} \ + e8_t$$

$$y9_t = \beta_{90} + \sum_{i=1}^{n} \beta1_{9i}\, y1_{t-i} + \sum_{i=1}^{n} \beta2_{9i}\, y2_{t-i} + \ \dots \sum_{i=1}^{n} \beta9_{9i}\, y9_{t-i} \ + e9_t$$

where *y1* is corn implied volatility, *y2* is soybeans implied volatility, *y3* is wheat implied volatility, *y4* is cotton implied volatility, *y5* is live cattle implied volatility, *y6* is feeder cattle implied volatility, *y7* is lean hog implied volatility, *y8* is crude oil implied volatility, and *y9* is natural gas implied volatility. Error terms are represented as e_t and *n* is the number of lags. The optimal lag length for the model was selected based on the overall minimum AIC while avoiding autoregressive errors in the individual equations. One multivariate VAR model consisting of the same nine equations was constructed for each of the three time periods tested.

Granger causality tests are performed using a chi-square test to determine if the estimations of the coefficients from the multivariate VAR equations are significantly different from zero. For example, a chi-square statistic on $\beta 2$ in the first equation with a p-value of less than 0.01 would lead to the conclusion that soybeans Granger causes corn with greater than 99 percent confidence.

4.2.2 Bivariate VAR Models

While the multivariate VAR causality tests are telling and quicker to construct than their bivariate counterparts, they are subject to a few issues. Collinearity likely exists in the multivariate model as there are a large number of variables and it is difficult to distinguish which variables are actually causing the effects on other variables. Therefore, pair-wise VAR models were also constructed and tested for causality to confirm results and reveal additional information.

Thirty-six bivariate VAR models were specified for each of the three time periods. These thirty-six models consist of every pair-wise combination of the nine commodities (i.e. corn and soybeans, corn and wheat, corn and cotton, etc.). The bivariate VAR models were also estimated using OLS and each model can be defined as:

(4.3)
$$y_t = \alpha_1 + \sum_{i=1}^{n} \beta_i \, y_{t-i} + \sum_{i=1}^{n} \gamma_i \, x_{t-i} + e_{1t}$$
$$x_t = \alpha_2 + \sum_{i=1}^{n} \delta_i \, x_{t-i} + \sum_{i=1}^{n} \mu_i \, y_{t-i} + e_{2t}$$

where *x* and *y* are implied volatility series of two different commodities, *n* is the optimal number of lags determined using the minimum AIC, and e_1 and e_2 are the respective error terms. Following the estimation of the bivariate models, Granger causality tests were conducted in the same manner as in the multivariate models.

4.3 Impulse Response Functions

After Granger causality tests, impulse response functions (IRFs) were used to determine the magnitude and persistence of shocks to implied volatility for the different commodities. The effects were analyzed over a 15 week period using orthogonalized shocks. The IRFs examine the deviation in the normal trend for implied volatility of a commodity due to a one-standard deviation shock to itself or another commodity's implied volatility. Typically, when using orthogonalized IRFs, variables are ordered from most endogenous to least endogenous since the IRFs are sensitive to the ordering of the variables. However, in this research, it was difficult to estimate which variables were endogenous and which were exogenous. Therefore, in the case of the multivariate model, there was little rationale placed behind the ordering of the variables and they were simply arranged in the same order in which they were originally presented: corn, soybeans, wheat, cotton, live cattle, feeder cattle, lean hogs, crude oil, and natural gas.

Table 4.1, Results of Augmented Dickey-Fuller Tests

	ADF Lag Length	ADF Test	Unit Root
1995-2012			
Corn	10	-5.90**	No
Soybeans	6	-3.90**	No
Wheat	7	-3.71**	No
Cotton	4	-3.36*	No
Live Cattle	12	-3.61**	No
Feeder Cattle	7	-4.38**	No
Lean Hogs	11	-4.36**	No
Crude Oil	8	-3.58**	No
Natural Gas	9	-5.49**	No
Pre-Ethanol Boom (1995-2005)			
Corn	10	-5.97**	No
Soybeans	10	-4.99**	No
Wheat	4	-5.22**	No
Cotton	2	-3.79**	No
Live Cattle	12	-3.24*	No
Feeder Cattle	2	-3.83**	No
Lean Hogs	10	-3.89**	No
Crude Oil	13	-3.72**	No
Natural Gas	9	-4.77**	No
Post-Ethanol Boom (2006-2012)			
Corn	5	-2.47	Yes
Soybeans	6	-2.09	Yes
Wheat	5	-2.42	Yes
Cotton	7	-2.15	Yes
Live Cattle	8	-2.49	Yes
Feeder Cattle	2	-3.17*	No
Lean Hogs	6	-3.00	Yes
Crude Oil	5	-1.90	Yes
Natural Gas	9	-3.84**	No

** indicates significance at the 5% level, * indicates significance at the 10% level

Chapter 5 - Results

The results of the models that were outlined in Chapter 4 are contained in this chapter. The Granger causality tests for the aggregate 1995 to 2012 time period, the pre-ethanol boom time period, and the post-ethanol boom time period are presented along with some of their corresponding IRFs. These results are analyzed side-by-side to evaluate differences in the time periods. They are also compared to the conclusions of previous literature. Inferences were drawn based on the observations and are also included in this chapter. More emphasis is placed on the bivariate VAR models as they are more straightforward and conclusive than the multivariate VAR models.

5.1 Multivariate VAR Models

As previously discussed, multivariate VAR models were designed to examine the implied volatility relationships between all nine commodity markets at once. Granger causality tests were used to test whether the estimated coefficients from the multivariate VAR equations were significantly different from zero. In cases where the chi-square test indicated significance, implied volatility of the commodity on the right-hand side of the equation is said to lead, or Granger cause, the dependent variable. Results of the multivariate VAR models for each of the three time periods are evaluated below. Appendix A contains graphs of the orthogonalized IRFs with 15 week lags for all of the commodity combinations assessed in the multivariate VAR model for the aggregate time period.

5.1.1 Aggregate Time Period

Initially, the multivariate VAR model was estimated over the 1995 to 2012 time frame to examine volatility spillover effects in the long-run. The time series were analyzed in levels, since they were stationary over this period. An optimal time lag length of three weeks was chosen based on the minimum AIC for all sets of series. The results of the Granger causality tests for this model are presented in Table 5.1.

This model indicates that in the long-run, the null hypotheses that corn volatility does not cause wheat volatility and wheat volatility does not cause corn volatility are both rejected at the 1 percent significance level. This strong, bidirectional relationship between corn and wheat is rational as the two grains are highly correlated in prices and volatilities and compete for the same resources. The model also indicates that live cattle and feeder cattle Granger cause cotton, a result that is somewhat perplexing. Live cattle Granger cause feeder cattle. This result was expected since the markets are closely related and live cattle volatility is probably evaluated by cattle buyers when purchasing feeder cattle. Crude oil leads corn, feeder cattle, and lean hogs, but natural gas is the main leader of agricultural commodities in this model. Natural gas leads corn, soybeans, feeder cattle, lean hogs, and crude oil, although only marginally in the cases of soybeans and feeder cattle.

Some weaker and less plausible relationships are found between the commodities as well. Corn Granger causes natural gas, soybeans Granger cause crude oil, and lean hogs Granger cause soybeans and feeder cattle at the 95 percent confidence level. Soybeans lead feeder cattle, cotton leads crude oil, and lean hogs lead corn at the 90 percent confidence level.

5.1.2 Pre-Ethanol Boom Time Period

Another multivariate VAR model was developed to evaluate volatility spillover in the pre-ethanol boom time frame between 1995 and 2005. Once again, the time series were determined to be stationary in this early period. A lag length of three weeks was also used in this model corresponding to the minimum AIC. The lead-lag relationships determined by the Granger causality tests are presented in Table 5.2.

In the pre-ethanol boom time period, corn volatility leads soybean volatility. Soybeans cause wheat and cotton, and wheat and cotton together have a bidirectional relationship. These spillover effects are reasonable since these crops compete for acreage, and thus are substitutes in production. Corn volatility is marginally bidirectional with lean hog volatility, probably because corn is the major input in hog rations. Live cattle volatility is bidirectional with feeder cattle volatility and lean hogs. Crude oil only leads feeder cattle and lean hogs, but natural gas Granger causes all of the other commodities except for cotton and live cattle.

Once again, there are a few results that appear spurious. Live cattle volatility leads cotton volatility at the 95 percent level. Soybeans cause feeder cattle and cotton causes crude oil at the 90 percent confidence level. Lean hogs also lead soybeans at the 90 percent significance level. However, this relationship is plausible since it is consistent with the results of other models and soybean meal is often used as an input in hog rations.

5.1.3 Post-Ethanol Boom Time Period

The last multivariate VAR model evaluates the data between 2006 and 2012. The ADF test determined the volatility series to be nonstationary during this period, so the data were first-differenced to create stationary series. The Granger causality tests are performed on the first-differenced stationary volatility series. For this reason, these results contrast those of the previous two models in that every commodity's volatility does not cause the future volatility of itself (e.g., corn does not Granger cause itself in this model). A lag length of three weeks was used. These results are found in Table 5.3.

In this time period, there are fewer overall volatility spillover effects than in the previous two models, but corn volatility leads more commodities than in the pre-ethanol boom. Corn Granger causes wheat at the 99 percent confidence level. It also leads soybeans, feeder cattle, lean hogs, and natural gas at lower levels of confidence. Feeder cattle Granger cause live cattle post-ethanol boom. Other than this, there are few noteworthy results. Surprisingly, there are no volatility spillover effects between the corn and crude oil markets in this post-ethanol boom multivariate VAR model.

5.2 Bivariate VAR Models

Because of the first-differencing in the post-ethanol boom multivariate model, it is difficult to compare the results of the multivariate VAR models directly. Even so, it is surprising that none of the causal relationships strongly permeate through the time periods. Results from the post-ethanol boom model were also not consistent with expectations since most previous literature has found some relationship between the corn and crude oil markets. For these reasons, bivariate VAR models were constructed to confirm results and combat possible collinearity issues in the multivariate VAR models. Bivariate VAR models were estimated for all 36 combinations of the nine volatility series over each of the three time periods. Again, Granger causality tests were conducted using chi-square tests. These results are examined in this section. Optimal time lag lengths were determined based on the minimum AIC for each of the 36 models in each of the three time periods. Tables 5.4 through 5.6 specify the optimal lag lengths for all of the bivariate models. IRFs for the bivariate model that covers the aggregate time period are located in Appendix B.

5.2.1 Aggregate Time Period

The long-run bivariate VAR models were analyzed first. The results of the Granger causality tests are shown in Table 5.7. Granger tests reveal statistically significant volatility linkages among commodity markets between 1995 and 2012. Bidirectional causality is found in the corn, soybeans, and wheat markets. Volatilities in all three of these markets are also determined to Granger cause volatility in the cotton market. Again, this is logical as these commodities use common inputs and are substitutes in production to an extent. Corn and wheat seem to exhibit the strongest relationship of all the crops, as there is either bidirectional or corn leads wheat in nearly all of the time periods in both the multivariate and bivariate VAR models. Figure 5.1 is a plot of corn and wheat volatilities. The two volatilities are highly correlated with a Pearson correlation coefficient of 0.830, and the plot reflects this.

IRFs, shown in Figure 5.2, are used to examine the time path of the spillover effects between corn and wheat. When corn volatility is shocked by one standard deviation, or approximately 1.7 percentage points, wheat volatility increases by about 0.8 percent two to three weeks after the initial shock. Likewise, when wheat volatility is shocked by one standard deviation, or approximately 1.25 percentage points, corn volatility increases by more than half a percentage point. The shock to the wheat market causes the change in corn market volatility to persist for more than 15 weeks. IRFs between corn and soybeans and between soybeans and wheat are illustrated in Figure 5.3 and Figure 5.4. The corn/soybeans IRFs are indicative of a unidirectional relationship from corn to soybeans, since a one standard deviation shock to corn volatility causes soybeans volatility to react over time, but a shock to soybeans has little effect on the corn market. This is probable, since the Granger causality test indicated that soybean volatility was bidirectional with corn volatility, but only at a 90 percent confidence level. The soybean/wheat IRFs show some responses to shocks of the two commodities, but they are limited.

The connection between the cattle markets is consistent across all models and time periods. The Granger causality test determines that live cattle volatility leads feeder cattle at the 99 percent confidence level. Figure 5.5 shows the live cattle and feeder cattle volatility series. They follow one another very closely, although it appears that feeder cattle may mimic live cattle. As presented in Chapter 3, live cattle volatility and feeder cattle volatility were the most highly correlated of all the commodities over the 1995 to 2012 time period with a correlation of 0.838. The IRFs in Figure 5.6 show that the relationship between live cattle and feeder cattle is truly unidirectional over the 1995 to 2012 time frame. A 1.05 percentage point shock in live cattle volatility causes a 0.85 percentage point increase in feeder cattle volatility. This increase in feeder cattle volatility peaks in the second week following the live cattle shock, but the fluctuation persists until at least the fifteenth week. Live cattle volatility does not react to a feeder cattle volatility shock.

This model also finds that the feeder cattle market leads the wheat market at the 95 percent confidence level. Feeder cattle and wheat were initially hypothesized to have some spillover relationship because feeder cattle are often grazed on wheat pasture depending on its price and availability. The wheat/feeder cattle IRFs are found in Figure 5.7. Despite the spillover relationship that was determined by the Granger causality test, the effect of a one standard shock to feeder cattle volatility has very little effect on wheat volatility.

Additionally, this model finds that corn, soybeans, and cotton cause feeder cattle at varying levels of significance. Live cattle volatility leads cotton volatilities and is bidirectional with lean hog volatility. Lean hog volatility strongly Granger causes corn, soybeans, and feeder cattle. Significant spillovers also occurred from crude oil to feeder cattle and lean hogs in the long-run. Natural gas volatility leads corn and lean hog volatilities. There is also evidence that between the fuel markets, natural gas volatility Granger causes crude oil volatility.

5.2.2 Pre-Ethanol Boom Time Period

The bivariate results from the 1995 to 2005 time period, shown in Table 5.8, are similar to the bivariate results of the aggregate time period, but there are a few important differences to note. Corn, soybeans, and wheat are not all bidirectional in the early era. Corn and wheat are bidirectional, but corn leads soybeans and soybeans leads wheat. Corn and soybeans Granger cause cotton, but wheat does not have a spillover relationship with cotton. Cotton volatility leads the livestock volatilities. Live cattle leads feeder cattle and feeder cattle leads wheat at the 99 percent confidence level. Interestingly, lean hogs lead all of the agricultural markets except for wheat in this model, even though correlations between lean hogs and the other commodities are low.

The focus of the analysis for pre-ethanol boom and post-ethanol boom bivariate VAR models was placed on evaluating the differences in volatility spillover of the crude oil and natural gas markets to other markets. In the pre-ethanol boom time period, crude oil volatility Granger causes feeder cattle and lean hog volatilities. Natural gas volatility Granger causes all of the agricultural commodity volatilities except for cotton, live cattle, and feeder cattle. Natural gas also leads crude oil in this time period. Graphs comparing corn, crude oil, and natural gas volatilities are in Figures 5.8, 5.9, and 5.10. These plots are consistent with our findings that corn volatility is negatively correlated with both crude oil volatility and natural gas volatility in early years. They also show that natural gas volatility led crude oil volatility until about 2007. IRFs confirm the observation that there was no volatility spillover between corn and crude oil in this time period. However, as Figure 5.11 illustrates, the corn/natural gas IRFs are not consistent with the Granger causality tests. There is minimal response in natural gas volatility when corn is shocked by one standard deviation, and there is no response in corn when natural gas is shocked one standard deviation.

5.2.3 Post-Ethanol Boom Time Period

Once again, the first-differenced data were used within the bivariate VAR model to analyze volatility spillover in the post-ethanol boom (2006 to 2012) time frame to avoid issues of nonstationarity. Results of the Granger causality tests are found in Table 5.9. Despite expectations that the number of causal linkages would increase in the post-ethanol boom time period due to more rapid information flow, there is actually a decline in the number of causal relationships. The most notable change between this time period and the 1995 to 2005 time period is the strengthened relationship between corn volatility and the other commodities. This model finds that corn is a leader for all commodities except for live cattle and crude oil. Soybeans and cotton are bidirectional, and lean hogs Granger cause soybeans and natural gas. Feeder cattle volatility leads live cattle volatility at the 99 percent confidence level. Soybean volatility leads crude oil volatility in this time period. This is an intriguing observation because although it seems spurious, the multivariate VAR model for the post-ethanol boom time period found the same result.

Consistent with other literature, the results for this model indicate that there is volatility spillover from the crude oil to the corn market, although only at the 90 percent confidence level. There is also a visible change in the data. Figure 5.8 shows that corn volatility and crude oil volatility changed from exhibiting an inverse relationship to exhibiting a positive relationship around 2006. In Figure 5.12, the IRFs reveal that a one standard deviation increase in crude oil causes a precipitous 0.2 percentage point response in corn volatility. This occurs around the second week after the initial shock, and then the corn market immediately returns to normal. Crude oil also leads feeder cattle, and natural gas leads corn and lean hogs during the post-ethanol boom period. Overall, natural gas leads fewer commodities than in the earlier years. The plots in Figure 5.10 imply that crude oil leads natural gas between 2007 and 2012, but the Granger causality tests and IRFs do not reveal any relationship between the two commodities in the later years.

5.3 Summary of Results

As previously mentioned, conclusions drawn from the bivariate VAR models are weighted with more certainty than conclusions drawn from the multivariate VAR models. However, results that are ubiquitous throughout the bivariate and multivariate models are the most convincing. Tables 5.10, 5.11, and 5.12 provide a summary of the results for all of the Granger causality tests. Despite previous literature's focus, the most prominent volatility spillover effects in this research are not between the corn and crude oil markets.

Overall, there is a decline in the number of causal relationships between the two time periods. It appears that there has been an evolution from lean hogs acting as the primary volatility leader for other agricultural commodities between 1995 and 2005 to corn taking this role between 2006 and 2012. This could be reflective of the actual levels of volatilities in the markets during those time periods. When evaluating the mean and standard deviation of implied volatilities, the lean hogs market was the most volatile agricultural market in the earlier time period, whereas corn was the most volatile agricultural market in the latter time period. Lean hogs consistently lead soybeans throughout the models and time periods, so there is a robust causal relationship between those two markets. The models also find that corn has consistently been a leader for soybeans, and it has been bidirectional with wheat over time. This conclusion matches expectations since the three commodities are so closely related in production. The bivariate models also suggest that corn and soybean volatilities have led cotton volatilities throughout the years.

There is an unexplainable, but persistent relationship between the cotton and cattle markets. Live cattle volatility leads cotton volatility in the pre-ethanol boom years, whereas cotton volatility leads feeder cattle volatility in the post-ethanol boom years. As originally predicted, the connection between volatilities in the cattle markets is strong. Interestingly however, there is substantial evidence that shows while live cattle Granger causes feeder cattle in the early era, feeder cattle Granger causes live cattle in the later time period. This may indicate that feedlot beef producers have begun to place more emphasis on the feeder cattle market when deciding the times to buy and sell cattle due to the scarcity of feeder cattle in recent years (Stotts, 2012).

This analysis also finds evidence of volatility spillover from the crude oil market to the feeder cattle and lean hog markets in the 1995 to 2005 time period. Despite the fact that the correlation between crude oil volatility and corn volatility increased from the pre-ethanol boom period to the post-ethanol boom period, there is no firm indication of a causal relationship between the two commodities. Nonetheless, there is a link between the natural gas and corn markets. The multivariate VAR models suggest that natural gas volatility leads corn volatility in the early years and lags corn volatility in the later years. The pair-wise VAR models suggest bidirectionality between the two commodities in both time periods. Pearson correlation coefficients show that natural gas and corn volatilities changed from being negatively correlated in the pre-ethanol boom time period to uncorrelated in the post-ethanol boom time period. The

Granger causality tests also determine that natural gas volatility strongly leads crude oil volatility in the first era, but not at all in the latter era. The decline in correlation between the two energies from the pre-ethanol boom time period to the post-ethanol boom time period also supports this observation.

Table 5.1, Granger Causality – Multivariate VAR Model (1995-2012)

Dependent Variable	Independent Variable Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	+++		+++				+	++	++
Soybeans		+++					++		+
Wheat	+++		+++						
Cotton				+++	+++	++			
LC					+++		++		
FC		+			+++	+++		++	+
LH							+++	++	++
CO		++		+				+++	+++
NG	++								+++

+++ is statistically significant at 0.01 level, ++ at 0.05 level, and + at 0.10 level

Table 5.2, Granger Causality – Multivariate VAR Model (Pre-Ethanol Boom: 1995-2005)

Dependent Variable	Independent Variable Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	+++						+		+++
Soybeans	++	+++					+		++
Wheat		++	+++	+					+
Cotton		++	+++	+++	++				
LC					+++	++	++		
FC		+			+++	+++		++	+
LH	+++				++		+++	+++	+++
CO				+				+++	+++
NG									+++

+++ is statistically significant at 0.01 level, ++ at 0.05 level, and + at 0.10 level

Table 5.3, Granger Causality – Multivariate VAR Model (Post-Ethanol Boom: 2006-2012)

Dependent	Independent Variable								
Variable	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn									
Soybeans	+	+++							
Wheat	+++		+++	++					
Cotton									
LC						++			
FC	+			+		++			
LH	++						+++		
CO		+						+++	
NG	+								+++

+++ is statistically significant at 0.01 level, ++ at 0.05 level, and + at 0.10 level

Table 5.4, Optimal Lag Lengths - Bivariate VAR Model (1995-2012)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	-	-	-	-	-	-	-	-	-
Soybeans	14	-	-	-	-	-	-	-	-
Wheat	11	3	-	-	-	-	-	-	-
Cotton	14	5	2	-	-	-	-	-	-
LC	14	3	3	15	-	-	-	-	-
FC	8	5	2	14	13	-	-	-	-
LH	14	3	2	14	13	2	-	-	-
CO	9	4	6	5	3	3	3	-	-
NG	8	10	6	6	6	6	6	6	-

Table 5.5, Optimal Lag Lengths – Bivariate VAR Model (Pre-Ethanol Boom: 1995-2005)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	-	-	-	-	-	-	-	-	-
Soybeans	14	-	-	-	-	-	-	-	-
Wheat	15	2	-	-	-	-	-	-	-
Cotton	15	15	2	-	-	-	-	-	-
LC	14	3	3	15	-	-	-	-	-
FC	14	3	2	15	13	-	-	-	-
LH	14	2	2	15	3	3	-	-	-
CO	11	3	3	15	3	3	3	-	-
NG	6	6	2	15	6	6	6	6	-

Table 5.6, Optimal Lag Lengths – Bivariate VAR Model (Post-Ethanol Boom: 2006-2012)

	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	-	-	-	-	-	-	-	-	-
Soybeans	3	-	-	-	-	-	-	-	-
Wheat	2	2	-	-	-	-	-	-	-
Cotton	2	4	2	-	-	-	-	-	-
LC	15	15	15	15	-	-	-	-	-
FC	5	4	4	4	17	-	-	-	-
LH	5	6	4	4	16	4	-	-	-
CO	2	3	2	2	15	5	5	-	-
NG	5	5	5	2	16	5	7	5	-

Table 5.7, Granger Causality – Bivariate VAR Model (1995-2012)

Dependent	Independent Variable								
Variable	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	+++	+	+++				+++		++
Soybeans	+++	+++	++				++		
Wheat	+++	+++	+++			++			
Cotton	+++	+++	+	+++	++				
LC					+++		+++		
FC	+	+++		+	+++	+++	+++	+++	
LH				+	++		+++	++	++
CO		++				+		+++	+++
NG									+++

+++ is statistically significant at 0.01 level, ++ at 0.05 level, and + at 0.10 level

Figure 5.1, Implied Volatilities for Corn and Wheat

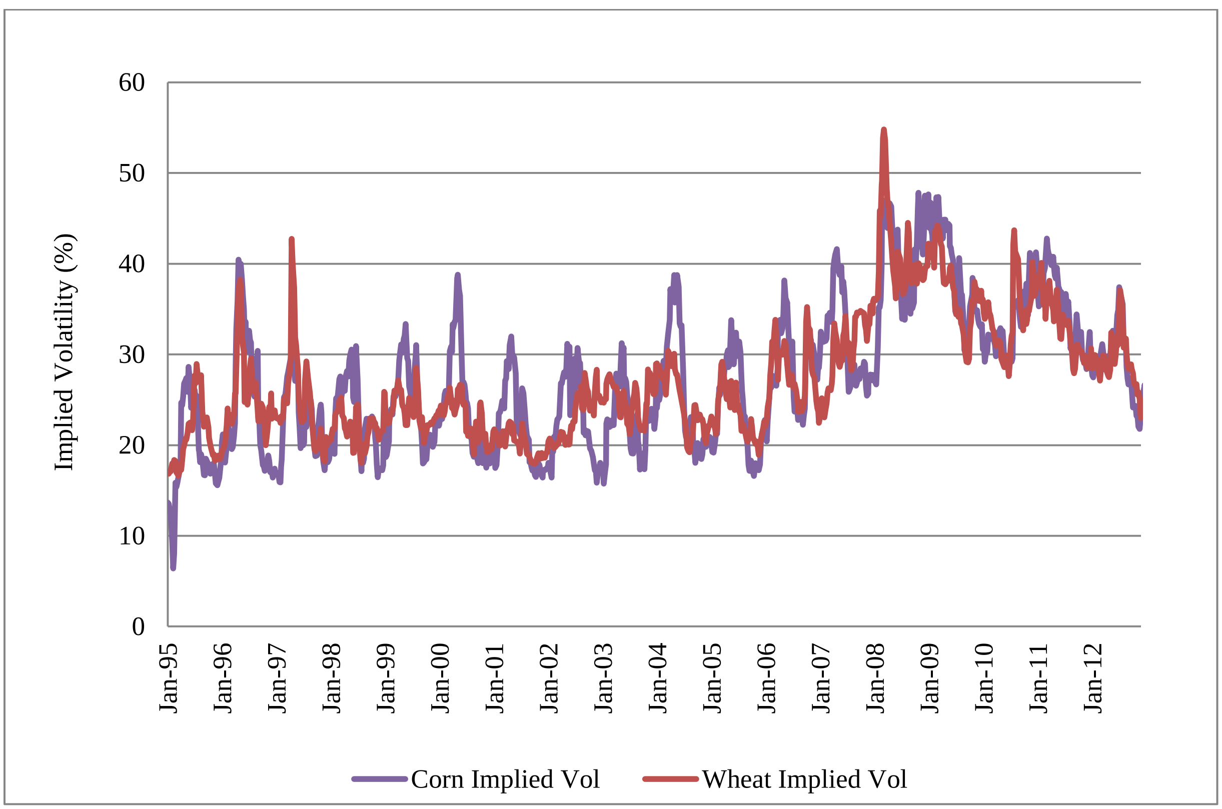


Figure 5.2, IRFs for Corn and Wheat – Bivariate Model (1995-2012)

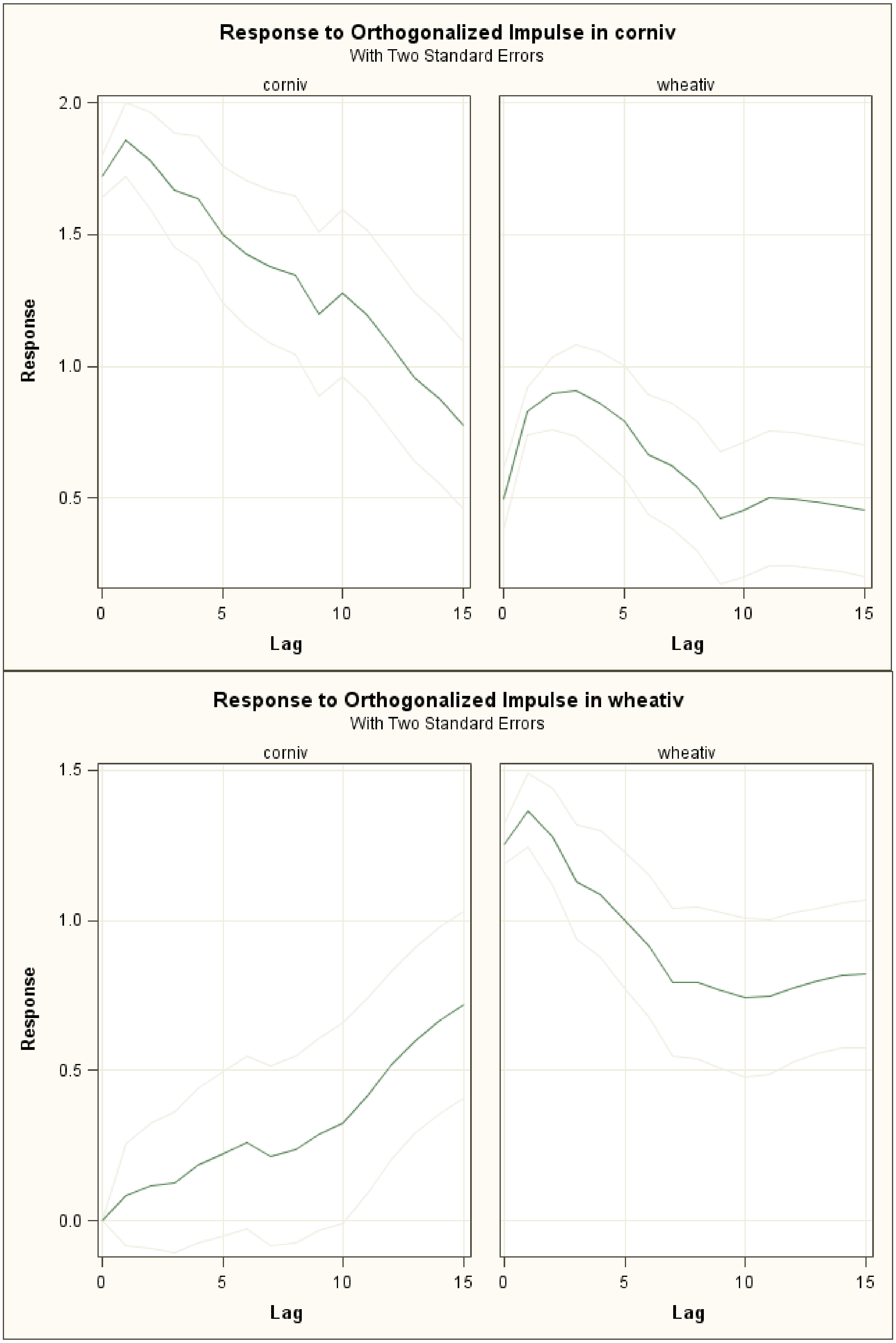
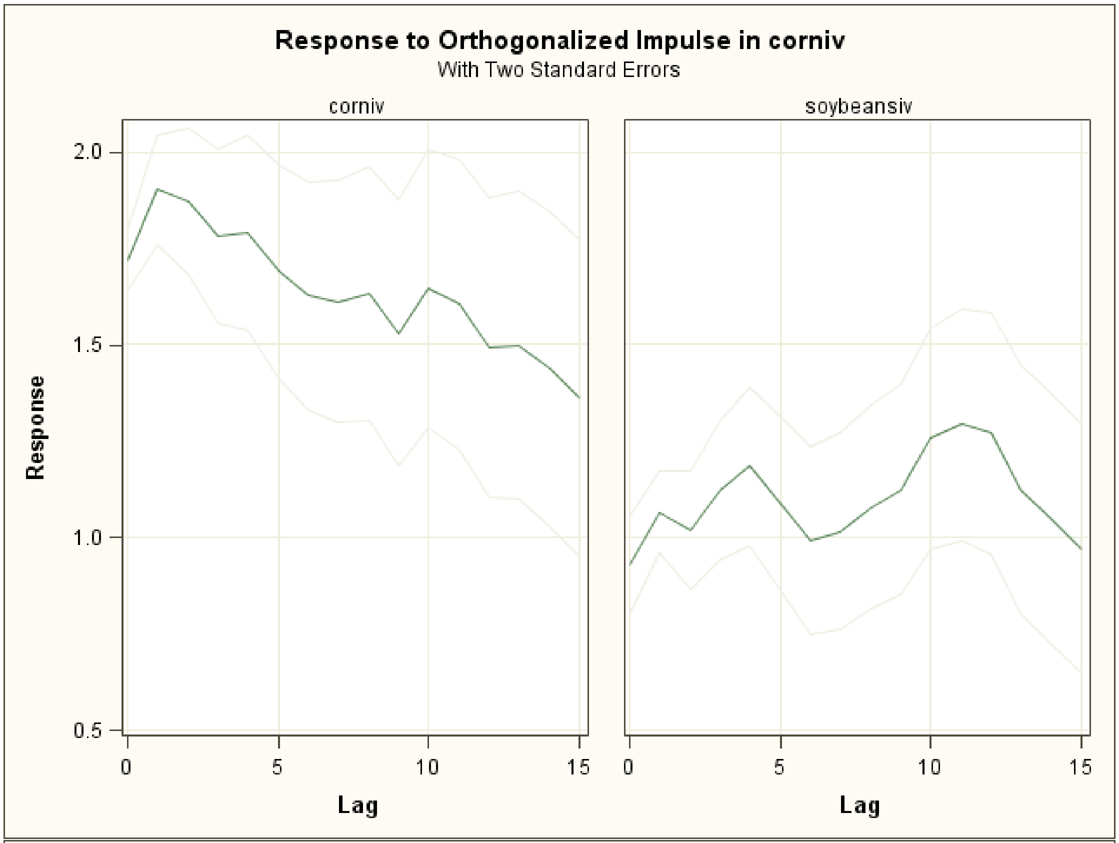


Figure 5.3, IRFs for Corn and Soybeans – Bivariate Model (1995-2012)



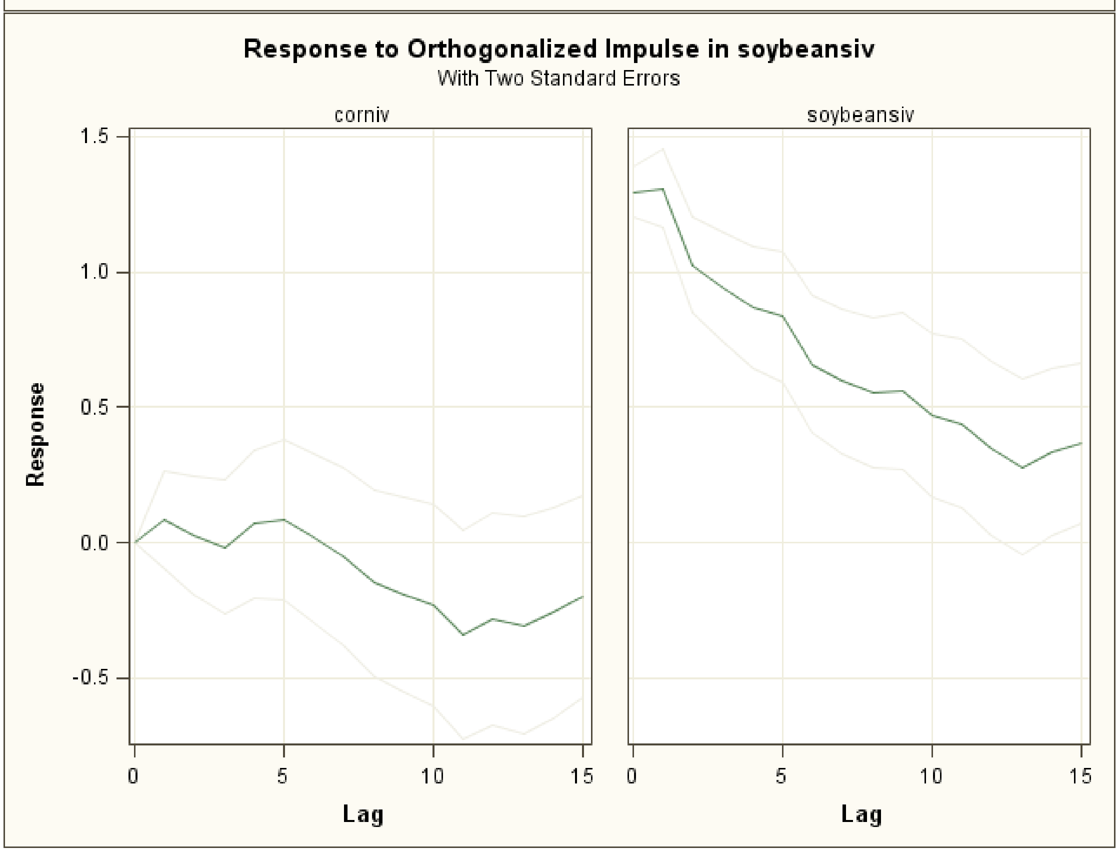
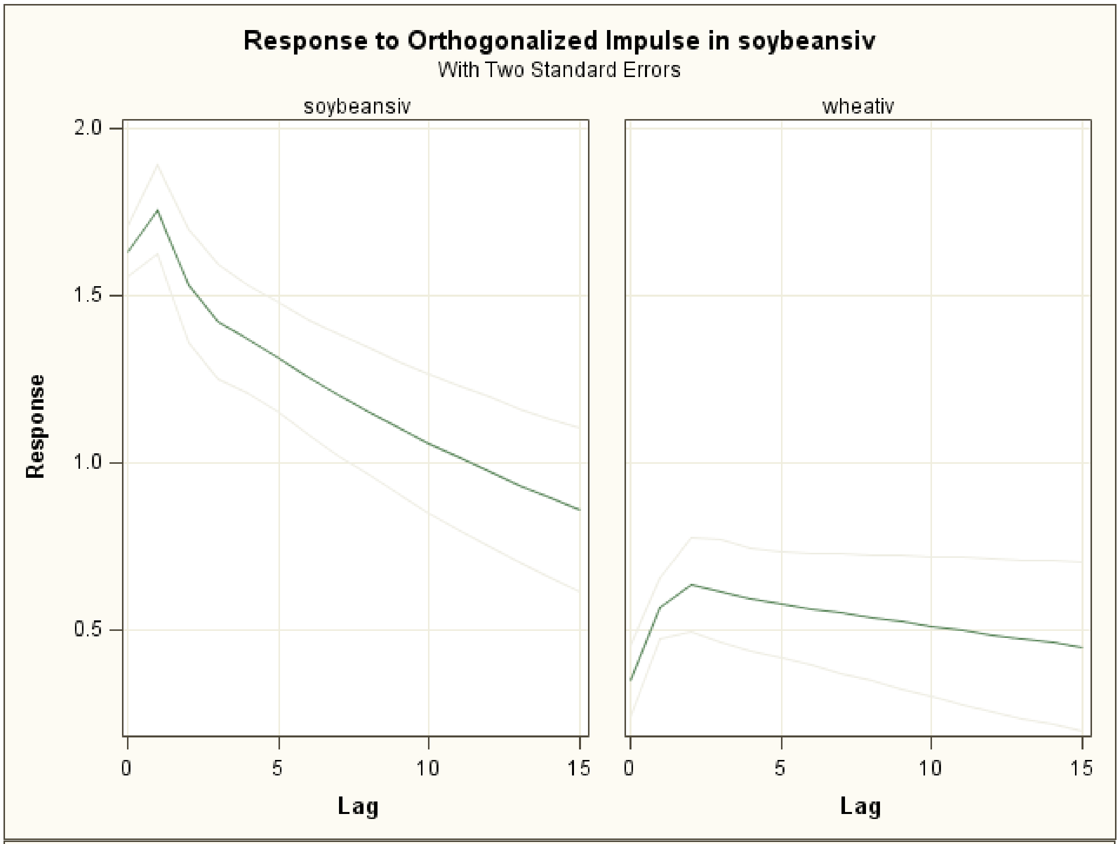


Figure 5.4, IRFs for Soybeans and Wheat – Bivariate Model (1995-2012)



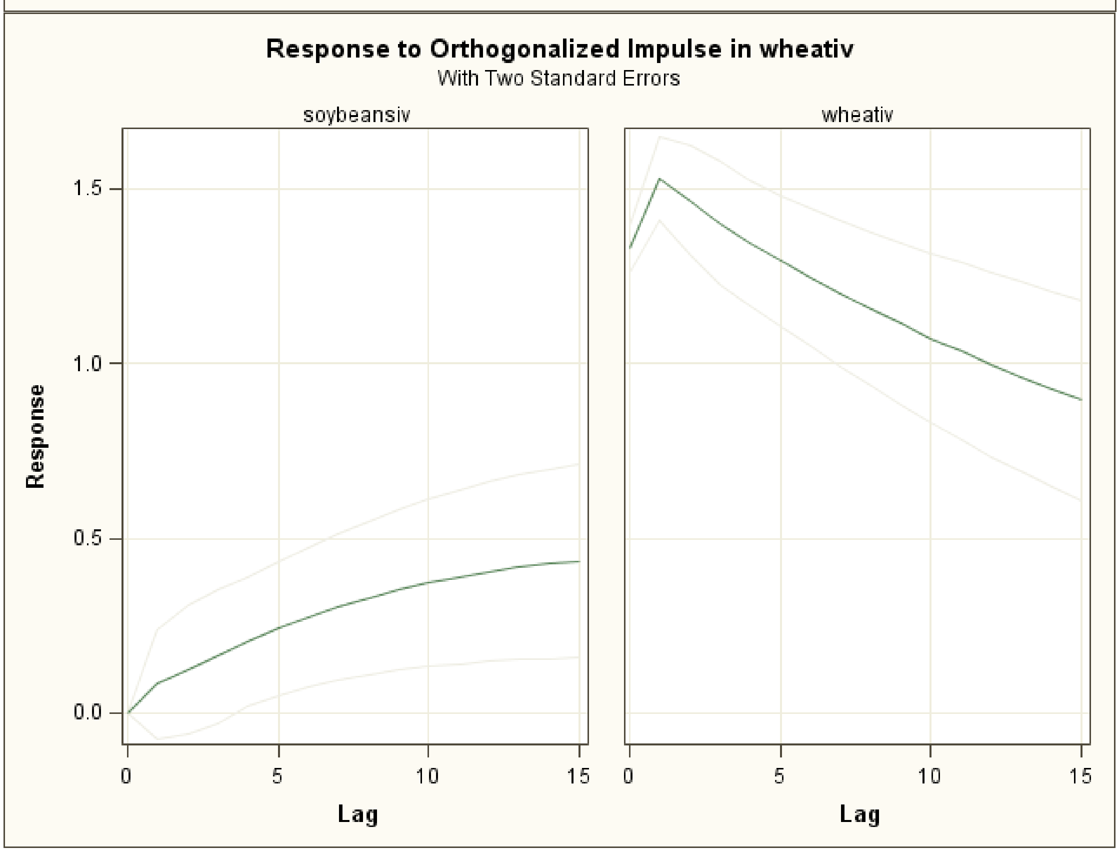


Figure 5.5, Implied Volatilities for Live Cattle and Feeder Cattle

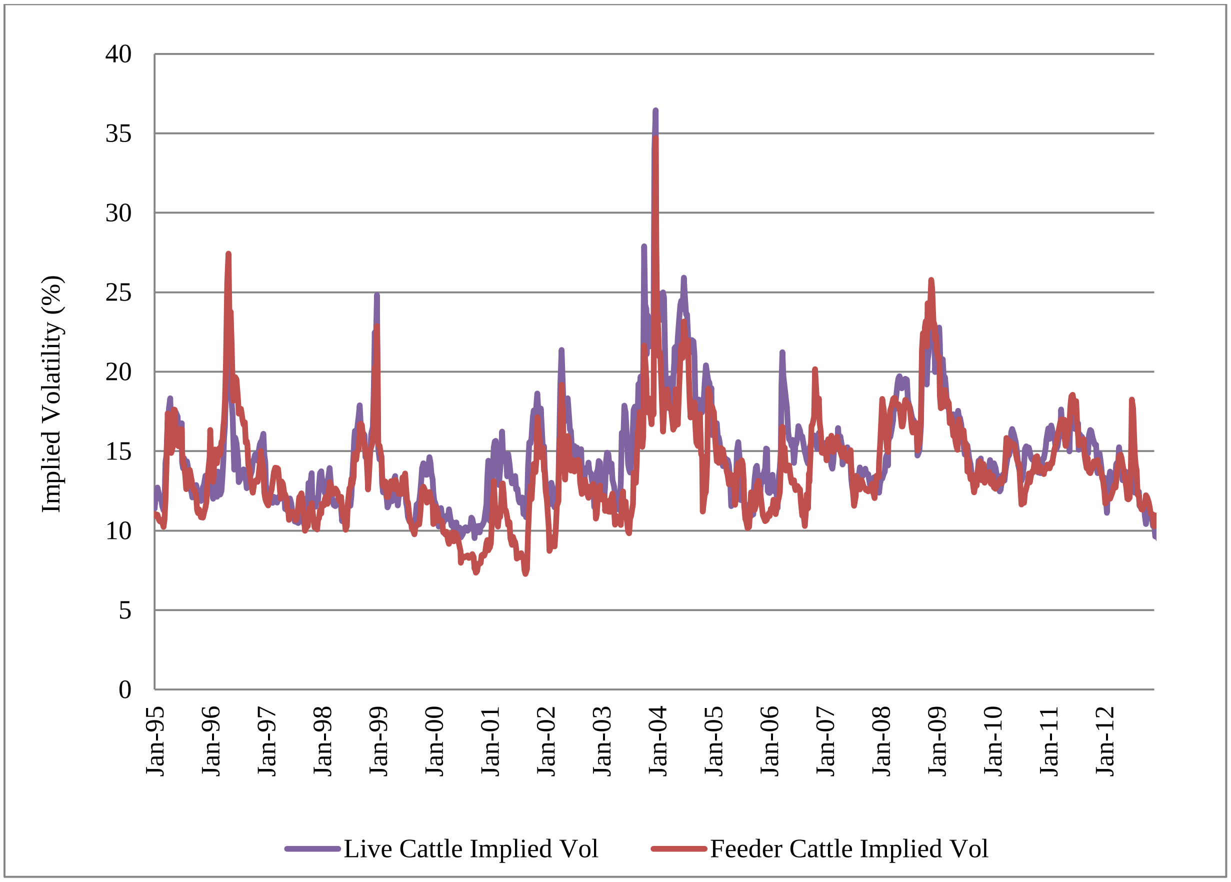


Figure 5.6, IRFs for Live Cattle and Feeder Cattle – Bivariate Model (1995-2012)

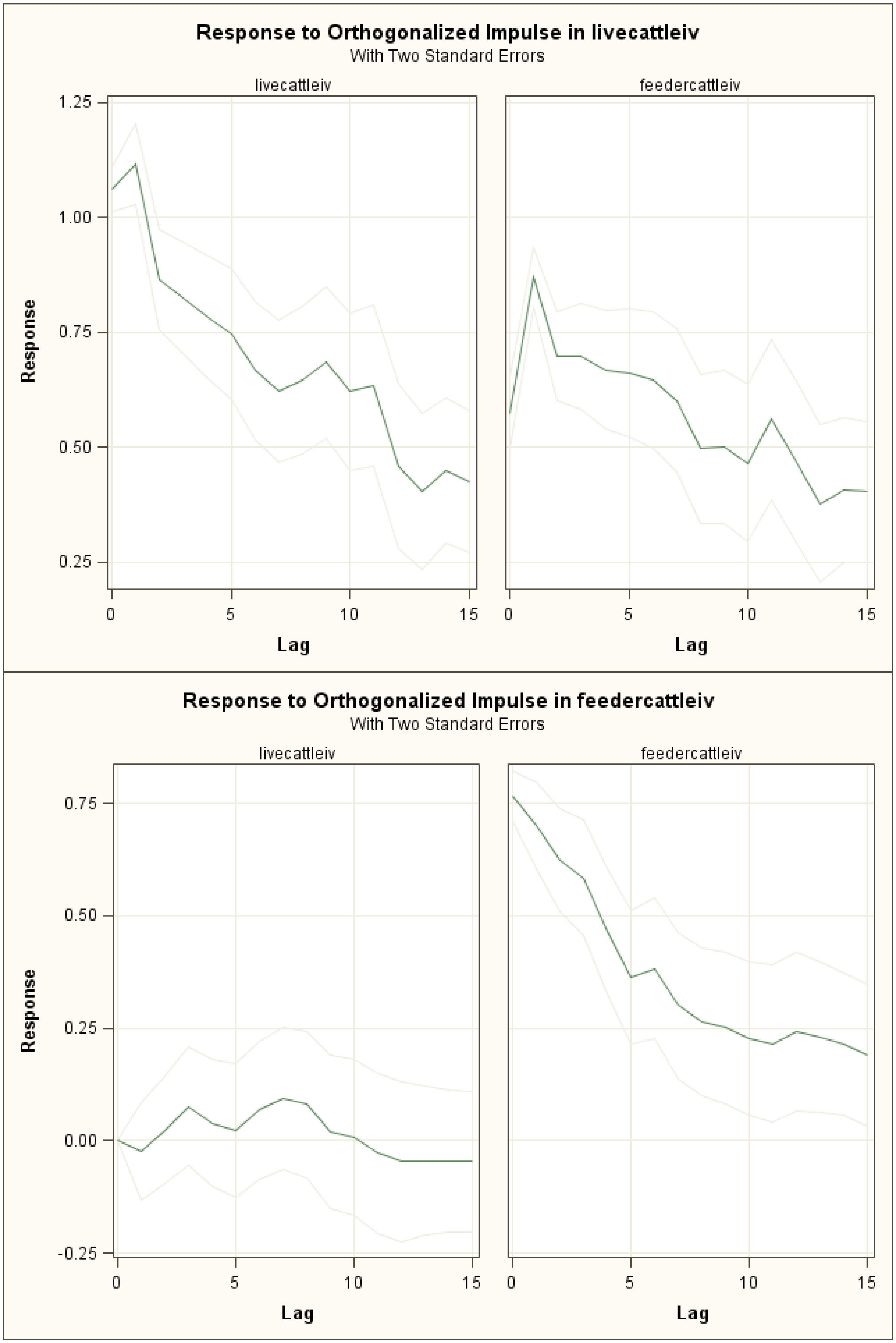


Figure 5.7, IRFs for Wheat and Feeder Cattle – Bivariate Model (1995-2012)

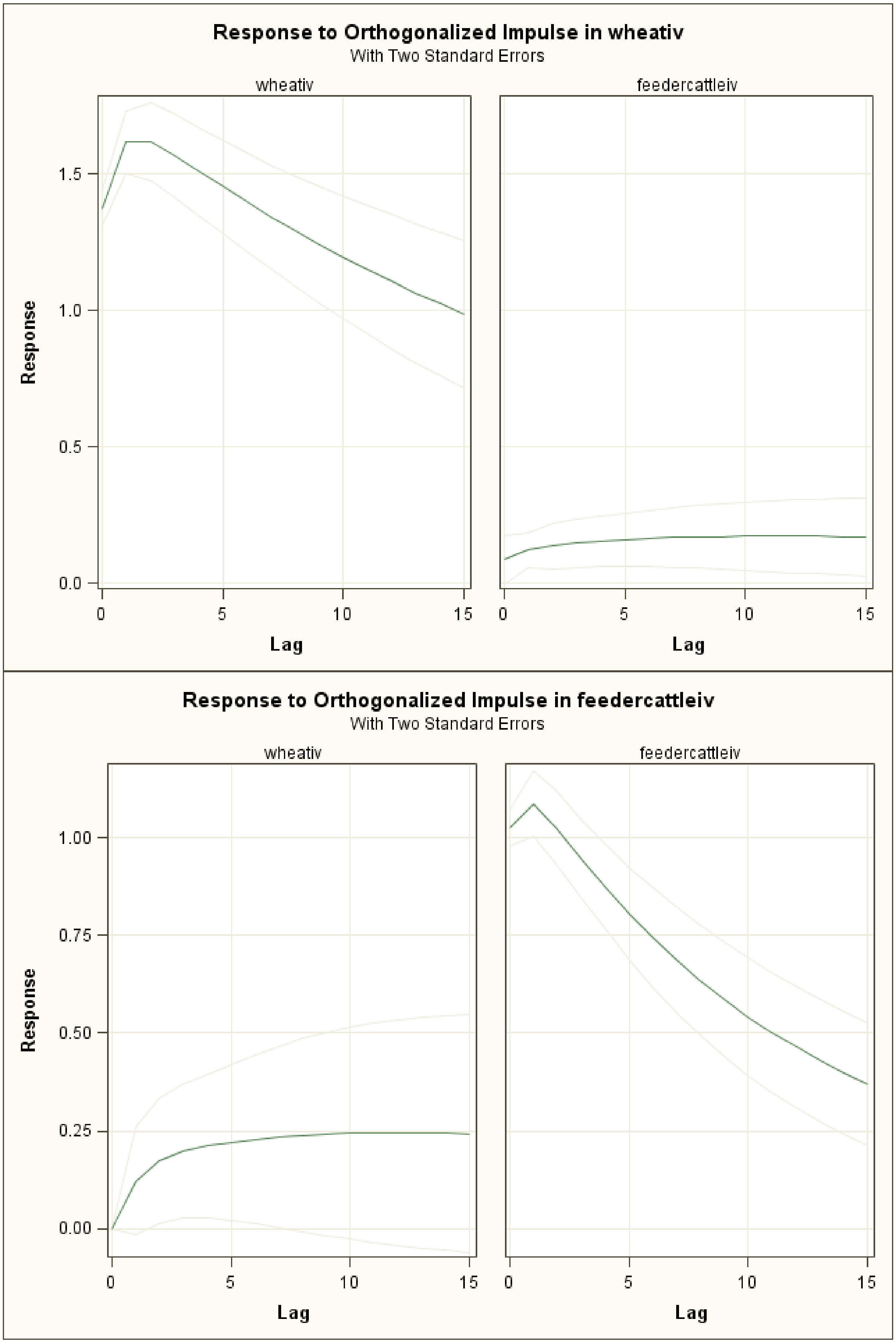


Table 5.8, Granger Causality – Bivariate VAR Model (Pre-Ethanol Boom: 1995-2005)

Dependent	Independent Variable								
Variable	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	+++		+				+++		+++
Soybeans	+++	+++					++		++
Wheat	+++	+++	+++			+++			+++
Cotton	+	+		+++	+++	+	++		
LC				+	+++		++		
FC		+		+++	+++	+++	+	++	
LH				++			+++	++	++
CO								+++	+++
NG	+								+++

+++ is statistically significant at 0.01 level, ++ at 0.05 level, and + at 0.10 level

Figure 5.8, Implied Volatilities for Corn and Crude Oil

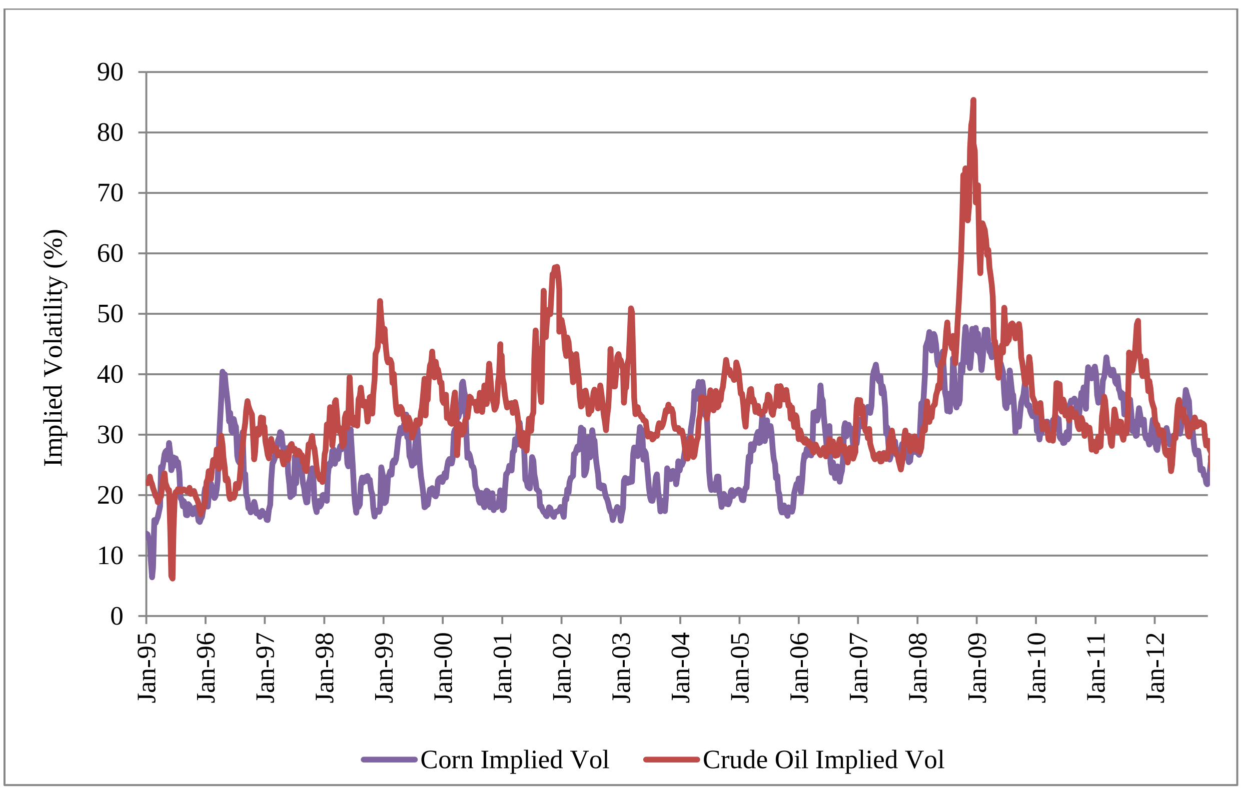


Figure 5.9, Implied Volatilities for Corn and Natural Gas

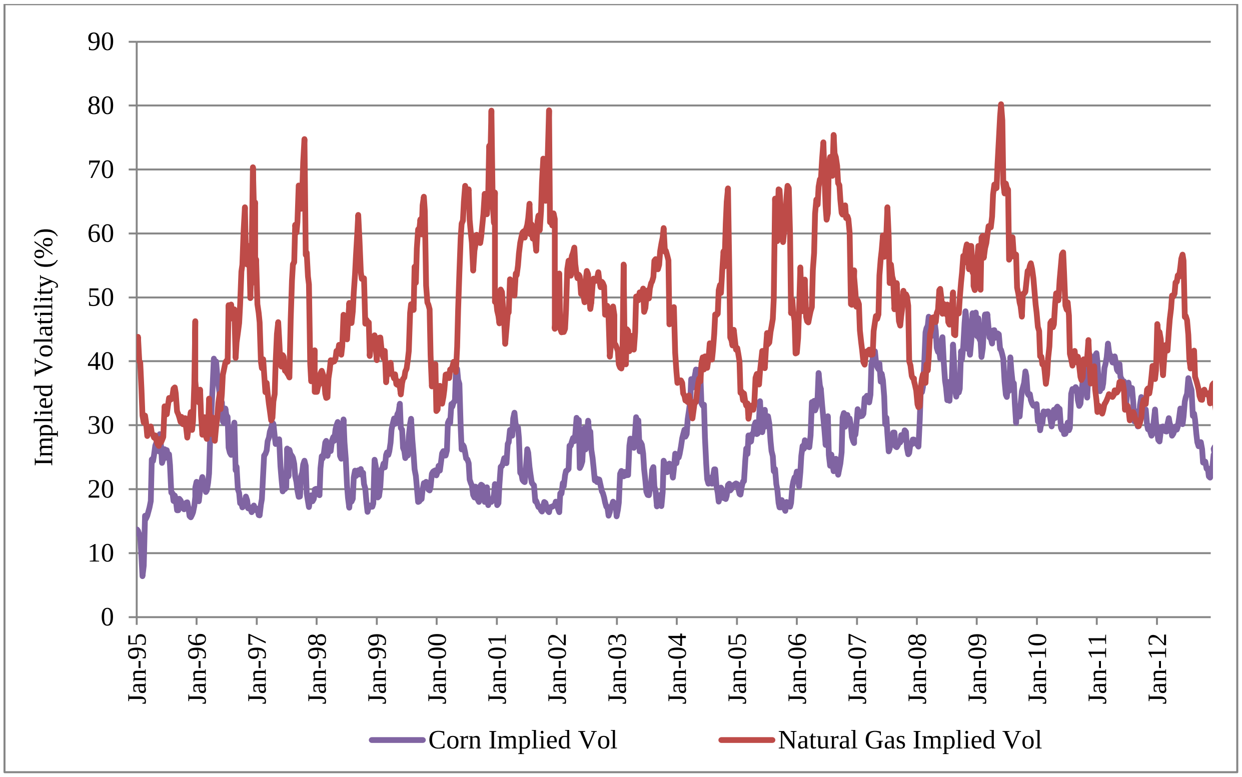


Figure 5.10, Implied Volatilities for Crude Oil and Natural Gas

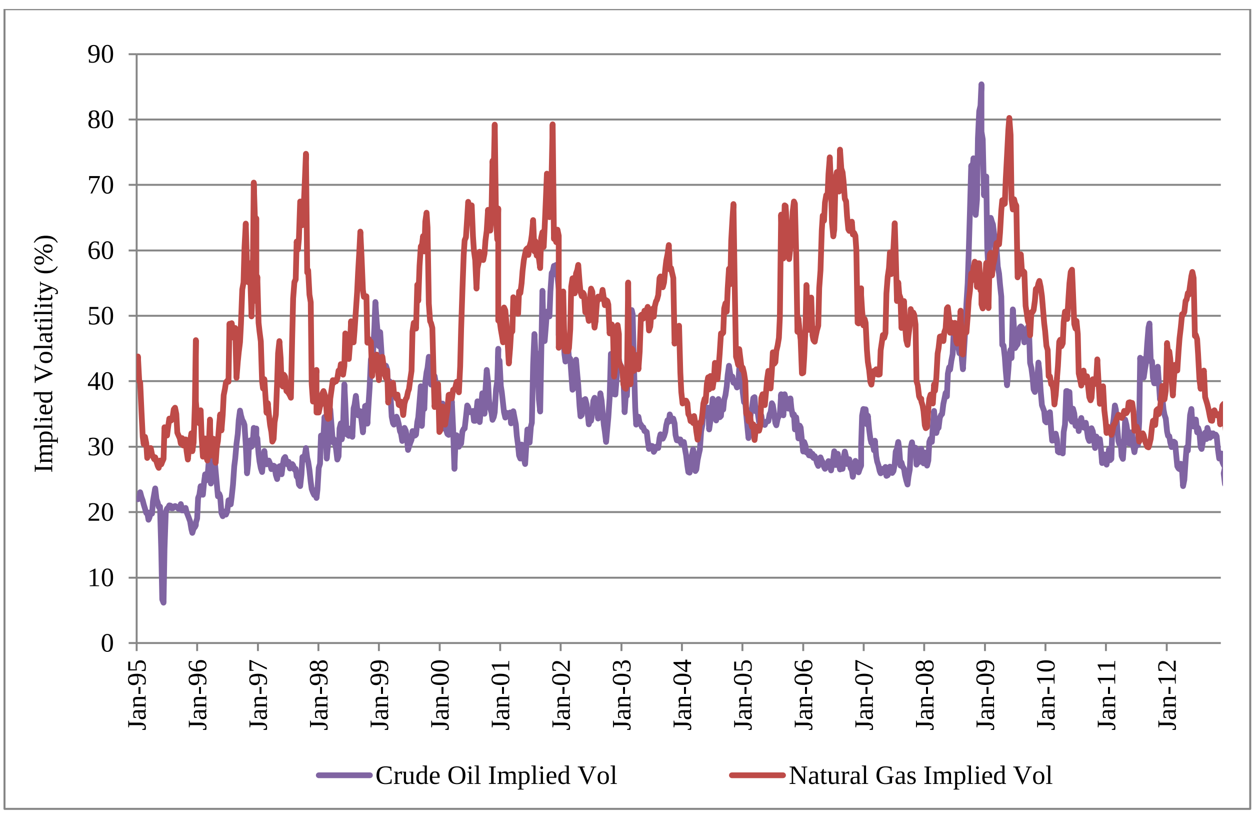


Figure 5.11, IRFs for Corn and Natural Gas - Bivariate Model (Pre-Ethanol Boom: 1995-2005)

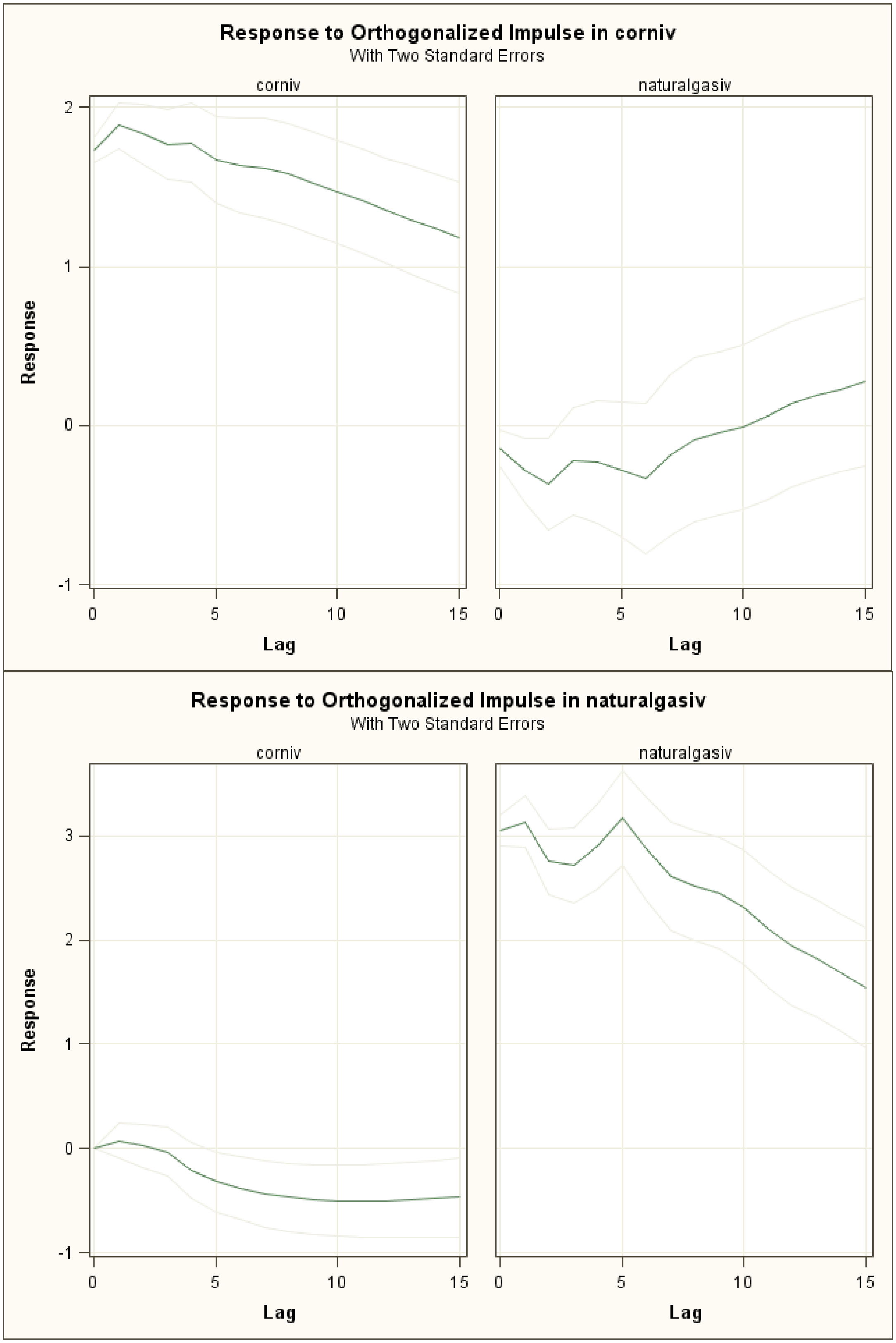


Table 5.9, Granger Causality – Bivariate VAR Model (Post-Ethanol Boom: 2006-2012)

Dependent Variable	Independent Variable								
	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn	++							+	+
Soybeans	+++	+++		++			+++		
Wheat	+++		+++	++					
Cotton	+	++							
LC					+++	+++			
FC	++			++		+++		+++	
LH	++						+++		++
CO		++						+++	
NG	+++						++		+++

+++ is statistically significant at 0.01 level, ++ at 0.05 level, and + at 0.10 level

Figure 5.12, IRFs for Corn and Crude Oil - Bivariate Model (Post-Ethanol Boom: 2006-2012)

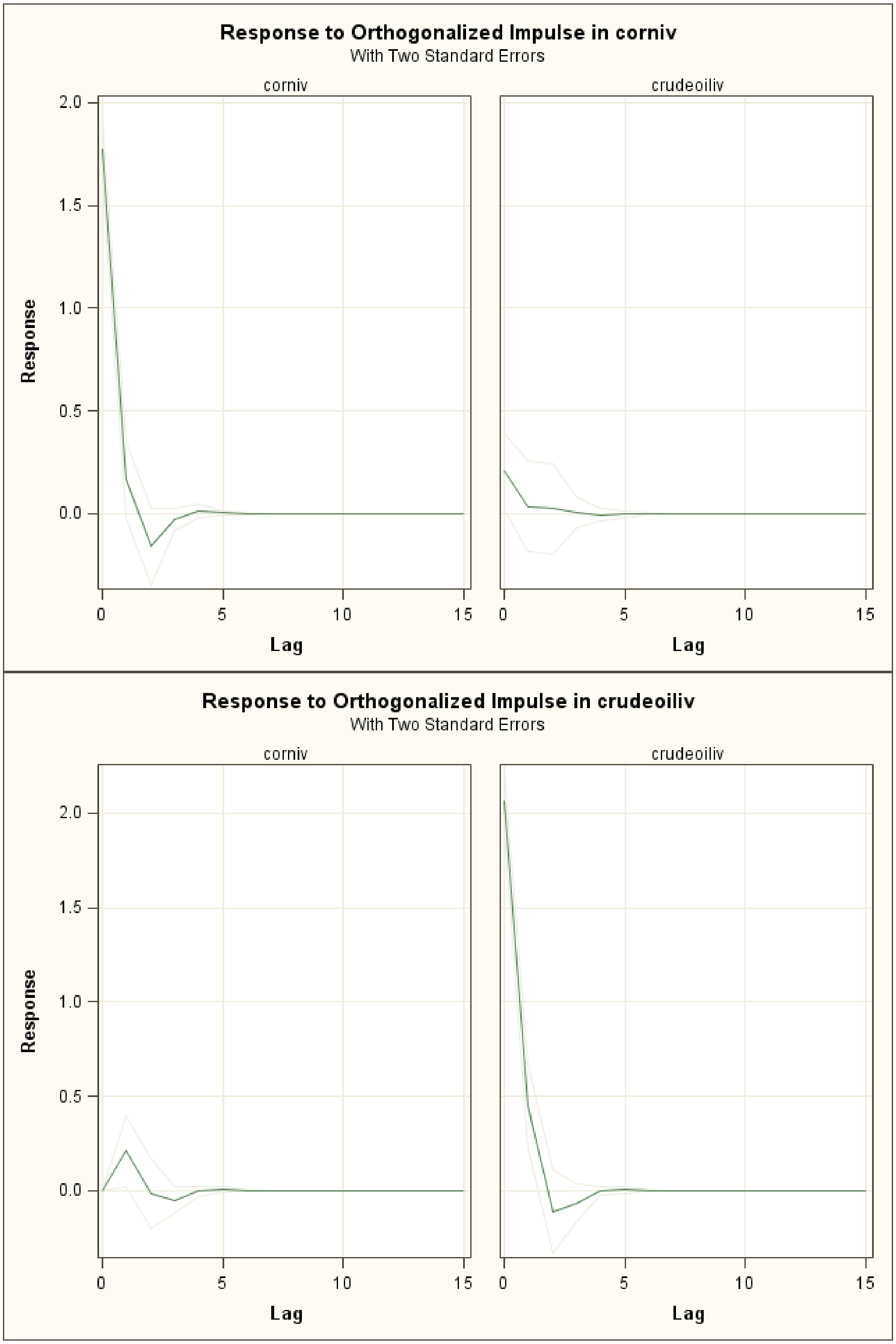


Table 5.10, Summary of Granger Causality Tests

Dependent Variable	Independent Variable								
	Corn	Soybeans	Wheat	Cotton	LC	FC	LH	CO	NG
Corn		B1	M1 B1 B2				M1 M2 B1 B2	M1 B3	M1 M2 B1 B2 B3
Soybeans	M2 M3 B1 B2 B3		B1	B3			M1 M2 B1 B2 B3		M1 M2 B2
Wheat	M1 M3 B1 B2 B3	M2 B1 B2		M2 B3		B1 B2			M2 B2
Cotton	B1 B2 B3	M2 B1 B2 B3	M2 B1		M1 M2 B1 B2	M1 B2	B2		
LC				B2		M2 M3 B3	M1 M2 B1 B2		
FC	M3 B1 B3	M1 M2 B1 B2		M3 B1 B2 B3	M1 M2 B1 B2		B1 B2	M1 M2 B1 B2 B3	M1 M2
LH	M2 M3 B3			B1 B2	M2 B1			M1 M2 B1 B2	M1 M2 B1 B2 B3
CO		M1 M3 B1 B3		M1 M2		B1	B2		M1 M2 B1 B2
NG	M1 M3 B2 B3						B3		

M1, M2, and M3 specify that the multivariate VAR Granger test indicates statistical significance at the 90 percent level or higher in the 1995-2012, 1995-2005, and 2006-2012 time periods, respectively.
B1, B2, and B3 specify that the bivariate VAR Granger test indicates statistical significance at the 90 percent level or higher in the 1995-2012, 1995-2005, and 2006-2012 time periods, respectively.

Table 5.11, Summary of Granger Causality Tests - Multivariate VAR Models

1995-2012	Pre-Ethanol Boom (1995-2005)	Post-Ethanol Boom (2005-2012)
Corn ↔ Wheat	Corn ⟶ Soybeans	Corn ⟶ Soybeans
Corn ↔ Natural Gas	Corn ↔ Lean Hogs	Corn ⟶ Wheat
Soybeans ⟶ Feeder Cattle	Soybeans ⟶ Wheat	Corn ⟶ Feeder Cattle
Soybeans ⟶ Crude Oil	Soybeans ⟶ Cotton	Corn ⟶ Lean Hogs
Cotton ↔ Feeder Cattle	Soybeans ⟶ Feeder Cattle	Corn ⟶ Natural Gas
Cotton ⟶ Crude Oil	Wheat ↔ Cotton	Soybeans ⟶ Crude Oil
Live Cattle ⟶ Cotton	Cotton ⟶ Crude Oil	Cotton ⟶ Feeder Cattle
Live Cattle ⟶ Feeder Cattle	Live Cattle ⟶ Cotton	Feeder Cattle ⟶ Live Cattle
Lean Hogs ⟶ Corn	Live Cattle ↔ Feeder Cattle	
Lean Hogs ⟶ Soybeans	Live Cattle ↔ Lean Hogs	
Lean Hogs ⟶ Live Cattle	Lean Hogs ⟶ Soybeans	
Crude Oil ⟶ Corn	Crude Oil ⟶ Feeder Cattle	
Crude Oil ⟶ Feeder Cattle	Crude Oil ⟶ Lean Hogs	
Crude Oil ⟶ Lean Hogs	Natural Gas ⟶ Corn	
Natural Gas ⟶ Soybeans	Natural Gas ⟶ Soybeans	
Natural Gas ⟶ Feeder Cattle	Natural Gas ⟶ Wheat	
Natural Gas ⟶ Lean Hogs	Natural Gas ⟶ Feeder Cattle	
Natural Gas ⟶ Crude Oil	Natural Gas ⟶ Lean Hogs	
	Natural Gas ⟶ Crude Oil	

⟶ indicates a unidirectional relationship between commodities, ↔ indicates a bidirectional relationship between commodities.

Table 5.12, Summary of Granger Causality Tests – Bivariate VAR Models

1995-2012	Pre-Ethanol Boom (1995-2005)	Post-Ethanol Boom (2005-2012)
Corn ↔ Soybeans	Corn ⟶ Soybeans	Corn ⟶ Soybeans
Corn ↔ Wheat	Corn ↔ Wheat	Corn ⟶ Wheat
Corn ⟶ Cotton	Corn ⟶ Cotton	Corn ⟶ Cotton
Corn ⟶ Feeder Cattle	Corn ↔ Natural Gas	Corn ⟶ Feeder Cattle
Soybeans ↔ Wheat	Soybeans ⟶ Wheat	Corn ⟶ Lean Hogs
Soybeans ⟶ Cotton	Soybeans ⟶ Cotton	Corn ↔ Natural Gas
Soybeans ⟶ Feeder Cattle	Soybeans ⟶ Feeder Cattle	Soybeans ↔ Cotton
Soybeans ⟶ Crude Oil	Cotton ↔ Live Cattle	Soybeans ⟶ Crude Oil
Wheat ⟶ Soybeans	Cotton ↔ Feeder Cattle	Cotton ⟶ Wheat
Wheat ⟶ Cotton	Cotton ↔ Lean Hogs	Cotton ⟶ Feeder Cattle
Cotton ⟶ Feeder Cattle	Live Cattle ⟶ Feeder Cattle	Feeder Cattle ⟶ Live Cattle
Cotton ⟶ Lean Hogs	Feeder Cattle ⟶ Wheat	Lean Hogs ⟶ Soybeans
Live Cattle ⟶ Cotton	Lean Hogs ⟶ Corn	Lean Hogs ↔ Natural Gas
Live Cattle ⟶ Feeder Cattle	Lean Hogs ⟶ Soybeans	Crude Oil ⟶ Corn
Live Cattle ↔ Lean Hogs	Lean Hogs ⟶ Live Cattle	Crude Oil ⟶ Feeder Cattle
Feeder Cattle ⟶ Wheat	Lean Hogs ⟶ Feeder Cattle	
Feeder Cattle ↔ Crude Oil	Lean Hogs ↔ Crude Oil	
Lean Hogs ⟶ Corn	Crude Oil ⟶ Feeder Cattle	
Lean Hogs ⟶ Soybeans	Natural Gas ⟶ Soybeans	
Lean Hogs ⟶ Feeder Cattle	Natural Gas ⟶ Wheat	
Crude Oil ⟶ Lean Hogs	Natural Gas ⟶ Crude Oil	
Natural Gas ⟶ Corn		
Natural Gas ⟶ Lean Hogs		
Natural Gas ⟶ Crude Oil		

⟶ indicates a unidirectional relationship between commodities, ↔ indicates a bidirectional relationship between commodities.

Chapter 6 - Conclusion

As the commodity markets evolve over time, the sources of risk and the translation of volatility between the markets will continue to be a topic of interest. Because the Energy Policy Act of 2005 redefined the corn market and strengthened the linkage between corn and energy, most recent literature focuses on the relationship between those markets. While this question is crucial in terms of understanding the impact of recent energy policies on the agricultural industry, it does not fully explain the nature of volatility translation across the agricultural markets. Past studies that have analyzed agricultural commodities tend to evaluate only price relationships. This research supplements existing literature by addressing the previously unexplored issue of volatility spillover across the energy, grain, and livestock markets. By using implied volatility, this analysis considers the market-determined expected price risk rather than the typical forecasted variance which is calculated using historical prices.

This thesis uses weekly implied volatilities from 1995 to 2012 to assess causal relationships between nine commodities: corn, soybeans, wheat, cotton, live cattle, feeder cattle, lean hogs, crude oil, and natural gas. To examine how the Energy Policy Act of 2005 may have affected the markets, the data are also divided and analyzed over a pre-ethanol boom time frame (1995-2005) and a post-ethanol boom time frame (2006-2012). Descriptive statistics indicated that all nine of the commodity markets experienced an upward shift in their mean prices between the two time periods. The mean volatilities of corn, soybeans, wheat, and cotton also increased. When comparing the markets over time, the energies were the most volatile while the livestock markets were the least volatile. All of the commodities, except natural gas, are experiencing an upward trend in prices that began around 2005. The Pearson correlation coefficients showed that all of the agricultural commodities' prices and volatilities were more highly correlated in the post-ethanol boom time period than in the pre-ethanol boom time period. Notably, the correlation between corn and crude oil changed from weakly negative to strongly positive between the time periods. This is consistent with previous literature and suggests that the two markets became more closely related as a result of the mandated ethanol expansion. Not surprisingly, the strongest correlation is between the live cattle and feeder cattle markets.

After all volatility series were either determined to be stationary or corrected for a unit root, multivariate and bivariate vector autoregressive (VAR) models were estimated. Granger causality tests were conducted using chi-square tests and impulse response functions (IRFs) were generated. The results that were deemed the most conclusive are the most persistent through the models and time periods. They are also plausible and consistent with expectations. Over time, corn volatility led soybeans volatility and was bidirectional with wheat volatility. Corn and soybeans volatilities Granger caused cotton volatility. Live cattle and feeder cattle always exhibited a unidirectional or bidirectional relationship, and lean hogs led soybeans throughout the years. Lean hogs volatility was a leader for most of the agricultural commodities' volatilities in the early years. In the later era, though, corn led most of the other agricultural commodities and lean hogs did not. Crude oil Granger caused feeder cattle and lean hogs in the pre-ethanol boom time period. Despite previous literature's conclusions and a noteworthy increase in correlation, the causal relationship between crude oil and corn in the post-ethanol boom period was determined to be relatively negligible. The bivariate VAR model for the 2006 through 2012 era found that crude oil led corn only at the 90 percent confidence level. However, corn and natural gas were either unidirectional or bidirectional throughout the models and time periods. Natural gas Granger caused crude oil in the early era, but no relationship was revealed between the energies in the later era. This was consistent with the decline in their correlation between the time periods.

6.1 Implications

A few general implications may be established from the results of this study. Many causal linkages exist between the agricultural commodities, and increased uncertainty in some markets can cause other markets to also become more uncertain. Since increases in implied volatility cause options prices to rise, uncertainty in some markets may affect options prices in other markets. Producers and market analysts should be aware of volatility spillover as they form risk management decisions. Implied volatility spillover also has implications for basis risk since increased fluctuations in the futures markets can cause more basis variability. Understanding volatility spillover could help producers foresee future basis movements.

Because of the movement from lean hogs as the leader of agricultural volatilities in the pre-ethanol boom time period to corn as the leader in the post-ethanol boom time period and those markets' corresponding volatility levels during those time periods, it could be that more volatile agricultural markets tend to lead less volatile markets. This is indicative of the possibility that more volatile markets create spillovers because related industries become less certain when one sector is experiencing particular uncertainty. For example, the high levels of implied volatility in the lean hogs market in the late 1990s and early 2000s may have caused corn and soybean growers and cattle producers to feel more uncertain about the risk associated with those markets as well.

This analysis also finds that there are relationships between the energy and agricultural markets. In the post-ethanol boom era, crude oil and corn are highly correlated in price and volatility and crude oil volatility may lead corn volatility. Causal relationships were also revealed to exist between the corn and crude oil markets over the years. Furthermore, volatility spillover occurs from the corn market to the soybeans, wheat, and cotton markets. Corn also leads feeder cattle and lean hogs in the post-ethanol boom period. Therefore, market effects due to policy changes can be much broader than anticipated. The Energy Policy Act of 2005 was likely a driver of this fundamental change in the markets that occurred around 2005. Policymakers should be aware of this when proposing and evaluating strategies for the energy and agricultural industries in the future.

6.2 Future Research

This research is not without limitations. Ideally, an implied volatility series for the ethanol market would have been included in this analysis. However, this was not possible since the CME Group did not implement an ethanol futures contract until 2005 and ethanol options are traded too infrequently for Bloomberg to provide a consistent implied volatility series. Existing papers that analyze spillover between the ethanol market and other markets, including those by Trujillo-Barrera, Mallory, and Garcia (2012) and Zhang, Lohr, Escalante, and Wetzstein (2009), use CME Group ethanol prices from recent years or ethanol cash prices to generate a volatility series based on historical price variance. In an extension of this thesis, ethanol volatilities could be calculated with an ethanol cash price series and generalized autoregressive conditional heteroskedasticity or a similar method and compared to the implied volatilities of the other commodities using Granger causality tests. However, the practicality and conclusiveness of that study would be debatable due to the different methods of calculating volatility.

In the future, some modifications could be made to this research to improve the consistency of the data series and analysis. First-differencing could be applied to the stationary pre-ethanol boom implied volatility series so that it is more comparable to the already first-differenced post-ethanol boom data series. Likewise, the pre-ethanol boom series could be shortened so that its number of observations matches the post-ethanol boom series. Data from the time frame encompassing the major change in the markets could be eliminated to create a gap between the two eras. This would reduce the possibility of bias in the results of either time period due to the possible structural shift in the markets. Since the results of the Granger causality tests are sensitive to the time period selected, other cut-off dates between the two eras could be tested and compared.

Another extension of this analysis is to create a comprehensive model using an exogenous dummy variable to differentiate the pre-ethanol boom time period from the post-ethanol boom time period. Similarly, monthly dummy variables could be added to the models to determine if any of the commodities' relationships are seasonal. Dummy variables could also be used to indicate major events, such as the bovine spongiform encephalopathy outbreak in 2003, to see if those events had any impacts on the causal linkages. To confirm the results of this analysis, future research could test trivariate combinations of the nine commodities. Additionally, forecast error decomposition could be evaluated to further investigate volatility interactions.

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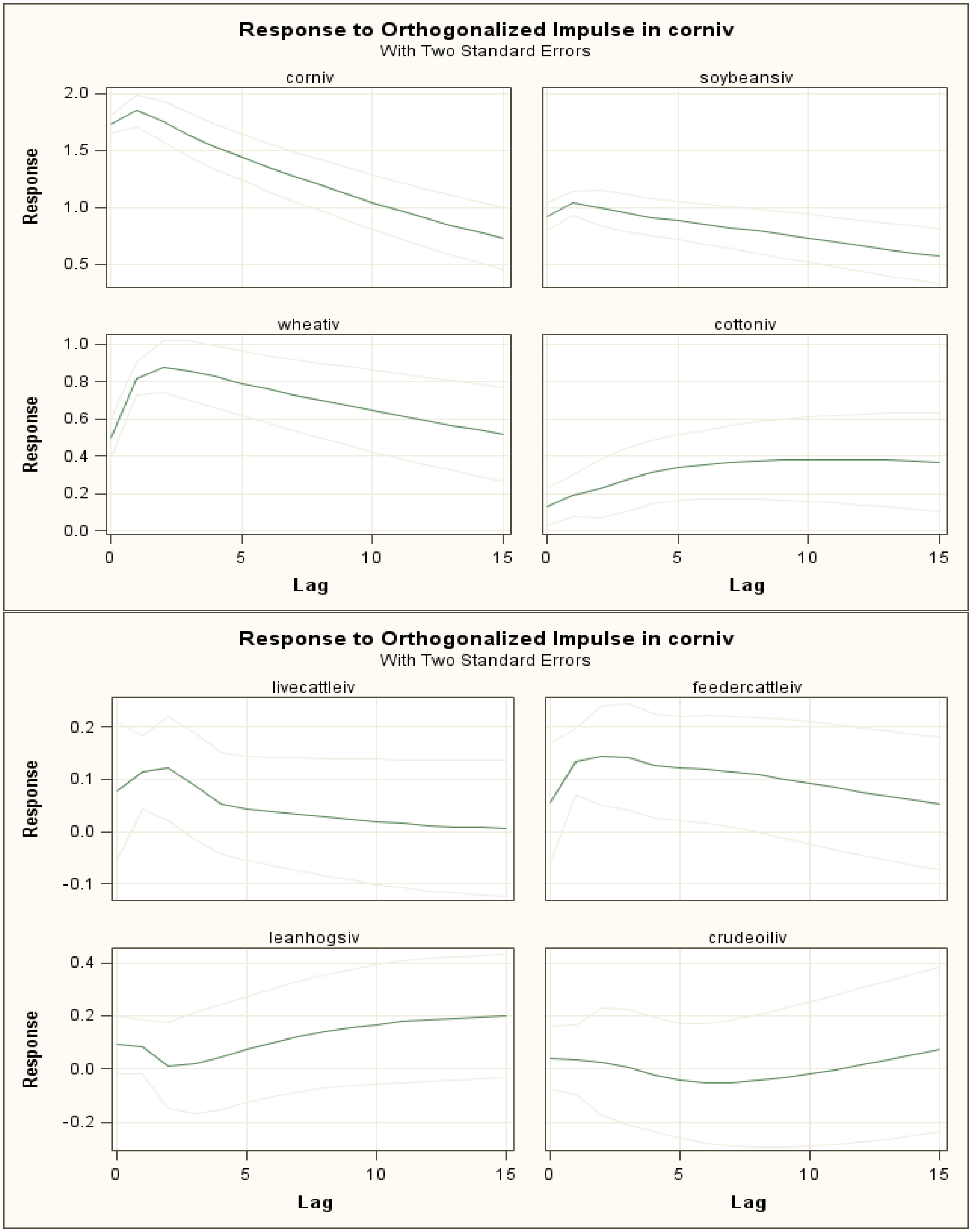
Appendix A - Impulse Response Functions for Multivariate VAR Model (1995-2012)

Figure A.1, IRFs for Corn Volatility – Multivariate Model (1995-2012)



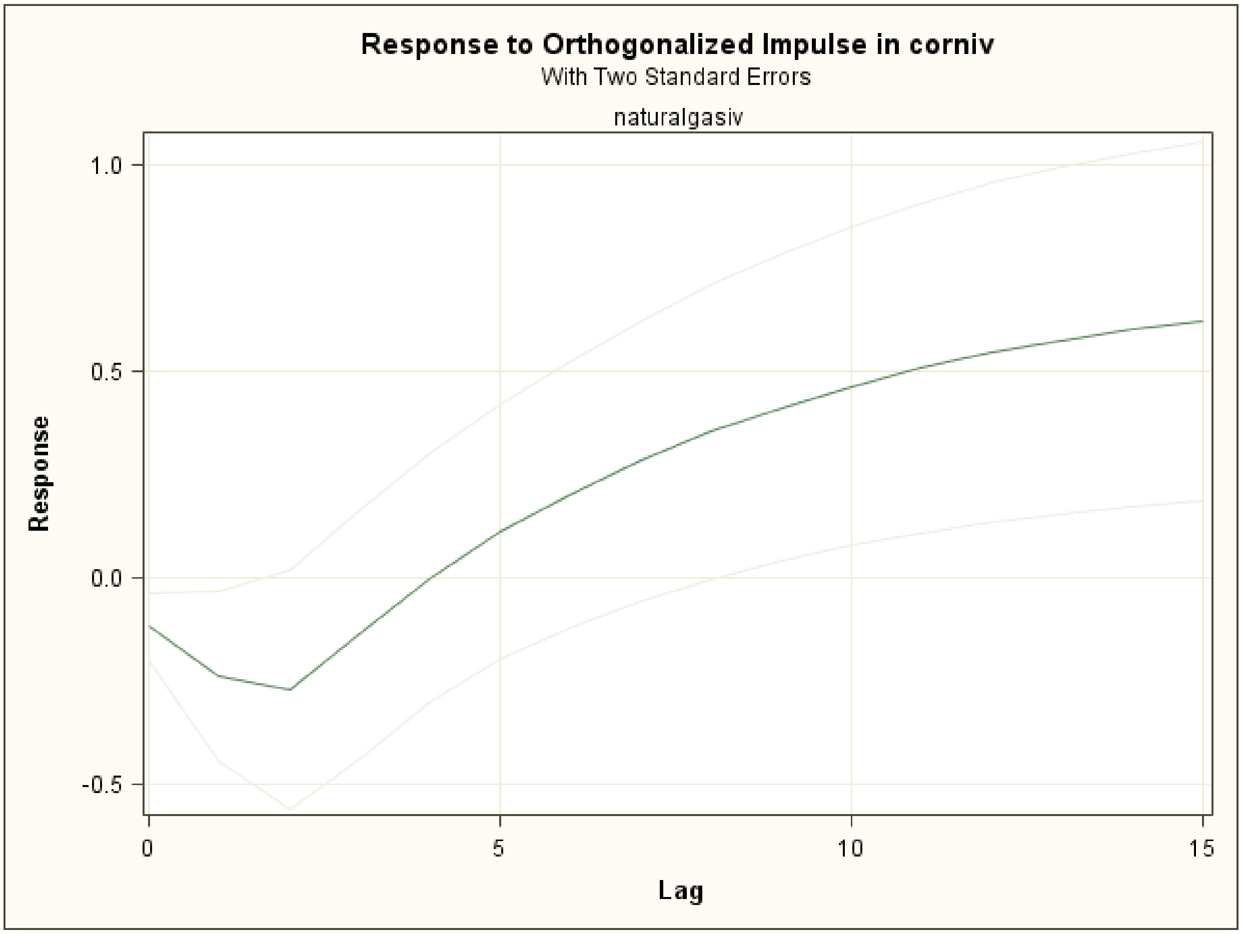
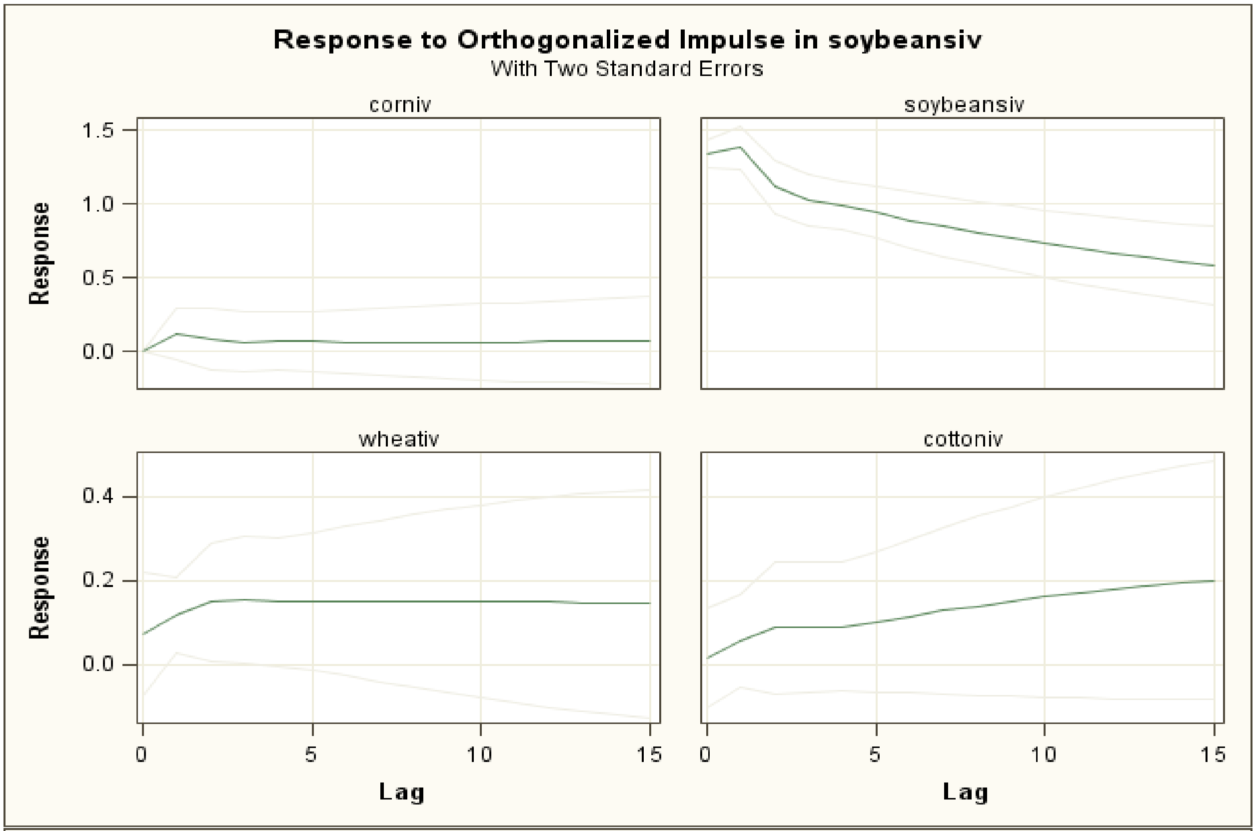
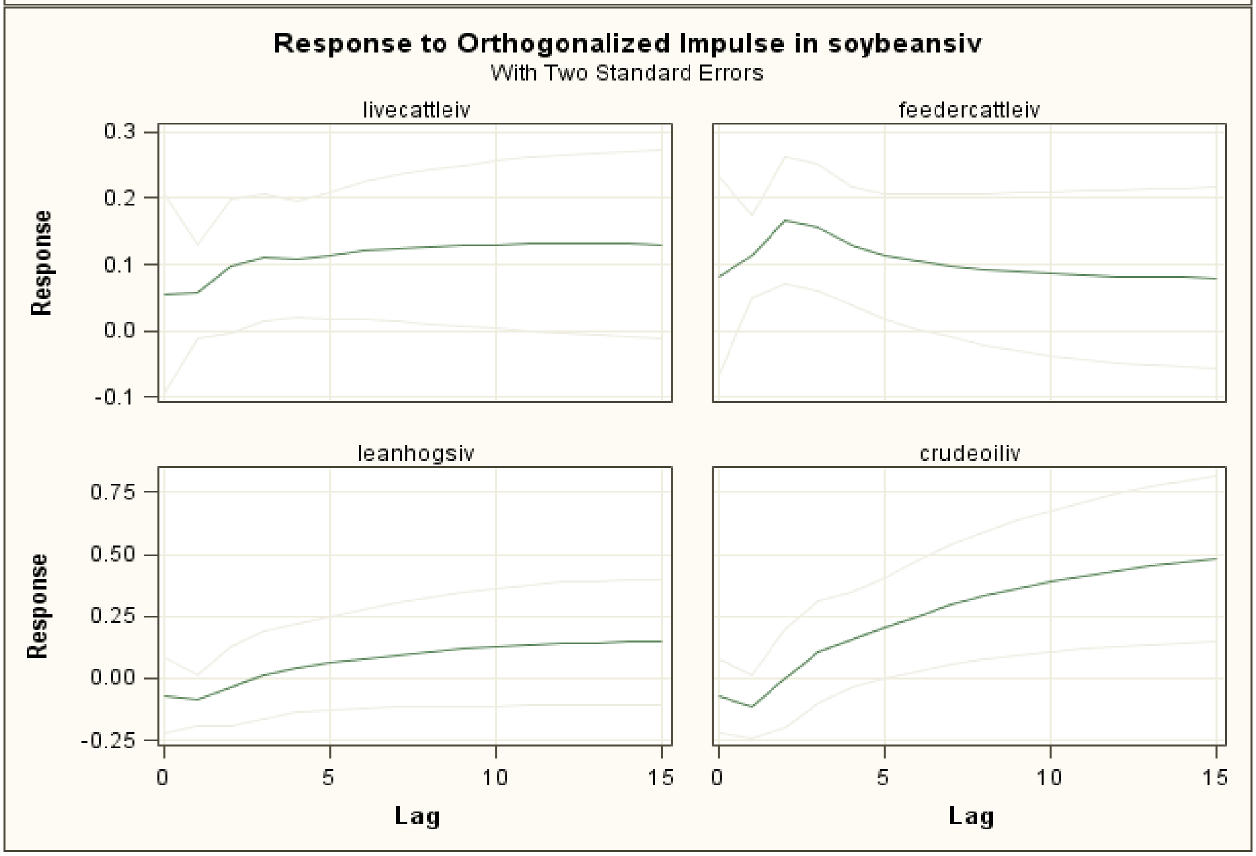

Response to Orthogonalized Impulse in corniv
With Two Standard Errors
naturalgasiv
Response
1.0
0.5
0.0
-0.5
0
5
10
15
Lag

Figure A.2, IRFs for Soybeans Volatility – Multivariate Model (1995-2012)





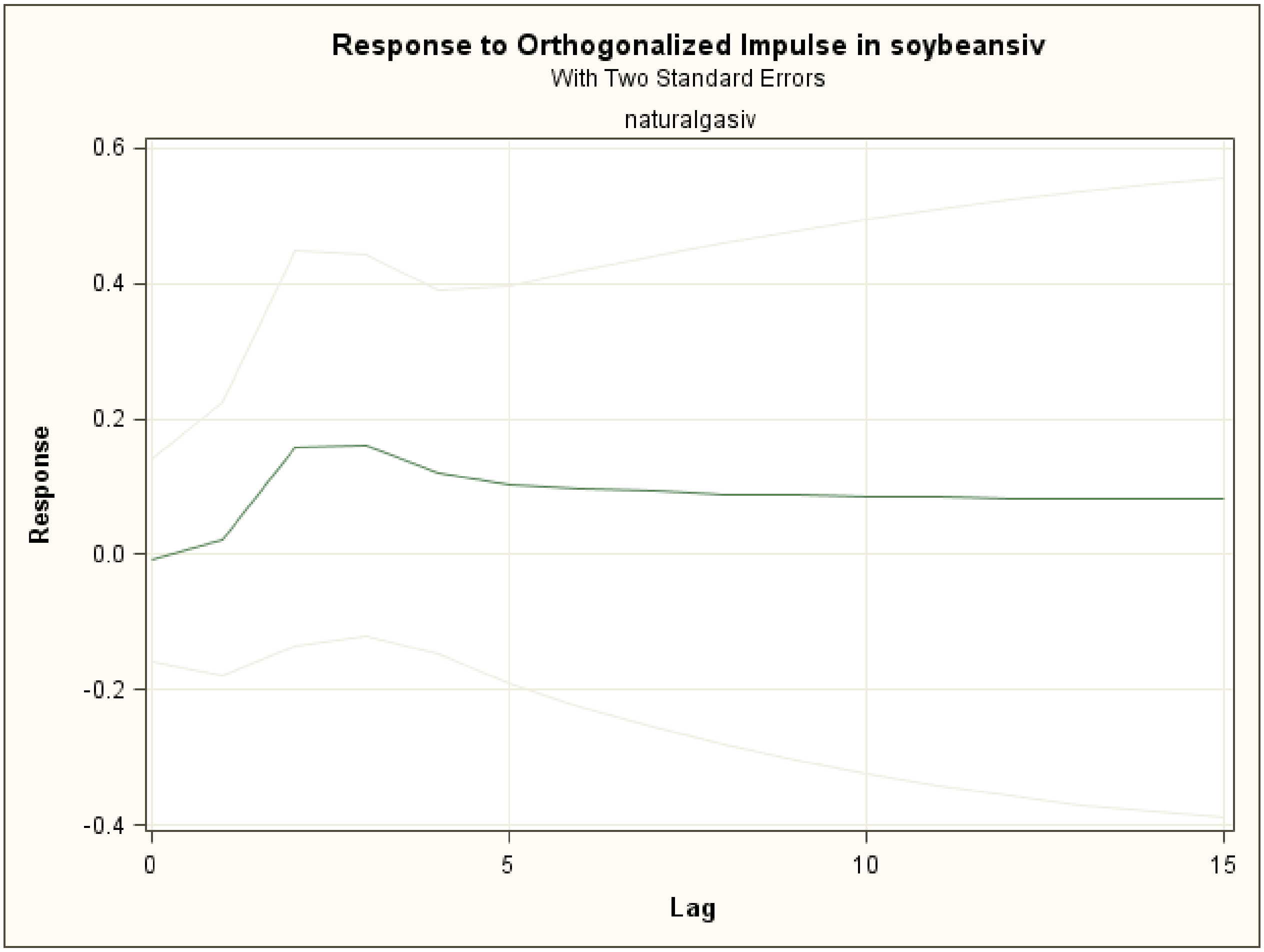
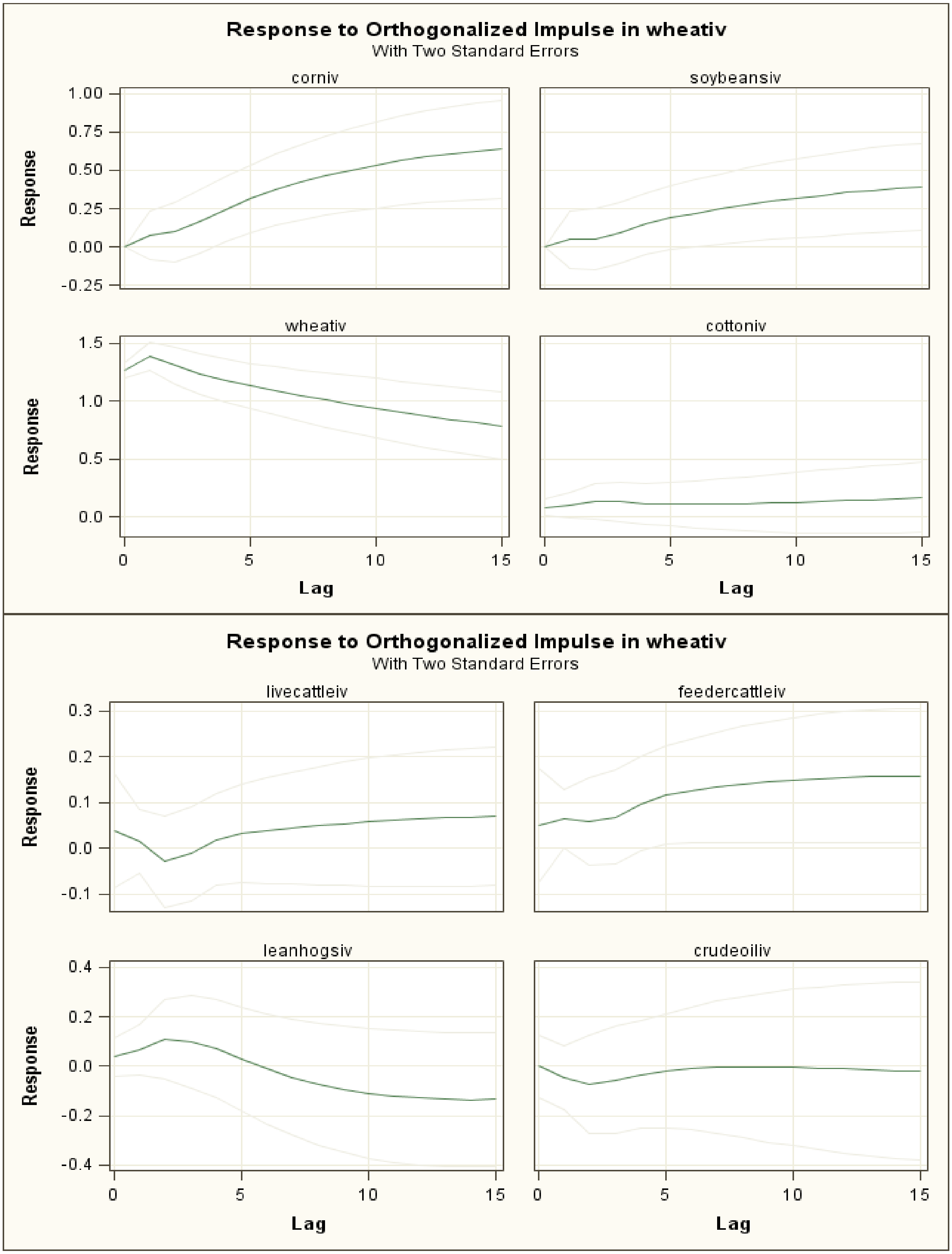
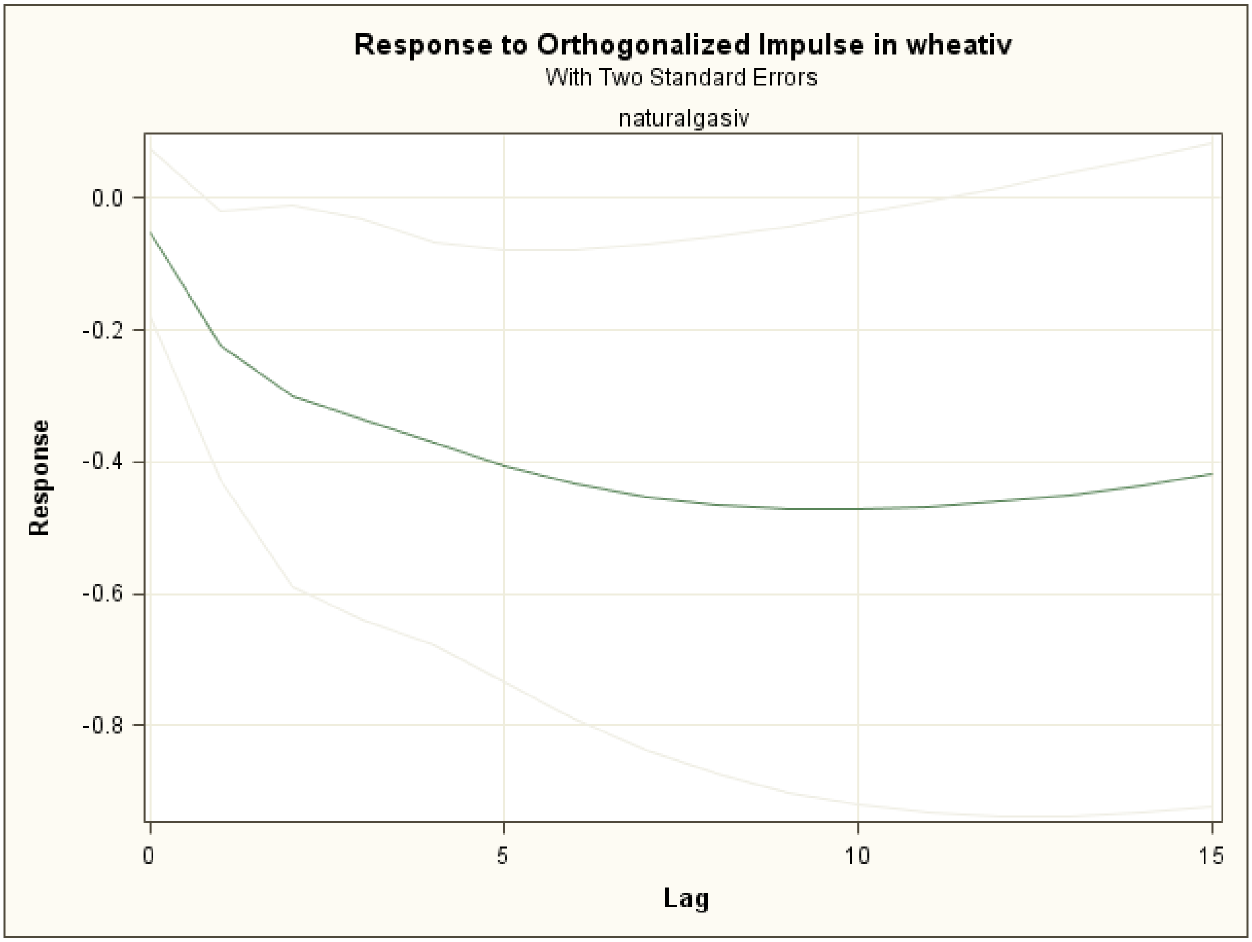

Response to Orthogonalized Impulse in soybeansiv
With Two Standard Errors
naturalgasiv
0.6
0.4
0.2
0.0
-0.2
-0.4
Response
0
5
10
15
Lag

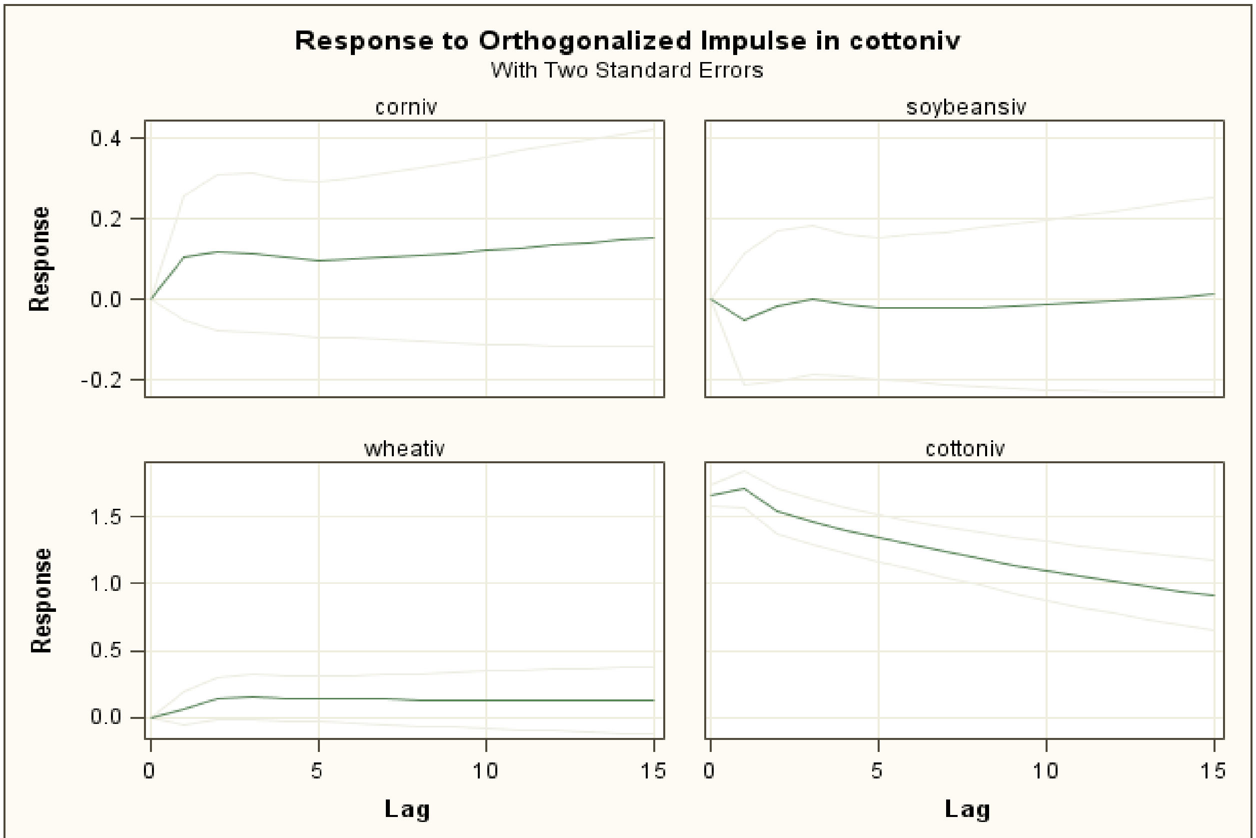
Figure A.3, IRFs for Wheat Volatility – Multivariate Model (1995-2012)

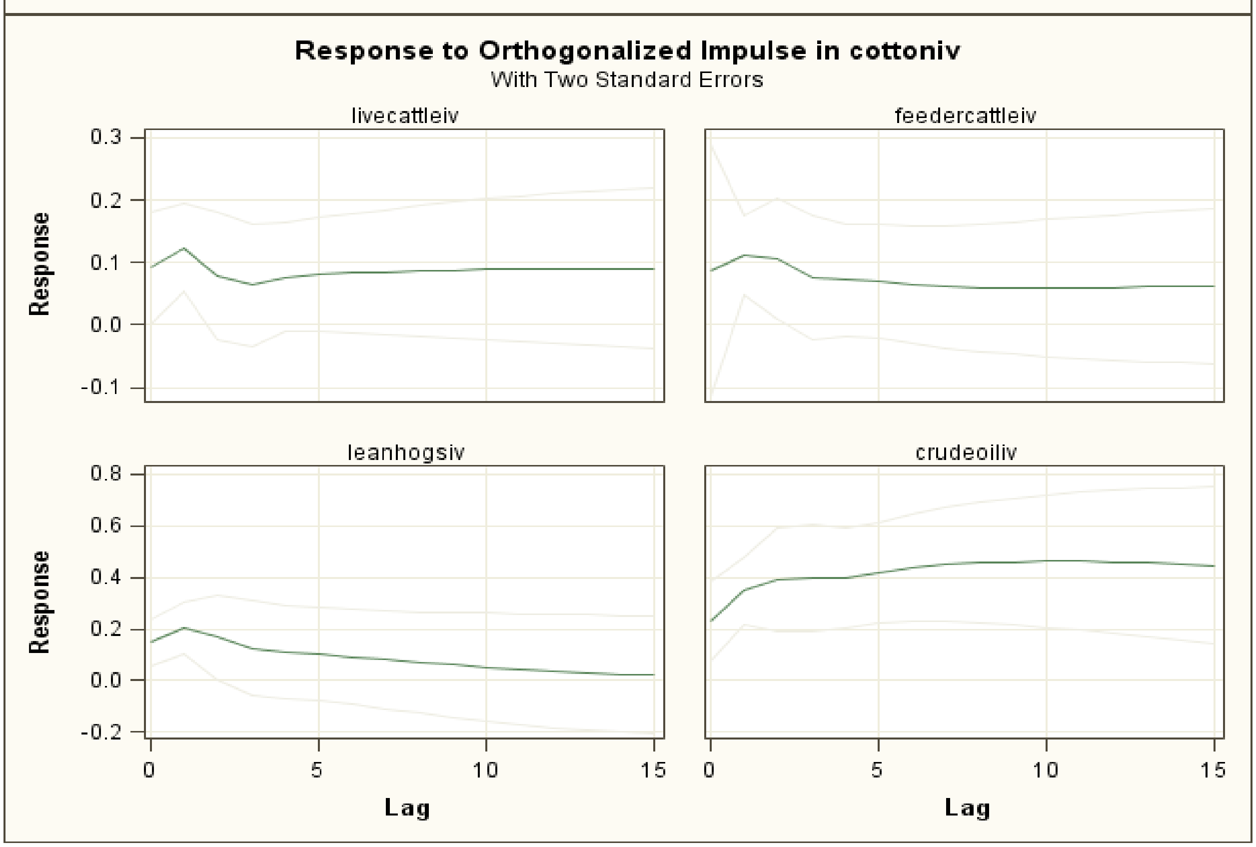




Response to Orthogonalized Impulse in wheativ
With Two Standard Errors
naturalgasiv
Response
Lag
0.0
-0.2
-0.4
-0.6
-0.8
0
5
10
15

Figure A.4, IRFs for Cotton Volatility – Multivariate Model (1995-2012)





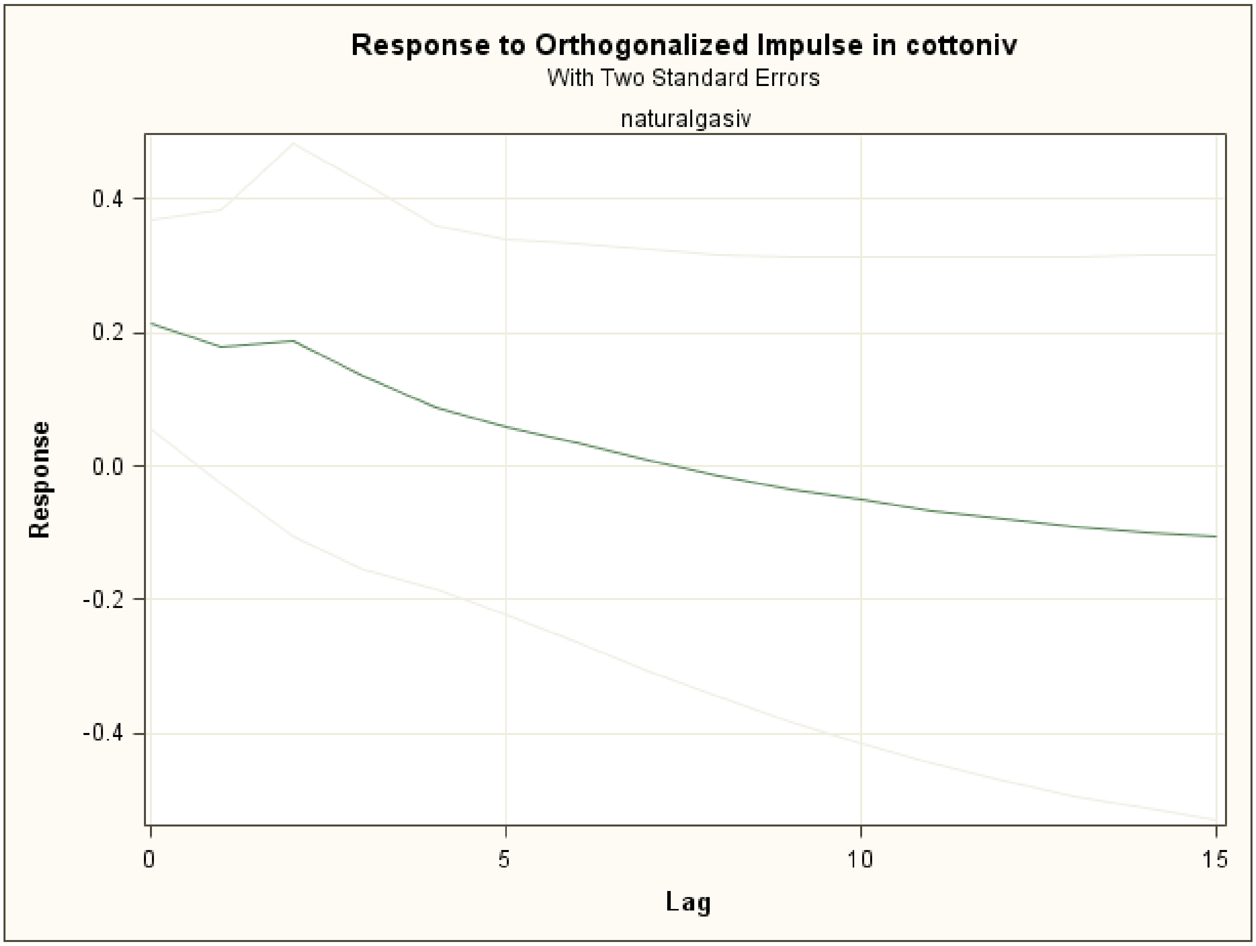
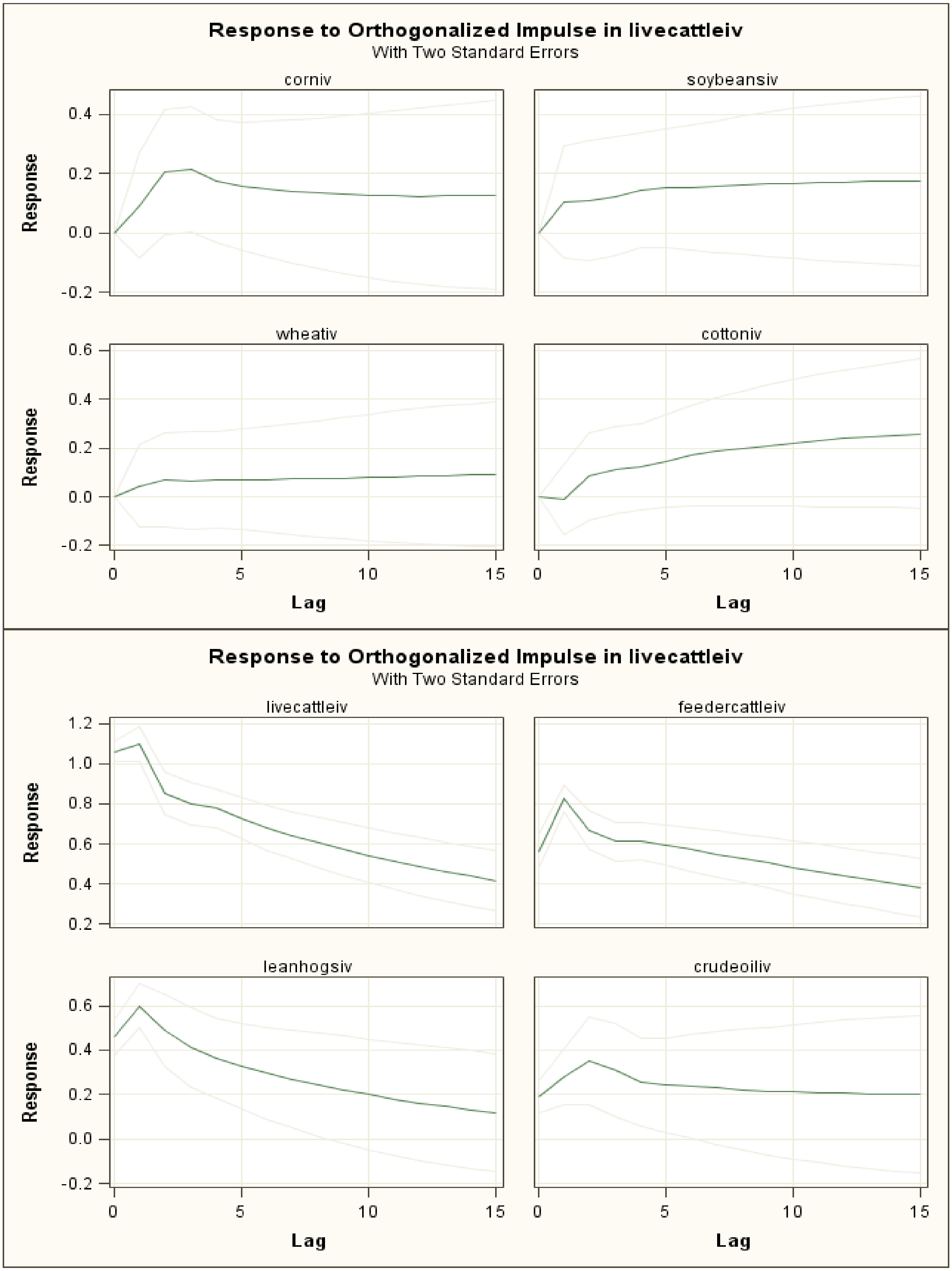

Response to Orthogonalized Impulse in cottoniv
With Two Standard Errors
naturalgasiv
Response
0.4
0.2
0.0
-0.2
-0.4
0
5
10
15
Lag

Figure A.5, IRFs for Live Cattle Volatility – Multivariate Model (1995-2012)



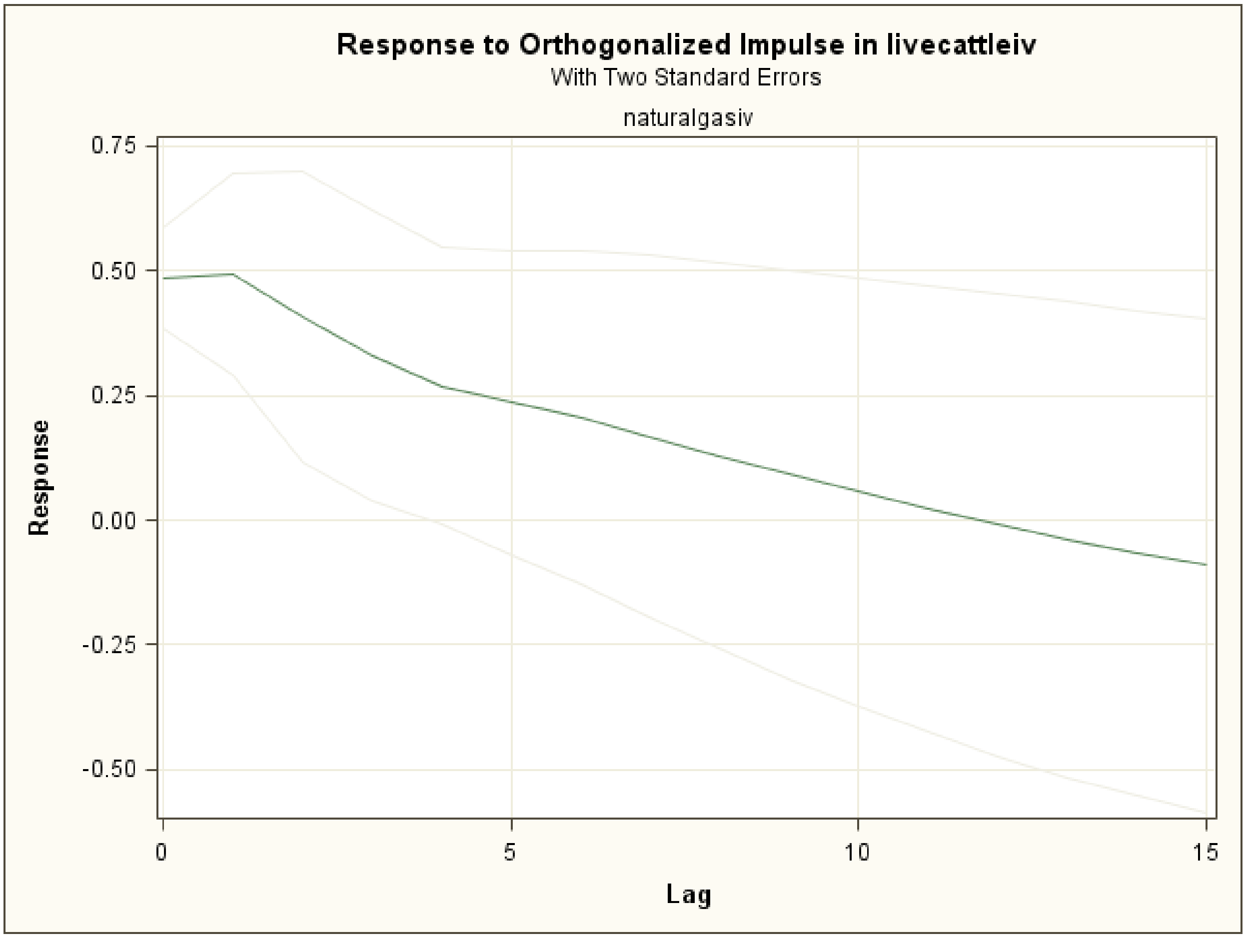
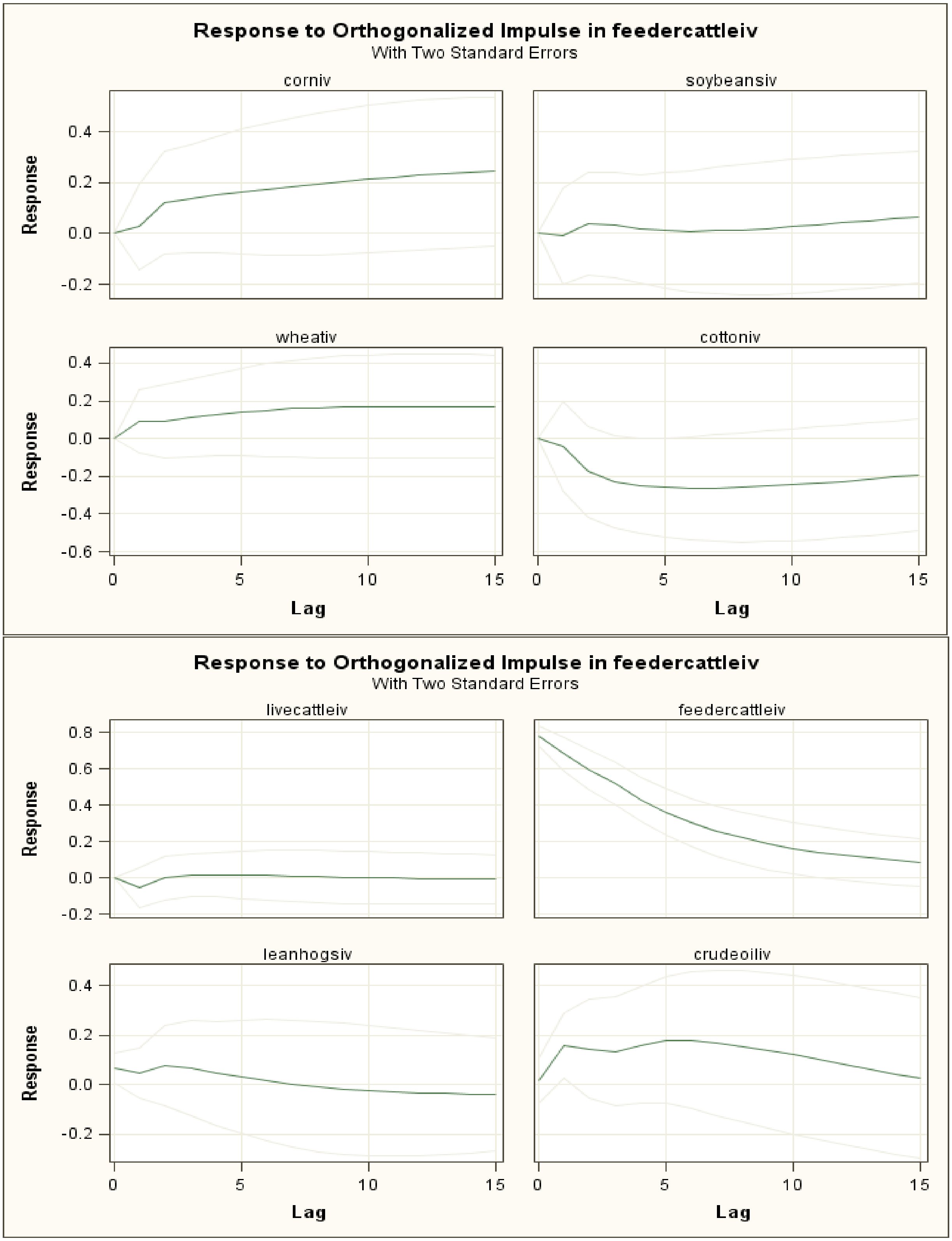

Response to Orthogonalized Impulse in livecattleiv
With Two Standard Errors
naturalgasiv
Response
Lag
0.75
0.50
0.25
0.00
-0.25
-0.50
0
5
10
15

Figure A.6, IRFs for Feeder Cattle Volatility – Multivariate Model (1995-2012)



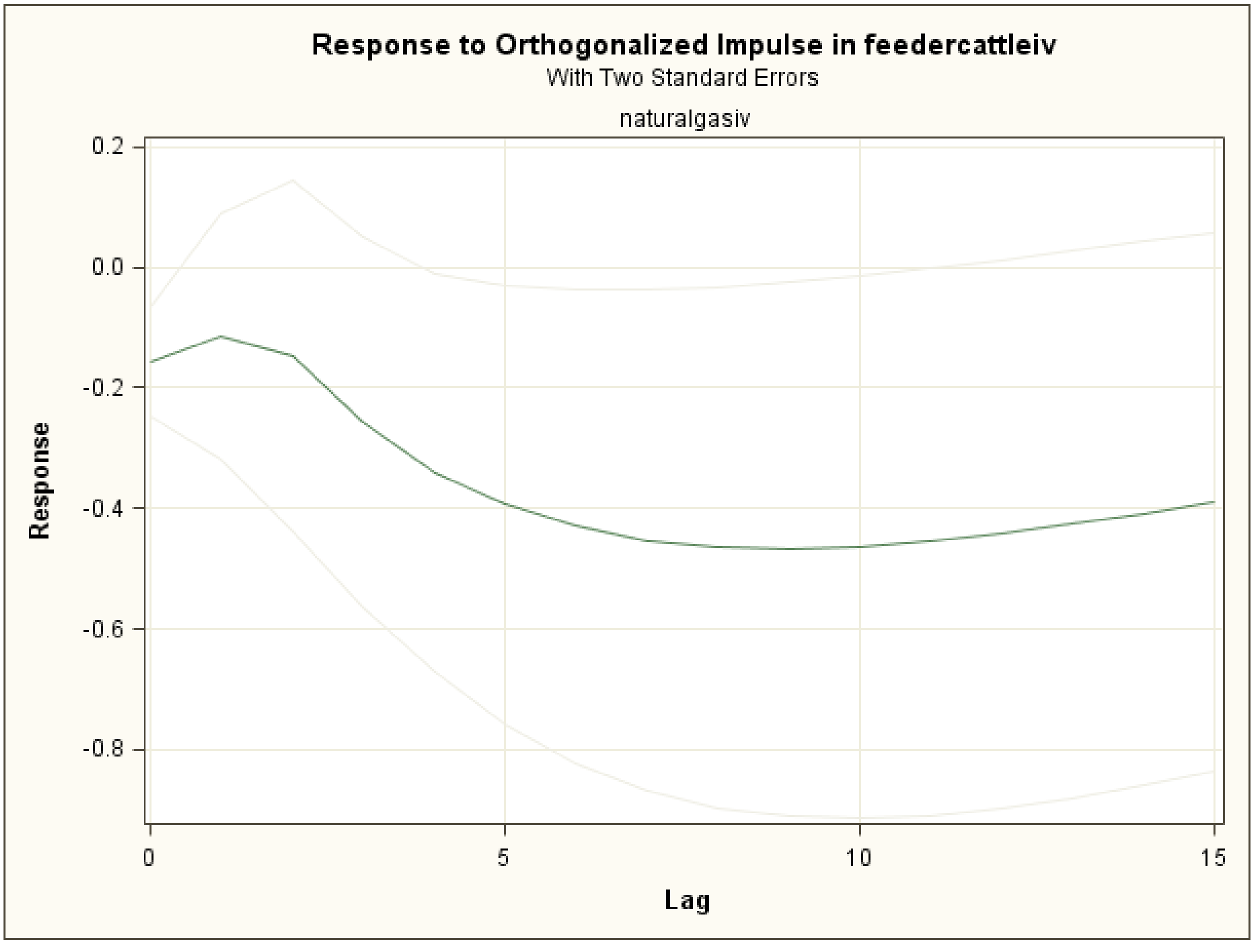
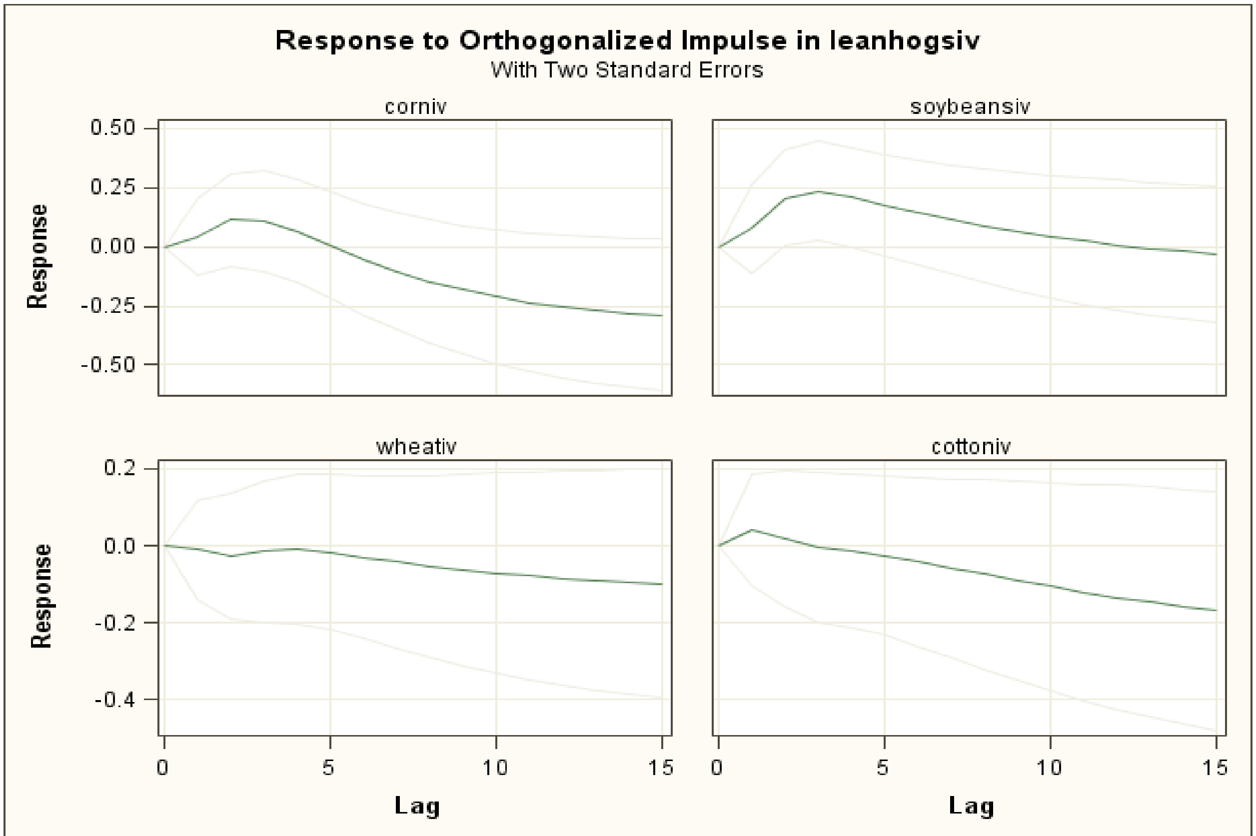
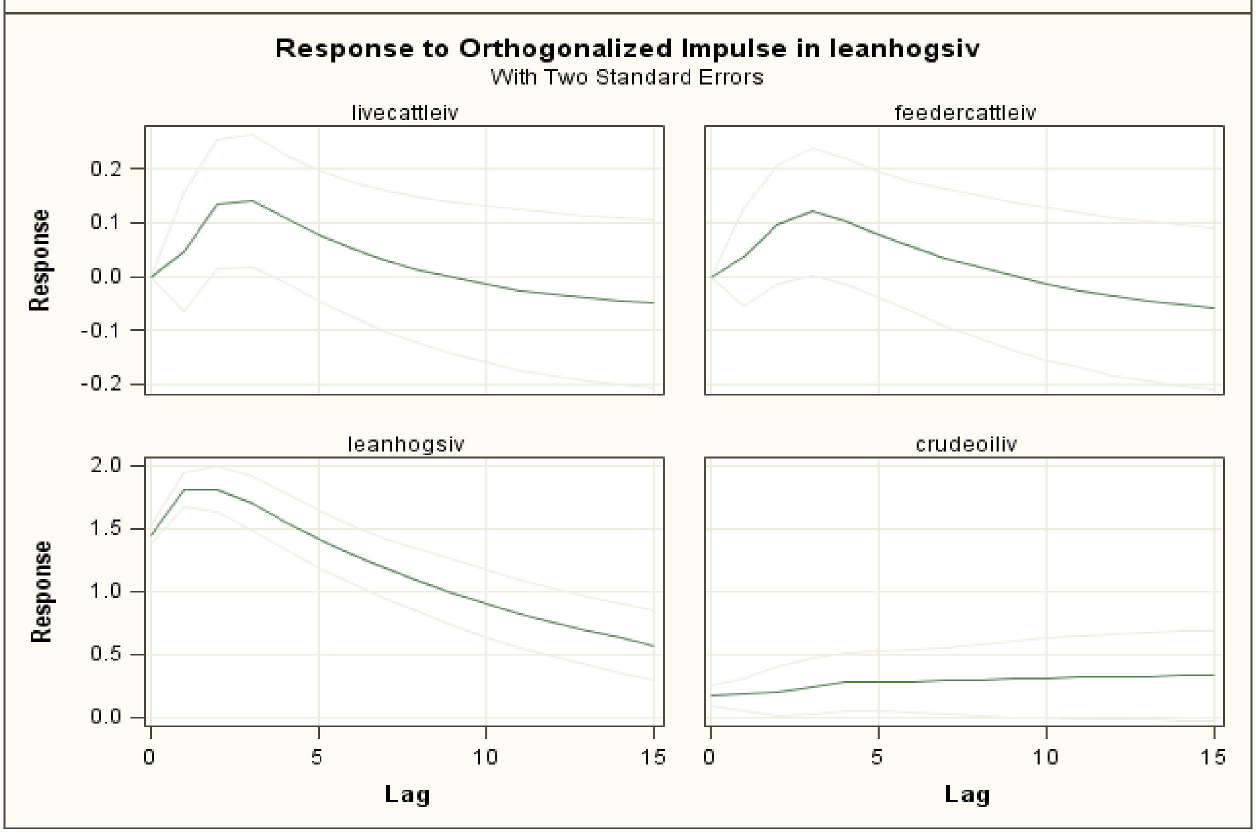

Response to Orthogonalized Impulse in feedercattleiv
With Two Standard Errors
naturalgasiv
0.2
0.0
-0.2
-0.4
-0.6
-0.8
Response
0
5
10
15
Lag

Figure A.7, IRFs for Lean Hogs Volatility – Multivariate Model (1995-2012)





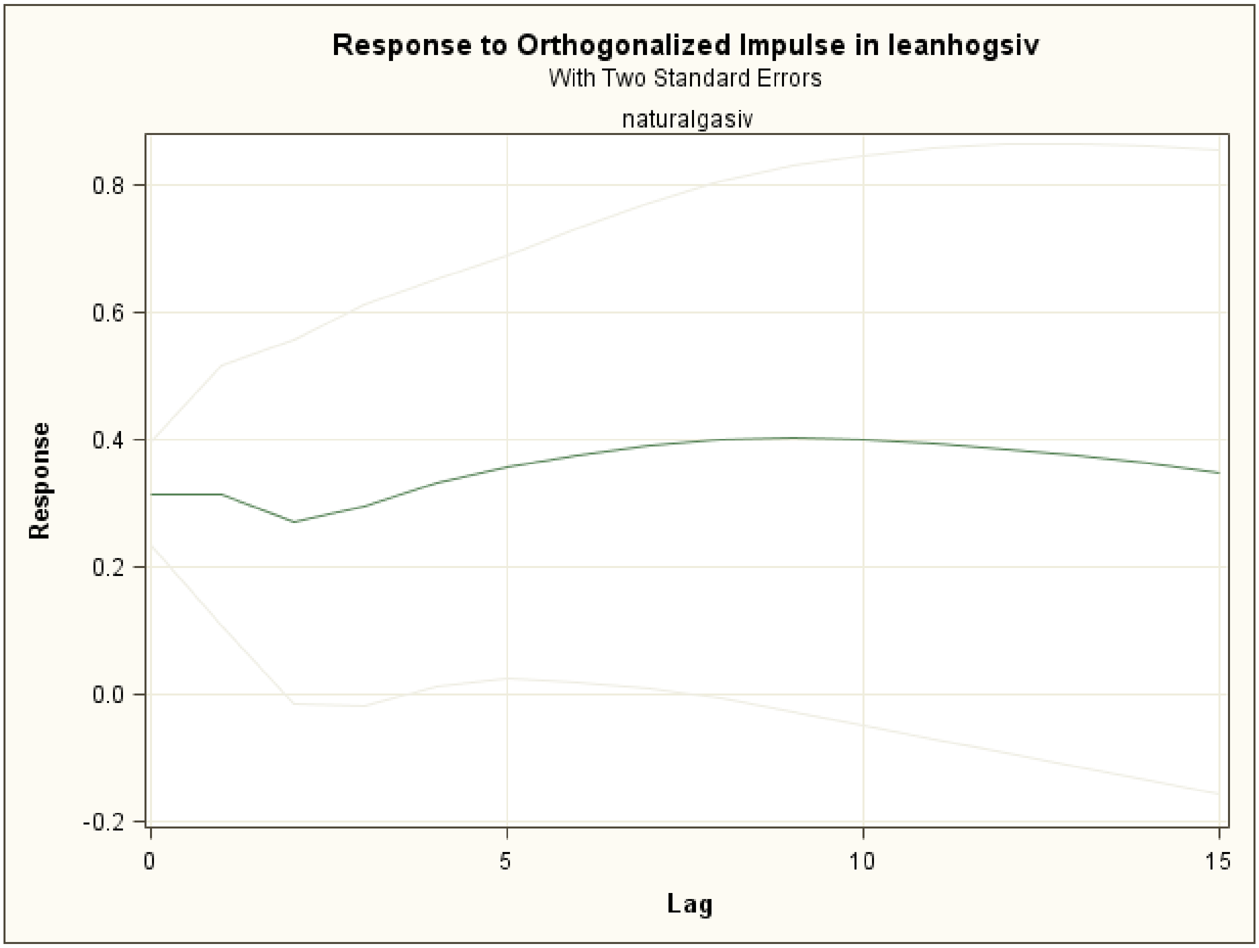
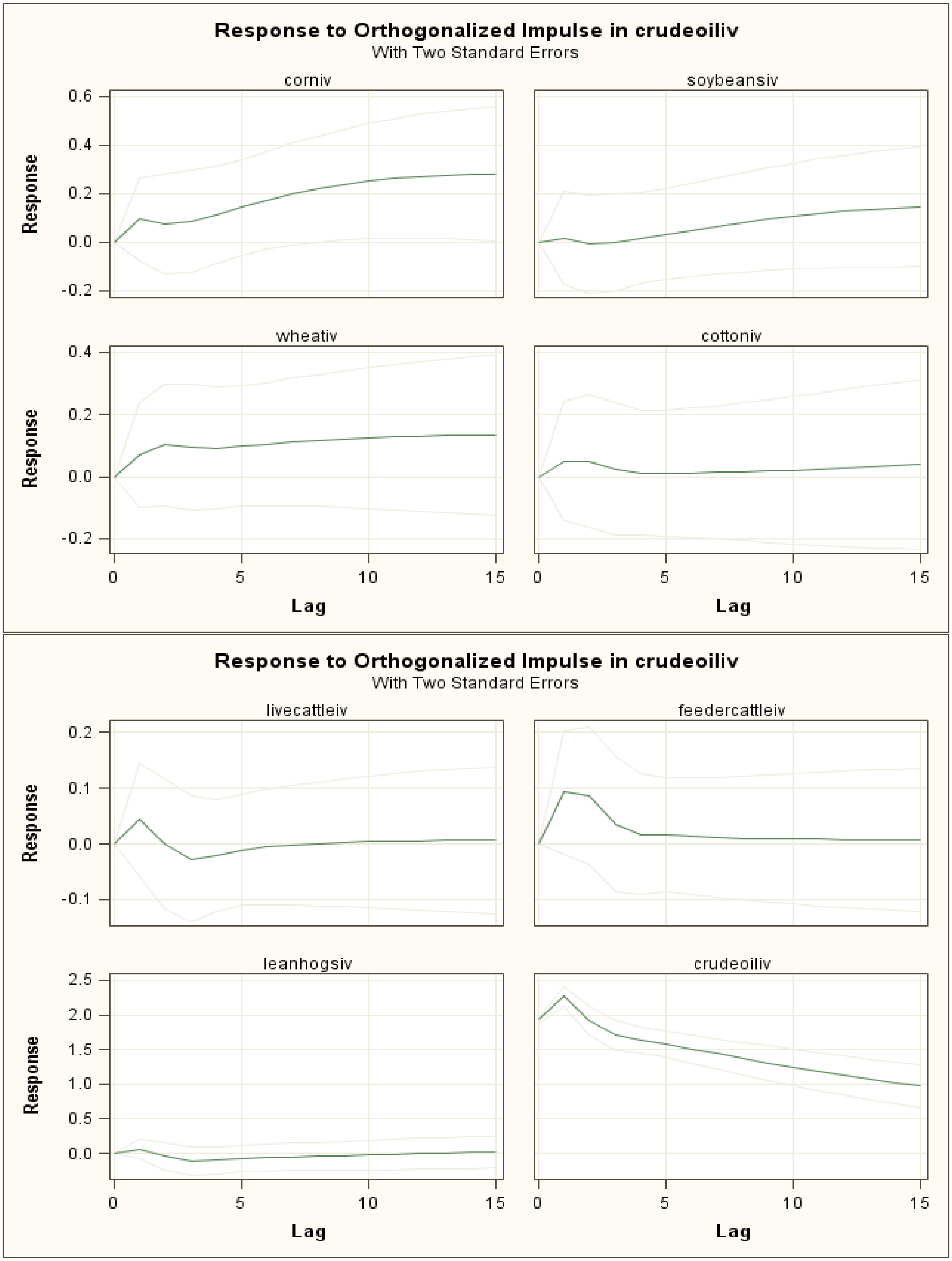
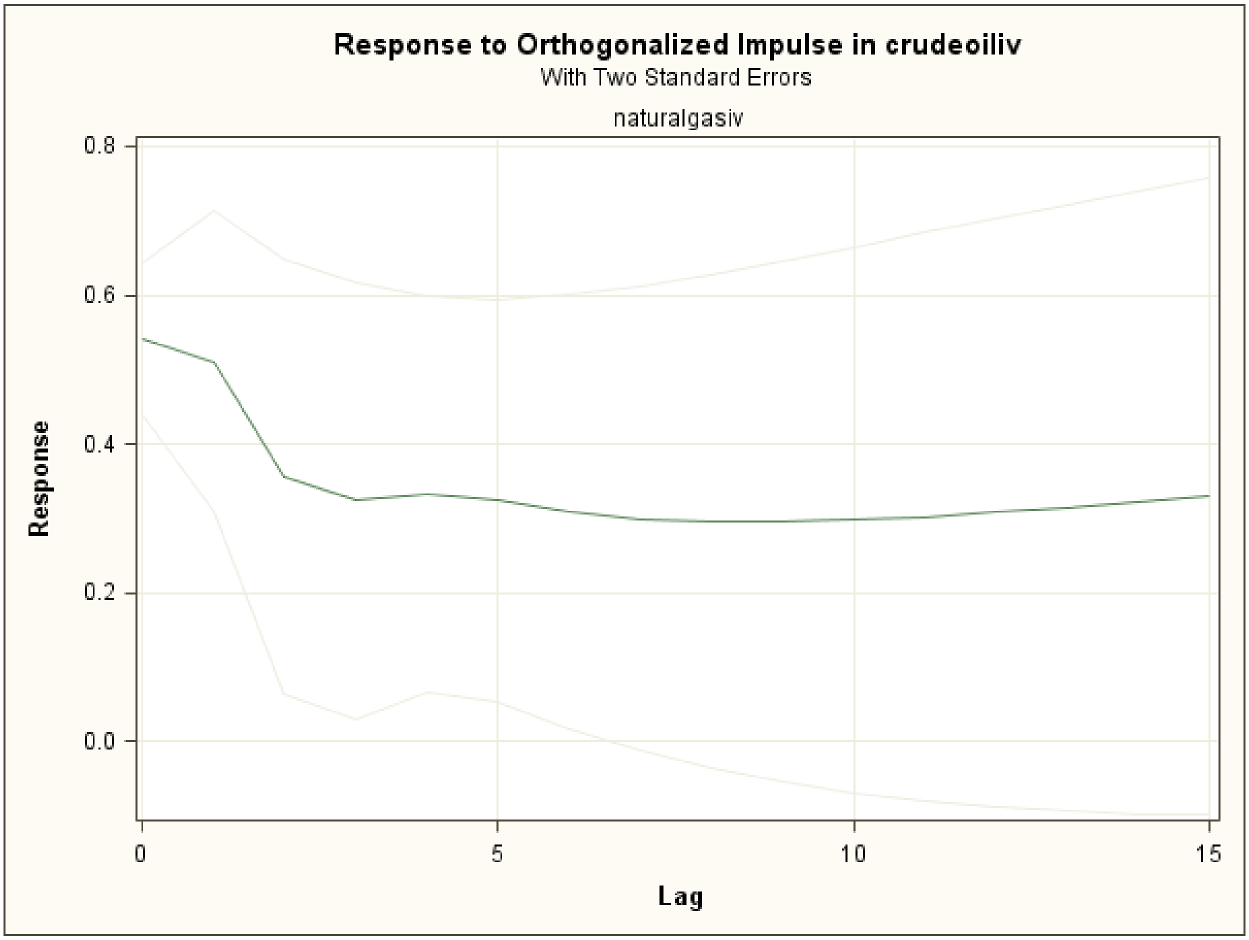

Response to Orthogonalized Impulse in leanhogsiv
With Two Standard Errors
naturalgasiv
0.8
0.6
0.4
0.2
0.0
-0.2
Response
0
5
10
15
Lag

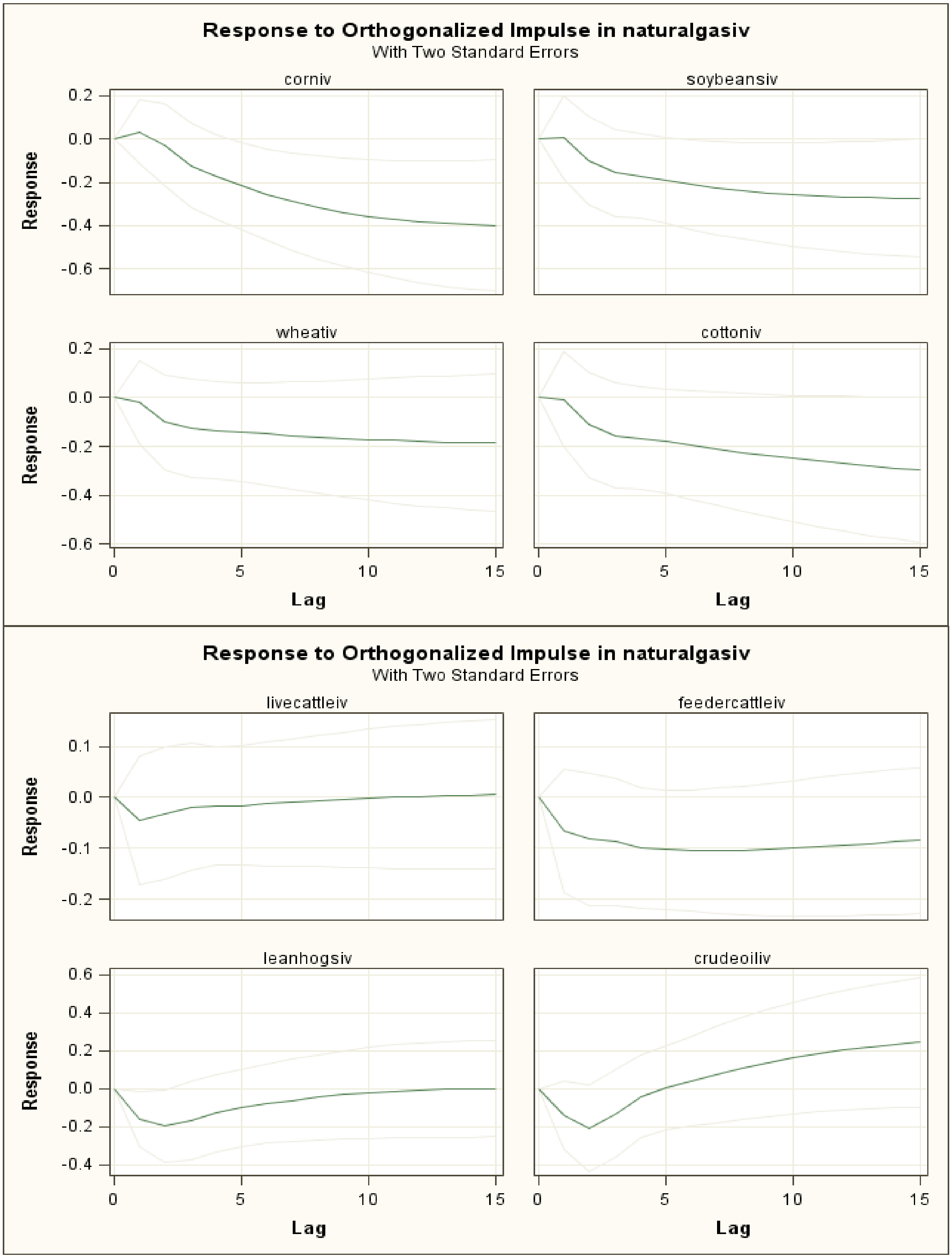
Figure A.8, IRFs for Crude Oil Volatility – Multivariate Model (1995-2012)

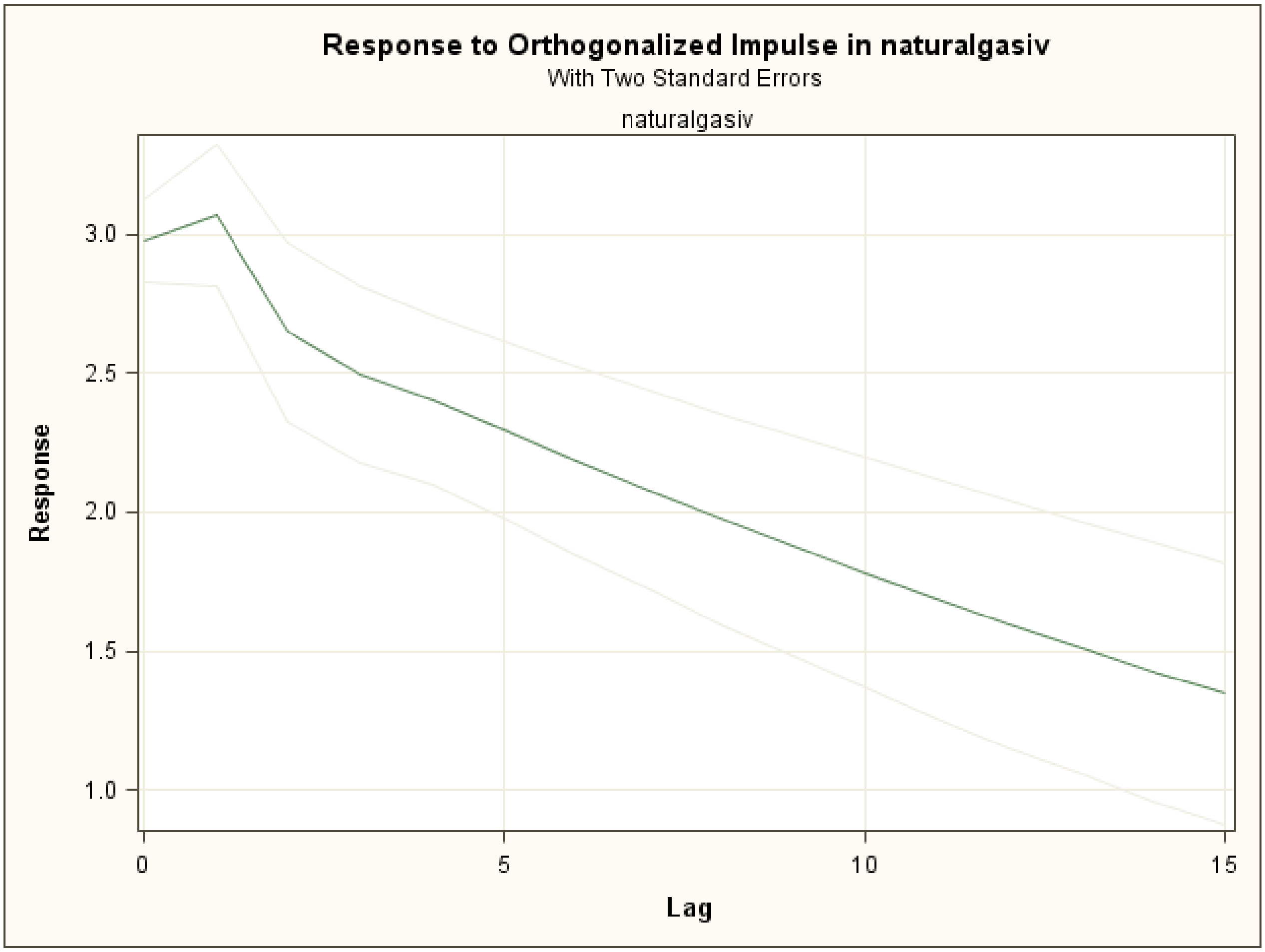




Response to Orthogonalized Impulse in crudeoiliv
With Two Standard Errors
naturalgasiv
Response
0.8
0.6
0.4
0.2
0.0
0
5
10
15
Lag

Figure A.9, IRFs for Natural Gas Volatility – Multivariate Model (1995-2012)





Response to Orthogonalized Impulse in naturalgasiv
With Two Standard Errors
naturalgasiv
Response
3.0
2.5
2.0
1.5
1.0
0
5
10
15
Lag

Appendix B - Impulse Response Functions for Bivariate VAR Model (1995-2012)

Figure B.1, IRFs for Corn and Soybeans Volatilities – Bivariate Model (1995-2012)

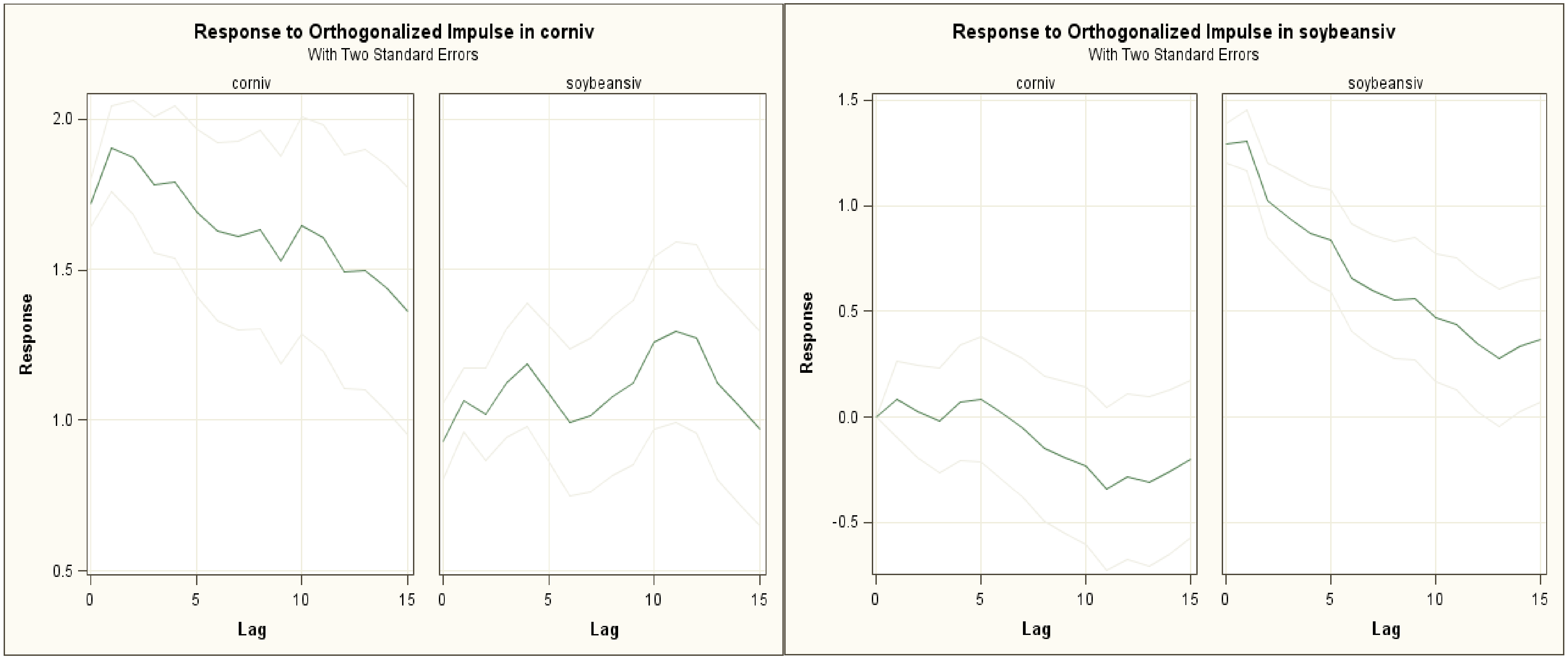


Figure B.2, IRFs for Corn and Wheat Volatilities – Bivariate Model (1995-2012)

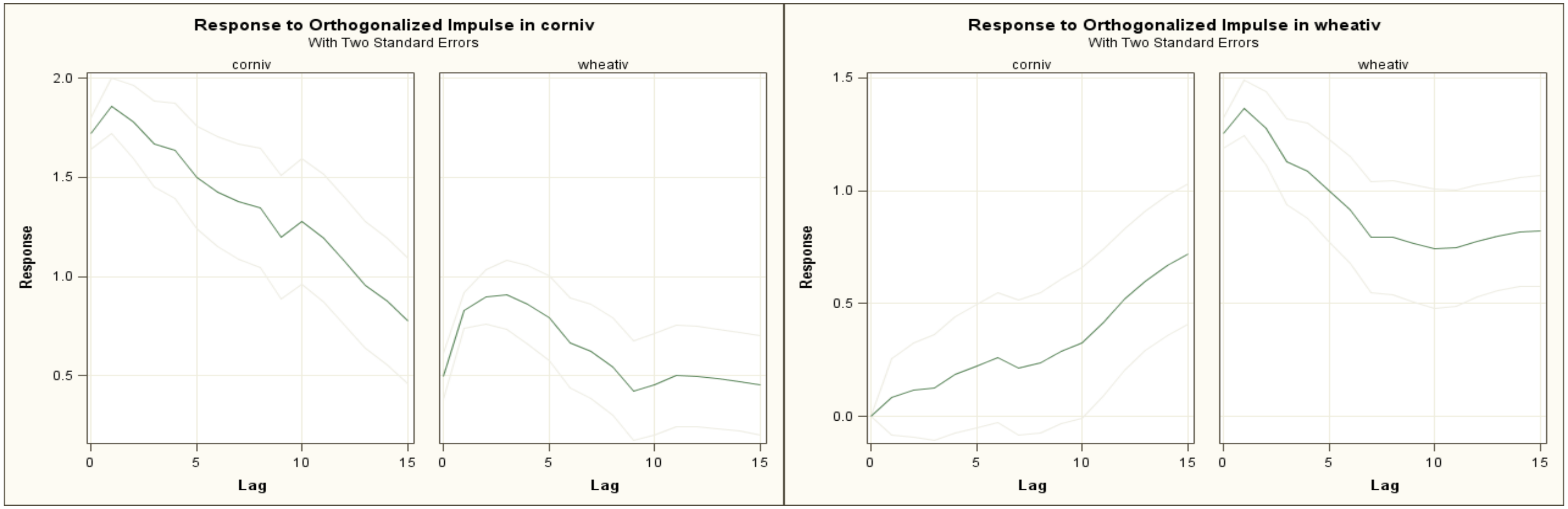


Figure B.3, IRFs for Corn and Cotton Volatilities – Bivariate Model (1995-2012)

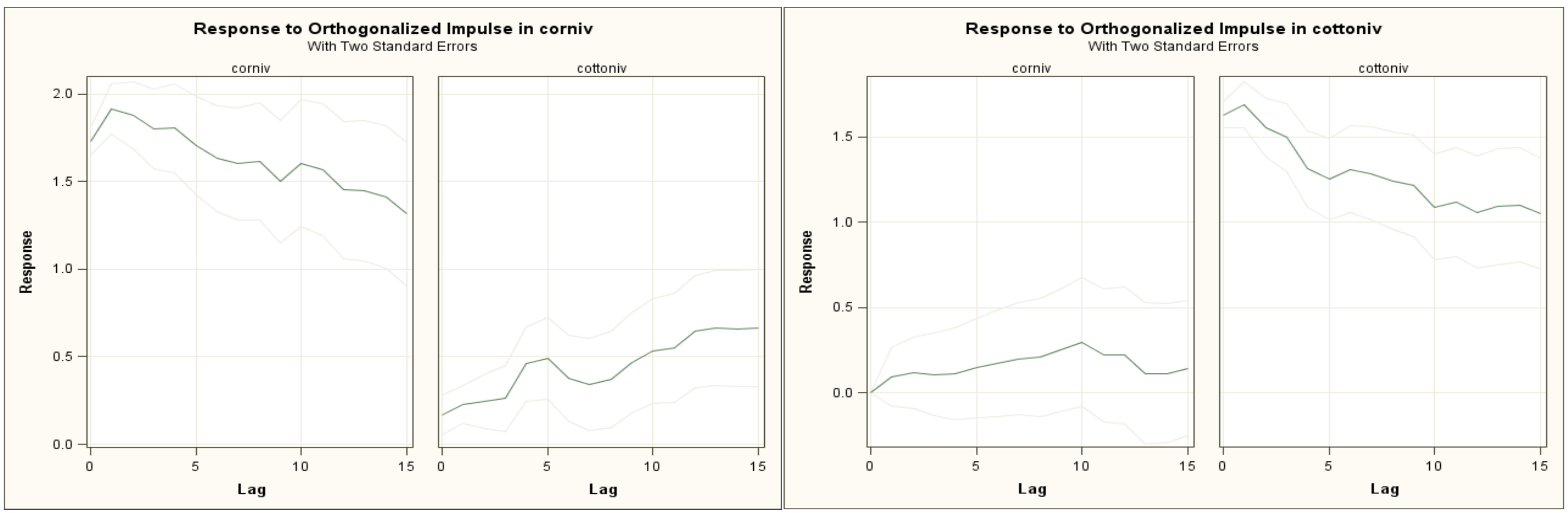


Figure B.4, IRFs for Corn and Live Cattle Volatilities – Bivariate Model (1995-2012)

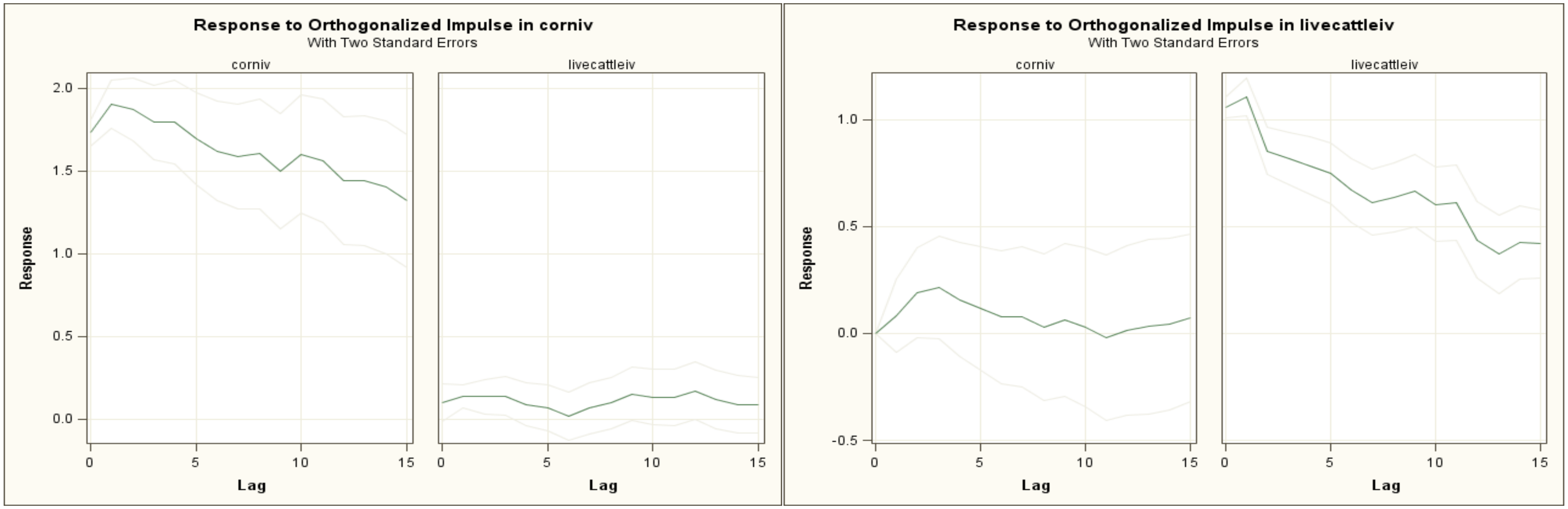


Figure B.5, IRFs for Corn and Feeder Cattle Volatilities – Bivariate Model (1995-2012)

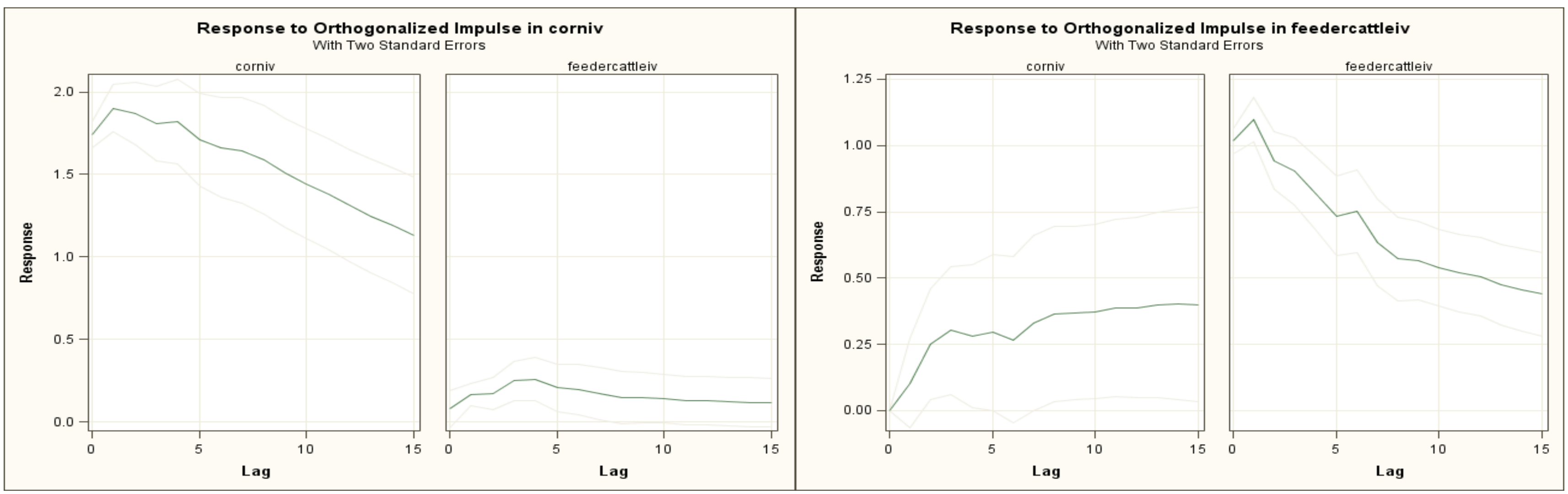


Figure B.6, IRFs for Corn and Lean Hogs Volatilities – Bivariate Model (1995-2012)

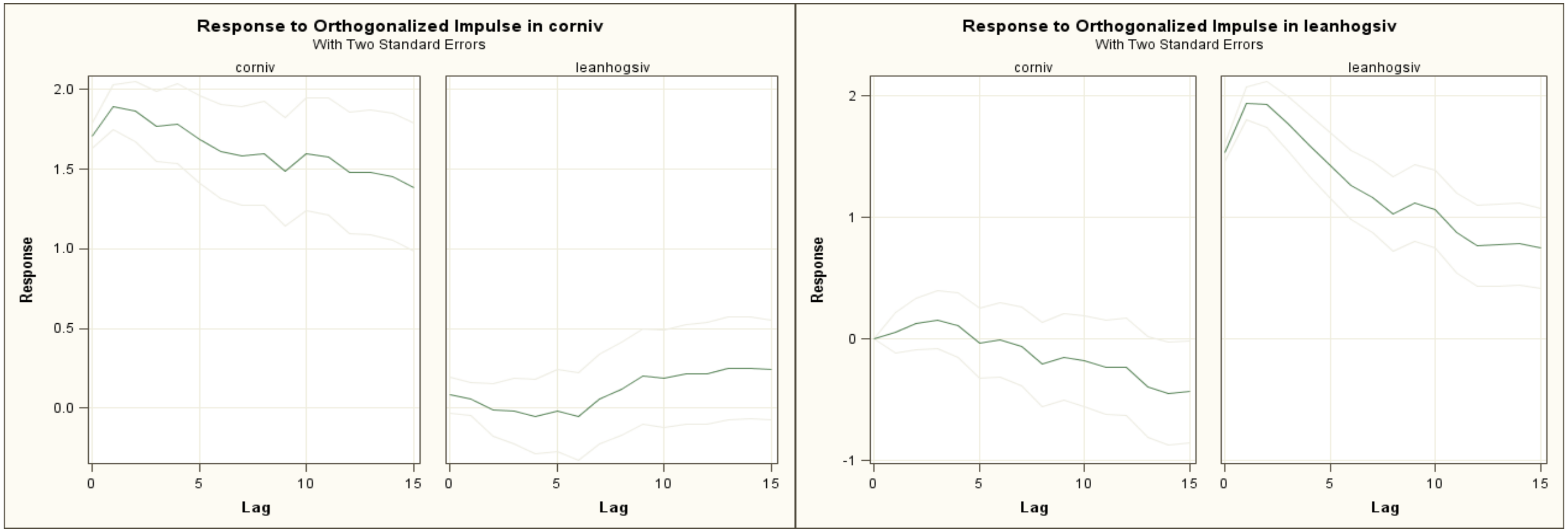


Figure B.7, IRFs for Corn and Crude Oil Volatilities – Bivariate Model (1995-2012)

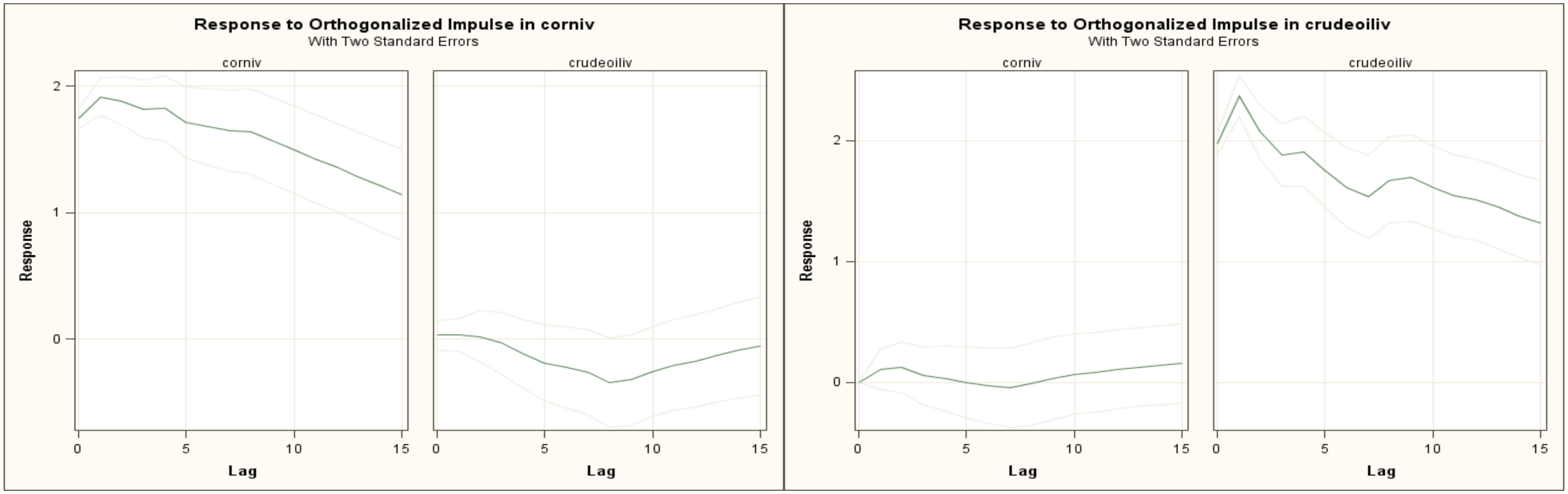


Figure B.8, IRFs for Corn and Natural Gas Volatilities – Bivariate Model (1995-2012)

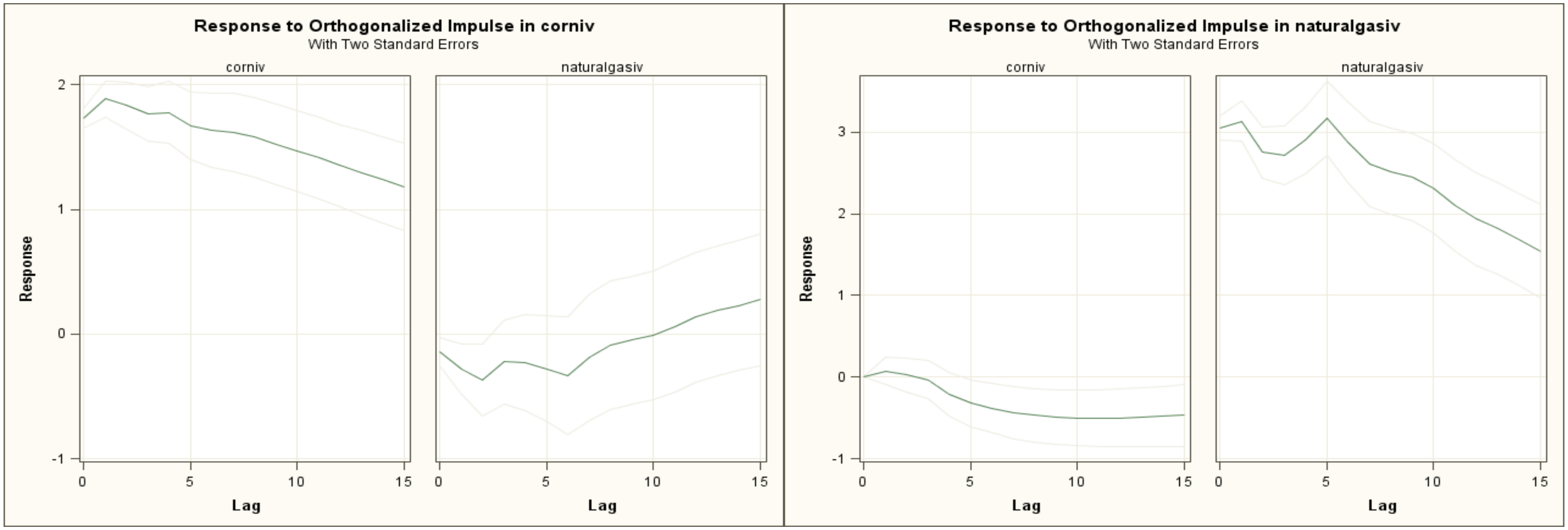


Figure B.9, IRFs for Soybeans and Wheat Volatilities – Bivariate Model (1995-2012)

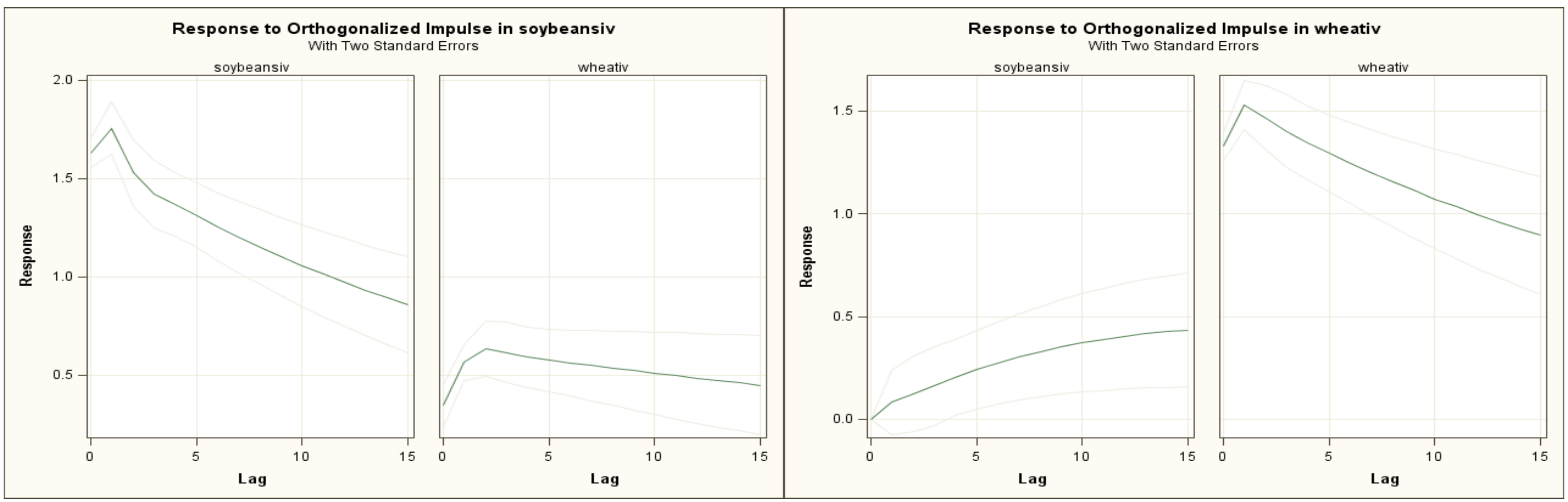


Figure B.10, IRFs for Soybeans and Cotton Volatilities – Bivariate Model (1995-2012)

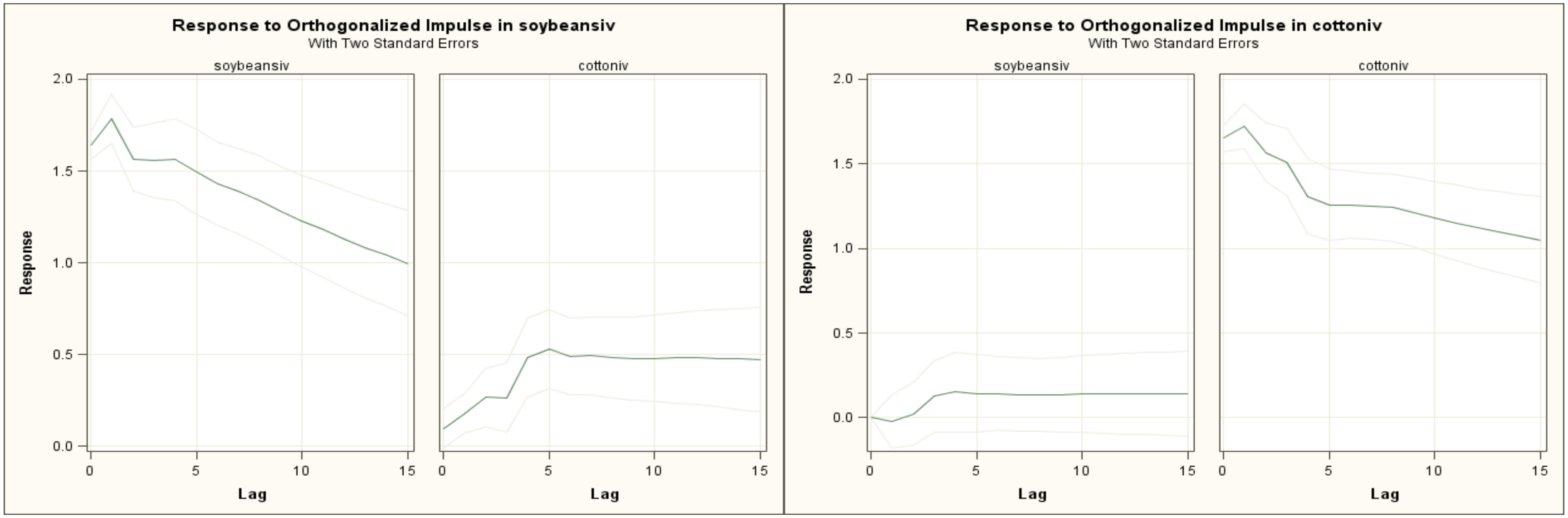


Figure B.11, IRFs for Soybeans and Live Cattle Volatilities – Bivariate Model (1995-2012)

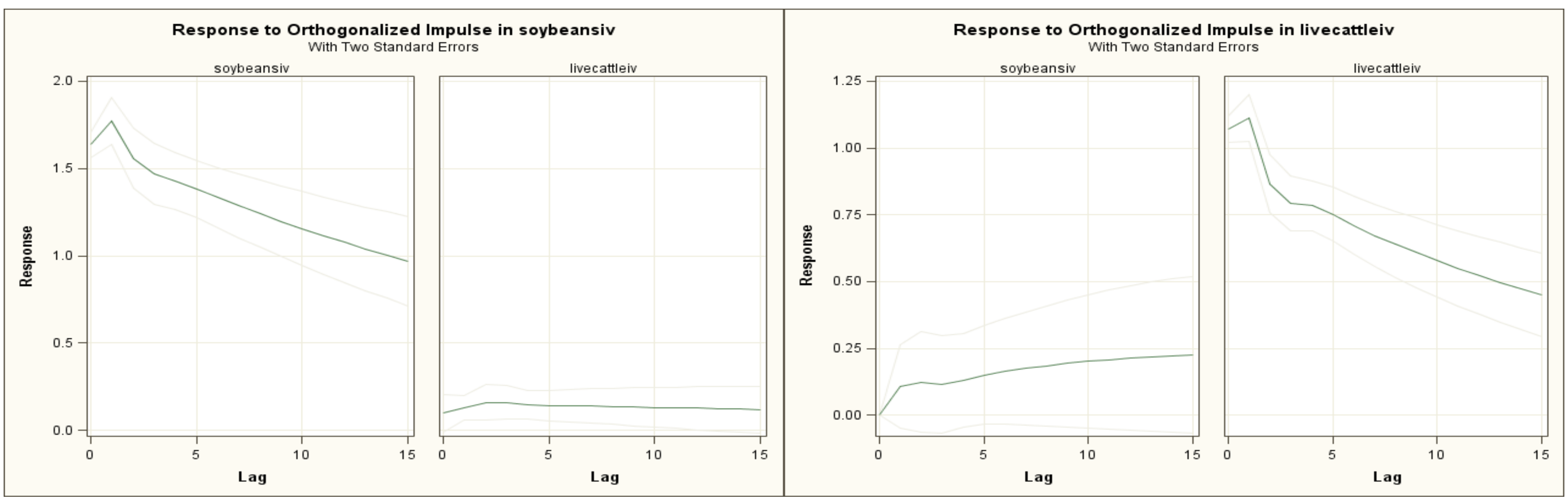


Figure B.12, IRFs for Soybeans and Feeder Cattle Volatilities – Bivariate Model (1995-2012)

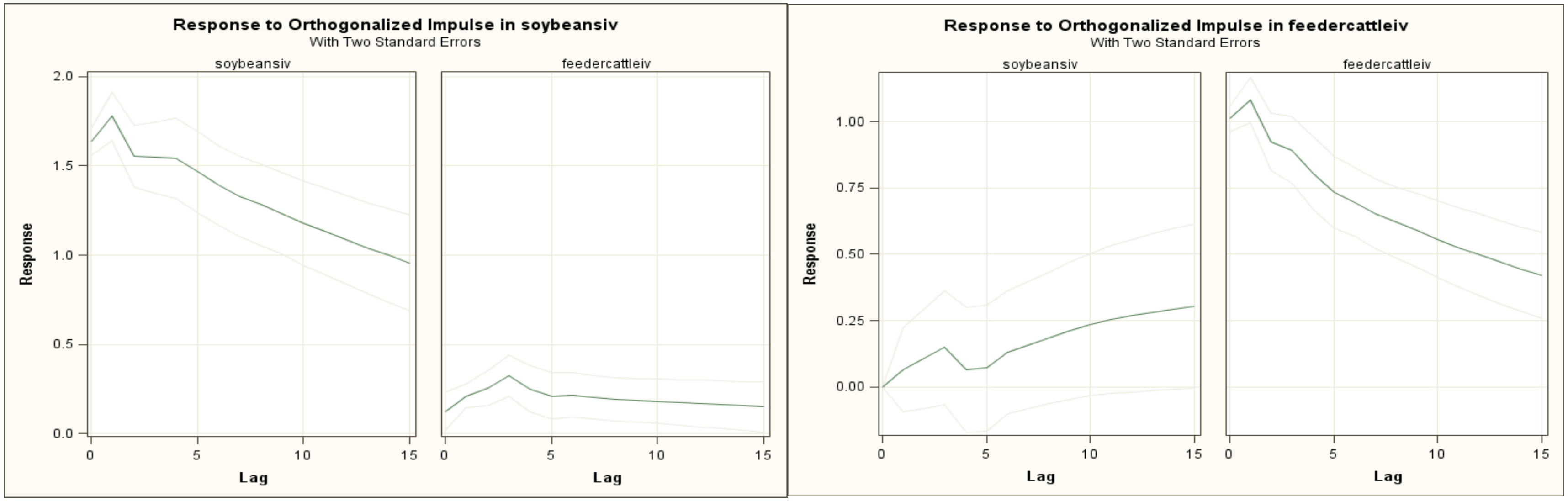


Figure B.13, IRFs for Soybeans and Lean Hogs Volatilities – Bivariate Model (1995-2012)

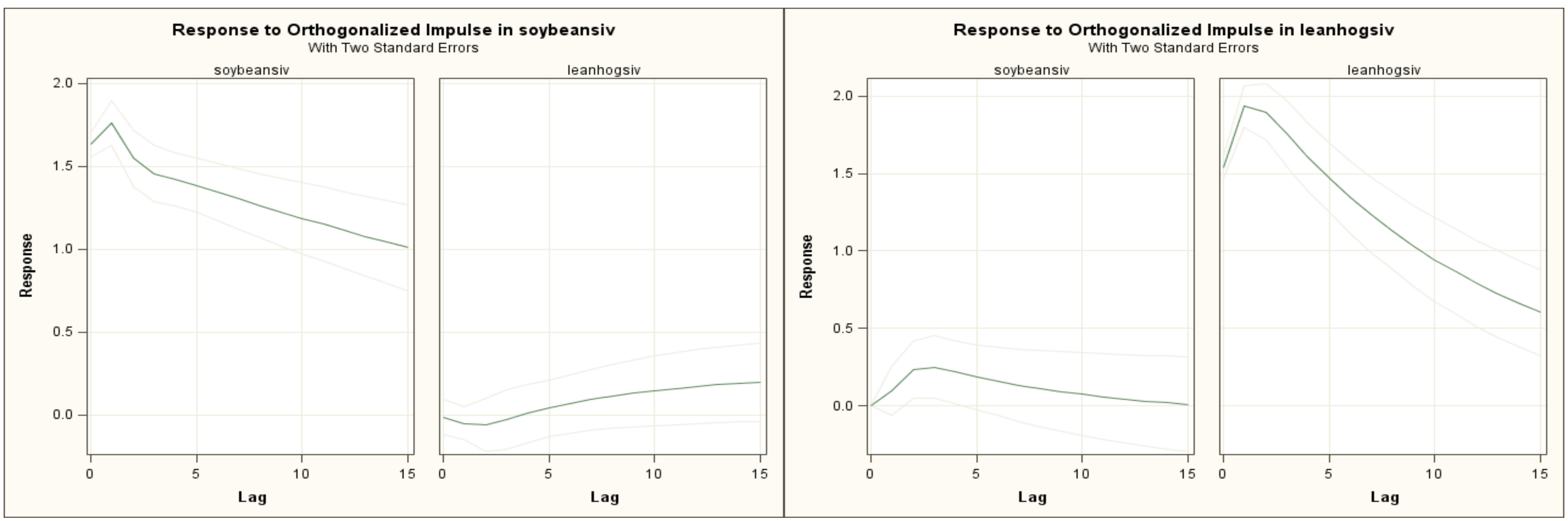


Figure B.14, IRFs for Soybeans and Crude Oil Volatilities – Bivariate Model (1995-2012)

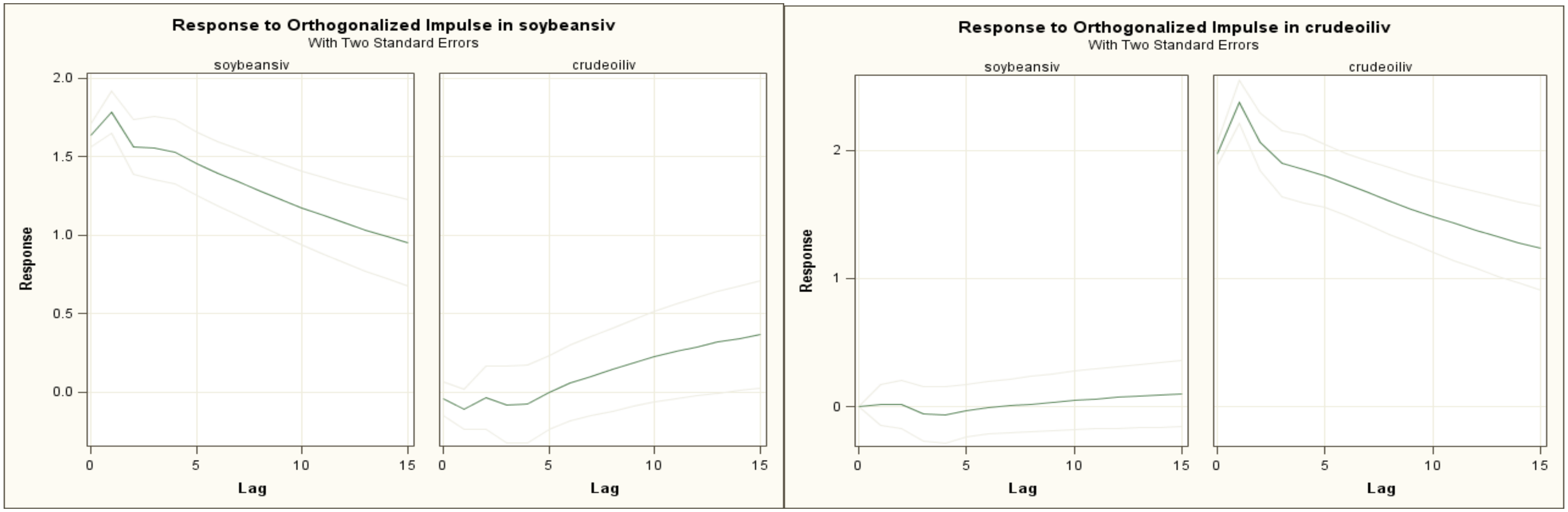


Figure B.15, IRFs for Soybeans and Natural Gas Volatilities – Bivariate Model (1995-2012)

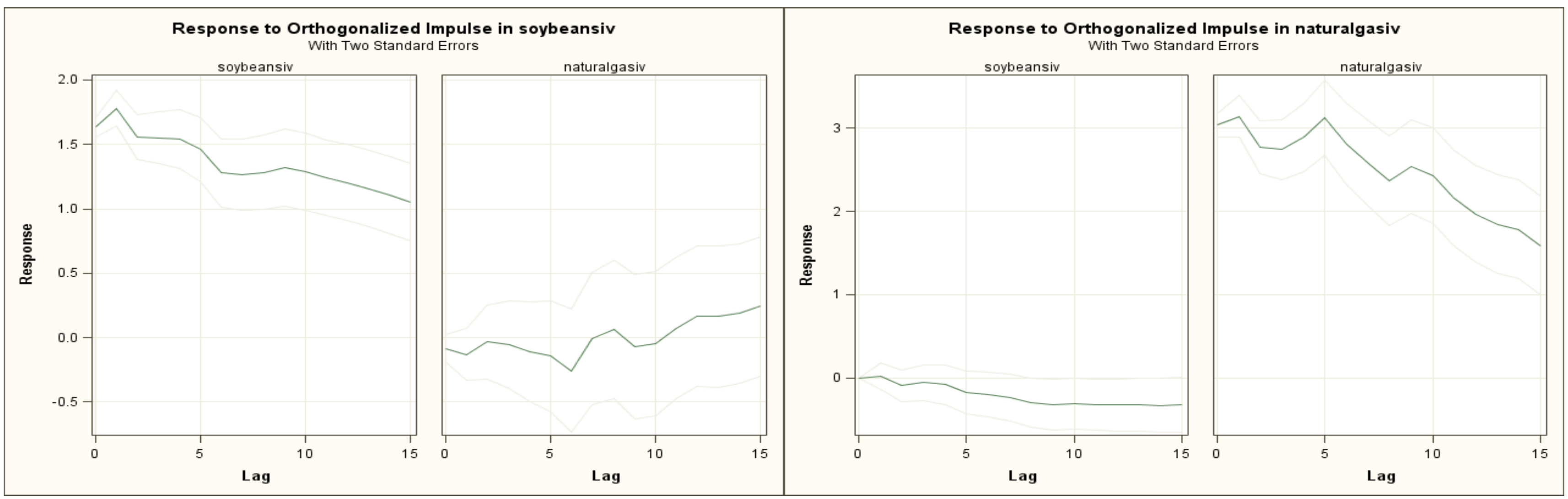


Figure B.16, IRFs for Wheat and Cotton Volatilities – Bivariate Model (1995-2012)

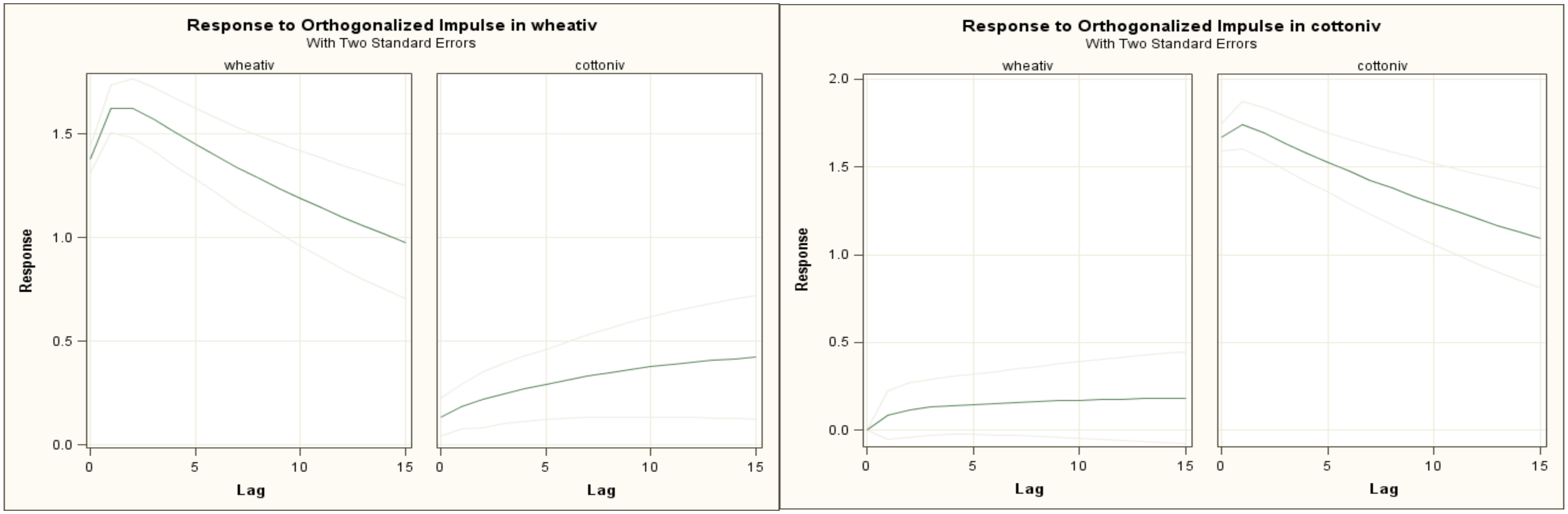


Figure B.17, IRFs for Wheat and Live Cattle Volatilities – Bivariate Model (1995-2012)

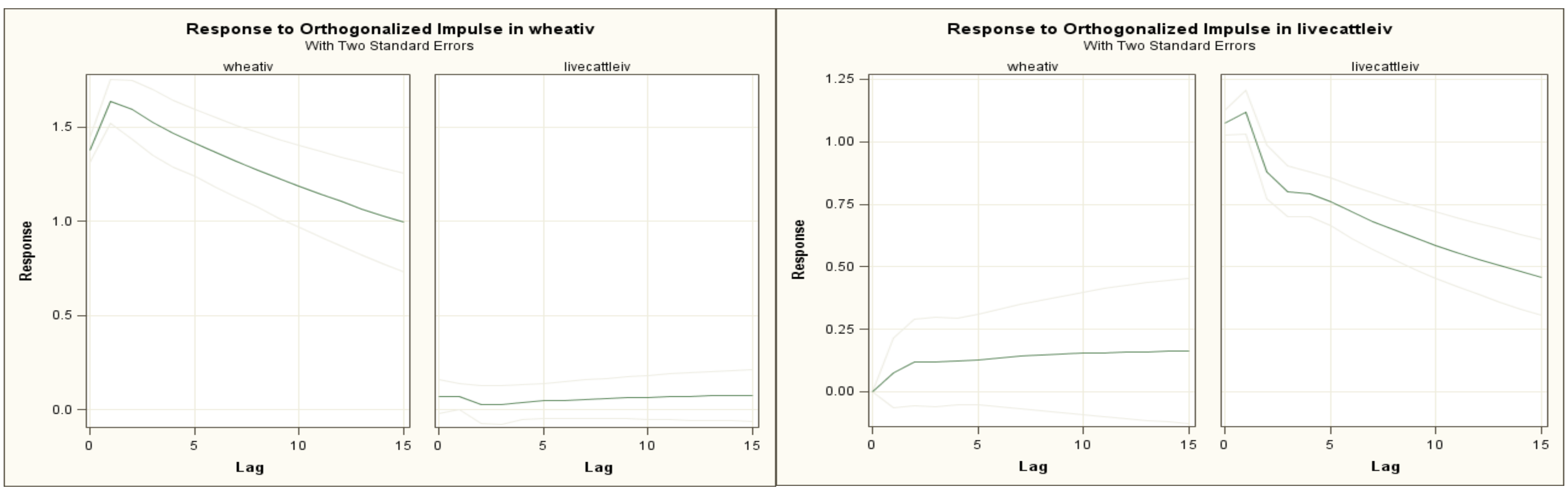


Figure B.18, IRFs for Wheat and Feeder Cattle Volatilities – Bivariate Model (1995-2012)

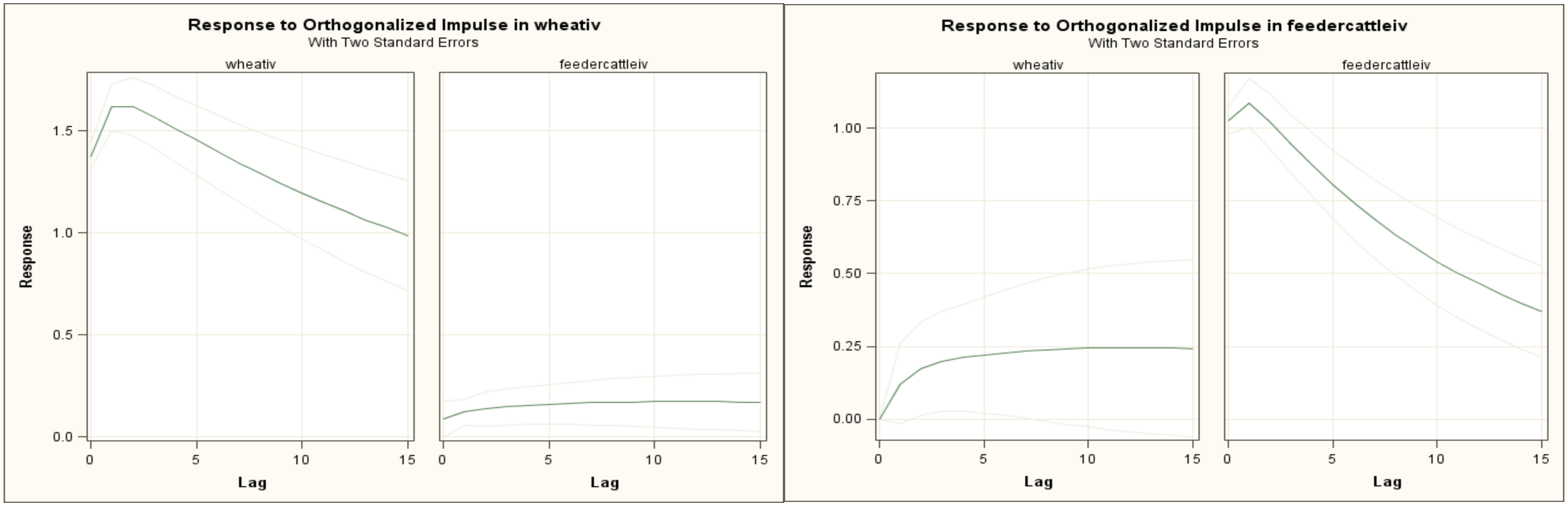


Figure B.19, IRFs for Wheat and Lean Hogs Volatilities – Bivariate Model (1995-2012)

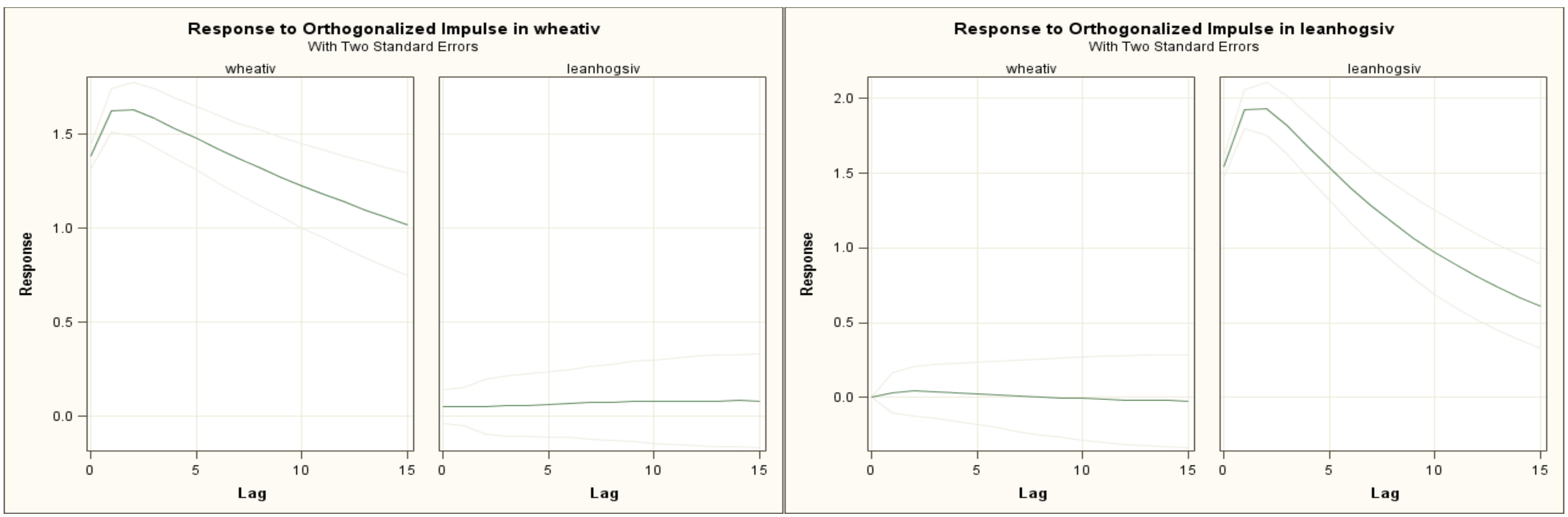


Figure B.20, IRFs for Wheat and Crude Oil Volatilities – Bivariate Model (1995-2012)

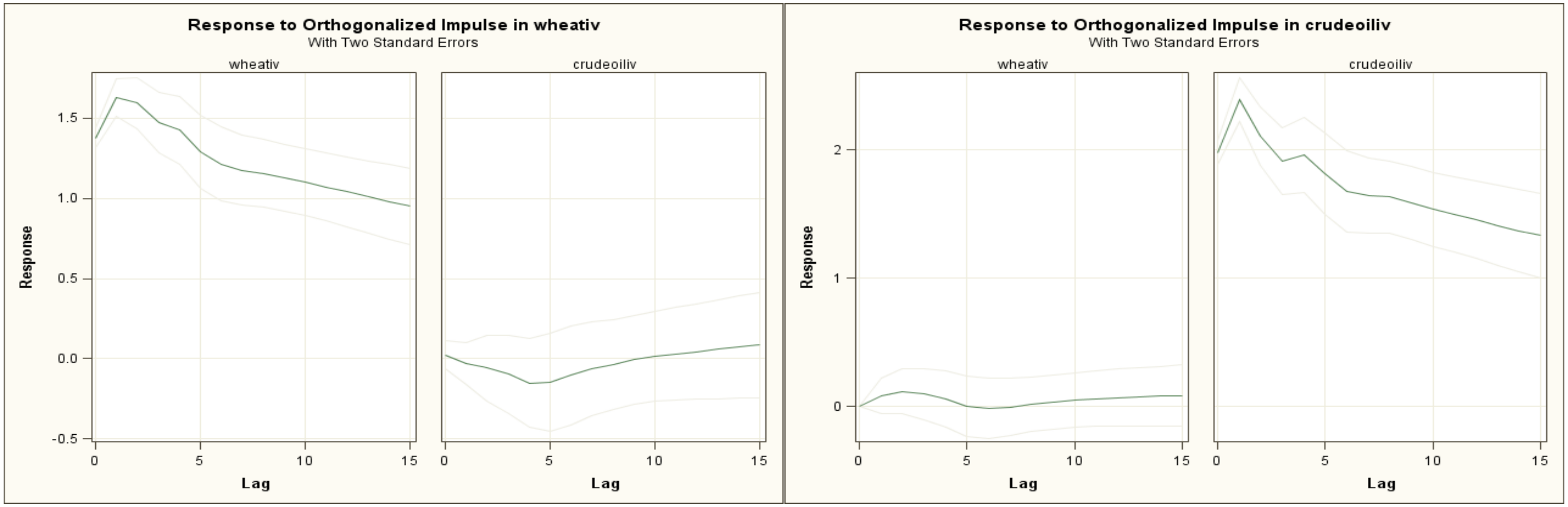


Figure B.21, IRFs for Wheat and Natural Gas Volatilities – Bivariate Model (1995-2012)

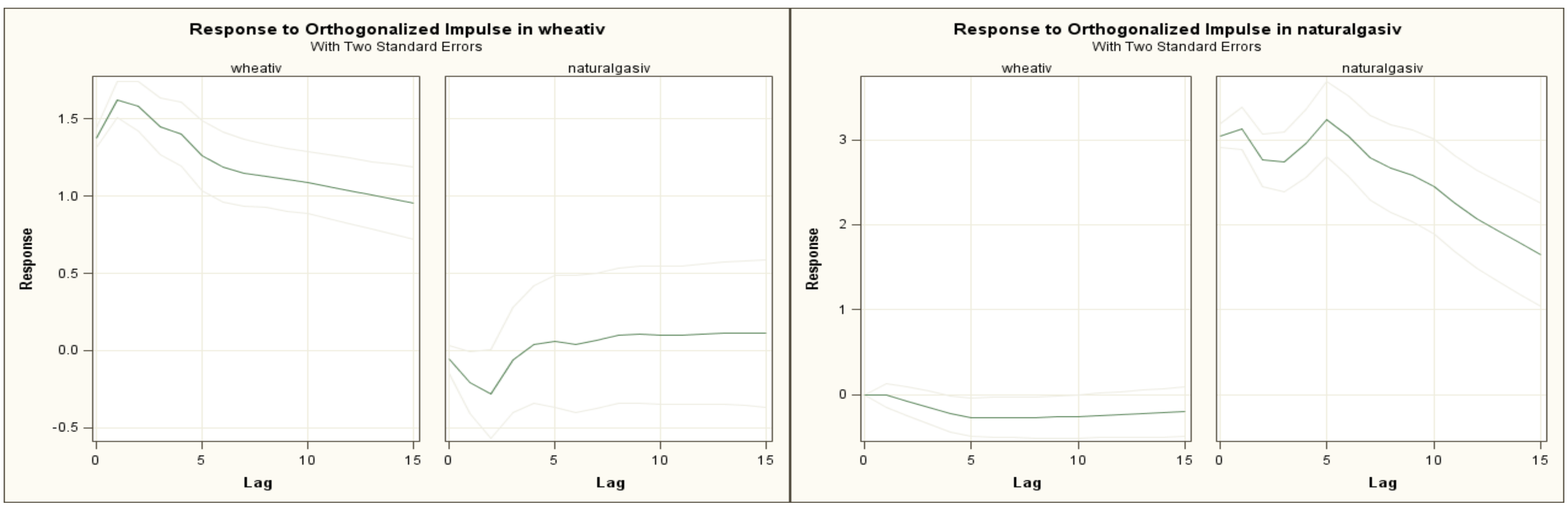


Figure B.22, IRFs for Cotton and Live Cattle Volatilities – Bivariate Model (1995-2012)

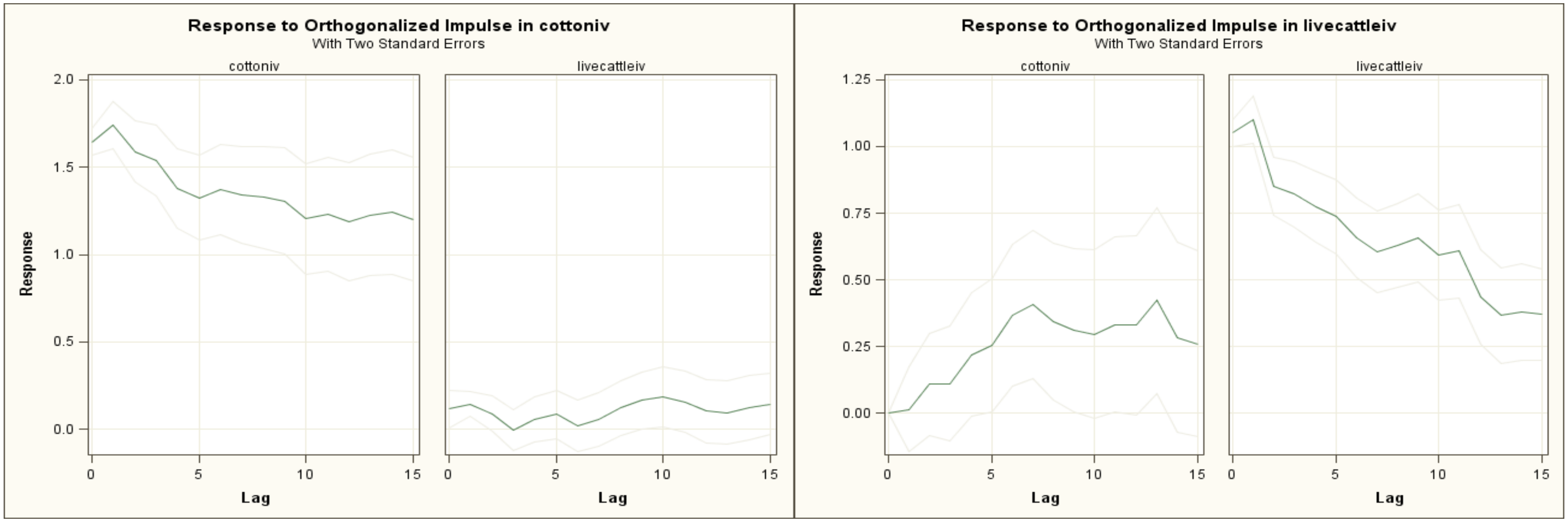


Figure B.23, IRFs for Cotton and Feeder Cattle Volatilities – Bivariate Model (1995-2012)

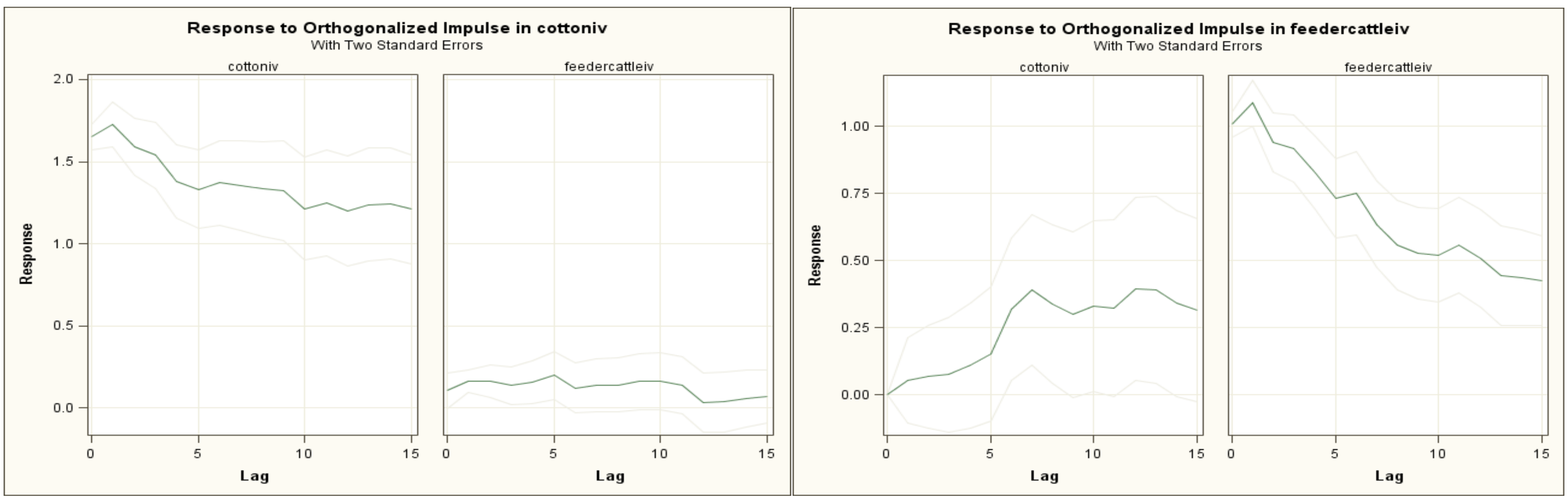
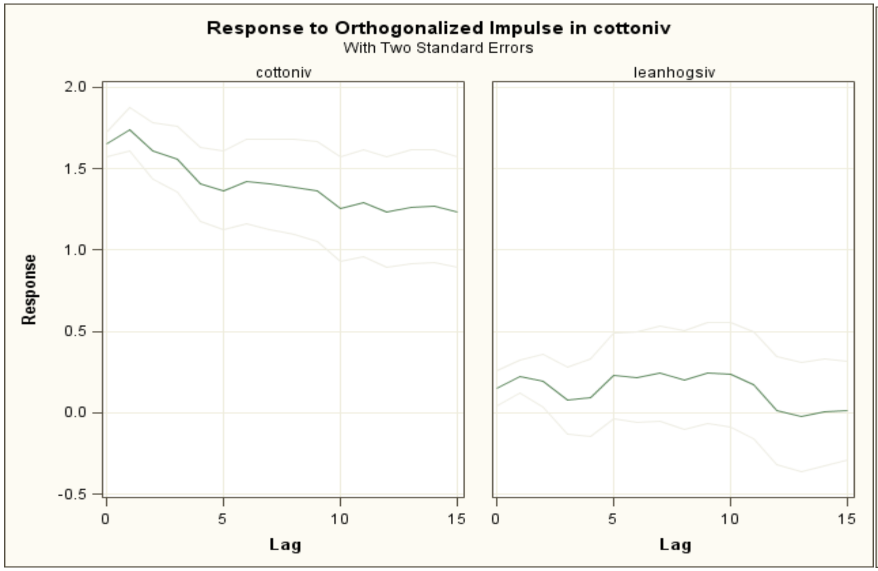


Figure B.24, IRFs for Cotton and Lean Hogs Volatilities – Bivariate Model (1995-2012)



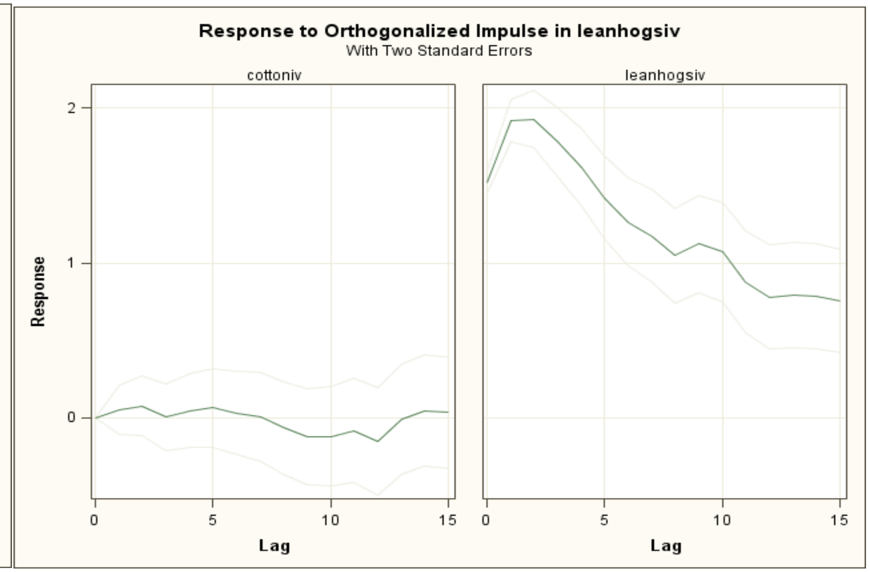
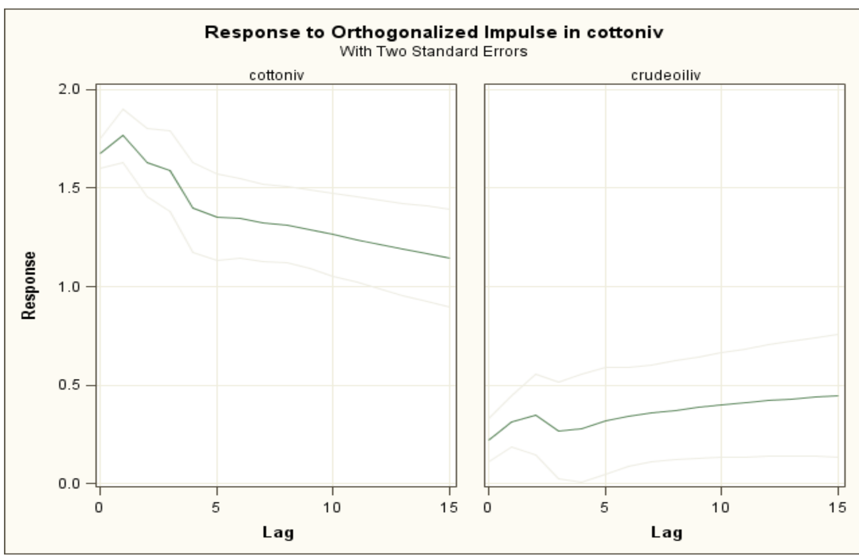


Figure B.25, IRFs for Cotton and Crude Oil Volatilities – Bivariate Model (1995-2012)



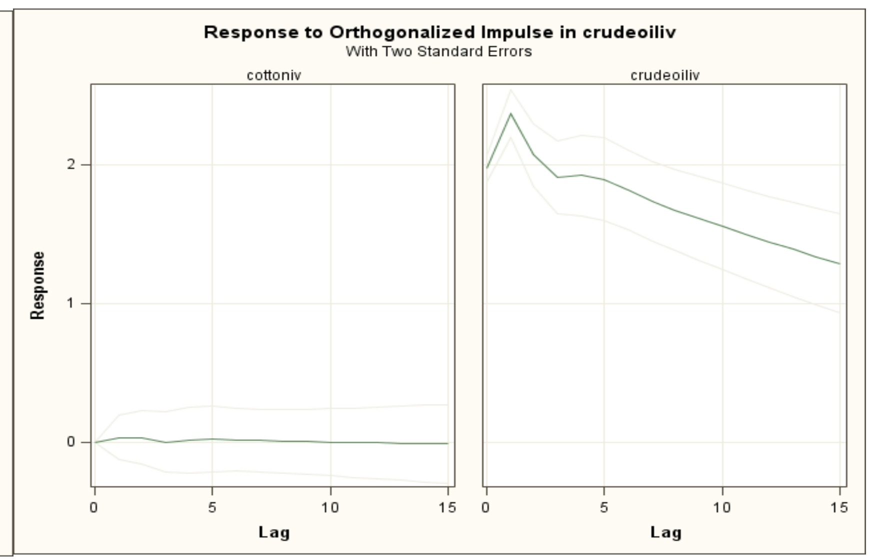


Figure B.26, IRFs for Cotton and Natural Gas Volatilities – Bivariate Model (1995-2012)

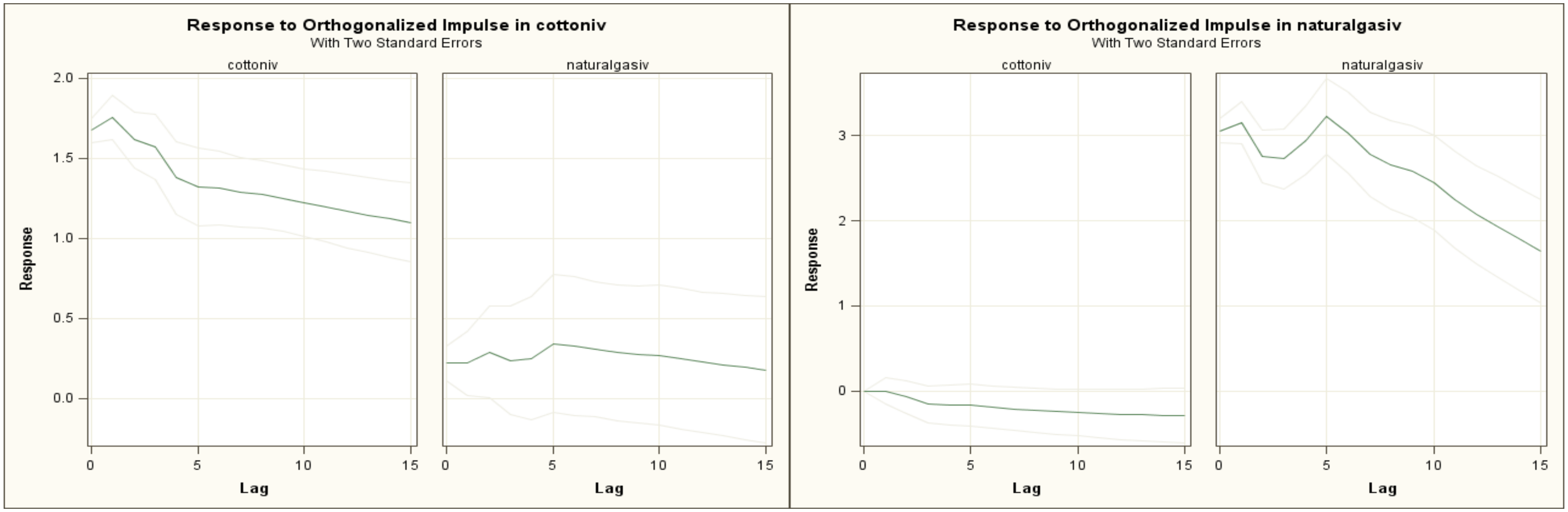


Figure B.27, IRFs for Live Cattle and Feeder Cattle Volatilities – Bivariate Model (1995-2012)

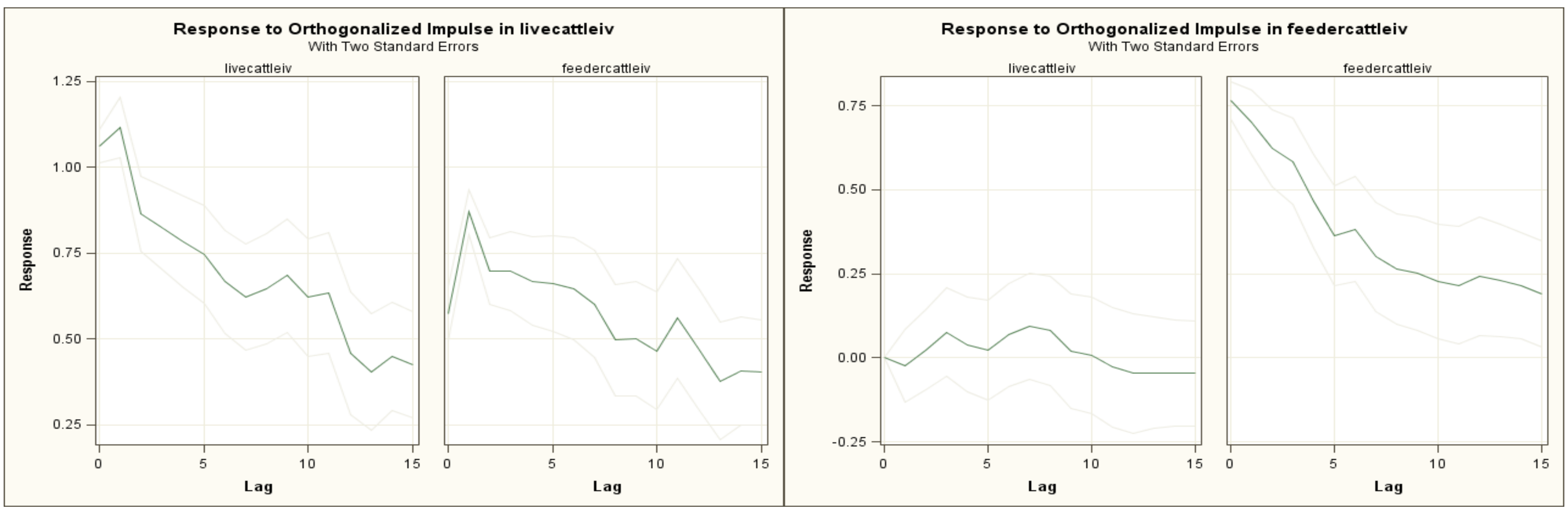


Figure B.28, IRFs for Live Cattle and Lean Hogs Volatilities – Bivariate Model (1995-2012)

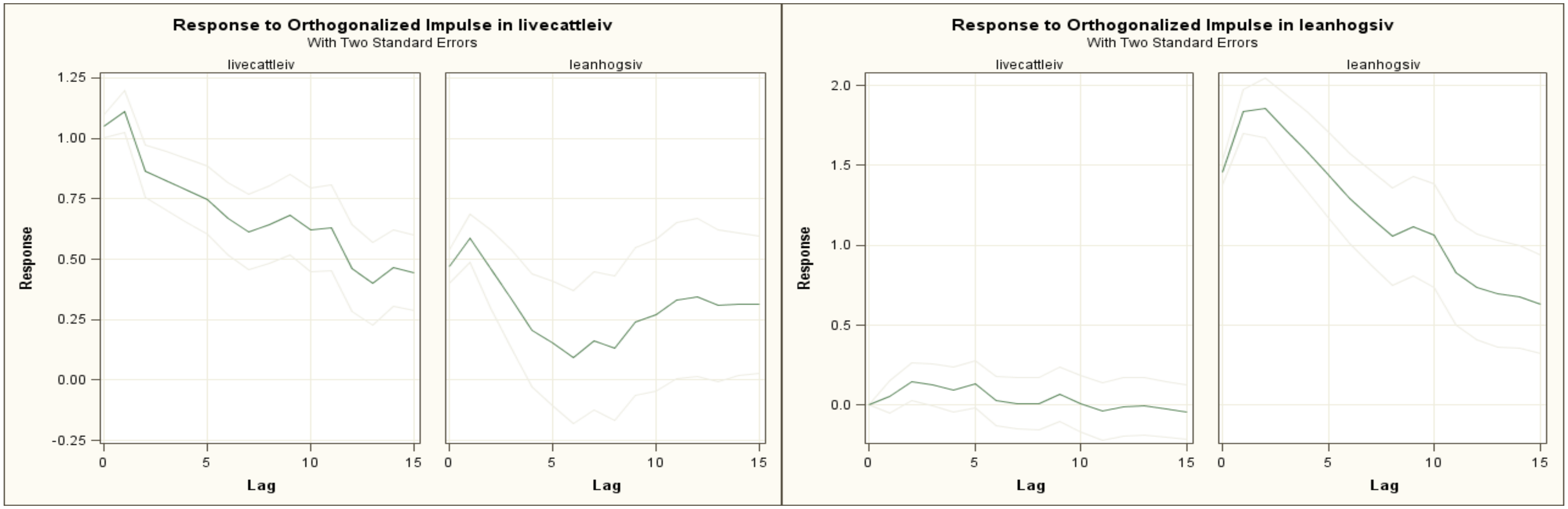


Figure B.29, IRFs for Live Cattle and Crude Oil Volatilities – Bivariate Model (1995-2012)

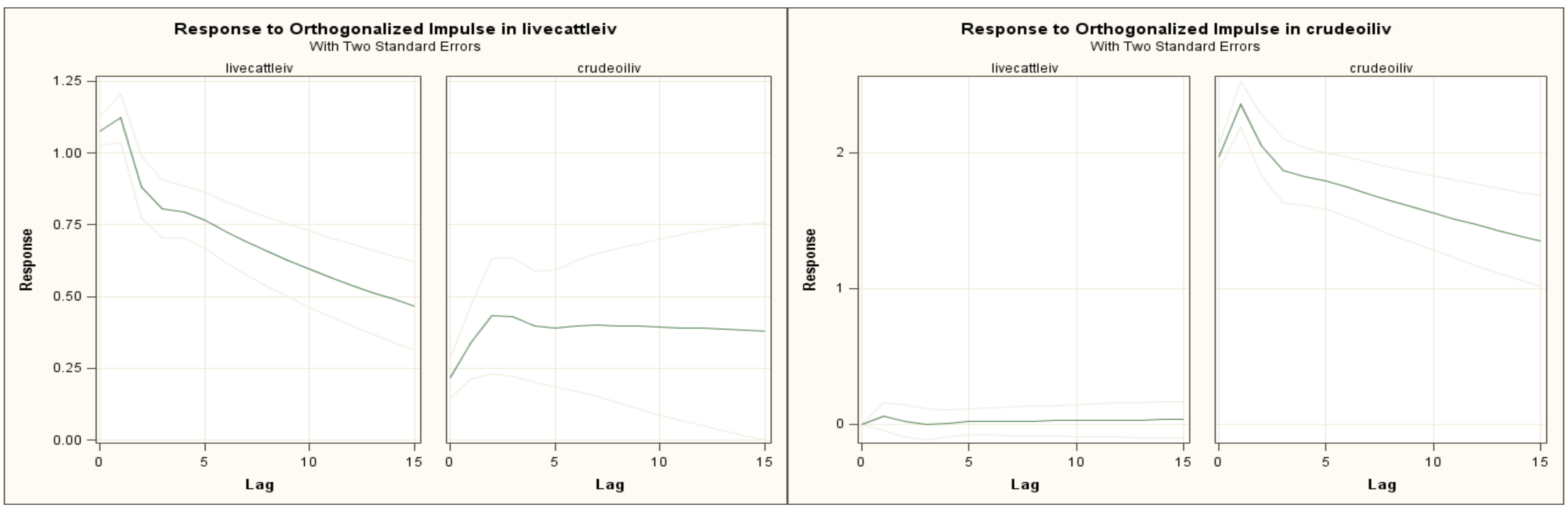


Figure B.30, IRFs for Live Cattle and Natural Gas Volatilities – Bivariate Model (1995-2012)

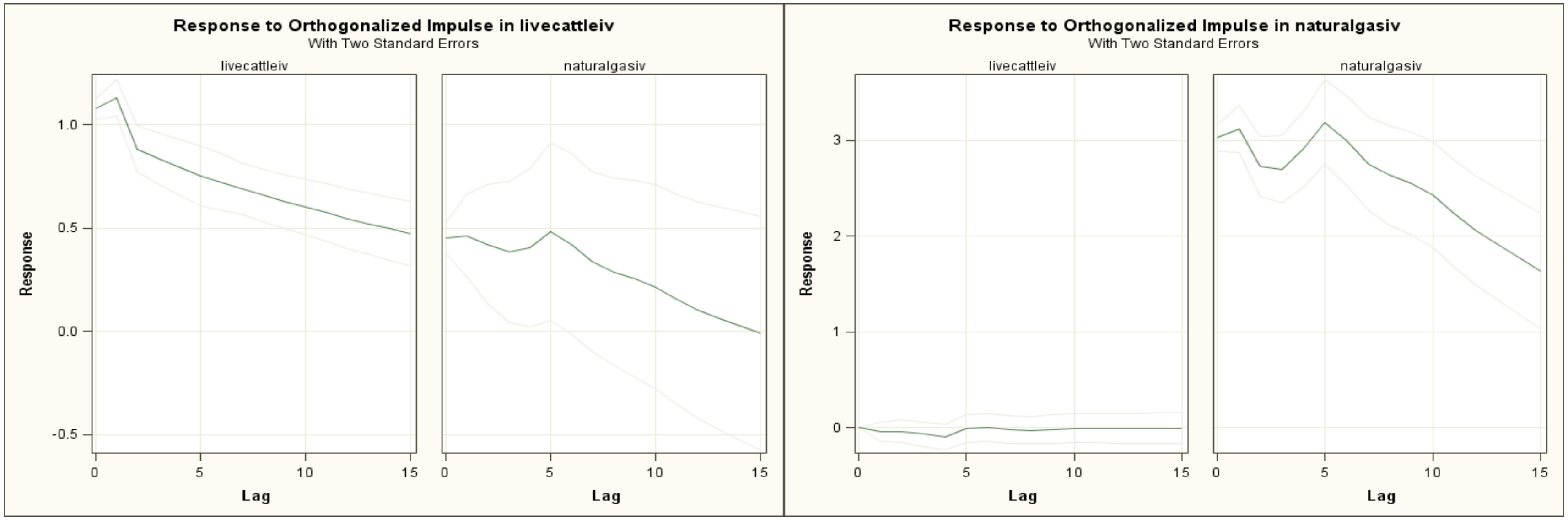


Figure B.31, IRFs for Feeder Cattle and Lean Hogs Volatilities – Bivariate Model (1995-2012)

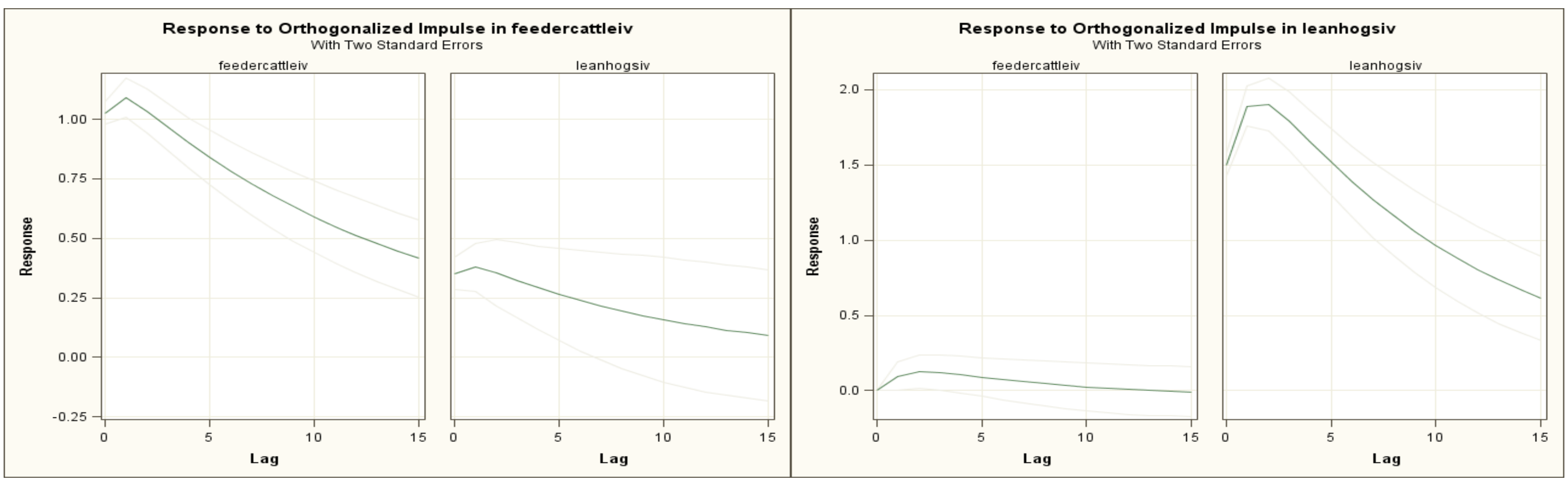


Figure B.32, IRFs for Feeder Cattle and Crude Oil Volatilities – Bivariate Model (1995-2012)

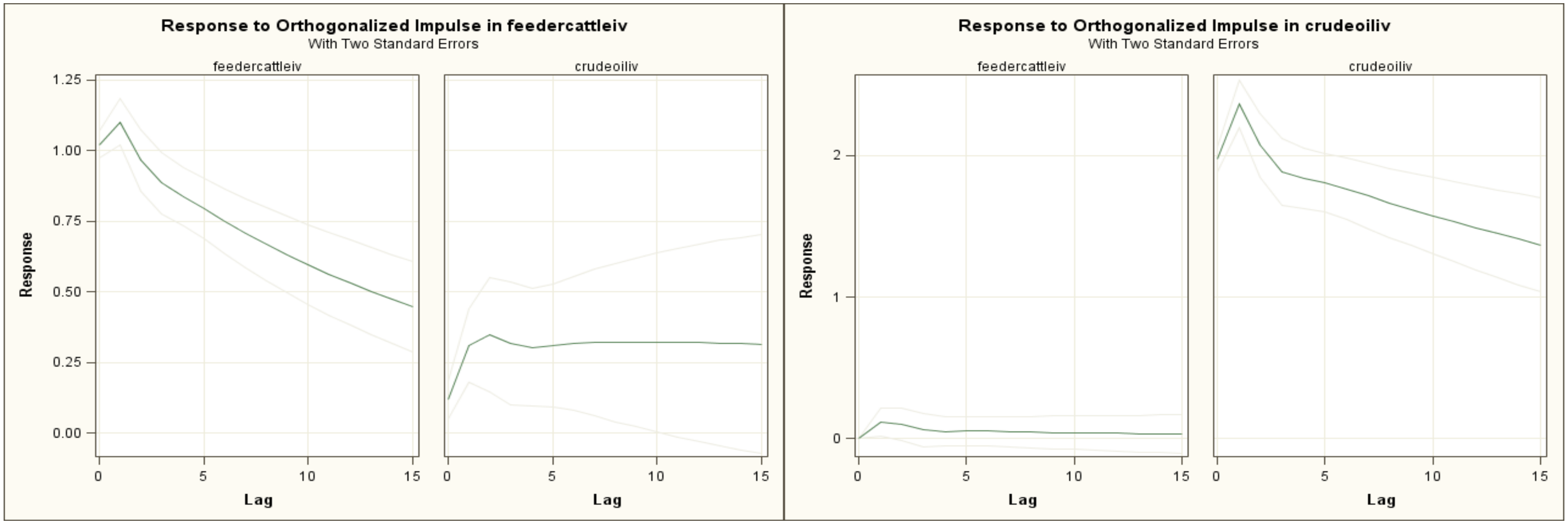


Figure B.33, IRFs for Feeder Cattle and Natural Gas Volatilities – Bivariate Model (1995-2012)

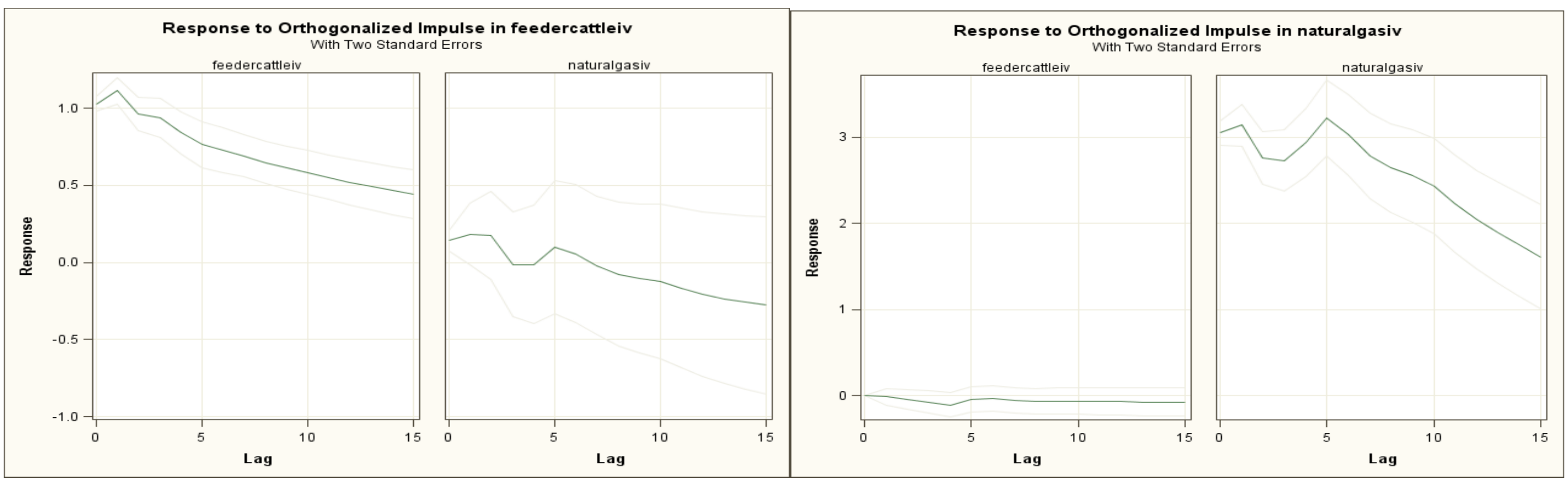


Figure B.34, IRFs for Lean Hogs and Crude Oil Volatilities – Bivariate Model (1995-2012)

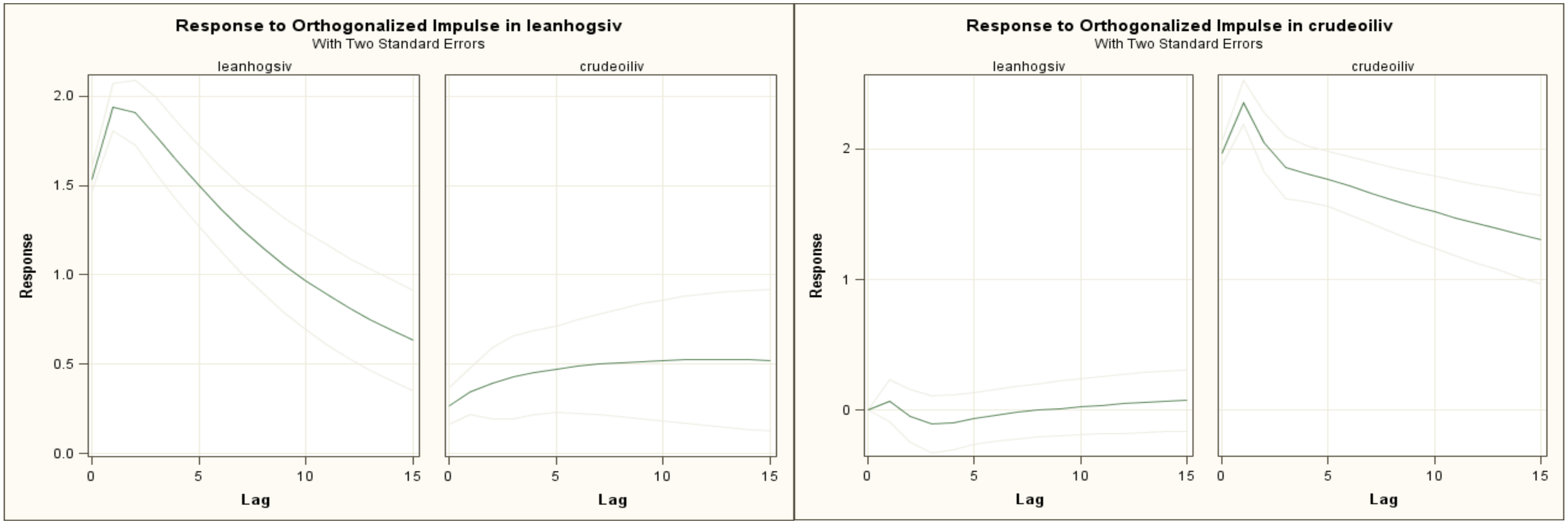


Figure B.35, IRFs for Lean Hogs and Natural Gas Volatilities – Bivariate Model (1995-2012)

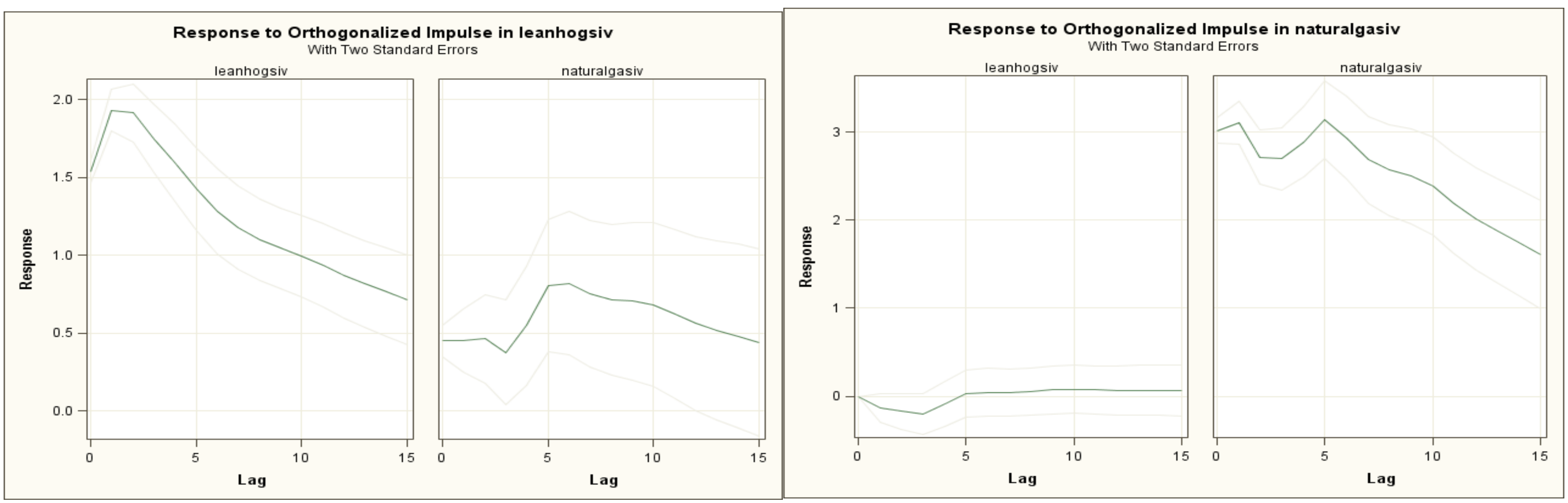


Figure B.36, IRFs for Crude Oil and Natural Gas Volatilities – Bivariate Model (1995-2012)